MACHINE LEARNING METHODS TO ADVANCE AR AND PRECIPITATION FORECAST SKILL

Luca Delle Monache

CW3E Deputy Director, UCSD/Scripps

ldm@ucsd.edu

Center for Western Weather and Water Extremes
SCRIPPS INSTITUTION OF OCEANOGRAPHY AT UC SAN DIEGO

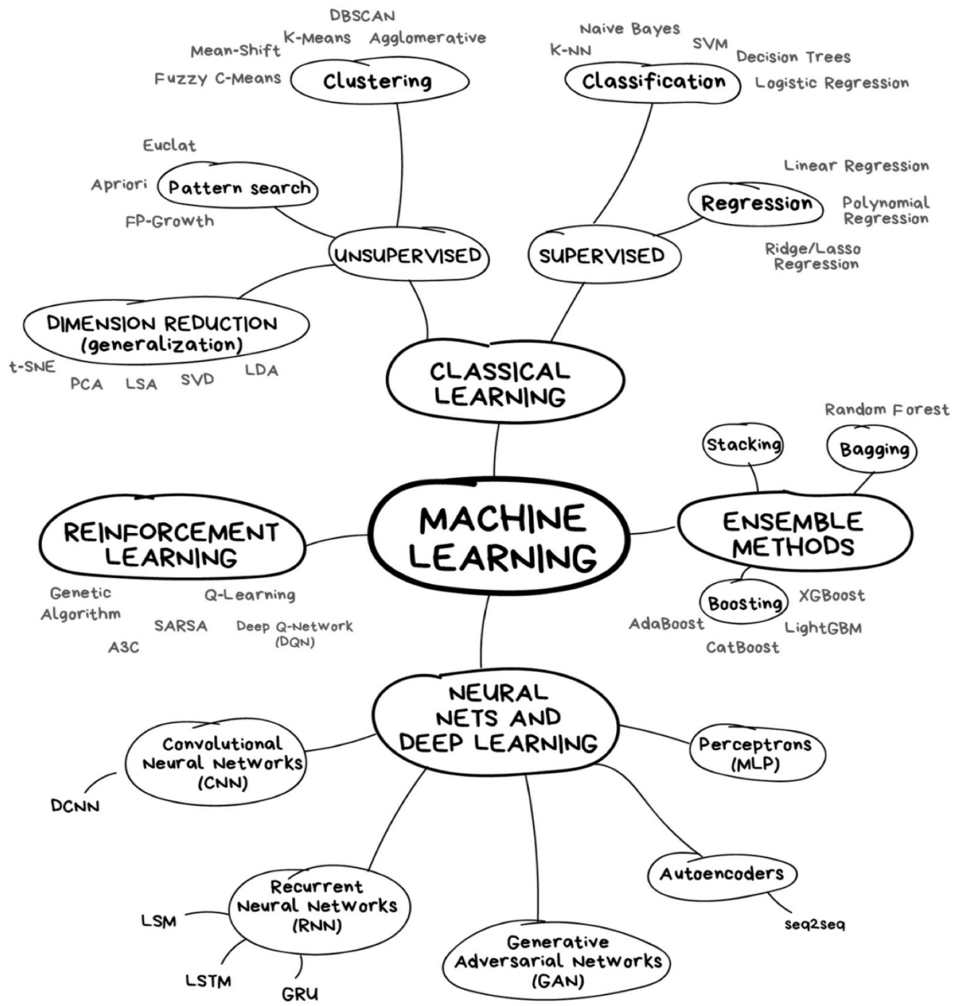
UC San Diego

SCRIPPS INSTITUTION OF OCEANOGRAPHY

OUTLINE

- Machine Learning (ML) methods
- ML for weather
- ML for Subseasonal to Seasonal (S2S) predictions
- What’s next?

