An objective, near real time US Drought Indicator

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Drought is complicated

- In different time scales:
 - long-term drought
 - short-term drought
 - flash drought

- In different impacts:
 - Streamflow
 - reservoir water level
 - vegetation
 - ground water

• In different drivers:

- Meteorological drought
- Hydrological drought
- Agricultural drought
- Ecological drought
- social-economical drought

• In different monitors:

- Human expert synthesize/blending
- Objective integration

Great Challenge : **objective, science-based integration** for merging/blending multiple drought information sources (Wood et al 2015 JHM)





Meteorological drought: SPIs

Water balance (P-E): SPEIs

Hydrological drought: SRIs

Agriculture drought: SMPs

Evapotranspiration demand: EDDI/ESI

Palmer drought: PMDI/PHDI/PSDI

GraceDA, VHI, QuickDry





- Integrated drought index (Mo and Lettenmaier 2014): SRI3 and SMP from NLDAS2 4 models, occurrence measure
- Optimal blended NLDAS drought index (Xia et al. 2014):
- UC Merced and DRI, multi-indicator Drought index (MIDI) => CPC expert weight
- NDMC high resolution blending => CPC expert weight

OBNDI = 0.6253SM1 + 0.0253SMT + 0.0033ET

+0.00001Q.

(10)

NDMC recent revised of CPC blending (expert weights)

CPC Short-Term	NDMC Short-	CPC Long-Term	NDMC Long-Term	CPC Long-Term	NDMC Long-Term
	Term	Western	Western	non-Western	non-Western
Palmer Z index (35%)	1-month SPEI (35%)	PHDI (30%)	9-month SPEI (30%)	PHDI (25%)	9-month SPEI (25%)
3-month nClimDiv	3-month SPI	60-month Z index	60-month SPEI	24-month nClimDiv	24-month SPI
precipitation (25%)	(25%)	(30%)	(30%)	precipitation (20%)	(20%)
1-month nClimDiv	1-month SPI	60-month nClimDiv	60-month SPI	12-month nClimDiv	12-month SPI
precipitation (20%)	(20%)	precipitation (10%)	(10%)	precipitation (20%)	(20%)
CPC soil moisture (13%)	Noah 0–100-cm soil moisture (13%)	24-month nClimDiv precipitation (10%)	24-month SPI (10%)	6-month nClimDiv precipitation (15%)	6-month SPI (15%)
PMDI (7%)	9-month SPI	12-month nClimDiv	12-month SPI	60-month nClimDiv	60-month SPI
	(7%)	precipitation (10%)	(10%)	precipitation (10%)	(10%)
		CPC soil moisture (10%)	Noah 0–200-cm soil moisture (10%)	CPC soil moisture (10%)	Noah 0–200-cm soil moisture (10%)

replace: Palmer Z => SPEI1, PMDI=> SPEI9 and PHDI => SPEI9 CPC SMP => Noah SMP

- 9-mon, 12-week time scale mismatch
- Overweight SPEI (over 60% in the west region)
- Underweight soil moisture (48% => 13%)
- remove hydrological drought, in particular west region (25%-30%)

Mutual Information (MI) analysis for the NDMC revised blends





- SPI ~= PRCP strong contribution (peak 6-12 mn)
- Runoff > streamflow moderate contribution
- Vegetation based weak contribution
- Satellite PRCP < Gauge based PRCP
- SPEI strong contribution, eq. SPI
- PMDI/PHDI strong contribution, stand out in other indicators
- SWE also weak contribution
- EDDIs weak contribution
- SM/Land water strong contribution
- CPC leaky ~advanced LSM > GRACEDA

Figure S6. Frication Information (FIs) for indicators grouped into subplots by indicator type for entire CONUS. All the indicators have the same sample size since only the samples where all 113 indicators together have valid values are considered. The colors of the x-axis tick labels correspond to the indicator subsets in Table 1, namely observation-based (blue), model-based (red) and remote sensing-based (green).



