Water Management in a Changing Climate: Challenges in the application of Hydroclimatological forecasting for decision making

Soroosh Sorooshian

Center for Hydrometeorology and Remote Sensing
University of California Irvine

WCRP Conf. for Latin America and the Caribbean:

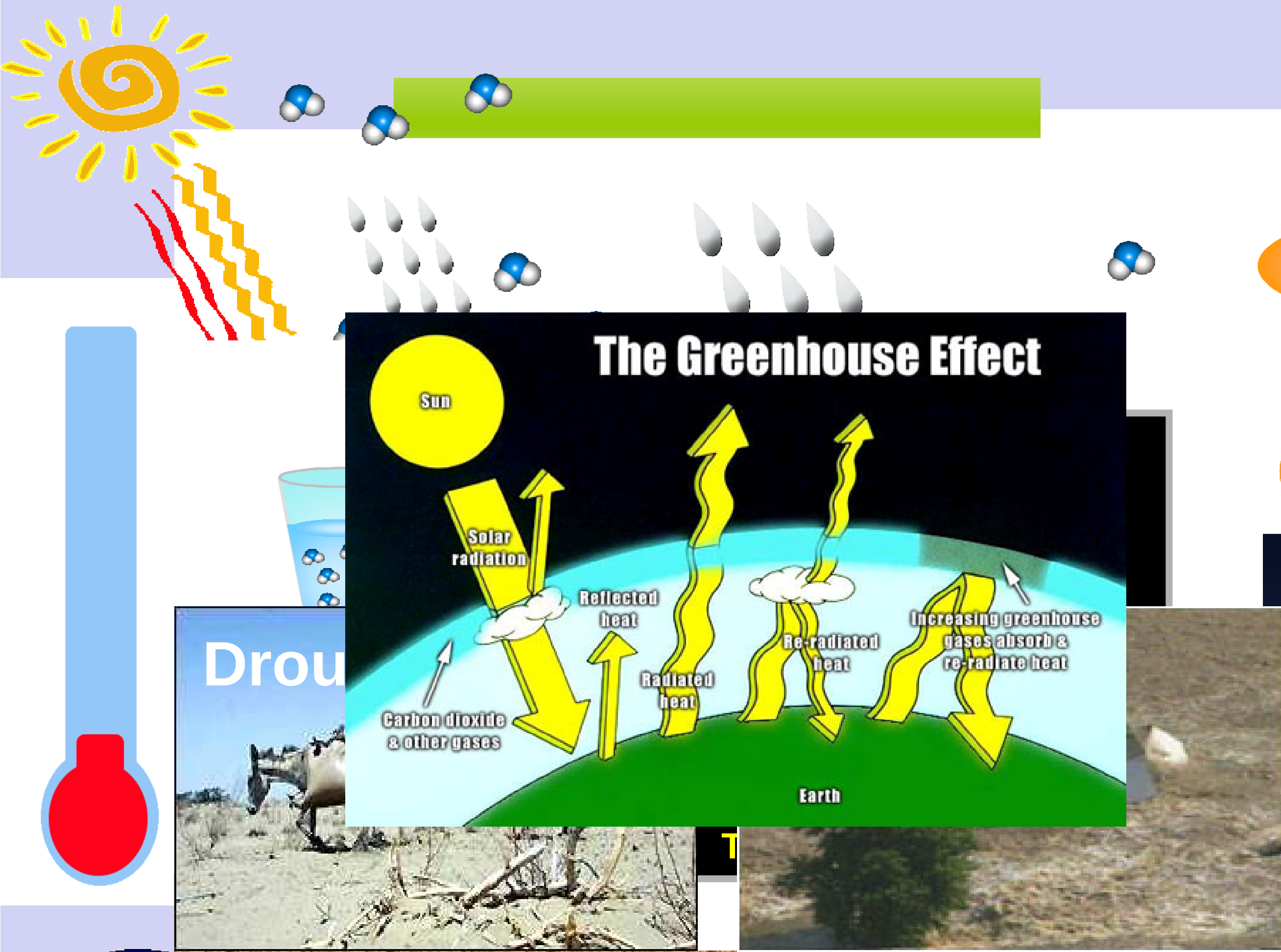
Developing, Linking & Applying Climate Knowledge

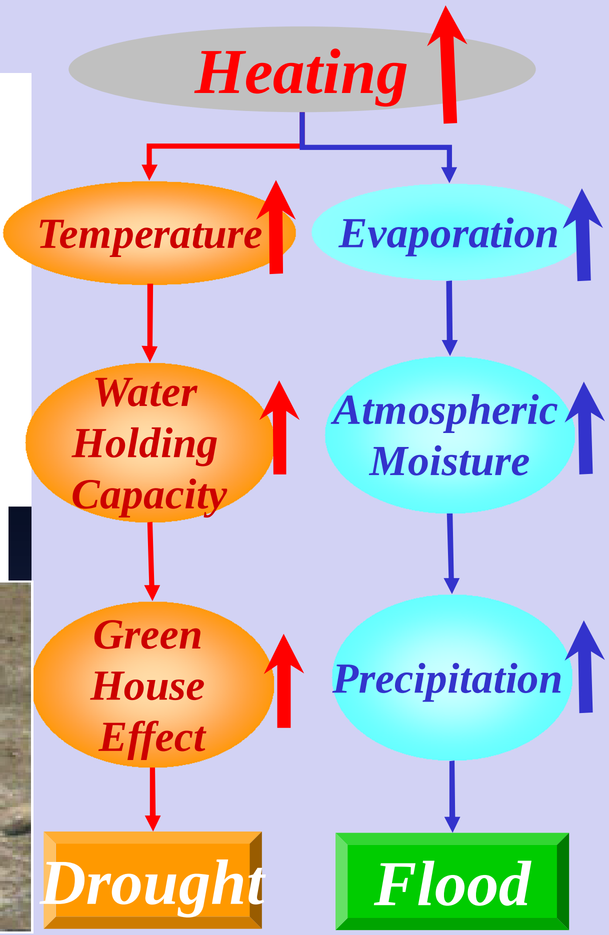
Montevideo, URUGUAY : March 17th– 22nd 2014

Research Team: Present and Recent Past
University of California Irvine (UCI)

and many more …

Global Warming And Hydrologic Cycle Connection





Created by: Gi-Hyeon Park

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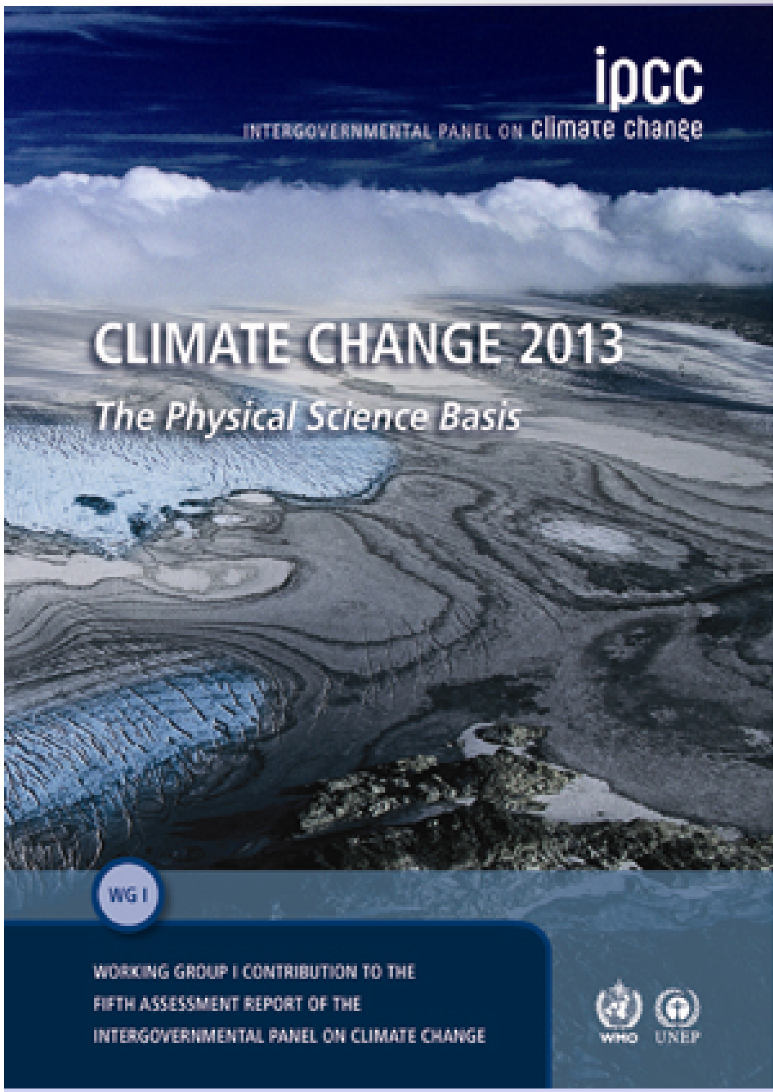
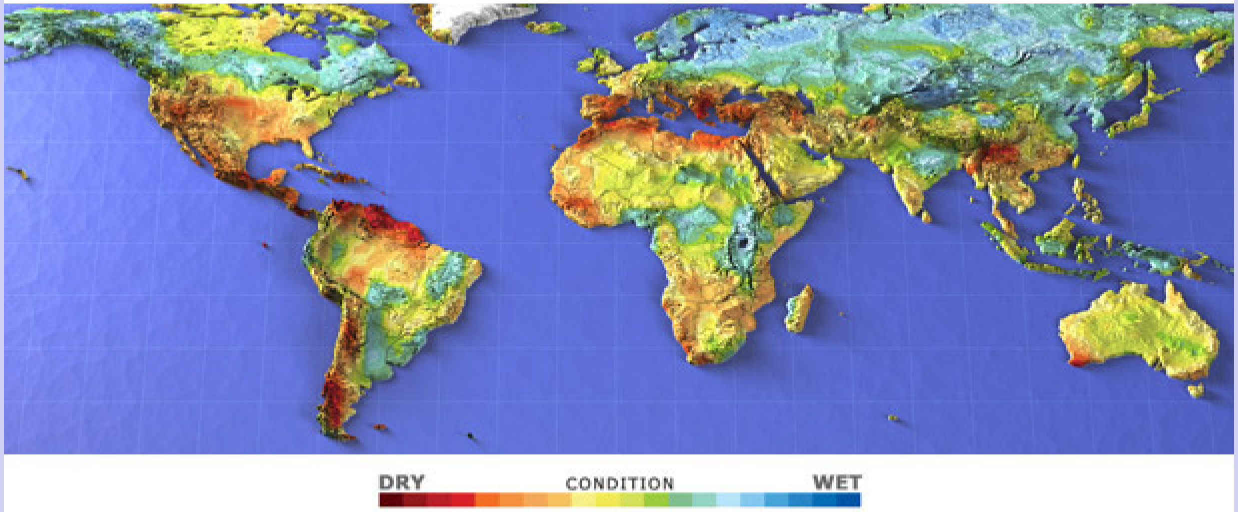
Recently Released IPCC Report (AR5) - Sept. 2013



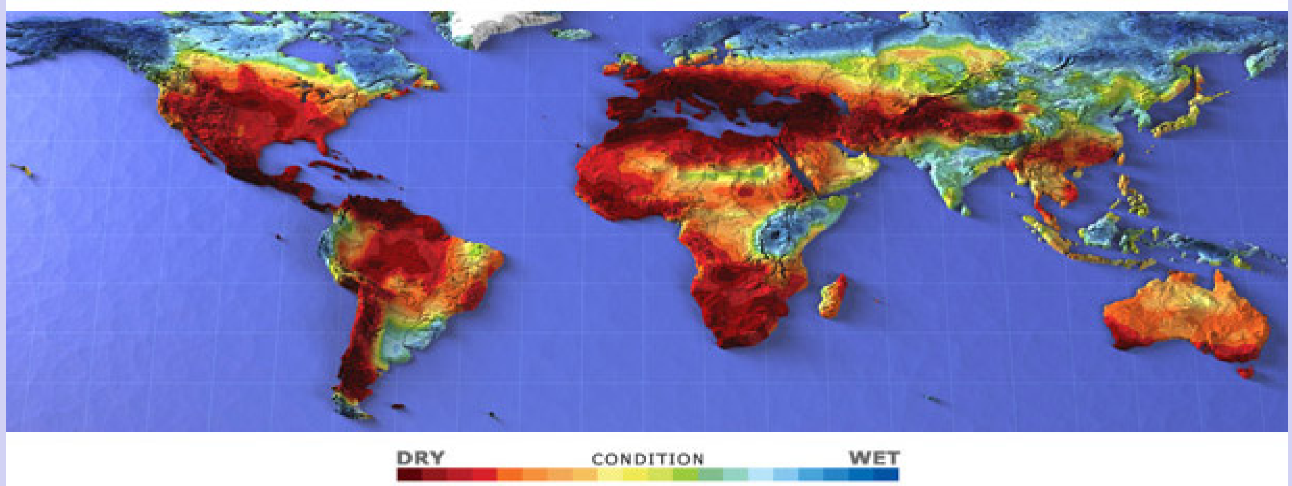
- ***"It is likely that since 1950 the number of heavy precipitation events over land has increased in more regions than it has decreased."***
- ***"……… there continues to be a lack of evidence and thus low confidence regarding the sign of trend in the magnitude and/or frequency of floods on a global scale"***

Global Climate: Past Decade and Prediction of End of 21st Centaury

2000–2009



2090–2099



<u>Fair Question:</u>

Where does all the additional Precipitation go?

