

APPLICATIONS OF PRECIPITATION CLIMATE DATA RECORDS

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with contributions from

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Workshop on “Precipitation Estimation from LEO Satellites: Retrieval and Applications”

March 2, 2023 @ 14:00-14:15 | Online

Outline

- ❑ **NOAA Climate Data Records (CDRs) & Gridded Precipitation Datasets**
- ❑ **Evaluation of Climate Data Records**
- ❑ **Application I : Tropical Cyclone Contribution & Extreme Rainfall**
- ❑ **Application II : Near-real Time Global Drought Monitoring**
- ❑ **R2O : US Drought Portal (Drought.gov)**
- ❑ **Transition to Cloud Computing Environment**
- ❑ **Conclusions**

Satellite Precipitation Products (SPPs)

❑ *Climate Data Record*

- “A CDR is a time series of scientifically-based measurements of the Earth’s environment with sufficient length, consistency, and continuity to assess and measure climate variability and change.”
- Available @ <https://www.ncdc.noaa.gov/cdr> and via [Amazon Web Services](#)

❑ *Precipitation CDRs*

- **CMORPH** (*gridded, PMW & in-situ*) (NOAA CPC P. Xie)
 - **Global (60N-60S), 30-min, 8x8-km, Daily, 0.25x0.25-deg, 1998-Present, Interim & Final**
- **PERSIANN-CDR** (*gridded, IR & in-situ*) (UC-Irvine S. Sorooshian)
 - **Global (60N-60S), Daily, 0.25x0.25-deg, 1983-Present, Final**
- **GPCP** (*gridded, IR & in-situ*) (UMD R. Adler)
 - **Global, Daily, 1x1-deg, 1997-Present, Final**

❑ *Other SPPs*

- **TMPA** (*gridded, multi-satellite precipitation analysis, PMW, IR & in-situ*) (NASA G. Huffman)
 - **Global (50N-50S), 3-hr, Daily, 0.25x0.25-deg, 1988-2019, Interim & Final**
- **IMERG** (*gridded, multi-satellite, PMW, IR & in-situ*) (NASA G. Huffman)
 - **Global, 30-min, Daily, 0.1x0.1-deg, 2000-Present, Interim & Final**

CDR Evaluation: Warm/Cold Precipitation

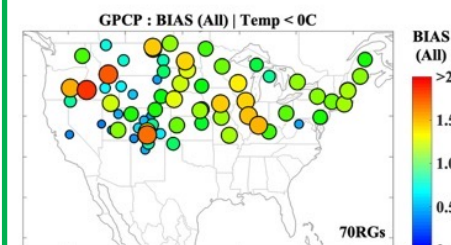
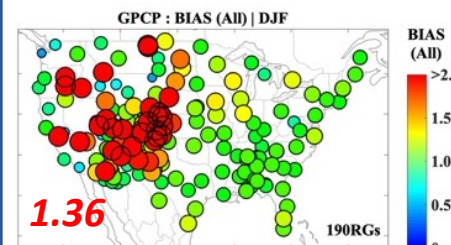
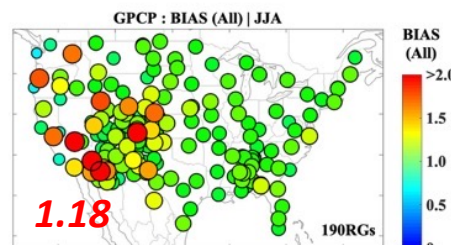
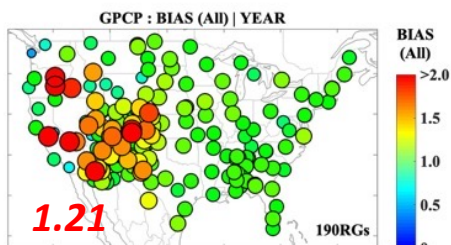
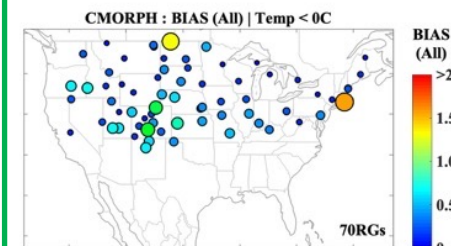
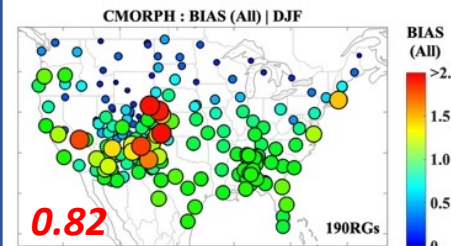
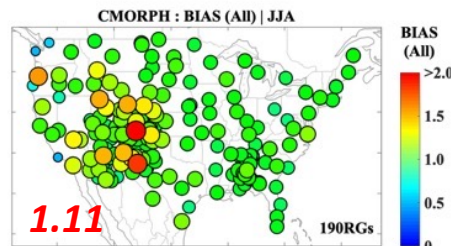
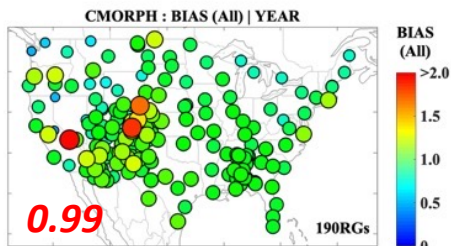
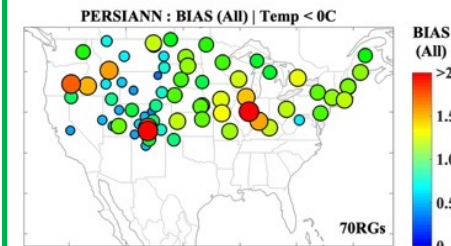
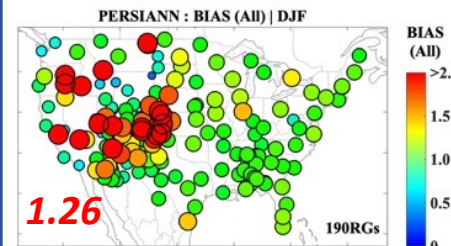
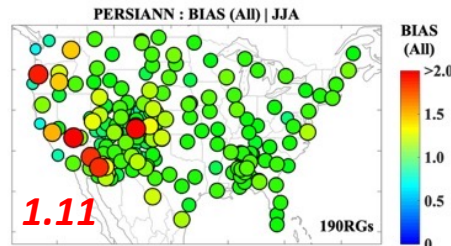
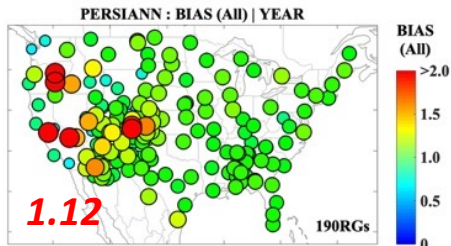
Bias

