A spatiotemporal quantification of the relative importance of indicator inputs for drought estimation

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Some project objectives

- **DATA**: Provide comprehensive database of drought indicators and the United States Drought Monitor (USDM)
- **ANALYSIS**: Use the database to quantify the relative importance of each indicator for the USDM drought by location and time of year
- **UTILITY**: Per user requirements and purpose, provide an importance-ordered list of indicators, either the full set or a reduced one that best and adequately represents the USDM

USDM weekly maps

U.S. Drought Monitor

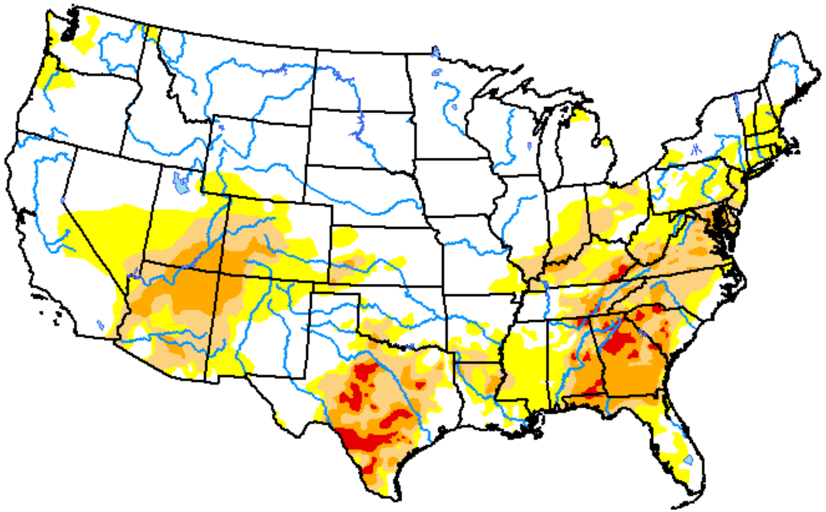
Continental U.S. (CONUS)

October 15, 2019

(Released Thursday, Oct. 17, 2019)

Valid 8 a.m. EDT

D0: Abnormally Dry	*70th* < Percentile < *80th*
D1: Moderate Drought	*80th* < Percentile < *90th*
D2: Severe Drought	*90th* < Percentile < *95th*
D3: Extreme Drought	*95th* < Percentile < *98th*
D4: Exceptional Drought	*98th* < Percentile



Intensity:

- None
- D0 Abnormally Dry
- D1 Moderate Drought
- D2 Severe Drought
- D3 Extreme Drought
- D4 Exceptional Drought

The Drought Monitor focuses on broad-scale conditions. Local conditions may vary. See accompanying text summary for forecast statements.

