Sandia National Laboratories

Machine Learning and Reservoir Computing for Watershed-Scale Drought Prediction

Nicole D. Jackson, Ph.D.

Climate Security Center

American Geophysical Union Fall Meeting 2024

09 December 2024

U.S. DEPARTMENT OF ENERGY NNSA

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SAND2024-16489C

Acknowledgements

The EPIC PLANN (Enhanced Prediction in Chaotic Systems with Physics-learned Autonomous Neural Networks) team

- William Chapman[†]
- Josh Mott[‡]
- J. Darby Smith
- Corinne Teeter

‡

- Louis Scuderi
- Zach Strasberg[‡]

† postdoc , ‡ Ph.D. student

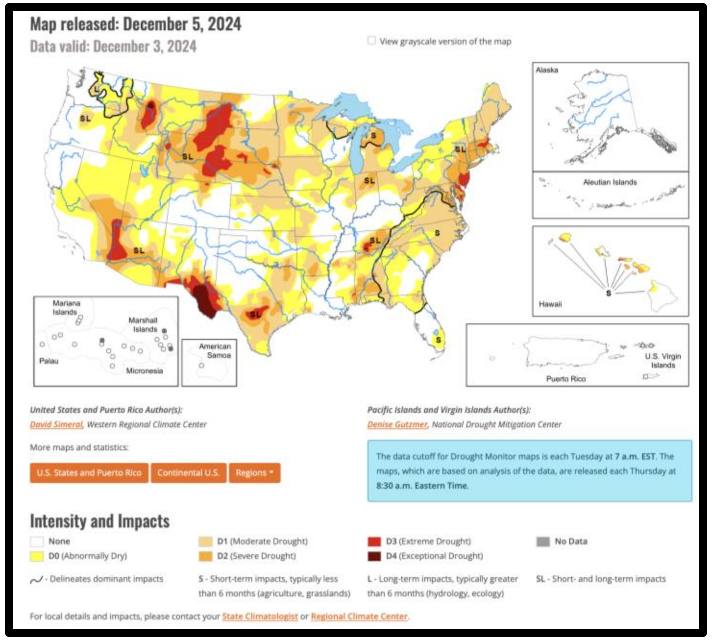
Sandia Earth Science Research Foundation

- Program Manager: Stephanie Kuzio

The US Drought Monitor provides weekly drought estimates

U.S. Drought Monitor

Last week's report

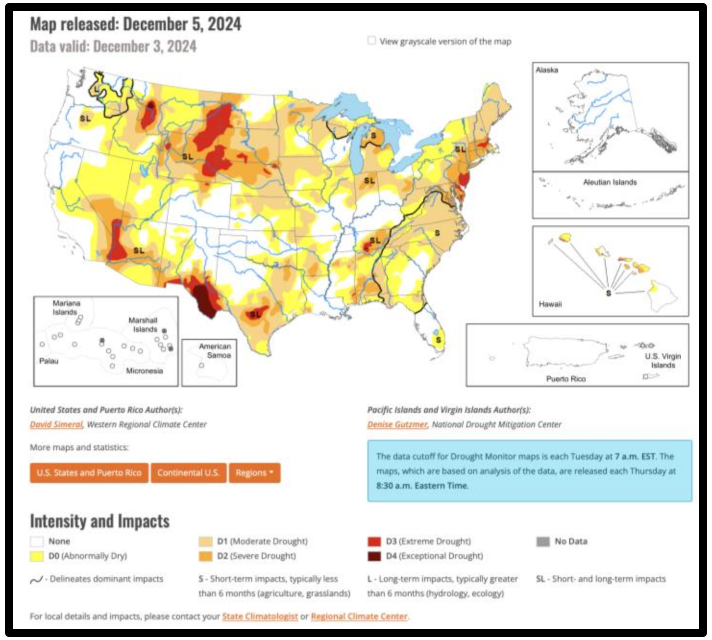


Source: [U.S. Drought Monitor]

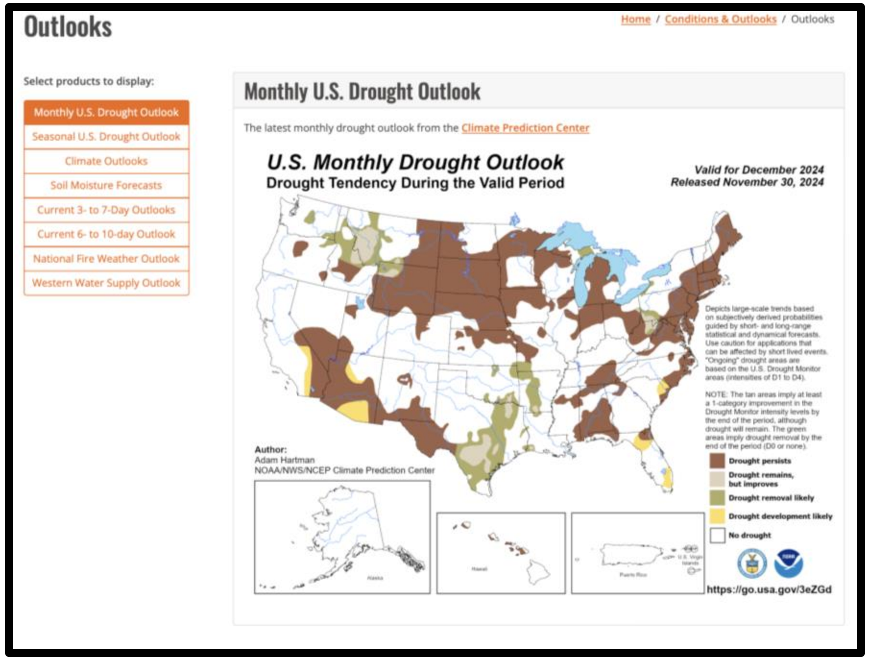
The US Drought Monitor provides weekly drought estimates as well as monthly forecasts

U.S. Drought Monitor

Last week's report



Monthly Outlook

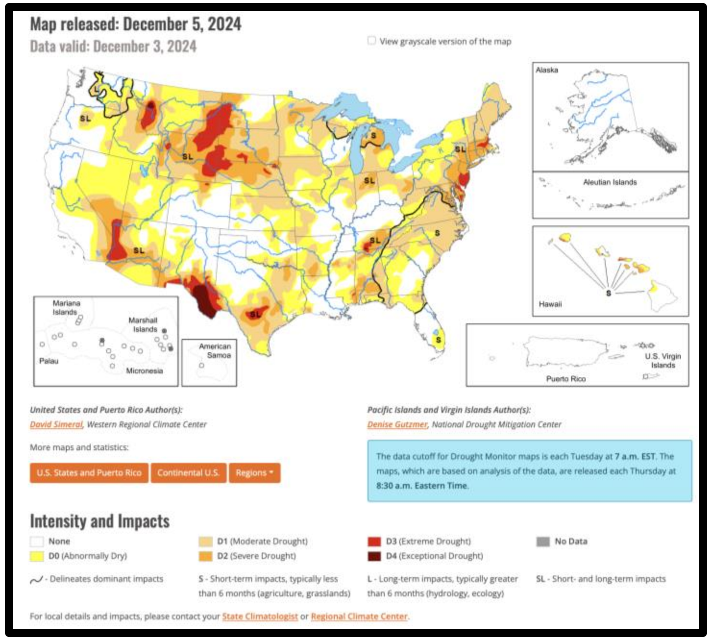


Source: U.S. Drought Monitor

The US Drought Monitor provides weekly drought estimates as well as monthly and seasonal forecasts

