Use of Machine Learned Mutual Information Between USDM and Correlated Drought Factors









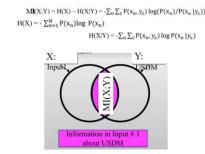


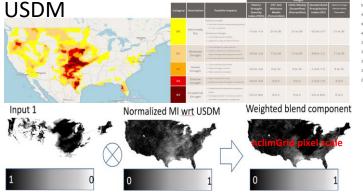
Michael Shaw, NIDIS, iSciences, <u>michael.shaw@noaa.gov</u>, Steve Ansari, NIDIS, <u>steve.ansari@noaa.gov</u>, Soni Yatheendradas, NASA, U. Md., soni.yatheendradas-1@nasa.gov, David Mocko, NASA, SAIC, david.mocko@nasa.gov, Justin Fain, NIDIS, iSciences, justin.fain@noaa.gov

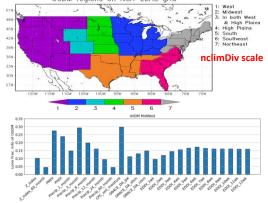
https://www.drought.gov/drought-research/quantifying-relative-importance-multiple-drought-indicators-us-drought-monitor

Soni Yatheendradas, David M. Mocko, Christa Peters-Lidard and Sujay Kumar, *Quantifying the Importance of Selected Drought Indicators for the United States Drought Monitor*, JHM.









Through mutual information, ClimateEngine.org, and Google Cloud

- Mechanistic understanding of what drives drought when, where (nclimGrid pixel scale; nclimDiv scale)
- · MIDIs (Multi Indicator Drought Indices) from, e.g., linear model out via remotely sensed, modeled, observed datasets
 - Forecasting (future)
 - Monitoring (present)
- drought.gov indices to present when, where (state, county, watershed pages: short term versus long term local, state, regional, and temporal scales matter...
- Stakeholder engagement and index priority wrt "drought" reflected to some extent implicitly via DM author localized priorities' use in MI/FI calculation