Standardized Index

4 > -4

Proof of concept of Deep learning (Multi-layer neural network) model



Vectorize the whole lon-lat grid to vector space

Realtime

Map released: March 28, 2024

Data valid: March 26, 2024

View grayscale version of the



Confusion Matrix of Drought classification (multi class)

DL drought indicator

Normalized accuracy

Fuzzy logic: +/- 1cat accuracy=0.95

"Worst" case scenarios

From https://droughtmonitor.unl.edu/DmData/TimeSeries.aspx

D0-D4

20

1.0

II.P

Drought Occurrence Percentage

Drought Occurrence Percentage based on the USDM >> theoretic Occurrence

Machine Vs Human

AI/ML Objective drought integrate	USDM author Expert drought synthesize		
 Ingest large amount information Speed & Accuracy Objectivity Consistency Scalability 	 Generalization Creativity and imagination Emotional intelligence and empathy Adaptability and flexibility 		
 Limited creativity and intuition Lack of common sense and context Vulnerability to errors and limitations Dependency on humans 	 Slowness and susceptibility to errors Subjectivity and bias Limited scalability Inconsistency and unpredictability 		

Summary

- Objective drought integration/blending is critical step for drought monitor and outlook
- Current CPC nClimDiv blending is out of date, need upgrade it
- A new CPC objective drought indicator:
 - Based on the real-time VIC mesoscale hydrological model analysis, No latency
 - Optimal integration with selected drought indices (Meteorological ,agricultural, hydrological, Evap. demand etc.) by Deep Learning model
 - Minimize the loss function of RMSE/MSE by training iteration
 - ½ degree over CONUS, match climate / drought outlook

Drought Occurrence Percentage Based on 2000-2017 USDM

From Chen et al 2019

NDMC objective blending (CPC weight) against USDM

From Joyce Leung

Mutual Information (MI)

- Information theory (Shannon 1948 ab), based on the Joint Entropy (common entropic information)
- Information Gain, how much information can be obtained from a random variable by observing another random variable

• measure I(X; Y) = H(X) - H(X|Y) for the ships, unlike Pearson corrcoef $I(X;Y) = \sum_{y \in Y} \sum_{x \in X} p_{(X,Y)}(x,y) \cdot \log\left(\frac{p_{(X,Y)}(x,y)}{p_X(x)p_Y(y)}\right)$ = H(Y) - H(Y|X)= H(X) + H(Y) - H(X, Y)= H(X, Y) - H(X|Y) - H(Y|X)H(X) H(Y) • Non-negative: $I(X; Y) \ge 0$ I(X;Y)• Symmetric: I(X; Y) = I(Y; X)H(X|Y)H(Y|X)

> • $I(X; Y) = 0 \Leftrightarrow X, Y$ independent, because in that case $P(x, y) = P(x) \cdot P(y)$

- MI is the amount of information obtained about the USDM by observing the other drought indicator ٠
- conditional entropy: residual information of one variable given the knowledge of another variable •
- could be utilize to discrete data (drought categories), not only the continuous data

NDMC recent revision of CPC expert blending

Short-Term:

- 7% SPEI (9-mon. precipitation totals)
- 13% Soil Moisture (0-100cm root zone: 1-week anomaly)
- 20% SPI (1-mon. precip. totals)
- 25% SPI (3-mon. precip. totals)
- 35% SPEI (1-mon. precip. totals)

Long-Term West:

- 10% Soil Moisture (0-200cm total column: 12-week anomaly)
- 10% SPI (12-mon. precip. totals)
- 10% SPI (24-mon. precip. totals)
- 10% SPI (60-mon. precip. totals)
- 30% SPEI (9-mon. precip. totals)
- 30% SPEI (60-mon. precip. totals)

Long-Term:

- 10% Soil Moisture (0-200cm total column: 12-week anomaly)
- 10% SPI (60-mon. precipitation totals)
- 15% SPI (6-mon. precip. totals)
- 20% SPI (12-mon. precip. totals)
- 20% SPI (24-mon. precip. totals)
- 25% SPEI (9-mon. precip. totals)

Flash Drought:

- 25% SPEI (1-mon. precip. totals)
- 25% NOAH Soil Moisture (0-40 cm)
- 20% EDDI (2-week)
- 20% ESI (4-week)
- 10% QuickDRI

replace: Palmer Z => SPEI1, PMDI=> SPEI9 and PHDI => SPEI9 CPC SMP => Noah SMP

- 9-mon, 12-week time scale mismatch
- Overweight SPEI (over 60% in the west region)
- Underweight soil moisture (42% => 13%)
- remove hydrological drought, in particular west region (25%-30%)