U.S. Drought Monitor

Last week's report



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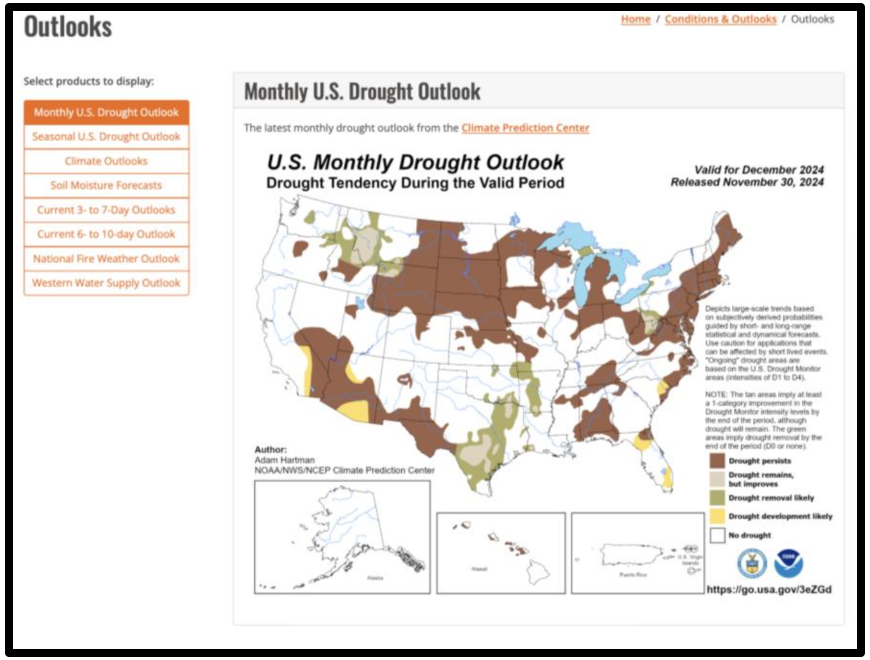
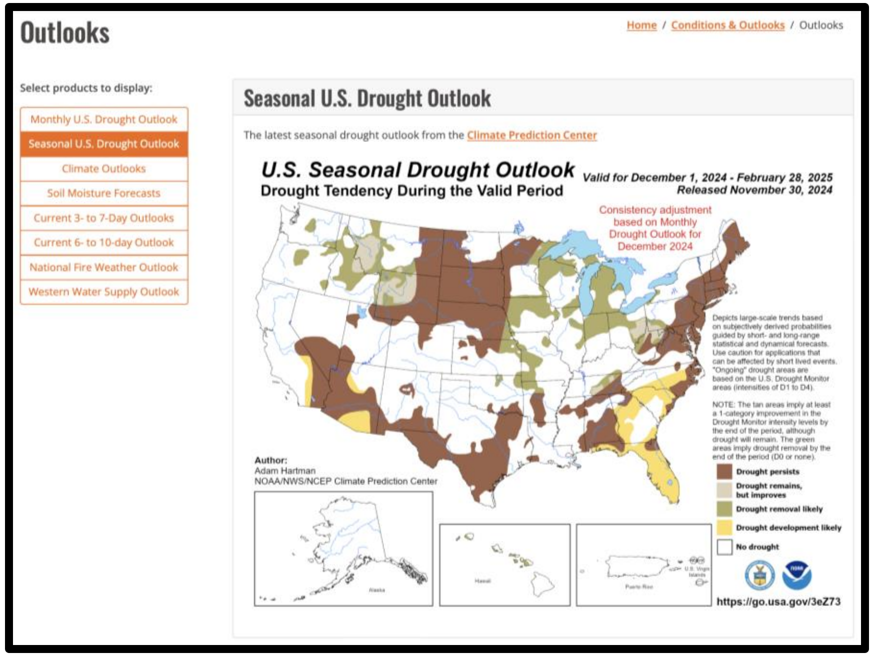


Seasonal Outlook



Source: U.S. Drought Monitor

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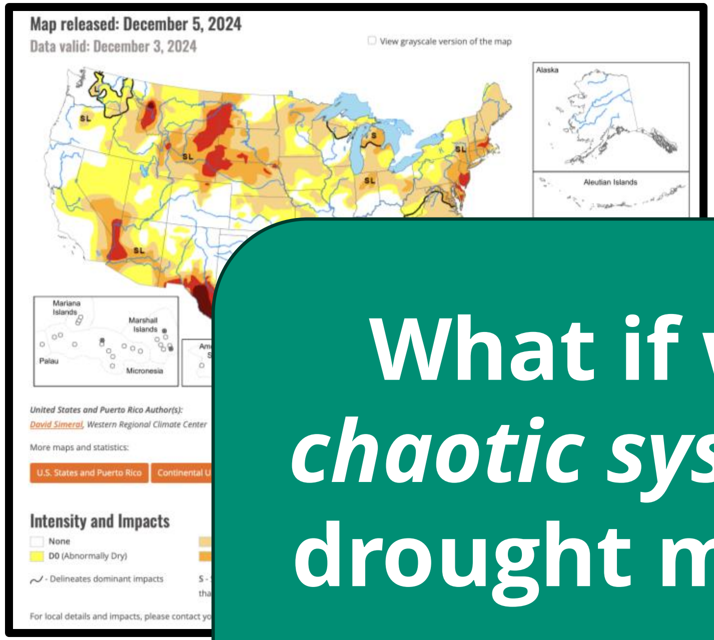
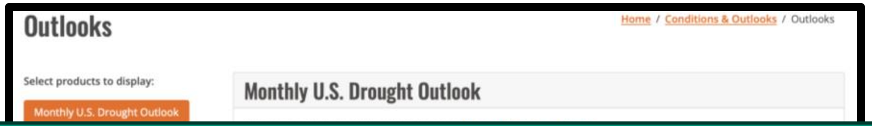
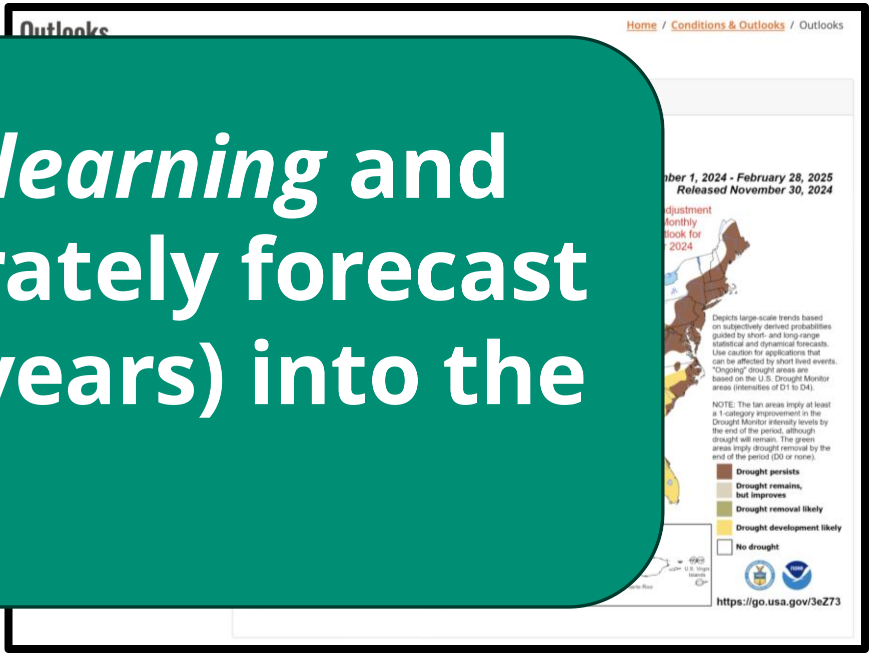


Monthly Outlook



Seasonal Outlook



What if we could use *machine learning* and *chaotic system modeling* to accurately forecast drought much farther (e.g., 1-2 years) into the future?

Source: U.S. Drought Monitor

Multiple machine learning—based algorithms have been used to forecast meteorological drought

Source: Agana and Homaifar (2017)

- Multilayer Perceptron (MLP)
- Support Vector Regression (SVR)

Source: Li et al. (2020)

- SVR
- Random Forest (RF)
- Extreme Learning Machine (ELM)

Source: Mokhtar et al. (2021)

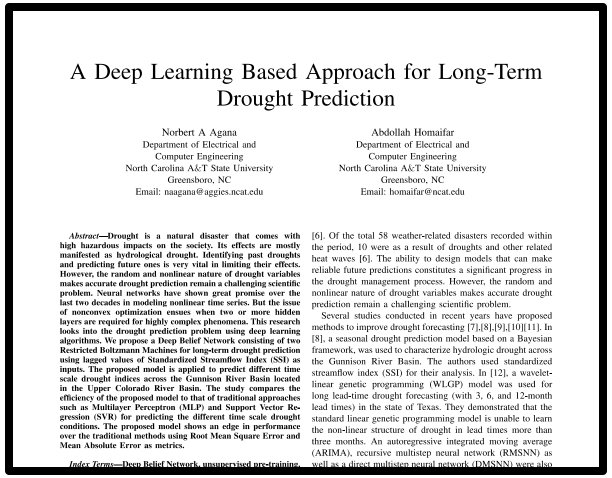
- RF
- Extreme Gradient Boost (XGB)
- Convolutional neural network (CNN)
- Long-term short memory (LSTM)

Source: Prodhan et al. (2022)

Meteorological Drought:

- Artificial neural network (ANN)
- SVR
- K-nearest neighbor
- Adaptive Neuro Fuzzy (ANF)
- SVM-Copula
- Wavelet Boosting-Support Vector Regression (WBS-SVM)

Multiple machine learning—based algorithms have been used to forecast meteorological drought