YEAR

JJA

DJF

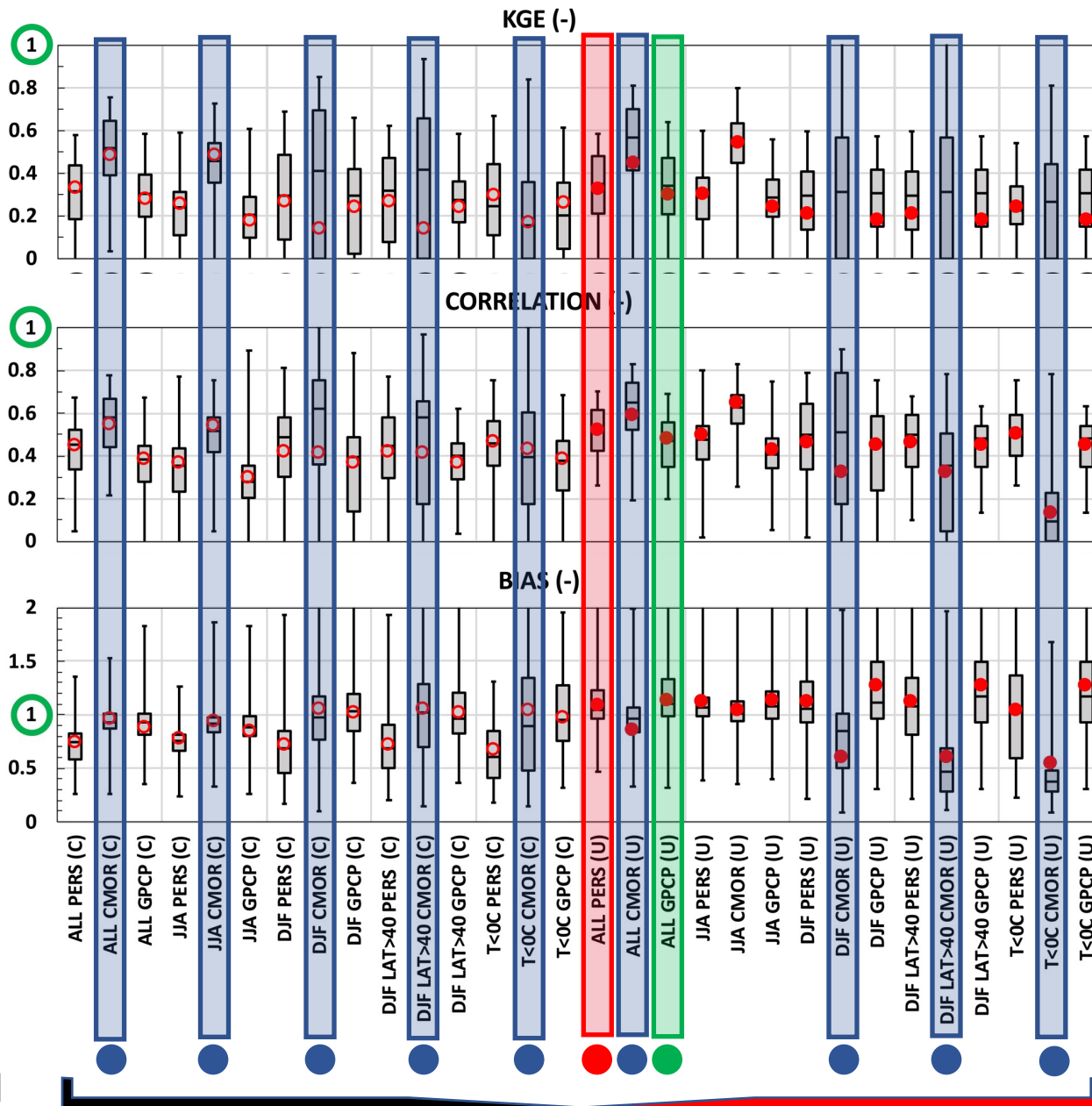
T<0°C



➤ Higher biases (overestimation) for PERSIANN and GPCP in winter (DJF) in the Western US.

➤ CMORPH displays rainfall underestimation in winter (DJF) and for daily T < 0°C.

