

A probabilistic framework for linking drought information to impact on agricultural production

Amir AghaKouchak

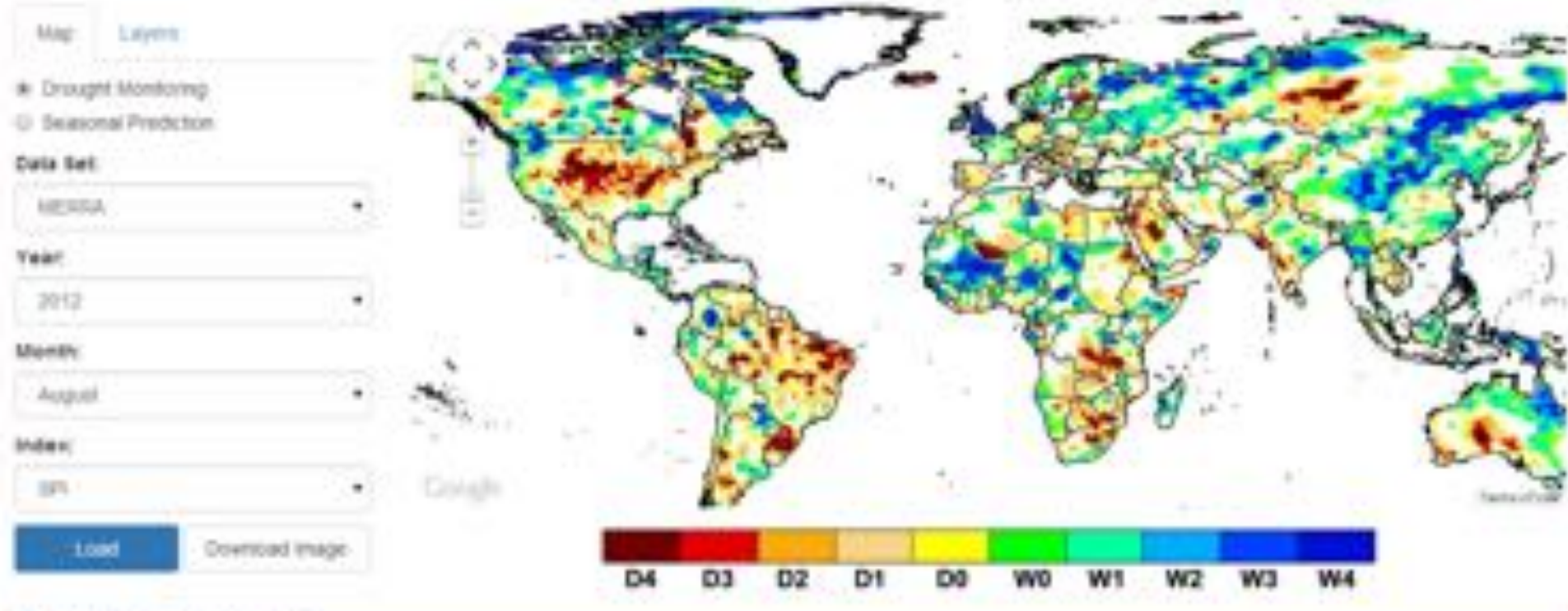
University of California, Irvine





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

Global Integrated Drought Monitoring and Prediction System (GIDMaPS)



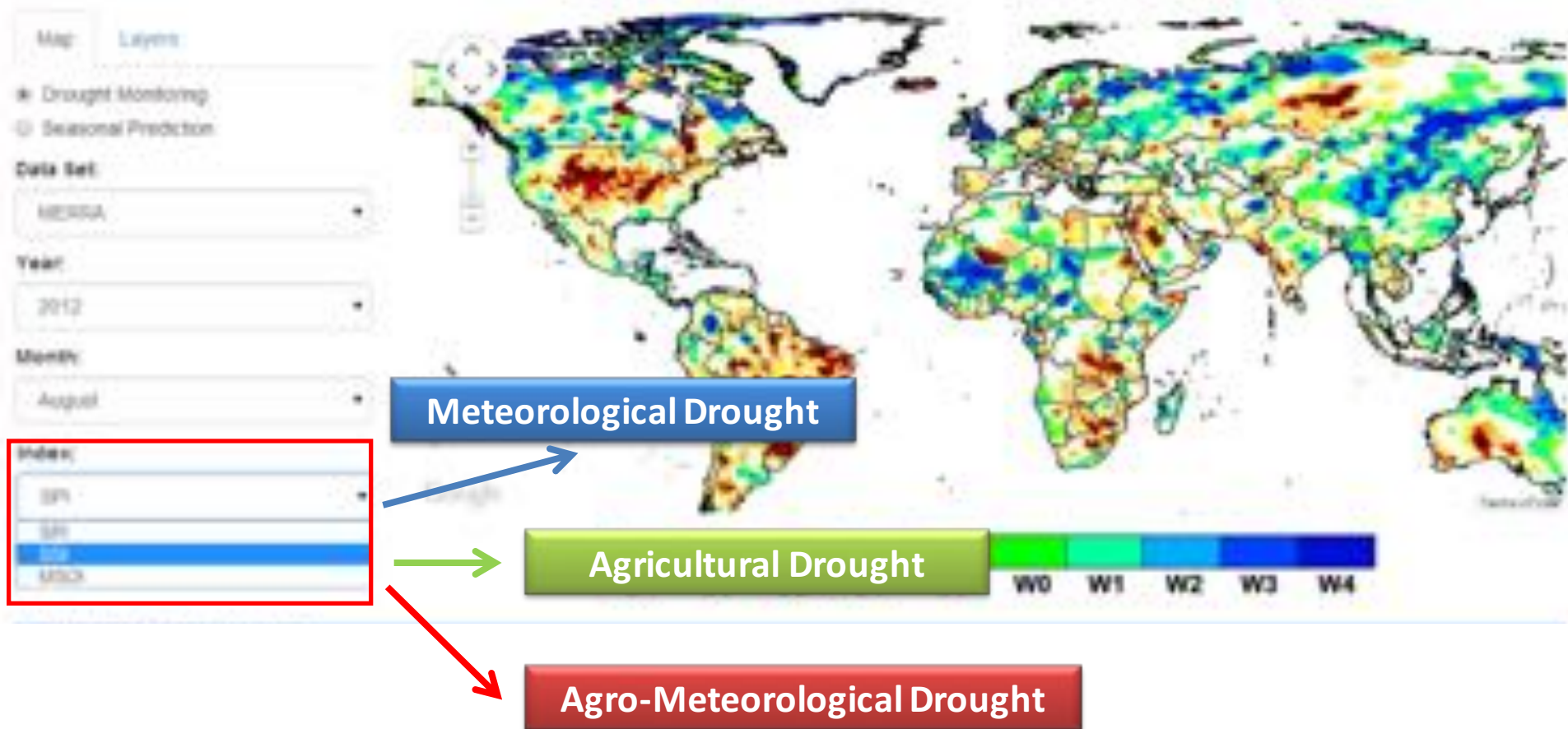
Hao Z., AghaKouchak A., Nakhjiri N., Farahmand A., 2014, Global Integrated Drought Monitoring and Prediction System, *Scientific Data*, 1:140001, 1-10, doi: 10.1038/sdata.2014.1.