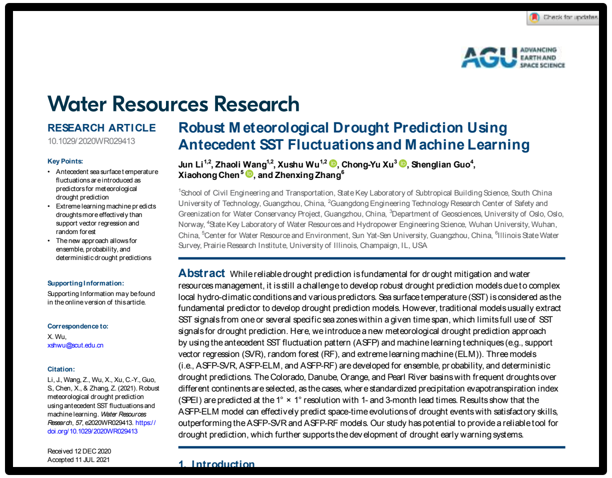


A Deep Learning Based Approach for Long-Term Drought Prediction

Norbert A Agana, Department of Electrical and Computer Engineering, North Carolina A&T State University, Greensboro, NC

Abdollah Homaifar, Department of Electrical and Computer Engineering, North Carolina A&T State University, Greensboro, NC

Source: [Agana and Homaifar (2017)]

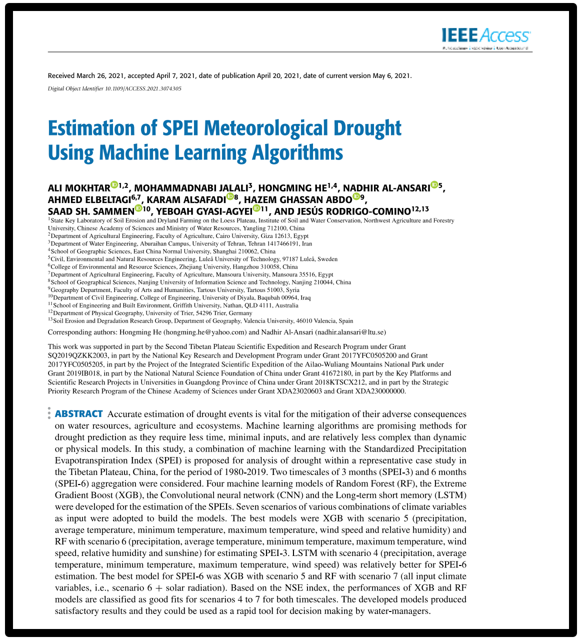


Water Resources Research

RESEARCH ARTICLE

Robust Meteorological Drought Prediction Using Antecedent SST Fluctuations and Machine Learning

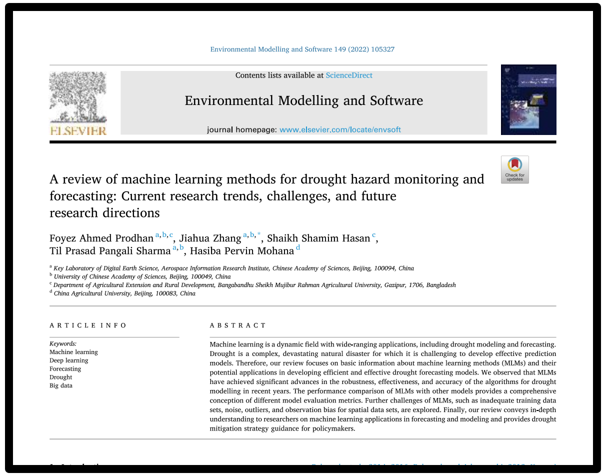
Source: [Li et al. (2020)]



IEEE Access

Estimation of SPEI Meteorological Drought Using Machine Learning Algorithms

Source: [Mokhtar et al. (2021)]



Environmental Modelling and Software

A review of machine learning methods for drought hazard monitoring and forecasting: Current research trends, challenges, and future research directions

Source: [Prodhan et al. (2022)]

- Multilayer Perceptron (MLP)
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- SVR
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- RF
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Meteorological Drought:

- Artificial neural network (ANN)
- SVR
- K-nearest neighbor
- Adaptive Neuro Fuzzy (ANF)
- SVM-Copula
- Wavelet Boosting-Support Vector Regression (WBS-SVM)

Gap: forecasting for periods beyond 3-6 months

Modeling supported by the high spatial resolution (4 km) NCAR/USGS CONUS404 dataset for period 1979-2021

- Climate Data (CONUS404)
- Drought Metrics

>100 including…

Precipitation

Temperature

Transpiration

Wind speed

Calculated **meteorological drought** metrics:

- Standardized Precipitation Index (SPI)
- Standardized Precipitation Evapotranspiration Index (SPEI)

Source: [Rasmussen et al. (2023)]

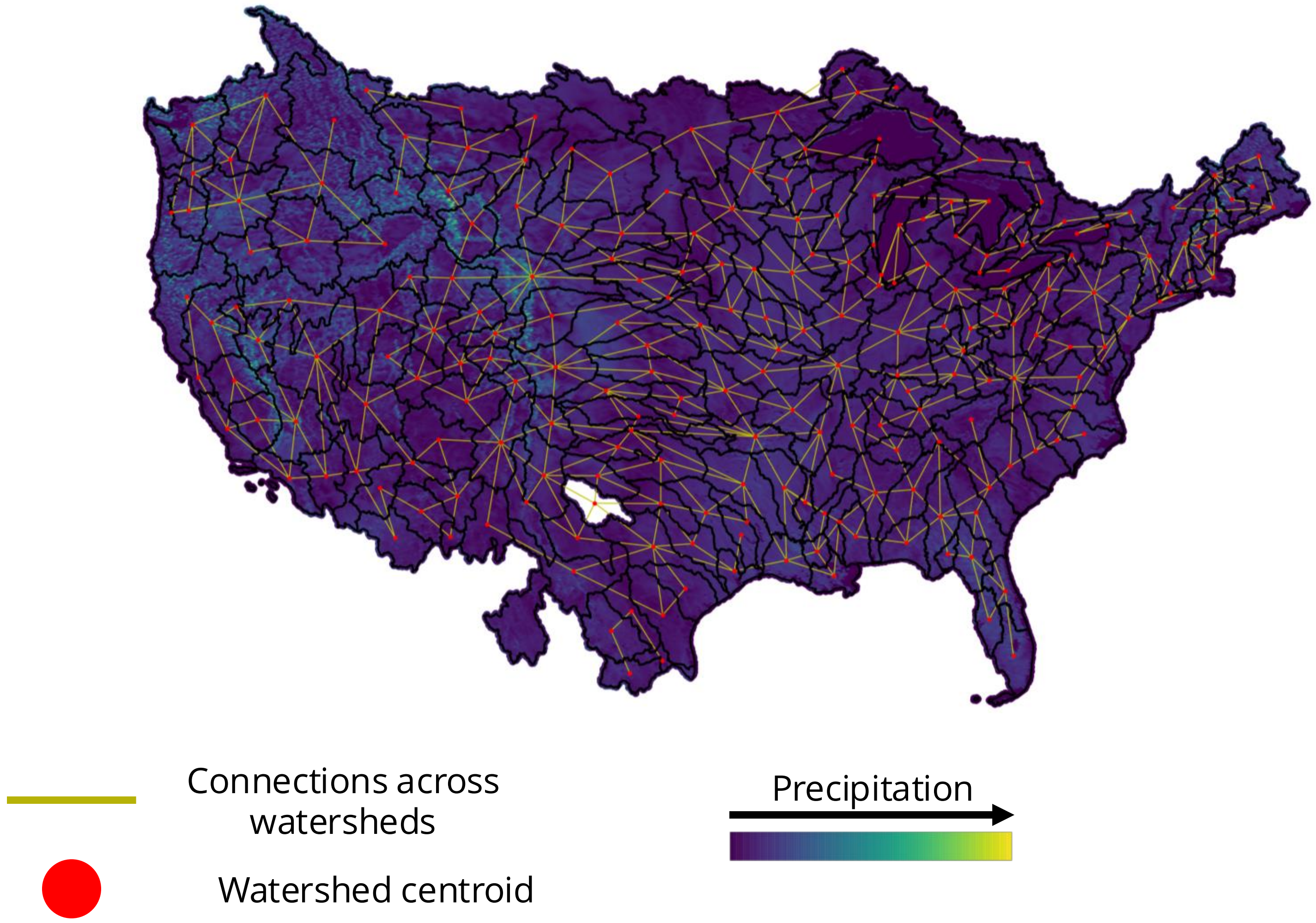
Data is statistically reduced to the weekly timescale at the HUC4 and HUC8 spatial scales