MACHINE LEARNING



source:
https://vas3k.com/blog/machine_learning

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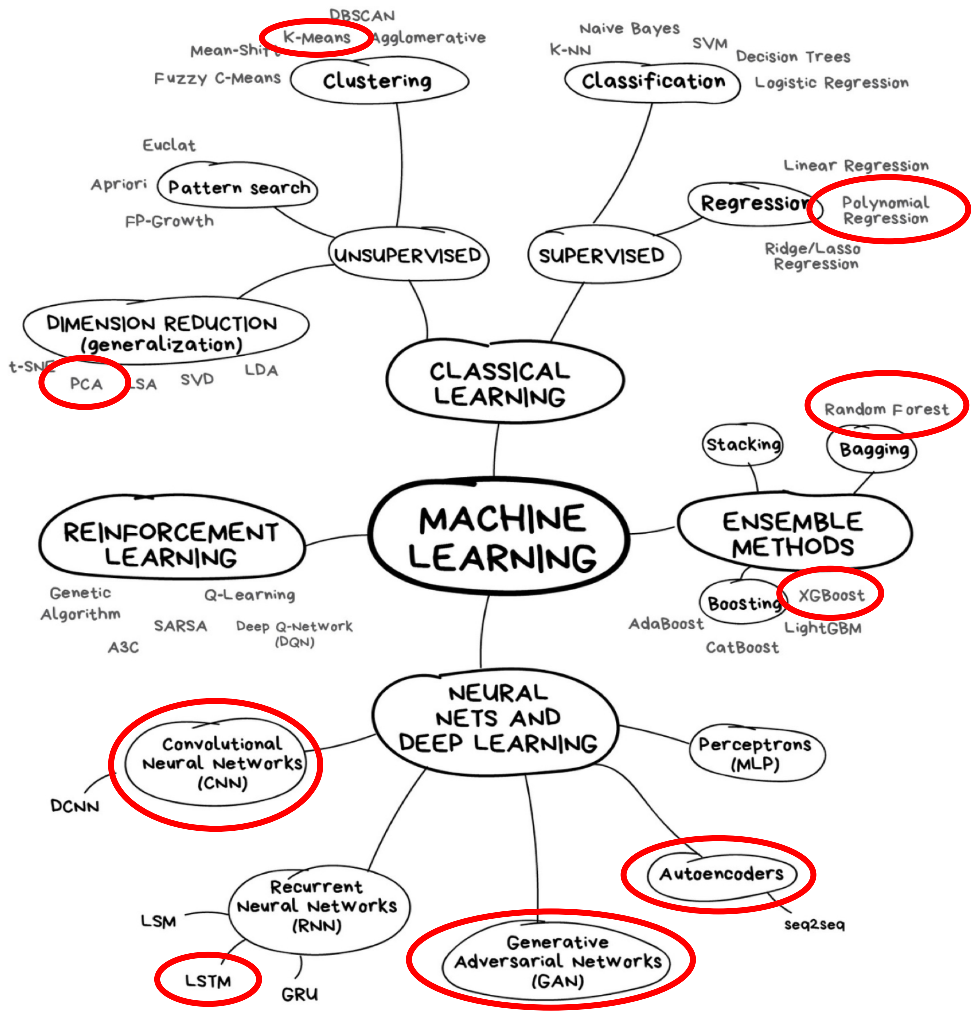
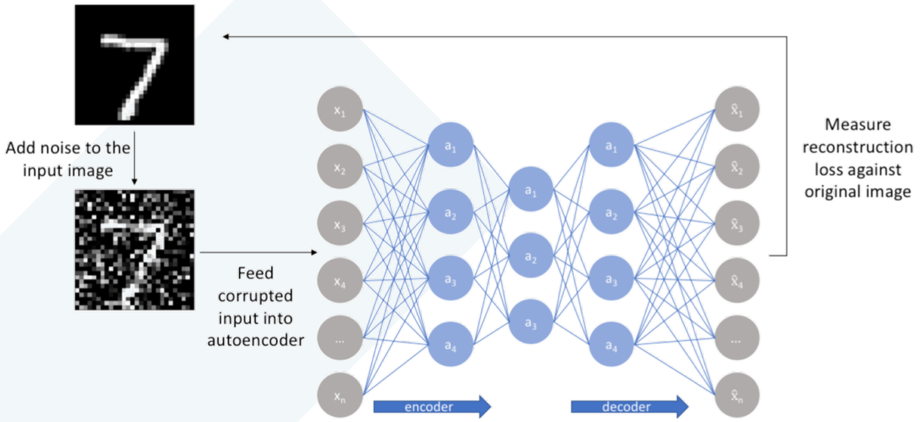
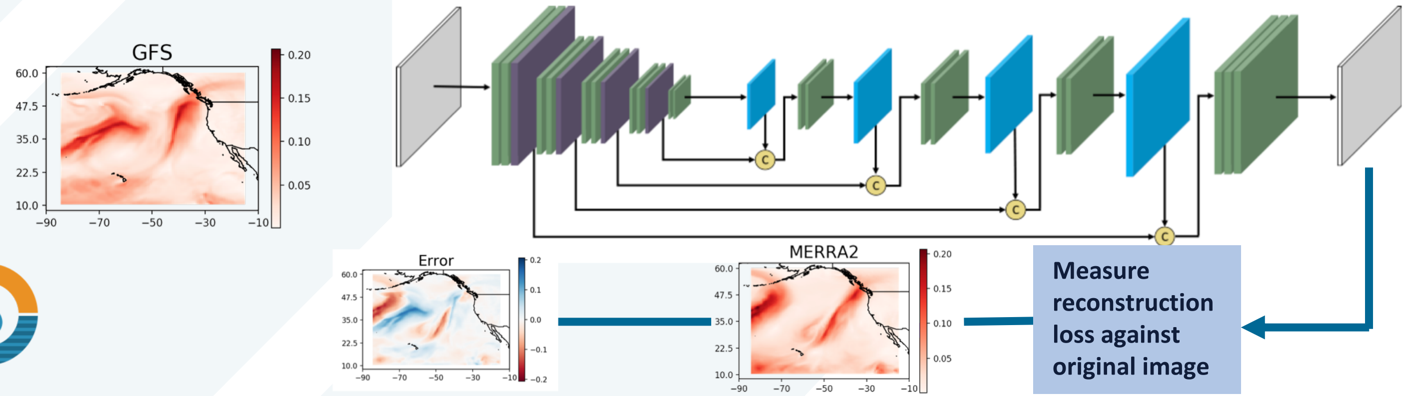


ML FOR WEATHER PREDICTIONS

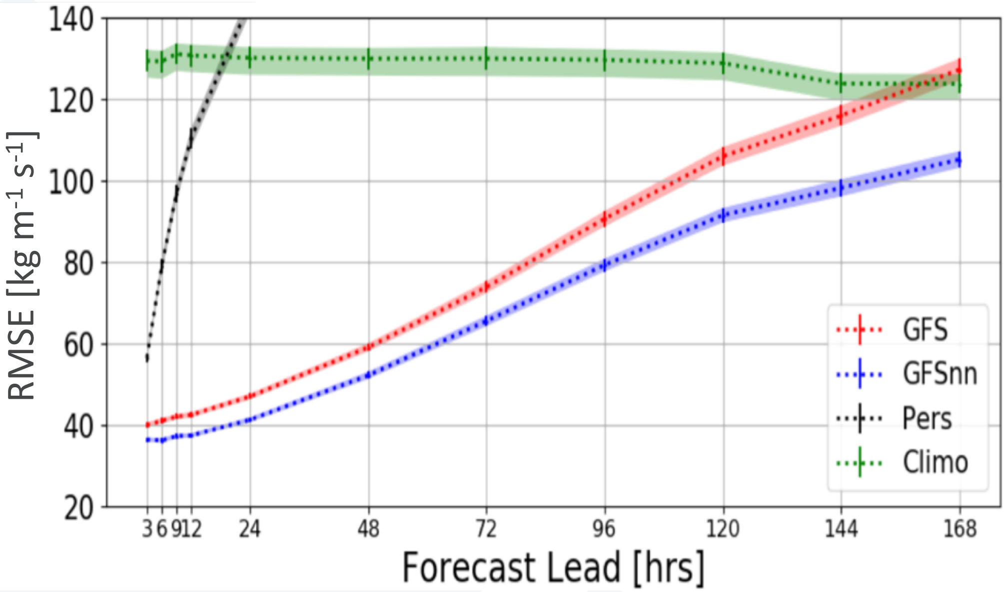
MACHINE LEARNING / CONVOLUTIONAL NEURAL NET (GFSNN)



Supervised ML
Training an algorithm to produce an inferred function, learned from input-output pairs



ML-BASED DETERMINISTIC PREDICTION OF IVT IN REAL-TIME



- ML Method: Convolutional Neural Network
- 0-168 h IVT Predictions
- Training: 10 years of GFS (Oct 2008 – Apr 2016)
- Testing: 1 Year (Oct 2017 – Apr 2018)
- Ground-truth: MERRA 2

Chapman et al. (2019, GRL)

