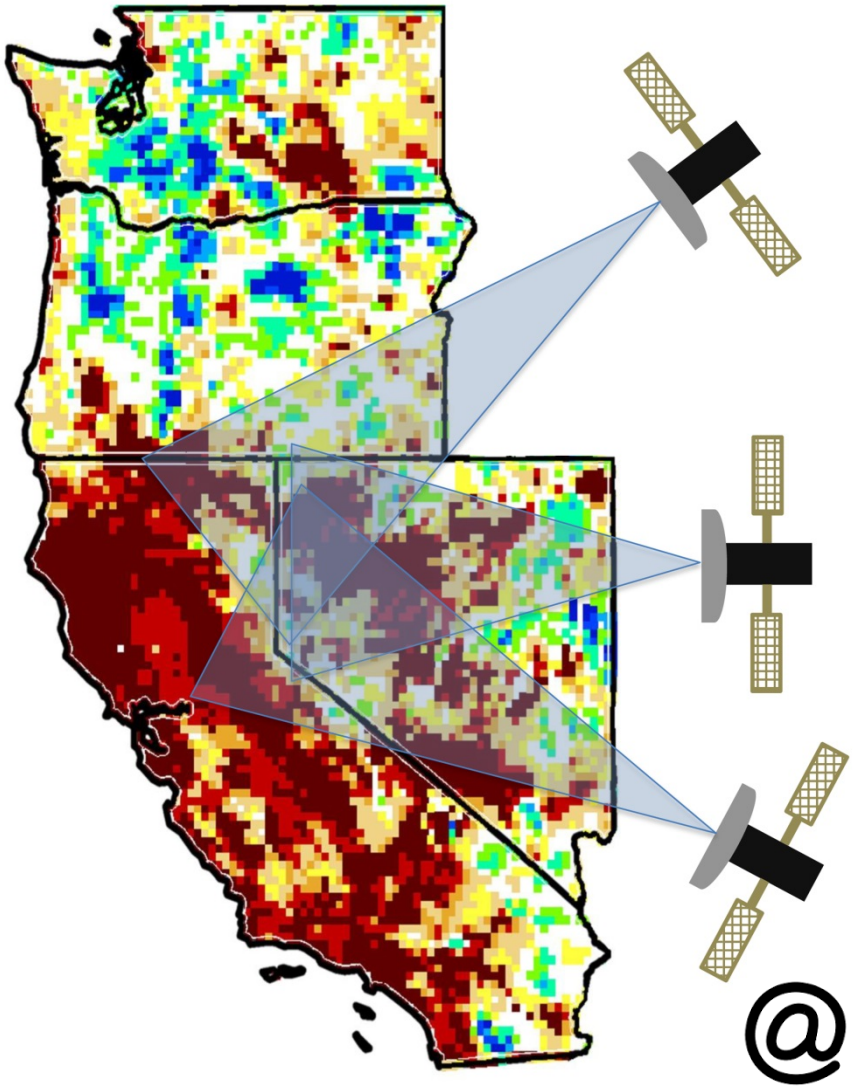
Remote Sensing of Drought: Progress, Challenges Opportunities for Improving Drought Monitoring



Amir AghaKouchak,

A. Farahmand

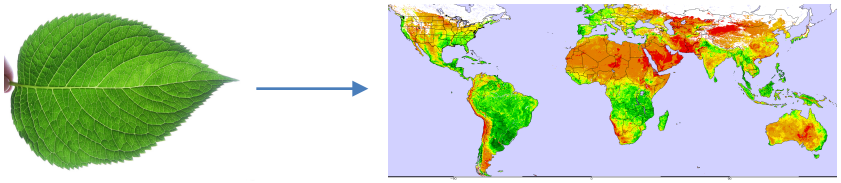
Center for Hydrometeorology and Remote Sensing,
University of California, Irvine

@ *amir.a@uci.edu*

@AmirAghaKouchak

Remote Sensing of Drought

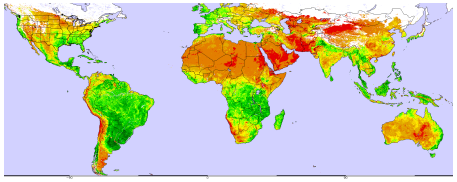
Remote Sensing of Drought

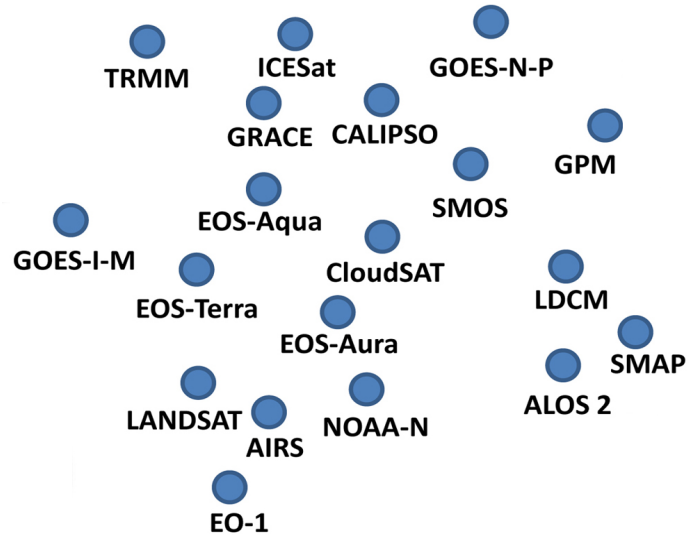


1970 1980 1990 2000

AVHRR

Remote Sensing of Drought





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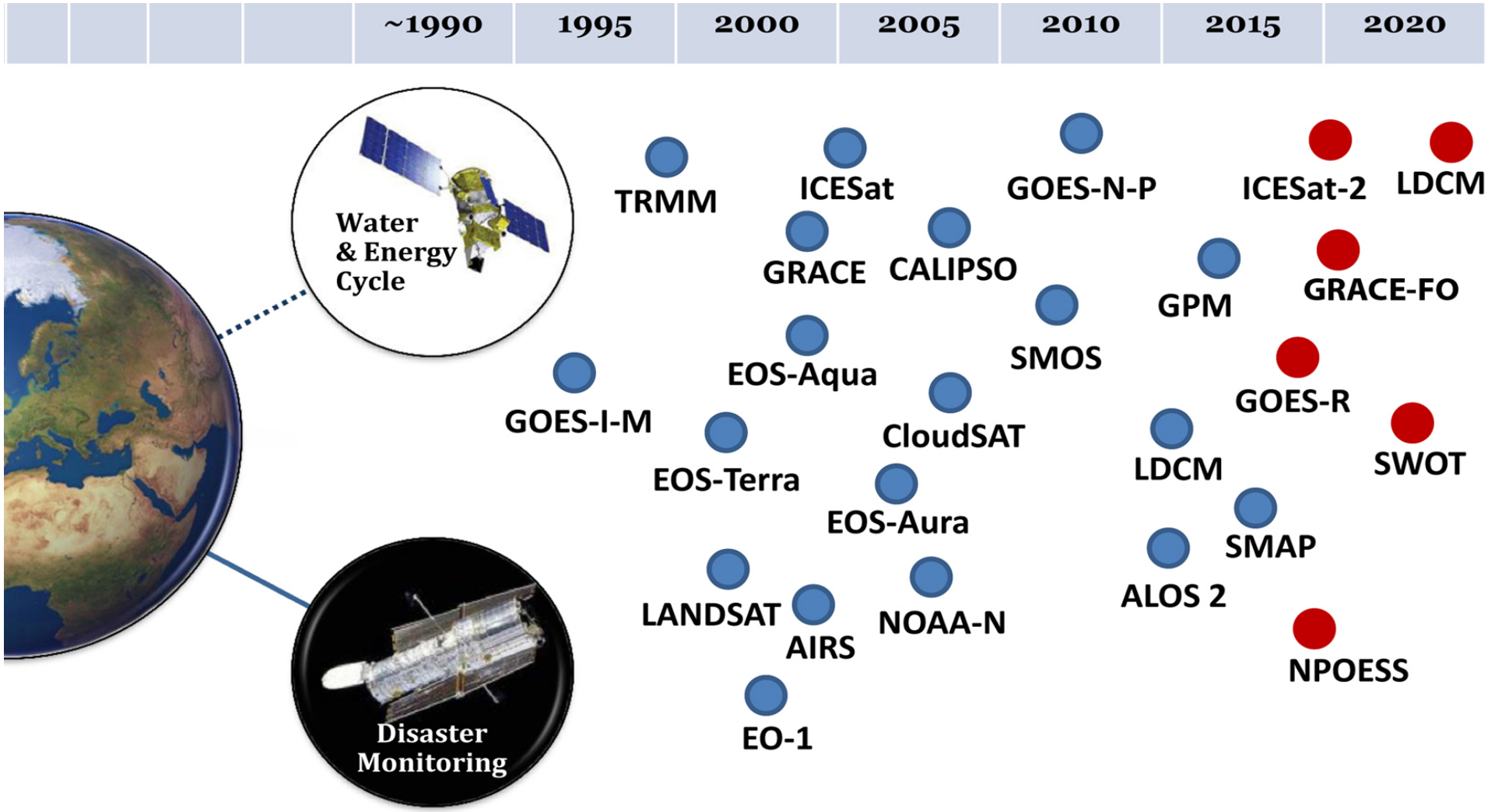
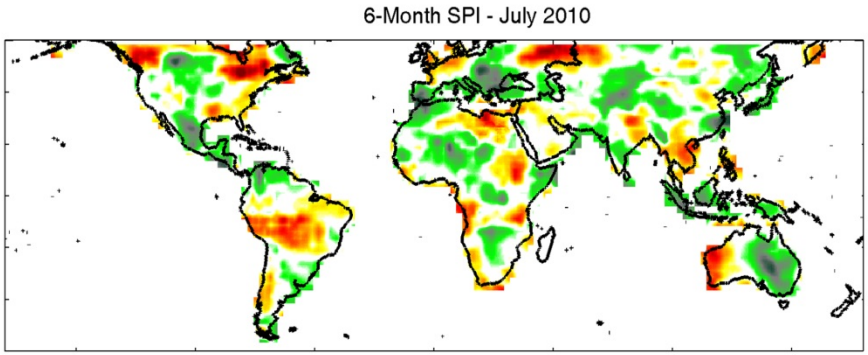
Remote Sensing of Drought

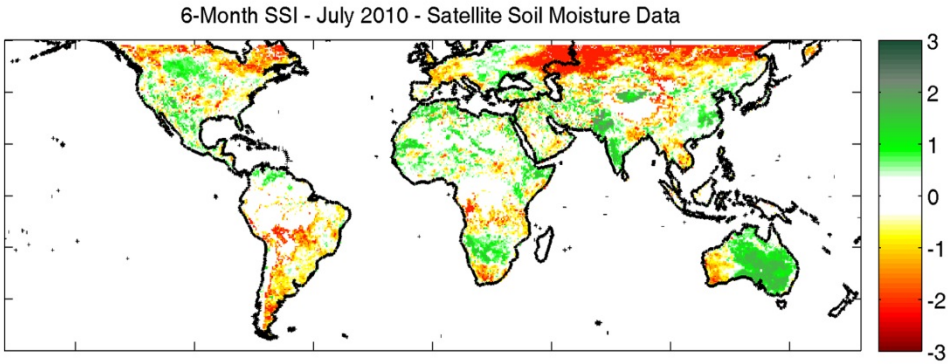


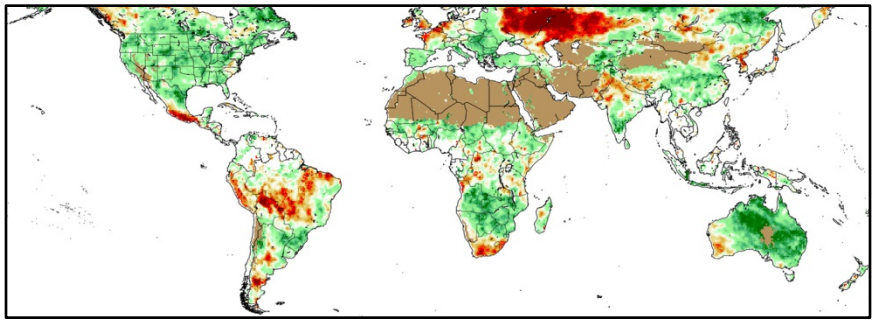
AghaKouchak et al., 2015, Remote Sensing of Drought: Progress, Challenges and Opportunities, *Reviews of Geophysics, 53 (2), 452-48.*