<http://www.nature.com/articles/sdata20141>



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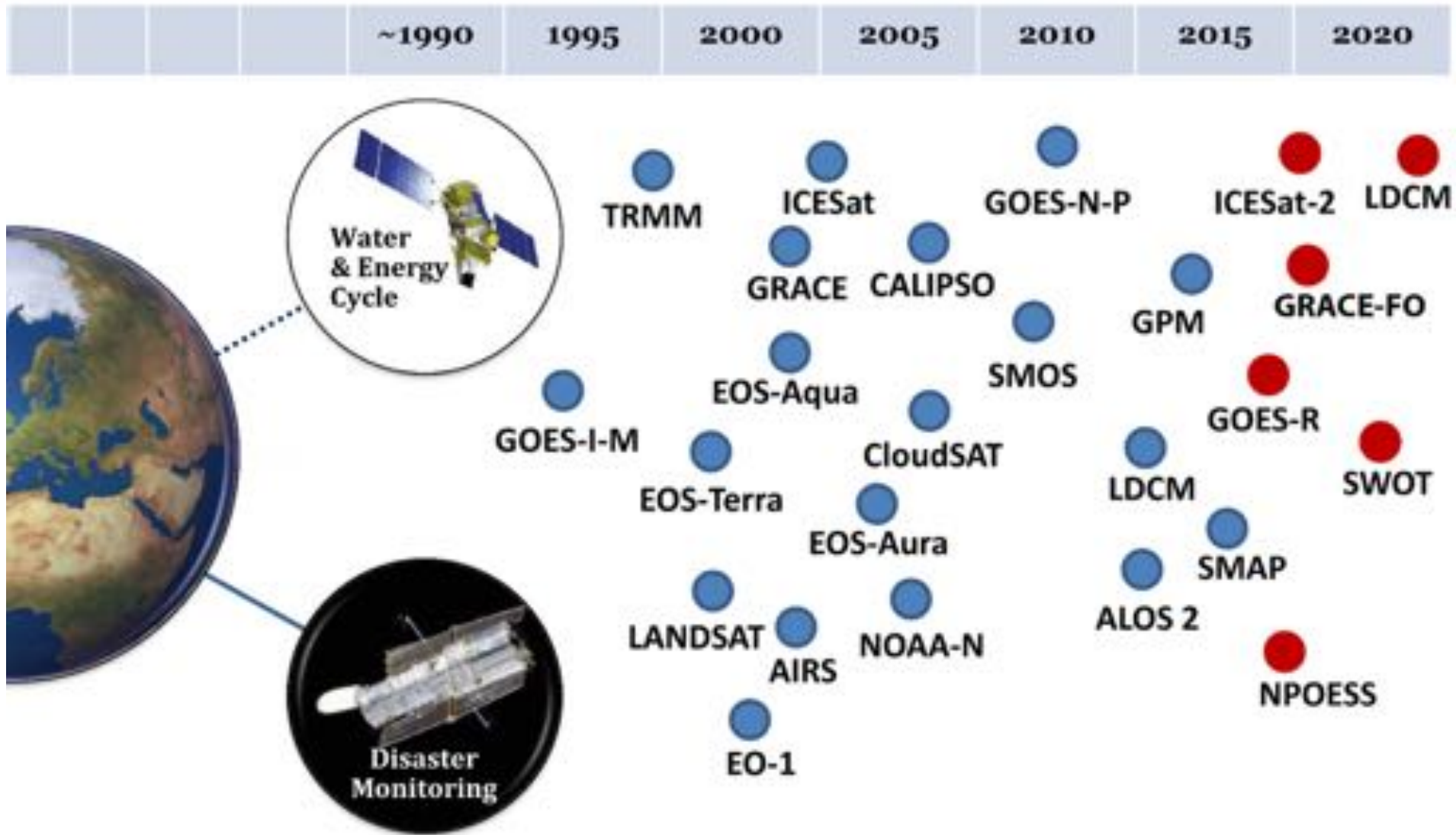


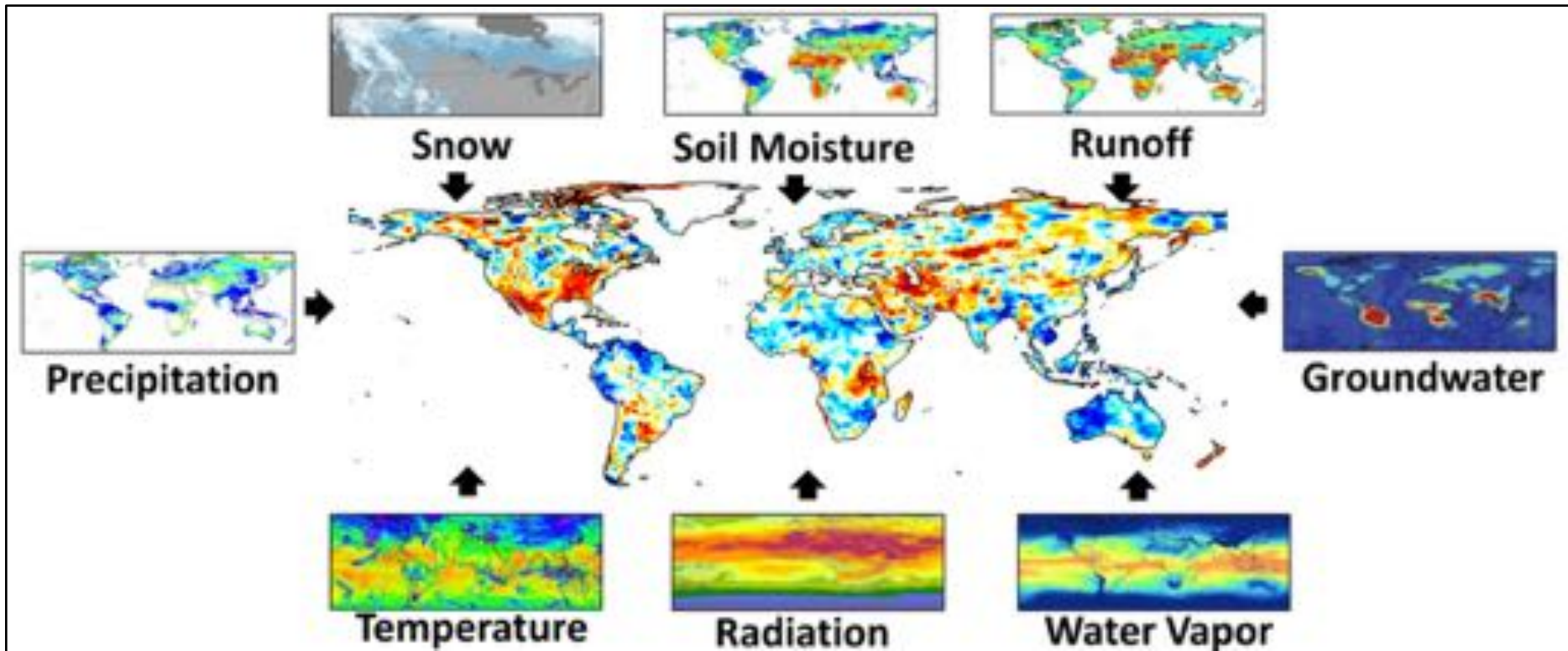
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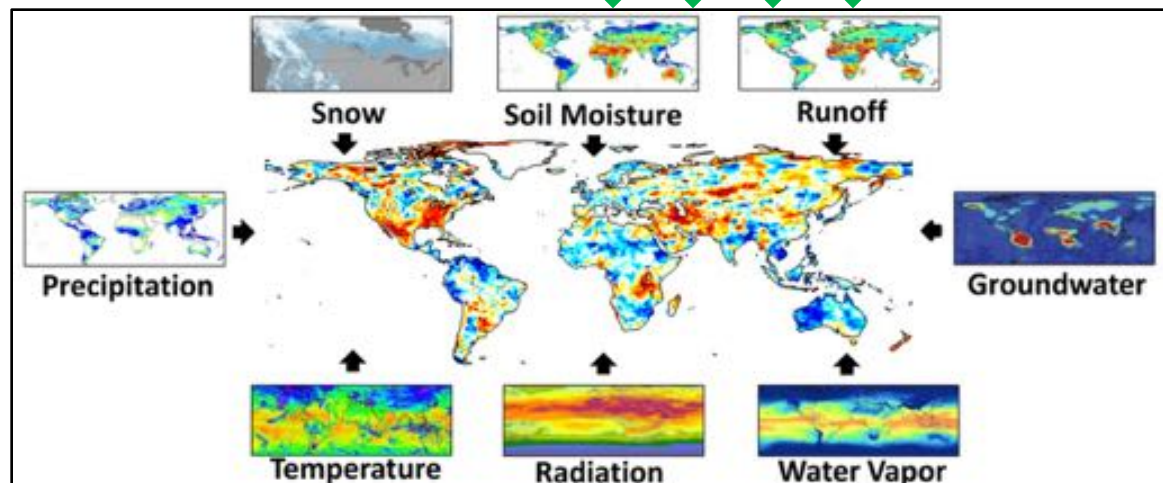
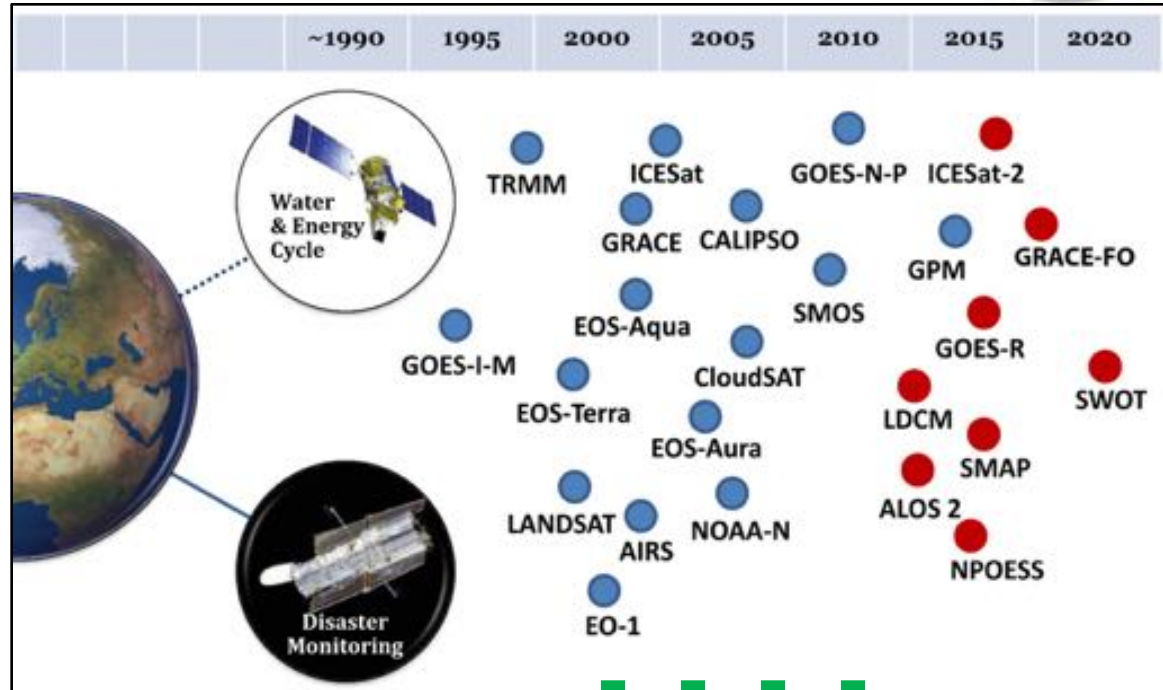
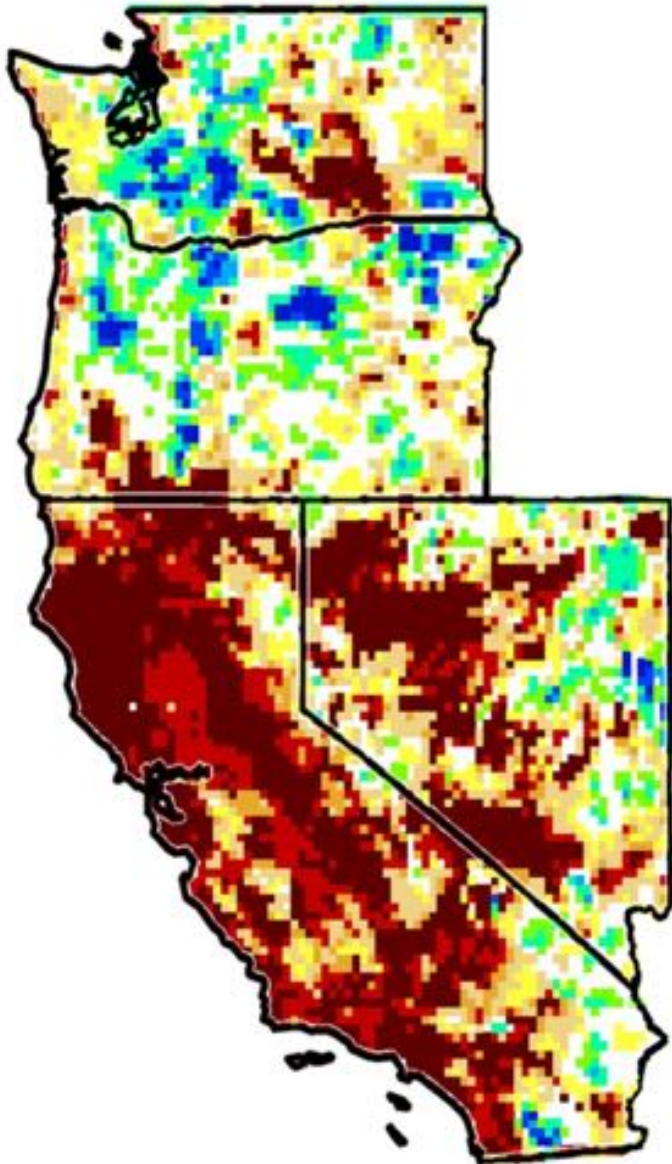
Remote Sensing of Drought