Two Primary Water Resources/Hydrology Challenges:

- ***Hydrologic Hazards (Floods and Droughts)***
- ***Water Supply Requirements (Quantity and Quality)***

Primary Solution To Satisfy Water Resources Needs and Address Hydrologic Extremes

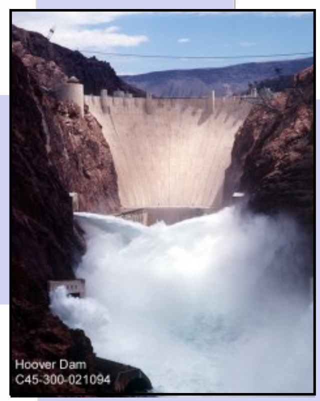
Engineering Approach:

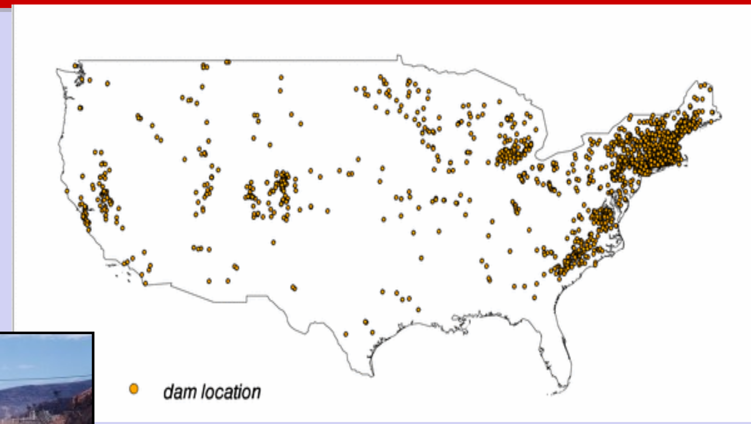
Control, Store, Pump and Transfer

Central Arizona Project Aqueduct

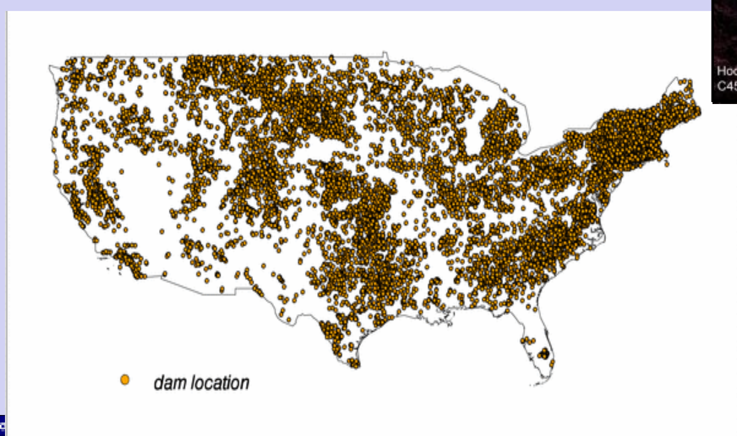
Impact of Dam & Reservoir Construction

1800

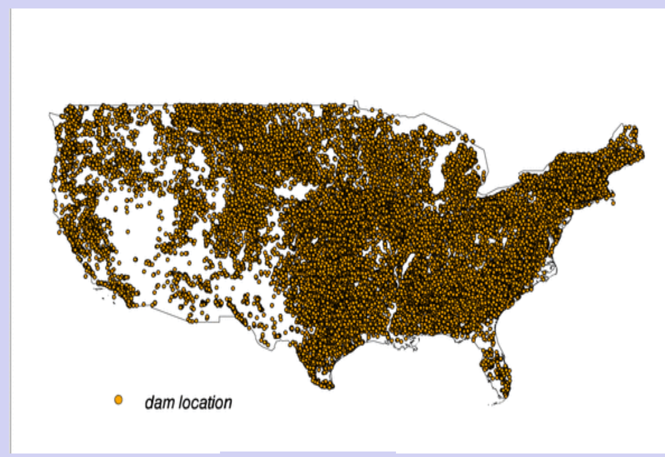




1900



1950



2000

More than 70,000 Dams in the U.S

Prediction Requirements for Water Resources

Short Range - · - · - · - · - · - · - · - · - · - · - · - · - · - · -> Long Range

hours - - - - -> days - - - - -> weeks - - - -> months - - -> seasons - - -> years - - - - - - -> decades

Short-range	***Mid-range***	***Long-range***

Climate-Scale approaches to addressing hydrologic extremes

Short Range – · – · – · – · – · – · – · – · – · – · – · – · – · – ->Long Range

hours - - - -> days - - - - -> weeks - - -> months - -> seasons - -> years - - - - - -> decades

Flash Flood Warning

Flash Flood Guidance

Headwater Guidance

Flood Forecast Guidance

Reservoir Inflow Forecas

Spring Sno

Water Sup

Long-range

Forecast Requirem

Climate-Scale approaches to addressing Regional hydrology

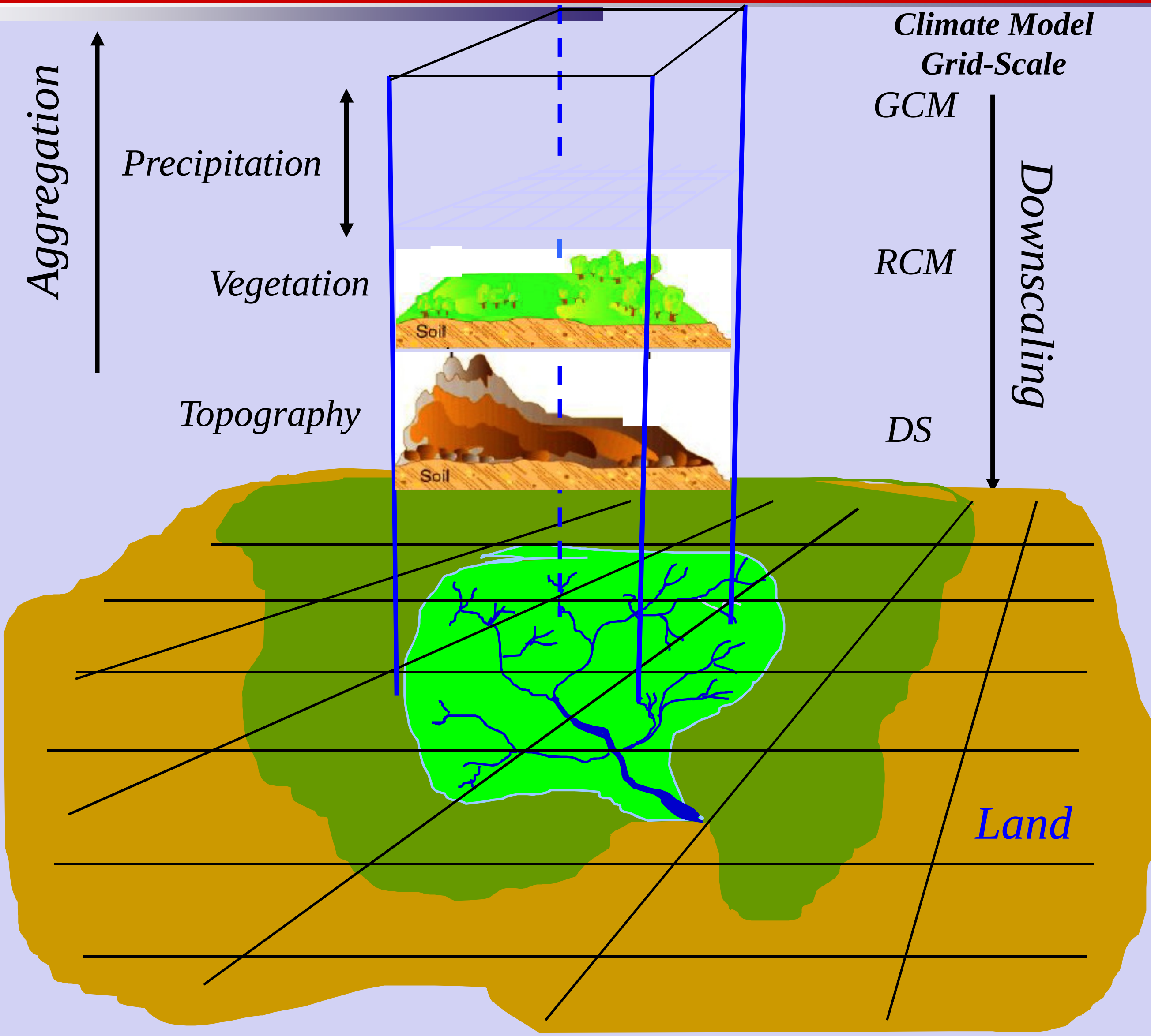
Short Range – · – · – · – · – · – · – · – · – · – · – · – · – · –> Long Range

hours ----> days ----> weeks ---> months --> seasons --> years ------> decades

•Use of climate models: down-scaling and ensemble schemes

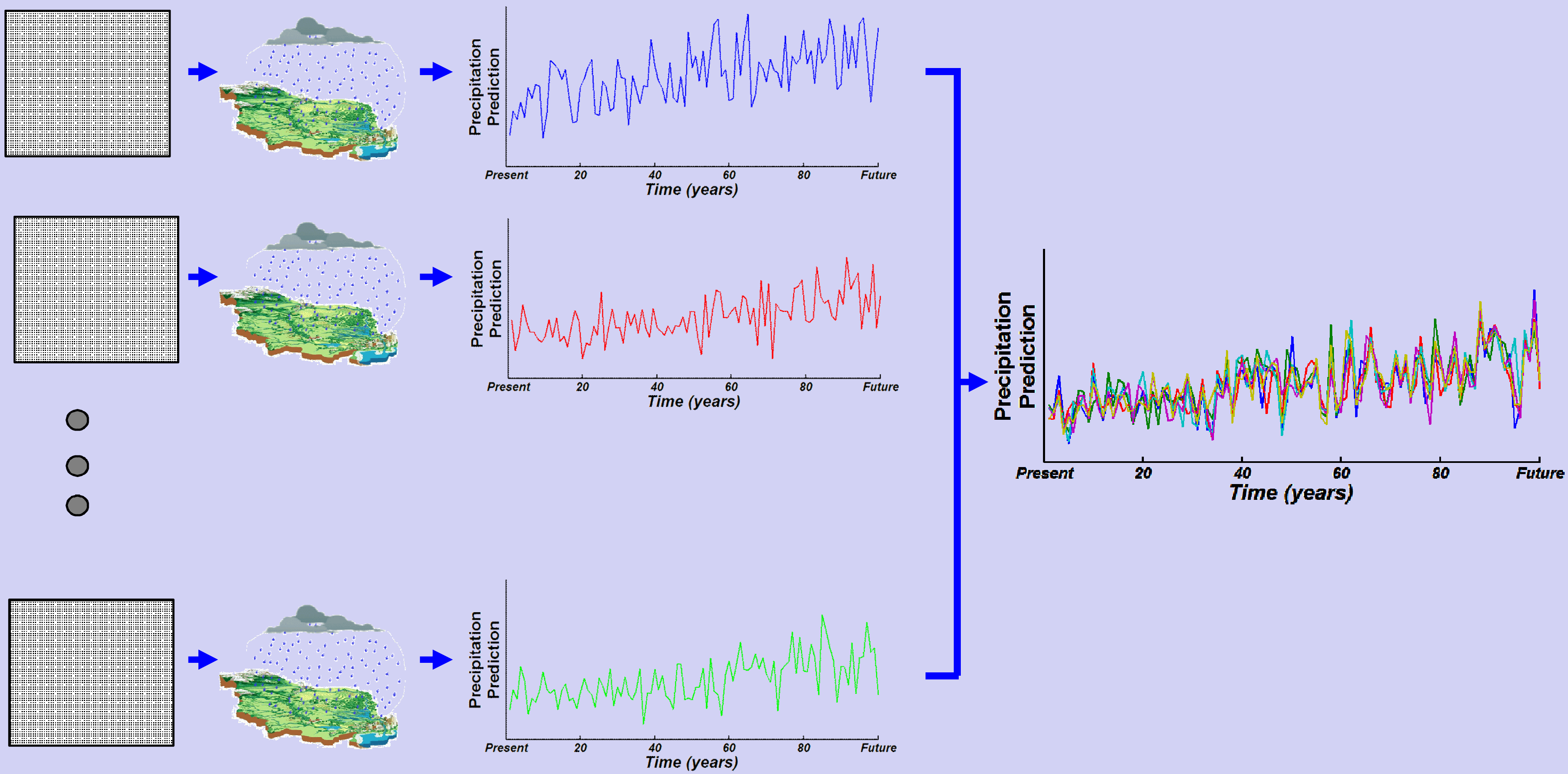
•Traditional statistical hydrology methods:

Climate Model Downscaling to regional/watershed Scale



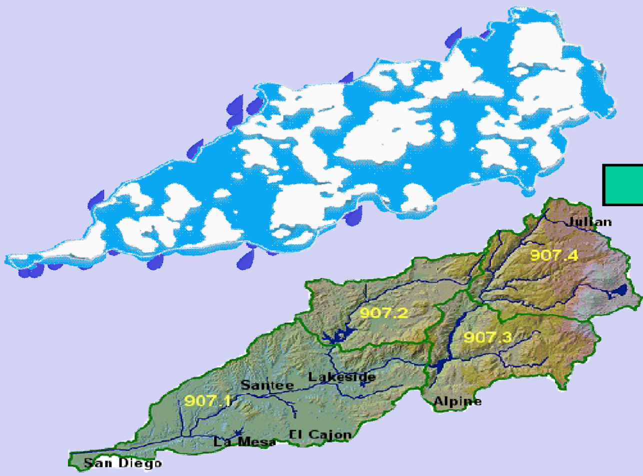
Ensemble Approach

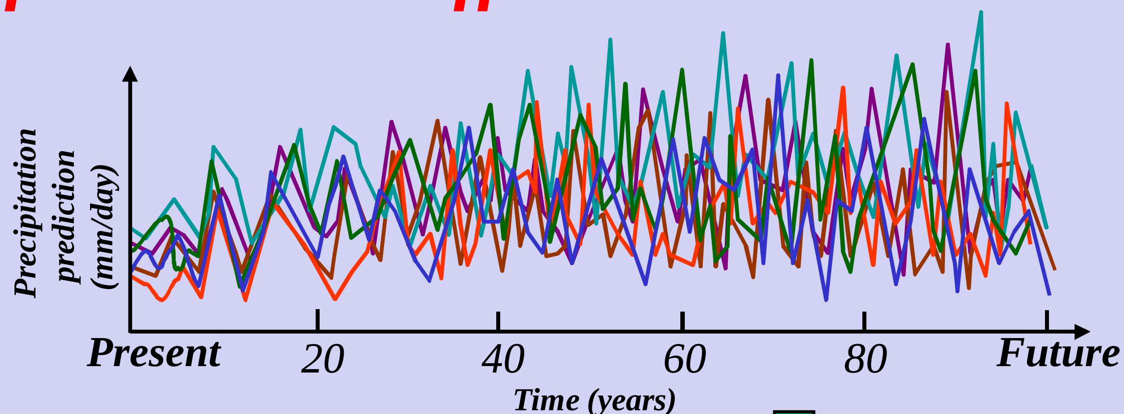
Generation of Future Precipitation Scenarios

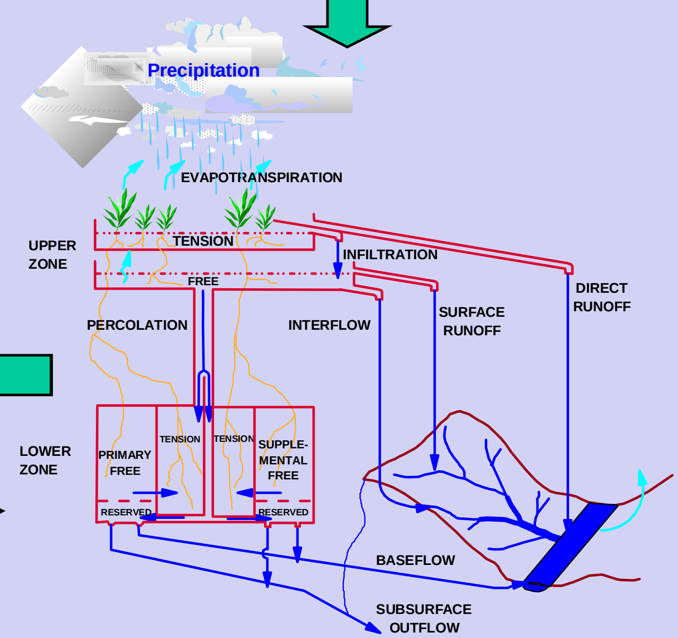


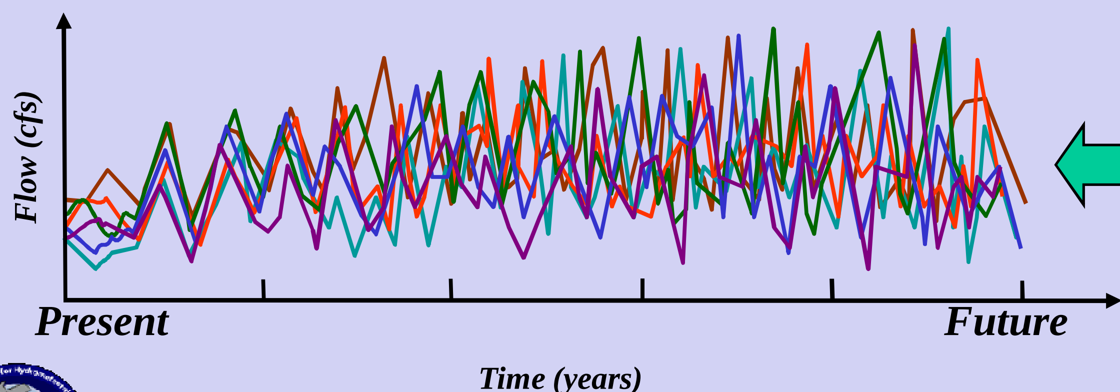
Downscaled Precipitation to Runoff Generation

Generation of Future Runoff Scenarios









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Hydrologically-Relevant Climate Variables

What Do Models Tell Us About Future Precipitation Patterns and Amounts?

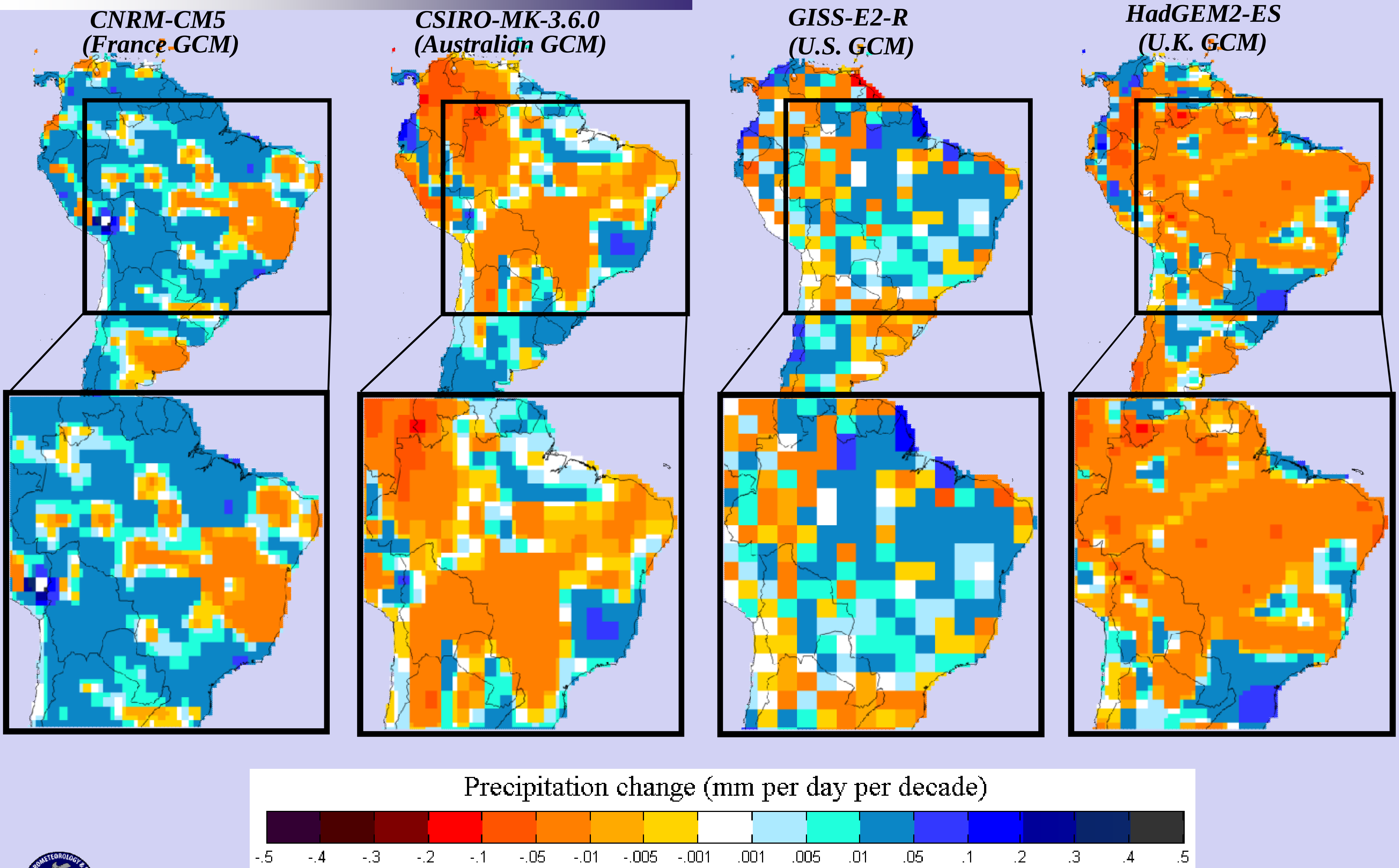
Center for Hydrometeorology and Remote Sensing, UCI
CHRS

South America

IPCC AR5 Scenarios

Time period: 2006-2099

RCP2.6 ("Low": 2.6 W/m², Equivalent CO_2 conc. 421 ppm by 2100)



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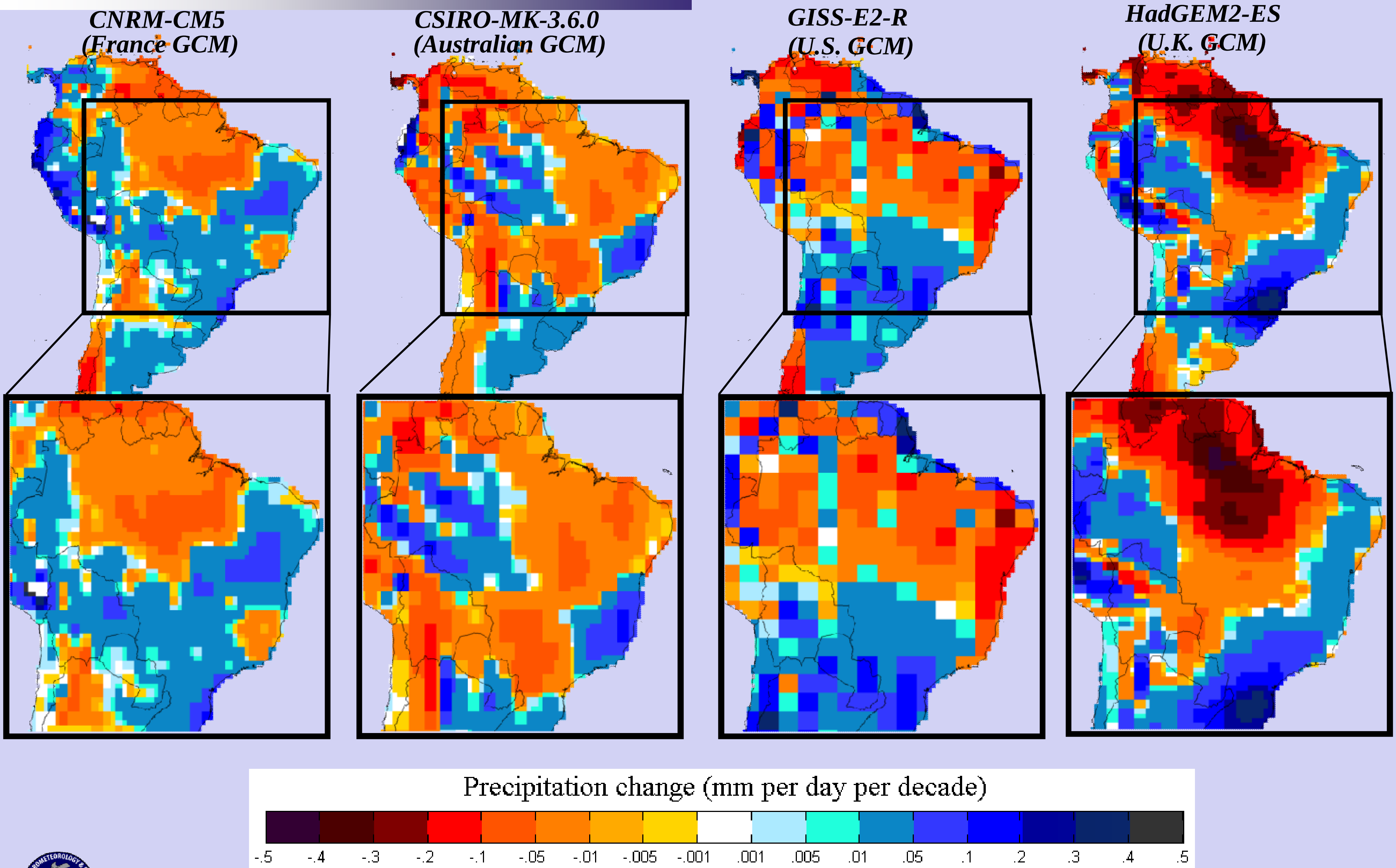
IPCC AR5 Scenarios

Time period: 2006-2099

RCP8.5 ("High": 8.5 W/m^2, Equivalent CO_2 conc. 936 ppm by 2100)



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Recent Evaluation of RCM/GCM over Western U.S.