Remotely Sensed Drought Indicators

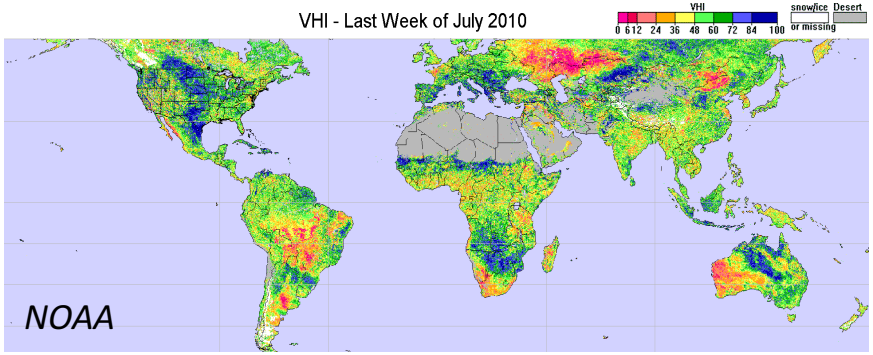
Climate and Land Surface

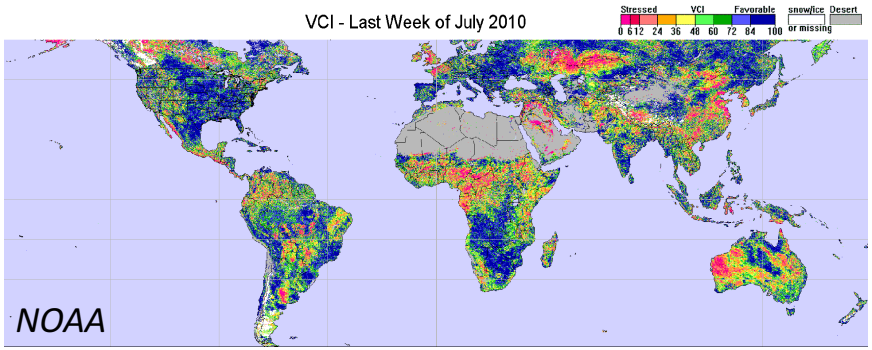




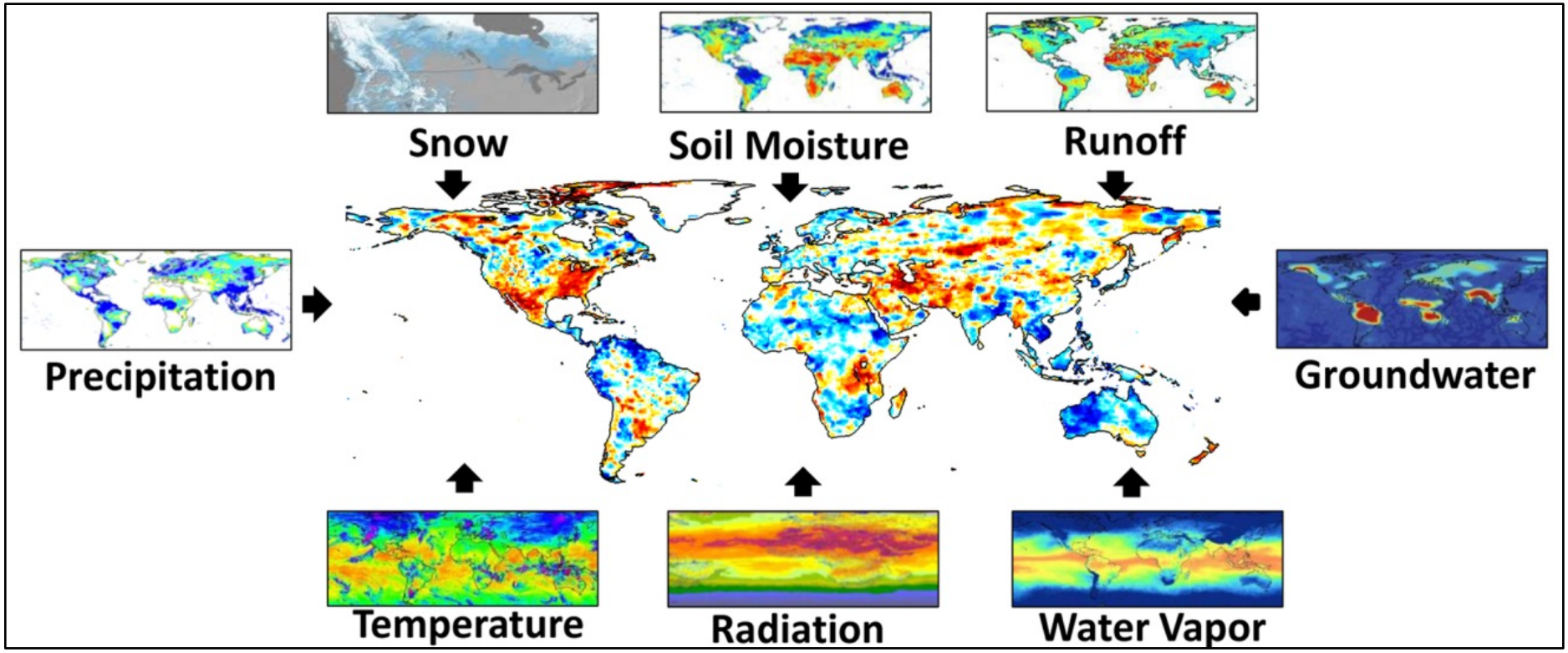


Ecosystem



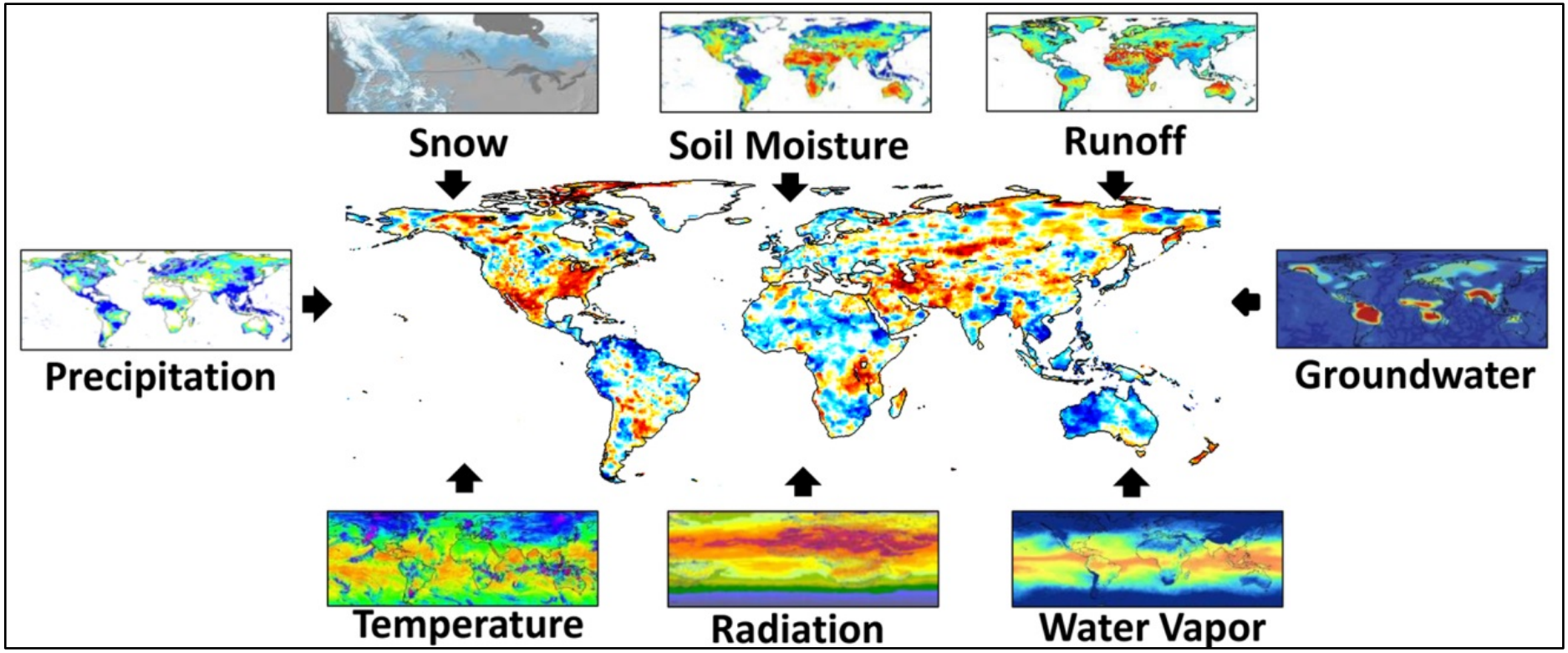


Remote Sensing of Drought



Multi-sensor (multi-index) composite drought monitoring using remote sensing observations

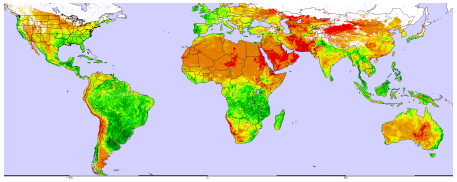
Remote Sensing of Drought

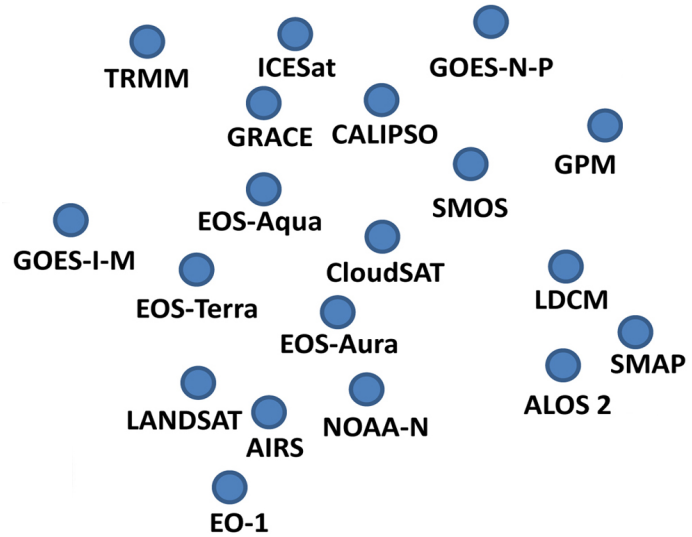


Data records are not consistent (often exhibit different distributions).

Lack of theoretical frameworks for linking different variables for multi-index drought assessment.

Remote Sensing of Drought





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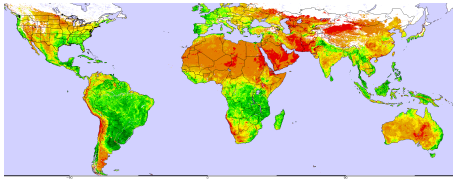
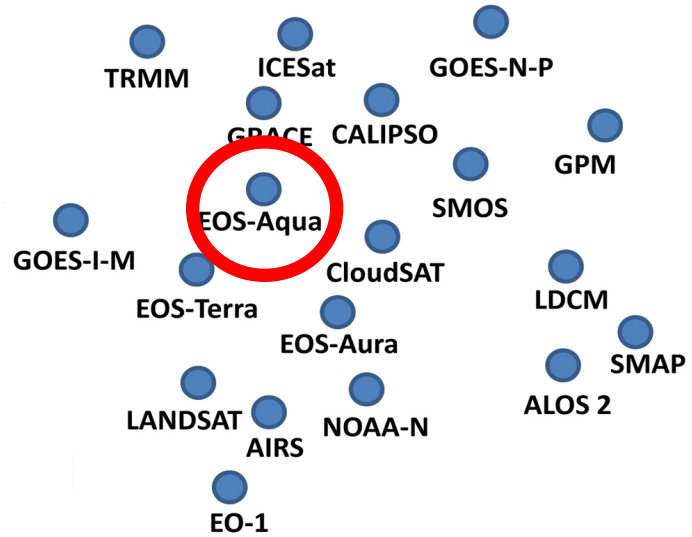
AVHRR

Remote Sensing of Drought





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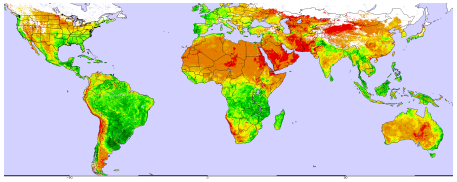
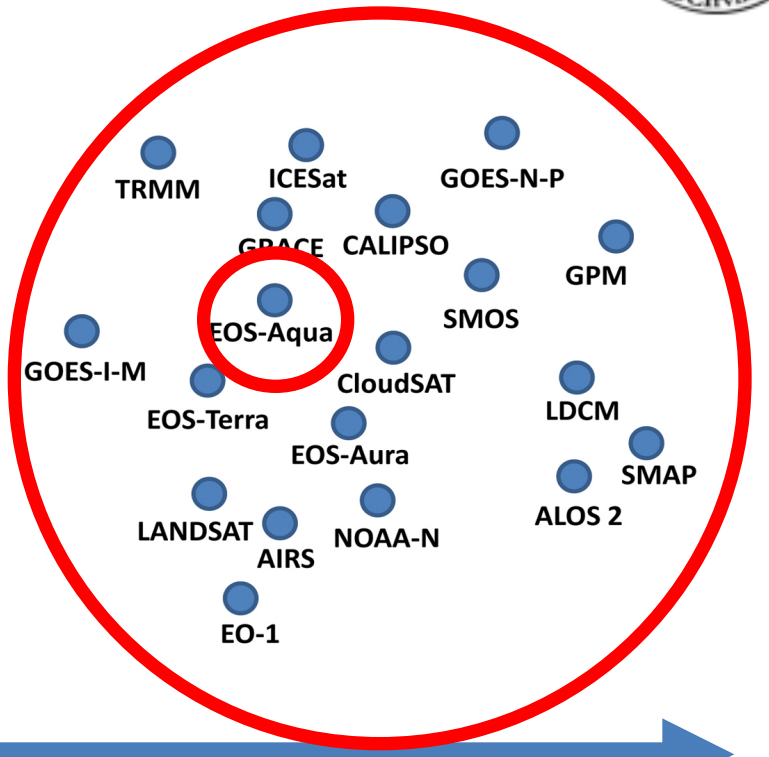