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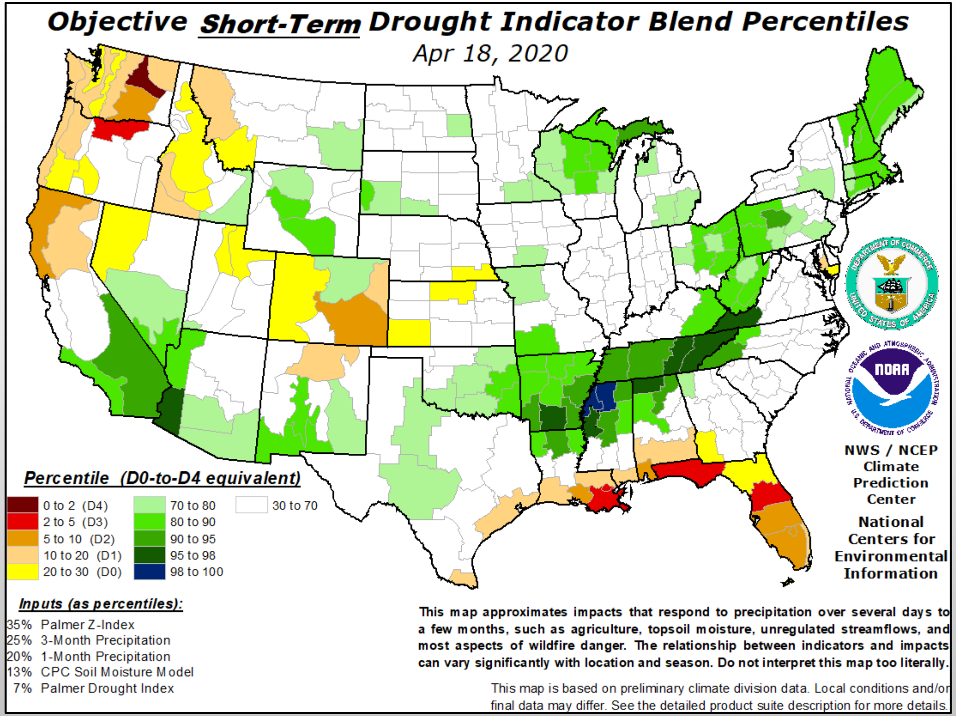
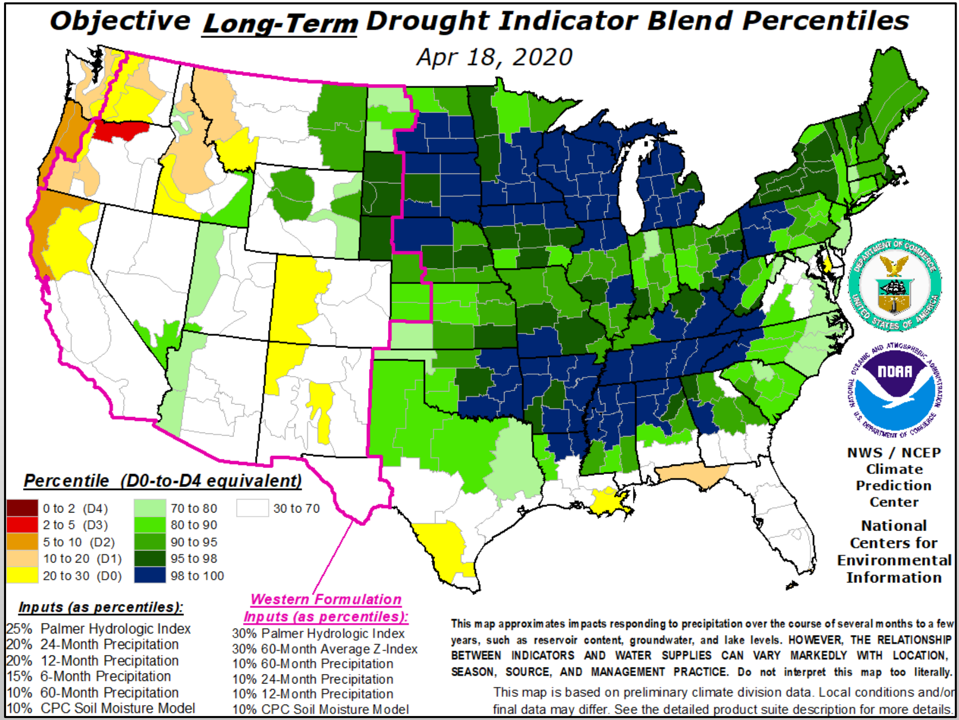
Pilot study: Using inputs indicators of CPC objective blends

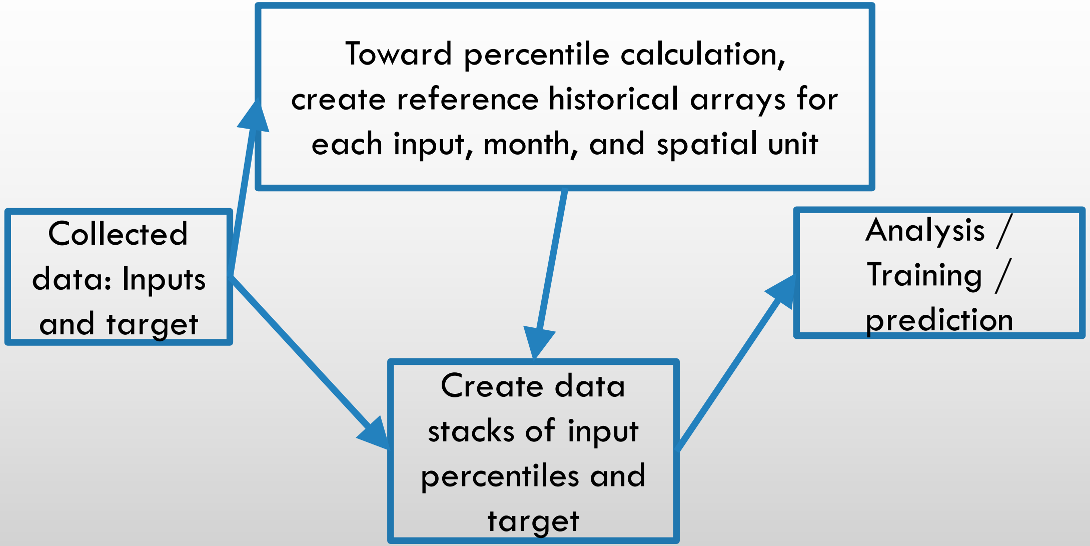




- CPC objective drought blends use 5-6 indicators, for short-term or for two different long-term regions
- Pilot study question: <u>*“What are the relative importances of the CPC objective blend inputs in reproducing the USDM?”*</u>

