Sonoma Technology

Bridging the Gap between Fire Weather Research and Use in Operations

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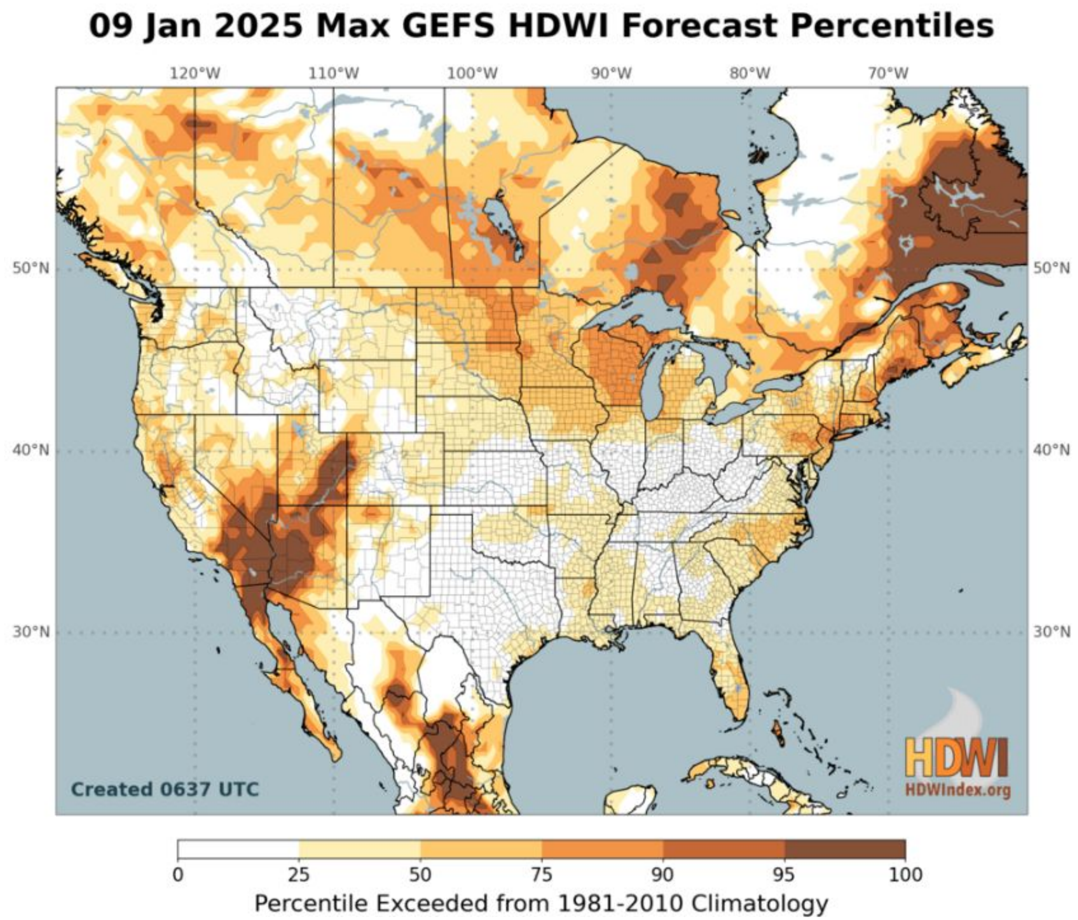
Background

- Fire weather indices, such as the Hot-Dry-Windy Index (HDWI),[1] are regularly used in wildfire operations to guide resource allocation and ensure safe and effective management.
- These metrics are limited by spatial and temporal resolution and are often lacking in formal verification.
- *New* Unified Forecast System Mid-Range Forecast (UFS S2S) prototypes forecast atmospheric conditions through four weeks.

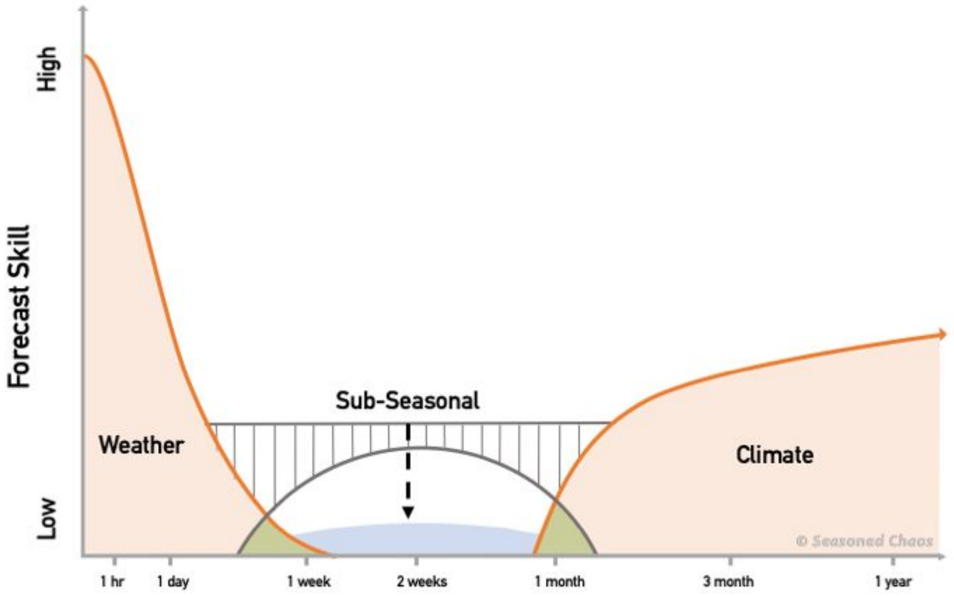


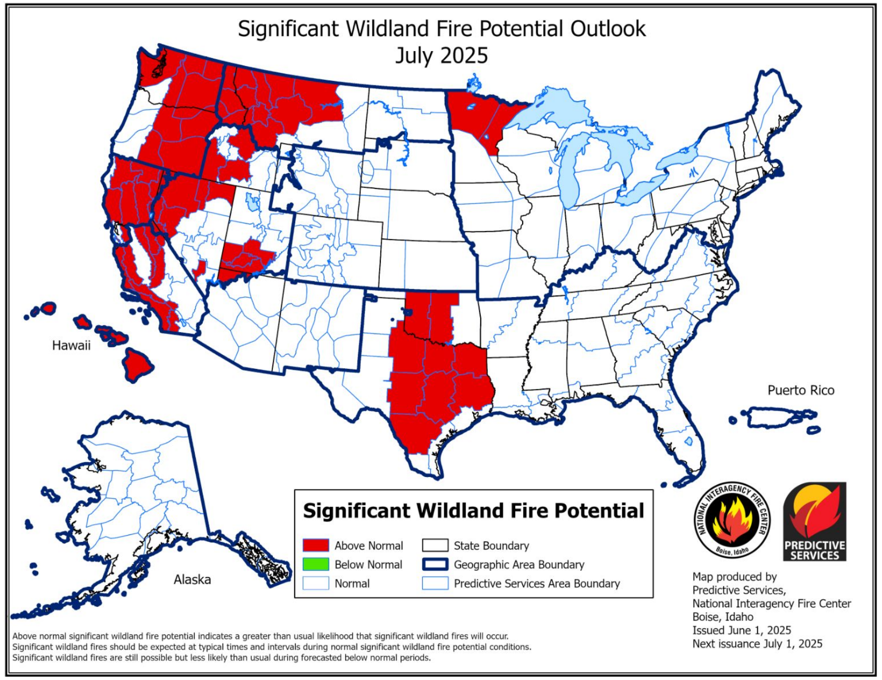
https://hdwindex.fs2c.usda.gov/

[1]Srock, A.F., Charney, J.J., Potter, B.E., and Goodrick, S.L., 2018: The Hot-Dry-Windy Index: A new fire weather index. *Atmosphere*, 9, 279. doi: https://doi.org/10.3390/atmos9070279