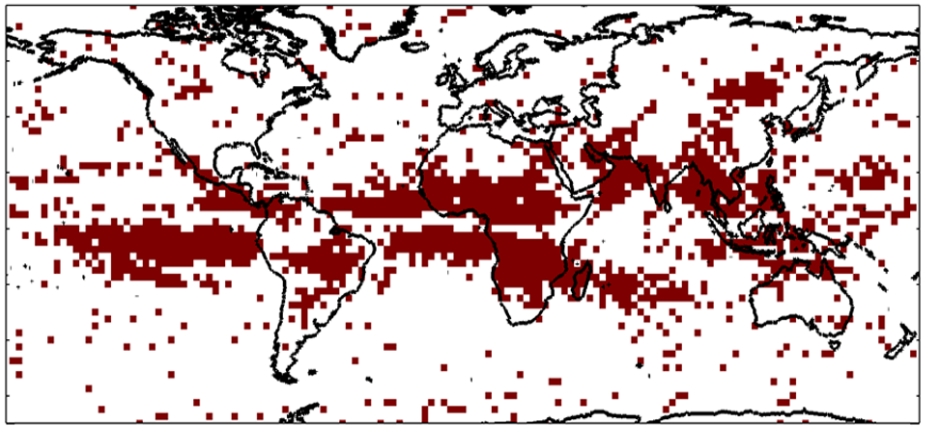


1970 1980 1990 2000

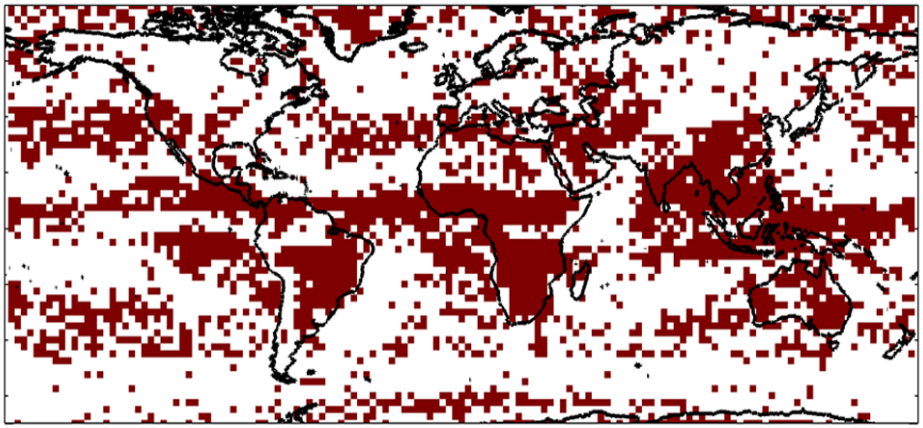
AVHRR

Representativeness of the Gamma (left) and lognormal (right) distributions for describing monthly precipitation accumulations. The dark pixels refer to locations where the Kolmogorov-Smirnov test rejects the null-hypothesis that the Gamma (left) or lognormal (right) distribution fits the precipitation data.

Gamma Distribution



Lognormal Distribution



A Generalized Framework for Deriving Nonparametric Standardized Drought Indicators

http://amir.eng.uci.edu/software.php

Farahmand A., AghaKouchak A., 2014, A Generalized Framework for Deriving Nonparametric Standardized Drought Indicators, *Advances in Water Resources*, 76, 140-145.

Non-parametric approach

The Empirical Gringorton probability:

$$p(x_i) = \frac{i - 0.44}{n + 12}$$

i Rank of non zero relative humidity from the smallest

n Sample size

x Precipitation/soil moisture

$$SI = \phi^{-1}(p(x_i))$$

ϕ Standardized normal distribution function

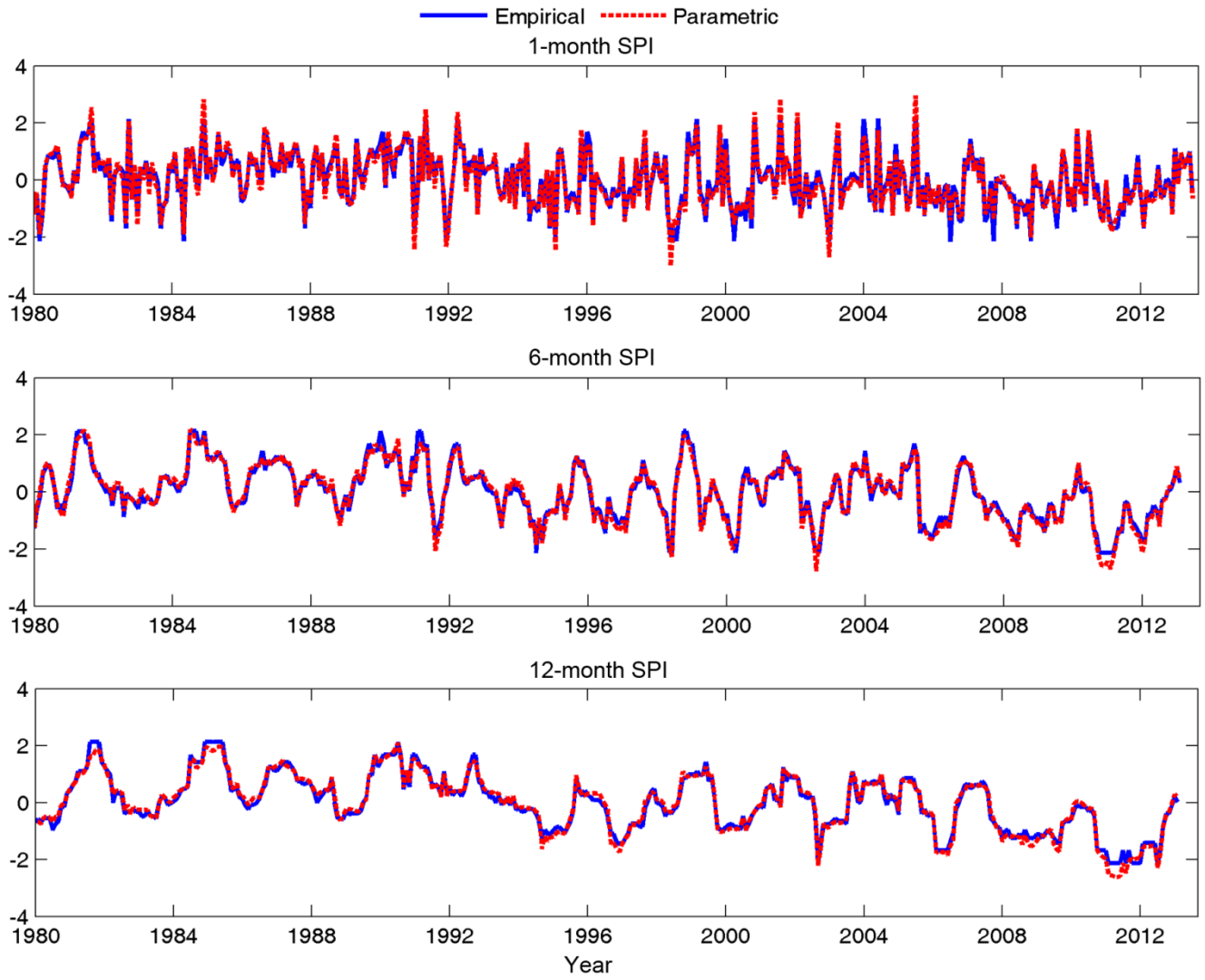
SI Standardized Index

$$SI = \begin{cases} -\left(t - \frac{C_0 + C_1 t + C_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) & \text{if } 0 < p(RH_i) \leq 0.5 \\ +\left(t - \frac{C_0 + C_1 t + C_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) & \text{if } 0.5 < p(RH_i) \leq 1 \end{cases}$$

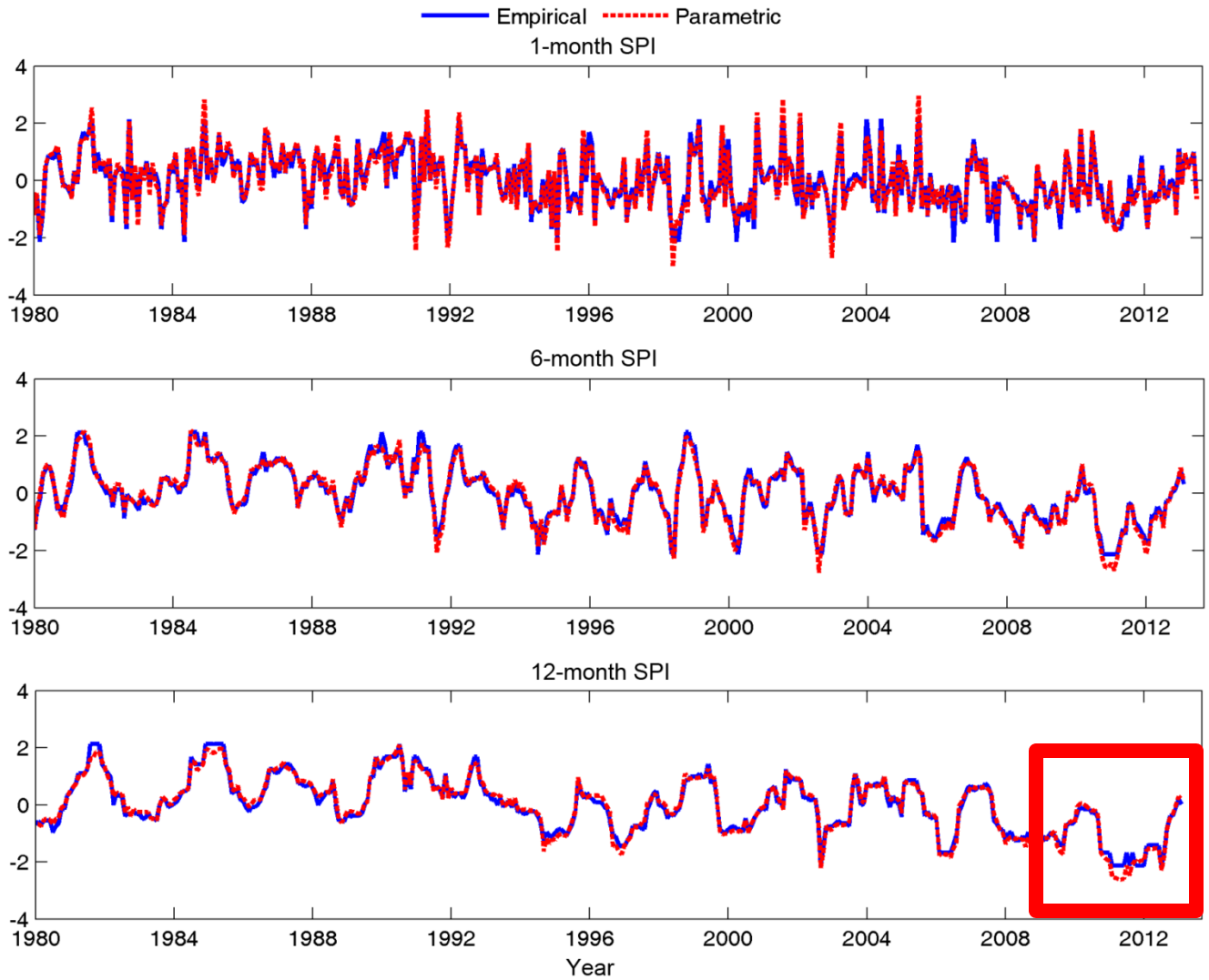
$$t = \begin{cases} \sqrt{\ln \frac{1}{p(RH_i)^2}} & \text{if } 0 < p(RH_i) \leq 0.5 \\ \sqrt{\ln \frac{1}{(1 - p(RH_i))^2}} & \text{if } 0.5 < p(RH_i) \leq 1 \end{cases}$$

C0=2.515517, c1=0.802583, c2=0.010328, d1=1.432788, d2=0.189269,d3=0.001308

Parametric vs. non-parametric approach



Parametric vs. non-parametric approach



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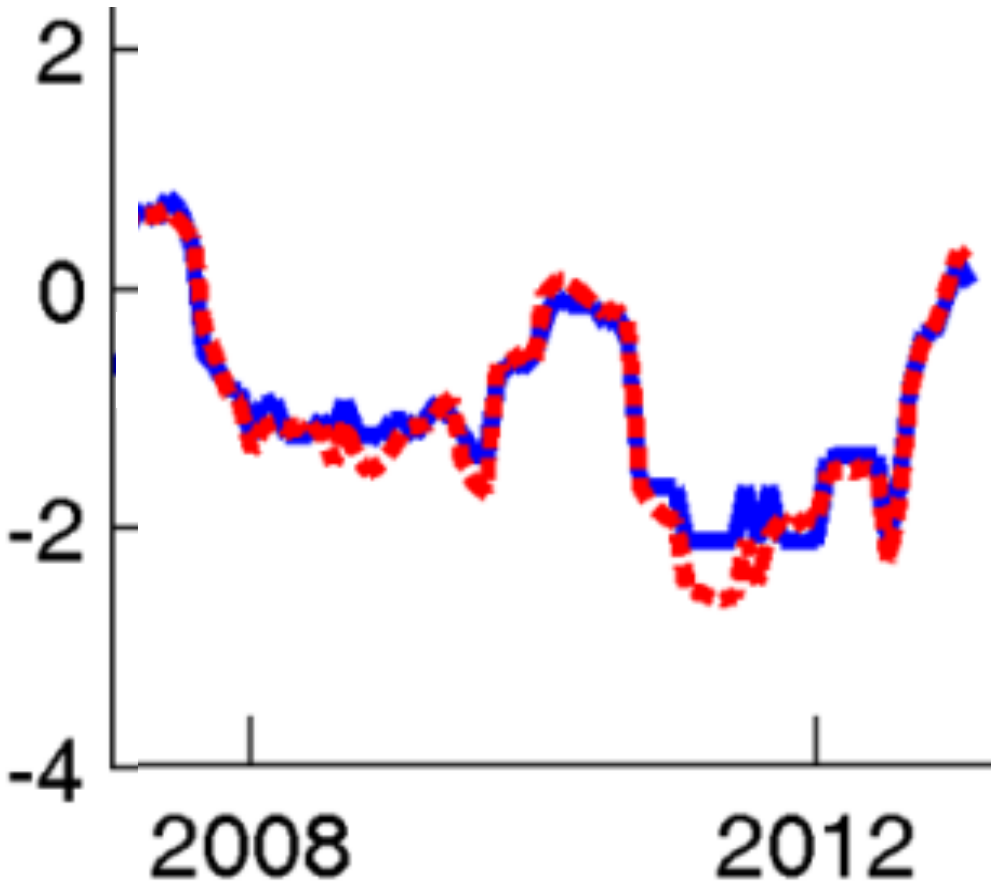