- Climate Data (CONUS404)
- Drought Metrics

↓

Watershed-scale Spatial Aggregation

Sample HUC8 aggregation for precipitation

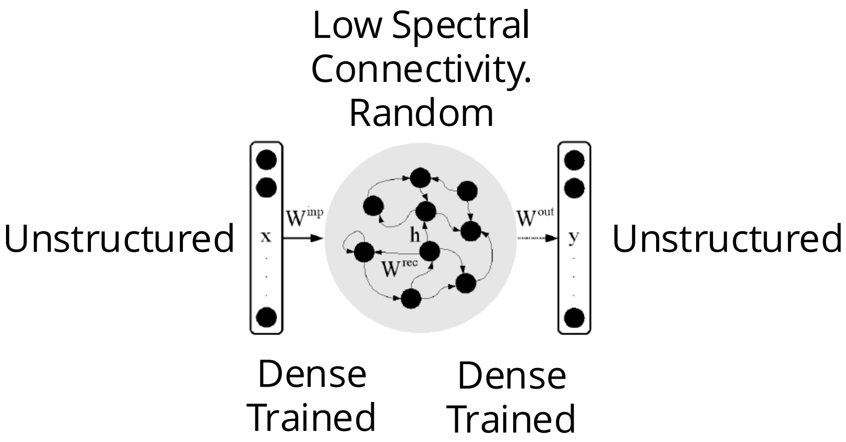


Reservoir networks use spectral normalization and random connectivity to autonomously mimic chaotic system

- Climate Data (CONUS404)
- Drought Metrics

Watershed-scale Spatial Aggregation

Reservoir Computing-based Predictive Drought Model



Graph-based reservoirs reduce normalized root mean square error during prediction period versus a single reservoir

- Climate Data (CONUS404)
- Drought Metrics

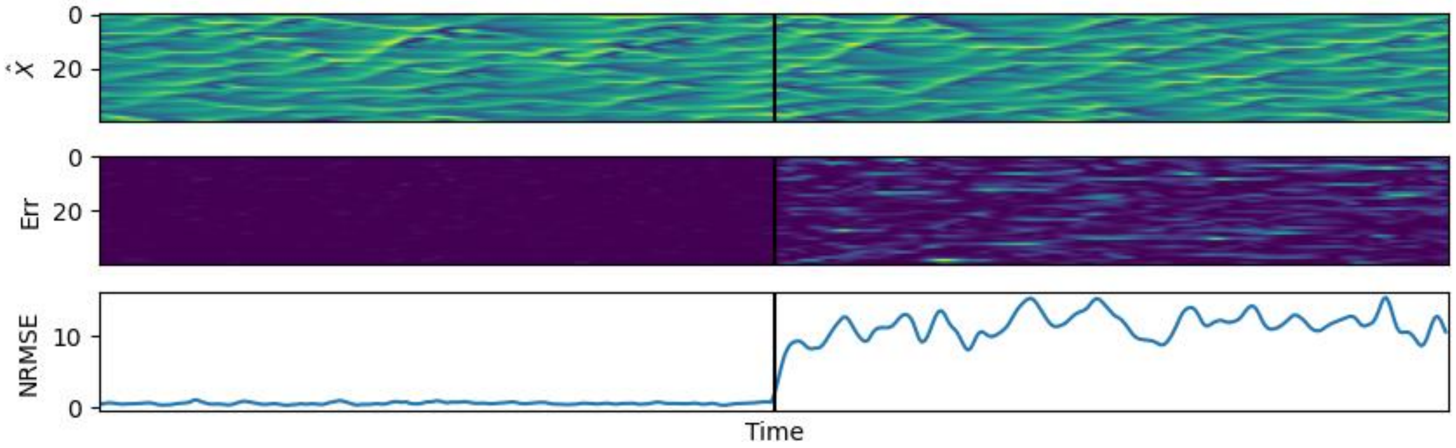
↓

Watershed-scale Spatial Aggregation

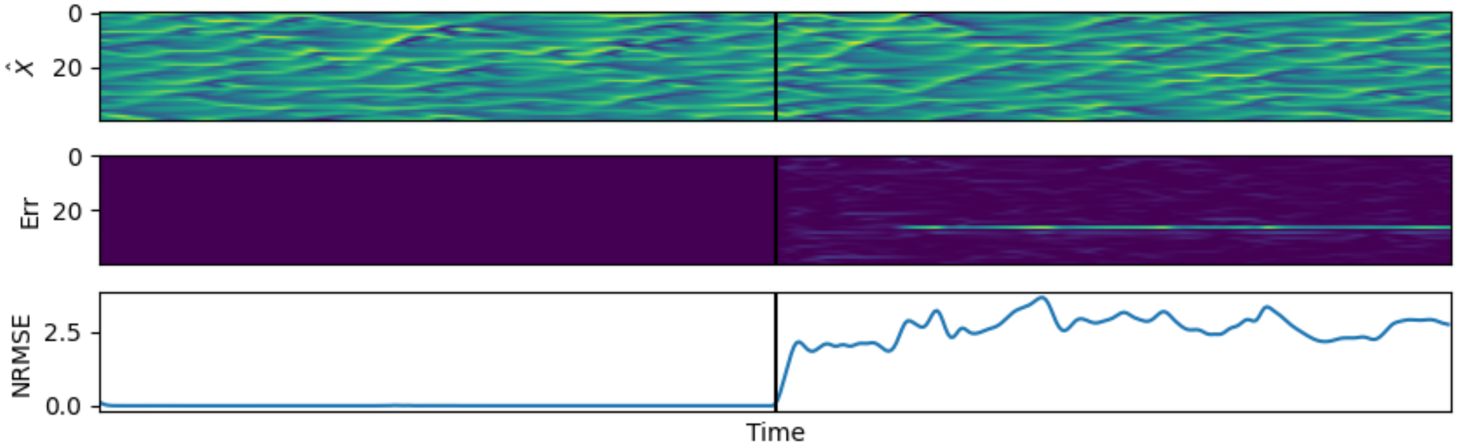
↓

Reservoir Computing-based Predictive Drought Model

Single Reservoir



Graph Reservoir



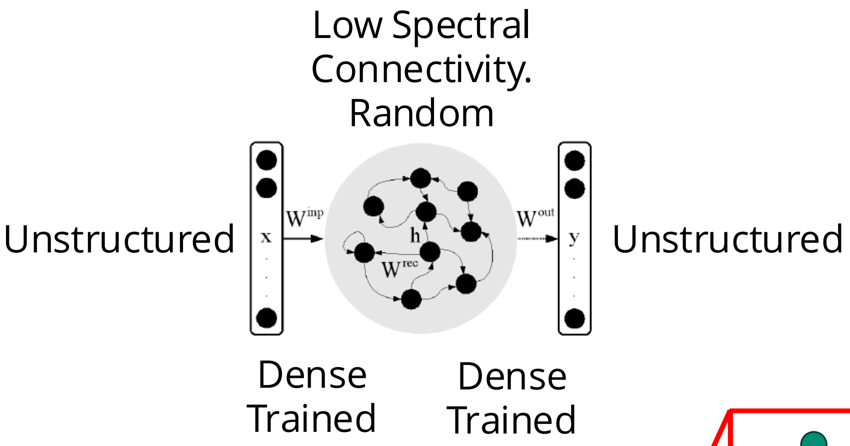
Source: Chapman et al. (*in prep*)

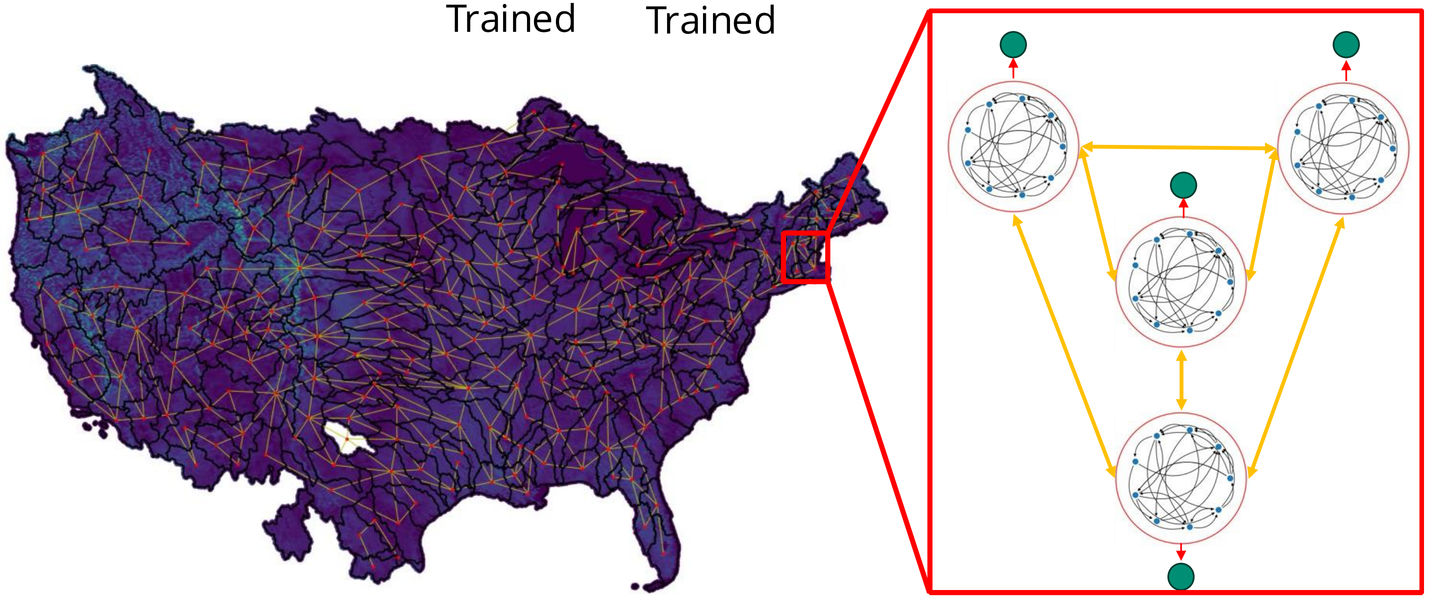
Graph reservoir nodes are generated for each watershed while maintaining the input layer’s spatial structure