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

Remote Sensing of Drought

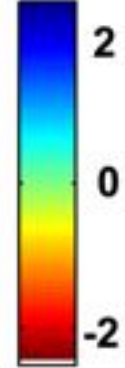
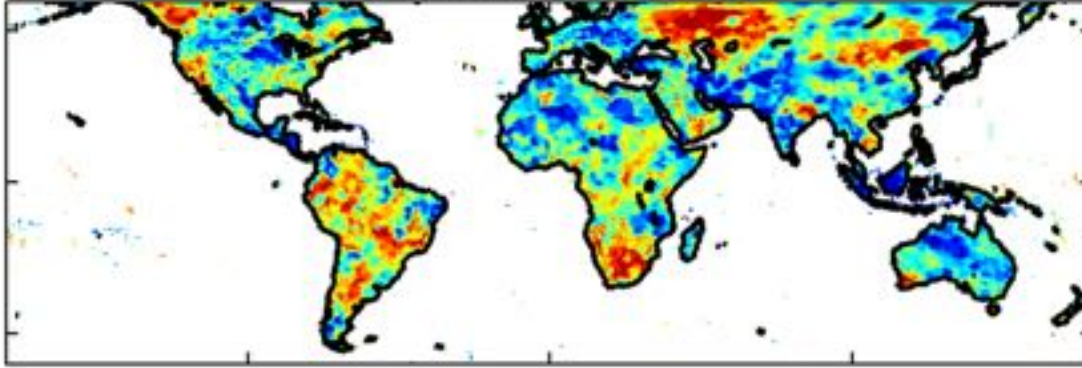




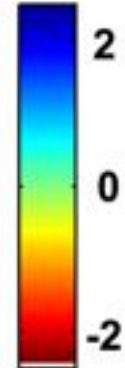
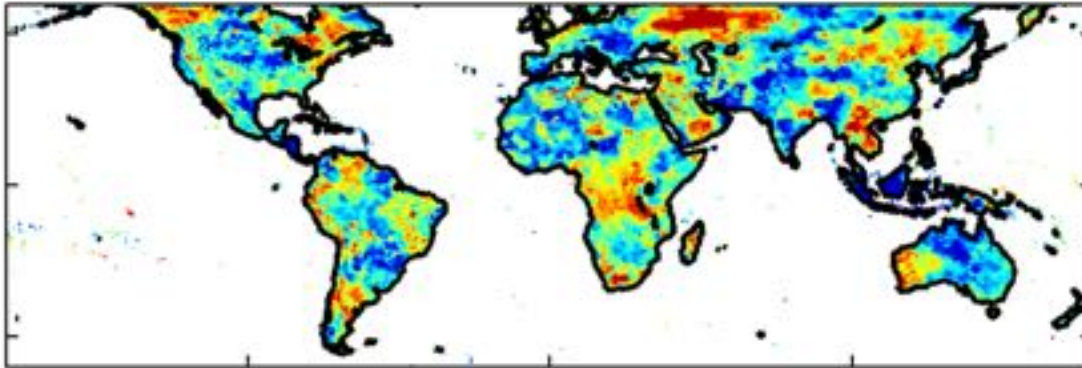
Integration of AIRS Data into GIDMaPS