Schematic of data flow and analysis

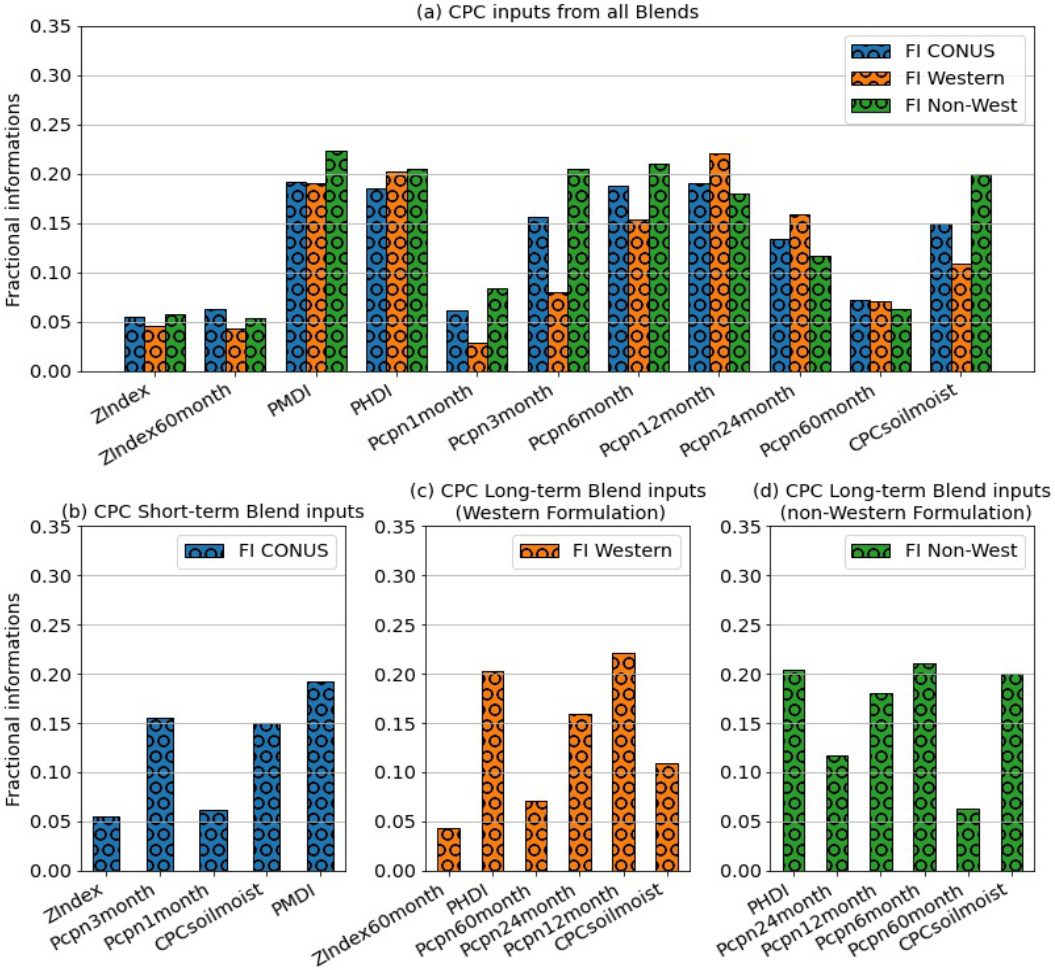
- USDM considered for the period 2006-2019 (input data-based)
- We try mutual information (MI), and machine learning techniques: Neural Network (NN) and Random Forest (RF)
- Relative importances of inputs calculated in each technique are similar to the CPC blend "weights"



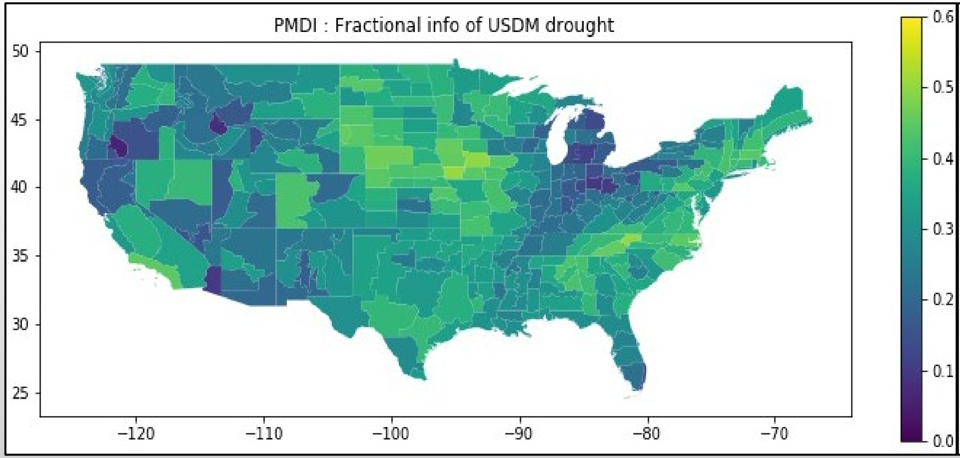
- MI and RF techniques have their own inherent technique for calculating these importances

