

# Predictability of Drought using Different Types of Drought Indices

Mohammad Hadi Bazrkar, Heechan Han, Seonggyu Park,  
Tadesse Abitew, Colleen HM Green\*, Jaehak Jeong

Blackland Research and Extension Center, Texas A&M AgriLife Research, USA

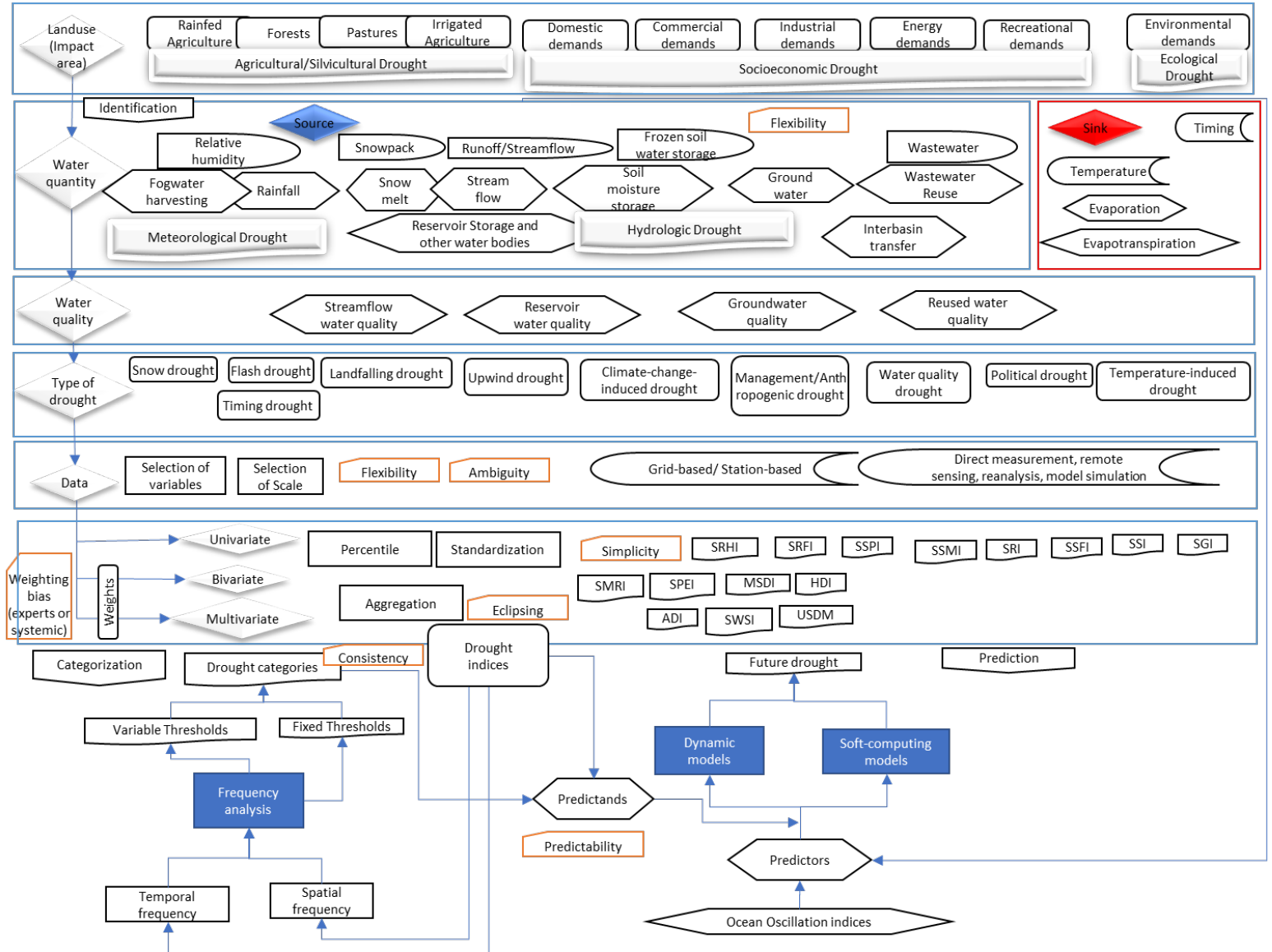
\*Bureau of Land Management, National Operations Center, Denver, Colorado, USA



# Criteria for selection of a suitable drought index

Proposed criteria	Swamee and Tyagi (2000 and 2007)	Steinemann et al. (2005)	Keyantash and Dracup (2002)	Narasimhan and Srinivasan (2005)
Predictability				
Experts' bias				
Anthropogenic				
Experts-opinions-included		Quantitative and qualitative indicators		
Eclipsing	Eclipsing in WQIs	Drought progressing and receding	Robustness	Be able to reflect developing short-term drought conditions
Ambiguity	Ambiguity in WQIs			
Variable threshold by spatial and temporal distributions (having well-defined thresholds and criteria)		Statistical consistency		
Transparency		Explicit combination methods		
		Clarity and validity	Transparency	
Simplicity			Sophistication	
Flexibility	Rigidity in WQIs		Extendability	
Landuse-based DI		Suitability for the drought type under study		
Rationality			Dimensionality	
Reproducibility		Data (availability, cost, consistency)	Tractability	
		Linked with drought management goals		
Seasonality		Temporal sensitivity and specificity		No seasonality
Climate adaptability		Spatial sensitivity and specificity		Spatially comparable

# Drought index recommender



# Drought Indices

Predictands	Type	Input	Method of calculation	Predictors
HAD	Multivariate	RF, SM, R, SMS	PCA	P, T, ET, DFCT
SSI	Univariate	SMS	Standardized	P, T, ET, DFCT
SRI	Univariate	R	Standardized	P, T, ET, DFCT
SPB	Bivariate	P, ET	Standardized	P, T
SMRI	Bivariate	SM, RF	Standardized	P, T
SPI	Univariate	P	Standardized	P

Notes: P: Precipitation, T: Temperature, ET: Evapotranspiration, RF: Rainfall, SM: Snowmelt, R: Runoff, SMS: Soil moisture, SP: Snowpack, BF: Baseflow, SWE: Snow water equivalent, DFCT: difference between precipitation and evapotranspiration, PCA: Principal component analysis

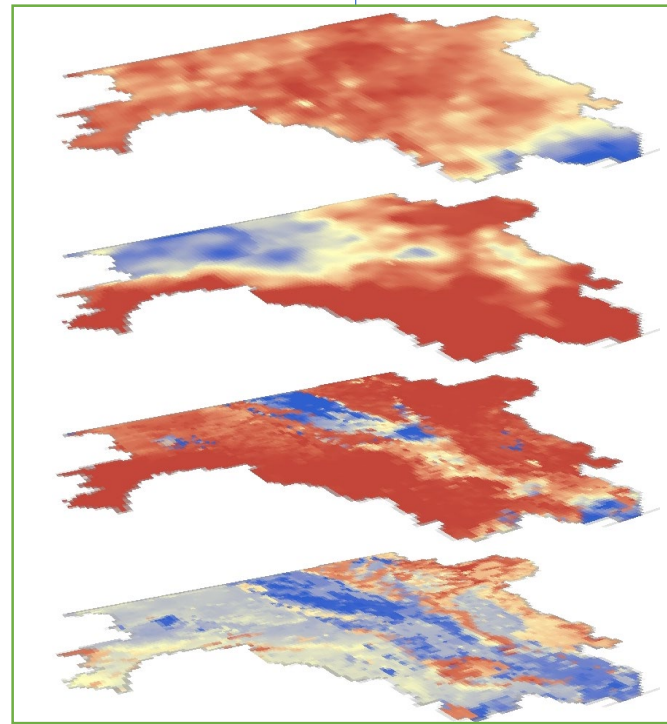
# Hydroclimatic Aggregate Drought Index (HADI)

$$HADI_{i,j} = \frac{PC_{i,j} - \mu_{PC_j}}{\sigma_{PC_j}}$$

where  $HADI_{i,j}$  is the new drought index;  $PC_{i,j}$  is the PC in month  $i$  and grid  $j$ ; and  $\mu_{PC_j}$  and  $\sigma_{PC_j}$  are the mean and standard deviation of PC in grid  $j$ .

$$A = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \end{bmatrix}$$

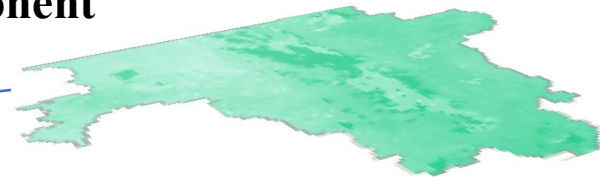
Rainfall  
Snowmelt  
Runoff  
Soil water storage



$$z_i = A S Y_i$$

1<sup>st</sup> principal component

$$z_i = \begin{bmatrix} z_{1i} \\ z_{2i} \\ z_{3i} \\ z_{4i} \end{bmatrix}$$



Time loop

SMRI

SRI

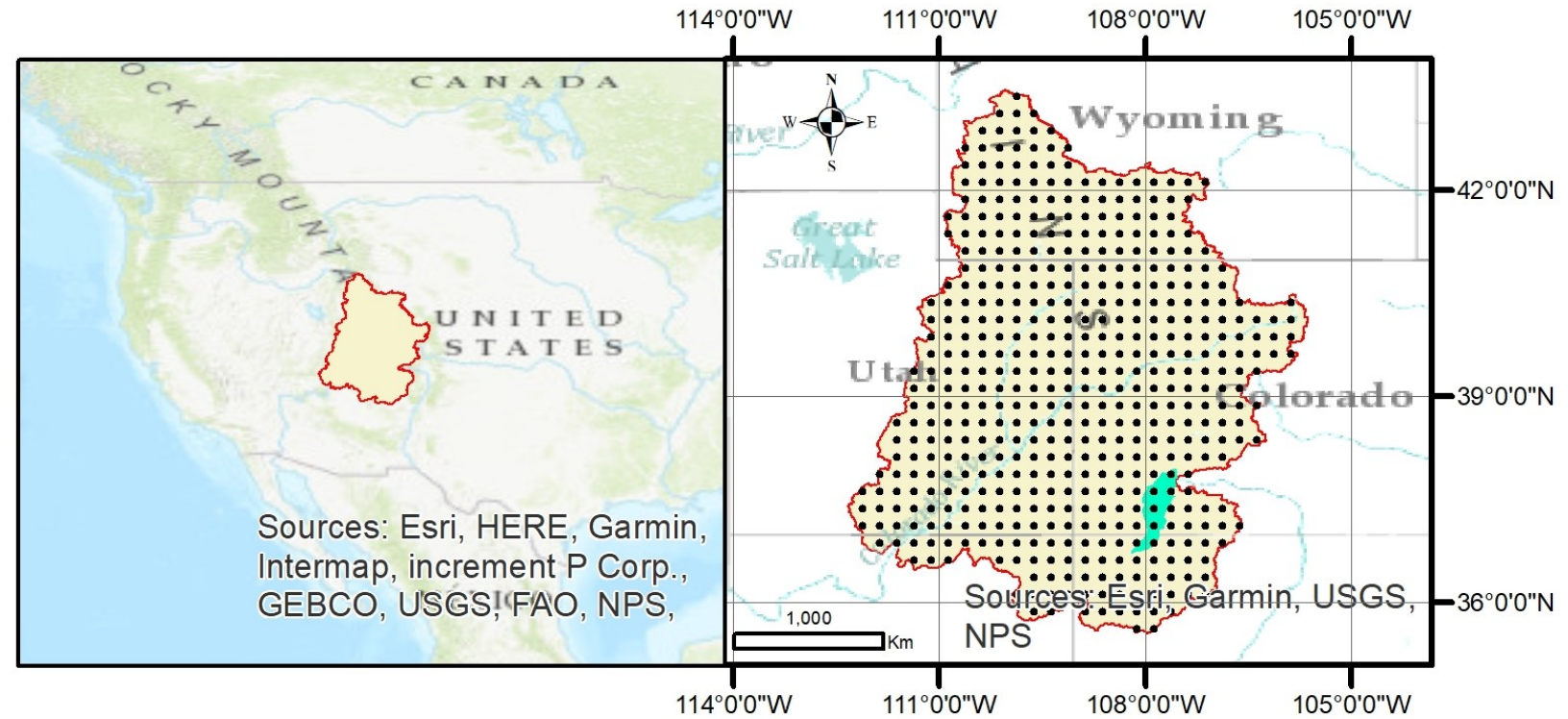
SSI



# Global Land Data Assimilation System (GLDAS)

- The goal of the Global Land Data Assimilation System (GLDAS) is to ingest satellite- and ground-based observational data products, using advanced land surface modeling and data assimilation techniques, in order to generate optimal fields of land surface states and fluxes (Rodell et al., 2004a).
- Daily and resolution of 0.25 degrees (25 km).
- 1950 - 2014

Rodell, M., P.R. Houser, U. Jambor, J. Gottschalck, K. Mitchell, C.-J. Meng, K. Arsenault, B. Cosgrove, J. Radakovich, M. Bosilovich, J.K. Entin, J.P. Walker, D. Lohmann, and D. Toll, The Global Land Data Assimilation System, Bull. Amer. Meteor. Soc., 85(3), 381-394, 2004.