Wei Chu 2011

Regional Models	Climate Models: GFDL	CGCM3	HADCM3	CCSM
CRCM	—		—	—
ECP2		—	—	—
HRM3	—	—		—
MM5I	—	—	—	
RCM3	—		—	—
WRFG	—	—	—	

<u>Outputs of six RCM/GCM sets:</u>

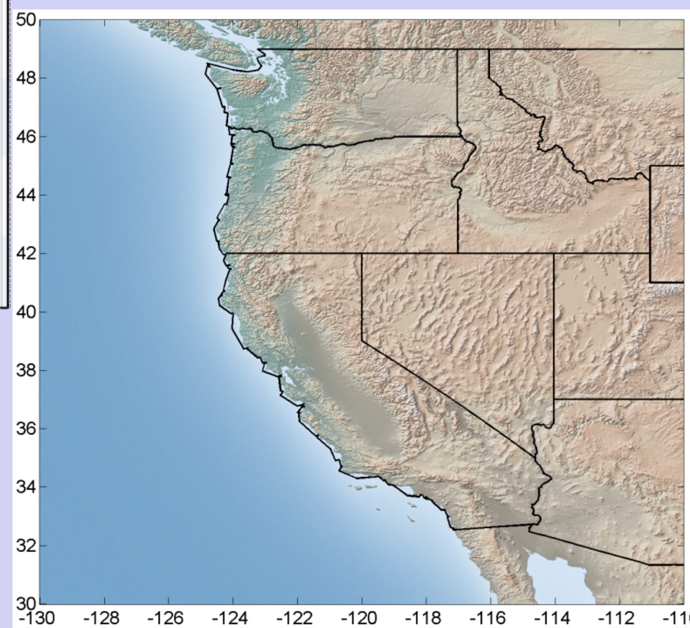
North American Regional Climate Change Assessment Program (NARCCAP)

Current period:1971-2000

Future period: 2041-2070

Spatial Res.: 50 km

Temporal Res.: daily



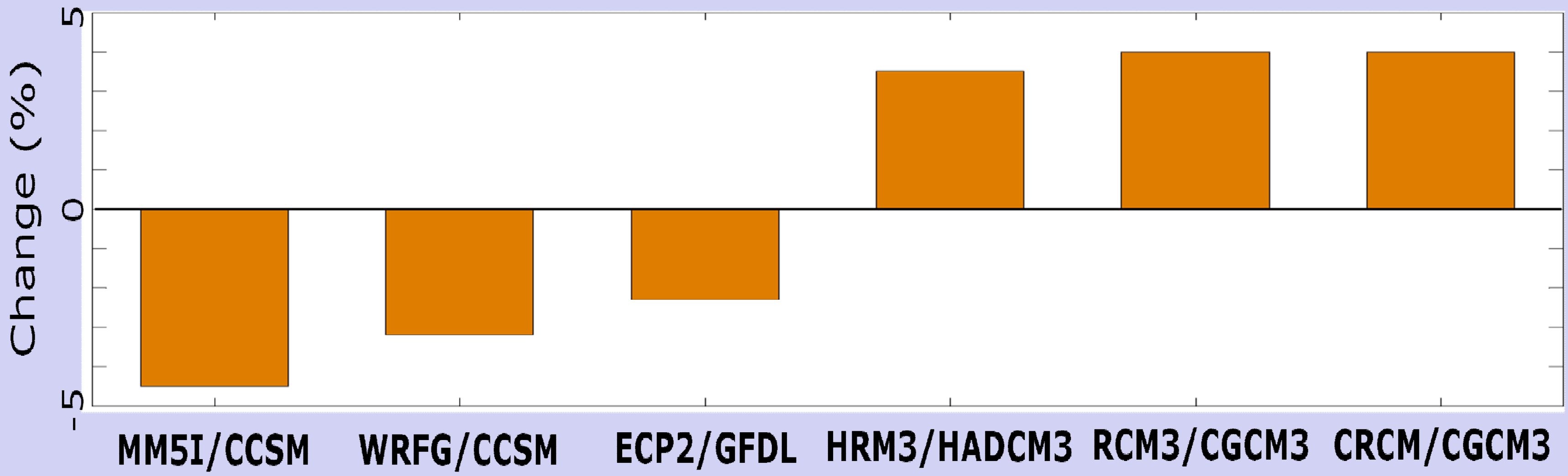
Emissions Scenario:

A2: regionally oriented and fast economic growth

study region

Recent Evaluation of RCM/GCM over Western U.S.

Models indicate different signs and magnitudes of changes in the mean precipitation over the Western U.S. under the SRES A2 emissions scenario.



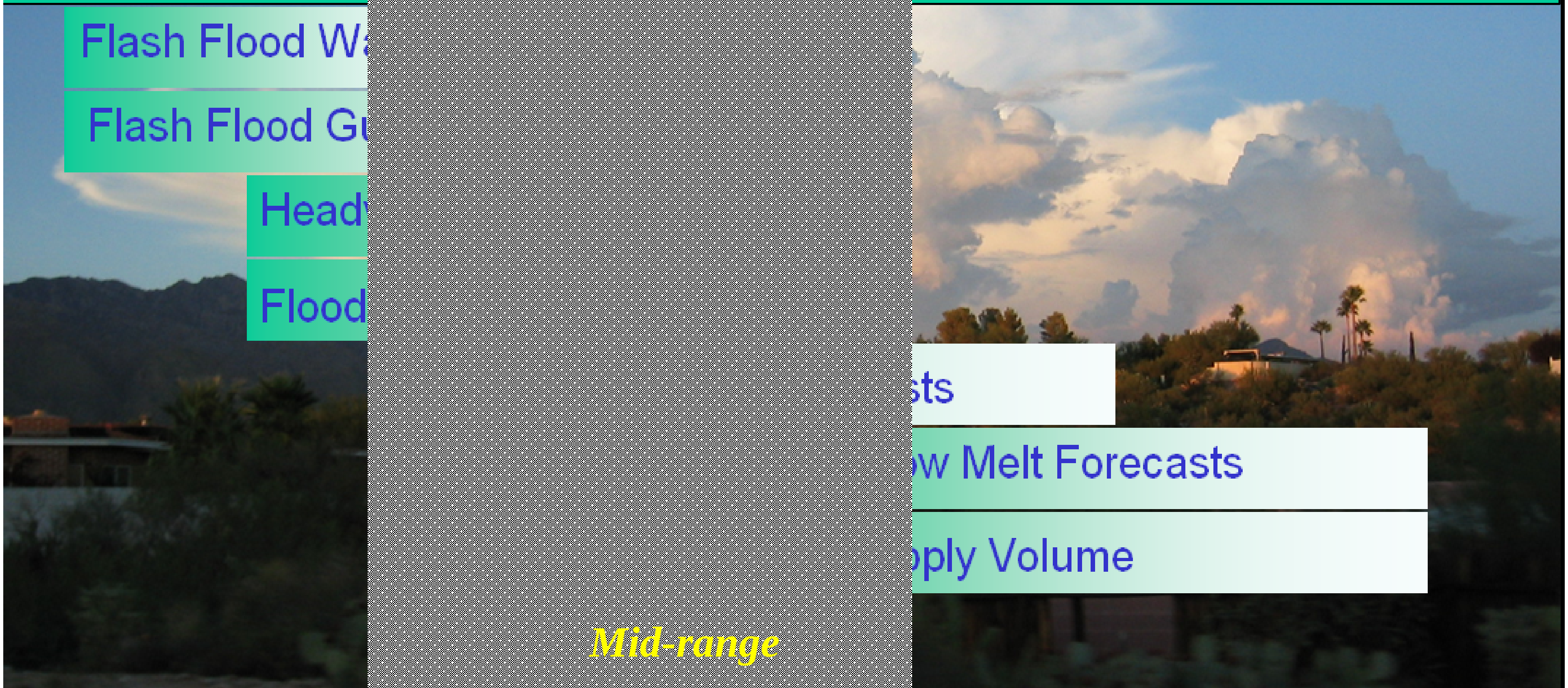
Trend of area-average precipitation (comparing 2040-2070 with 1970-2000)

Wei Chu 2011

Seasonal-Scale Predictions

Short Range - · - · - · - · - · - · - · - · - · - · - · - · - · - · - · ->Long Range

hours - - - - -> days - - - - -> weeks - - - -> months - - -> seasons - - -> years - - - - - - -> decades



Flash Flood W

Flash Flood Gu

Head

Flood

sts

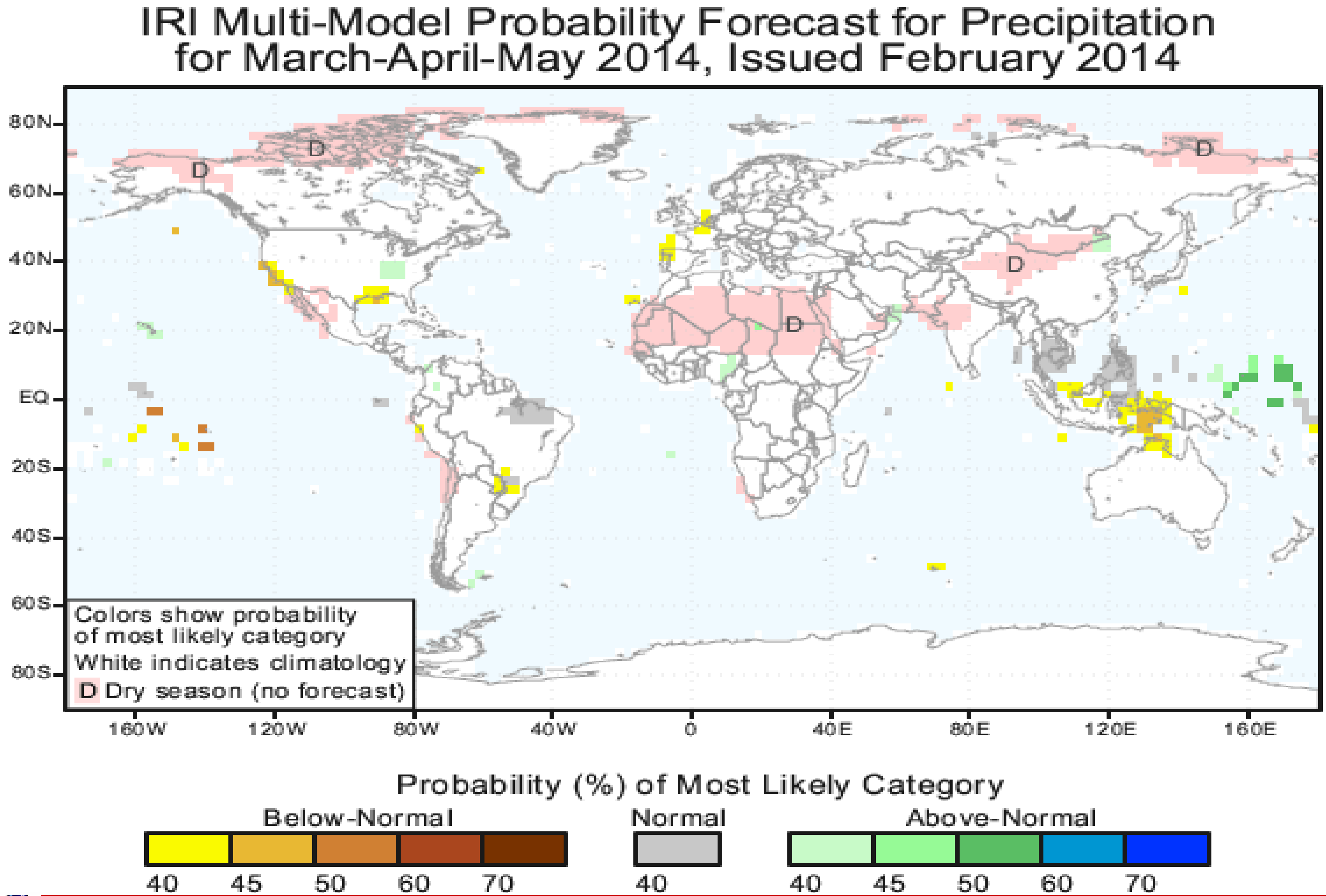
w Melt Forecasts

ply Volume

Mid-range

ents

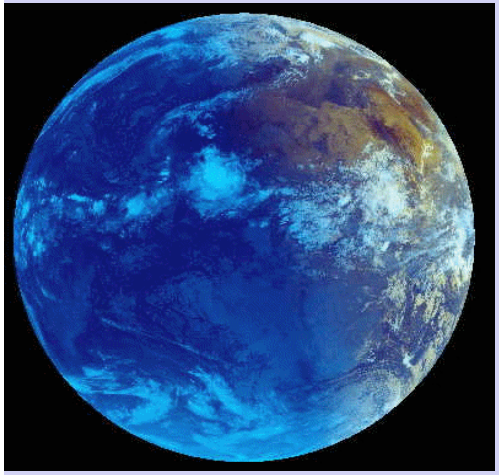
IRI 3-Month Multi-Model Probability Precipitation Forecast