Background

- Subseasonal-to-Seasonal (S2S) forecasting is a growing area and priority for decision support and improvement
  - Subseasonal: two weeks through three months
  - Seasonal: the months to two years
- S2S fire weather information may help protect life and property but must be evaluated specifically to meet operational needs.
- There is limited previous work on calibration and downscaling efforts needed to produce high-quality, high-resolution, subseasonal-to-seasonal (S2S) forecasts.





Driving Question

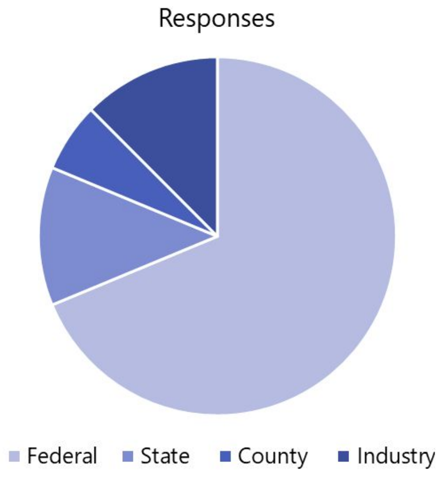
Are S2S forecast products, primarily the UFS, useful for fire weather decision making?

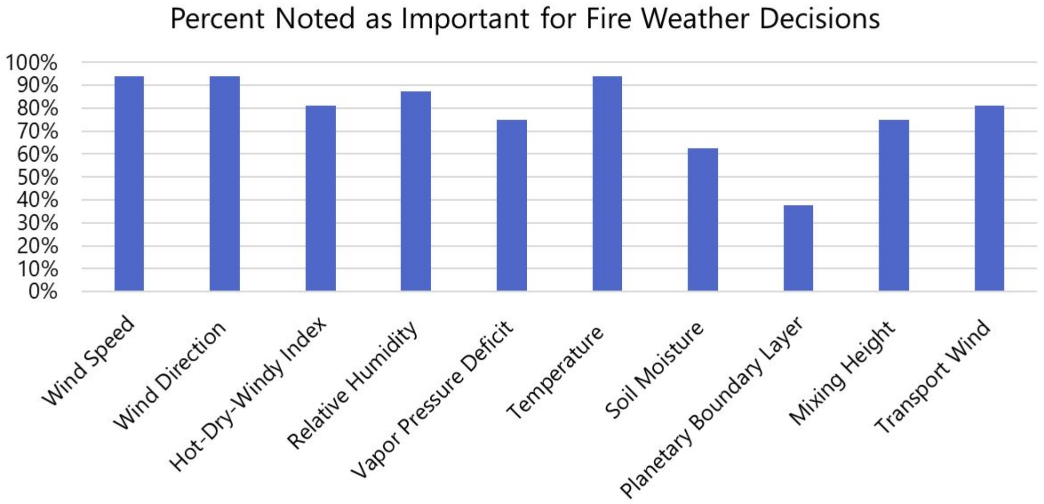
- Reduce the 'human component' burden
  - Holistic forecast performance evaluation (e.g., reliability, accuracy) grounded with real-events
  - Identify differences between tools that could lead to conflicting information or interpretation
  - Identify new patterns and signals
- Gain trust and broad use with end-users
  - Continual involvement with stakeholders through polls and workshops (federal, state, local, private, academic)
- Reduce technical barriers and spin-up time for additional research
  - All work is designed to be open-source (codes, database, documentation)

Research Components

- Iteratively communicate with fire weather end-users to guide study
- Generate open-source fire weather database and code repository
  - [Reanalysis, S2S Retrospective Forecasts, Observations]
- Cross comparison, analysis, and performance evaluation
  - Baseline and post processes forecast skill
  - Regression and lag analysis, pattern assessment, fire case studies
- Test downscale methods for UFS retrospective forecasts
  - Statistical, dynamical (EPIC SRW-App), machine-learning based
- *Generate and demonstrate example fire weather forecast products*

End-User Input





N= 18/70 sent

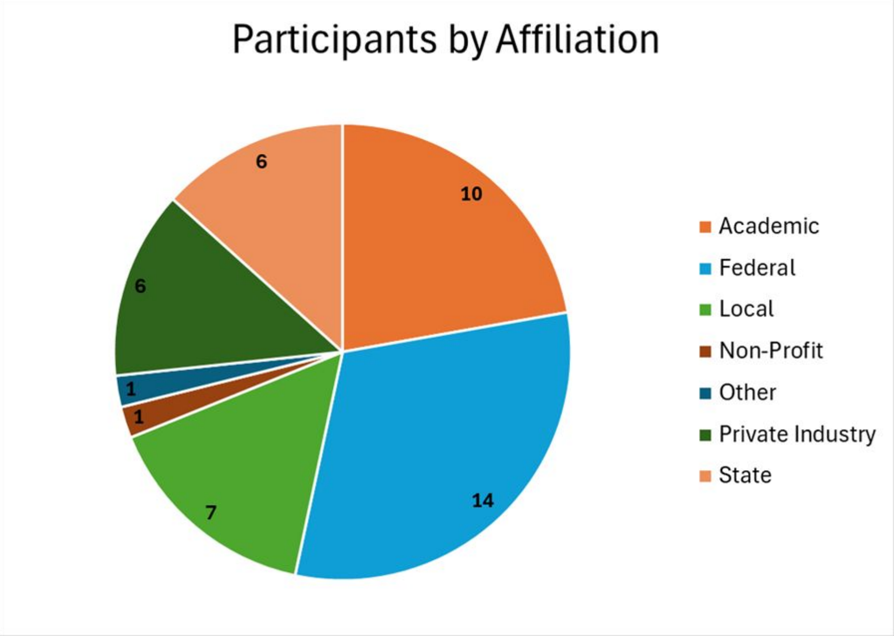
(25% response rate)

88% indicated interest in continued involvement

- Responses to the fire weather stakeholder poll came from a broad audience, including:
  - (Federal) National Park Service, U.S. Forest Service, National Interagency Fire Center, and National Interagency Coordination Center, including Predictive Services meteorologists from each Geographic Area Coordination Center
  - (State) California Energy Commission, California Department of Forestry and Fire Protection
  - (County) Marin Wildfire Prevention Authority
  - (Industry) Pacific Gas & Electric, Idaho Power, Sonoma Technology–Forecast Team