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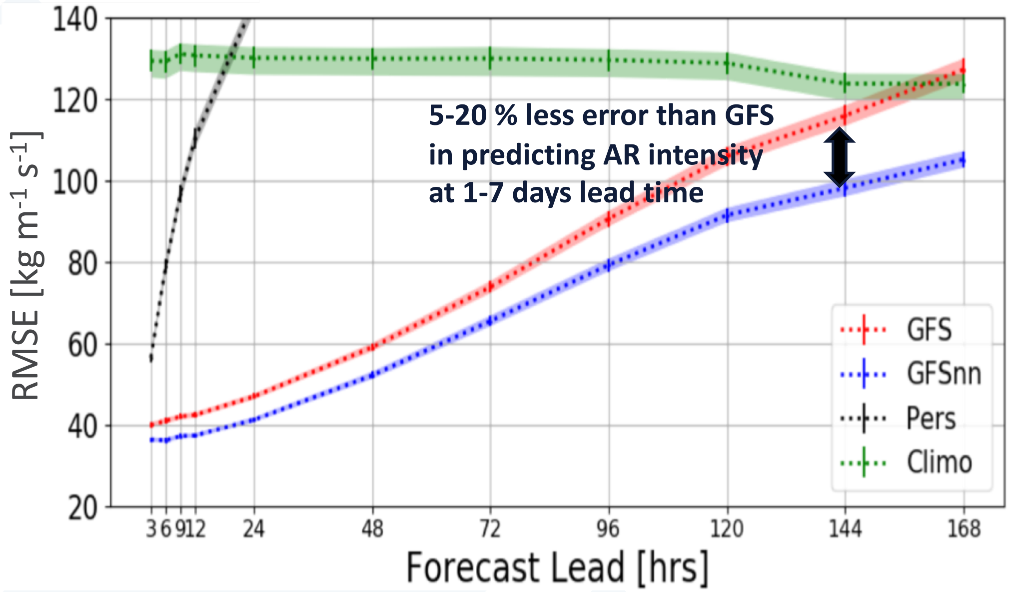

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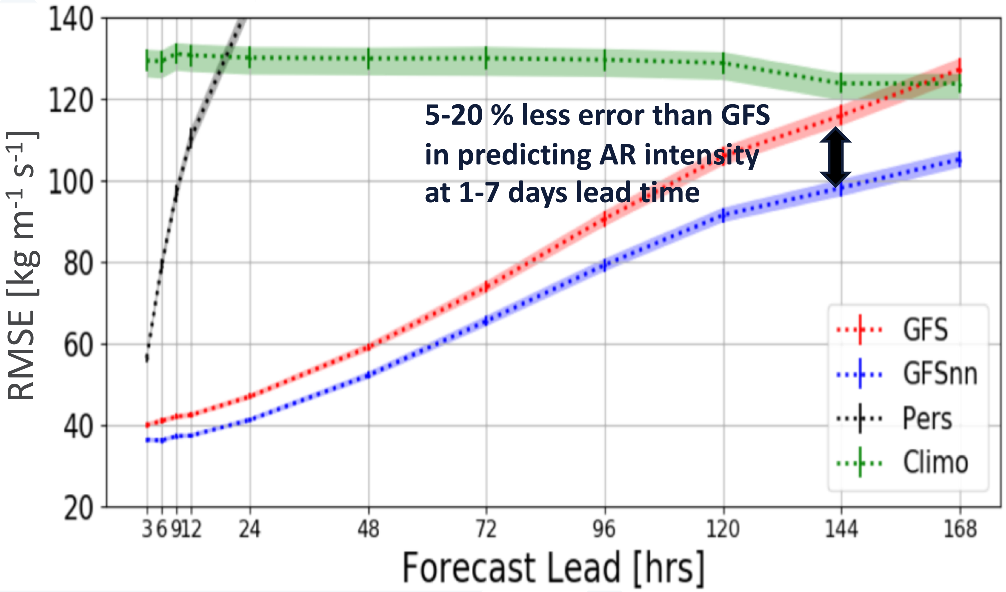

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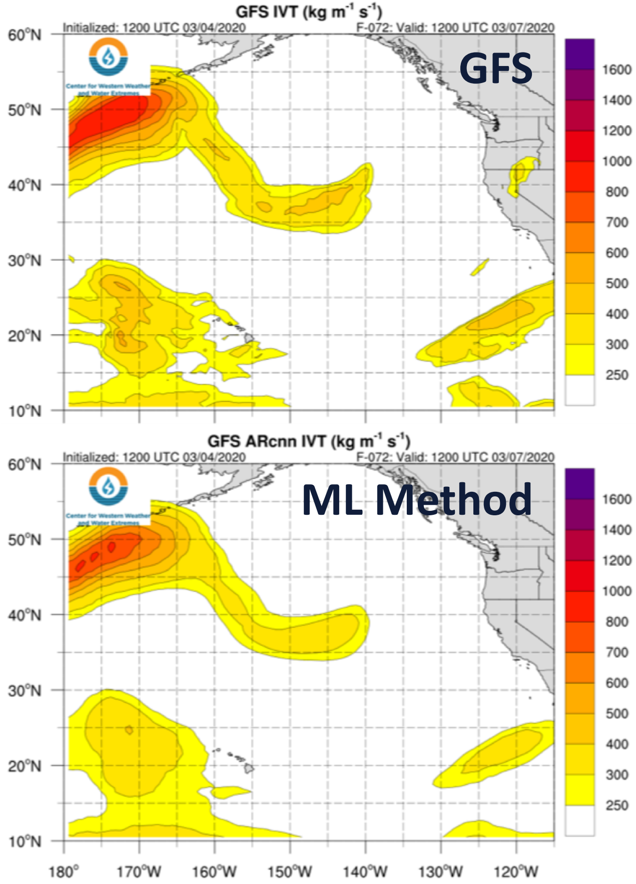

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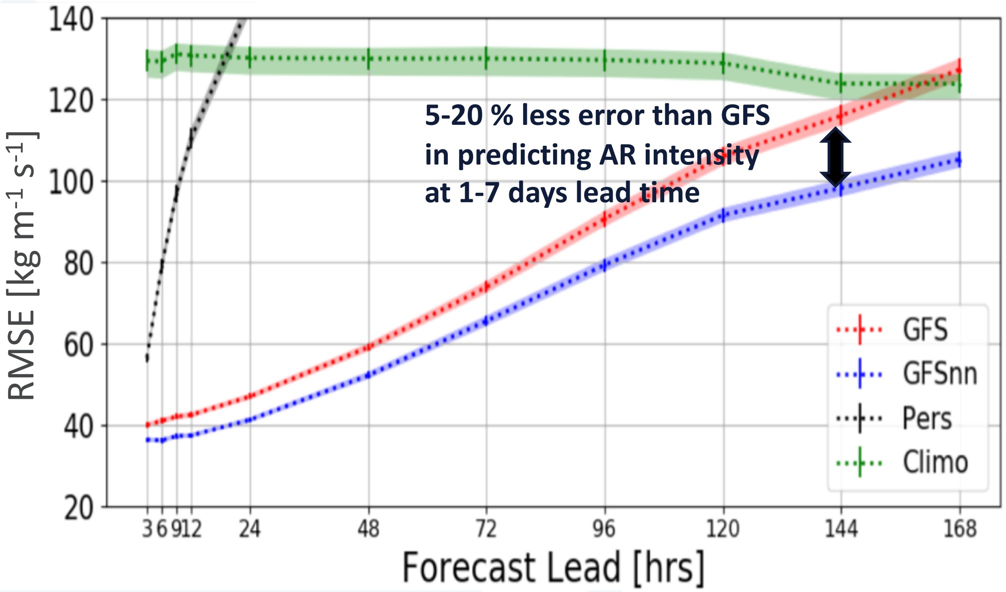