CDR Performance vs. USCRN

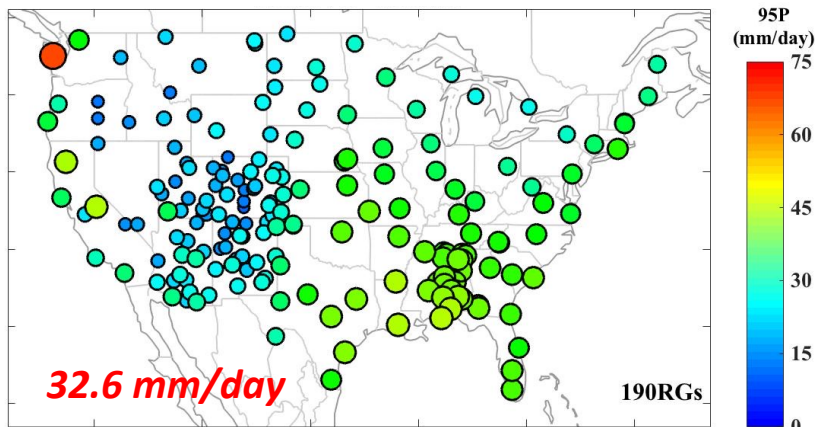


Conditional

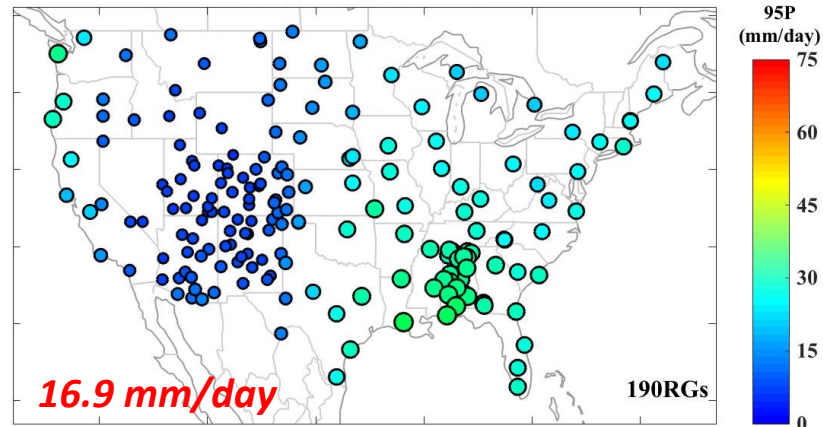
Unconditional

CDR Evaluation: Extreme Precipitation : 95th

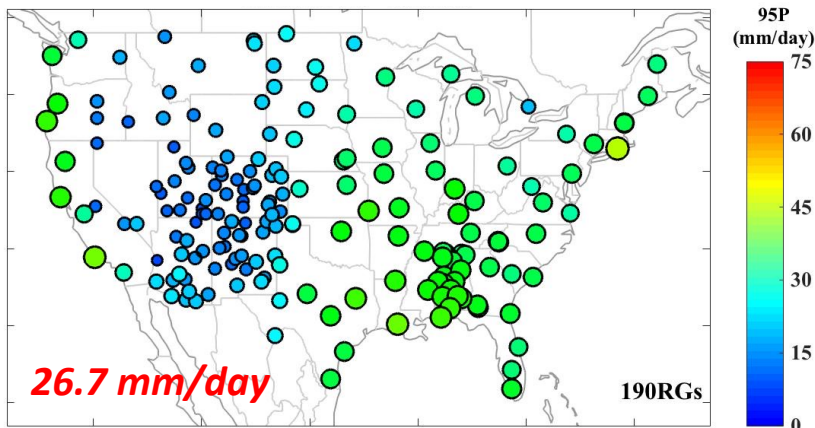
USCRN



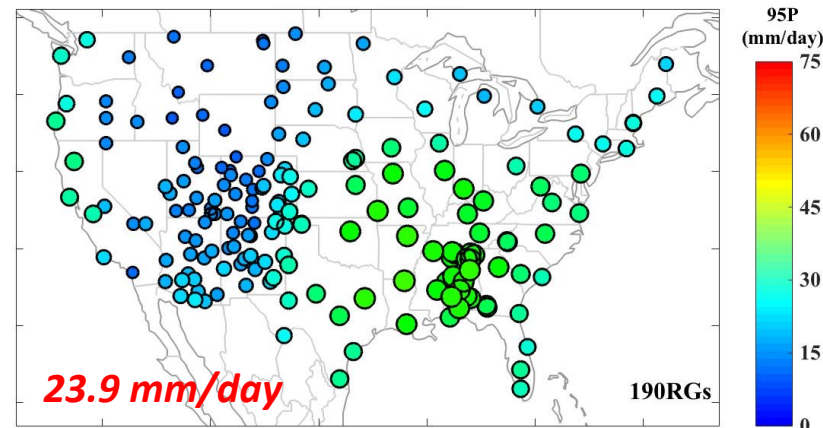
PERSIANN-CDR



CMORPH-CDR



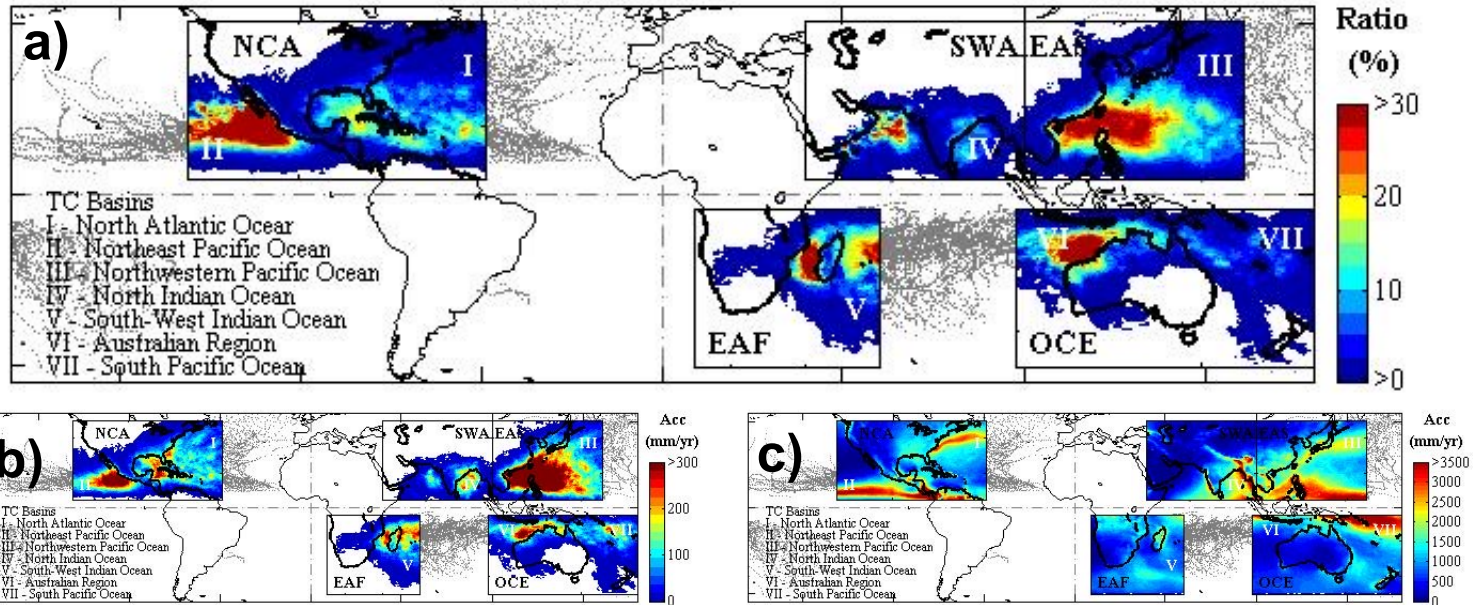
GPCP



► All SPPs underestimate extreme precipitation from 19% to 48% at the 95th percentile.

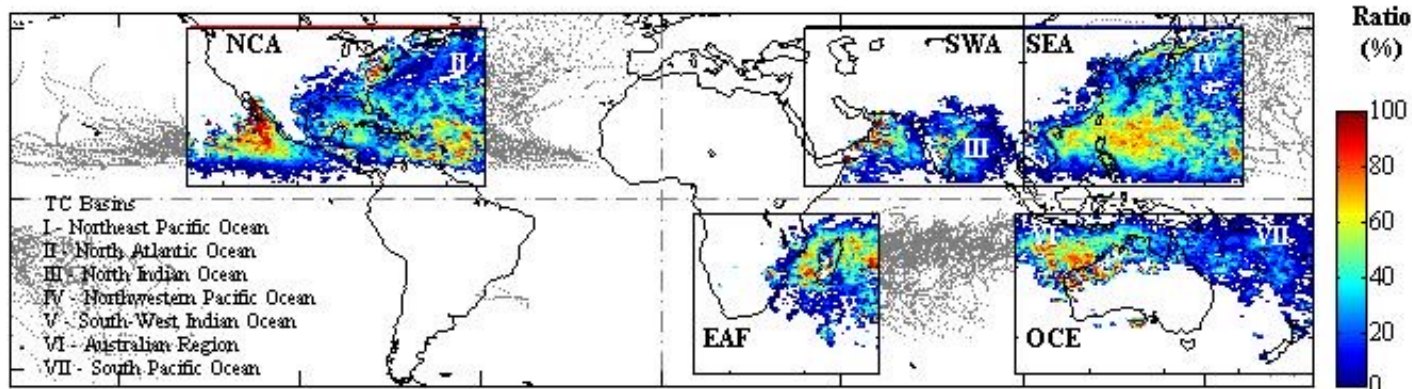
Global TC Contribution : TMPA 3B42

TC Contribution (a) = 100 x TC Rainfall (b) / Total Rainfall (c)