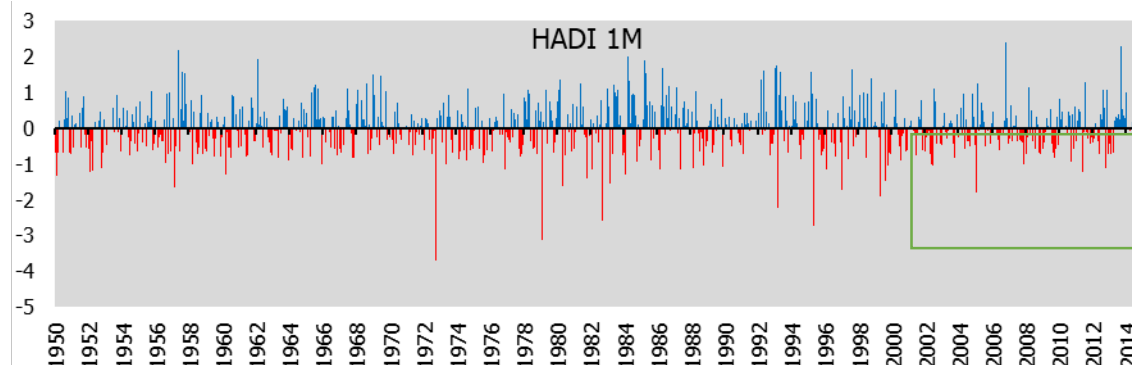
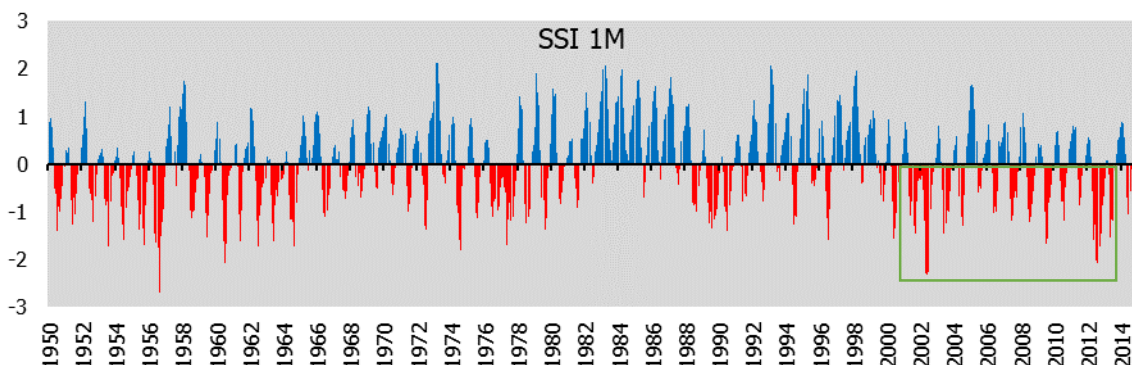
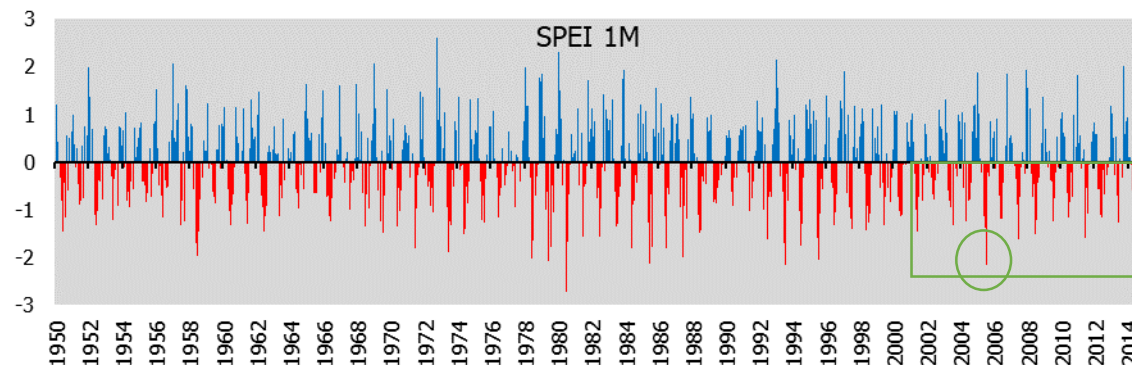
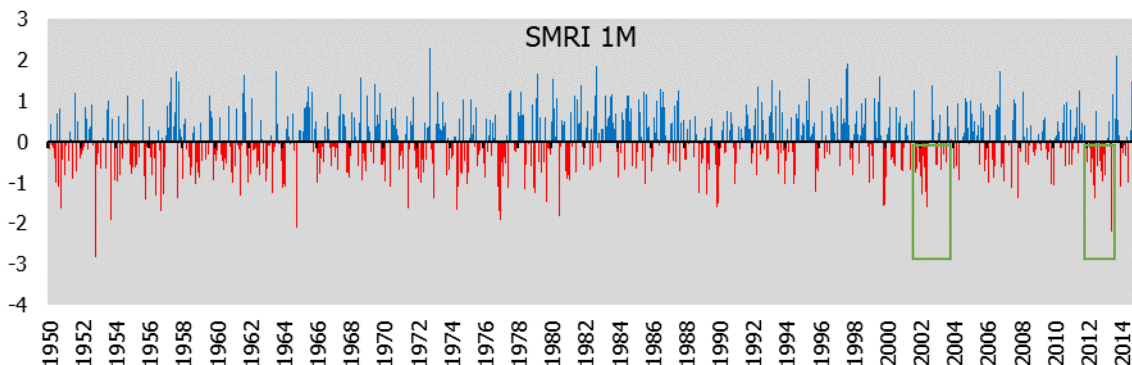
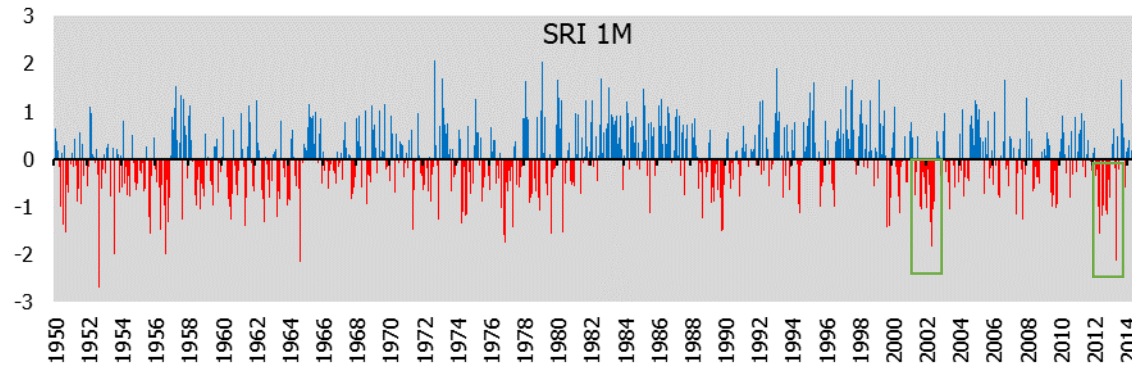
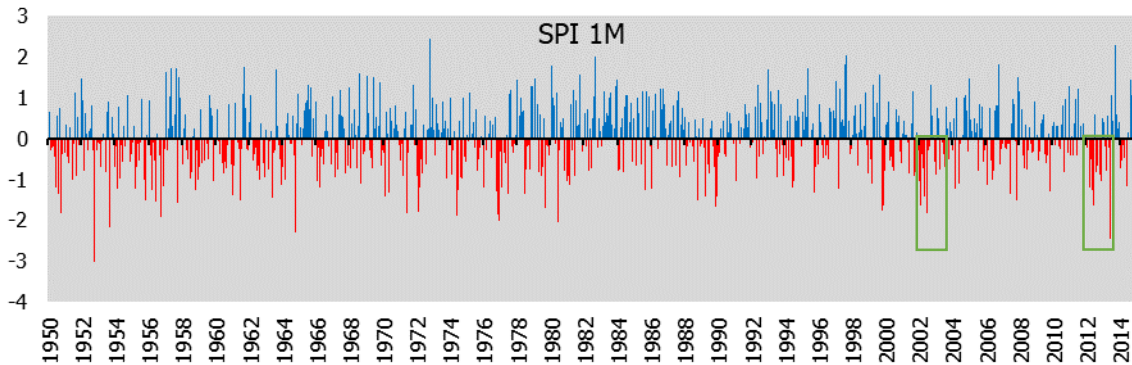
# CRB and Animas Basin



-  Animas Basin
-  Upper CRB



# Drought Identification





# Agricultural drought

- Agricultural drought by definition refers to conditions that result in adverse plant responses, which can range from reduced crop and forage yields to total crop or forage failure.

National Integrated Drought Information System (NIDIS) (2022) retrieved from <https://www.drought.gov/topics/agriculture#:~:text=Agricultural%20drought%20by%20definition%20refers,total%20crop%20or%20forage%20failure.>





# Pasture drought

- Grazing is the main sources of feeding livestock and mainly relied on the pastures' conditions. Drought affects quantity, quality, and diversity of pastures. Nutritive value of plants is high during periods of rapid growth, primarily occurring during spring and early summer. Consequently, livestock performance is highest when grasses are lush and leafy. Seasonal changes in the botanical composition of livestock diets on rangeland correspond to seasonal patterns of plant growth. Learn how to determine when cool- and warm-season grasses are elongating, or in rapid growth windows. Since rangeland in good to excellent condition has many plant species, the time when high quality forage is available is extended, with overlapping periods of rapid growth for different plant species (NDMC 2022).