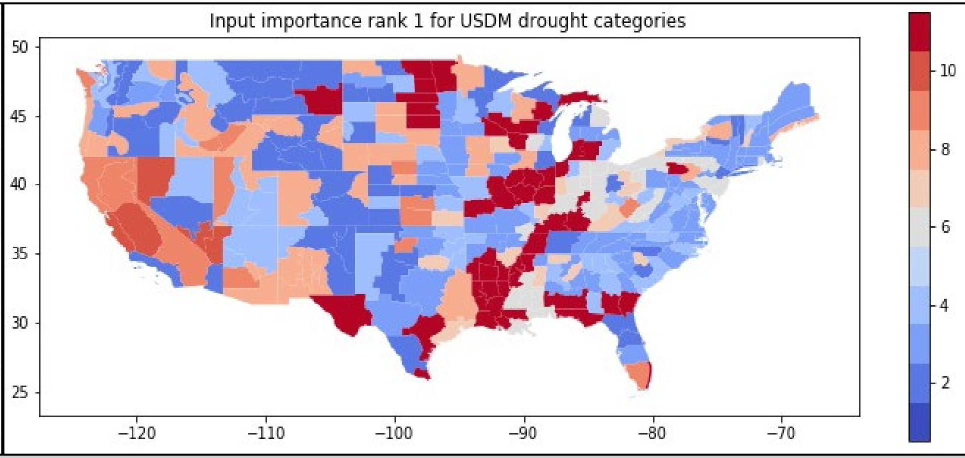
Mutual Information-based analysis

- **Mutual information (MI)**
  - calculates **common information entropy** between USDM and input
  - calculated **independently** for each input indicator
  - **uses only the data** – unlike machine learning that also involves model/s
- **Fractional Information (FI)** shown is the MI normalized by the entropy of USDM
- For comparison against ML, next slides show the **Normalized FI (NFI)** that is the FI normalized by the **sum of FIs of the considered set of inputs**