- Climate Data (CONUS404)
- Drought Metrics

Watershed-scale Spatial Aggregation

Reservoir Computing-based Predictive Drought Model





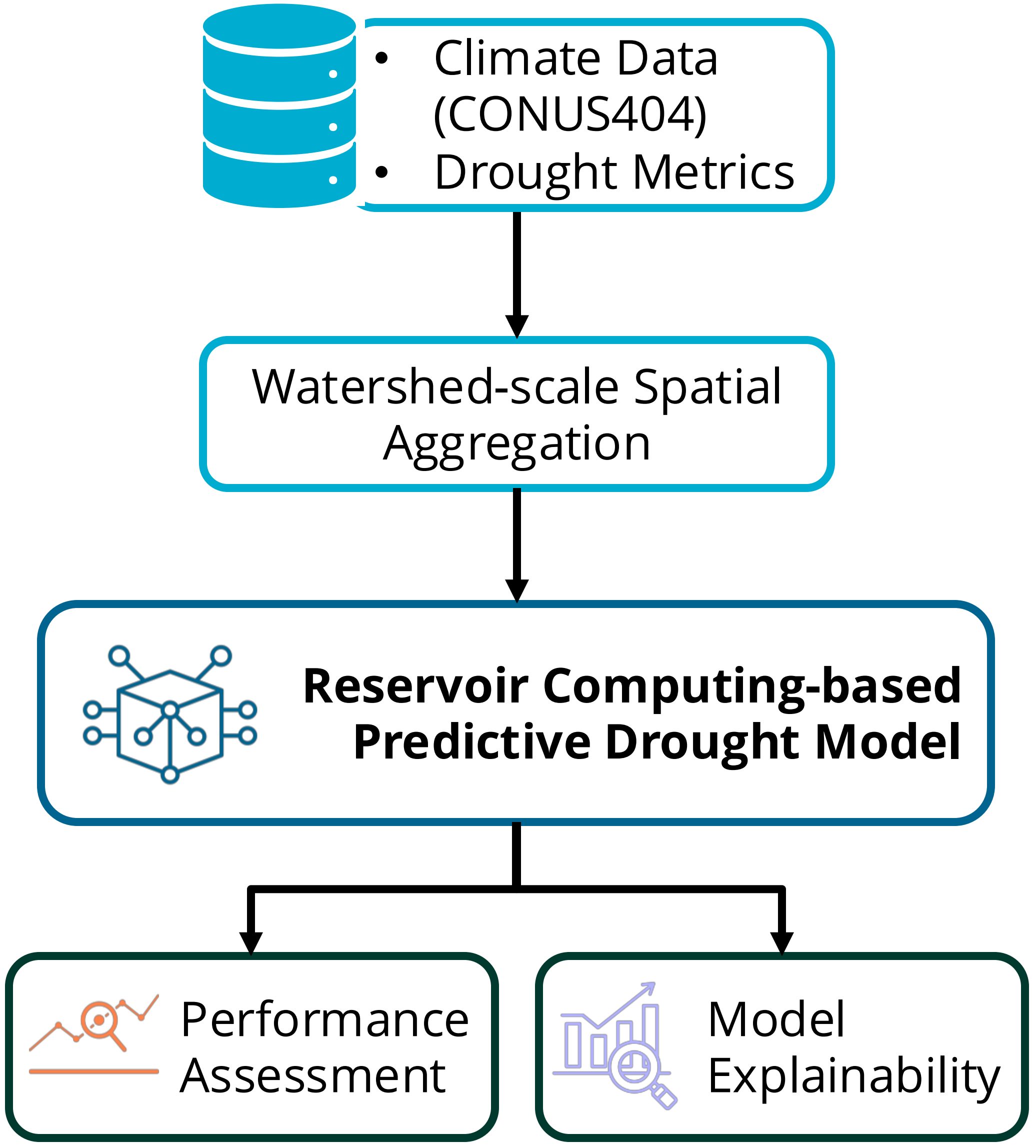
Connections across watersheds

Watershed centroid

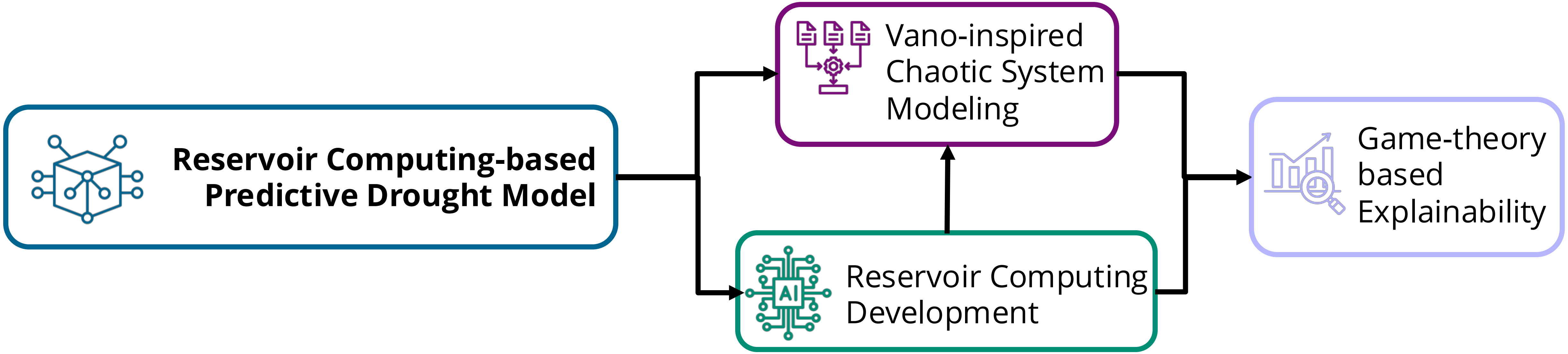
Connection to spatially close watershed

Local observable variable

The EPIC PLANN project is using a standard framework to develop its ML-based predictive model for drought



Reservoir model development inspired by chaotic systems modeling and game theory



A graph-based reservoir network is trained to predict two sets of Vano models side by side

Input layer

$X_1(t_0), \ldots, X_1\left(t_{N_k}\right)$
$X_2(t_0), \ldots, X_2\left(t_{N_k}\right)$
$X_3(t_0), \ldots, X_3\left(t_{N_k}\right)$
$X_4(t_0), \ldots X_4\left(t_{N_k}\right)$
$Y_1(t_0), \ldots, Y_1\left(t_{N_k}\right)$
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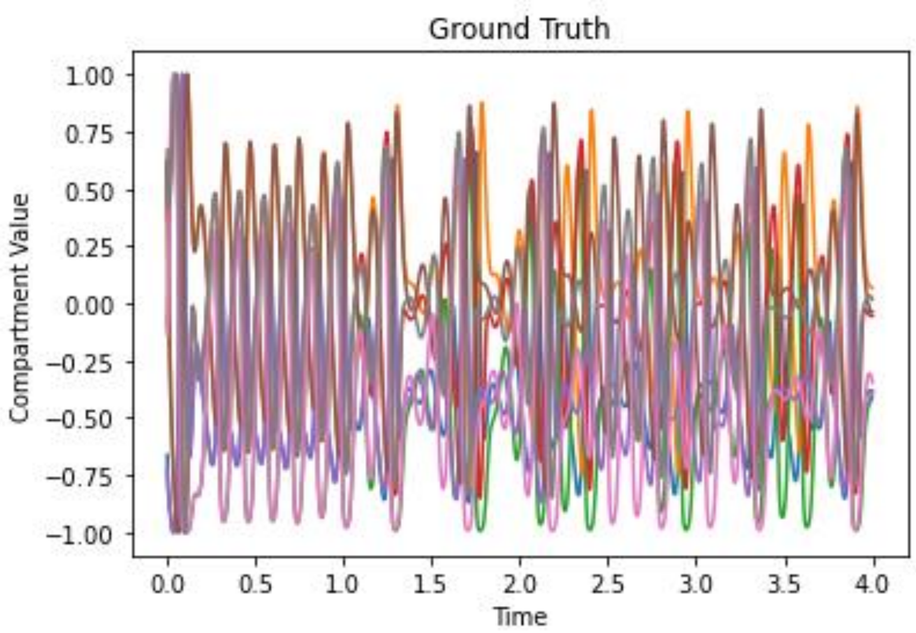