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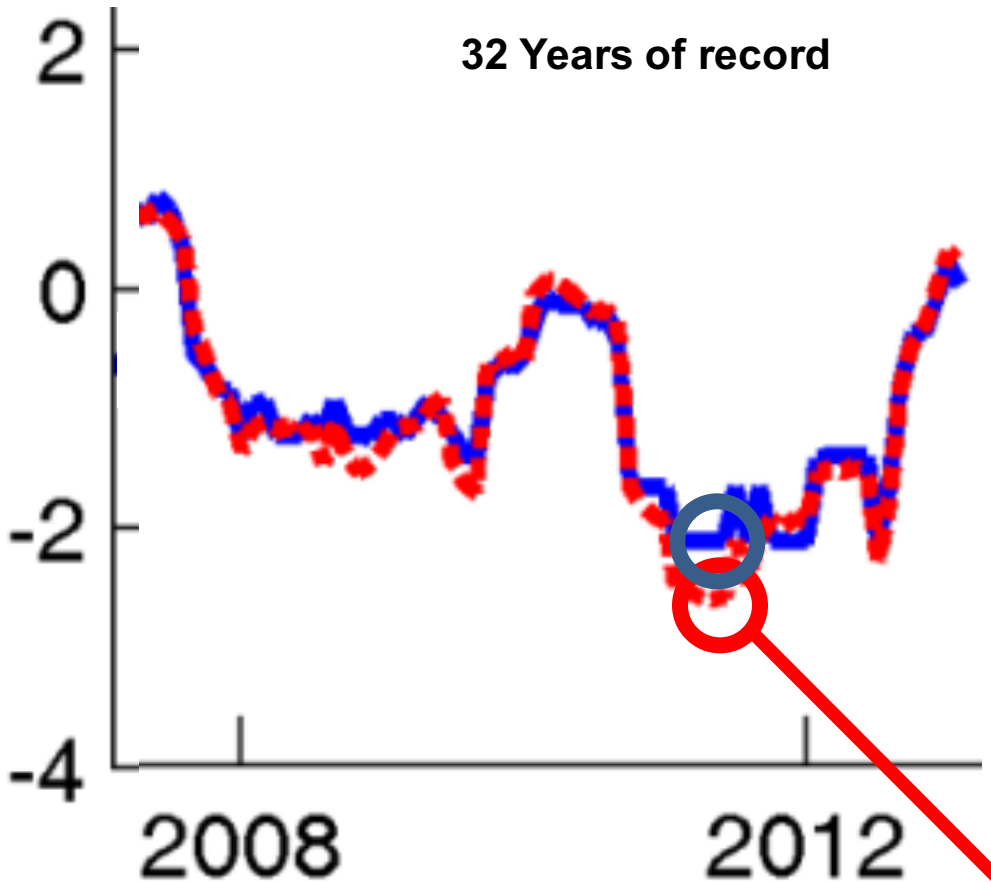
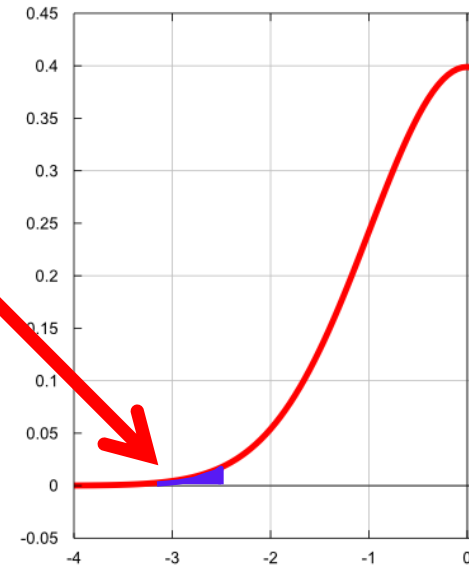
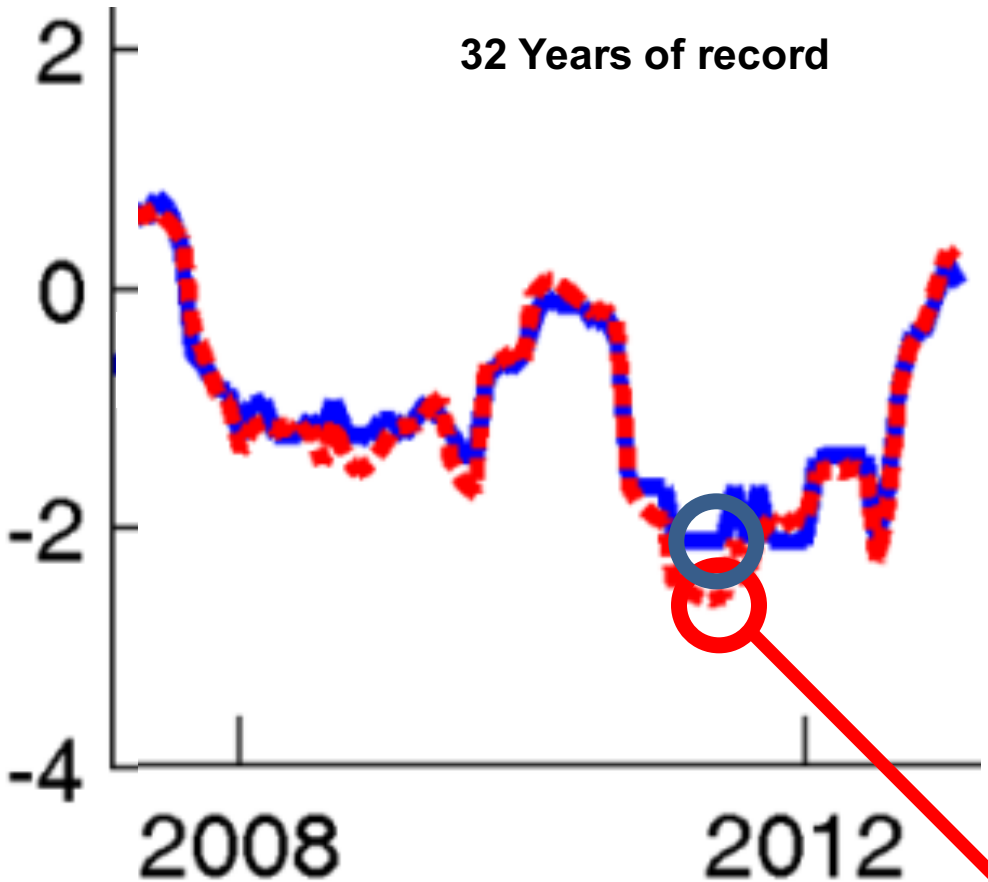
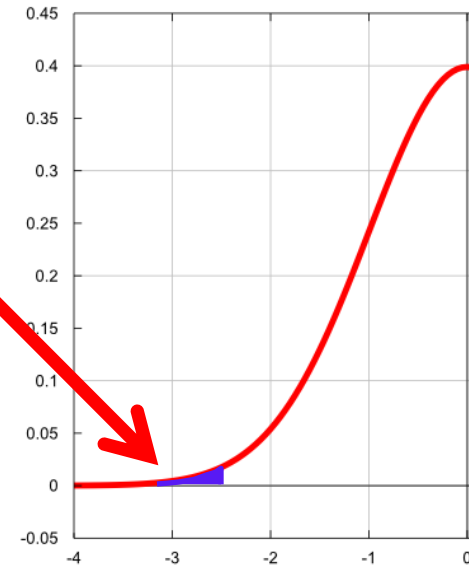




Return period: 161 years

Parametric vs. non-parametric approach

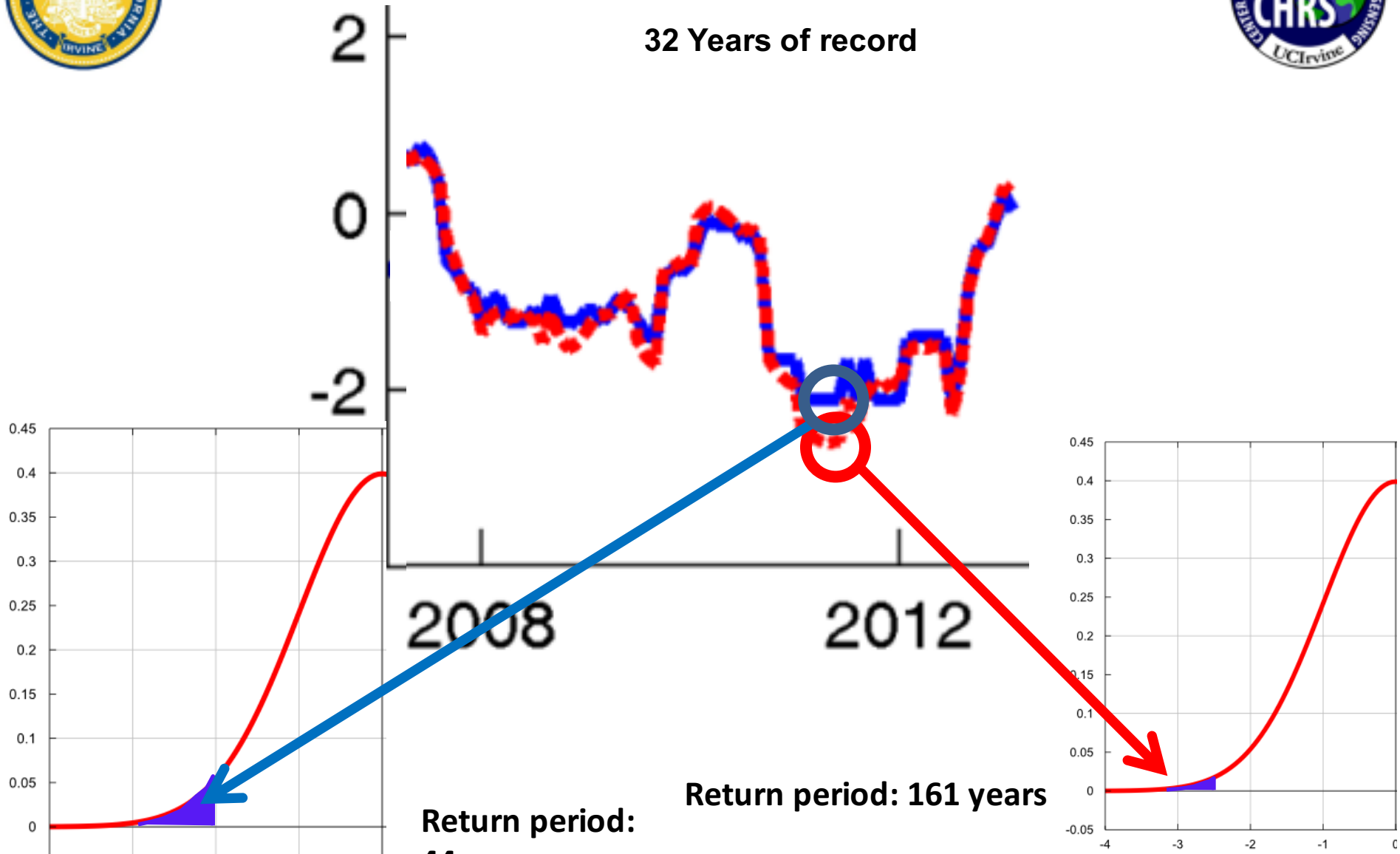




Return period: 161 years

Unreliable estimate: there is only ~ 20% chance for a 161-yr drought to occur in a 32-yr period