Example spatial maps: fractional info & most important input

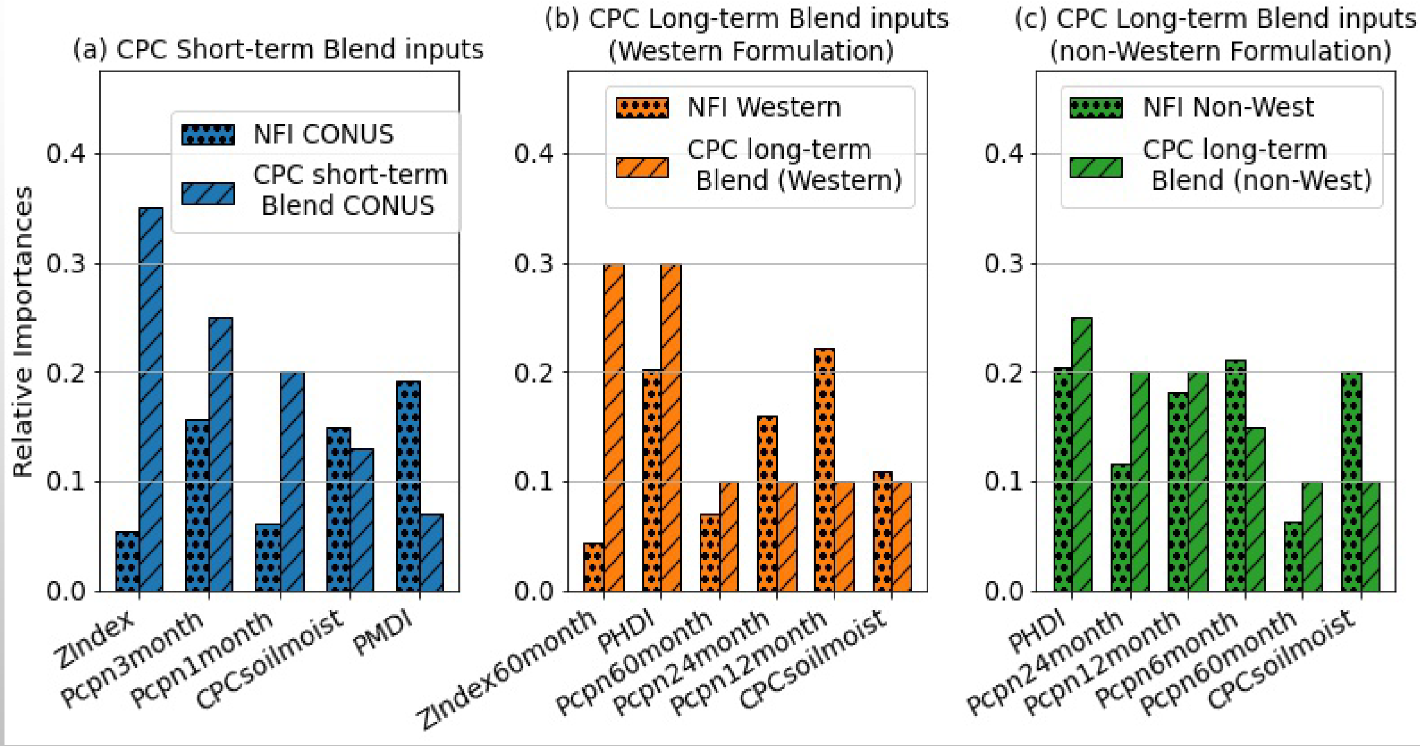




PMDI: Palmer (Modified) Drought Index

Legend: **1**: Z-index, **2**: 60-month Z-index, **3**: PMDI,
4: PHDI, **5**: 1-month precip,
6: 3-month precip, **7**: 6-month precip,
8: 12-month precip, **9**: 24-month precip,
10: 60-month precip, **11**: CPC soil moisture

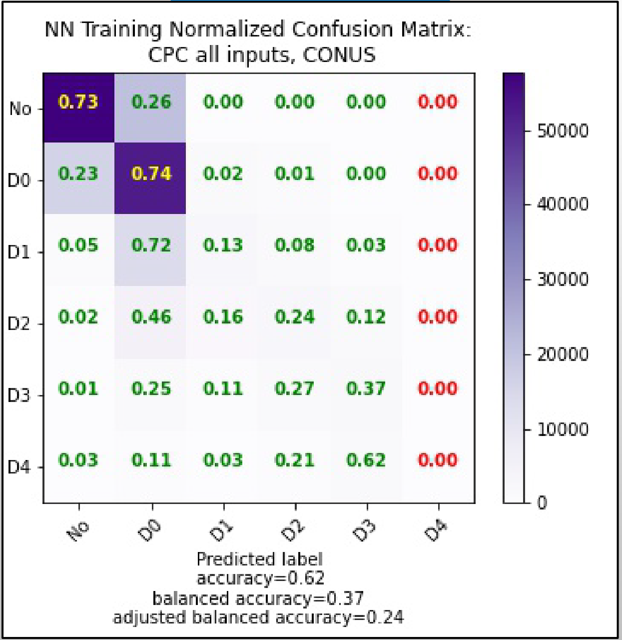
Normalized Fractional Information vs. CPC Blend weights



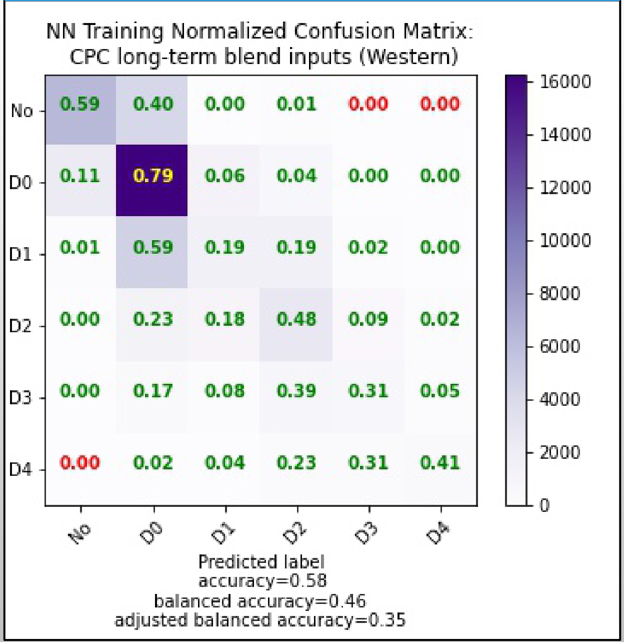
CPC Blend is a linear model plus a mapping to categories,
while the mutual information-derived NFI considers all nonlinearity

Example NN with one 16-neuron intermediate layer: Training confusion Matrices for example inputs and spatial domains