Source: Smith et al. (*in prep*)

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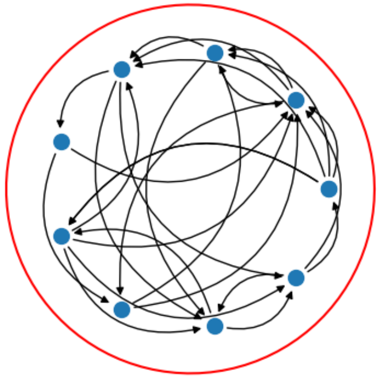
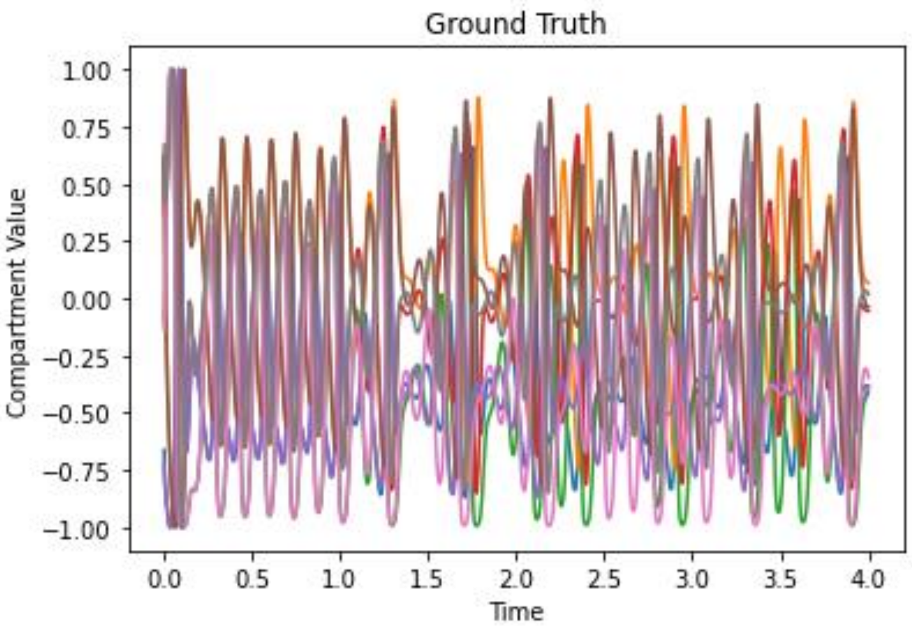
$X_4(t_0), \ldots X_4\left(t_{N_k}\right)$
$Y_1(t_0), \ldots, Y_1\left(t_{N_k}\right)$
$Y_2(t_0), \ldots, Y_2\left(t_{N_k}\right)$
$Y_3(t_0), \ldots, Y_3\left(t_{N_k}\right)$
$Y_4(t_0), \ldots, Y_4\left(t_{N_k}\right)$

Trained Reservoirs





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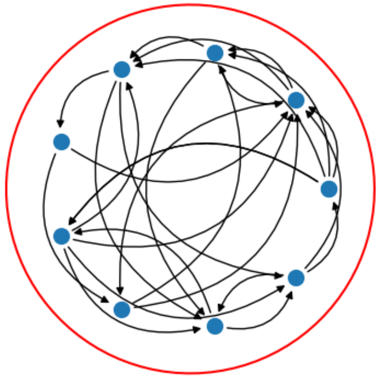
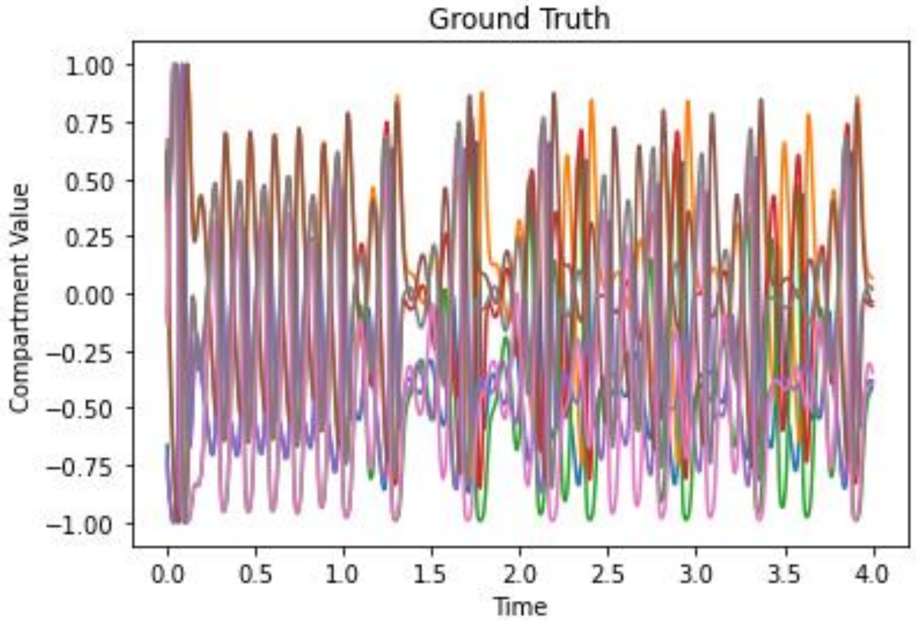
$Y_2(t_0), \dots, Y_2\left(t_{N_k}\right)$
$Y_3(t_0), \dots, Y_3\left(t_{N_k}\right)$
$Y_4(t_0), \dots, Y_4\left(t_{N_k}\right)$