Recent Assessment of Seasonal Climate Forecasts

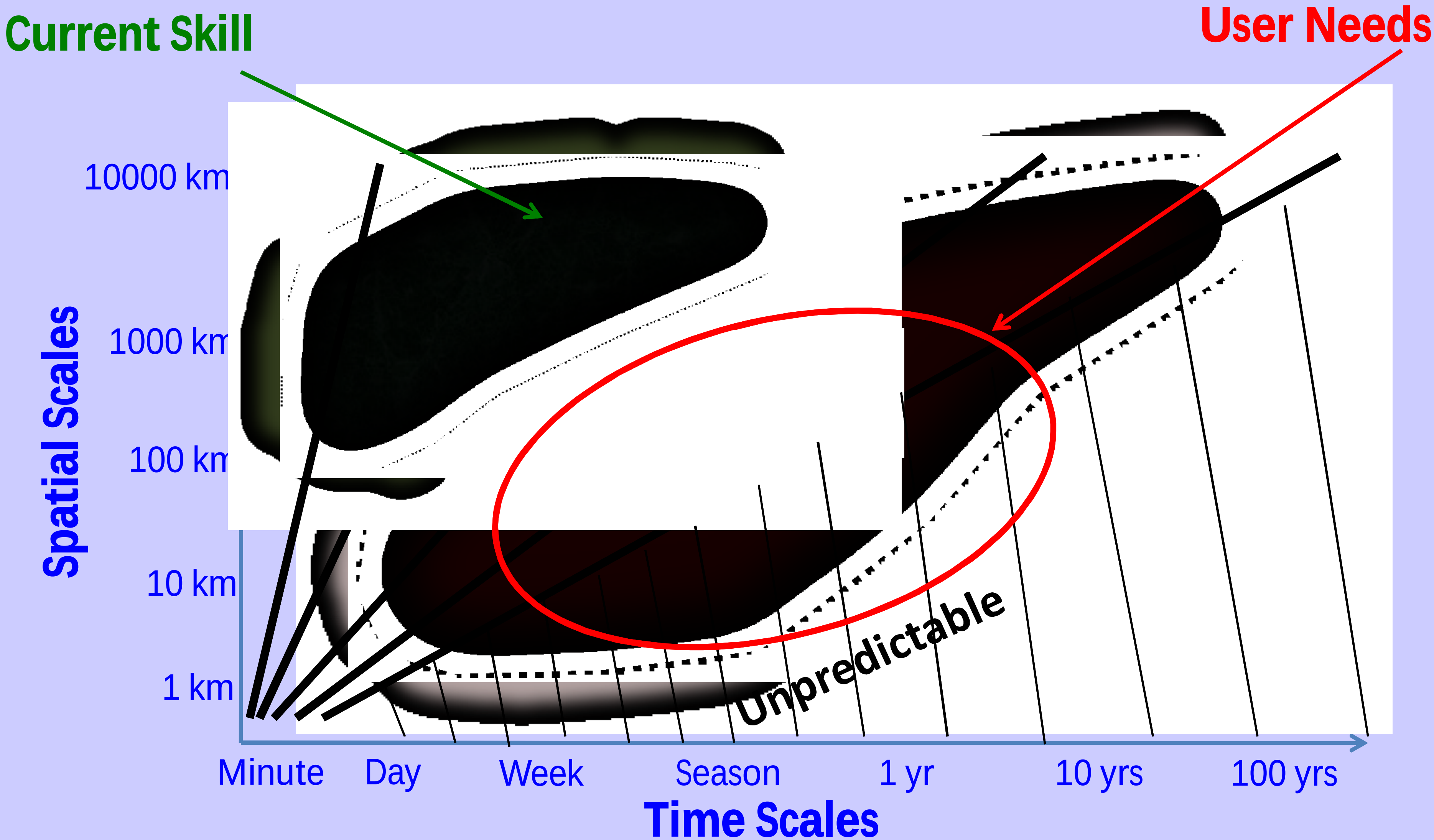
Quoting from Science, Vol. 321, 15th August 2008

Livezey &Timofeyeva - BAMS, June 2008.



- *"About the only time forecasts had any success predicting precipitation was for winters with an El Nino or a La Nina"*

Drought Predictability



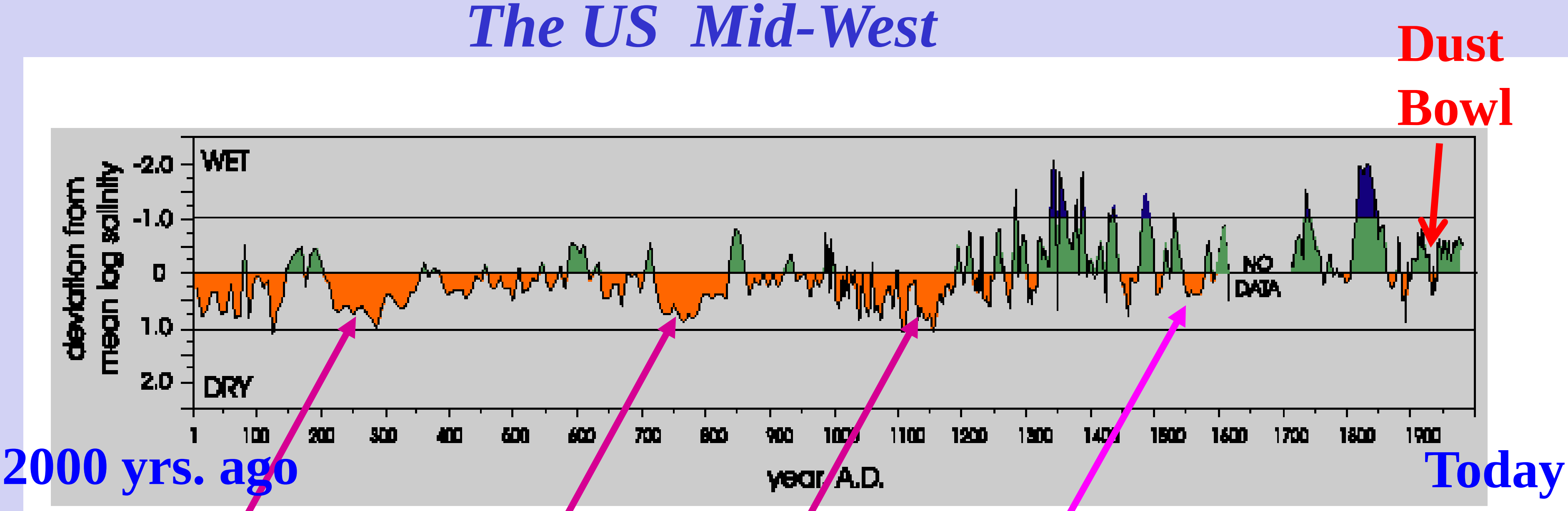
Provided by Siegfried Schubert 2011

Hydrologically-Relevant Climate Variables

What Does History Tell Us?

2000-year Climate history of central U.S.

The US Mid-West



1930's dustbowl

16th century "megadrought"

>100 year "megadroughts"

Source: Overpeck 2004

What is the Message?

- ***Presently, the accuracy of Hydroclimate model predictions fall short of meeting the requirements of water resources planning.***

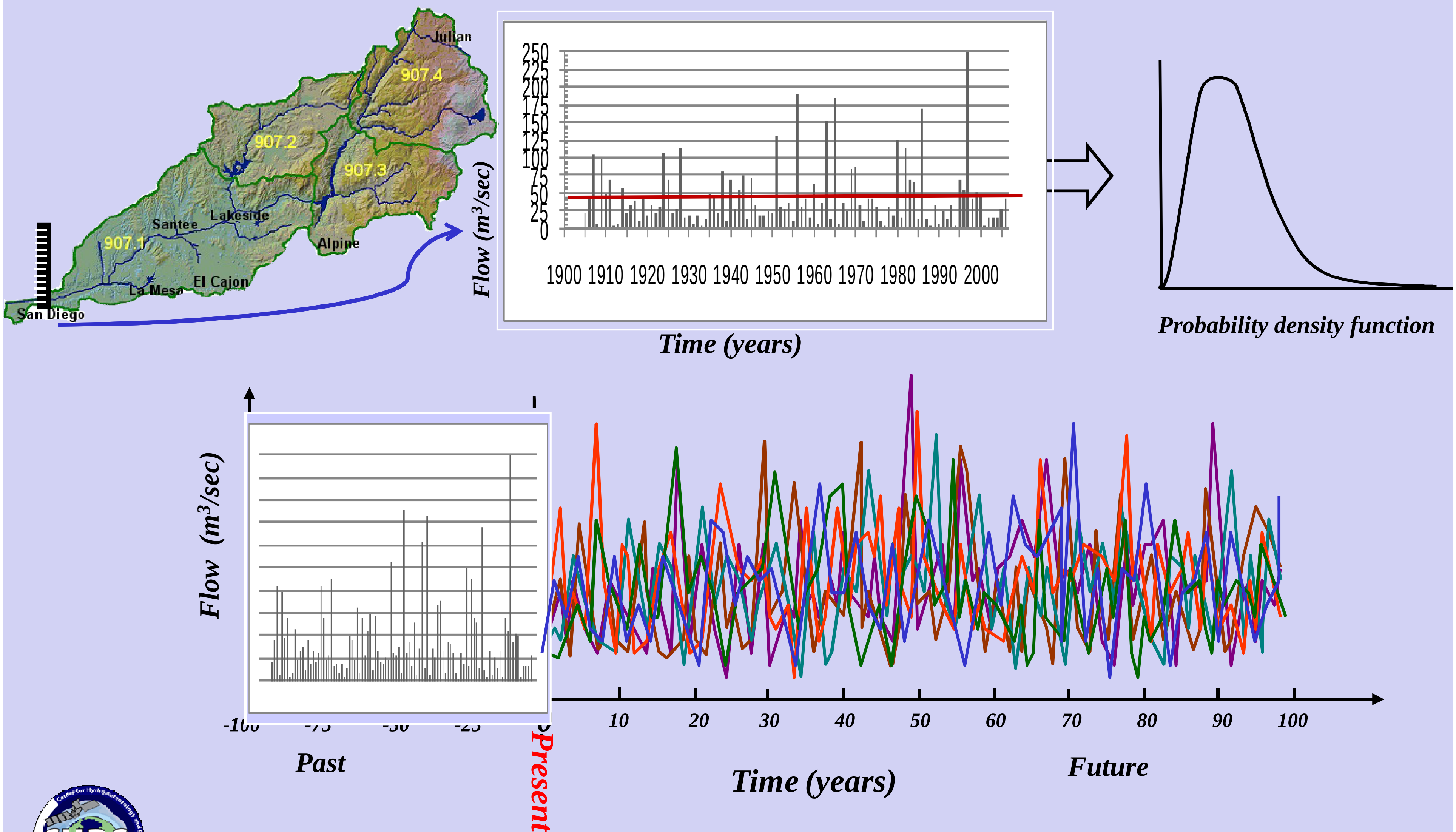
- ***Hardly used for operational Purposes and unwise to push their use while highly uncertain.***

Therefore, Factoring in Resiliency in water resources system's design and planning is still the safest approach!