# Leaf Area Index (LAI)

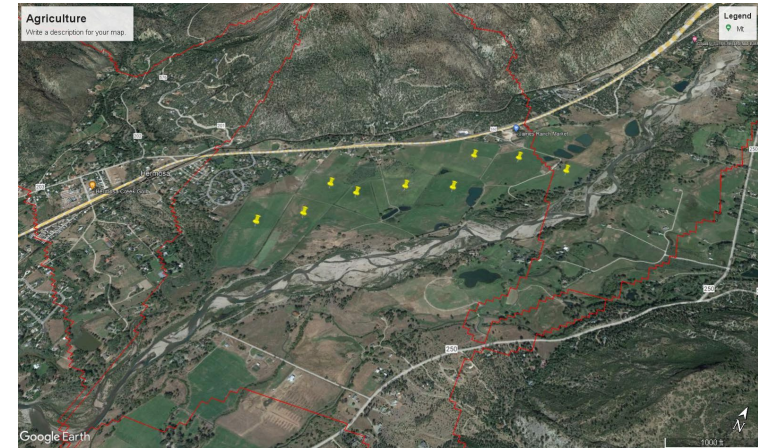
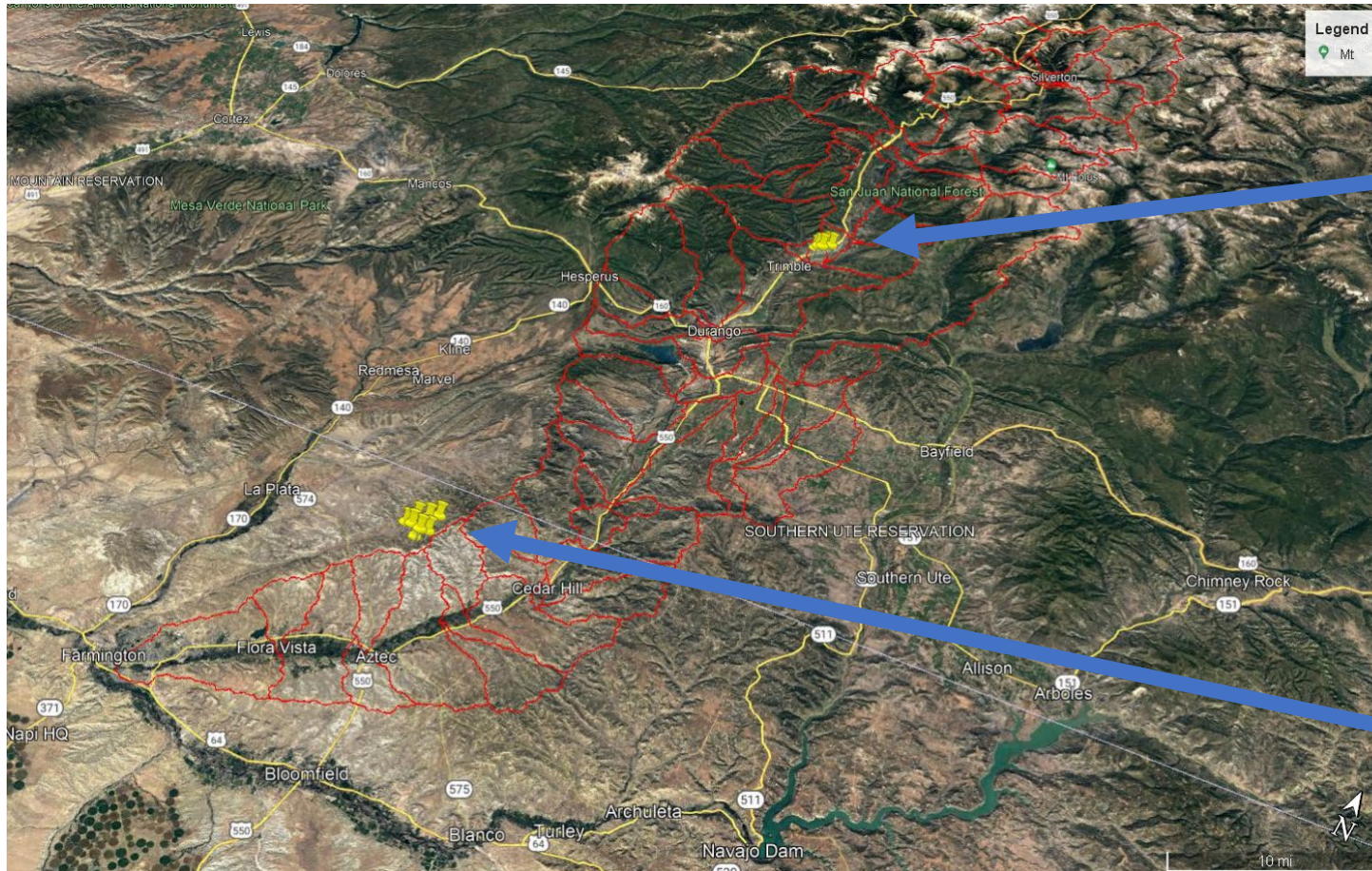
- NOAA CDR AVHRR LAI FAPAR Leaf Area Index and Fraction of Absorbed Photosynthetically Active Radiation, Version 5
- This dataset is derived from the NOAA AVHRR Surface Reflectance product and is gridded at a resolution of  $0.05^\circ$  (5 km) on a daily basis. The values are computed globally over land surfaces, but not over bare or very sparsely vegetated areas, permanent ice or snow, permanent wetland, urban areas, or water bodies.

Martin Claverie, Eric Vermote, and NOAA CDR Program (2014): NOAA Climate Data Record (CDR) of Leaf Area Index (LAI) and Fraction of Absorbed Photosynthetically Active Radiation (FAPAR), Version 4. [indicate subset used]. NOAA National Climatic Data Center. doi:10.7289/V5M043BX