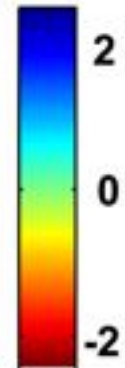
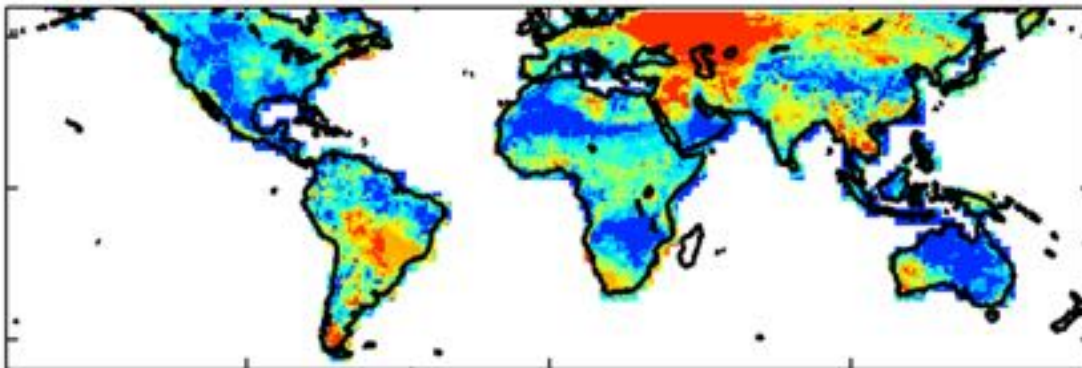
3-month SPI August 2010



3-month SSI August 2010



3-month SRHI August 2010



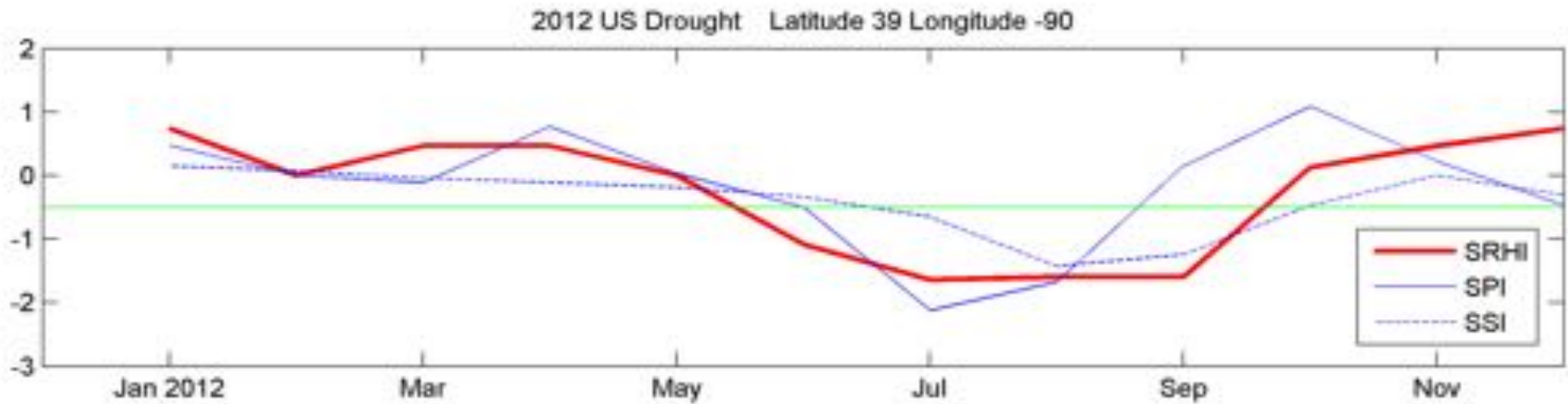
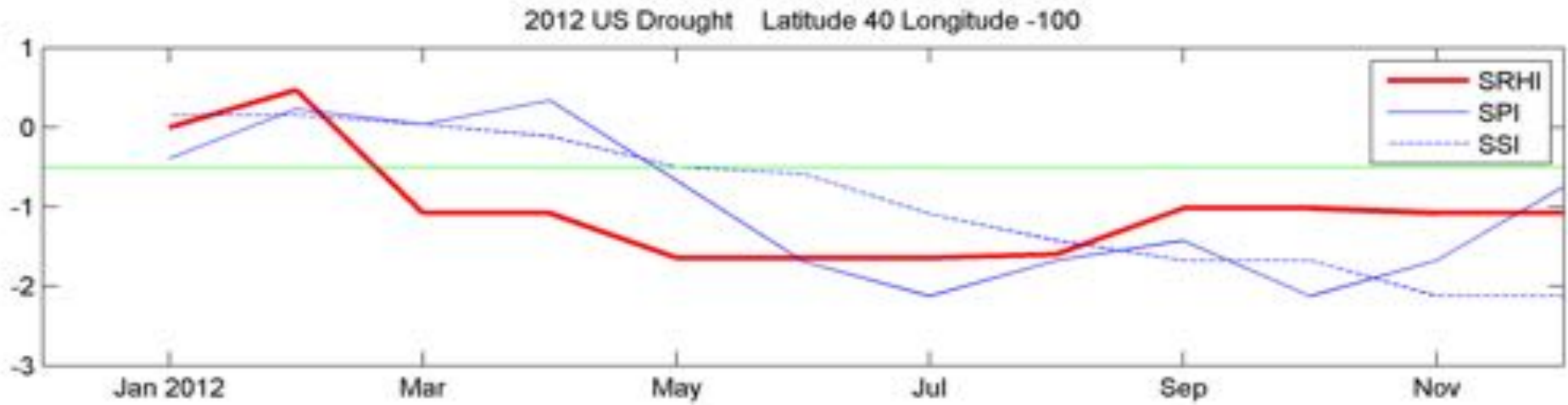
**Precipitation
(MERRA)**