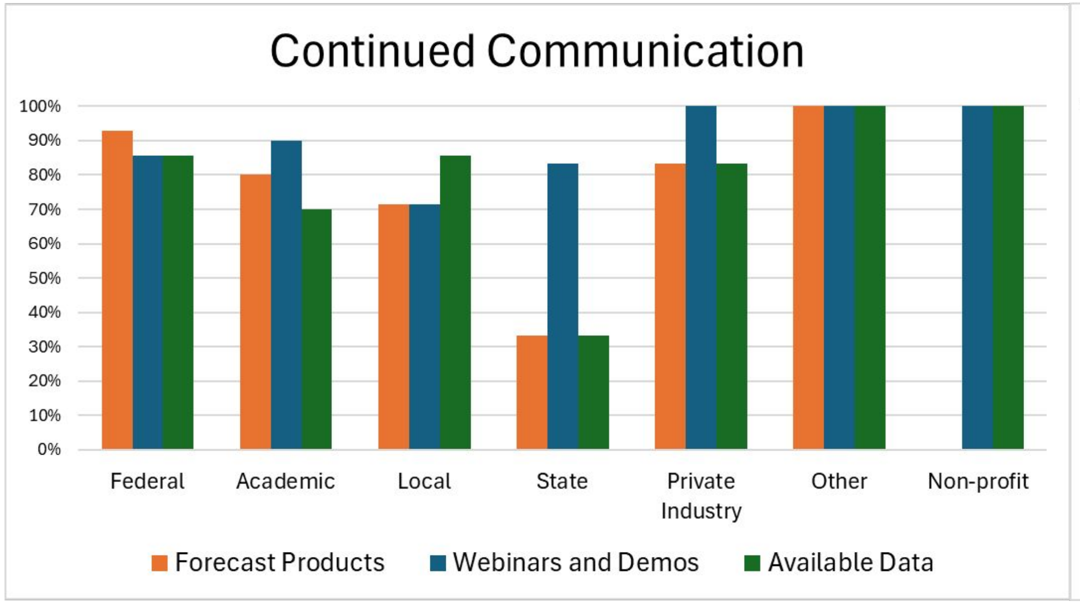
End-User Input

- 'Gathering User Input for Long-term Fire Weather Outlooks' workshop at the 7th International Fire Behavior and Fuels Conference, Boise, ID: April 15, 2024.
- Improve communication between research and operational sectors. Link research and end-user priorities to improve current and future project impacts.
- Bridge the language gap between research and in-field deployment.
- Gather actionable suggestions to increase understanding and trust.

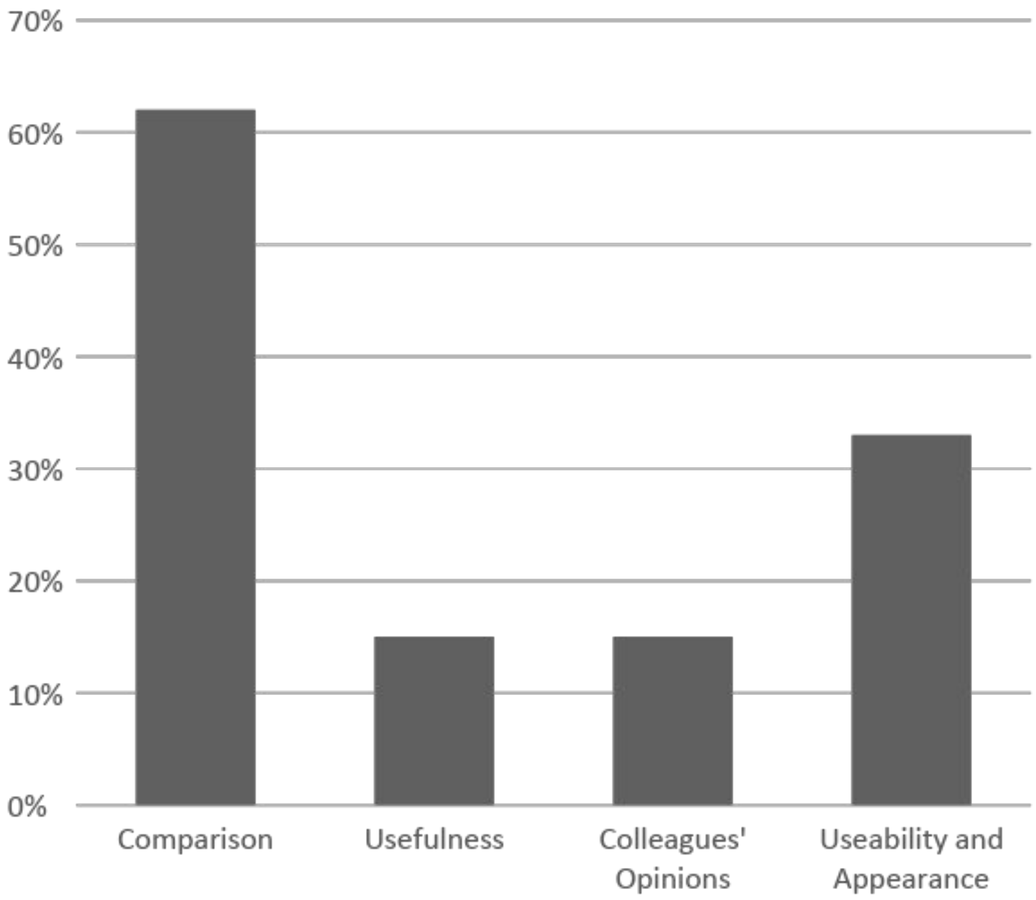


End–User Input

"In my opinion, one of the biggest challenges is sifting through all the guidance (tools, data, etc.) [to] see what is useful and for what purpose. Make sure we are actually creating guidance that solves the questions we have."