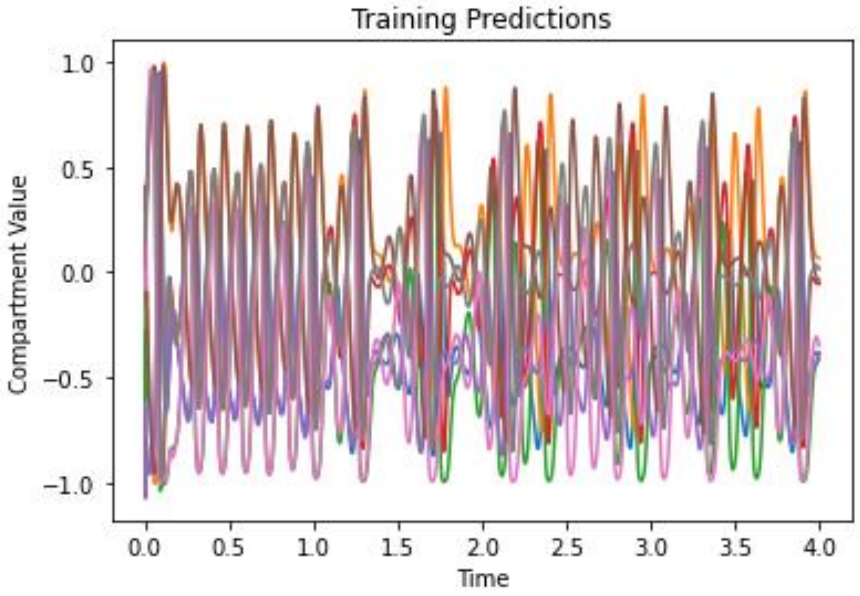
Trained Reservoirs



Output layer

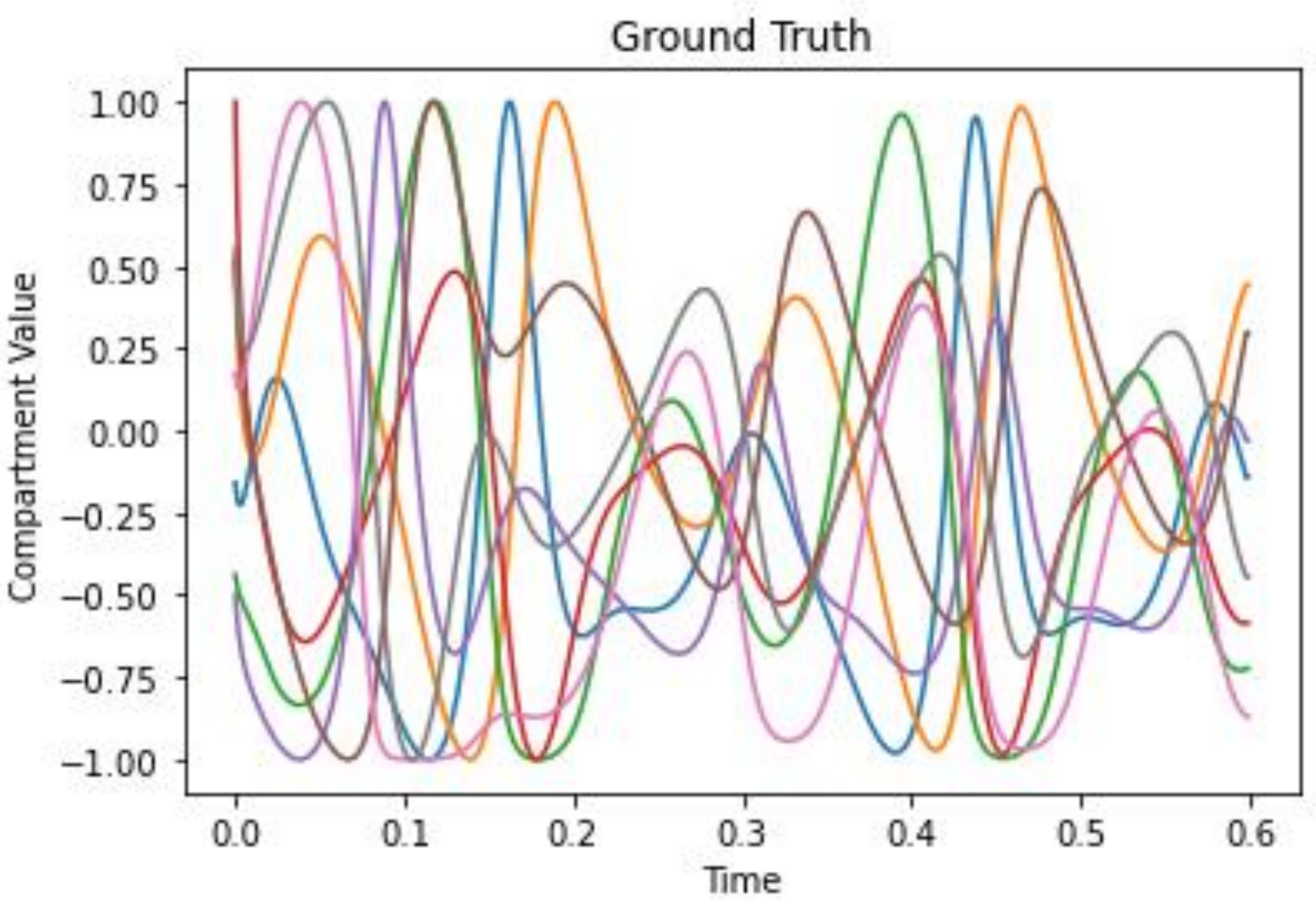
$X_1\left(t_{N_k+1}\right), \dots, X_1\left(t_{N_p}\right)$
$X_2\left(t_{N_k+1}\right), \dots, X_2\left(t_{N_p}\right)$
$X_3\left(t_{N_k+1}\right), \dots, X_3\left(t_{N_p}\right)$
$X_4\left(t_{N_k+1}\right), \dots, X_4\left(t_{N_p}\right)$
$Y_1\left(t_{N_k+1}\right), \dots, Y_1\left(t_{N_p}\right)$
$Y_2\left(t_{N_k+1}\right), \dots, Y_2\left(t_{N_p}\right)$
$Y_3\left(t_{N_k+1}\right), \dots, Y_3\left(t_{N_p}\right)$
$Y_4\left(t_{N_k+1}\right), \dots, Y_4\left(t_{N_p}\right)$
$\boxed{g\left(t_{N_k+1}\right), \dots, g\left(t_{N_p}\right)}$ Mystery function



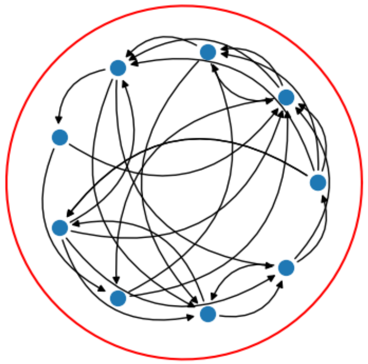


Source: Smith et al. (*in prep*)

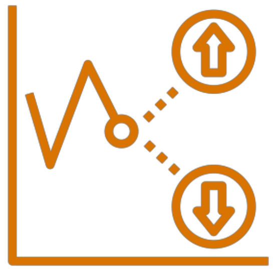
A new time series using perturbed initial conditions is generated to support prediction with trained reservoirs



Previously trained reservoirs

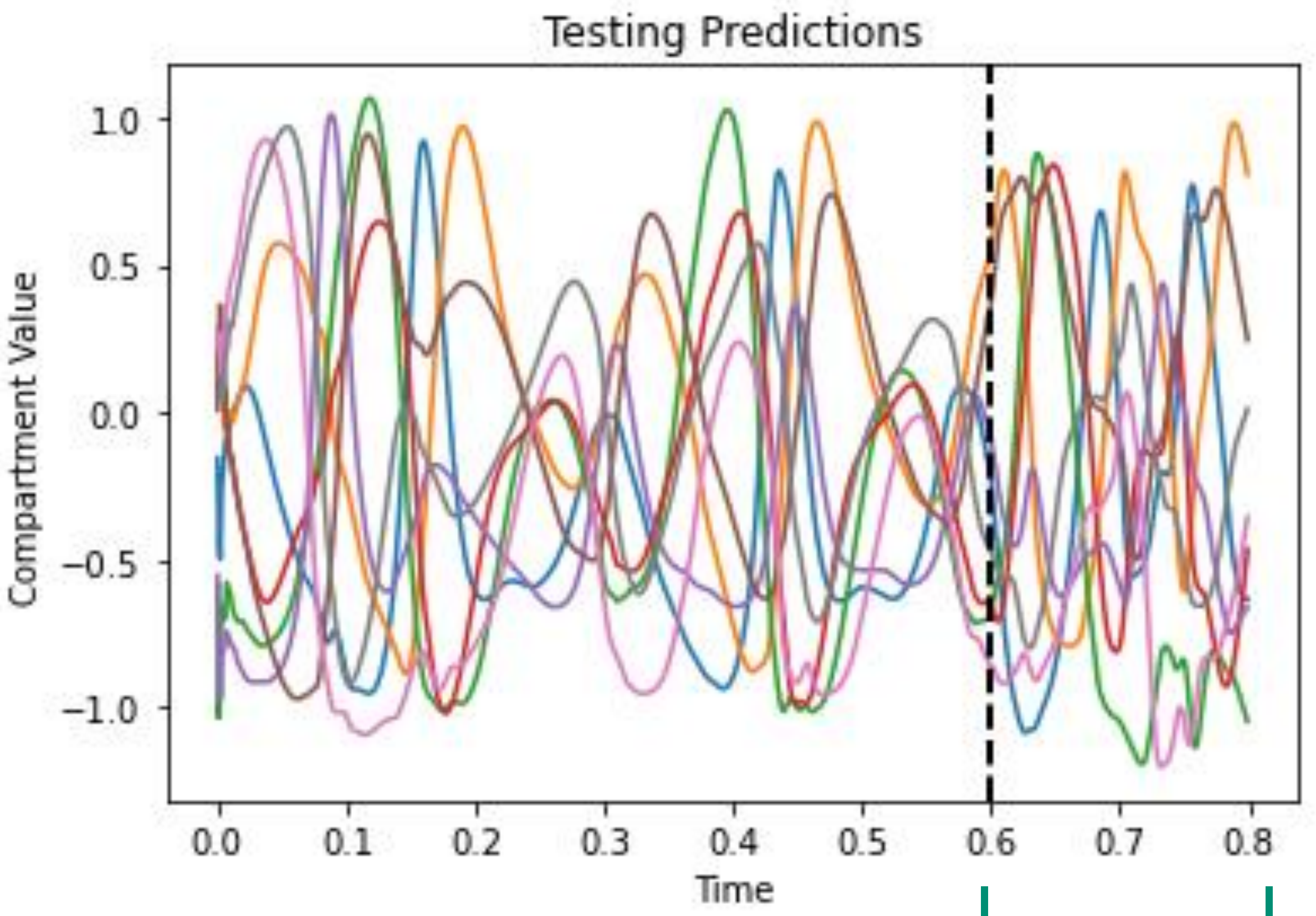


Predicted time series



Source: Smith et al. (*in prep*)

Predicted time series using perturbed data and trained reservoirs with rollout



Rollout using only trained reservoirs

Source: Smith et al. (*in prep*)

Shapley Additive Explanation Values (SHAP) are used to determine influence of inputs on changes to outputs