# Selected locations (three rangeland and one cropland)





# Drought indices vs LAI (NOAA) with no lag

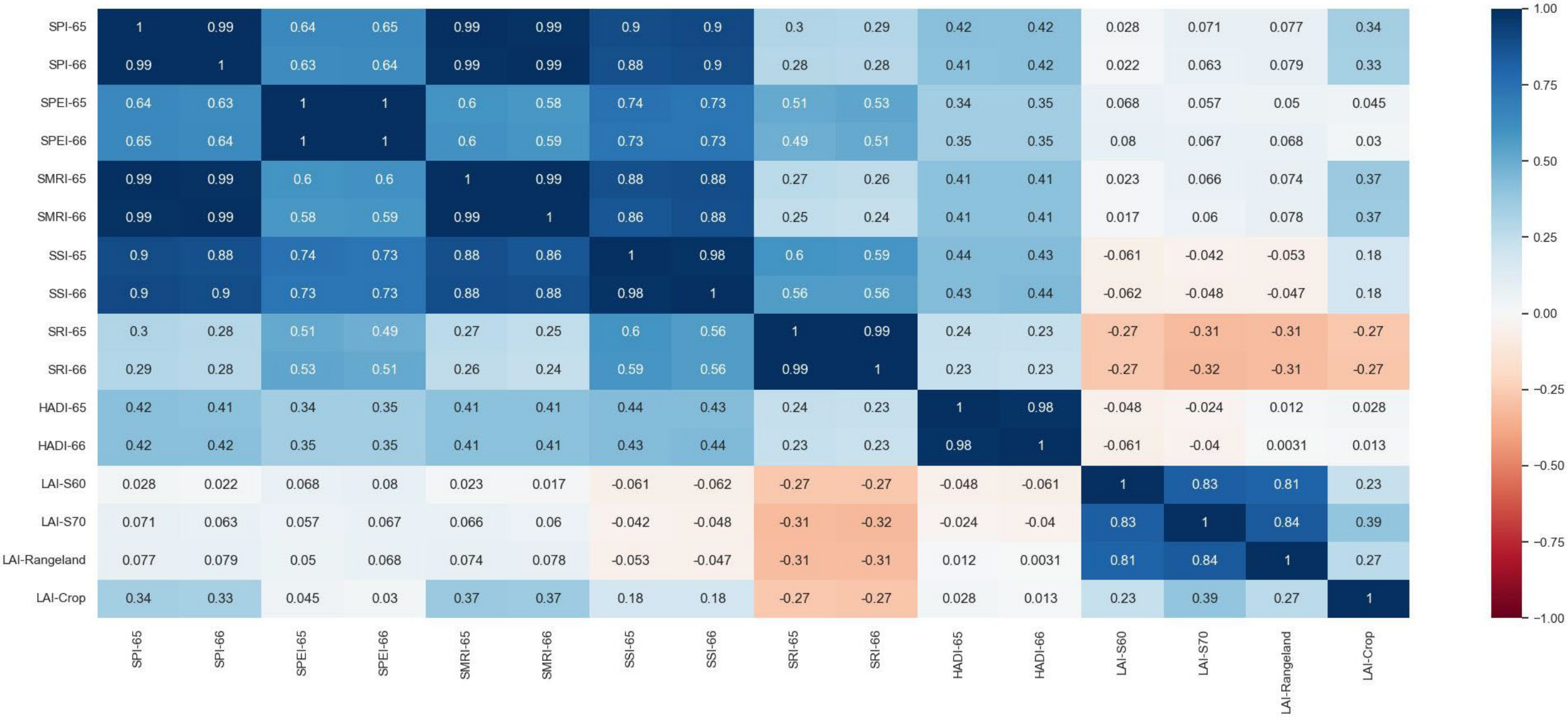


# Drought indices vs LAI (NOAA) with a 1-month lag

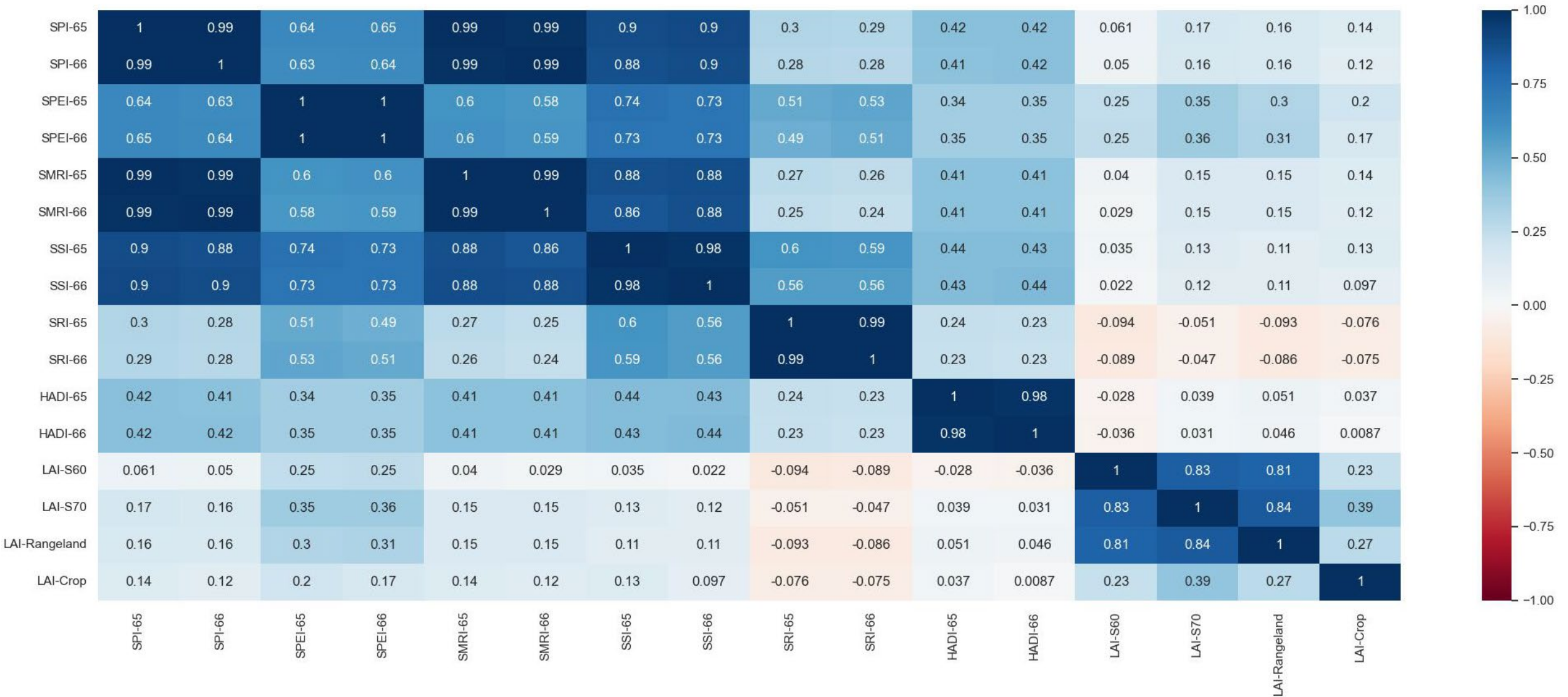




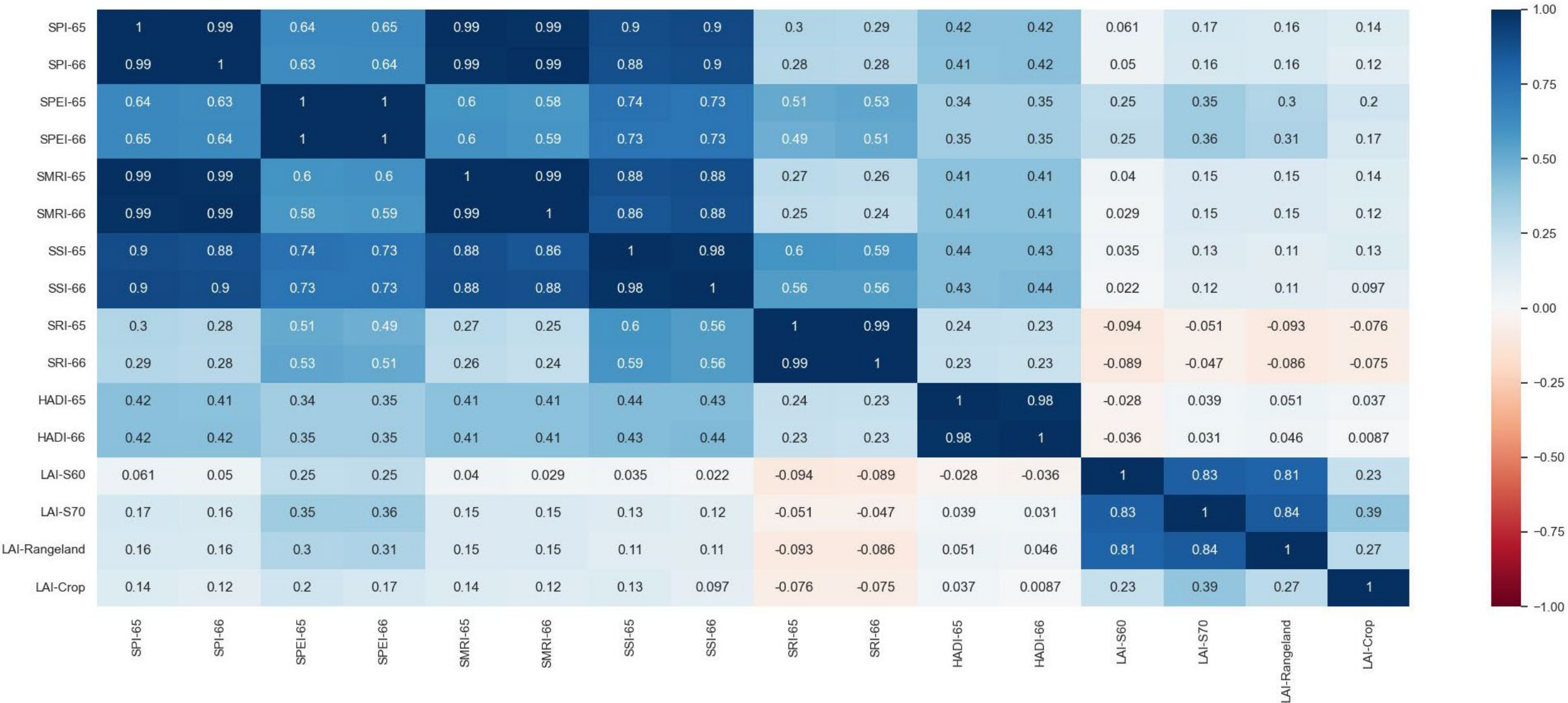
# Drought indices vs LAI (NOAA) with a 2-month lag