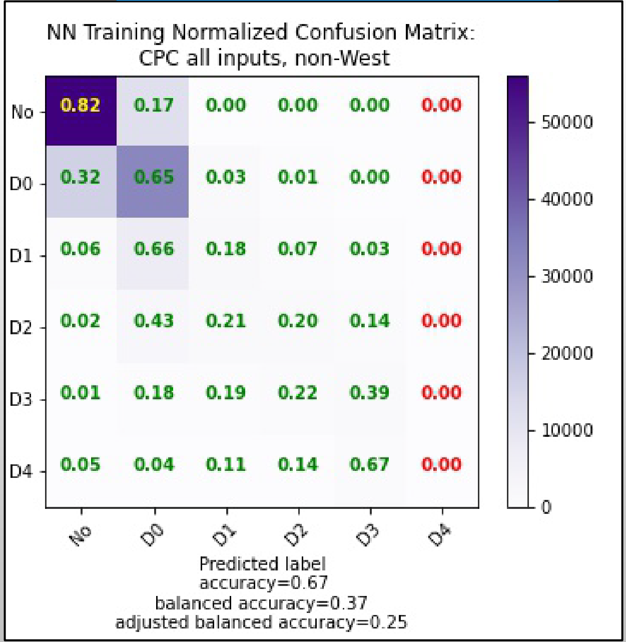
CONUS, all inputs



Western domain, Western formulation inputs



Non-Western domain, all inputs



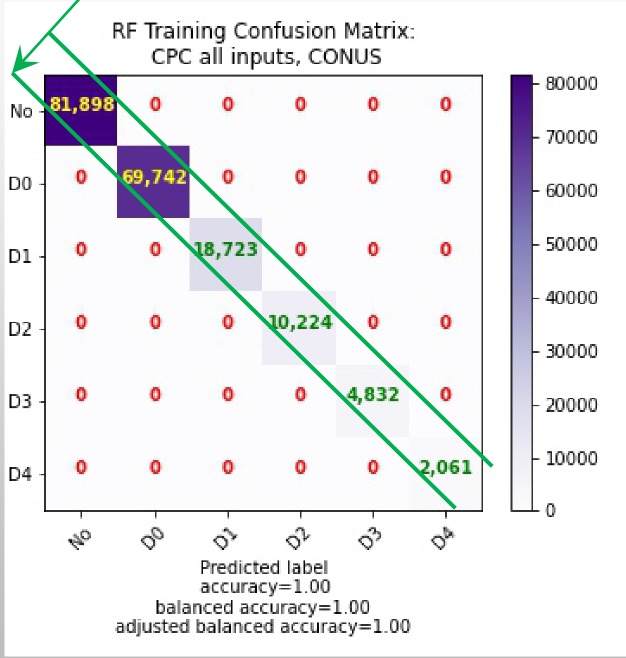
- High misclassification levels, especially at extreme drought categories, likely due to class imbalance and remediable by category-weighted loss functions
- Can a technique unaffected by class imbalance (e.g., random forests) provide acceptable confusion matrices?

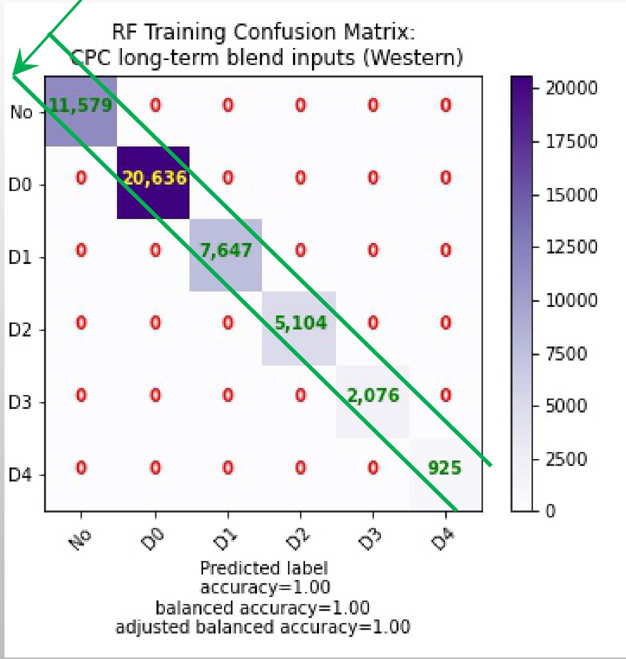
Random Forests & its implementation

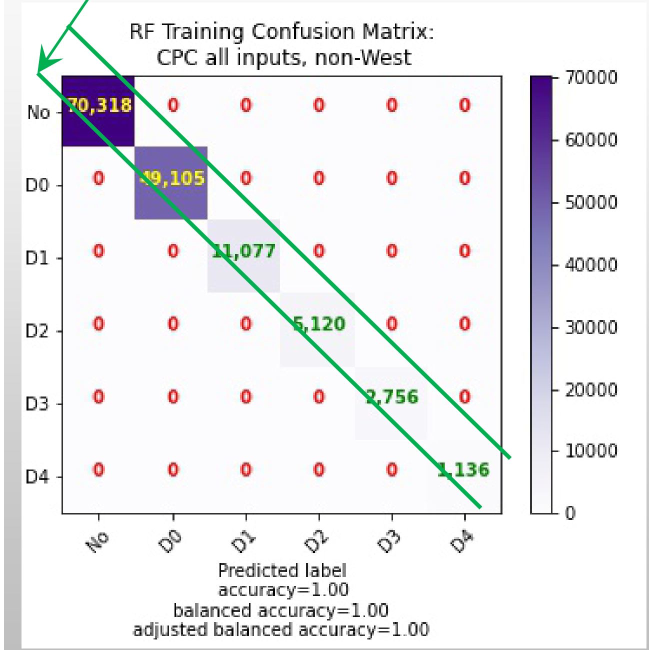
- About Random Forests:
  - Random forest technique considers an ensemble of decision trees
  - Each decision tree considers a random bootstrapped set of training examples
  - For classification, ensembling done through majority vote
- Our implementation:
  - Initial Stratified Shuffle Split of all data into cross-validation and out-of-sample sets
  - A stratified K-Fold cross-validation training with 3 folds
  - Further out-of-sample evaluation
  - Each tree considers ALL input features