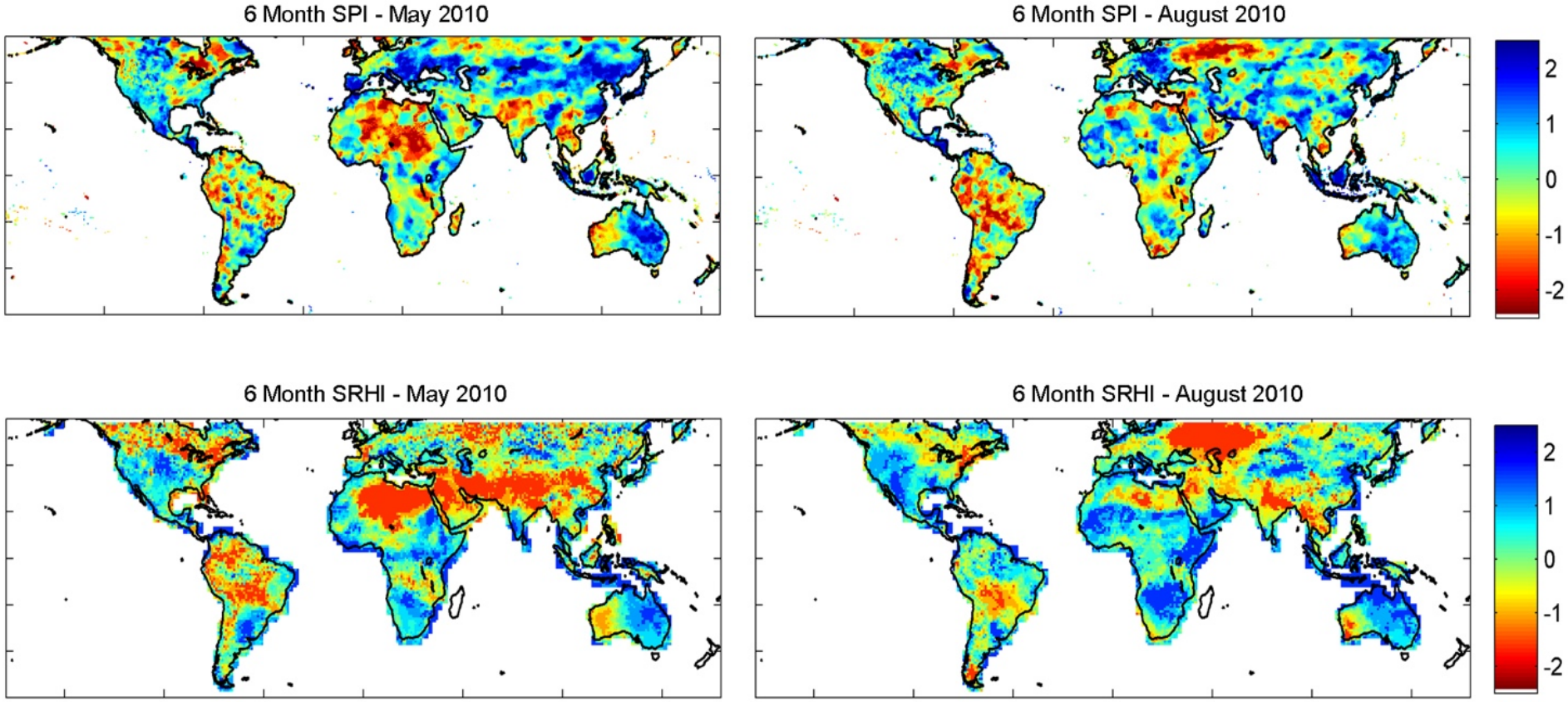
Parametric vs. non-parametric approach



Return period: 44 years

Return period: 161 years

Unreliable estimate: there is only ~ 20% chance for a 161-yr drought to occur in a 32-yr period



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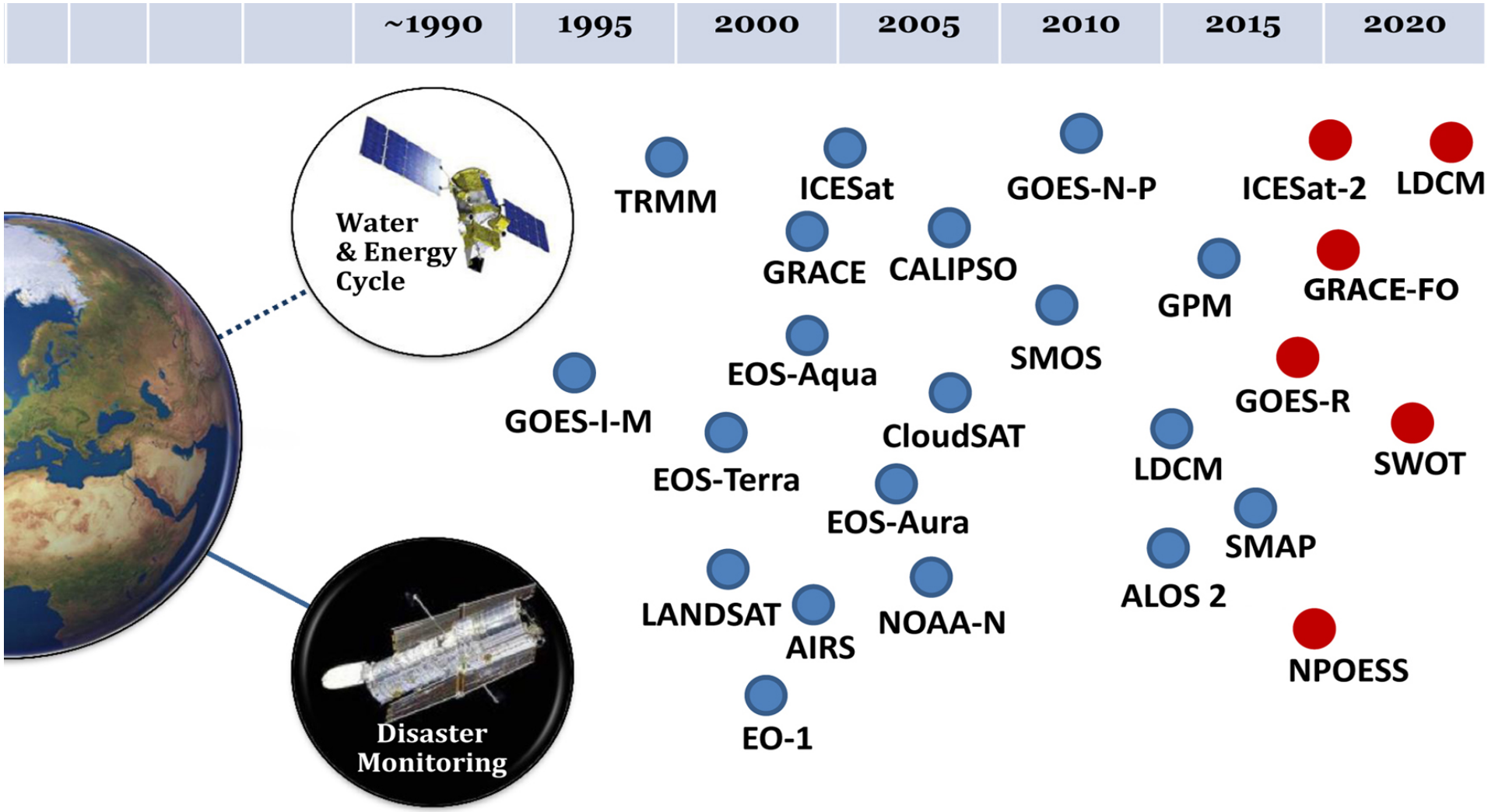

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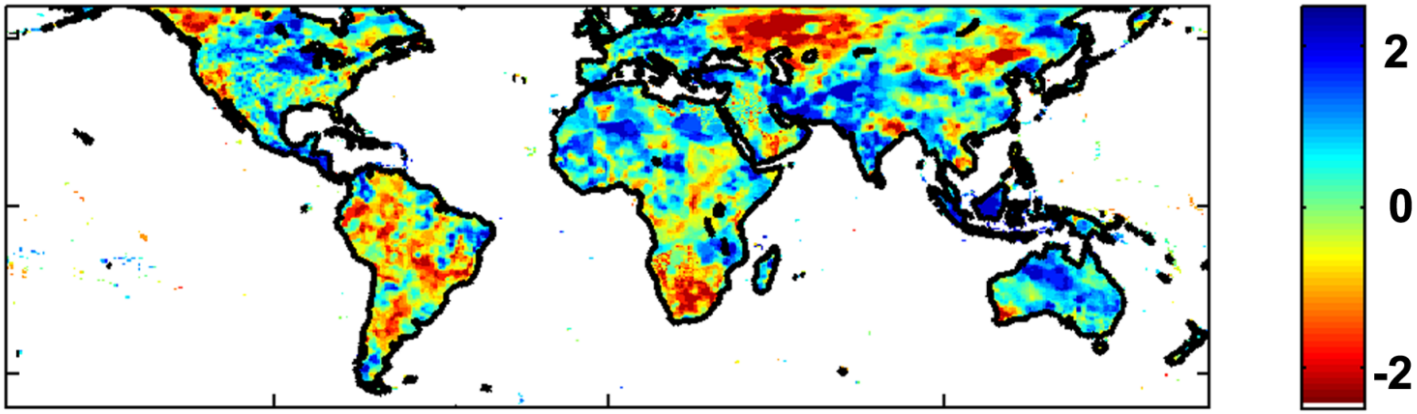
Drought Monitoring Using AIRS Data

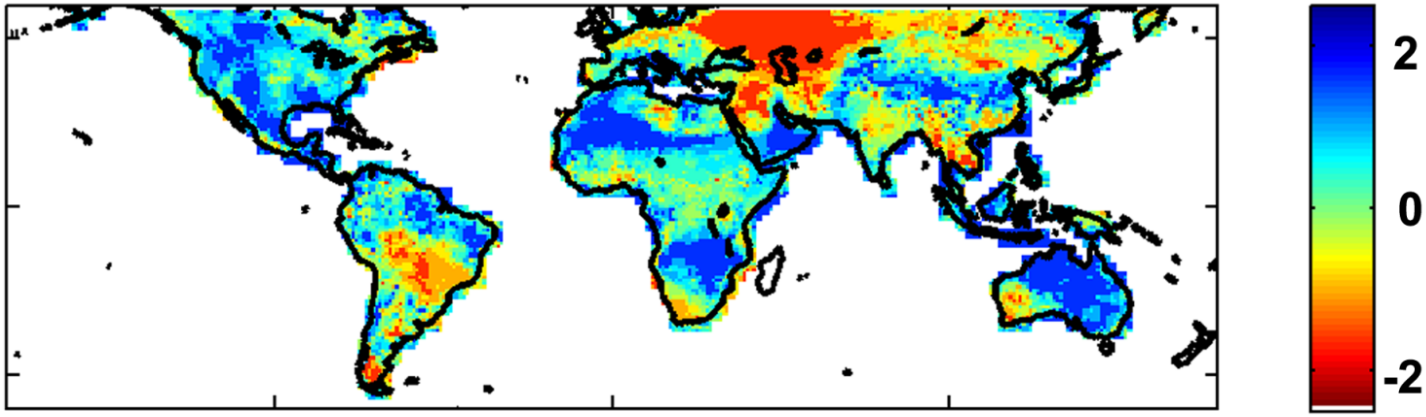
Precipitation (MERRA)

3-month SPI August 2010



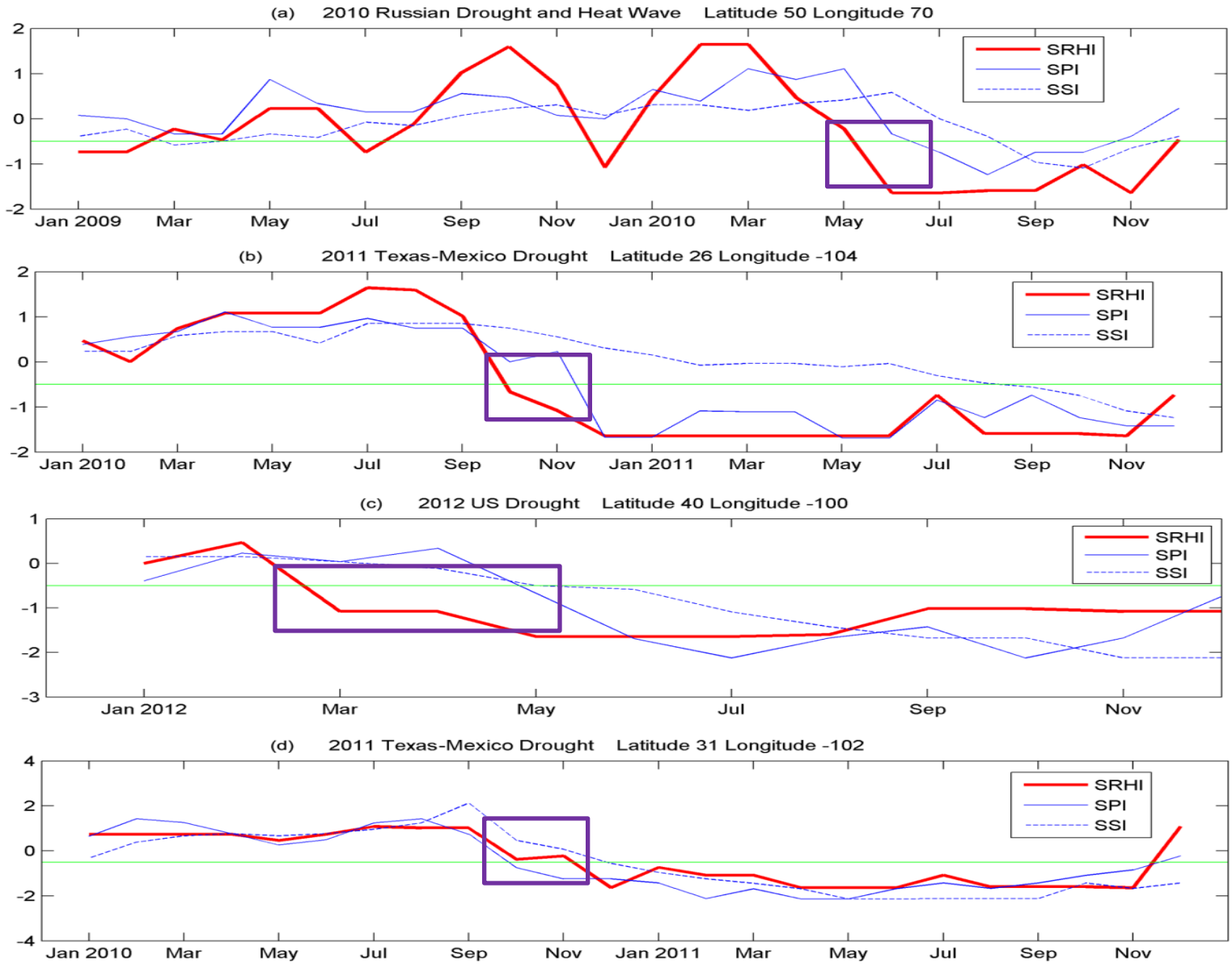
Relative Humidity (AIRS Data)