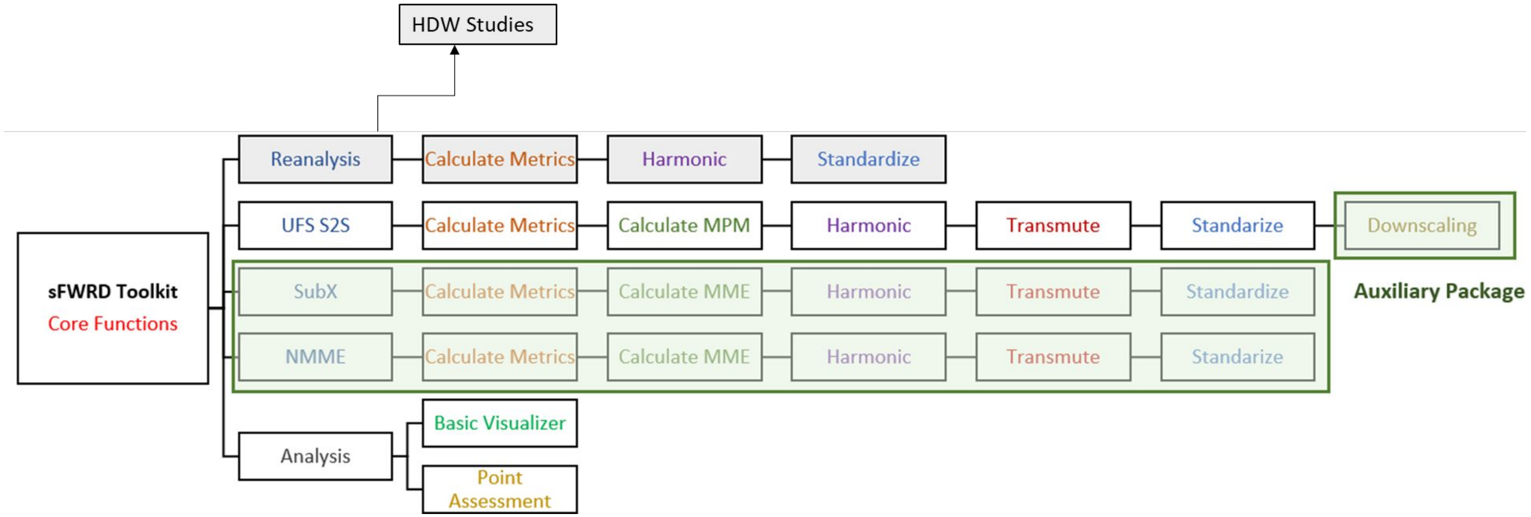


Discussion Point: How do you evaluate a new product or tool?

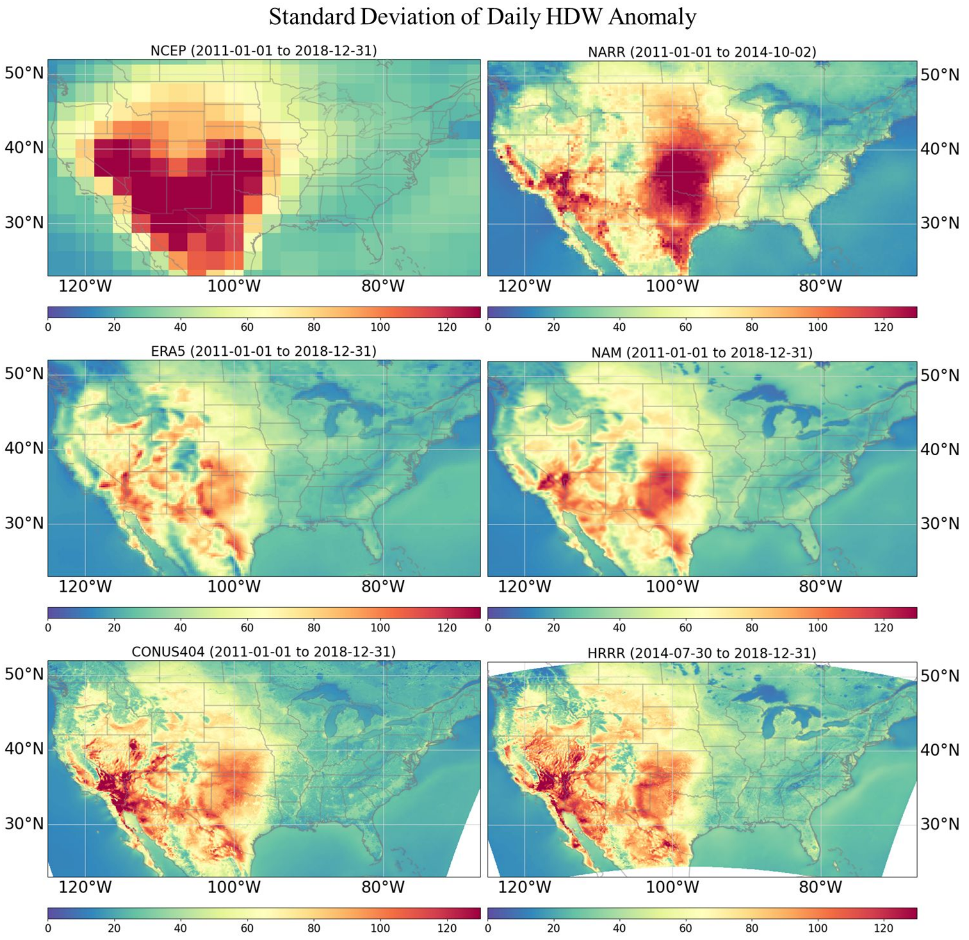


Open-Source Tools

Code Repository



Standardized Fire Weather Research Database (sFWRD)



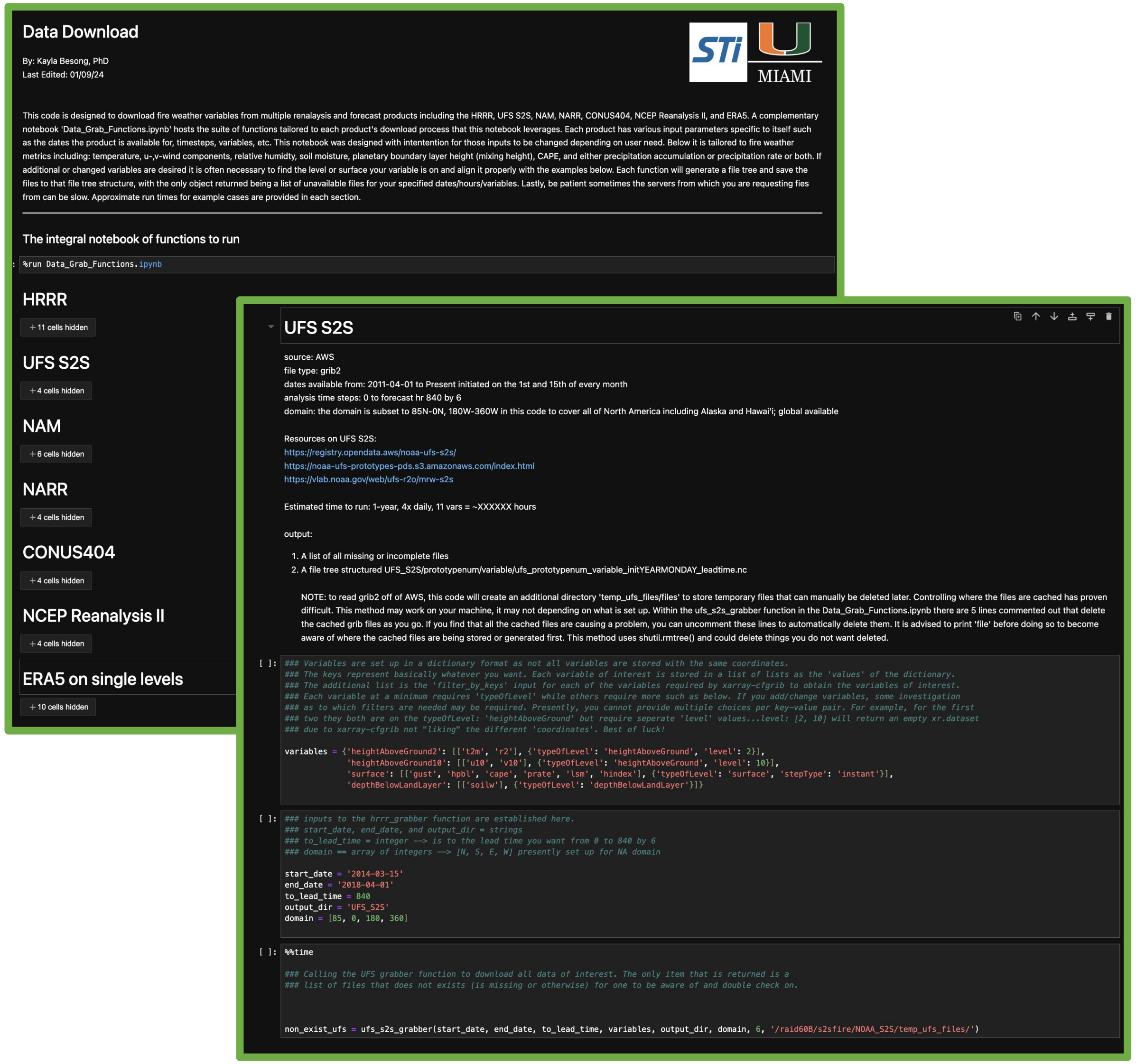
Code Repo: https://github.com/s2sfire/sFWRD