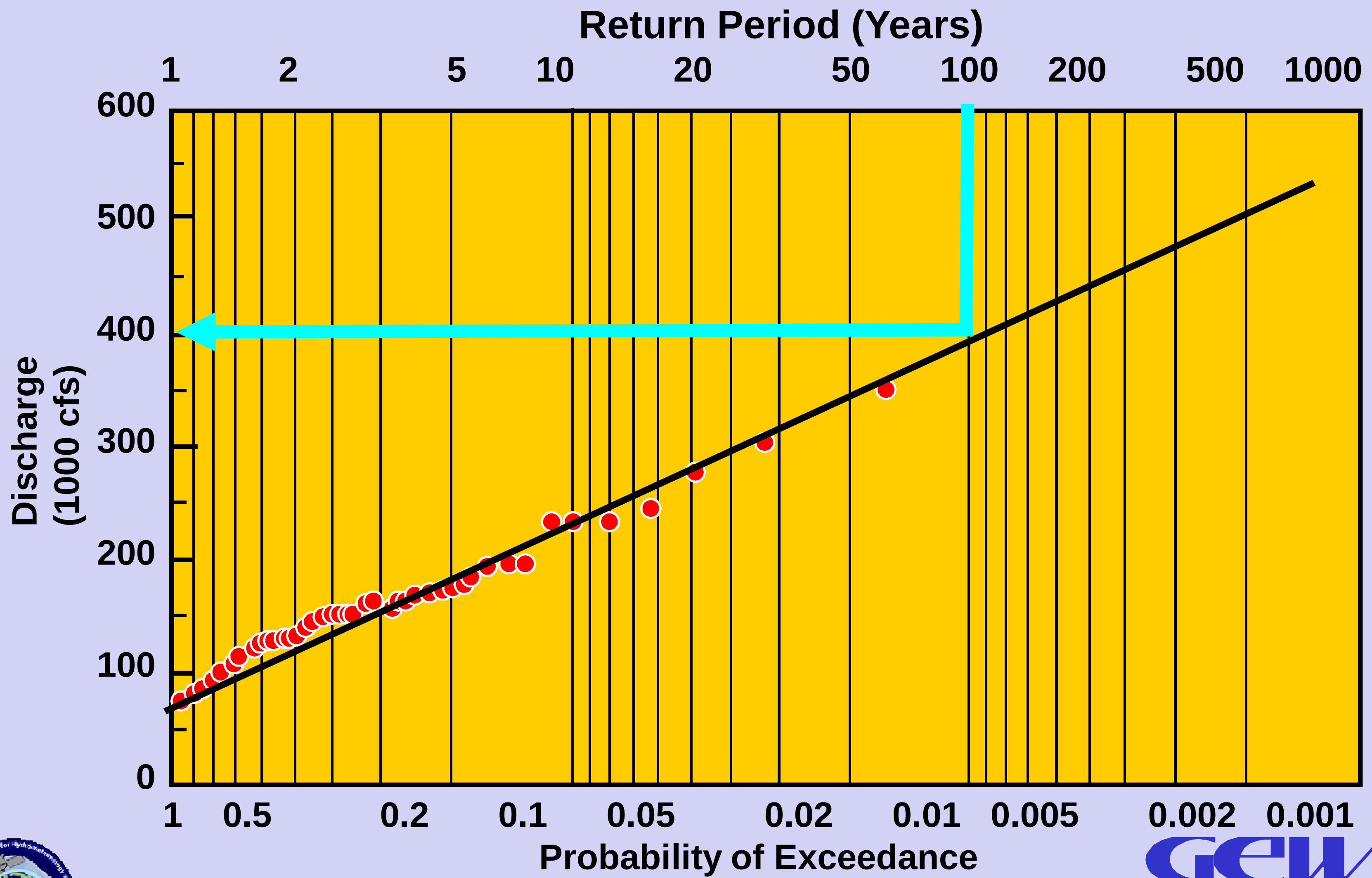
Addressing "Extremes" in Water Resources Planning:

Stochastic Hydrology

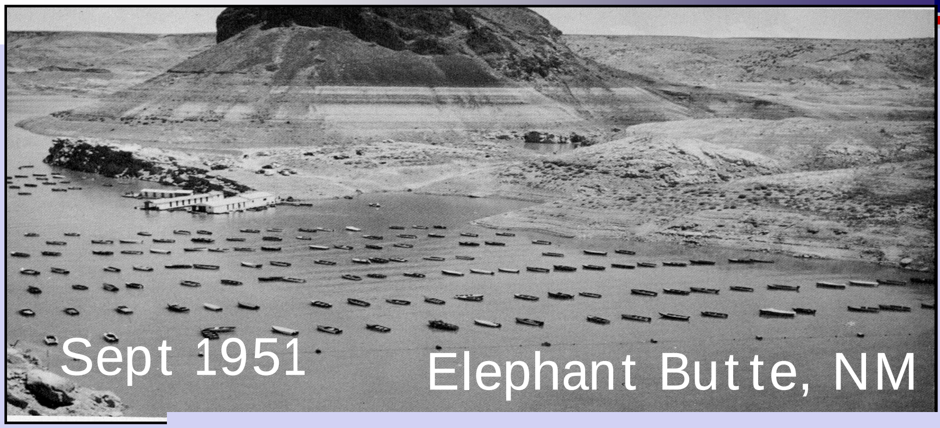
Statistical Hydrology: "synthetic" stream flow Generation



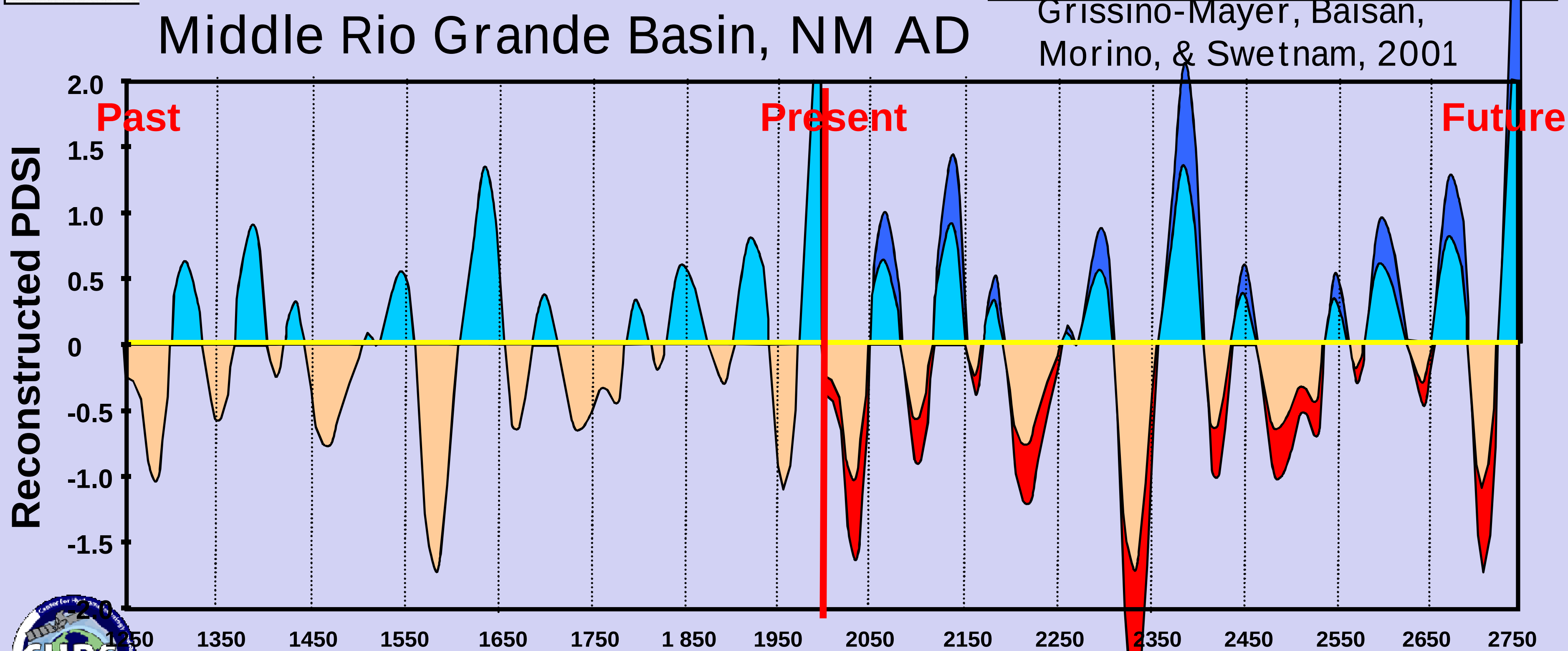
Flood Frequency Analysis: Stationarity!



Statistical Hydrology Developed Based on Stationarity Assumption



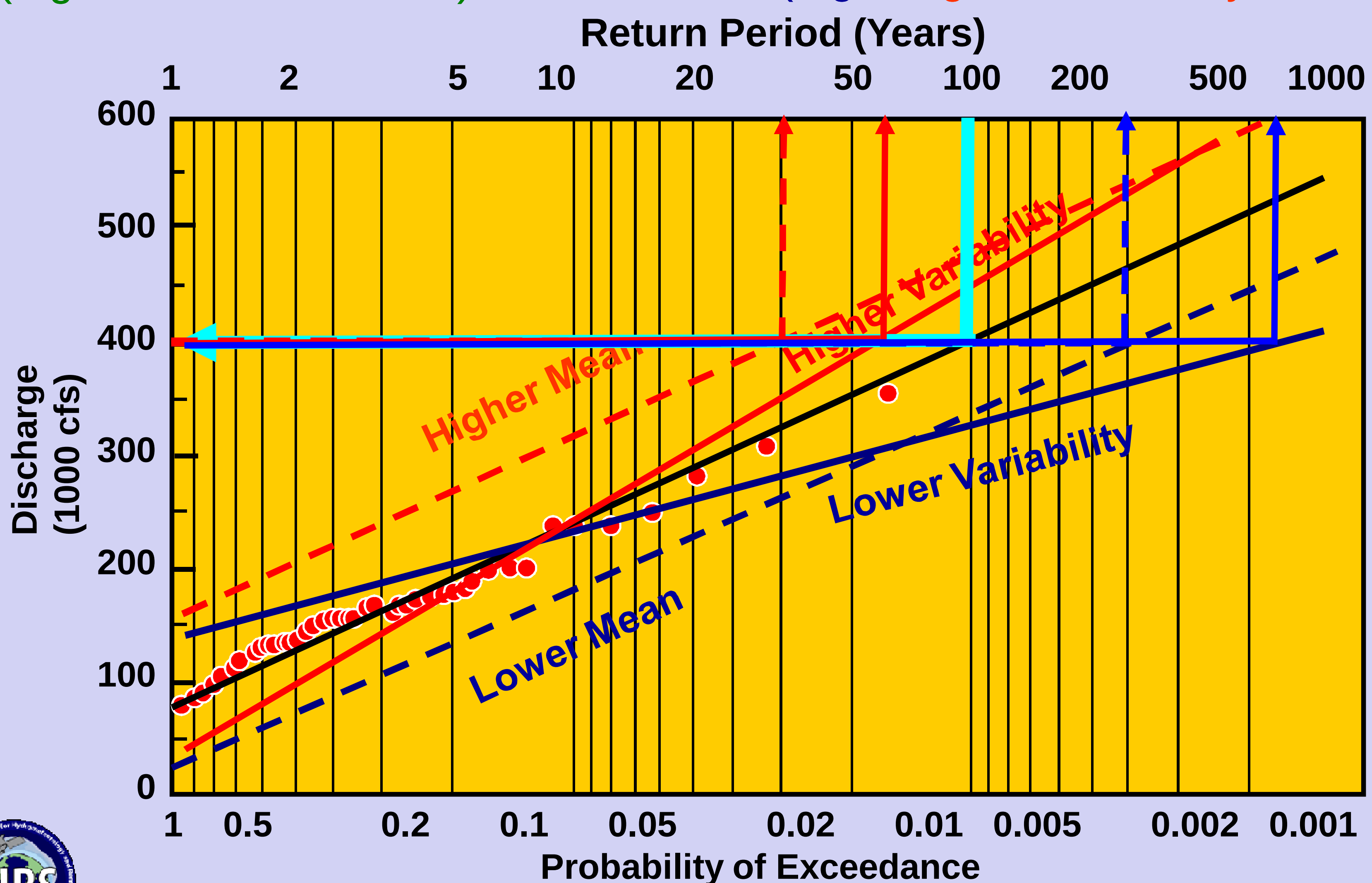
Grissino-Mayer, Baisan, Morino, & Swetnam, 2001