Cross-validation Confusion Matrices for Random Forests

Perfect simulation of exact drought category: see "one-to-one" line !

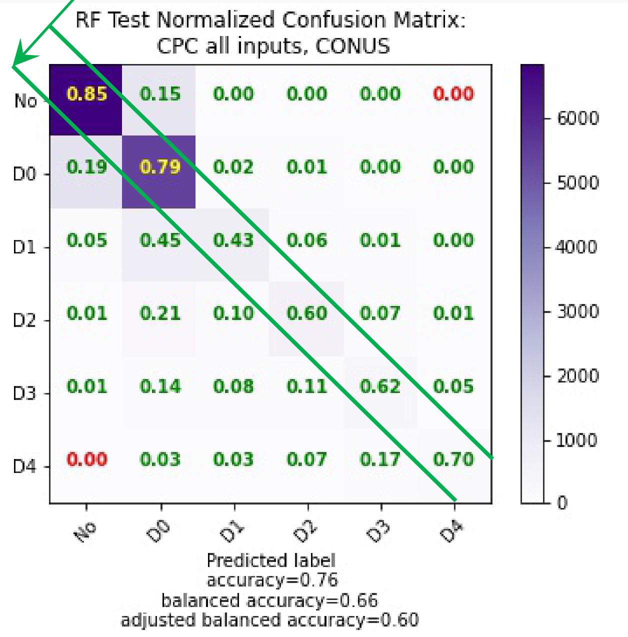


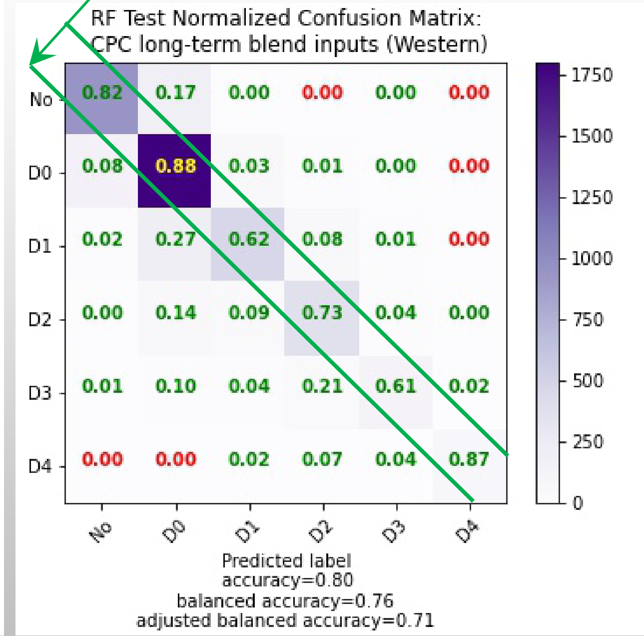


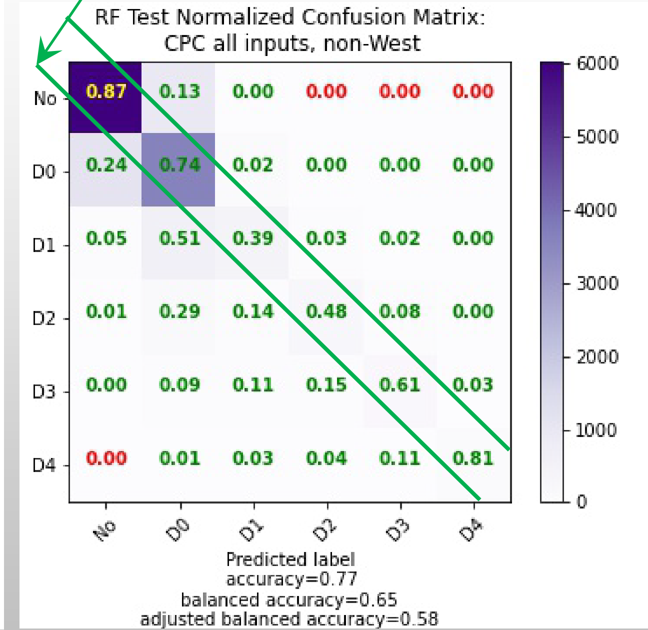


Out-of-sample Normalized Confusion Matrices for Random Forests

For majority of true labels, correct prediction occurs and seen along the "one-to-one" line