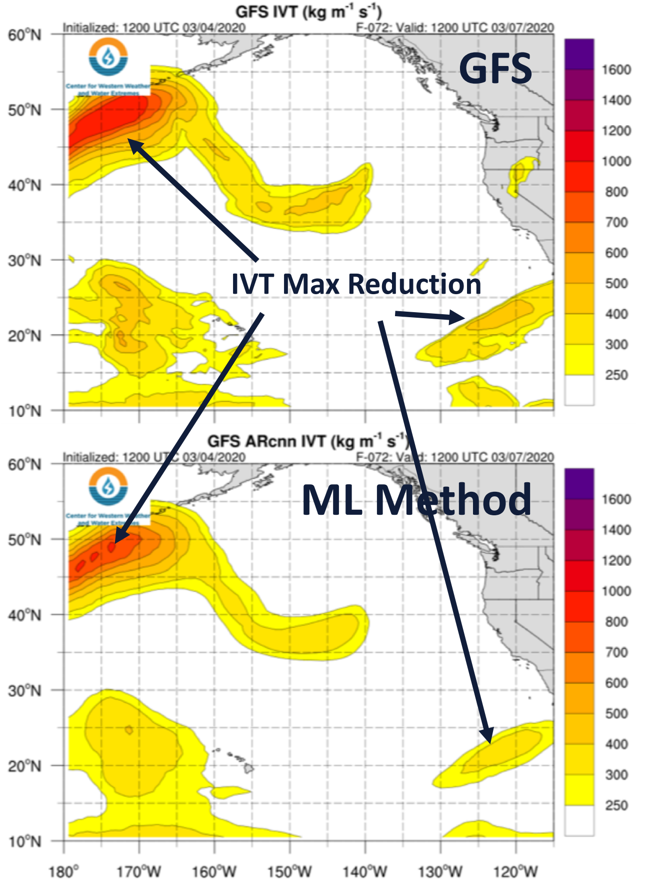

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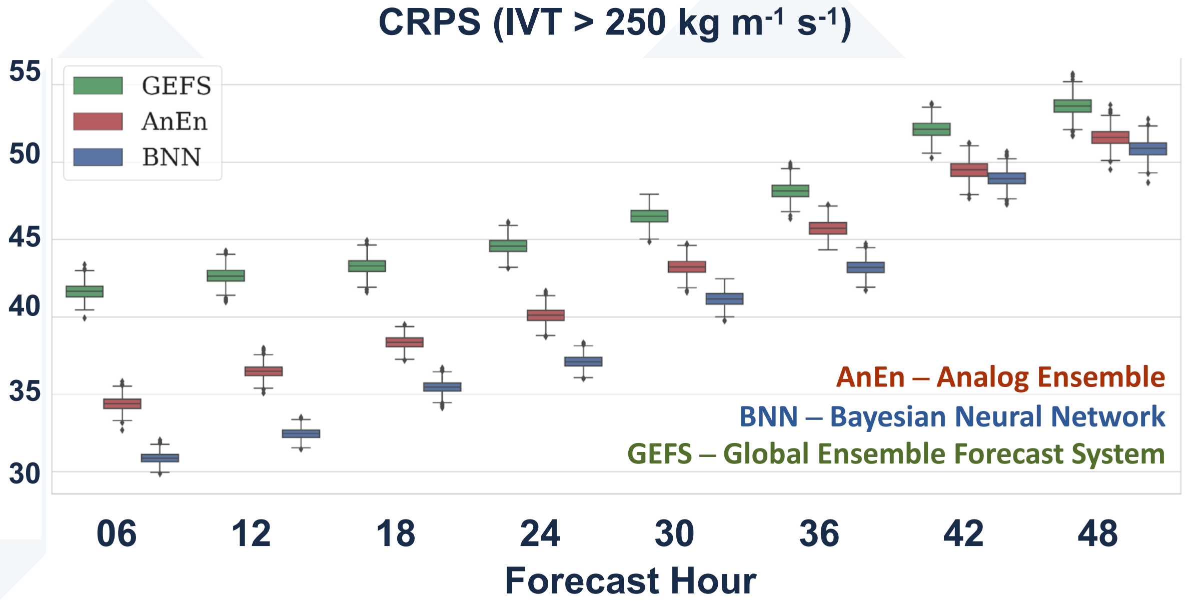
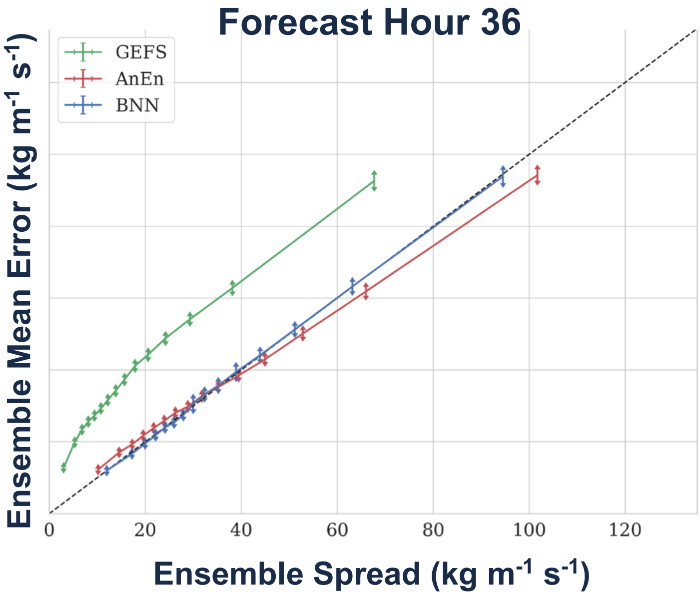
Chapman et al. (2019, GRL)