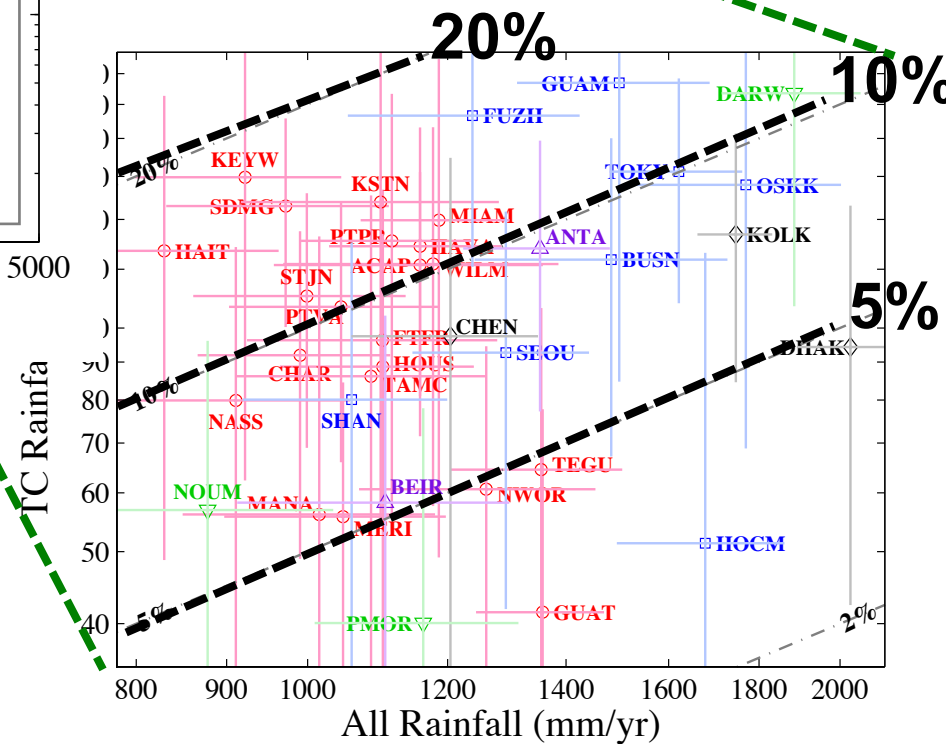
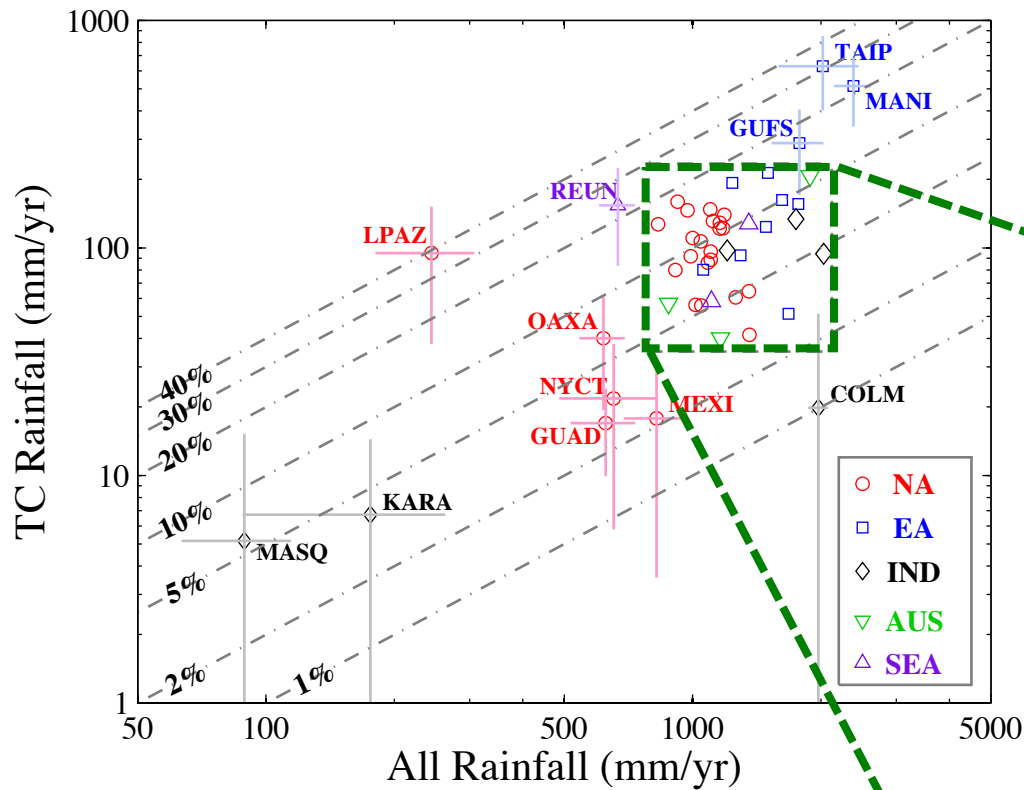


TC and Daily Extreme Rainfall

EPD > 2 in/day



TC Contribution for Selected Urban Areas



Examples of recent studies using gridded (level III) satellite precipitation products (SPPs) for applications in relationship with extreme precipitation

Products	Location	Duration	Applications	Conclusions	Authors
CMORPH, PERSIANN (PERSIANN, CCS), TMPA (RT, 3B42)	Western US	10-yr (2003-2012)	Atmospheric rivers (AR)	SPPs significantly underestimate precipitation and barely capture orographic precipitation with difficulties over snow/frozen surfaces. Concerns regarding near-real time SPPs monitoring of ARs.	Behrangi et al. (2016)
CMORPH, PERSIANN, TMPA (RT, 3B42)	Central US	12-yr (2003-2014)	Atmospheric rivers (AR)	TRMM 3B42 is found to be the best SPP for accumulation and rain rates associated with ARs. ARs contribute to about 35% to annual rainfall.	Nayak and Villarini (2018)
TMPA 3B42	(a) Southeastern US, (b) Global	12-yr (1998-2009)	Tropical cyclones (TC)	The percentage of rainfall associated with TC increases with increasing rain intensity and represents about 20% of heavy rainfall (> 20 mm/h) (a). Globally, TCs contribute to 5-10% of annual precipitation for basins around the world (b).	Prat and Nelson (2013a,b)
TMPA 3B42	Global	15-yr (1998-2012)	Tropical cyclones (TC)	TCs account for 3.5±1% of the total number of rainy days over TC basins. TC days represent between 13% and 31% of daily extremes (> 100mm/day).	Prat and Nelson (2016)
GPCP-Monthly (a), TMPA 3B42 (b)	Global	(a) 27-yr (1979-2005) (b) 8-yr (1998-2005)	ENSO	Monthly and daily precipitation extremes in relation to ENSO. Frequency of intense rain rates (> 20-, 50-mm/day) show a relationship with ENSO.	Curtis et al. (2007)
TMPA 3B42	Ghana	7-yr (1998-2006)	IDF curves	SPP useful to develop IDF curves for short gauge records or poorly gauged areas. Limitation of SPP IDF curves to durations of 3-hr or higher.	Endreny and Imbeah (2009)
CMORPH	Eastern Mediterranean	16-yr (1998-2013)	IDF curves	Good agreement between SPP and radar IDF curves for a range of varying climates. Potential for using SPP IDF curves in ungauged areas.	Marra et al. (2017)
PERSIANN-CDR	CONUS (river basins)	33-yr (1983-2015)	IDF curves	Adjustment of annual maximum time series of SPP prior to drive IDF curves. Method improves Annual Maximum Series (AMS) in particular at high elevation. SPP IDF curves fall within Atlas 14 IDF curves uncertainties.	Faridzad et al. (2018)
PERSIANN-CDR	CONUS	35-yr (1983-2017)	IDF curves	Method to develop IDF curves from SPP. SPP IDFs show considerable underestimation before adjustment. Extensive assessment of SPP uncertainties prior to computation of IDF curves.	Ombadi et al. (2018)
TMPA 3B42	Angola	16-yr (1998-2013)	Annual Max Daily Rainfall	TMPA 3B42 slightly underestimate annual maximum daily precipitation. SPP useful for estimating extreme precipitation values for different return periods.	Pombo and de Oliveira (2015)
TMPA RT	Global	15-yr (1998-2012)	Extreme rainfall frequency	Provides useful early warning information for potentially extreme events as a complement to surface based data. Large uncertainties in Average Recurrence Interval (ARI) for regions with complex topography.	Zhou et al. (2015)
PERSIANN-CDR	Western US (CA, CO)	35-yr (1983-2017)	Extreme rainfall frequency	Correction of SPP Annual Maximum Series (AMS) to match gauged data. The method allows using SPP for extreme frequency analysis in ungauged areas.	Gado et al. (2017)
CMORPH, PERSIANN-CDR, TMPA 3B42	China (basin)	16-yr (1998-2013)	Probable Maximum Precipitation (PMP)	CMORPH and TMPA 3B42 agree well with gauge data over complex terrain (correlation, 24h PMP) and can be used for PMP estimation in ungauged regions.	Yang et al. (2018)
TMPA 3B42 (a), IMERG (b)	Italy	(a) 16-yr (1998-2013) (b) 1-yr (2014-2015)	Hydrologic design	TRMM 3B42 underestimates rainfall for deep convection systems. Preliminary analysis using IMERG shows significant improvement.	Libertino et al. (2016)
CMORPH	Ethiopia (river basin)	3-yr (JJA: 2007-2009)	Flood early warning	Development of a SPP based flood index (rainfall+DEM) for flood early warning. Effectiveness of SPPs for flood early warning	Koriche and Rientjes (2016)
TMPA RT	Saudi Arabia	14-yr (2000-2013)	Flood forecasting	Flood forecasting indexes derived from SPP capture high rain rates, daily, and seasonal variations of extreme events.	Tekeli and Fouli (2016)
TMPA 3B42	Global	13-yr (1998-2010)	Landslides	SPP rainfall variability significantly correlates with increase in landslide activity. Use of SPPs for developing a global rainfall-triggered landslide climatology.	Kirschbaum et al. (2012)