Database: soon to be available at the (SJSU) Wildfire Interdisciplinary Research Center

Code Repository

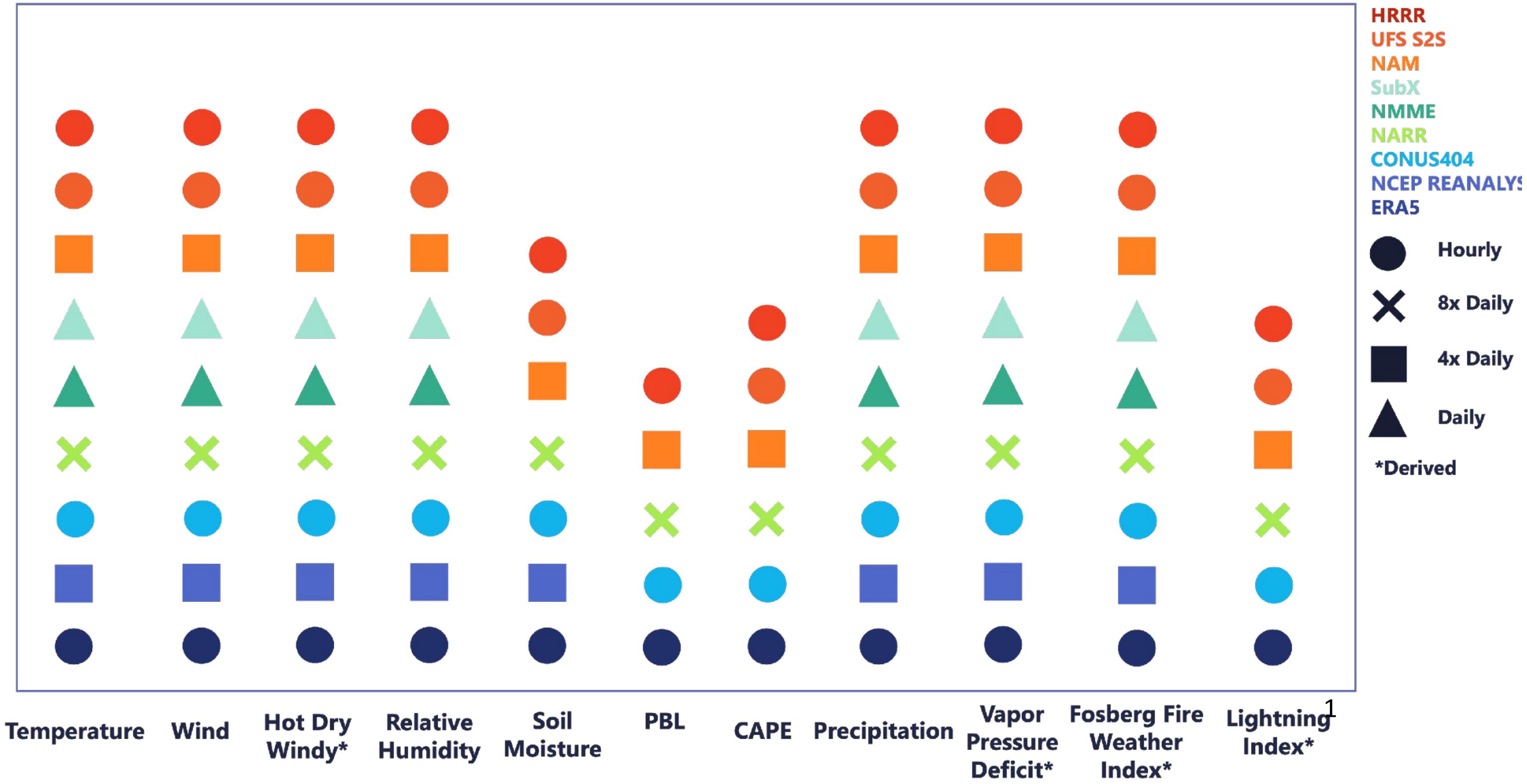
Python & Jupyter Notebooks

- Standardized environment and handling
  - Heavily annotated for transparency
- Easily transferable code base that can be re-used for study expansion and other topics
- Main data grab notebook only requires inputs
  - Dates, variables, domain
- Imported function notebook does all the lifting
- Keeps clean interface for users
- Utilizes mostly xarray
- Handles:
  - Data grabbed from:
    - AWS, Google Cloud, THREDDS, RDA, Copernicus
  - File types:
    - grib, grib2, netcdf, zarr



GitHub: https://github.com/s2sfire/sFWRD
*preliminary, in-progress

sFWRD: Data That is Ready-To-Use!