ML-BASED PROBABILISTIC PREDICTION OF IVT



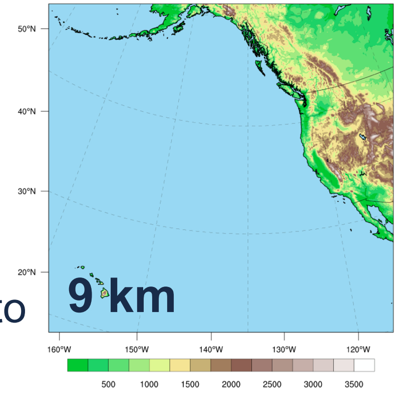


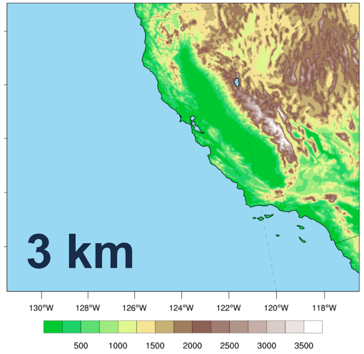
- Predictors: IVT, u500, v500, Z500, lat/lon of prediction
- Training: 10 years of GFS (Oct 2008 – Apr 2016)
- Testing: 1 Year (Oct 2017 – Apr 2018)
- Ground-truth: MERRA 2

Will Chapman, Luca Delle Monache, Stefano Alessandrini (NCAR)

34-YEAR WEST-WRF REFORECAST

- We dynamically downscaled with West-WRF the ~0.5 degree Global Ensemble Forecast System to 9 and 3 km for a 34-year period
- Computing resources provided were by the U.S. Army Engineer Research and Development Center (ERDC)
- West-WRF daily initializations at 00 UTC from 1 Dec – 31 March, out to 5 days (3-km domain) and 7 days (9-km domain). 60 vertical levels, adaptive timestep
- Goals
  - Further develop ML algorithms
  - Assessing the benefits to CNFRC operations of using the reforecast to calibrate the Meteorological Ensemble Forecast Processor (MEFP)
  - In-depth process-based studies

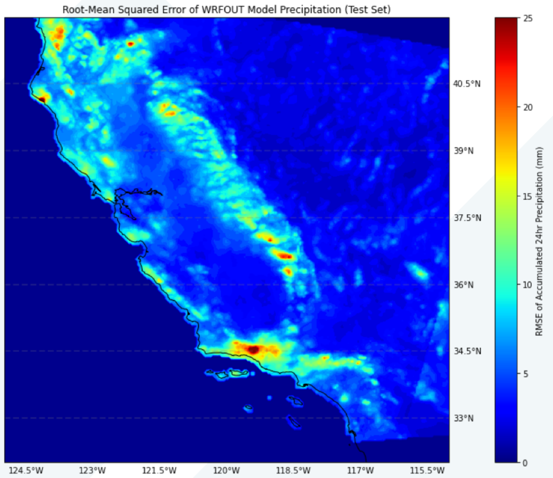




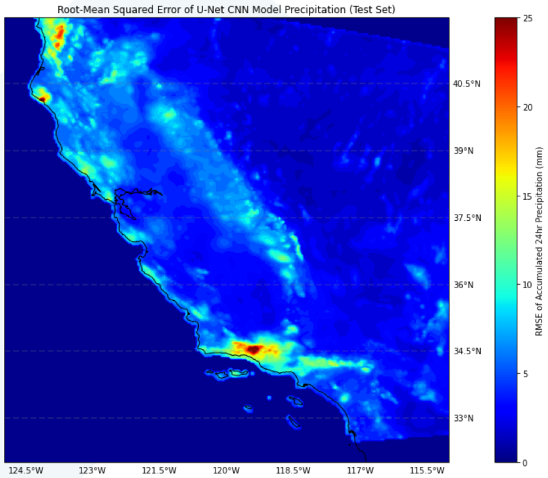
Dan Steinhoff, Brian Kawzenuk, Rachel Weihs, Caroline Papadopoulos + CW3E Team

A CONVOLUTIONAL NEURAL NETWORK FOR PRECIPITATION PREDICTION

West-WRF



CNN



- ML Method: Convolutional Neural Network
- 24-h accumulated precipitation
- Training: 31 years of West-WRF Reforecast
- Testing: 2 Years (1987-1988)
- Ground-truth: PRISM

METRICS	WRF	CNN	IMPROVEMENTS (%)
RMSE (mm)	5.35	4.47	16.5 %
Correlation	0.76	0.80	5 %
Bias (mm)	0.14	0.12	1.6 %

Anirudhan Badrinath (UC Berkeley, CW3E Summer Intern), Will Chapman, Negin Hayatbini, Forest Cannon, Luca Delle Monache

ML FOR SUBSEASONAL-TO-SEASONAL (S2S) PREDICTIONS

MACHINE LEARNING FOR S2S

- **Can recent developments in machine learning improve our (limited) seasonal forecasting skill for Western US precipitation?**

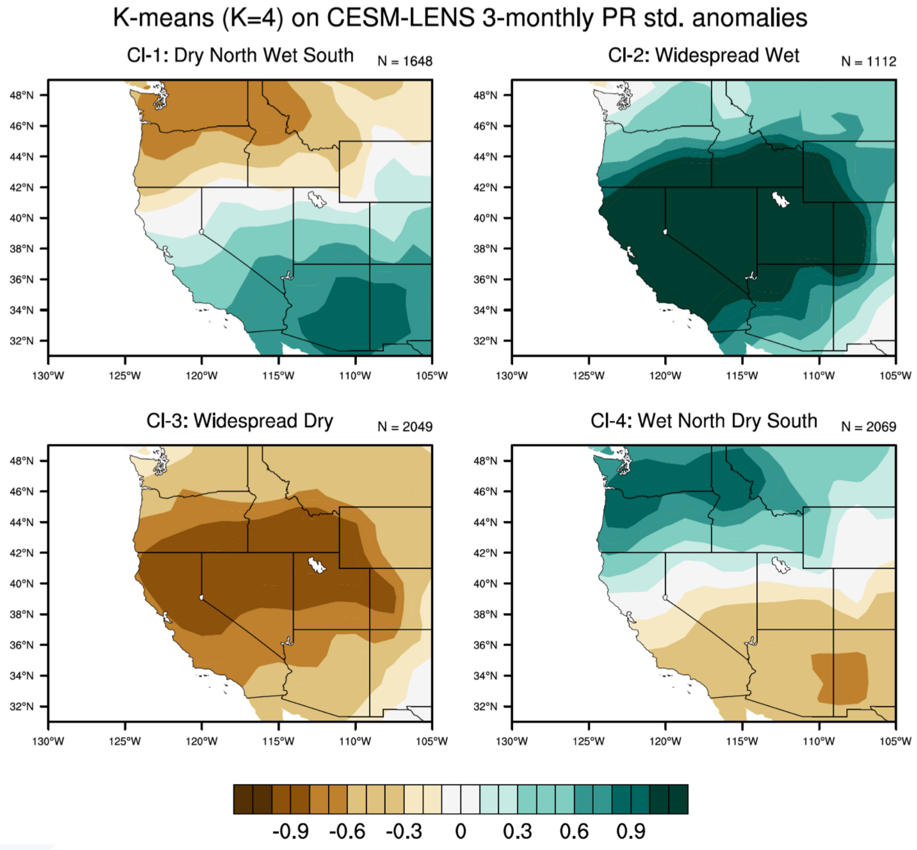
- Few studies have attempted machine learning for S2S – mainly because these tools are extremely data hungry, whereas at seasonal timescales observations are heavily data limited