Potential Hydrologic Scenarios

1. Precipitation and Runoff Trends
   (e.g. increase/decrease)

2. Hydrologic Variability
   (e.g. magnitude/severity/duration)



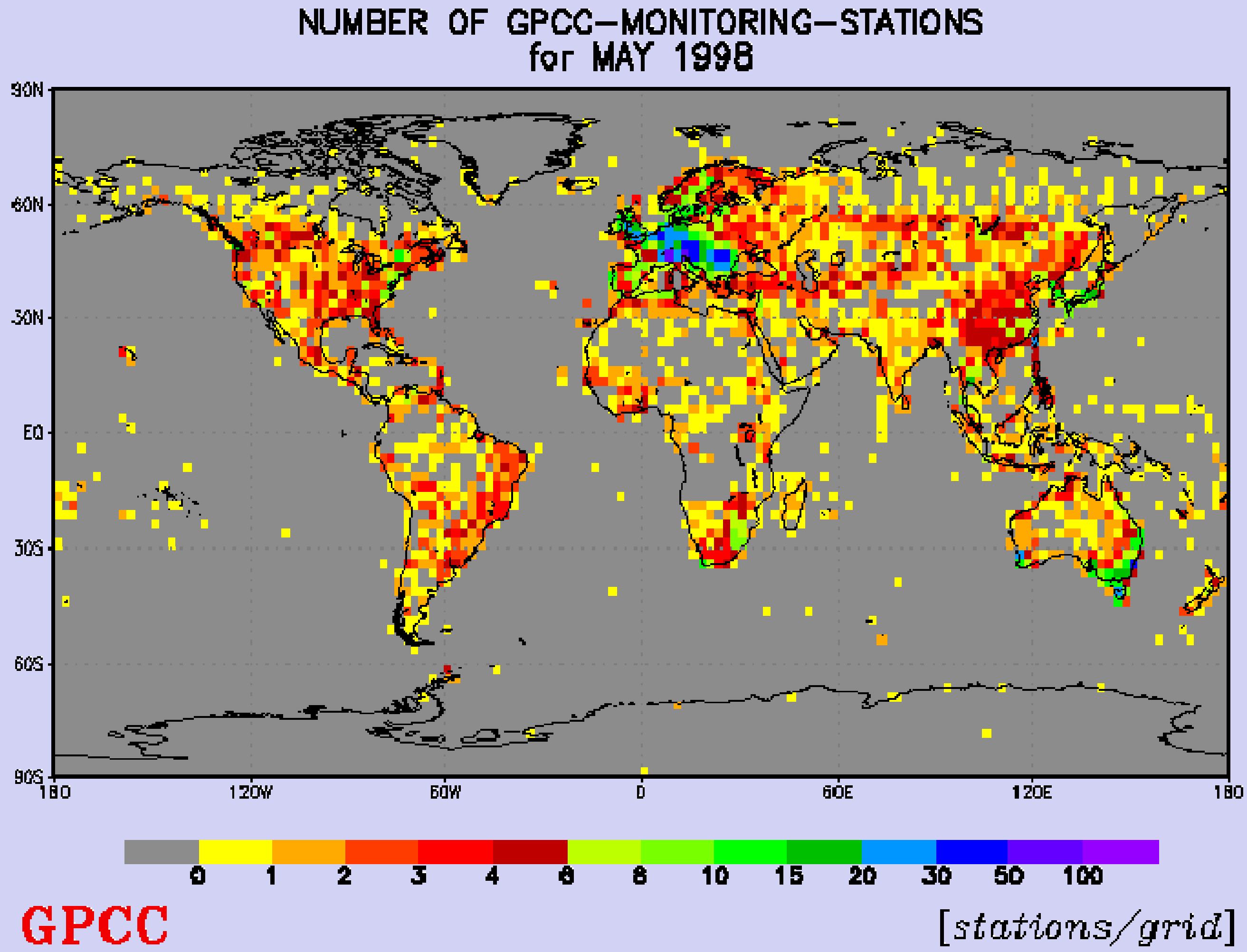
Big Challenge

Adequacy of Hydrologic Observations for model Input, Calibration and Testing

Observation of Primary Hydrologic Variables

Precipitation

Stream flow

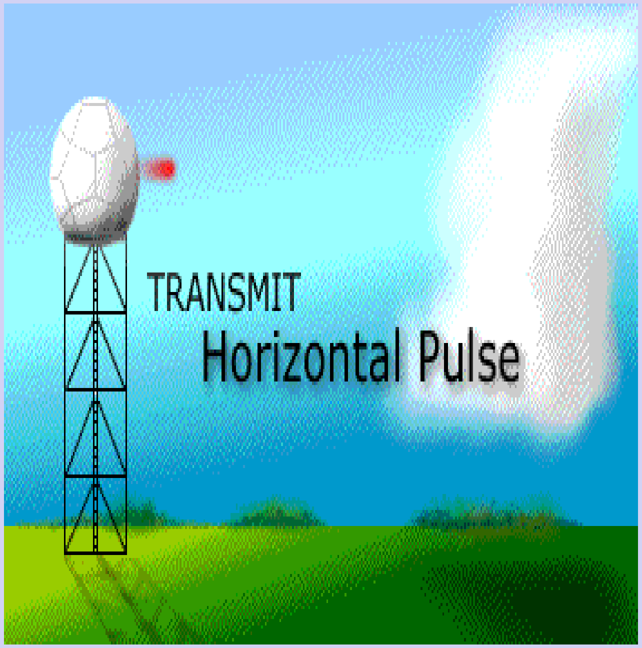


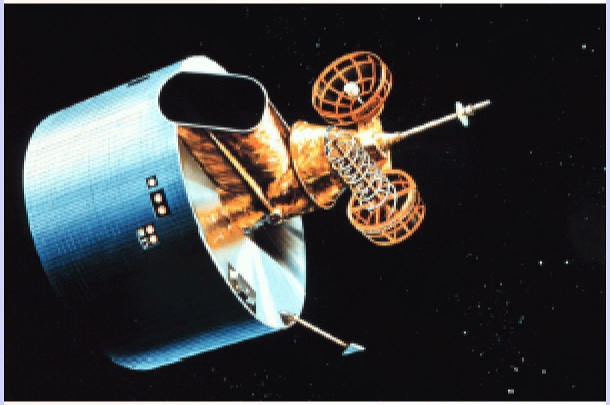
Number of range gauges per grid box*. These boxes are* ***2x2 degrees***

(Source: Global Precipitation Climatology Project)

Precipitation Observations: Which to trust??

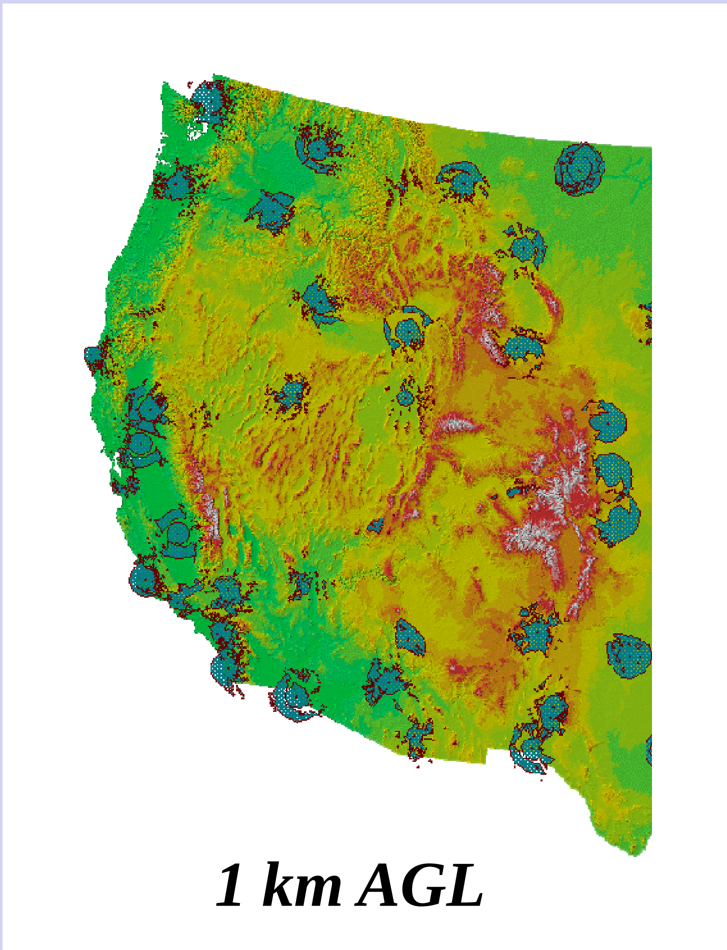
Rain Gauges



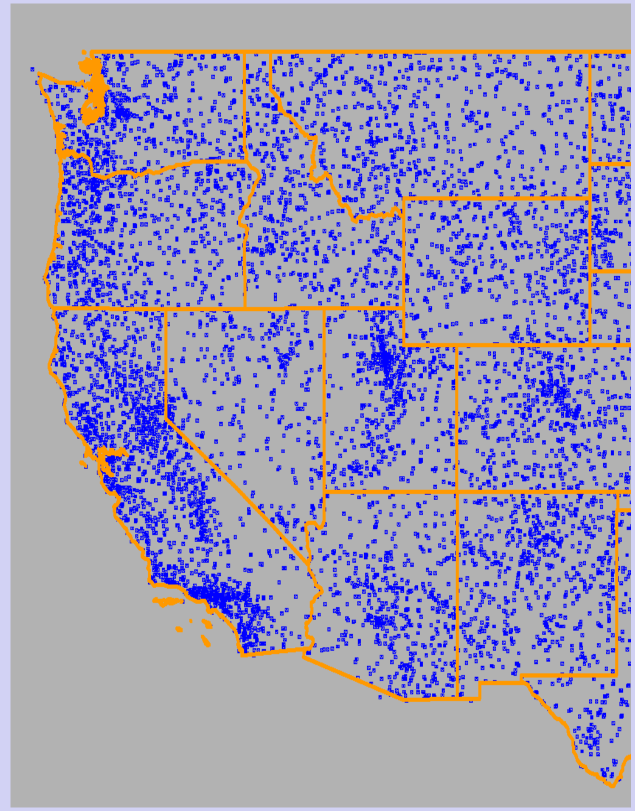


Satellite

Coverage of the WSR-88D and gauge networks

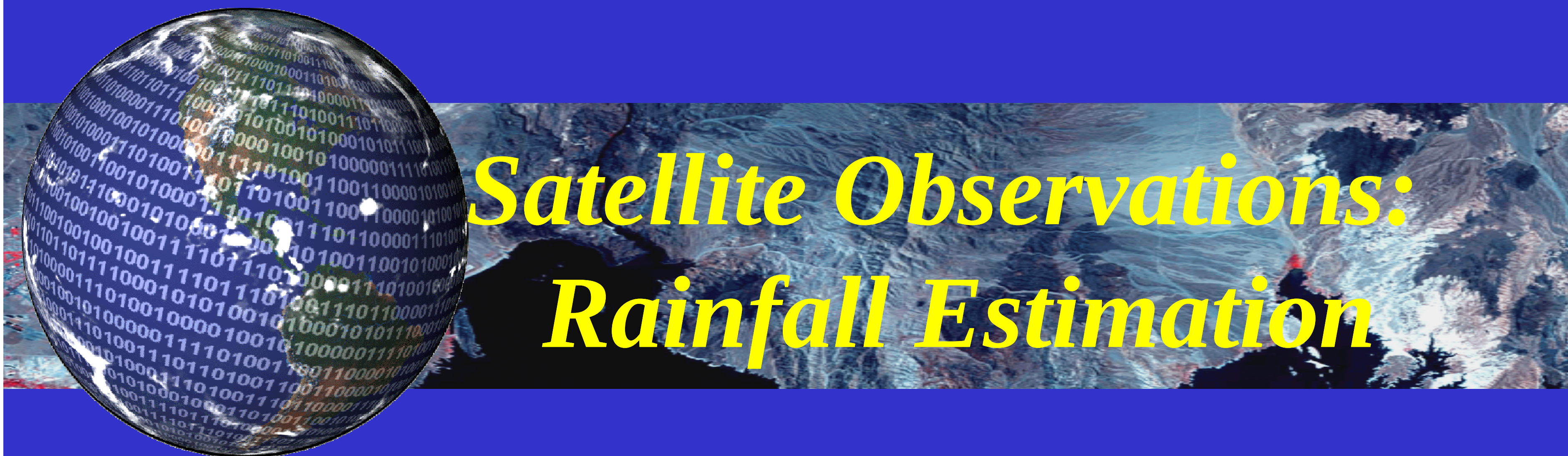


Maddox, et al., 2002



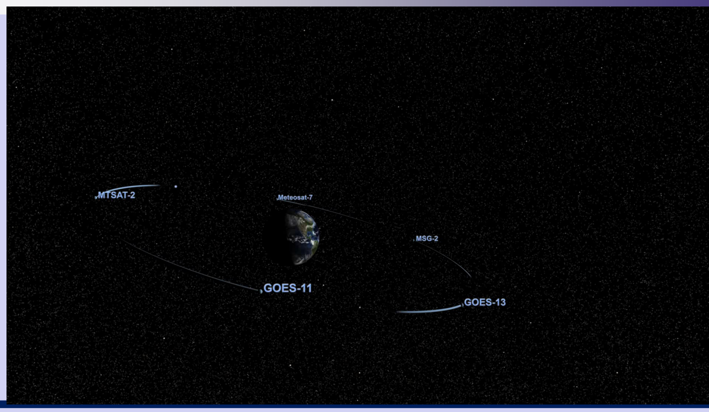
Daily precipitation gages (1 station per 600 km^2 for Colorado River basin) hourly coverage even more sparse