Prat and Nelson 2020, Satellite precipitation measurements and extreme rainfall. In Satellite Precipitation Measurement, Springer

Near-real Time Drought Monitoring

□ Goals

- Compute a daily **Standardized Precipitation Index (SPI)** in near-real time based on high-resolution in-situ and satellite precipitation products.
- Provide **near-real time drought monitoring** resources to the public.

□ Precipitation Datasets

- **CMORPH-CDR** (gridded multi-satellite precipitation, PMW & in-situ)
Global, Daily, 0.25x0.25-deg, 1998-present, 1-day (ICDR), 4-month (CDR)
- **NCLimGrid** (gridded in-situ precipitation, based on GHCN-D)
CONUS, Daily, 5x5-km, 1950-present, 3-day (prelim), 1-month (final)
- **IMERG** (multi-satellite & in-situ) (upcoming)
Global, Daily, 0.1x0.1-deg, 2000-present, 12-hr (late run), 3.5-month (final)

□ Methods

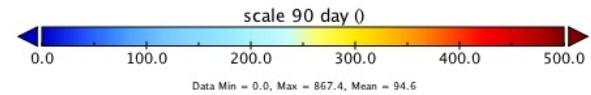
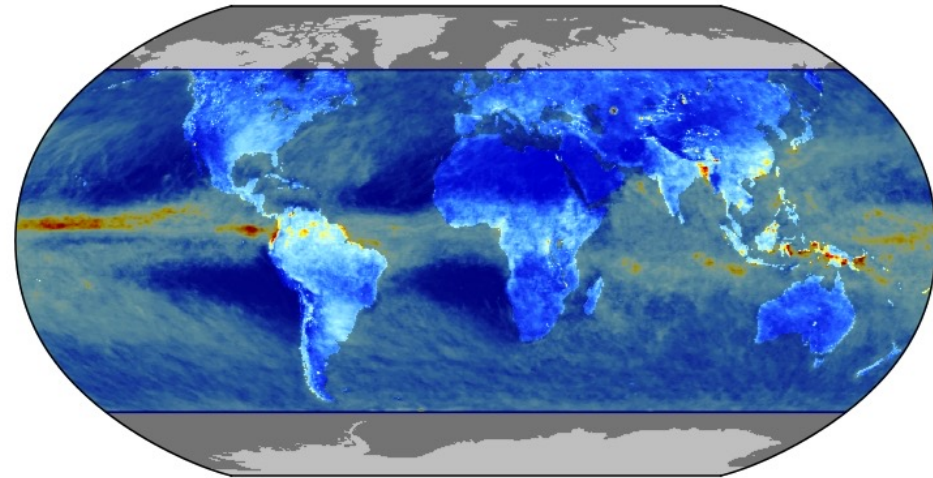
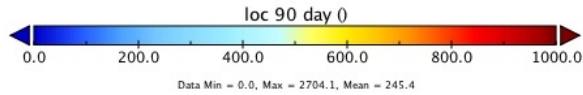
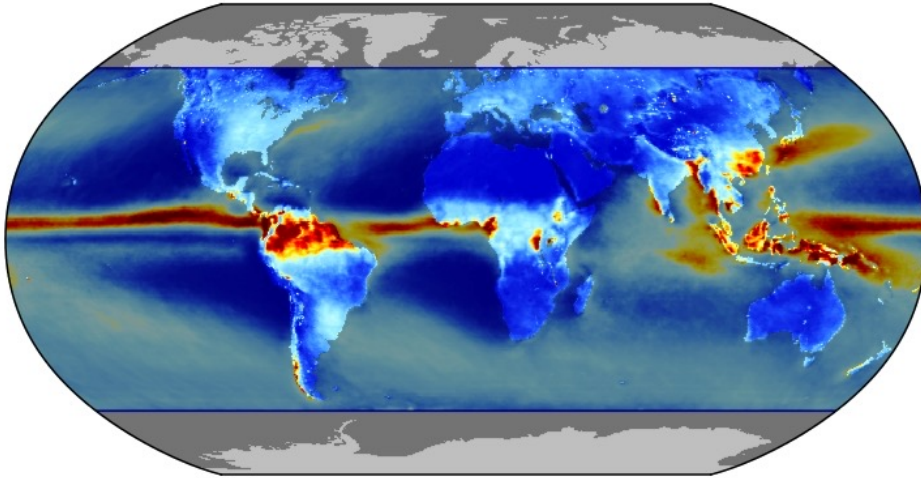
- **SPI Algorithm** (2-parameter Gamma & 3-parameter Pearson distributions)
- **30-, 90-, 180-, 270-, 365-, and 730-day daily SPI** (rainfall accumulation)
- Droughts are characterized as **Mild ($0 \geq SPI \geq -0.99$)**, **Moderate ($-1 \geq SPI \geq -1.49$)**, **Severe ($-1.5 \geq SPI \geq -1.99$)**, and **Extreme ($SPI \leq -2$)**.