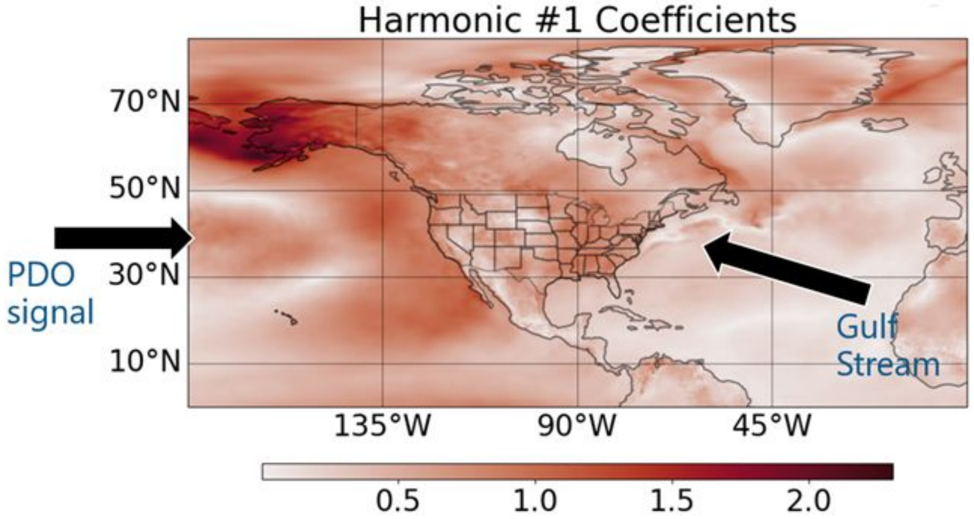


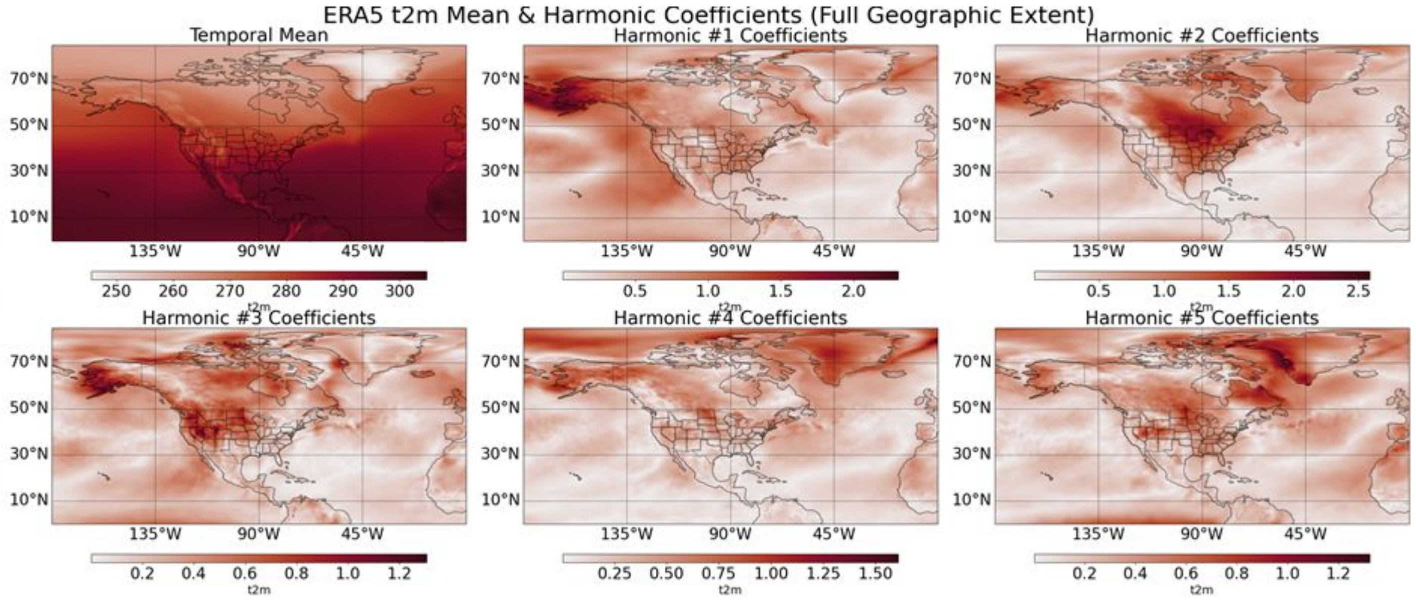
Files are netCDF with the same columns, naming convention, formats, structure throughout. All variables have the same names, abbreviations, units across all models. Sub-daily, as available, and daily aggregates (min, max, avg).

[1]Malloy K., Tippett M.K., and Koshak W.J. (2023) ENSO and MJO modulation of U.S. cloud-to-ground lightning activity. *Monthly Weather Review, 151(12), 3255-3274, December 1. Available at* *https://doi.org/10.1175/MWR-D-23-0157.1.*, *coming soon*

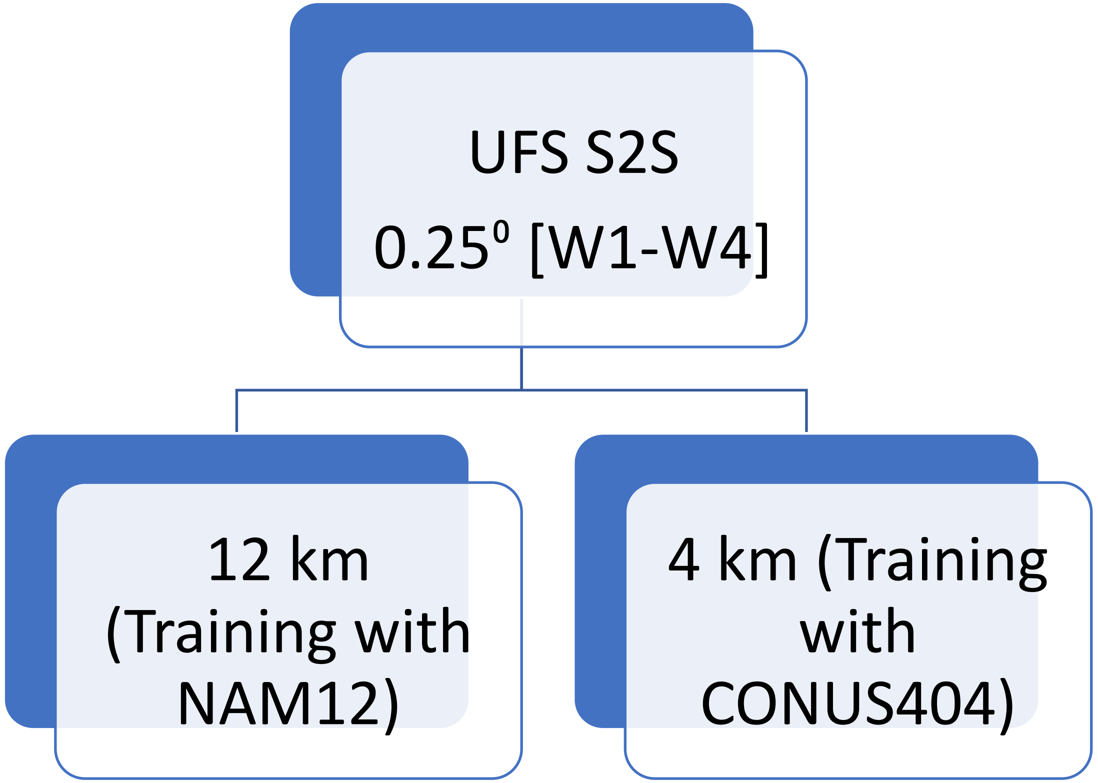
sFWRD: ‘Period Normal’

- Anomalies typically computed by subtracting the 30-yr mean to capture long-term trends.
- Harmonics provide a better fit to low-frequency variations than a simple mean with less than 30 years of coverage.
- Spatial variability of harmonics coefficients resolves known physical features.
- Harmonics will be used to help evaluate S2S forecast skill.