3-month SRHI August 2010



Farahmand et al. 2015, Scientific Reports;
http://www.nature.com/srep/2015/150225/srep08553/full/srep08553.html

Drought Monitoring Using AIRS Data



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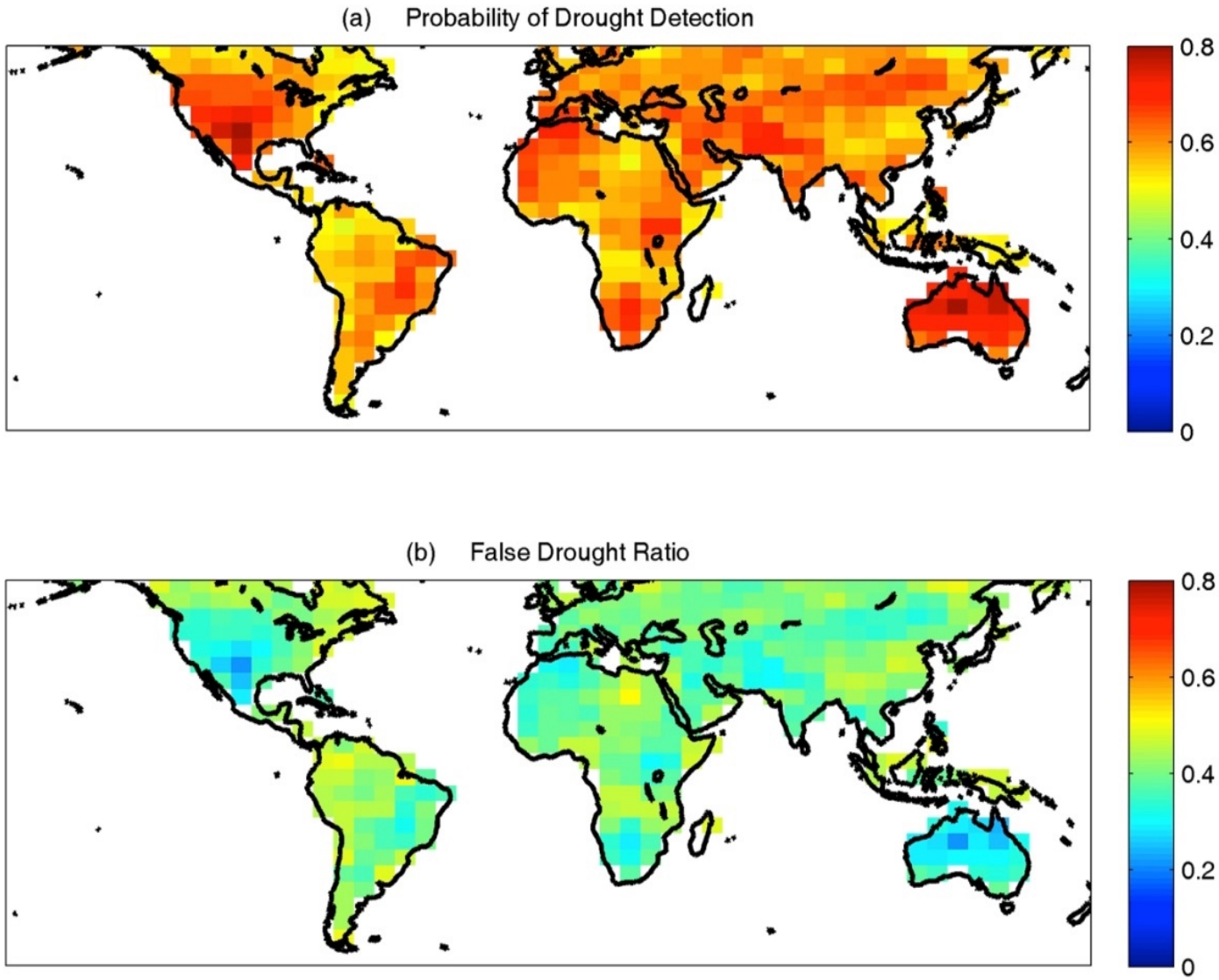

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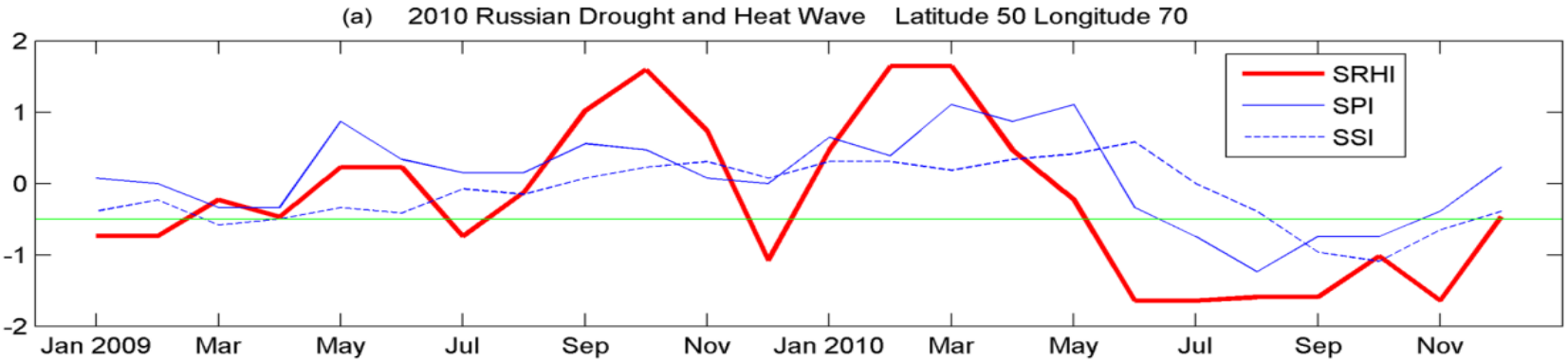
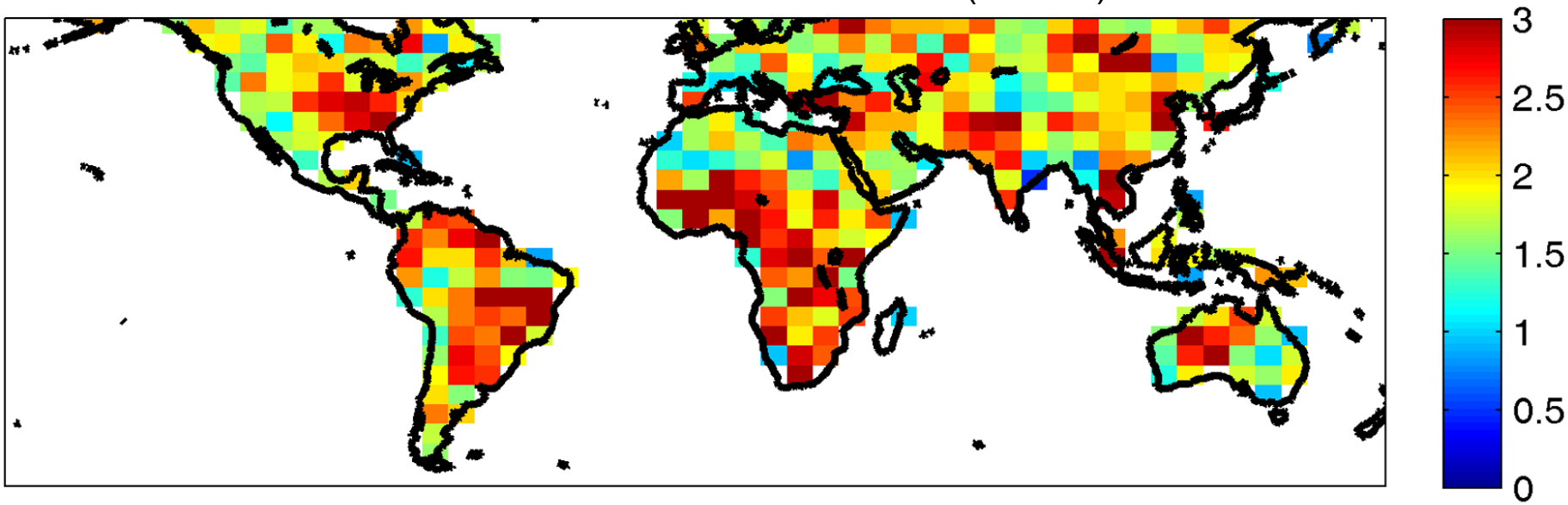
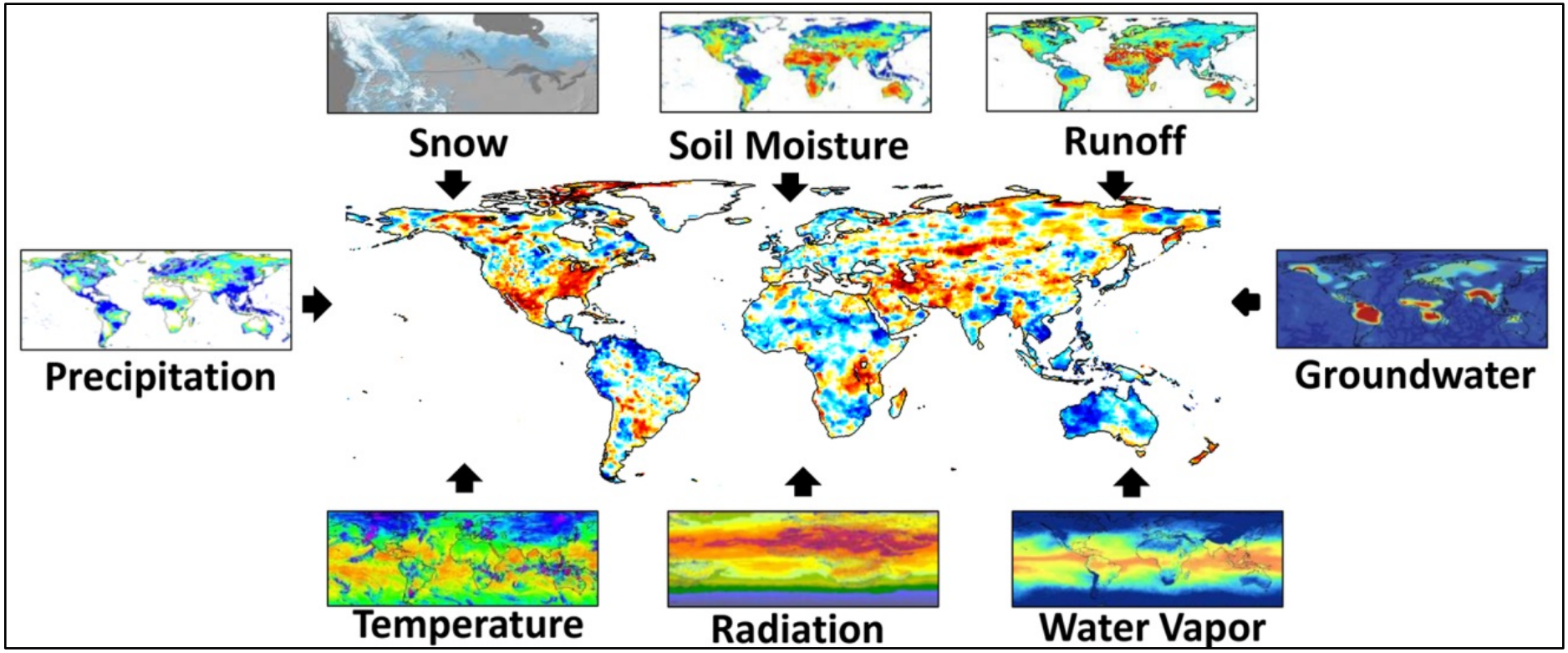


Mean lead time based on SRHI relative to SPI (months)



Remote Sensing of Drought



Multi-sensor (multi-index) composite drought monitoring using remote sensing observations

A Multi-Index Approach Using a Joint Distribution Function

$$p = P(X \leq x, Y \leq y)$$

$$p = C\left[F(X), G(Y)\right]$$

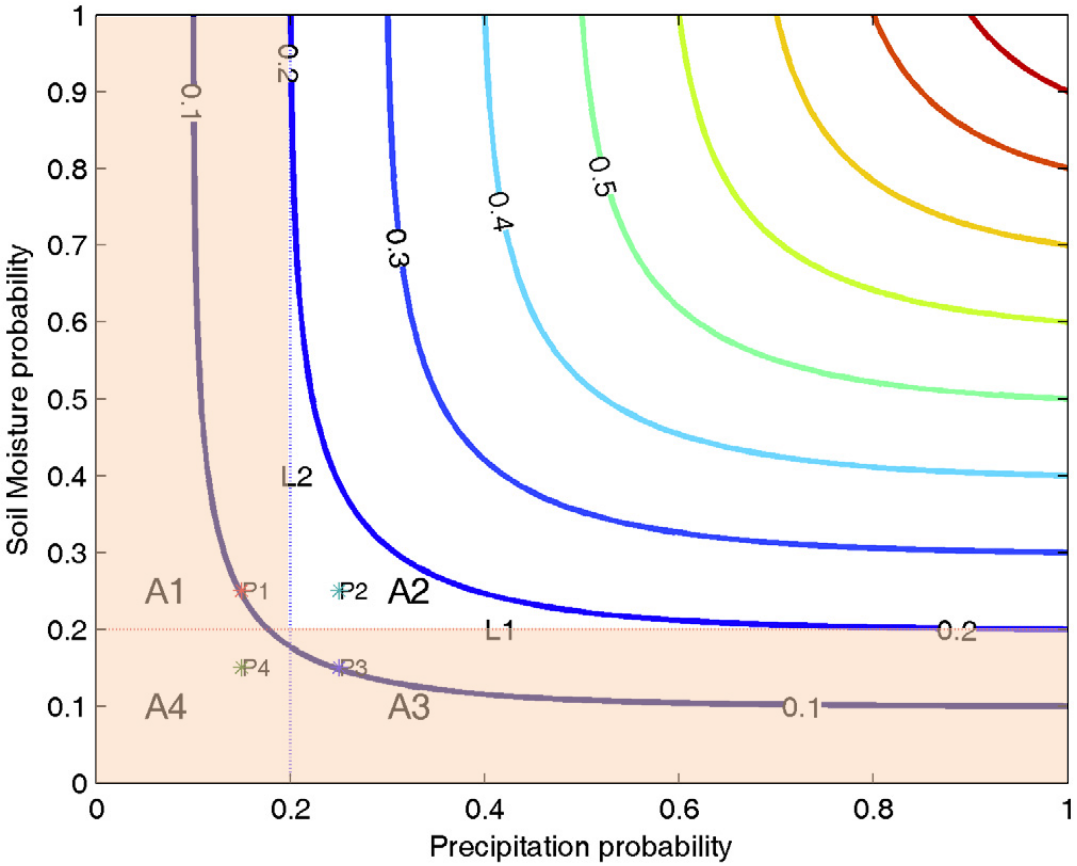
C is the copula and *F(X)* and *G(Y)* are the marginal cumulative distribution functions of precipitation (*X*) and soil moisture (*Y*), respectively

Multivariate Standardized Drought Index (MSDI)

$$MSDI = \phi^{-1}(p)$$

where ϕ is the standard normal distribution function.