Pearson III Distribution Parameters (CMORPH)

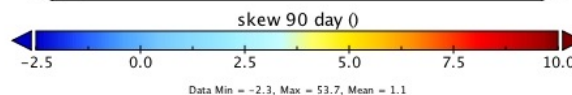
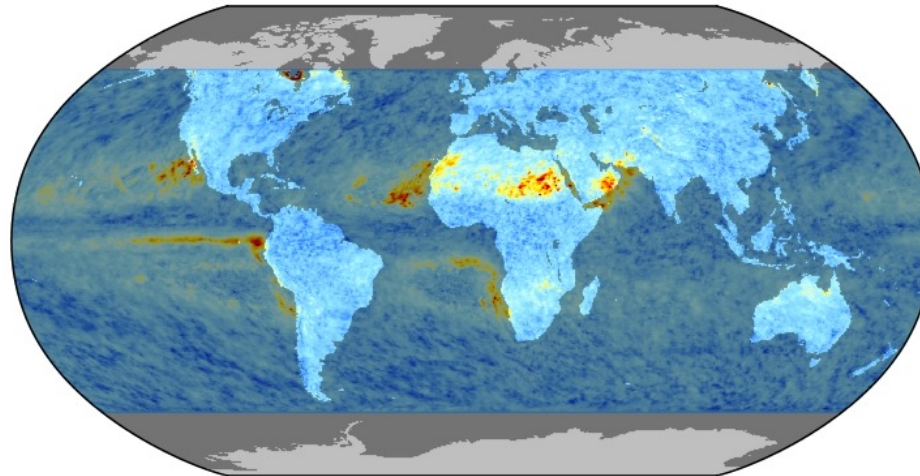
ξ – Location

90-Day

β – Scale



γ – Skewness



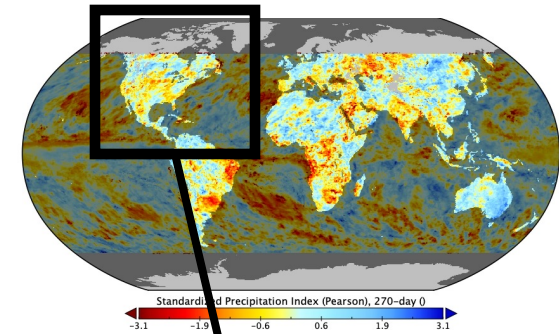
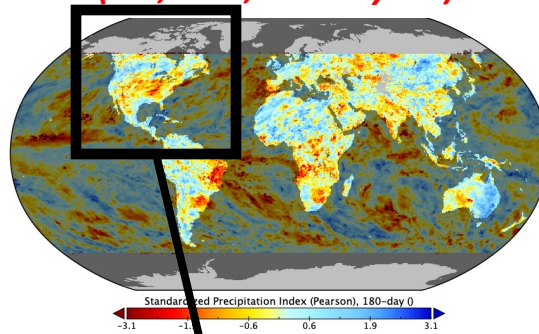
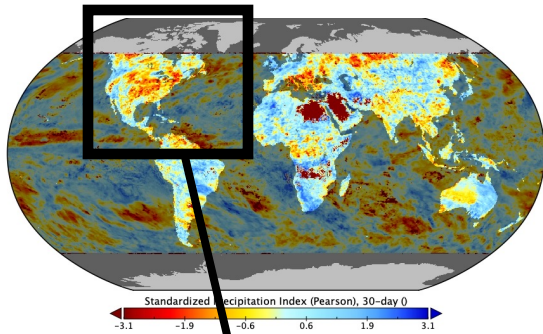
Location (ξ), Scale (β), and Skewness (γ) computed on a 1998-2021 reference period

July 1st

CMORPH-SPI on July 15th 2012 (0.25x0.25-deg)

(30-, 180-, 270-day SPI)

CMORPH-SPI

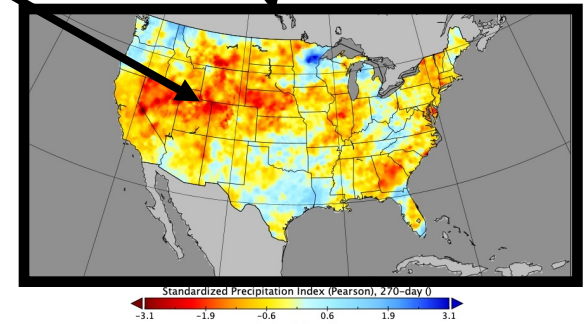
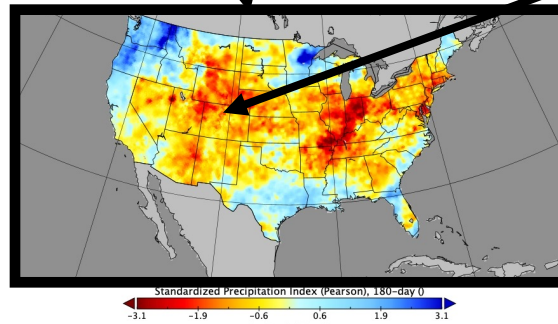
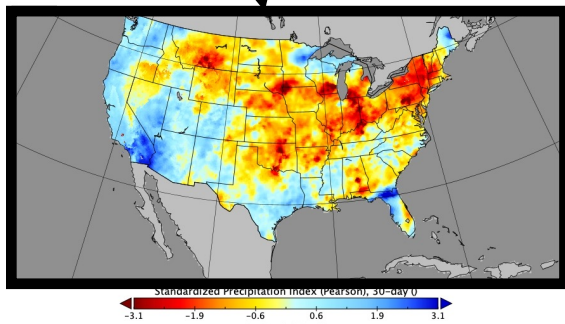


NclimGrid-SPI on July 15th 2012 (5x5-km)

(30-, 180-, 270-day SPI)

2012-2013 North American drought

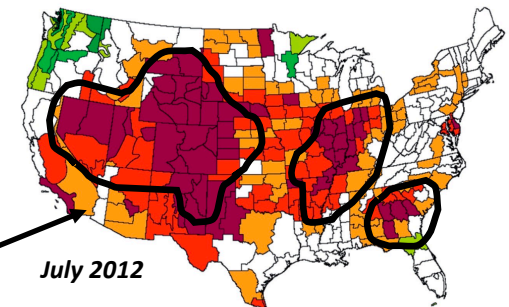
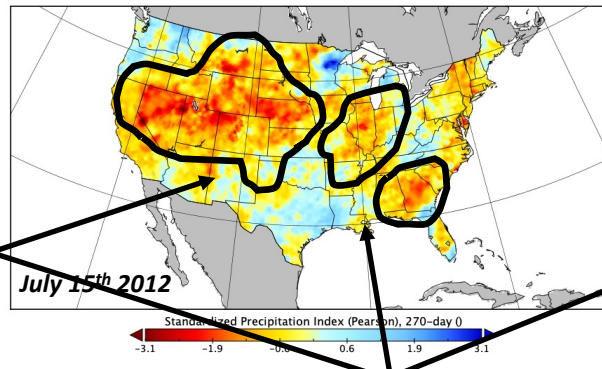
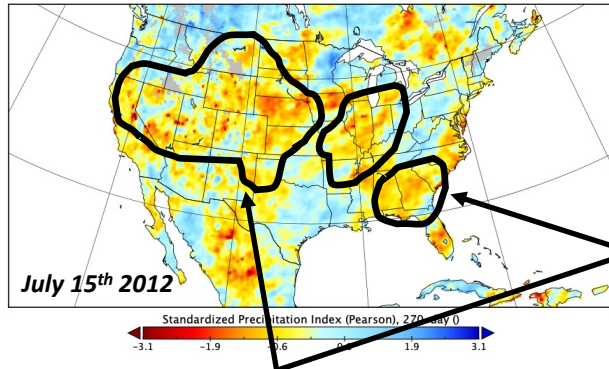
NclimGrid-SPI



270-day SPI (CMORPH)

270-day SPI (NclimGrid)