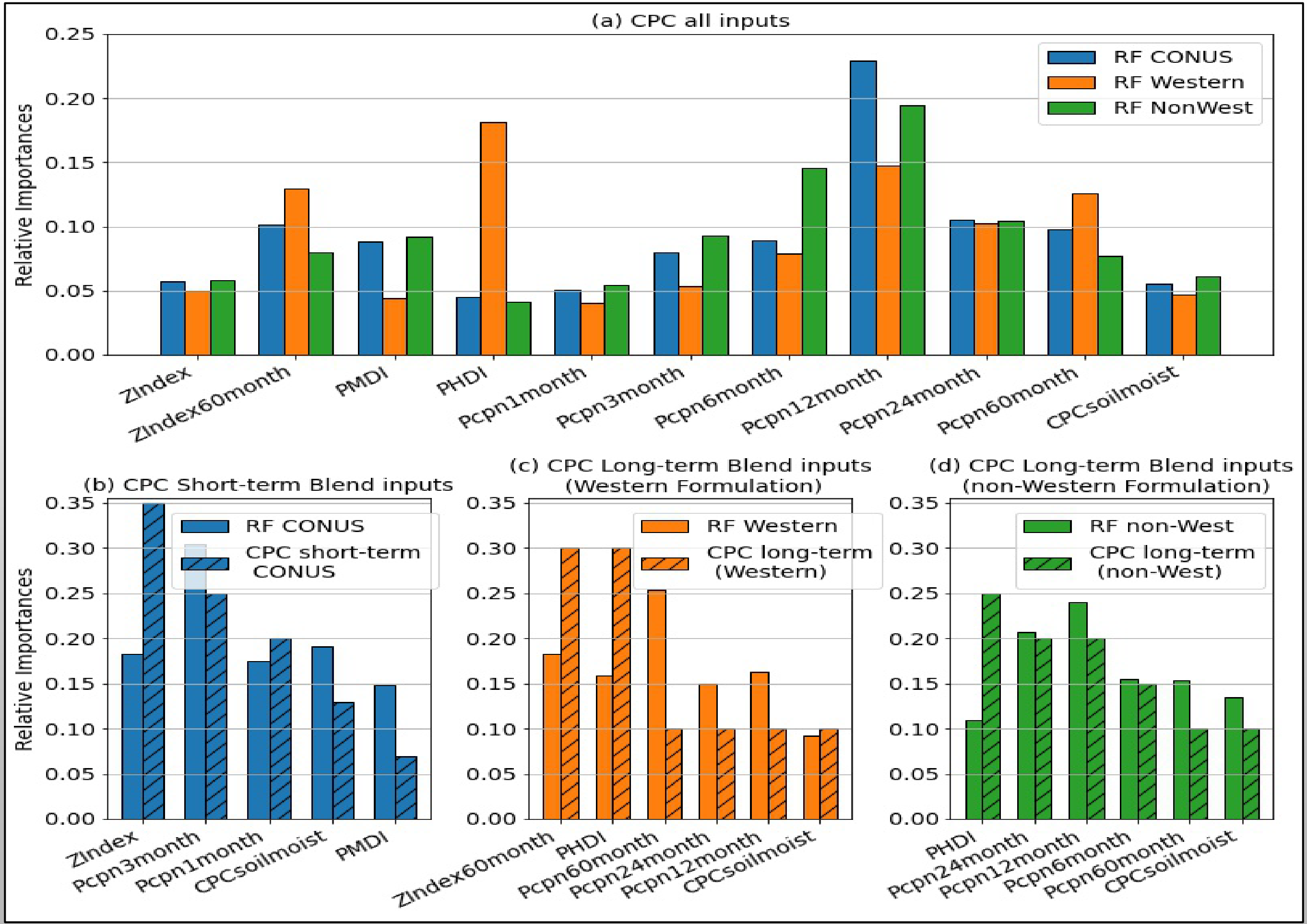






But adding this out-of-sample into previous slide's training set to create new bigger training set again gives a perfect prediction!

Random Forest-based importances vs. CPC Blend weights



Summary & ongoing work

- Mutual information-based importance measures are importance reference points for machine learning technique-based measures
  - We have developed a library to obtain combined mutual information of any set of indicators with USDM for ongoing investigation of the incremental utility of inputs
- Class imbalance hampers training in neural network, and potentially remedied by category-weighted loss functions
  - We are testing out these coded category-weighted functions and their predictions
- Excellent prediction of random forests before pruning generalization is highly encouraging for obtaining similar prediction levels using category-weighted loss functions in hyperparameter-tuned neural network (and its input relevance calculation)
- Input indicators: We are acquiring and processing additional inputs (100+ that go into the USDM, modeled products, remotely sensed products etc.)