- To circumvent this, **we propose training various machine learning algorithms on large climate model ensembles**. These climate model ensembles span several thousands of years (perturbed initial condition experiments) providing unique opportunities to “learn” relevant teleconnections and non-linear interactions

MACHINE LEARNING FOR S2S – PREDICTAND CLUSTERS

Predictand Variable (trained on CESM-LENS*)

- K-means clustering applied to 3-month total precipitation anomalies (standardized)
- Tested K = 3, 4, 5, 6
- The same clusters show up in observations as found in CESM (suggesting model captures these broad precipitation patterns well)

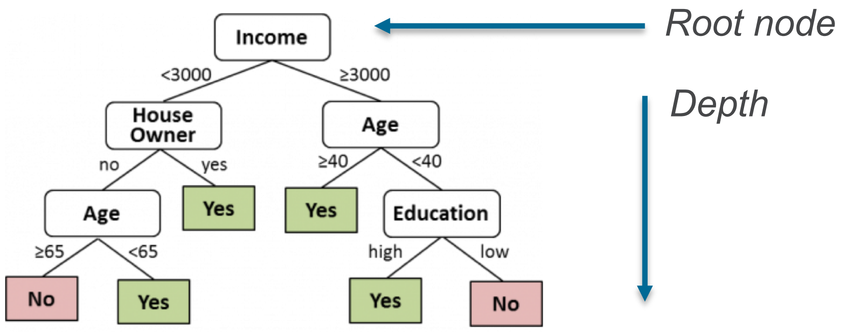


***CESM-LENS:**
Community Earth System Model Large Ensemble

Lead: Peter Gibson

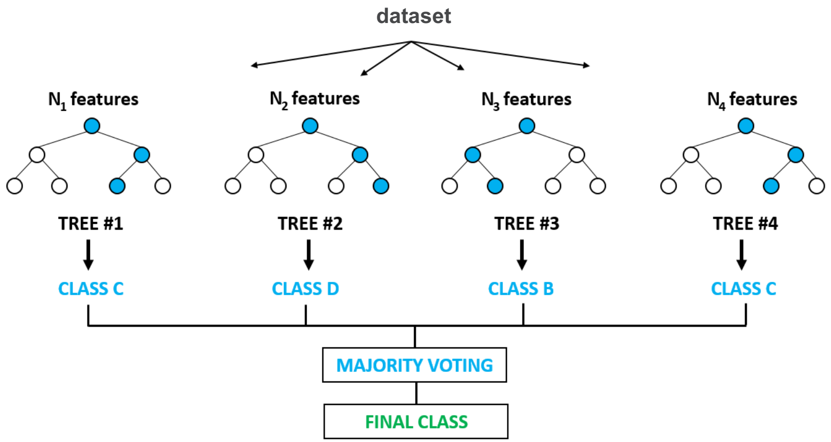
DECISION TREES -> RANDOM FORESTS

Decision tree



Binary classification from decision tree for deciding to give credit based on income, age, education and home ownership

Random Forest



- More important variables are generally closer to the root (i.e. lower depth)
- Random forests are made up of several decision trees (each tree gives a vote)
- Non-linear interactions between variables can be represented

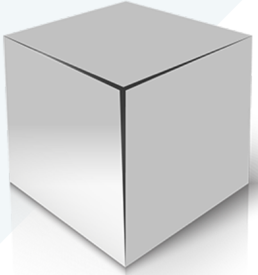
Lead: Peter Gibson

MACHINE LEARNING FOR S2S – METHOD SUMMARY

Lagged predictor variables (~100)

- *SST*
- *Tropical Deep convection*
- *Height anomalies*
- *Jet stream*
- .
- .
- .
- .