# Drought indices vs LAI (NOAA) with a 3-month lag

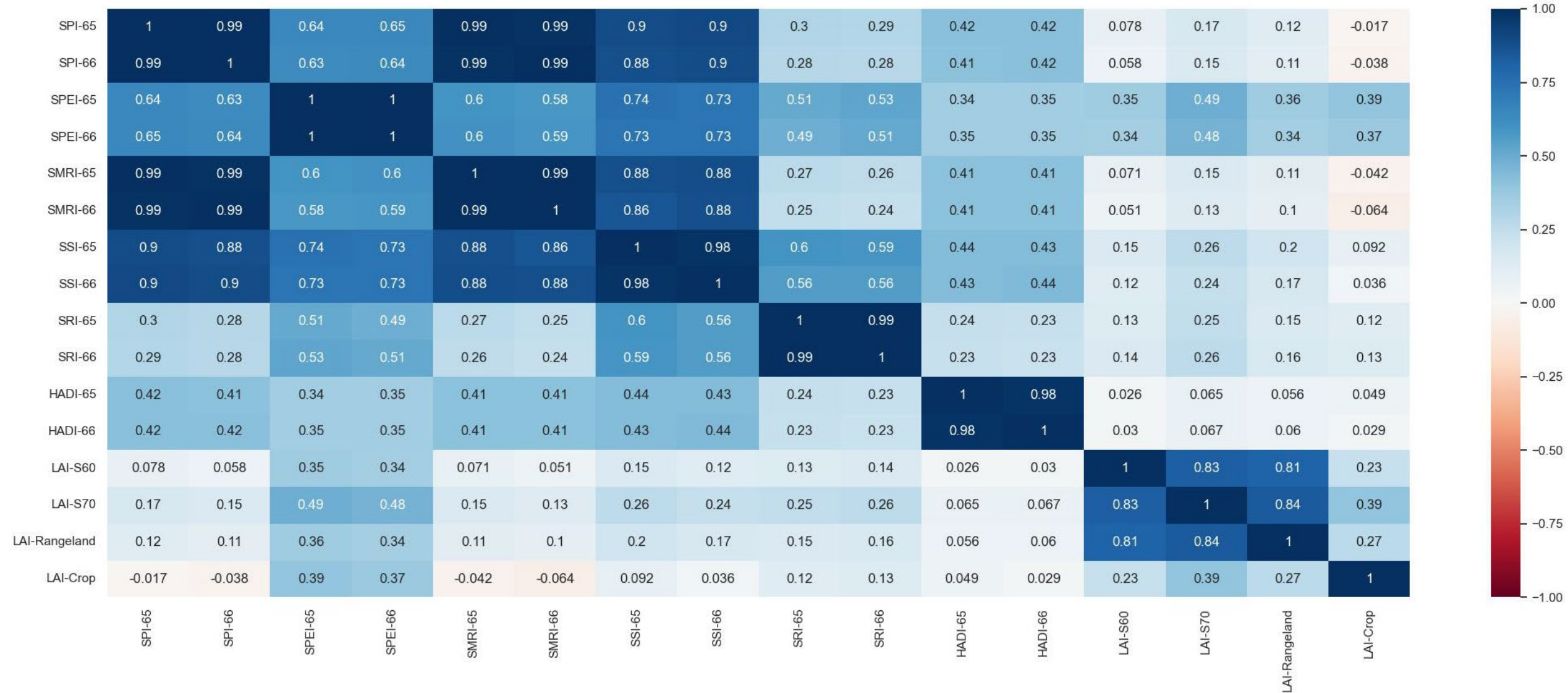


# Drought indices vs LAI (NOAA) with a 4-month lag

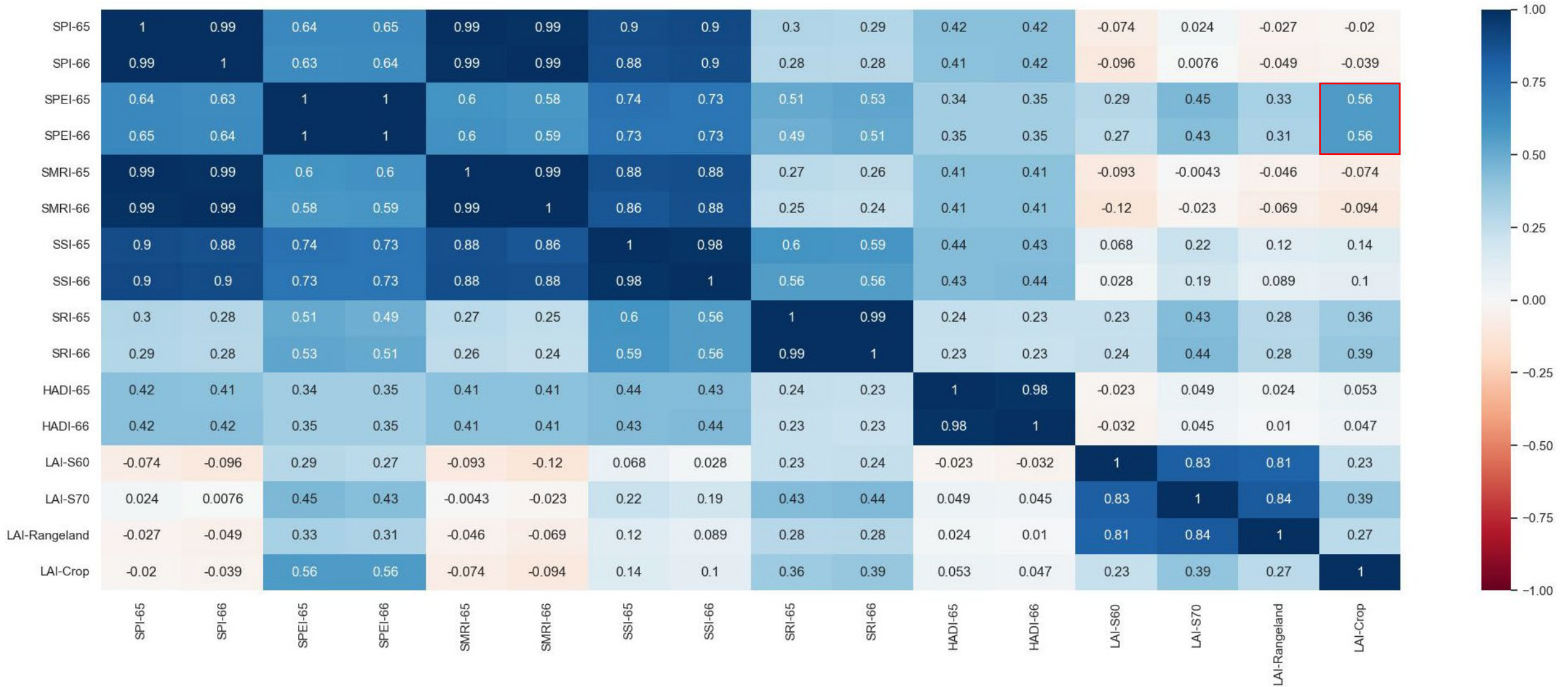




# Drought indices vs LAI (NOAA) with a 5-month lag



# Drought indices vs LAI (NOAA) with a 6-month lag



# Drought indices vs LAI (NOAA) with a 7-month lag



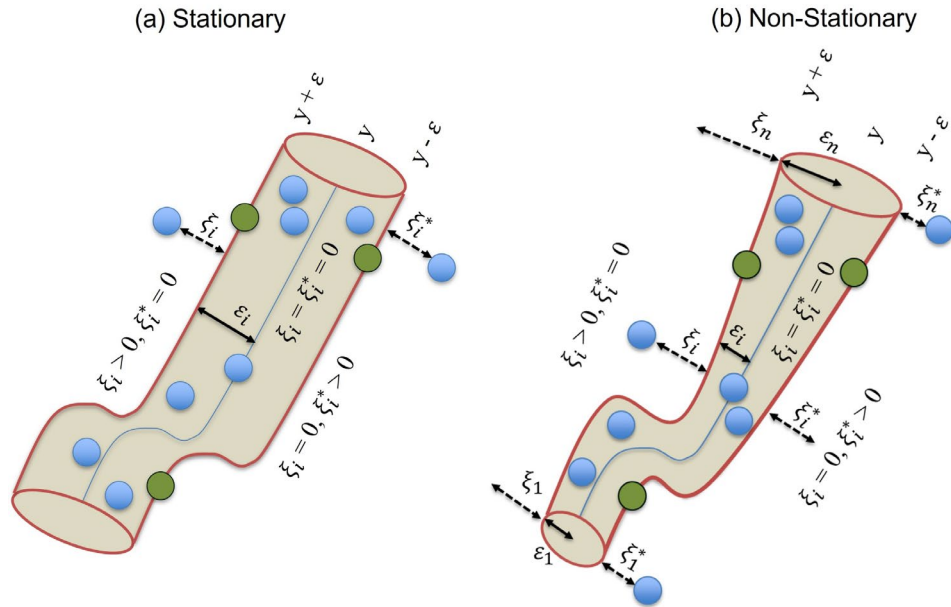


# Drought indices vs LAI (NOAA) with an 8-month lag



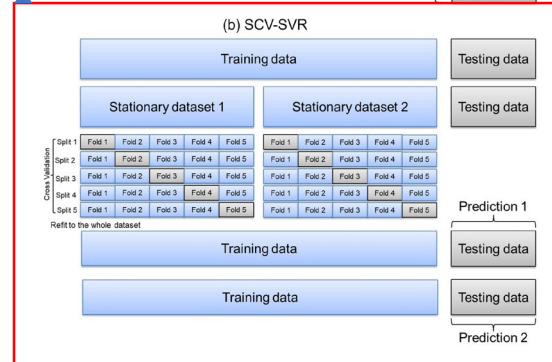
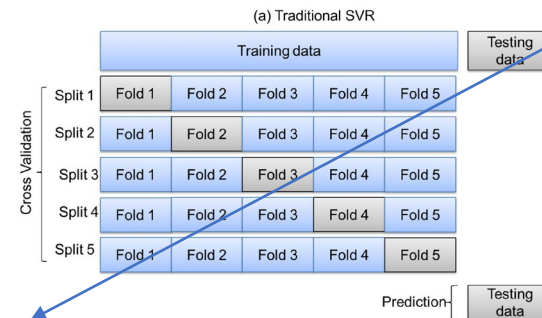
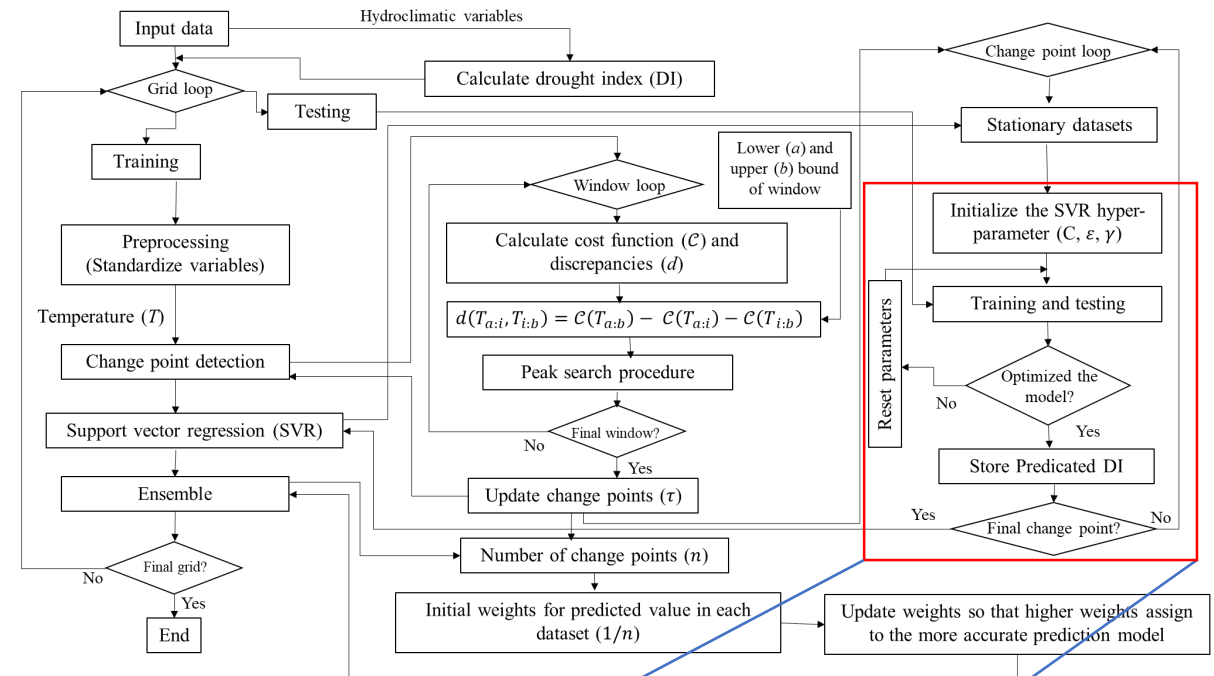
## METHODOLOGY FOR PREDICTION

The non-stationarity issue in the traditional support vector regression (SVR) model reduces the capability of SVR in prediction of droughts in a warming climate.



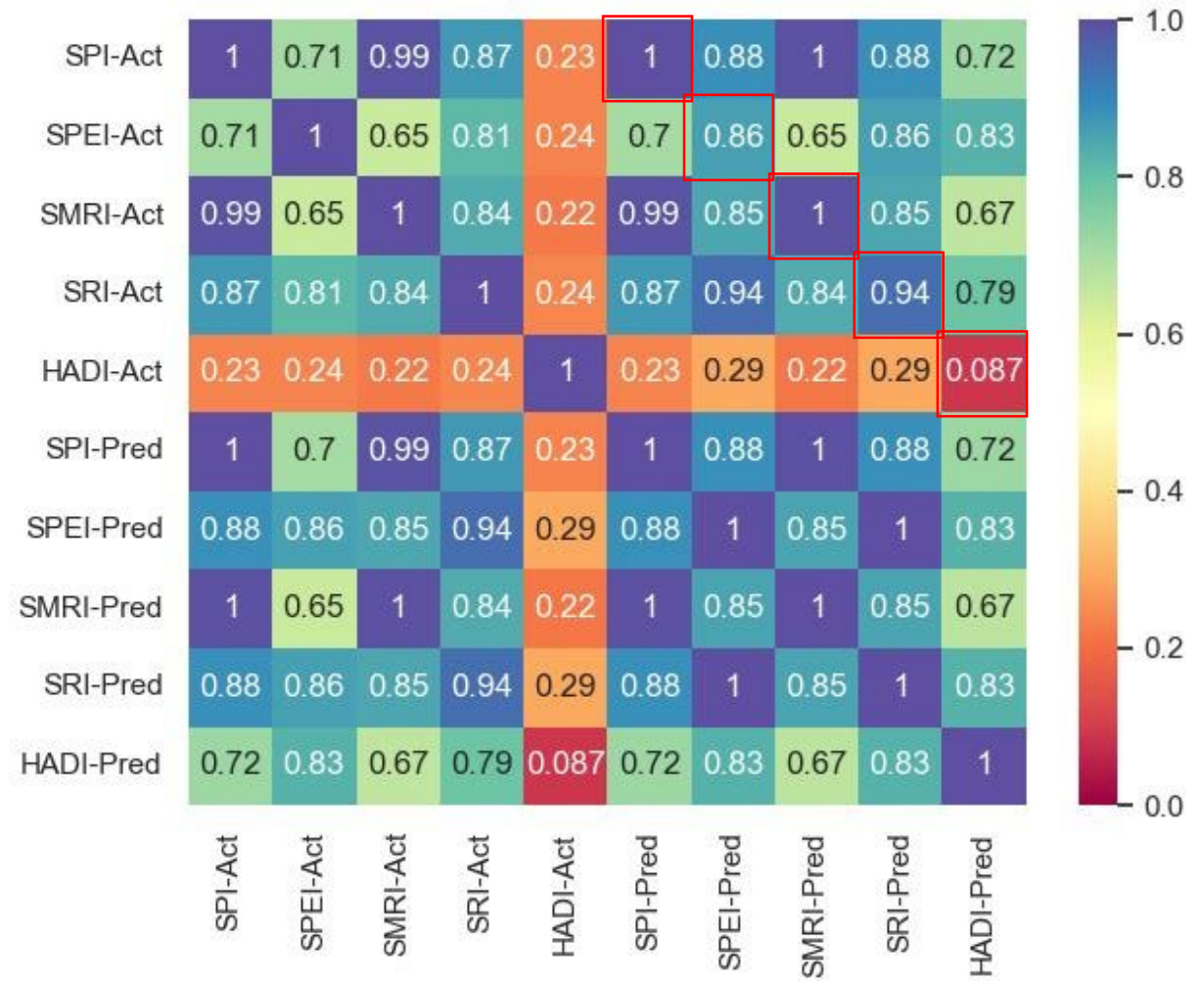
To improve the prediction of droughts in a changing climate by developing a new stationary-based cross validation support vector regression (SCV-SVR) method.

A fast-approximate window-based change point detection method, window sliding (Truong et al., 2020) is used to split the nonstationary time series into multiple stationary time series.

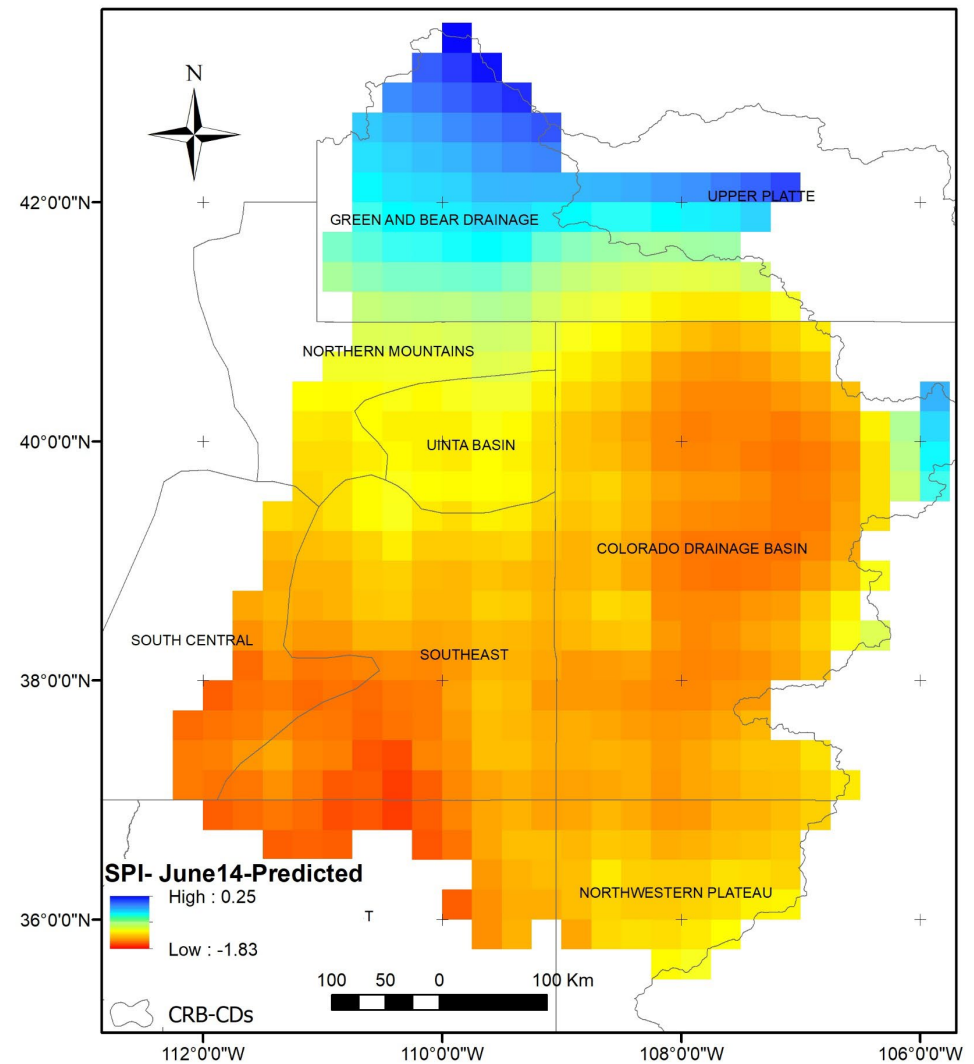
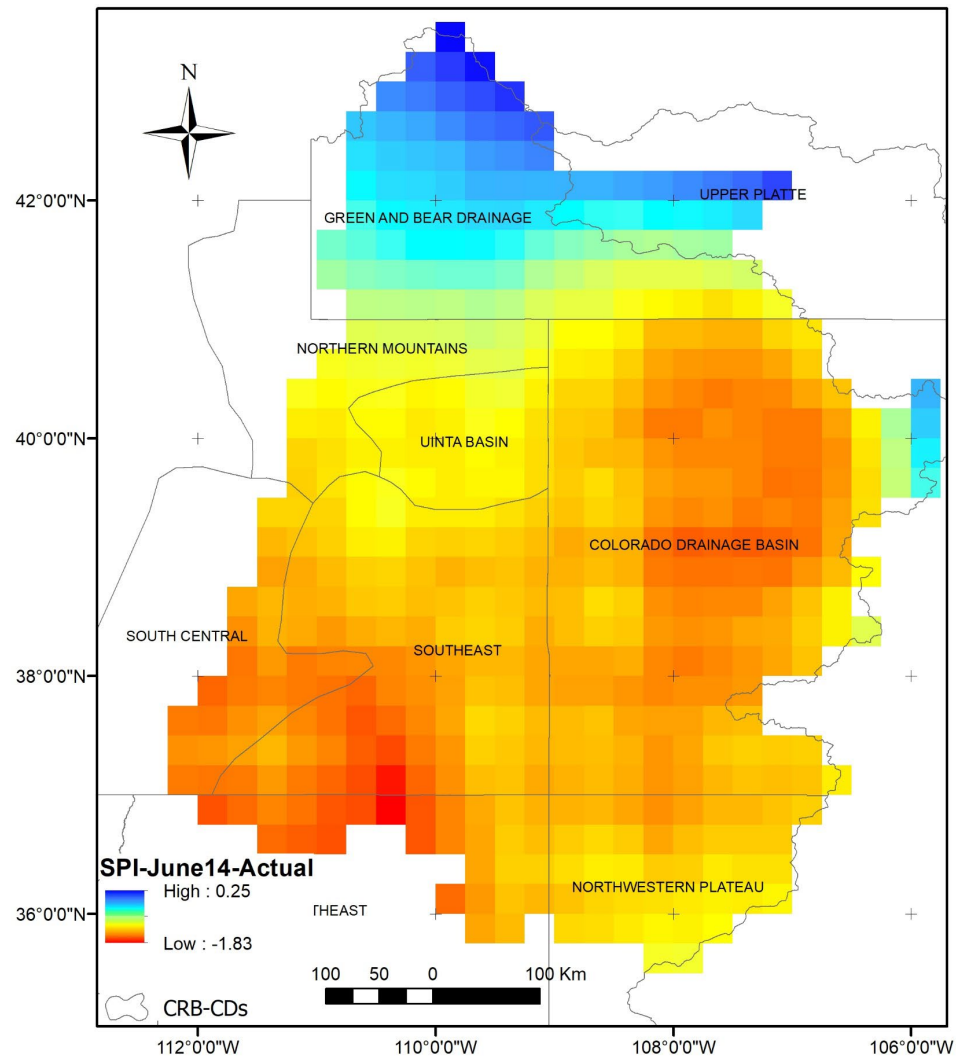