**Soil Moisture
(MERRA)**

**Relative
Humidity
(AIRS Data)**

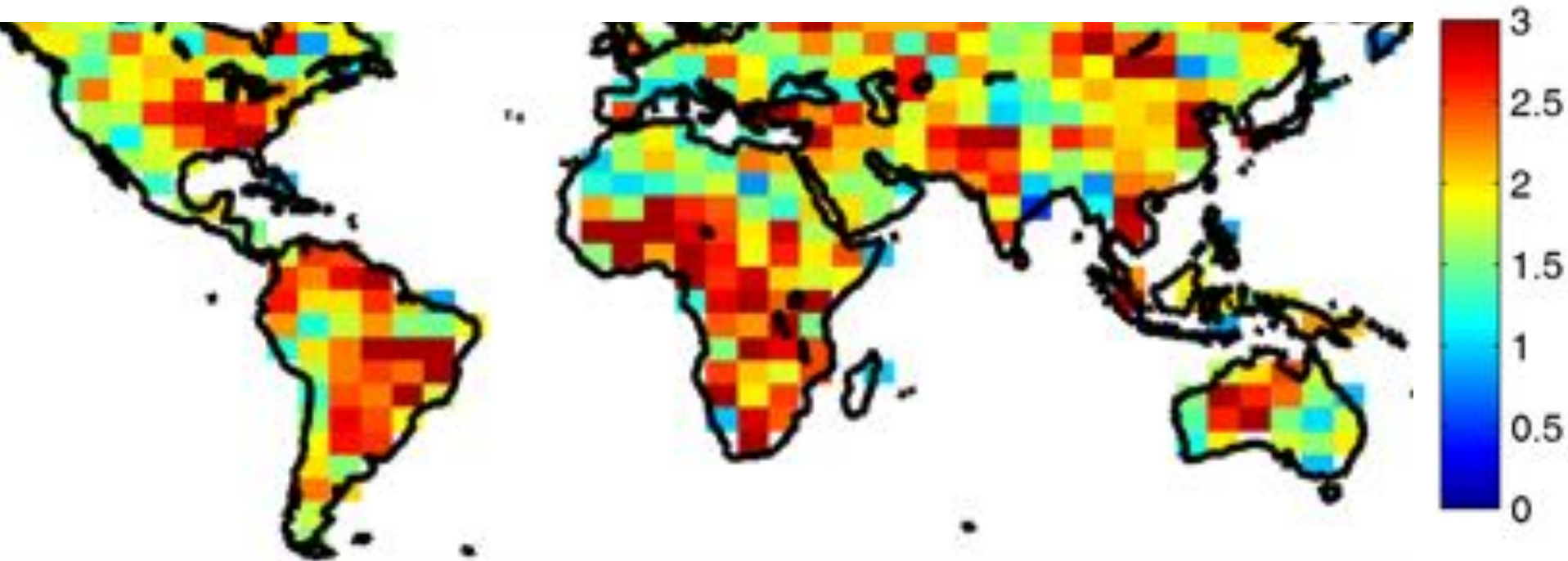


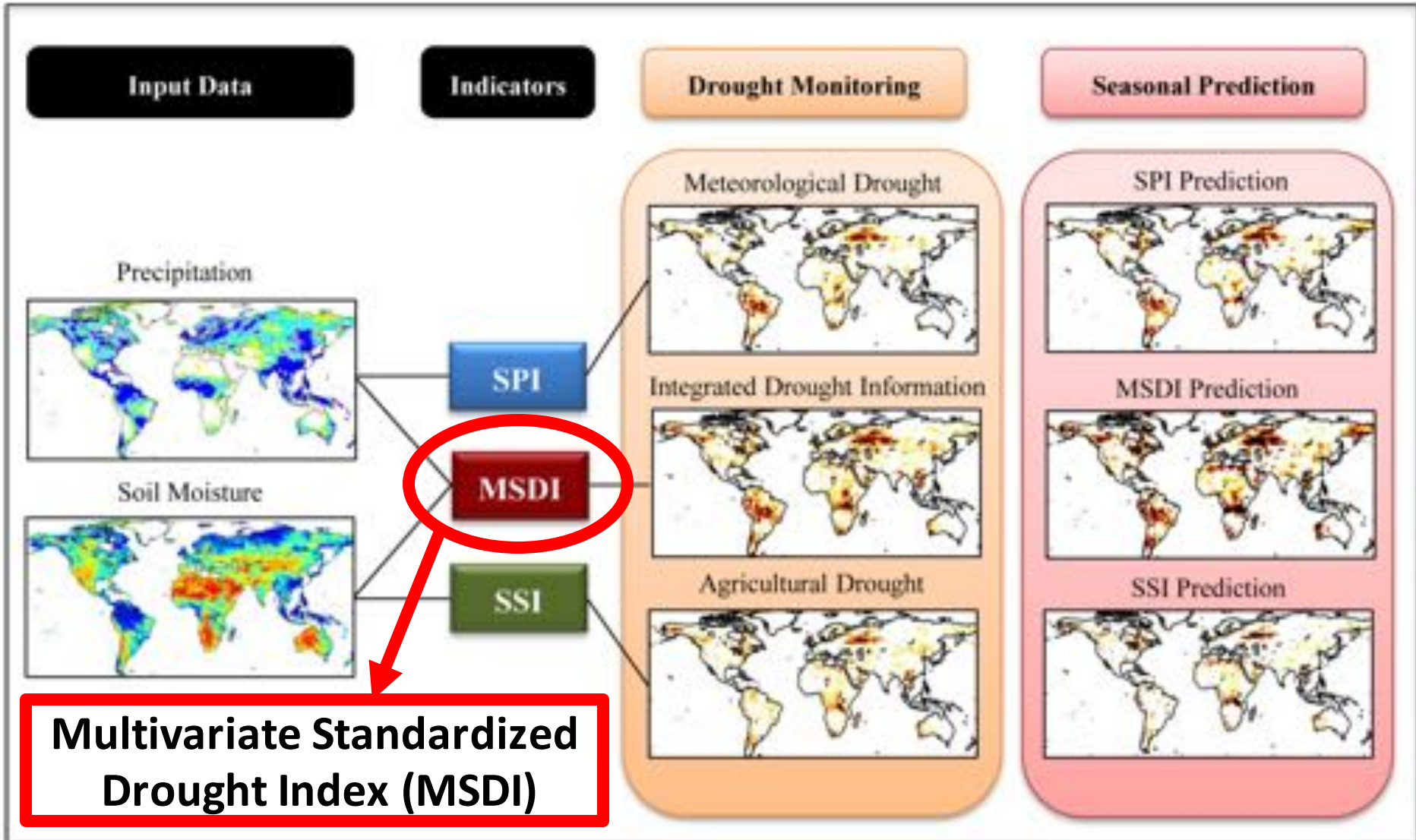
Integration of AIRS Data into GIDMaPS





Mean lead time based on satellite relative humidity data relative to precipitation (months)