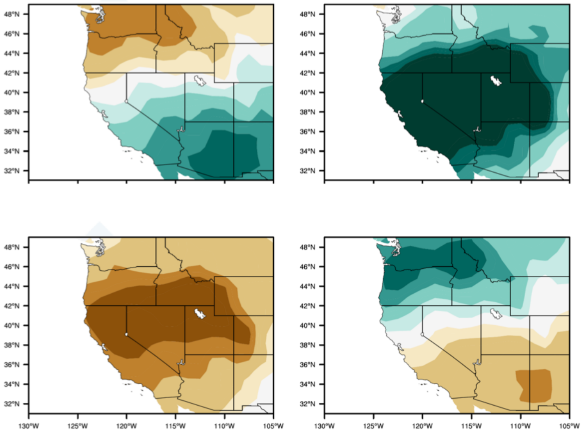
ML algorithm



- Random Forest
- XGBoost
- Neural Networks
- LSTM Neworks

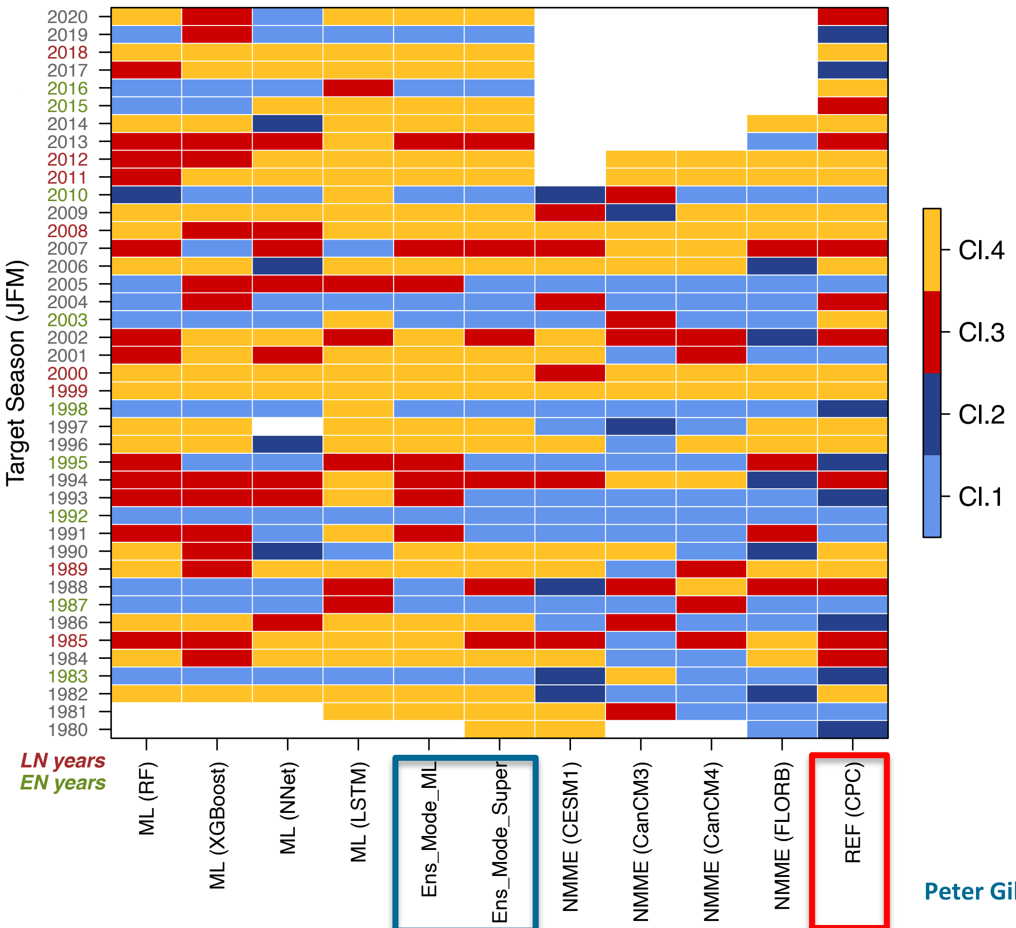
Predictand

Predict 1 of 4 Classes



Model is trained separately for predicting NDJ and JFM 3-monthly seasons

COMPARISONS TO NMME PHASE 2 MODELS – JFM SUMMARY

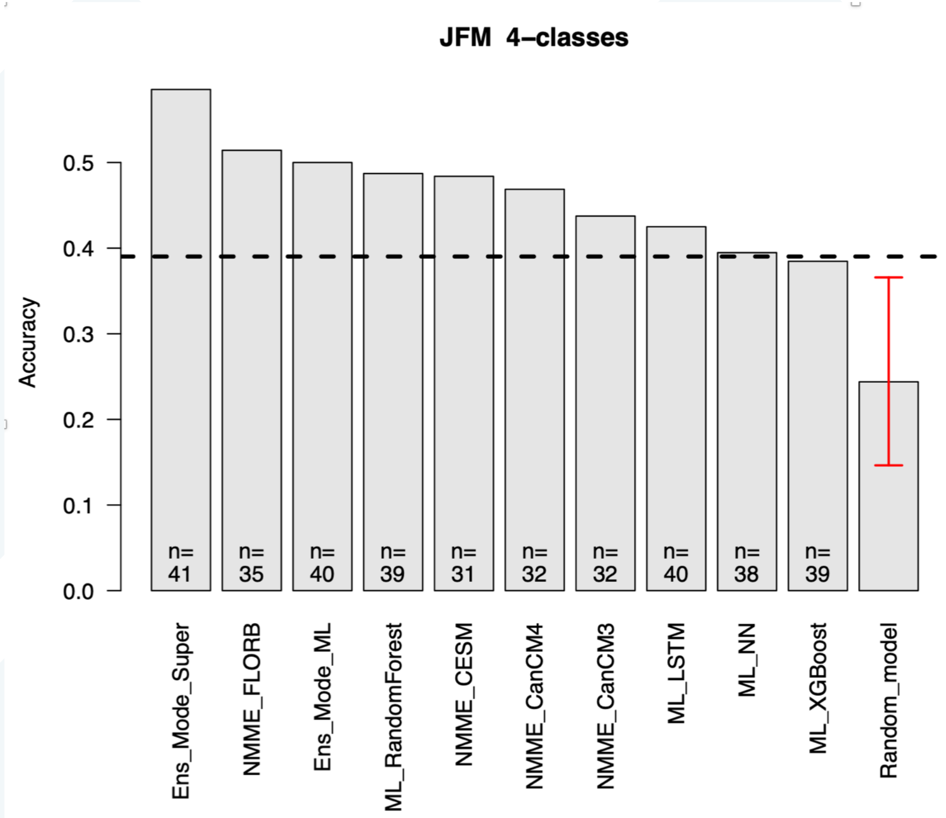


- Correct classification possible outside of ENSO years
- When the model is wrong sometimes it still gets the sign correct (e.g. Cl3/Cl4 and Cl1/Cl2 for SoCal)
- Ens_mode_ML = mode ensemble of the four ML models
- Ens_mode_Super = mode ensemble of the eight ML + NMME models

If the mode is not unique – the forecasted class is the historically most frequent class

Peter Gibson, Will Chapman, Alphan Altinok (JPL), Mike DeFlorio, Luca Delle Monache