The prediction which is closer to the actual values will be selected as the final prediction

- SPI and SMRI, the highest accuracy
- SRI the second best
- SPEI the third best
- HADI unacceptable and the lowest accuracy

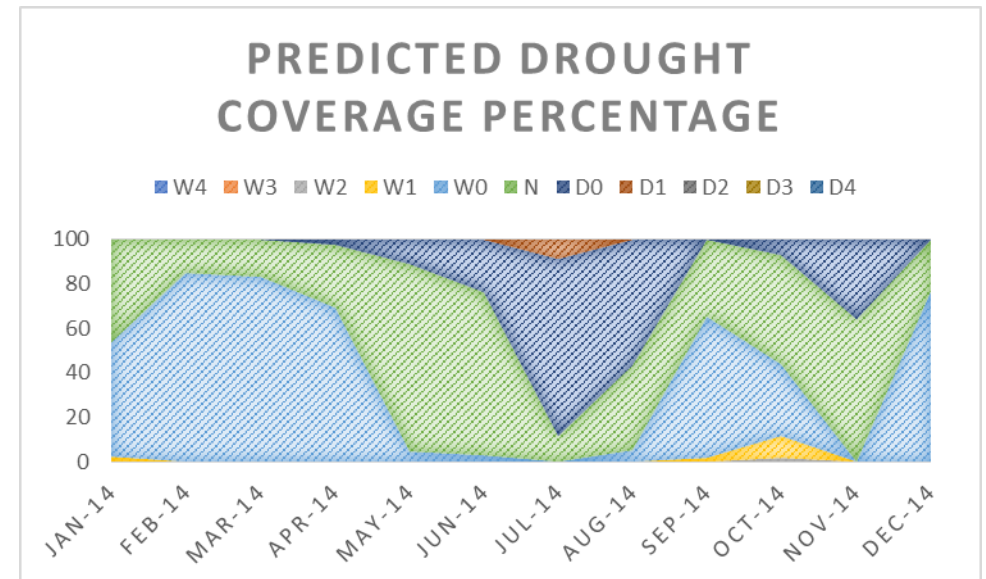
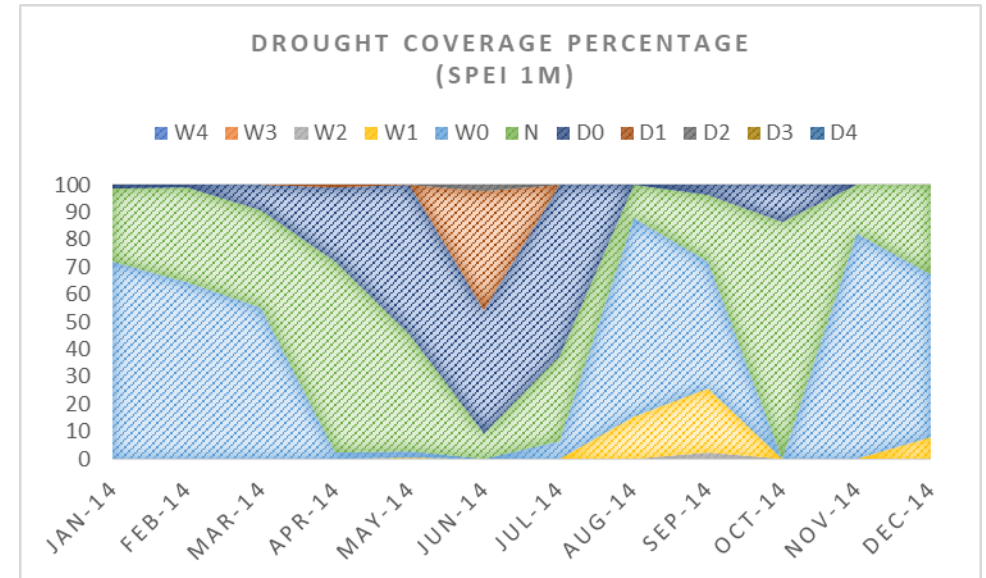
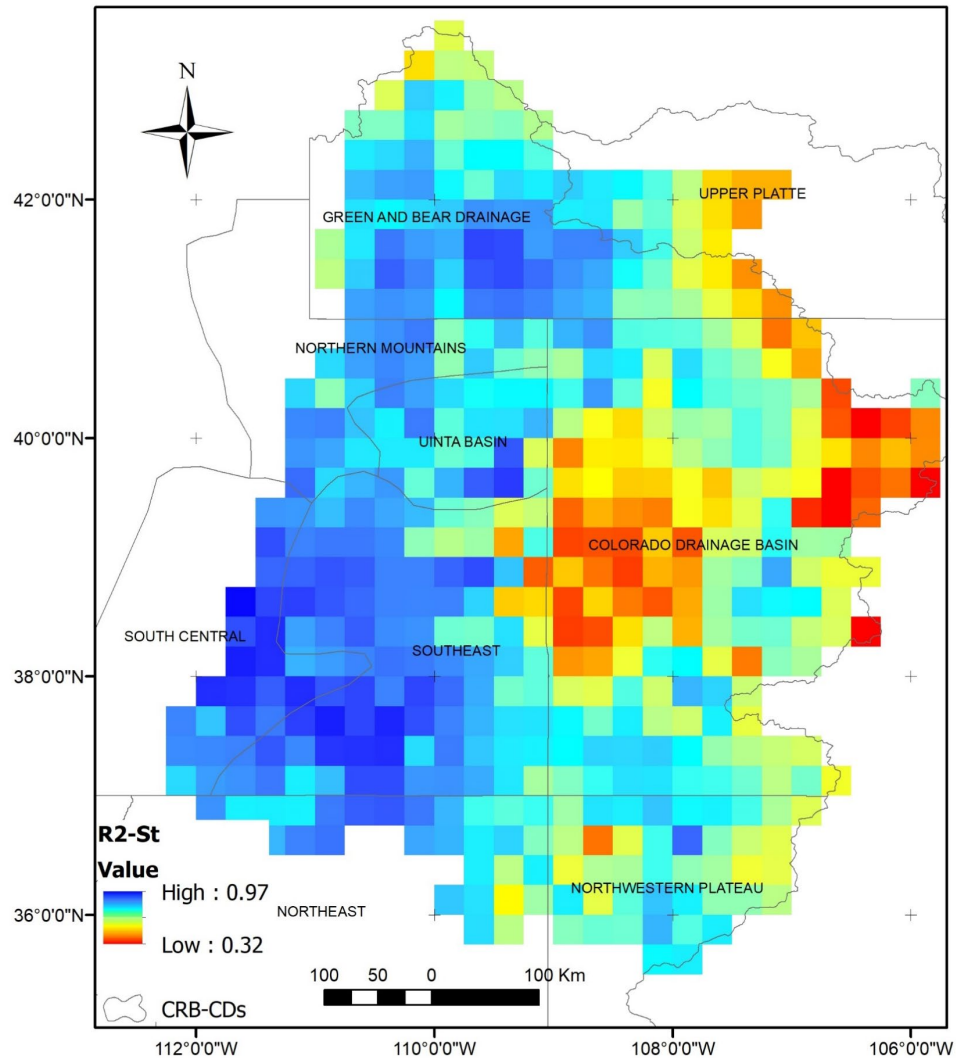