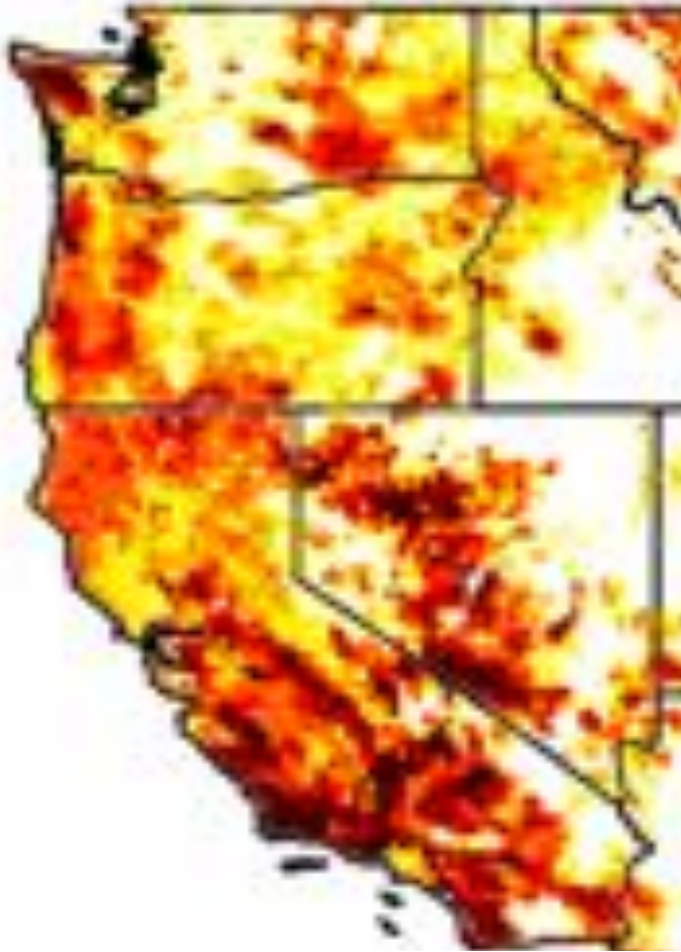




Probabilistic Drought Prediction



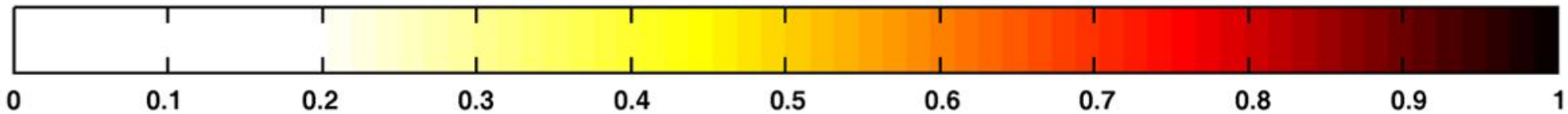
2-Month Lead
Dec. 2014

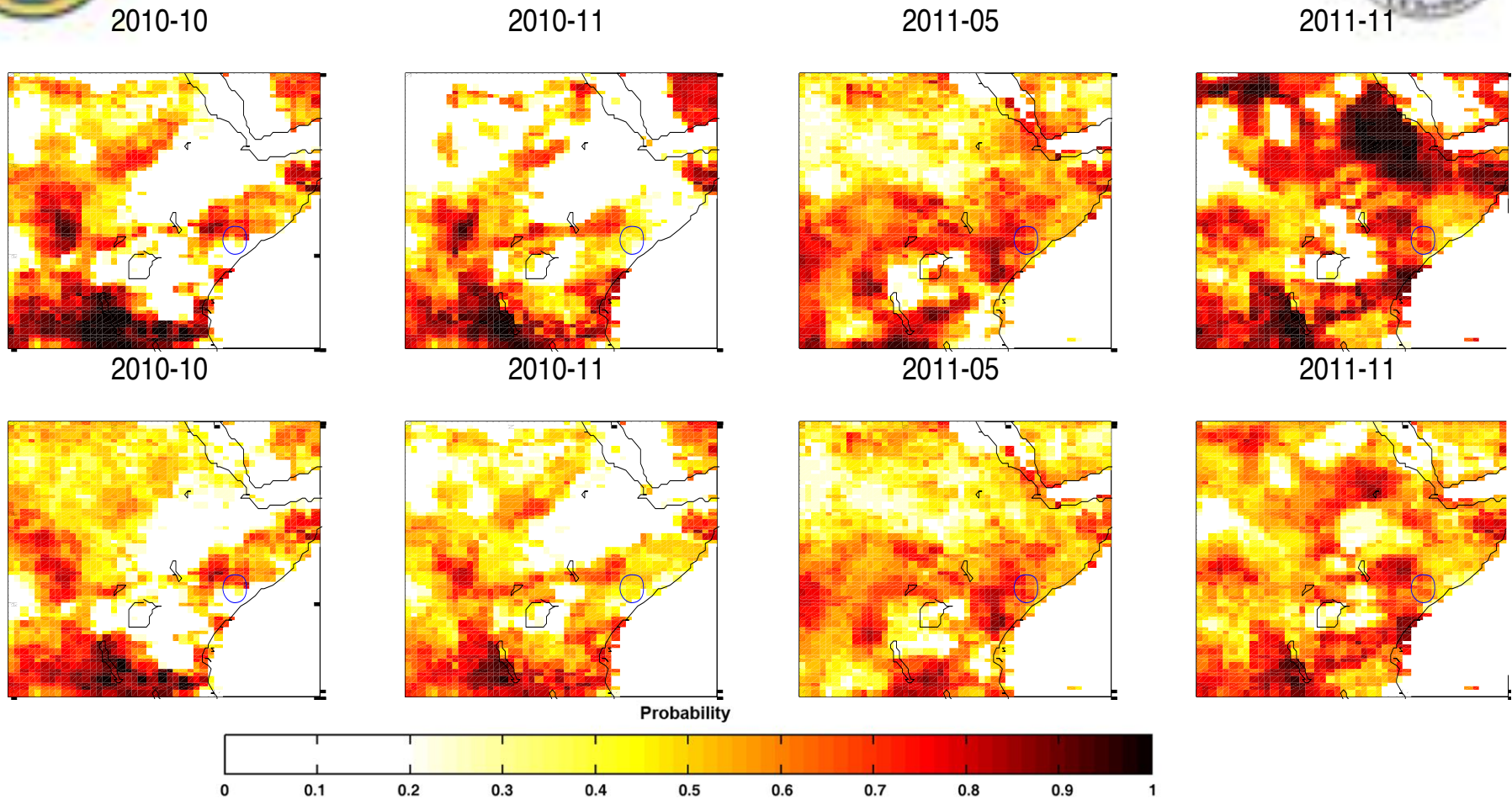


2-Month Lead
Jan. 2015



Probability

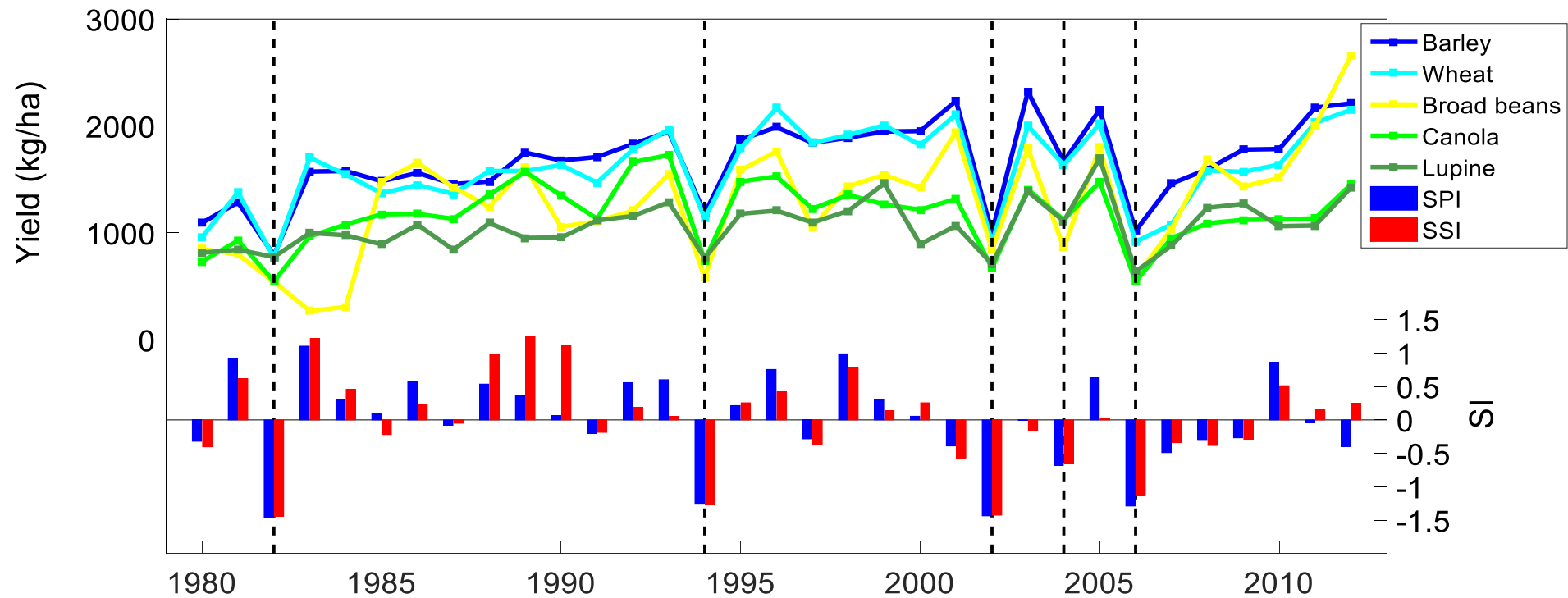




3- and 4-month lead predictions of the ensemble median (top two rows), and their corresponding drought probability (bottom two rows) for a number of time-steps throughout the event. Based on a UNDP report, the first official warning was received December 2010. Our results show high probability of drought 3 to 4 months prior to October 2010 (top left panel).



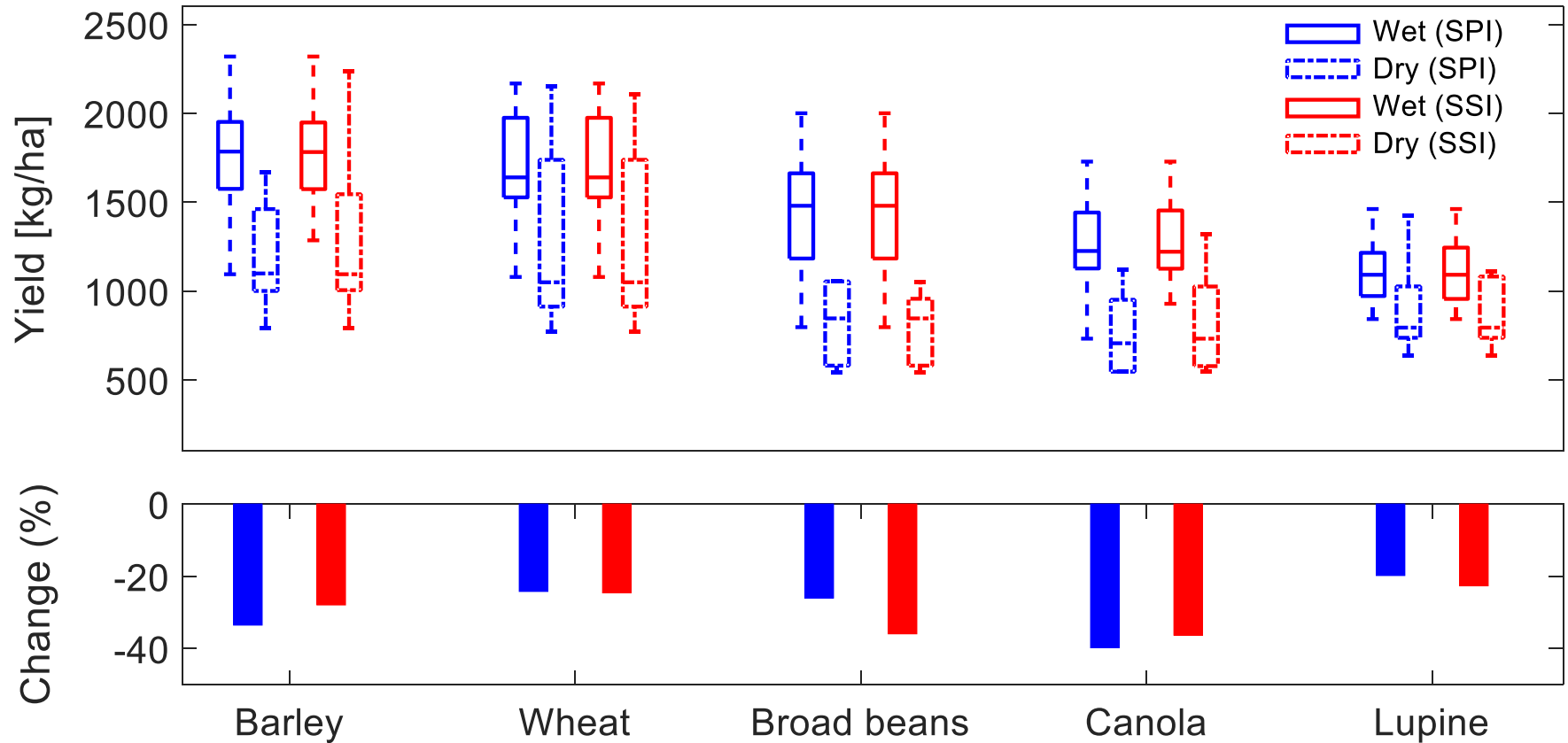
Linking Drought Information to Crop Yield