Input layer

$X_1(t_0), \ldots, X_1(t_{N_k})$
$X_2(t_0), \ldots, X_2(t_{N_k})$
$X_3(t_0), \ldots, X_3(t_{N_k})$
$X_4(t_0), \ldots X_4(t_{N_k})$
$Y_1(t_0), \ldots, Y_1(t_{N_k})$
$Y_2(t_0), \ldots, Y_2(t_{N_k})$
$Y_3(t_0), \ldots, Y_3(t_{N_k})$
$Y_4(t_0), \ldots, Y_4(t_{N_k})$

$\rightarrow$

Output layer

$X_1(t_{N_k+1}), \ldots, X_1(t_{N_p})$
$X_2(t_{N_k+1}), \ldots, X_2(t_{N_p})$
$X_3(t_{N_k+1}), \ldots, X_3(t_{N_p})$
$X_4(t_{N_k+1}), \ldots, X_4(t_{N_p})$
$Y_1(t_{N_k+1}), \ldots, Y_1(t_{N_p})$
$Y_2(t_{N_k+1}), \ldots, Y_2(t_{N_p})$
$Y_3(t_{N_k+1}), \ldots, Y_3(t_{N_p})$
$Y_4(t_{N_k+1}), \ldots, Y_4(t_{N_p})$
$\boxed{g(t_{N_k+1}), \ldots, g(t_{N_p})}$

$\rightarrow$

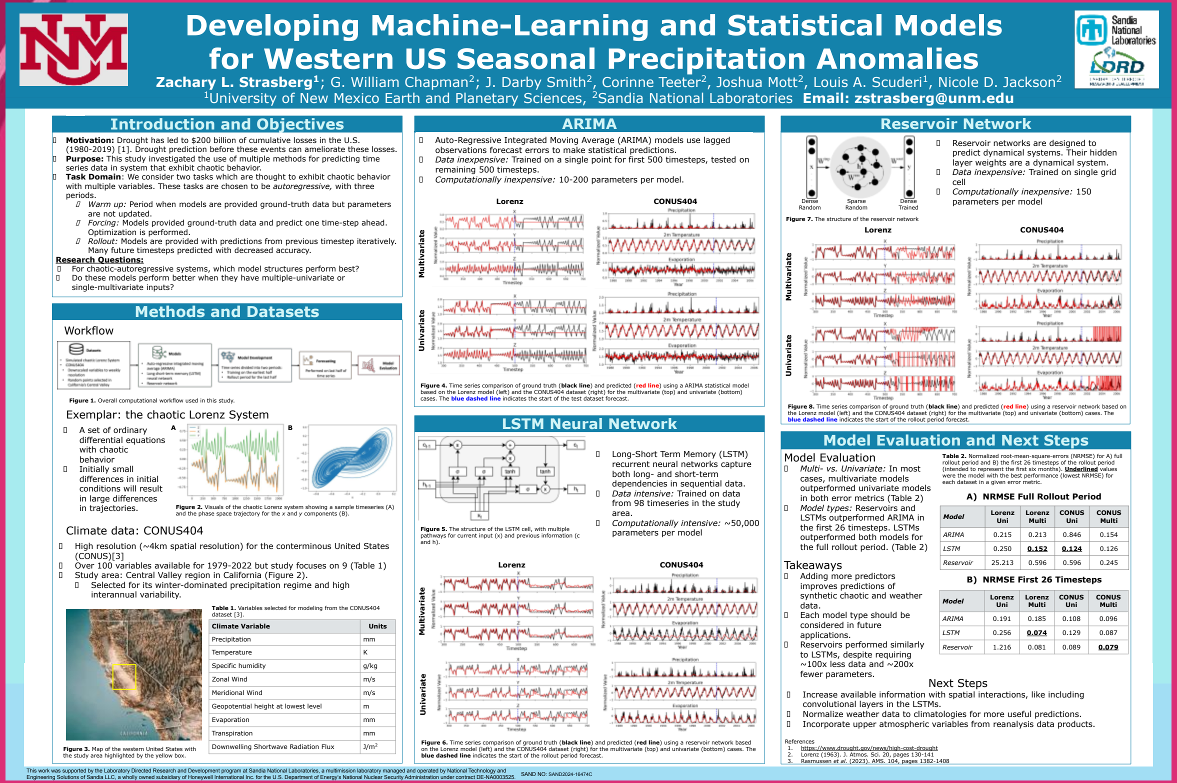
SHAP Values

$$\begin{bmatrix} 0.02147524 \\ 0.02505524 \\ 0.02095524 \\ 0.01256381 \\ 0.00879333 \\ 0.00837357 \\ 0.00999976 \\ 0.00241643 \end{bmatrix}$$

Source: Smith et al. (*in prep*)

A51L-1838: Developing Machine-Learning and Statistical Models for Western US Seasonal Precipitation Anomalies

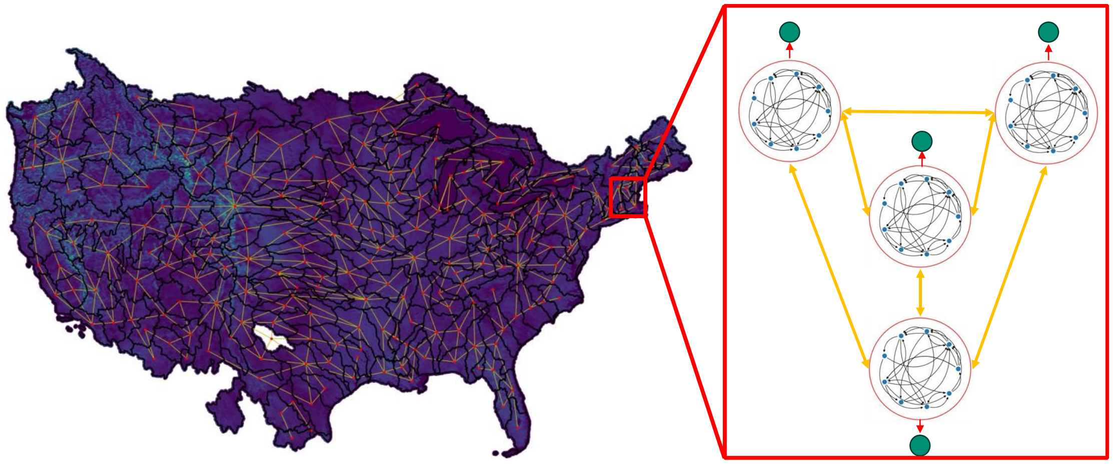
- Presenter: Zach Strasberg
- Friday, 13 December 2024
- 08:30 – 12:20
- Poster Halls B-C

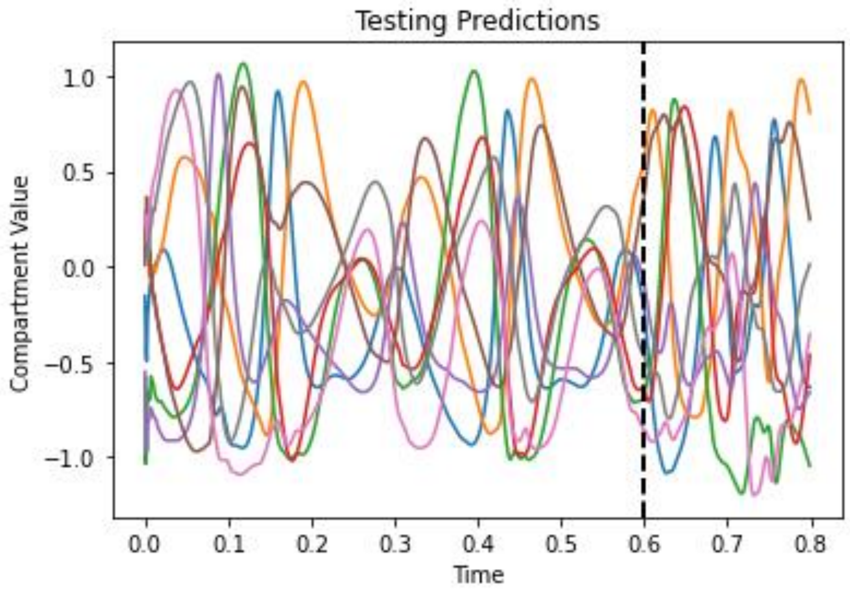


AGU24

In conclusion, we have developed reservoir computing-based predictive time series models for chaotic, dynamic systems

- Graph reservoirs reduce error compared to single reservoirs
- Reservoir-based predictive model developed using the Vano system with chaotic behavior
- SHAP identified 3 key variables driving Vano model performance





Future Work

- Increase variables and explainability techniques for the Vano model
- Consideration of multiple drought metrics (SPEI, SPI, etc.)
- Increase spatial extent of modeled watersheds

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