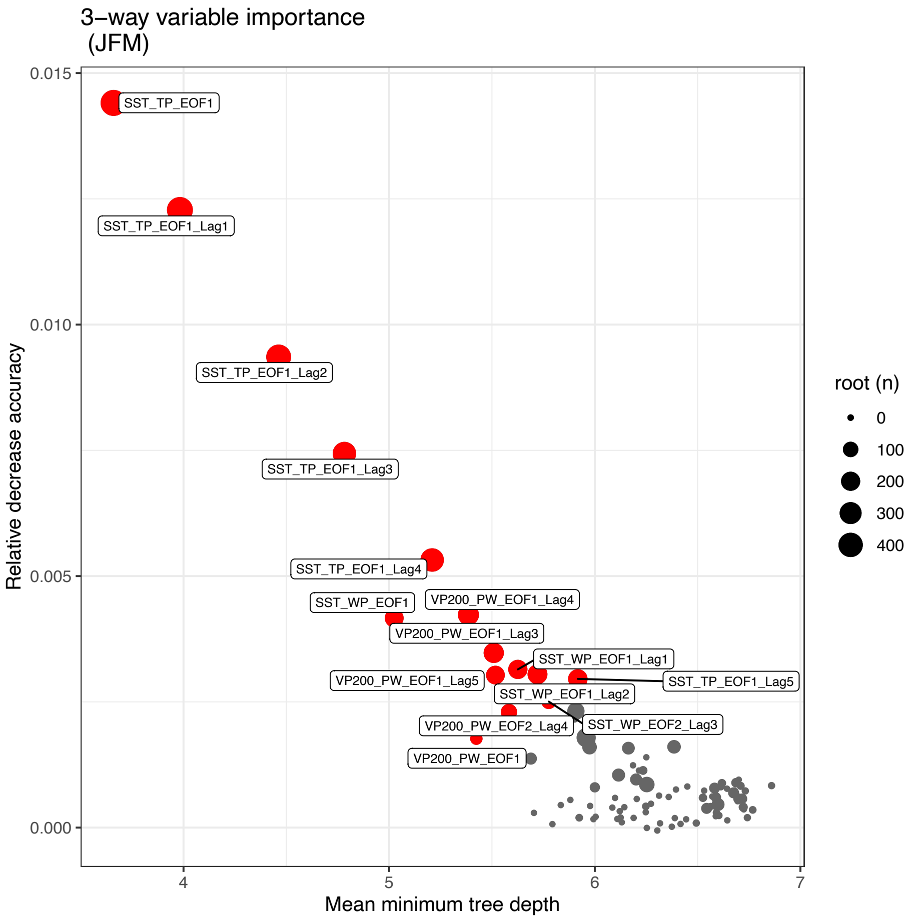
ENSEMBLE WITH NMME MODELS – JFM



- Accuracy: correct predictions / total predictions
- Baseline: horizontal line determined by most frequent class
- Random model: a random guess prediction repeated 1000 times (error bars 5/95th percentile
- Ens_model_ML: mode ensemble of the four ML methods
- Ens_mode_Super: mode ensemble from all eight ML + NMME models

Peter Gibson, Will Chapman, Alphan Altinok (JPL), Mike DeFlorio, Luca Delle Monache

INTERPRETABLE ML: LOOKING UNDER THE HOOD



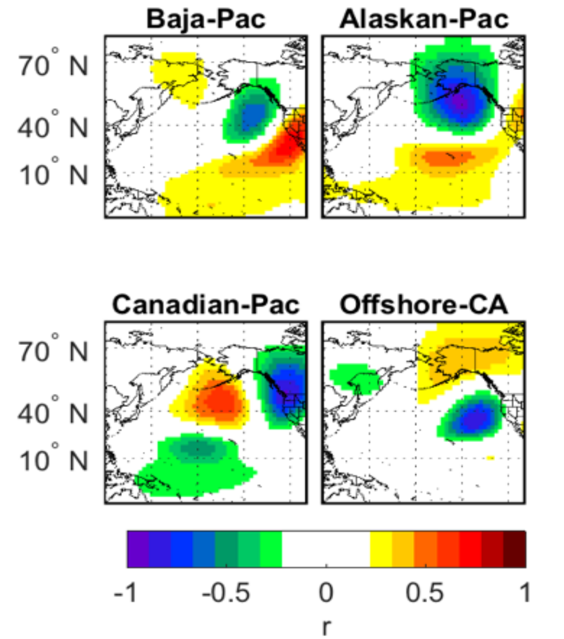
Variable importance

Physically reasonable predictors are showing up ….

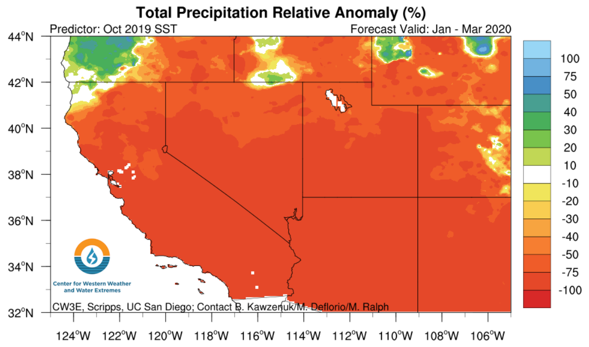
- Tropical Pacific SST (ENSO related) is most important predictor
- Western Pacific SST also important
- Tropical deep convection (VP200) also important
- Local SST (NP) and local circulation (U200/Z500) far less important (but are used as interaction variables)

Lead: Peter Gibson

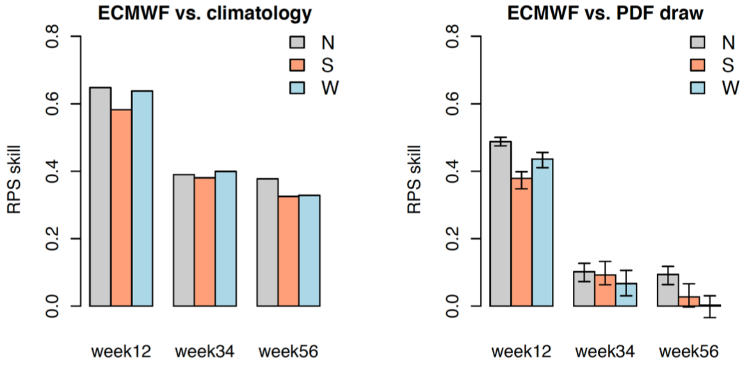
OTHER MACHINE LEARNING EFFORTS



Guirguis et al. (GRL, 2020)



Shulgina et al. (In preparation, 2020)



Gibson et al. (In preparation, 2020)

WHAT'S NEXT?

- Develop ML models for precipitation (0-5 days)

  Negin Hayatbini (CW3E Postdoc), Anirudhan Badrinath (CW3E Summer Intern, UC Berkeley Undergrad, CS), Siva Prasad Varma Chiluvuri (UCSD Graduate Student, Physics)

- Probabilistic Predictions of IVT (0-7 days)
  - Complete development and testing of Bayesian Neural Networks (Lead: Will Chapman)
  - Explore Convolutional Neural Networks (Lead: Will Chapman)
- ML for S2S
  - Complete development and testing of Decision Tree and other ML methods and comparison with Dynamical models (Peter Gibson, Will Chapman, Alphan Altinok – JPL, S2S Team)
  - Interpretable learning (Peter Gibson, Will Chapman, S2S Team)
  - Generate operational outlooks for best performing methods (S2S team)
- ML for the Ensemble Forecast Operations (EFO; Delaney et al., WRR 2020)

Thank you!

Luca Delle Monache
ldm@ucsd.edu