Variation of rain-fed crop yields in Australia versus SPI (blue bars) and SSI (red bars) during 1980-2012. The grey vertical dash lines associate the driest years with their corresponding annual yields.



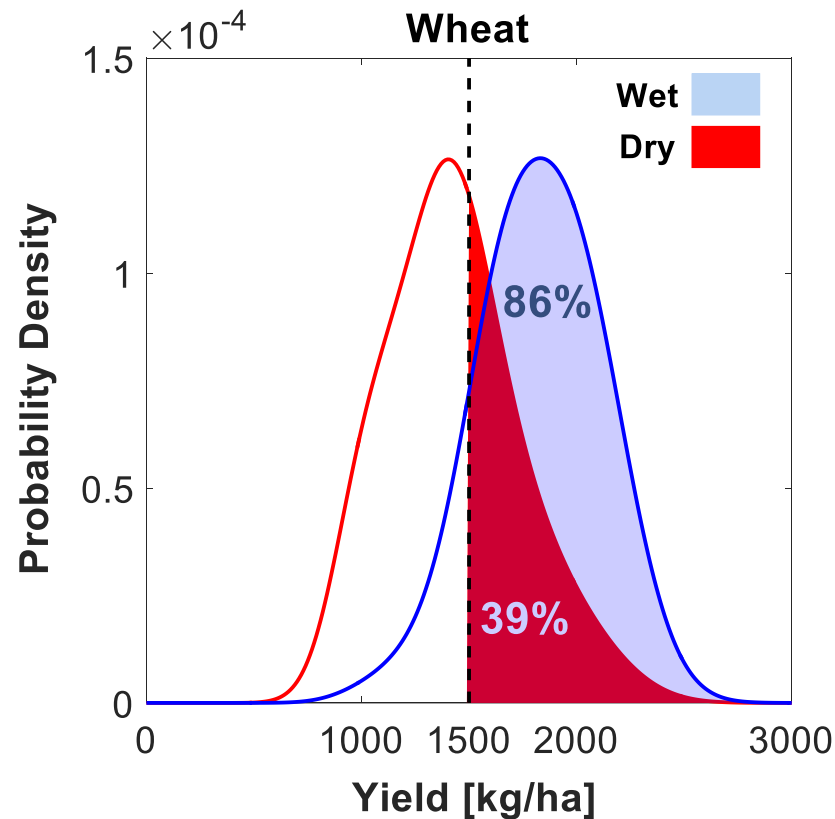
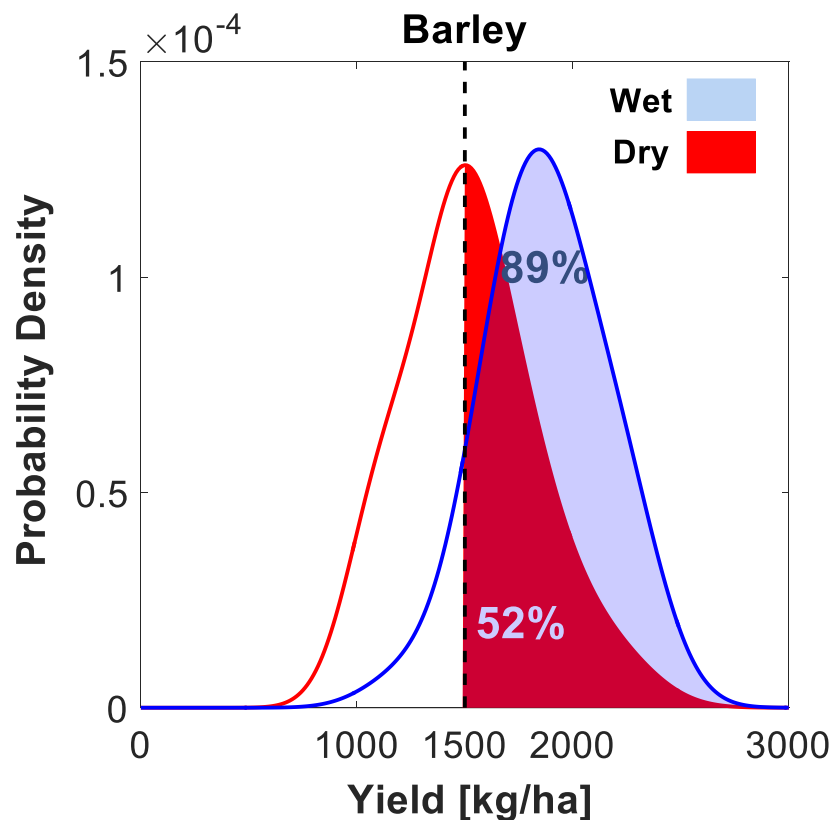
Linking Drought Information to Crop Yield



Crop yield distributions for different drought conditions based on SPI (blue boxes and bars), and SSI (red boxes and bars). The solid and dash-lined boxes are associated with wet/normal ($SI > -0.4$) and dry ($SI < -0.4$) conditions, respectively. The bars on the bottom indicate the average change of annual crop yield (in percent) in dry conditions ($SI < -0.4$) relative to wet/normal conditions ($SI > -0.4$) defined based on either SPI (blue) or SSI (red).