PDSI*



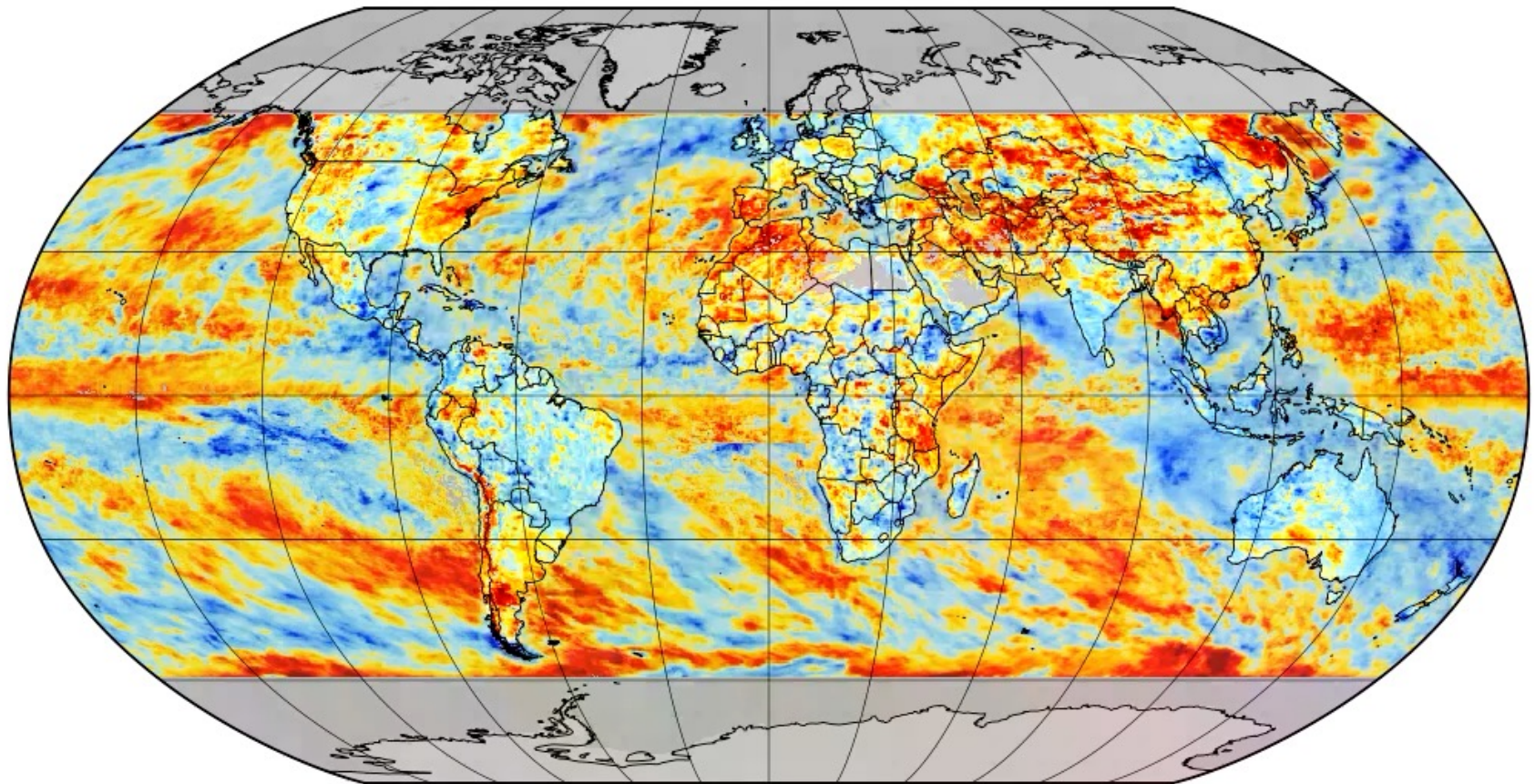
Differences in magnitude

Similar patterns

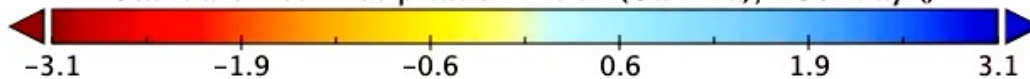
*Palmer Drought Severity Index (PDSI) maps (Heim 2017)

CMORPH-SPI : 180-day

Starting point of time period: 1999-01-01 00:00:00



Standardized Precipitation Index (Gamma), 180-day ()



Data Min = -3.1, Max = 3.1, Mean = -0.1

U.S. Drought Portal (Drought.gov) : NIDIS/NCEI

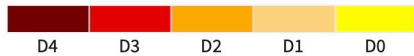
Global Drought Conditions

[Daily SPI \(CMORPH\)](#) [Monthly SPI \(GPCC\)](#) [Vegetation Health Index](#)

CMORPH (CPC MORPHing technique) produces global precipitation analyses at very high spatial and temporal resolution. This technique uses precipitation estimates that have been derived from low orbiter satellite microwave observations exclusively, and whose features are transported via spatial propagation information that is obtained entirely from geostationary satellite IR data.

This map shows the 3-month Standardized Precipitation Index (SPI) and is updated daily with a delay of 2-3 days. [Learn more.](#)

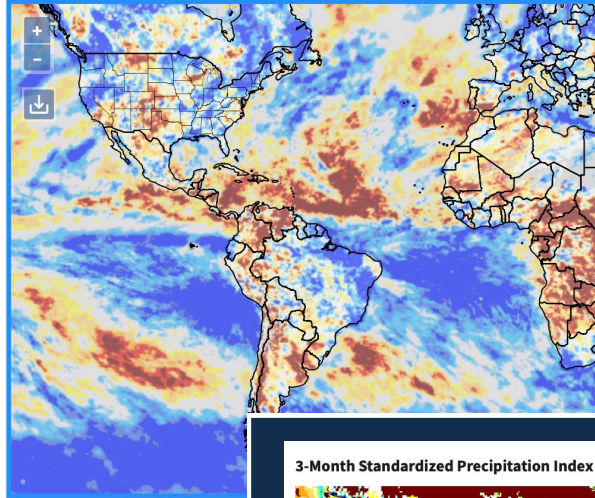
Drought Categories



Wetness Categories



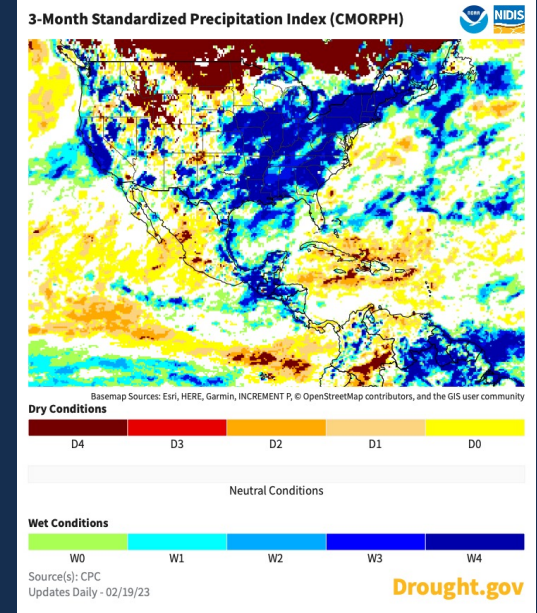
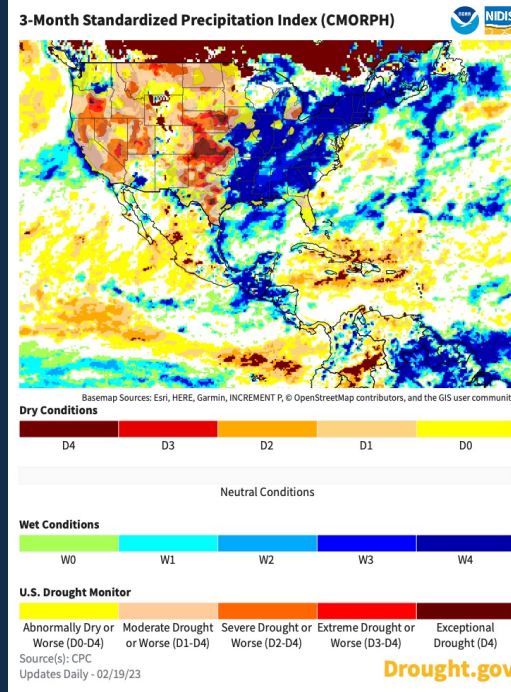
Source(s): CPC