# Comparison of Actual and Predicted SPI in June 2014

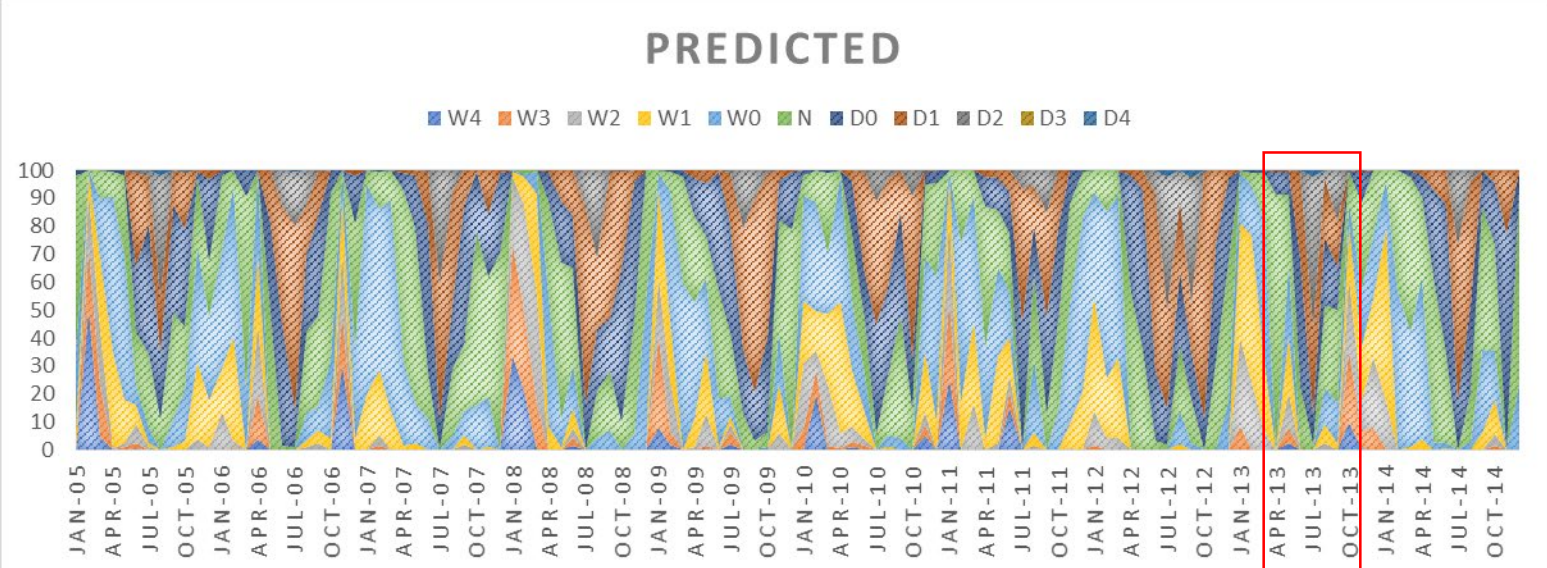
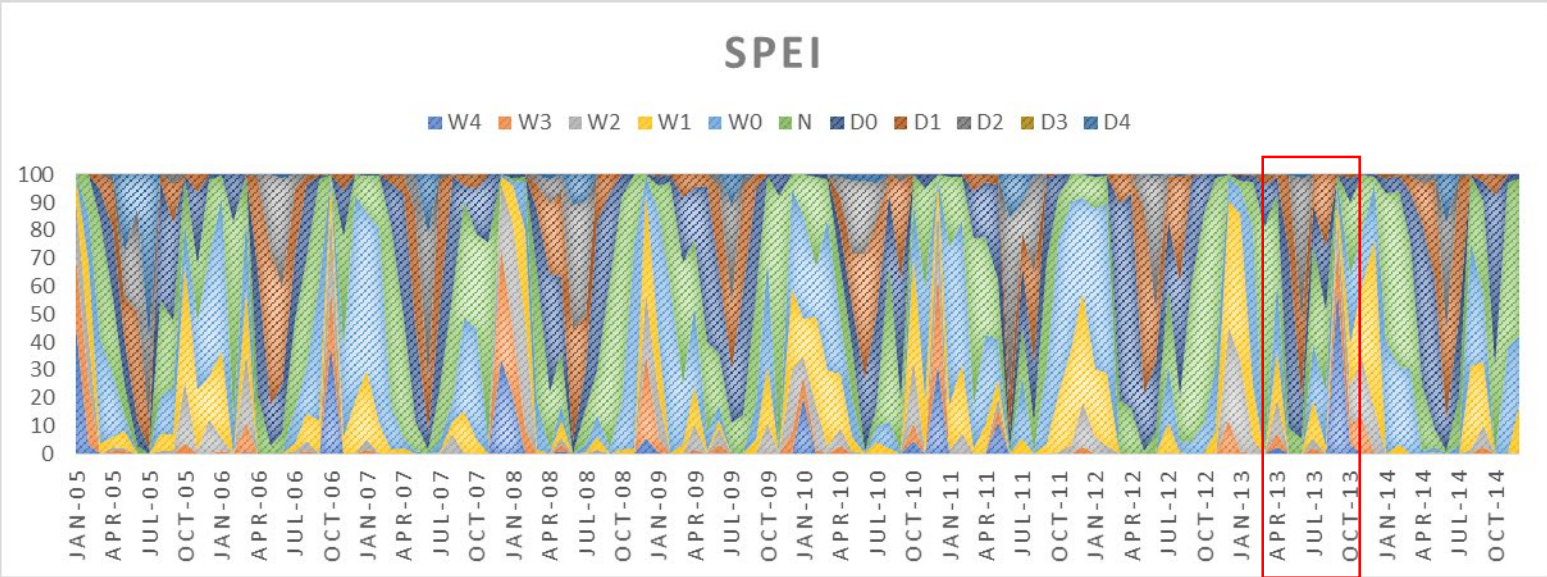
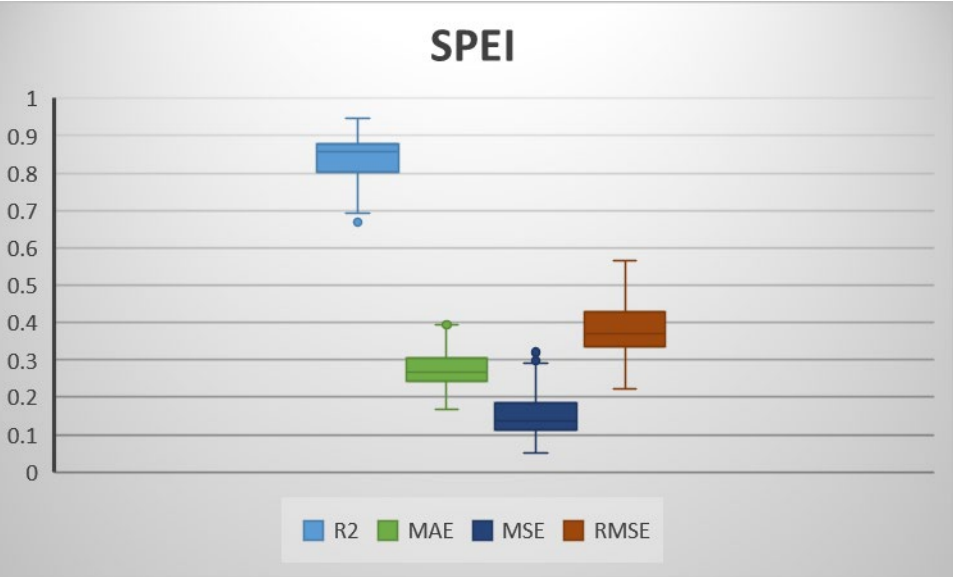




# Drought prediction based on SPEI

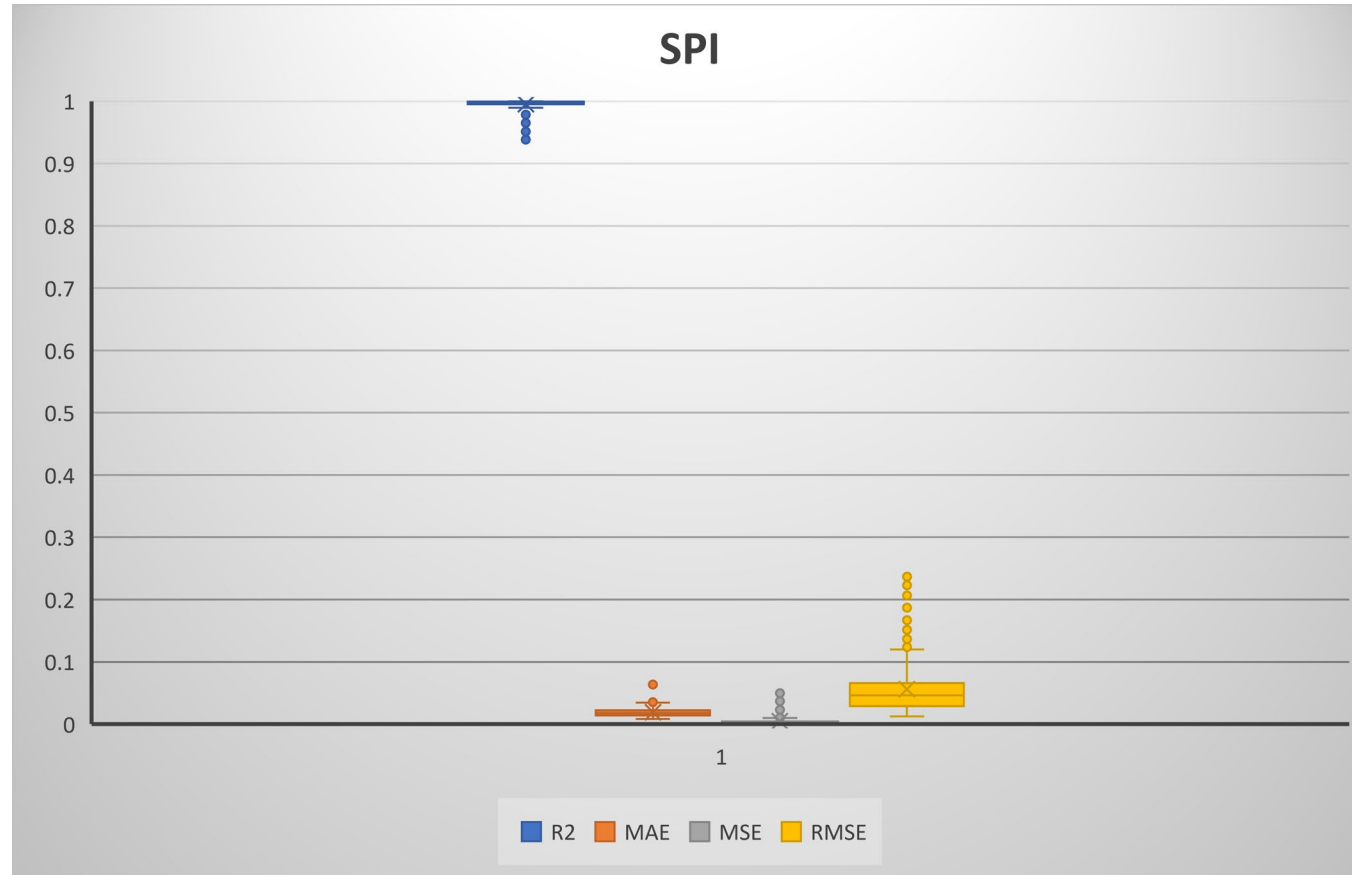


# Drought coverage percentage for SPEI

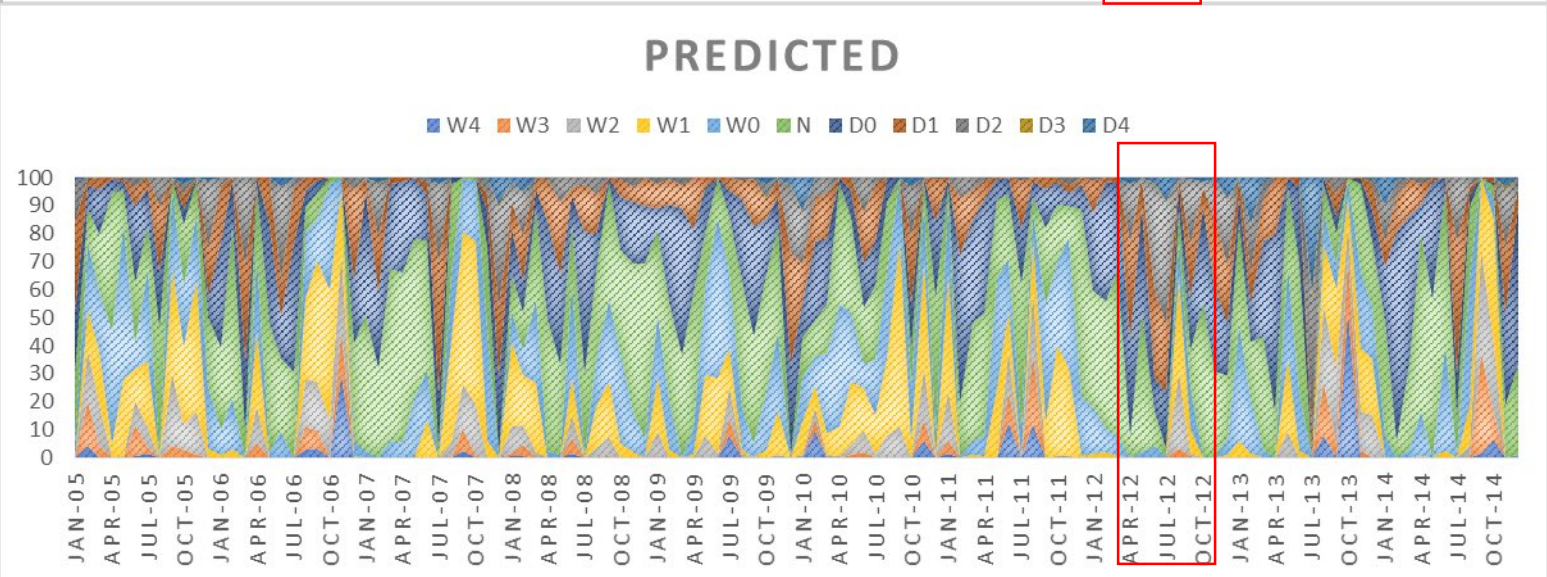
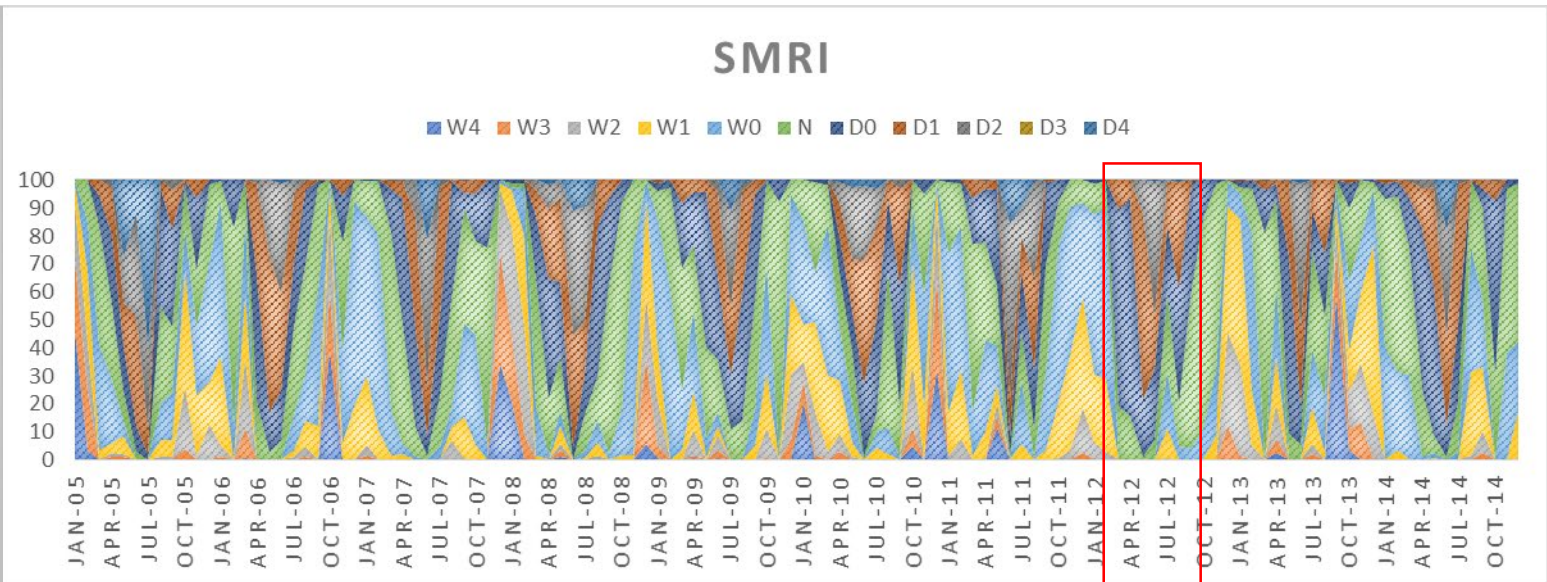
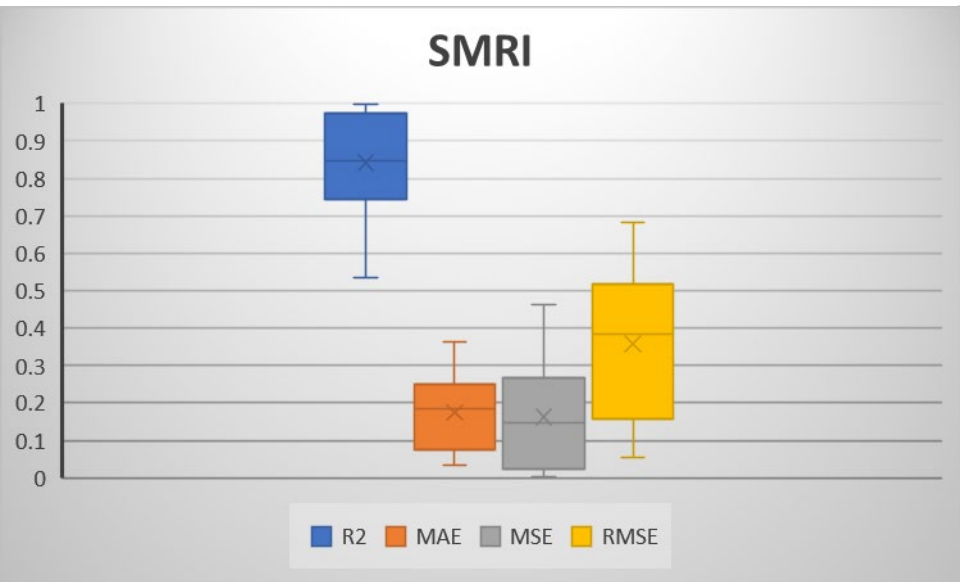