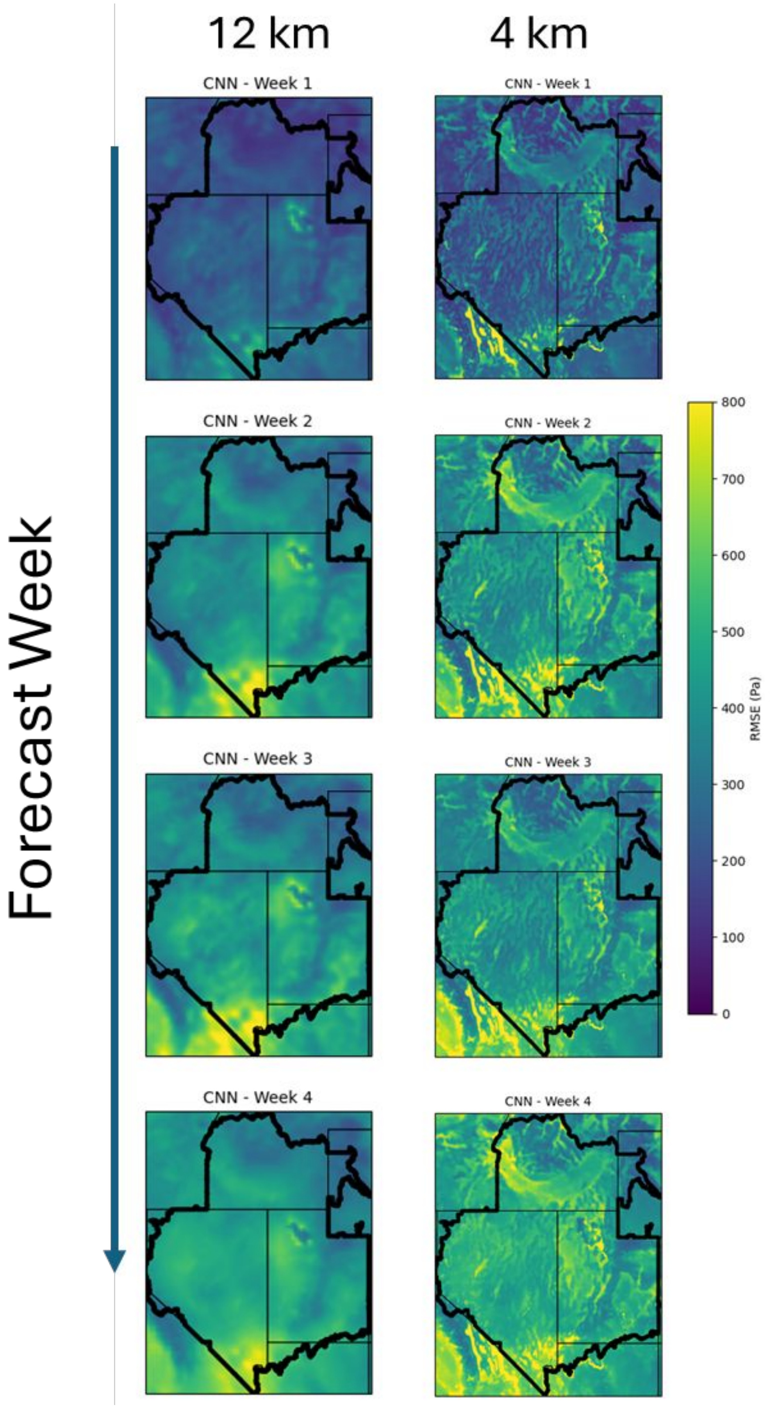




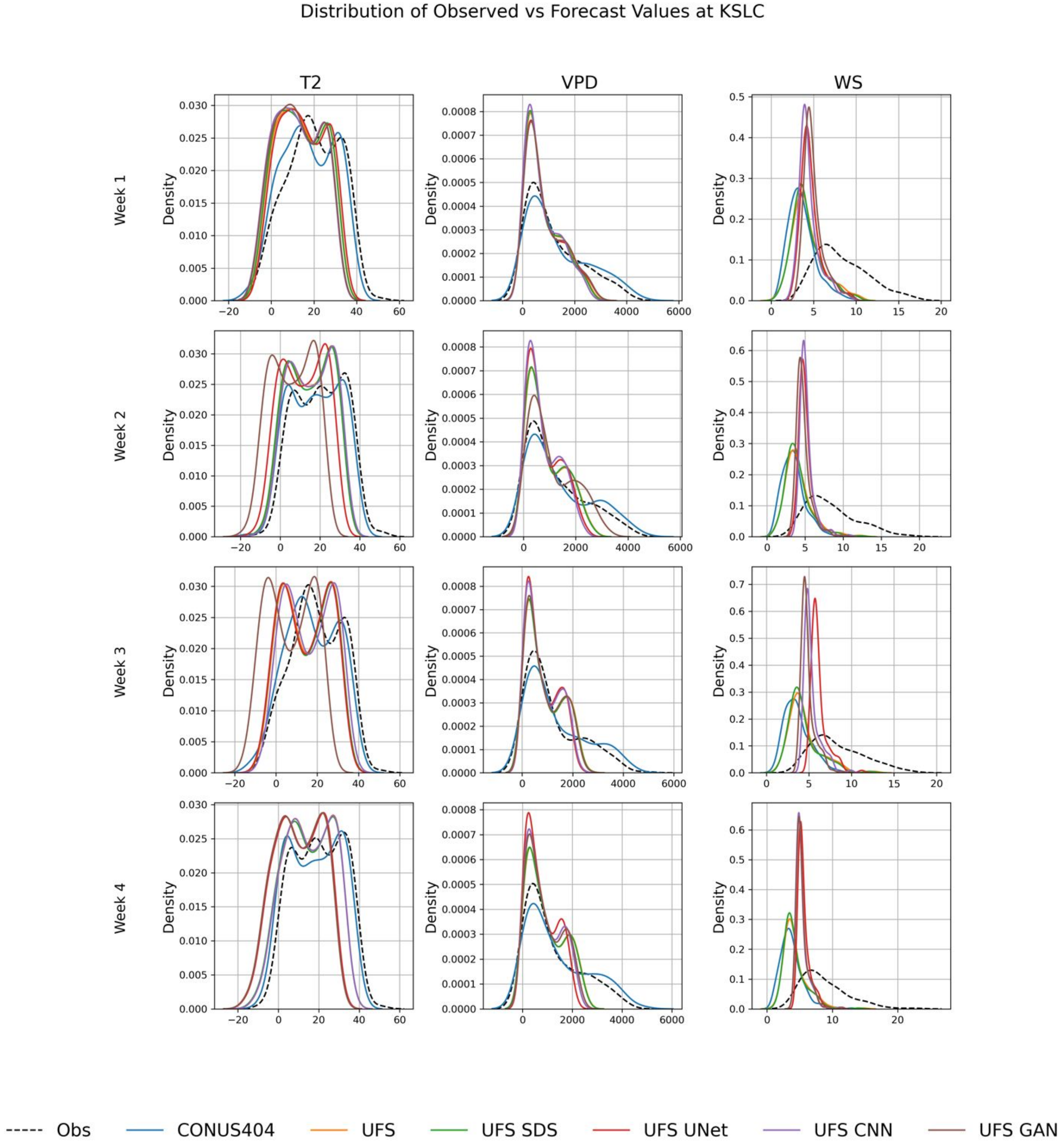
Machine Learning for a Higher Resolution Forecast