← *CMORPH-SPI is available in the NIDIS Drought.gov portal to display global drought conditions. The 3-month Standardized Precipitation Index (SPI) and is updated daily with a delay of 2-3 days:*

<https://www.drought.gov/international>

→ *Current drought conditions. Figure displaying the US Drought Monitor (top layer on the left figure) on top of the 90-day CMORPH-SPI (right figure).*



Current drought conditions

Cloud-based Computing

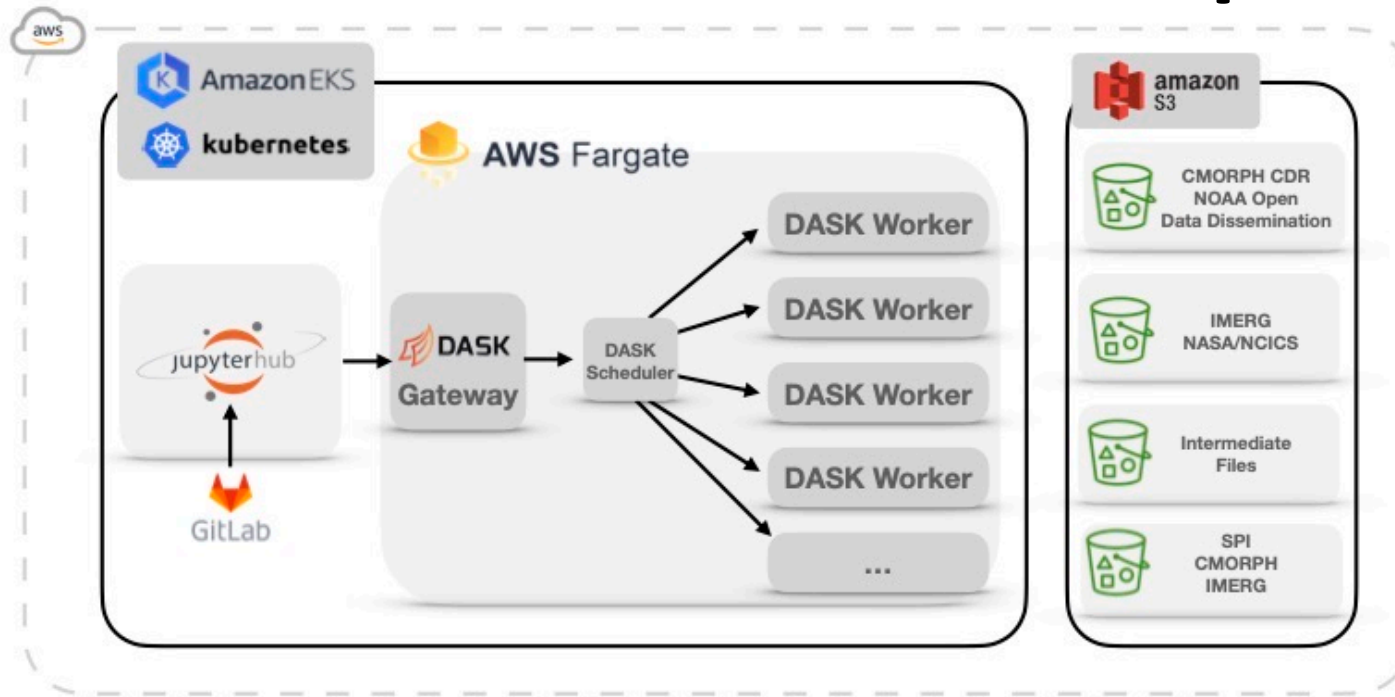
❑ **Why Convert to Cloud Resources ?**

- **Very slow computation for a daily process**
- **Memory intensive process**
 - *Holds loaded data in global arrays*
 - *Pre- and post-processing involve very large sets of files that don't fit well into memory, even on large servers*
- **Output is enormous and difficult for users to access**
 - *For CMORPH a 20GB file, produces 6x20GB SPI files and a 30GB parameter file*

❑ **Progression to Cloud-based Computing**

- **Store data on cloud servers**
- **Aggressive subdivision of input data**
 - *48x48 chunks of CMORPH data to 300 files, 80MB apiece*
- **Containerization of SPI code package**
 - *Known environment that can be copied anywhere via Docker*
- **Run hundreds of Lambda functions**
 - *Simultaneous computation of accumulation, parameters, and SPI domain-wide*

Architecture for SPI Cloud Computation



- Using AWS resources for SPI computation (i.e. Kubernetes, S3 ...).
- AWS Fargate is a serverless container manager that scales the workers for parallel processing.
 - ⇒ *The DASK environment allows for massive parallel processing and to rapidly scale resources from zero to a cluster of up to 500 workers and back to zero.*
- AWS S3 is used for data storage
 - ⇒ *S3 allows for fast parallel data access. All data including input (SPP datasets), intermediate (Accumulation, Distribution Parameters), and output files (SPI) are stored on S3.*
- SPI source code is in GitLab (Python). Jupyterhub is the scientific computing environment.
- Combining and optimizing all pieces to work together ⇒ *Framework (i.e. Kubernetes) allows the code to be transferable to other cloud environments (Google, Microsoft Azure).*

Conclusions

- ❑ Near-real time daily global **SPI** derived from **CMORPH** is available on [Drought.gov](https://drought.gov)
- ❑ Extending to **IMERG** (*late, final runs*) for a higher resolution SPI (*i.e. 6-fold increase*).
- ❑ **Fast processing time:** Adaption to the **cloud computing environment**.
 - **CMORPH-SPI** computation is **reduced by 2 orders of magnitude** (9-hr to 5-min)
 - *Ultimately the **daily updates** will take **less than 1-min***
- ❑ **Flexible framework:** Use of other precipitation products (*SPPs, radar, in-situ*) and other data sets (*temperature, ET, groundwater*) to derive more complex droughts indices (*SPEI, agricultural drought, hydrological drought*).
- ❑ **SPP requirements & improvements:** It depends on the application.
 - *TCs monitoring: Ability to capture extreme precipitation, low latency (minutes), high resolution.*
 - *Drought monitoring: More sensitive to average quantities (anomalies), daily updates are sufficient (using interim product), cold precipitation retrieval is important at high latitudes and at high elevation.*