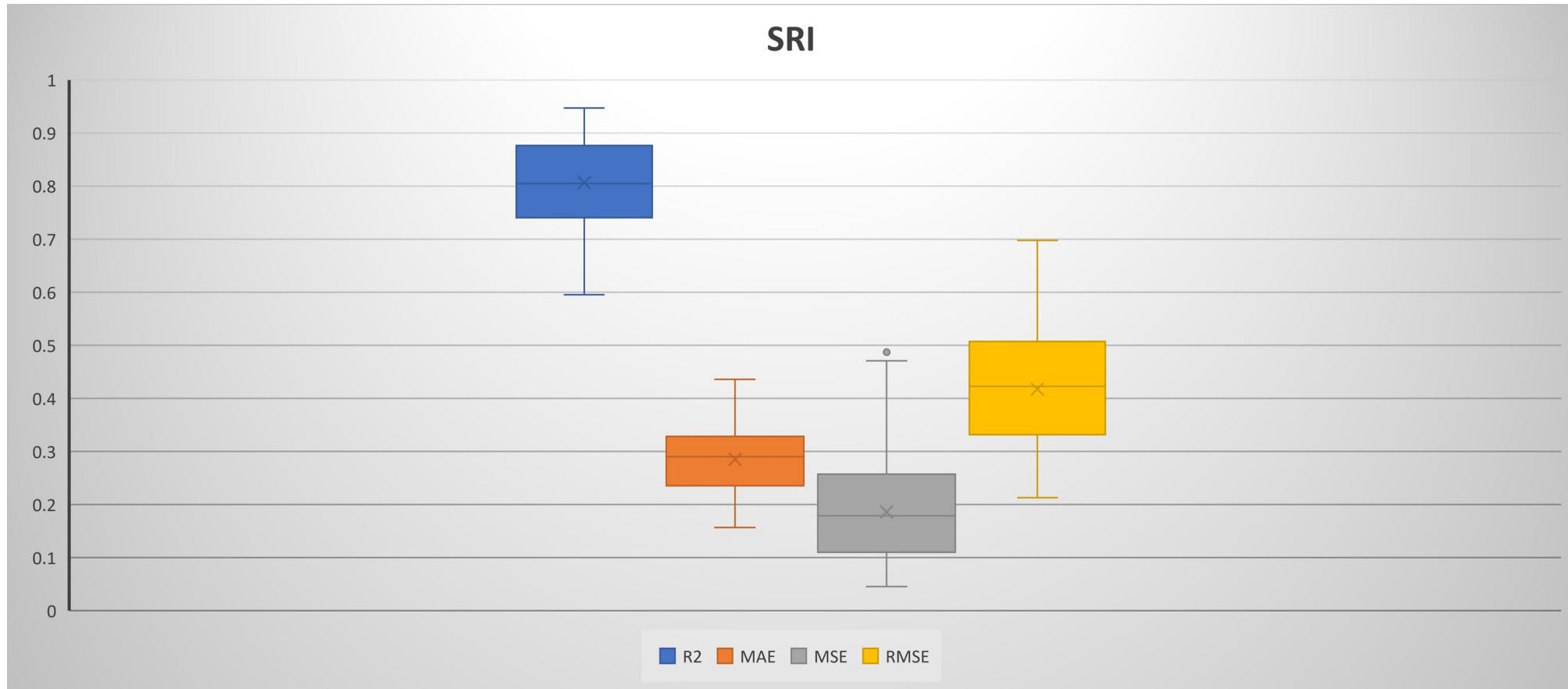
# Drought coverage percentage for SPI



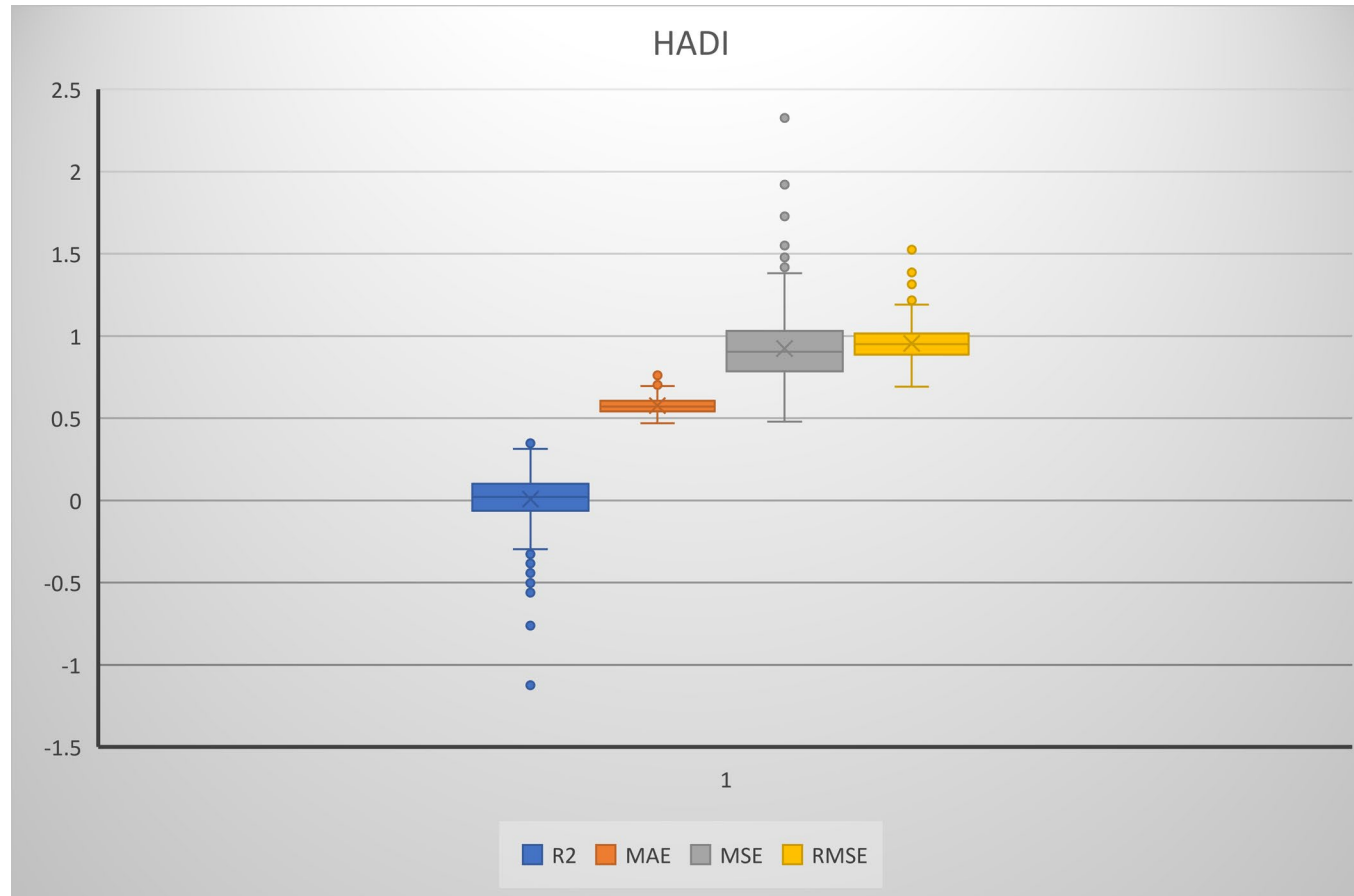
# Drought coverage percentage for SMRI



# Drought coverage percentage for SRI



# ESSVR Performance for HADI



# Conclusion

- SPEI was the best for identification of drought with 6-month lag.
- SRI was the best for identification of drought with 7 and 8-month lag.
- SPI and SMRI were the best in prediction but one of the worst for accurate identification of drought.
- Although SPI is a perfect index for prediction but there is no point to use SPI for prediction while the predictor P can be used for calculation of SPI instead of using more complex prediction models.
- SPEI showed a good capability for prediction and identification of drought.

Predictors include P and T

SMRI and SPEI are both bivariate indices, but SPEI based on water balance (Deficit =  $P - ET$ ).

- HADJ was the worst in identification and prediction due to the following:

Eclipsing (Complex formula, weights based on variance and statistics)

Variable selection

Predictors

# Conclusion

- Water-balance based drought indices can be more applicable.
- The importance of landuse-based drought indicators
- Drought monitoring needs more meaningful conceptions.
- Capability of drought indices are an important criterion of drought indices that has been neglected in the defined criteria.
- Hybrid drought indices need to be checked for eclipsing and predictability.
- Variable selection and combination methods are crucial factors in success of a drought index.
- Essence of an integrated algorithm for identification, categorization, and prediction of drought



**Thank you! Questions?**