- Three Methods Tested
  - Convolutional Neural Networks (CNN),
  - Generative Adversarial Networks (GAN)
  - UNET (CNN based package)
- Trained with supervised learning approach: mean squared error (MSE) loss
- No specialized tuning of parameters applied

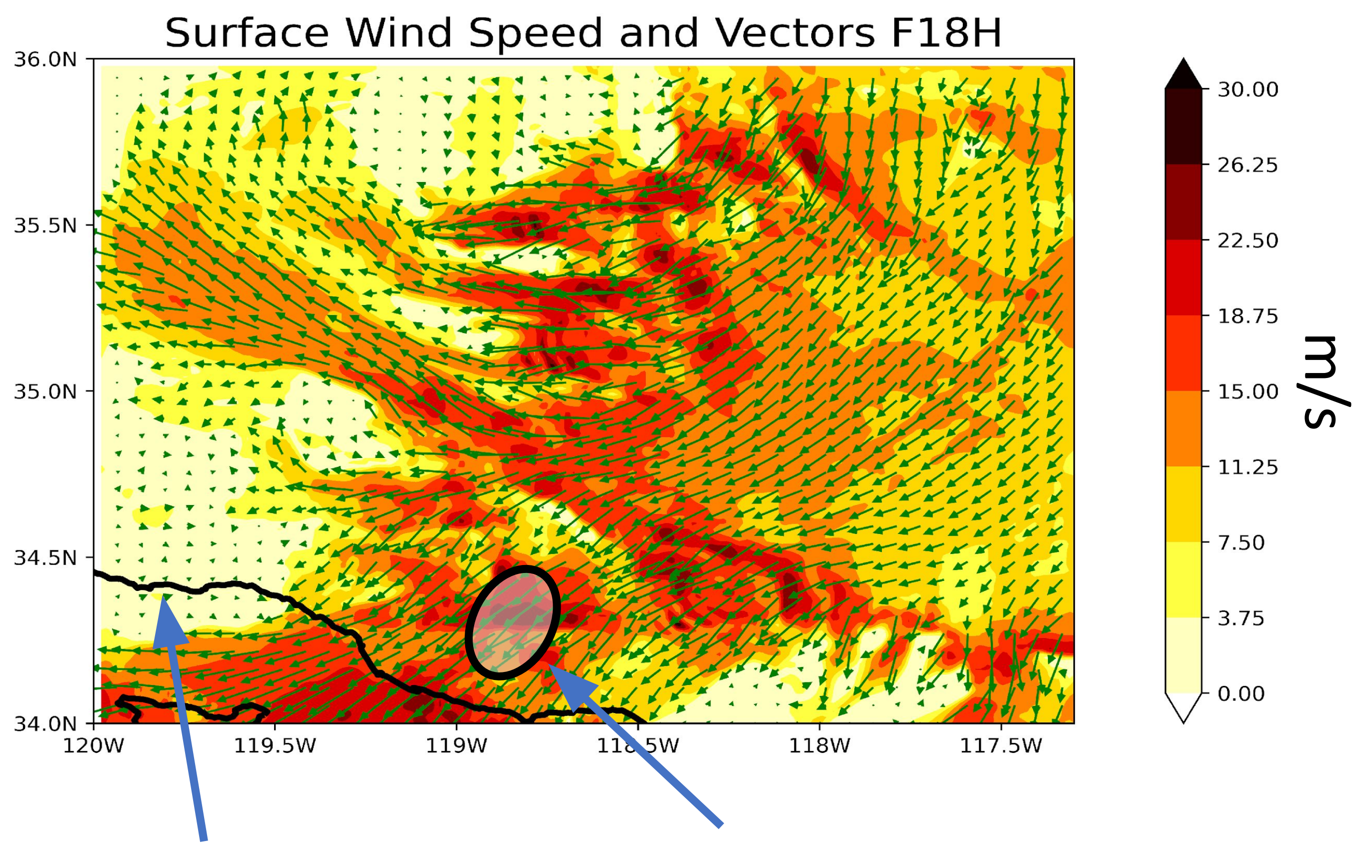


12 km
4 km
Forecast Week
CNN - Week 1
CNN - Week 2
CNN - Week 3
CNN - Week 4
RMSE (Pa)
0
100
200
300
400
500
600
700
800



Distribution of Observed vs Forecast Values at KSLC
T2
VPD
WS
Week 1
Week 2
Week 3
Week 4
Density
Obs
CONUS404
UFS
UFS SDS
UFS UNet
UFS CNN
UFS GAN

UFS Forecast & Dynamic Downscaling



Coastline

Approximate Fire Extent

Ventura County Mountain Fire

Regional Unified Forecast System (UFS)
1 km Horizontal Resolution

Fire Started 11/6/2024 8:51 am

18 Hour Forecast Valid 10:00 am 11/6/2024

Forecast Performance Evaluations

- For all UFS S2S fire weather variables (4 prototypes) at its native output resolution (0.25^0)
  - [WS, WS-gust, PR, T2, RH, HDW, FFWI, VPD, and CAPE]
    - Root-mean-square error
    - Mean-absolute error
    - Correlation
    - Reliability scores
  - Comparison to reanalysis at the gridded level, observation at point locations
- Direct and usable metrics for confidence/accuracy/reliability of UFS S2S forecast products by week!

Summary

- Project is guided by stakeholder feedback and includes prototyping forecasts with each approach to evaluated operational potential
- Unified code base with standardization implemented for this work will be publicly available to be leveraged in other projects and to expand this work
  - Will reduce 'spin-up' time for UFS and reanalysis projects
  - Will allow for easier transition to operations for future UFS S2S forecast products (back-end environment complete)
- Includes regions typically excluded from CONUS model evaluations where possible (i.e., AK, HI)
- We are adding in analysis studies to guide and inform work along the way

Summary

- National scale forecast performance is generally strong, localized performance varies significantly
- ML-based downscaling can enhance the visual appeal and interpretability of forecasts for end-users.
  - ML methods do not necessarily translate into better technical performance.
- Variables like T2 and VPD showed better performance compared to WS.
- Future work should explore training with global datasets (teleconnection patterns), which may influence local outcomes.
- Further experiments with model tuning and regional customization could unlock more meaningful gains in forecast accuracy and reliability.
- Dynamical downscaling may be a promising solution to the wind speed low-bias
- Even without downscaling, long-range forecasts are promising for many variables