Multi-Index Drought Monitoring



Standardized Precipitation Index (SPI)

$$p_{SPI} = P(X \le x) \quad SPI = \phi^{-1}(p_{SPI})$$

Standardized Soil moisture Index (SSI)

$$p_{SSI} = P(Y \le y) \quad SSI = \phi^{-1}(p_{SSI})$$

Multivariate Standardized Drought Index (MSDI)

$$p_{MSDI} = P(X \le x, Y \le y)$$

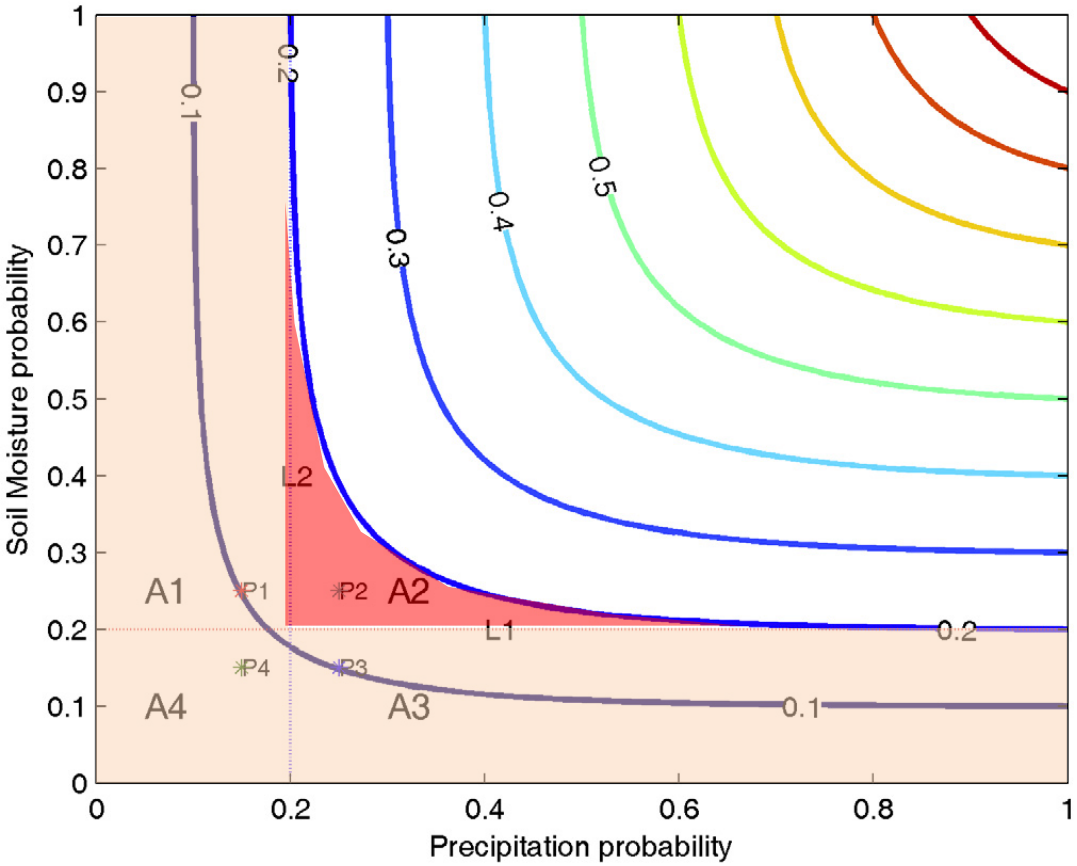
$$MSDI = \phi^{-1}(p_{MSDI})$$

Where: *X*: accumulated precipitation;
Y: accumulated soil moisture;
φ: standard normal distribution

MSDI (Hao and AghaKouchak, 2013):

- Standardized index similar to SPI
- Improves drought onset detection
- A multi-Index for composite meteorological -agricultural drought monitoring

Multi-Index Drought Monitoring



Standardized Precipitation Index (SPI)

$$p_{SPI} = P(X \le x) \quad SPI = \phi^{-1}(p_{SPI})$$

Standardized Soil moisture Index (SSI)

$$p_{SSI} = P(Y \le y) \quad SSI = \phi^{-1}(p_{SSI})$$

Multivariate Standardized Drought Index (MSDI)

$$p_{MSDI} = P(X \le x, Y \le y)$$

$$MSDI = \phi^{-1}(p_{MSDI})$$

Where: *X*: accumulated precipitation;
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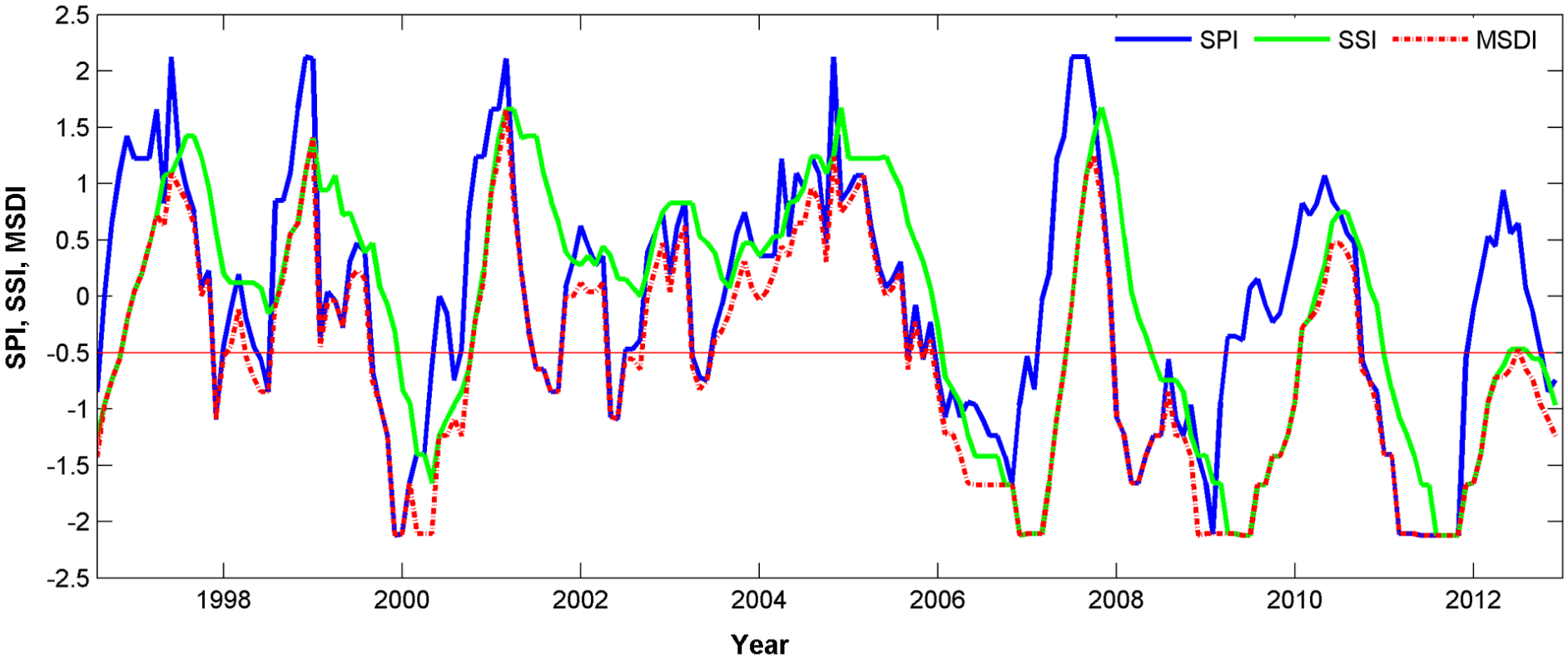
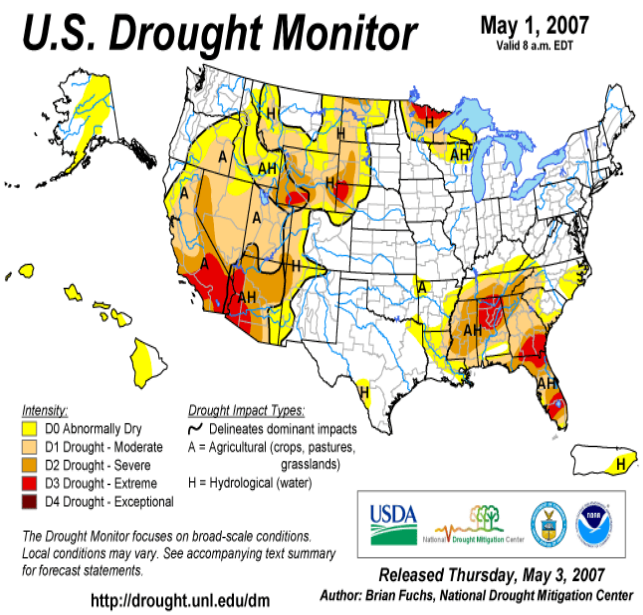


Sample time series of the 6-month SPI, SSI and MSDI for a grid cell in Texas (Location: longitude 100 W and latitude 30 N).

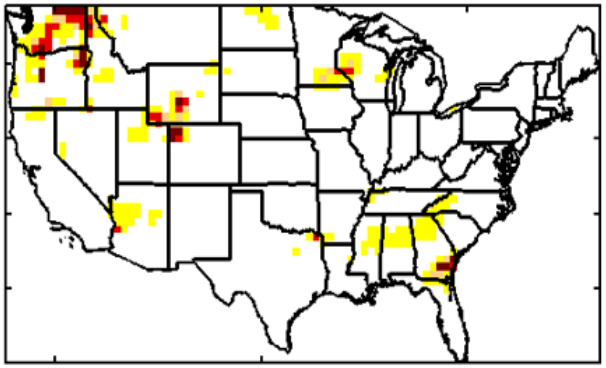
Hao Z., AghaKouchak A., 2014, A Nonparametric Multivariate Multi-Index Drought Monitoring Framework, *Journal of Hydrometeorology*, 15, 89-101, doi:10.1175/JHM-D-12-0160.1.

Multi-Index Drought Monitoring

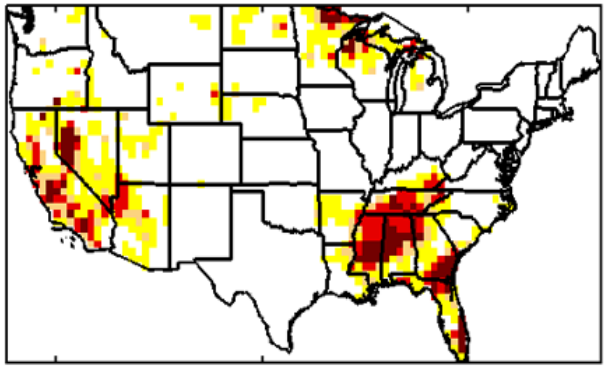
SPI and SSI Derived Using NASA MERRA-LAND Precipitation and soil moisture Data.