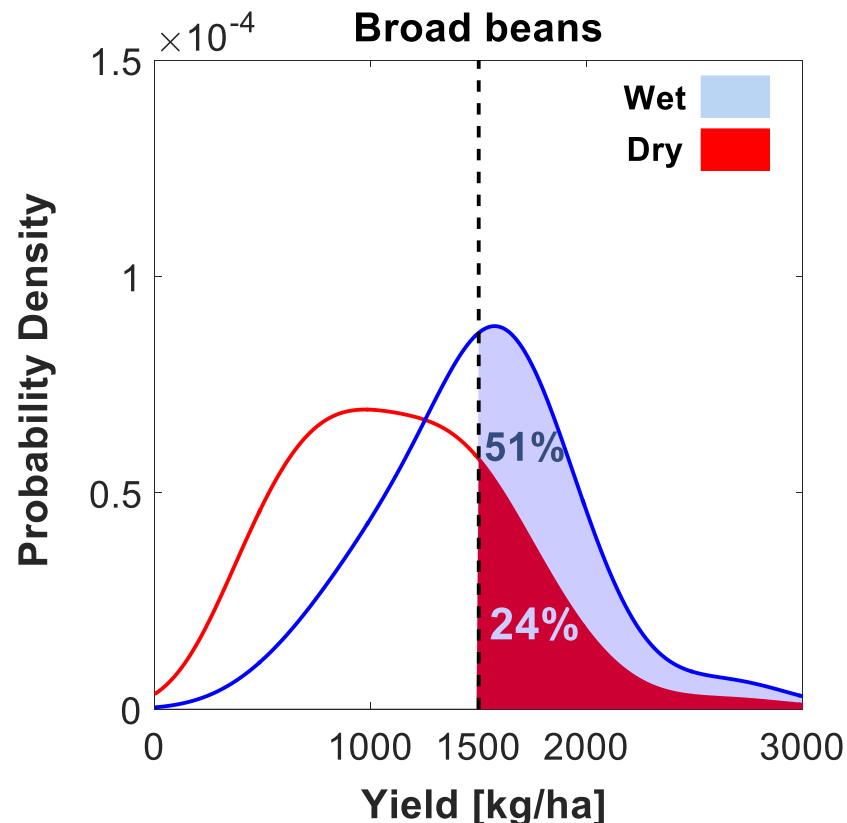
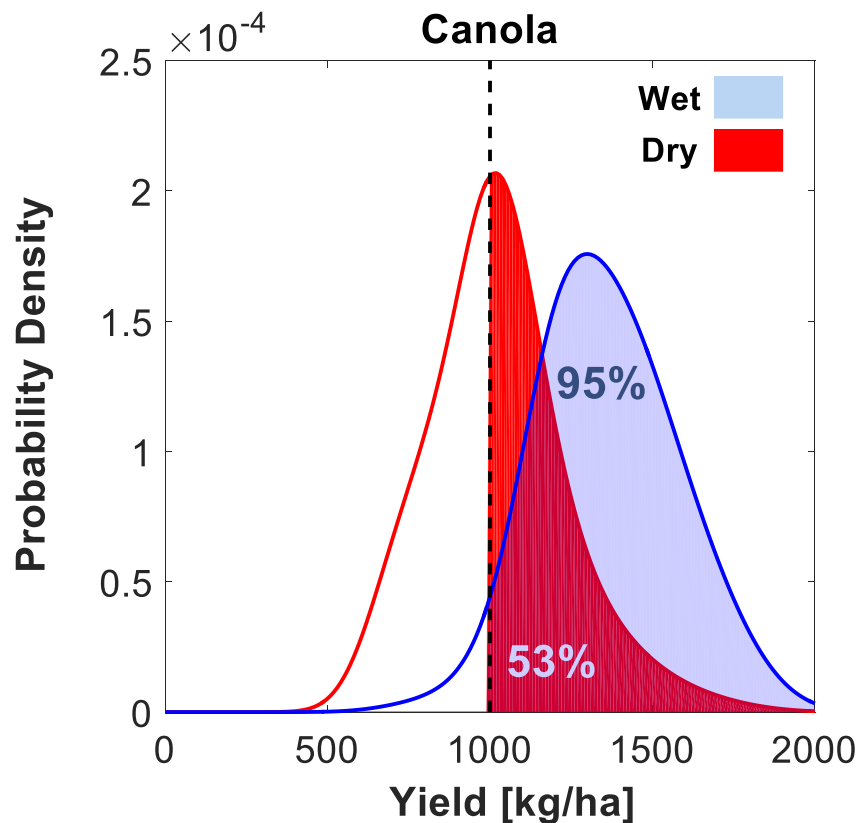
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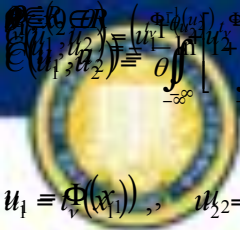
Conditional probability distribution of different crop yields at dry (red curves) and wet (blue curves) conditions. The shaded area and associated numbers indicate the probability (in percent) of annual crop yield exceeding its annual average (vertical dash line). The conditional probabilities are defined as $\Pr(\text{Yield} > y \mid \text{SPI} = x)$



Linking Drought Information to Crop Yield



Conditional probability distribution of different crop yields at dry (red curves) and wet (blue curves) conditions. The shaded area and associated numbers indicate the probability (in percent) of annual crop yield exceeding its annual average (vertical dash line). The conditional probabilities are defined as $\Pr(\text{Yield} > y \mid \text{SPI} = x)$



Linking Drought Information to Crop Yield

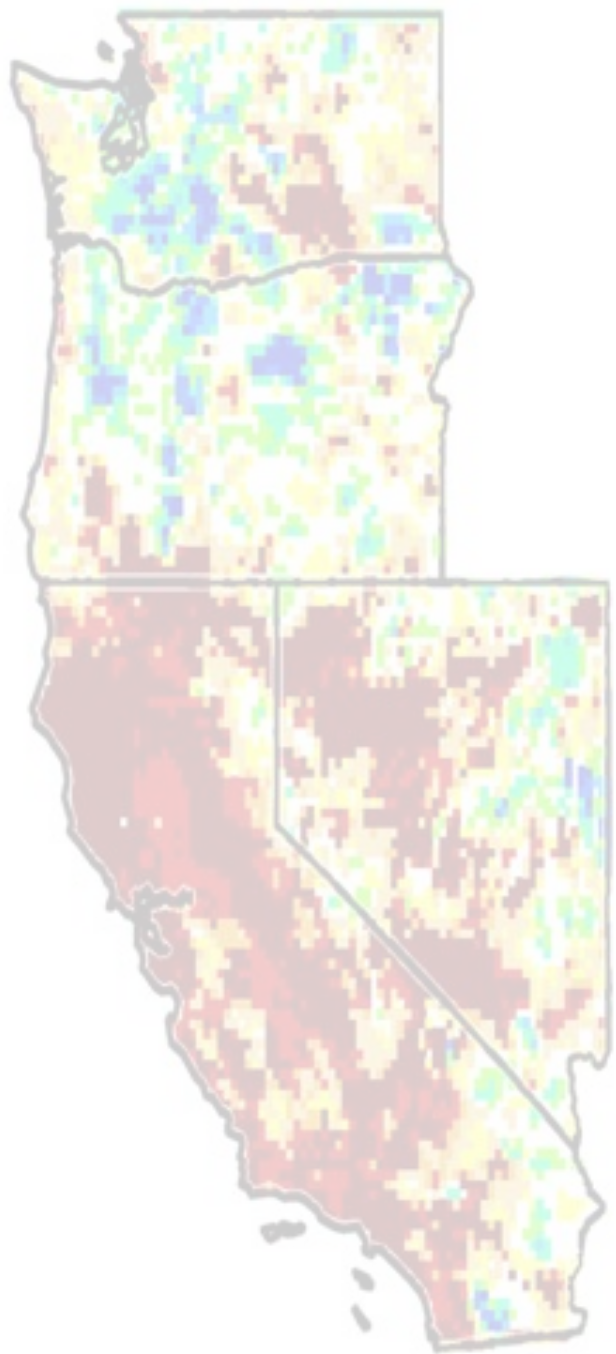


$$u_1 = \Phi(x_1), \quad u_2 = \Phi(x_2)$$

$$F_{XY}(x, y) = C[F_X(x), F_Y(y)]$$

$$F_{Y|X}(Y > y | X)$$

Copula	Function	Domain
Gaussian	$C(u_1, u_2) = \int_{-\infty}^{\Phi^{-1}(u_1)} \int_{-\infty}^{\Phi^{-1}(u_2)} \frac{1}{2\pi(1-\rho^2)^{1/2}} \exp\left\{-\frac{x_1^2 + x_2^2 - 2\rho x_1 x_2}{2(1-\rho^2)}\right\} dx_1 dx_2$ $u_1 = \Phi(x_1), \quad u_2 = \Phi(x_2)$ <p>ρ : Linear correlation coefficient Φ : Standard normal cumulative distribution function</p>	$x_1, x_2 \in \mathbb{R}$
t	$C(u_1, u_2) = \int_{-\infty}^{\tau^{-1}(u_1)} \int_{-\infty}^{\tau^{-1}(u_2)} \frac{1}{2\pi(1-\rho^2)^{1/2}} \exp\left\{1 + \frac{x_1^2 + x_2^2 - 2\rho x_1 x_2}{\nu(1-\rho^2)}\right\}^{-\frac{\nu+2}{2}} dx_1 dx_2$ $u_1 = \tau_\nu(x_1), \quad u_2 = \tau_\nu(x_2)$ <p>ρ : Linear correlation coefficient τ_ν : Cumulative distribution function of t distribution with ν degree of freedom.</p>	$x_1, x_2 \in \mathbb{R}$
Clayton	$C(u_1, u_2) = (u_1^{-\theta} + u_2^{-\theta} - 1)^{-1/\theta}$ <p>θ : Measure of dependency between u_1 and u_2.</p>	$\theta \in (0, \infty)$
Frank	$C(u_1, u_2) = -\frac{1}{\theta} \ln \left[1 + \frac{(e^{-\theta u_1} - 1)(e^{-\theta u_2} - 1)}{e^{-\theta} - 1} \right]$ <p>θ : Similar to Clayton copula.</p>	$\theta \in \mathbb{R}$



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