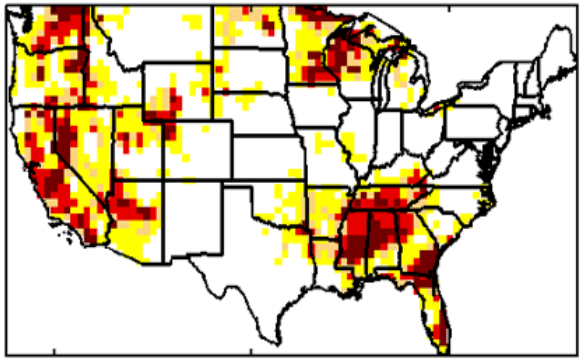
SPI, Apr 2007



SSI, Apr 2007



MSDI, Apr 2007



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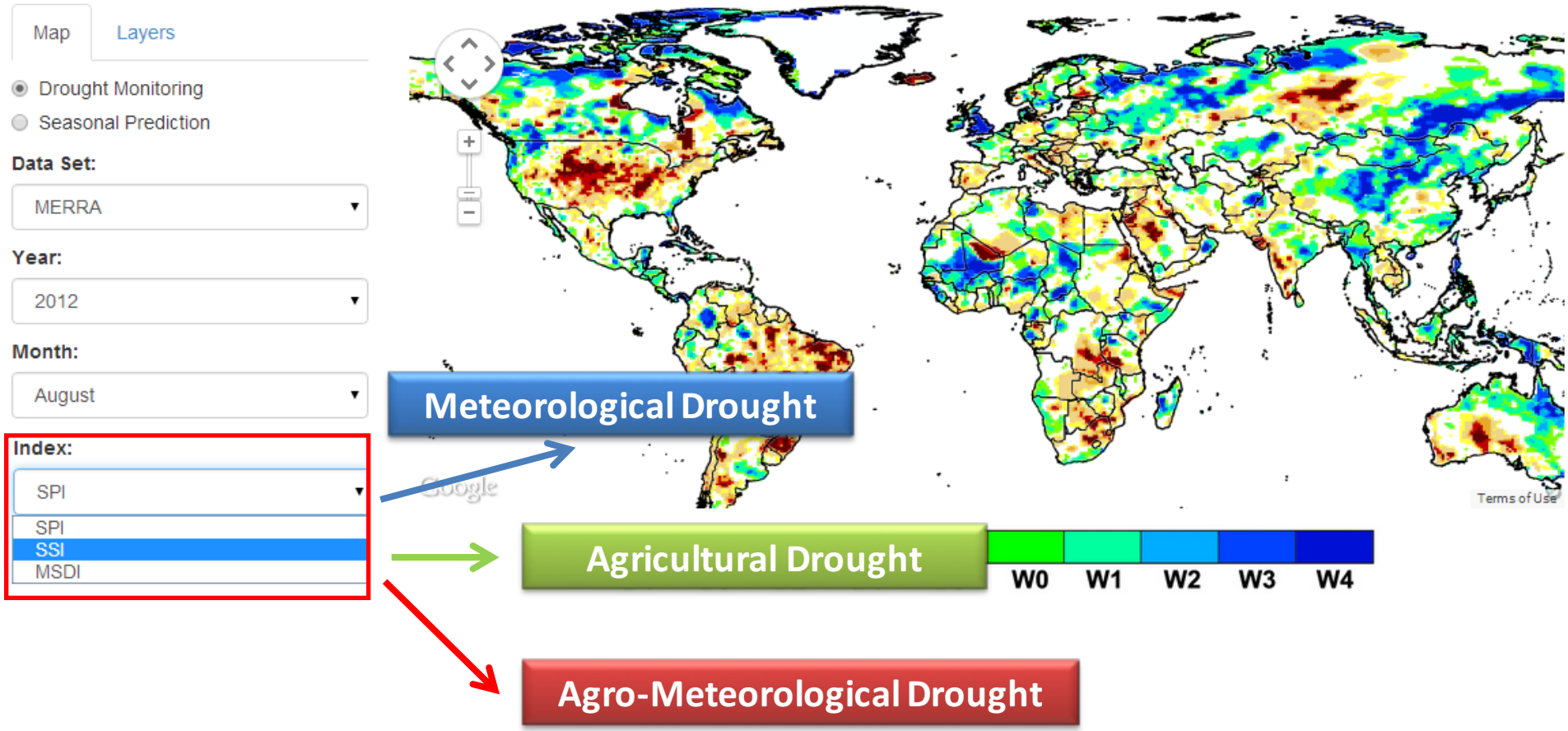
GIDMaPS: Global Integrated Drought Monitoring and Prediction System

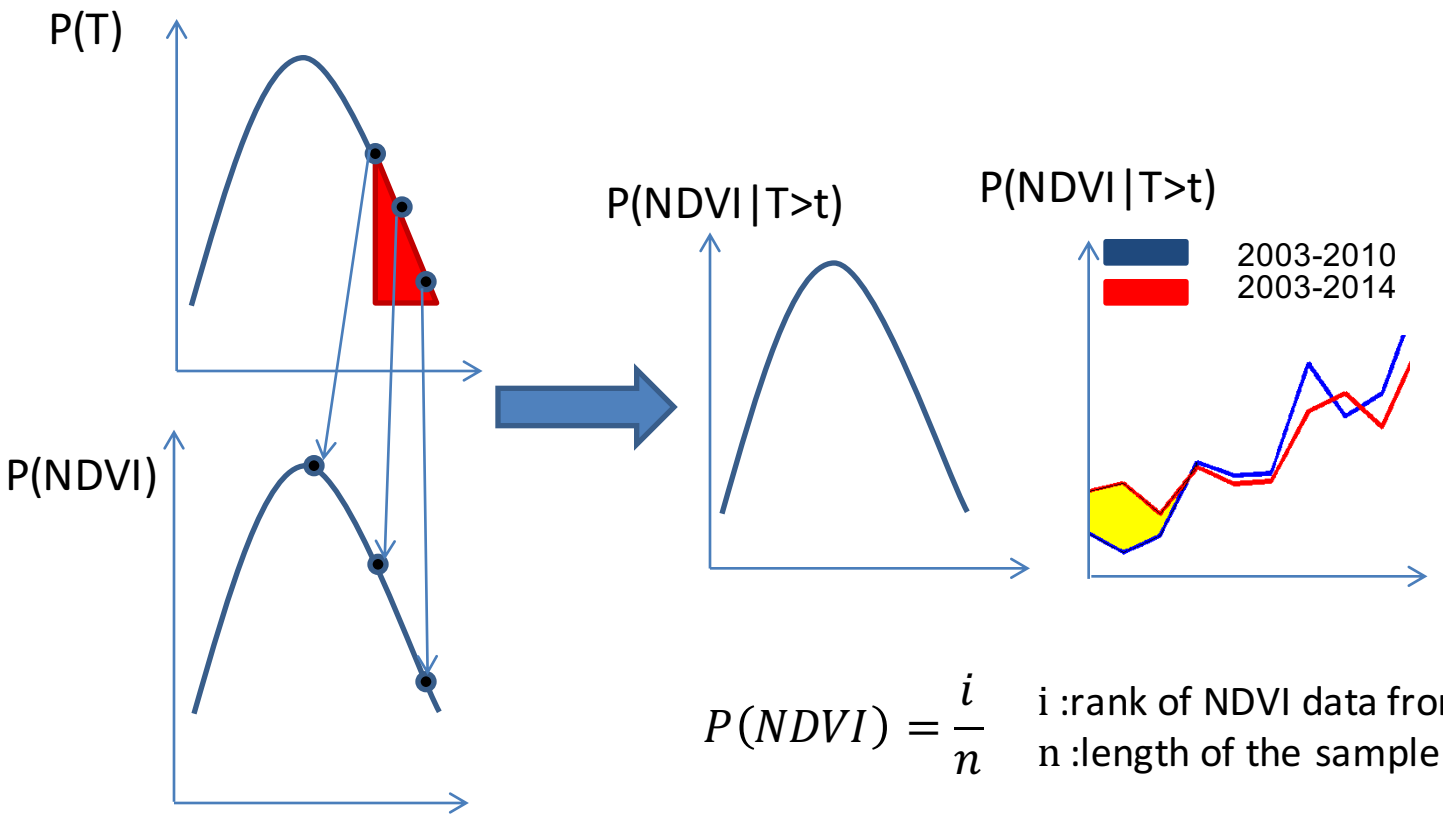
http://drought.eng.uci.edu/

Global Integrated Drought Monitoring and Prediction System (GIDMaPS)



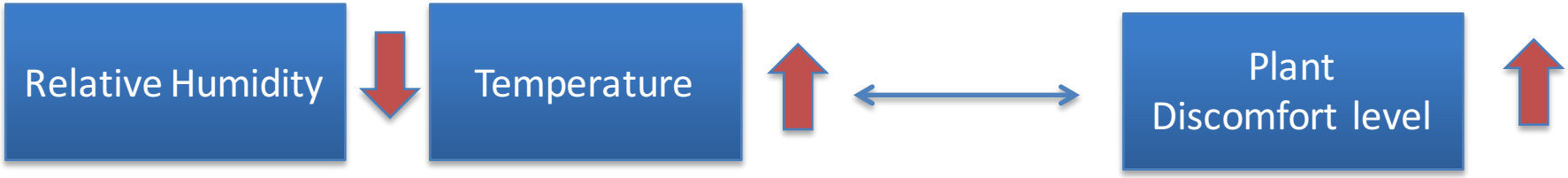
Hao Z., AghaKouchak A., Nakhjiri N., Farahmand A., 2014, Global Integrated Drought Monitoring and Prediction System, *Scientific Data*, 1:140001, 1-10, doi: 10.1038/sdata.2014.1.
http://www.nature.com/articles/sdata20141

Drought Monitoring Using AIRS Data

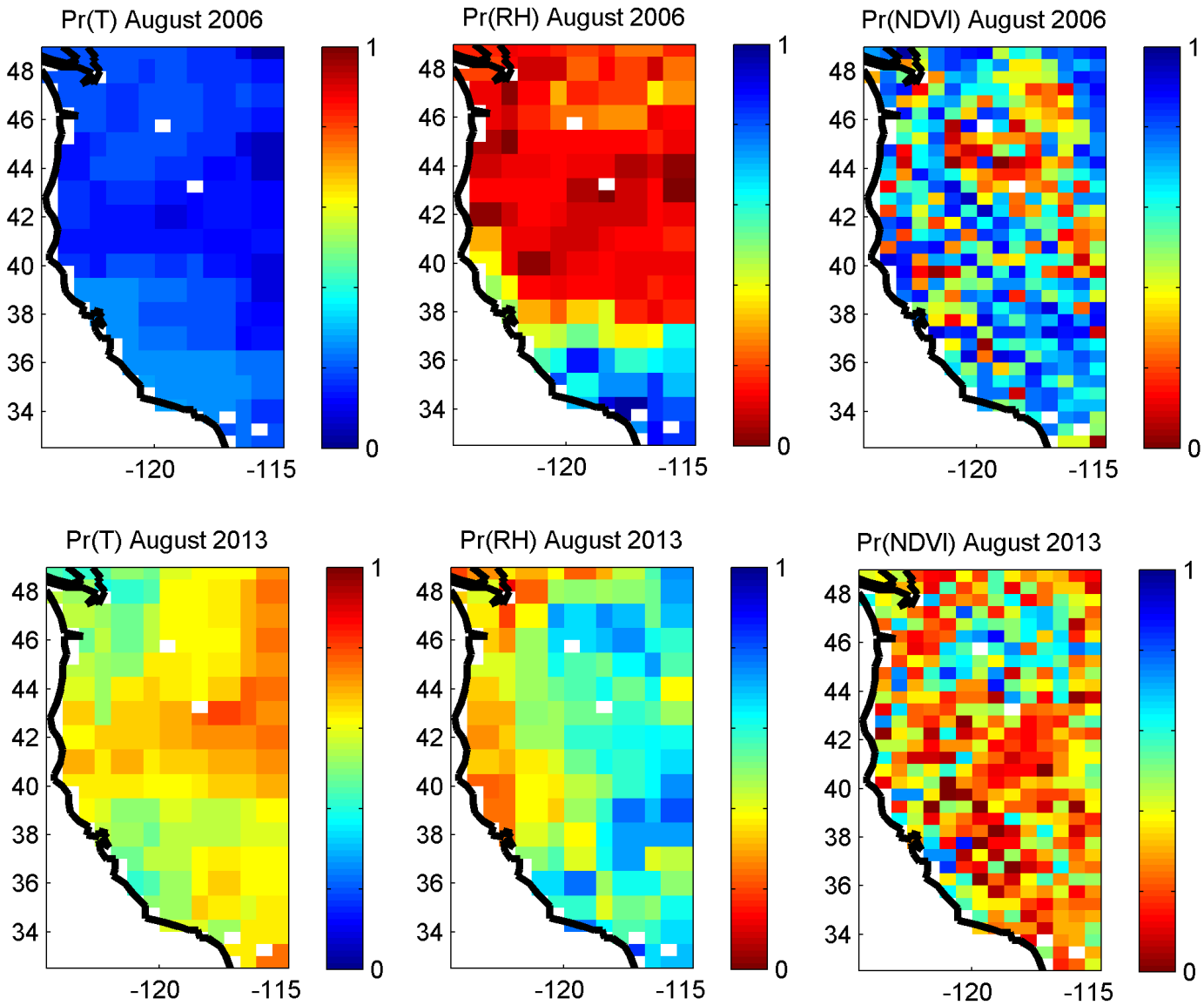


$$P(NDVI) = \frac{i}{n}$$

i :rank of NDVI data from the smallest
n :length of the sample



Drought Monitoring Using AIRS Data



Summery and Conclusions

There are significant opportunities for improving multi-index multi-variate drought monitoring using satellite observations.

Data records are not consistent (often exhibit different distributions). There are concerns about data continuity.

AIRS relative humidity data can improve early drought onset detection.

There are opportunities to improve multi-index drought monitoring by combining AIRS temperature and relative humidity information.

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REVIEW ARTICLE

10.1002/2014RG000456

Key Points:

- Current and emerging approaches in satellite remote sensing of drought
- Limitations of currently available satellite observations and challenges ahead

Remote sensing of drought: Progress, challenges and opportunities

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Alireza Farahmand[1], Amir AghaKouchak[1] & Joao Teixeira[2]

http://www.nature.com/articles/srep08553

Questions?

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