Space-Based Observations

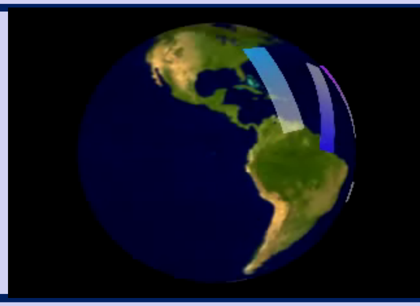


Satellite Observations: Rainfall Estimation

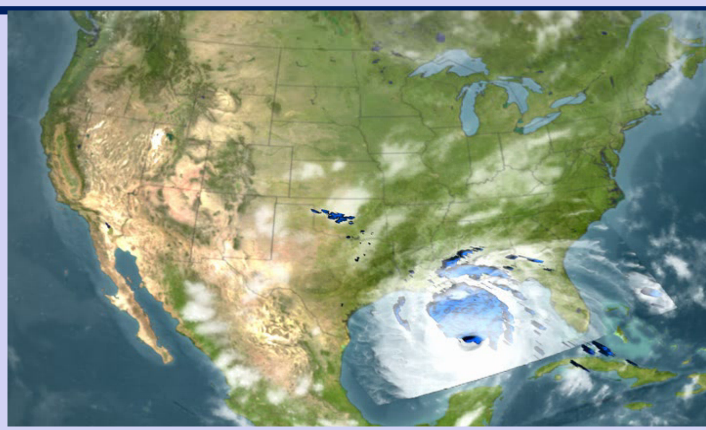
Satellite Data for Precipitation estimation



Geostationary IR
Cloud top data
15-30 minute temporal resolution



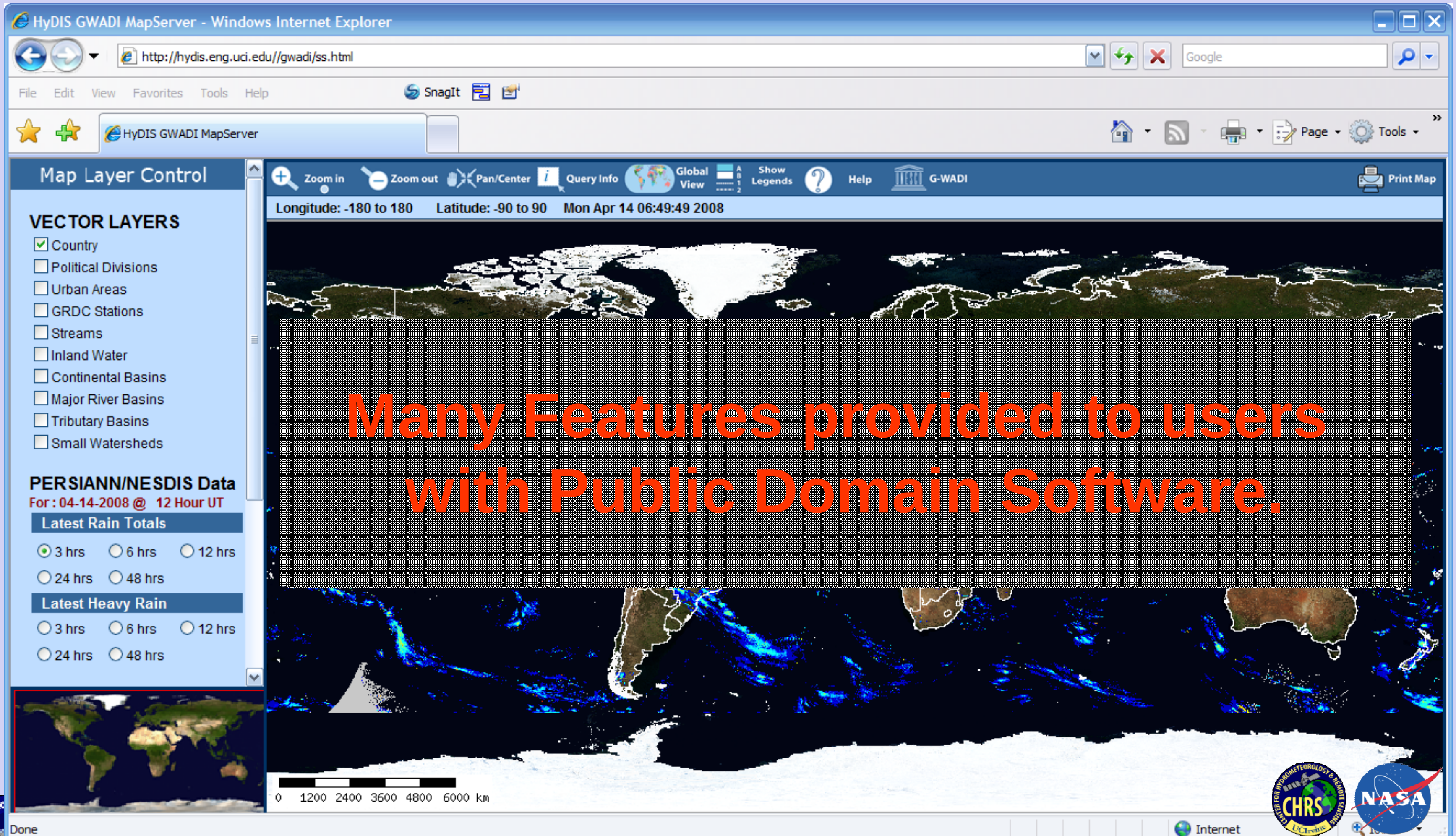
Passive Microwave (SSM/I)
Some characterisation of rainfall
~2 overpasses per day per spacecraft, moving to 3-hour return time (GPM)



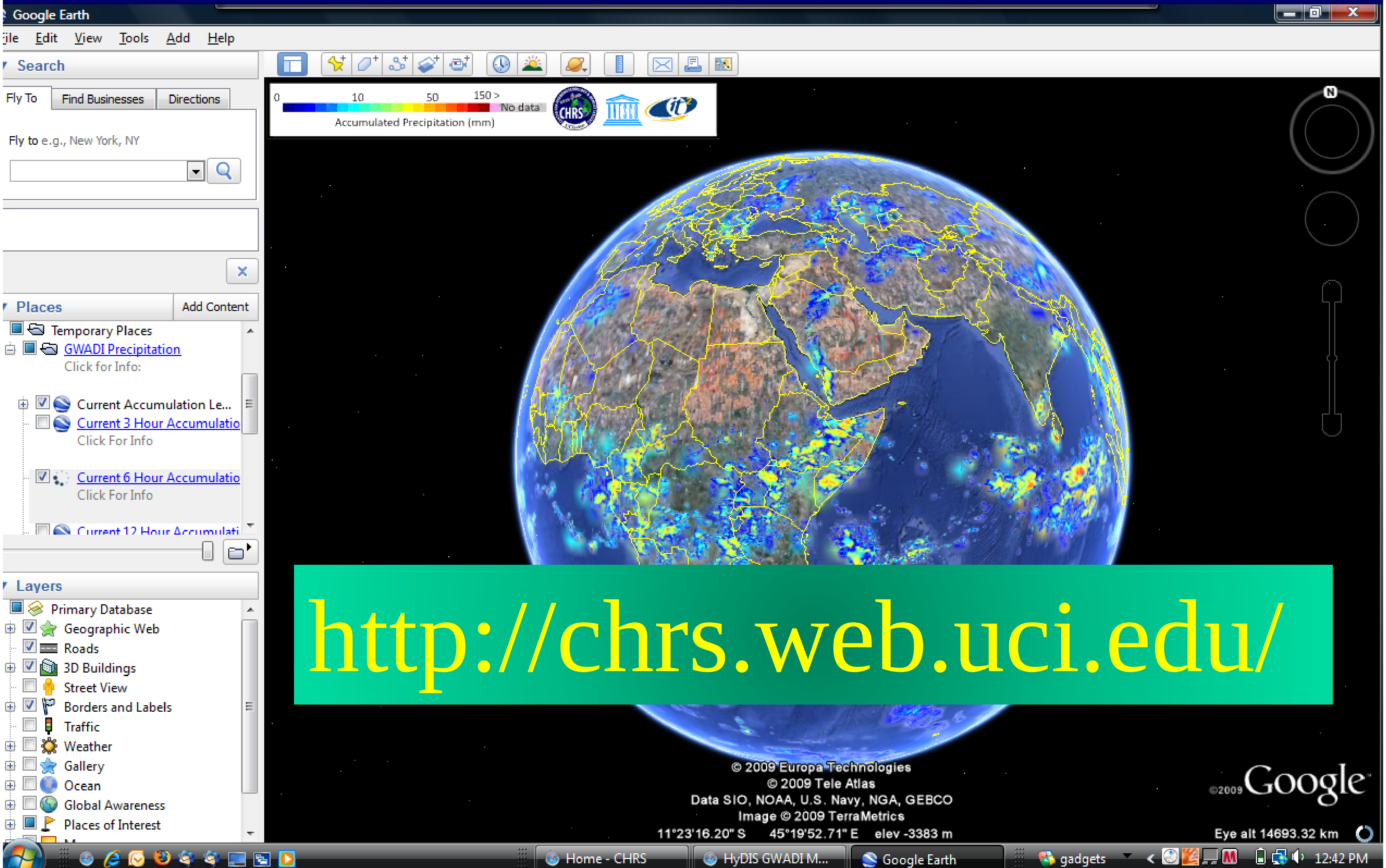
TRMM precipitation RADAR
3D imaging of rainfall
1-2 days between overpasses
(S-35°N-35 °)

Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN)

Real Time Global Data: Cooperation With UNESCO



PERSIANN Satellite Product On Google Earth



http://chrs.web.uci.edu/

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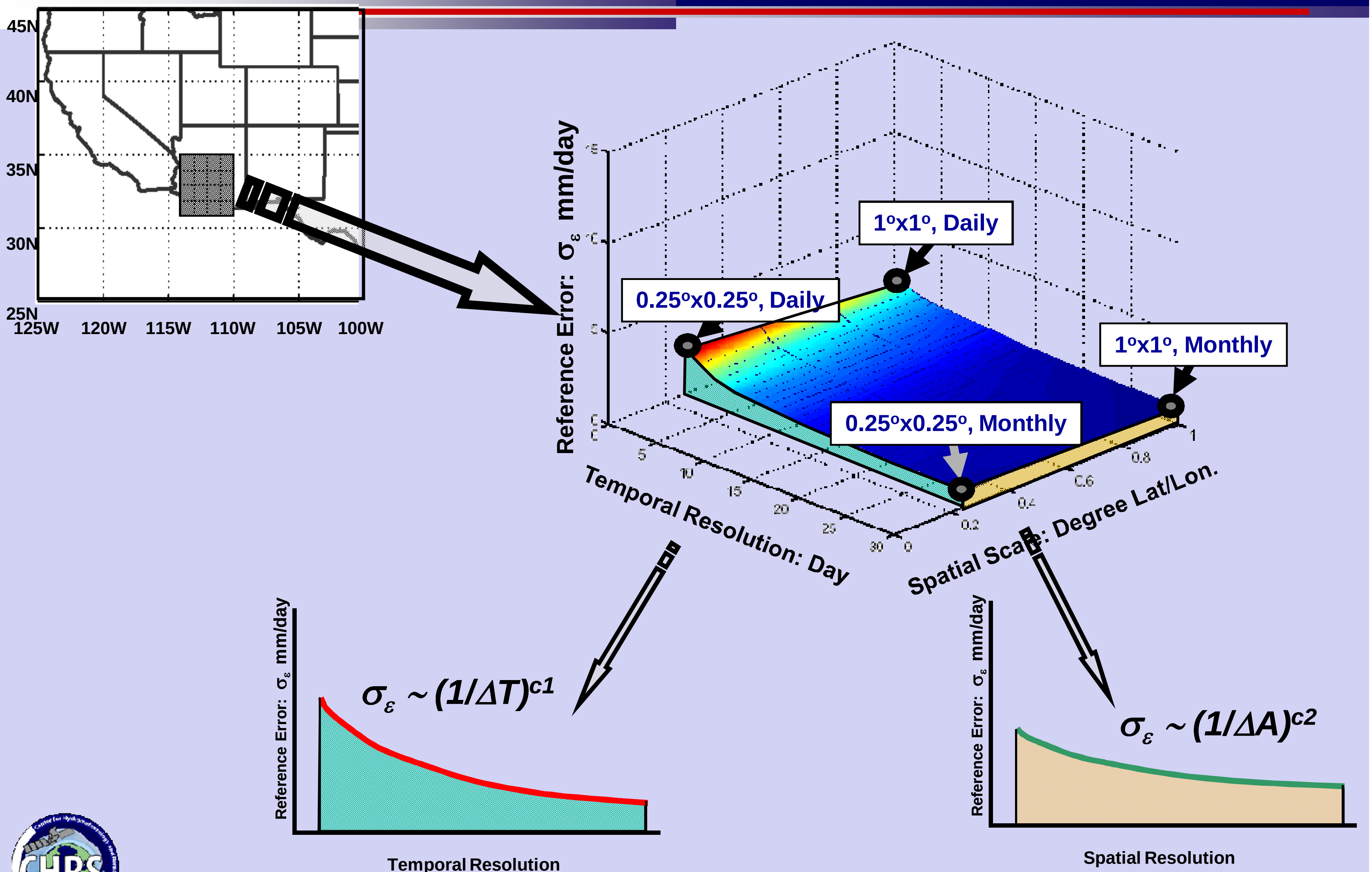
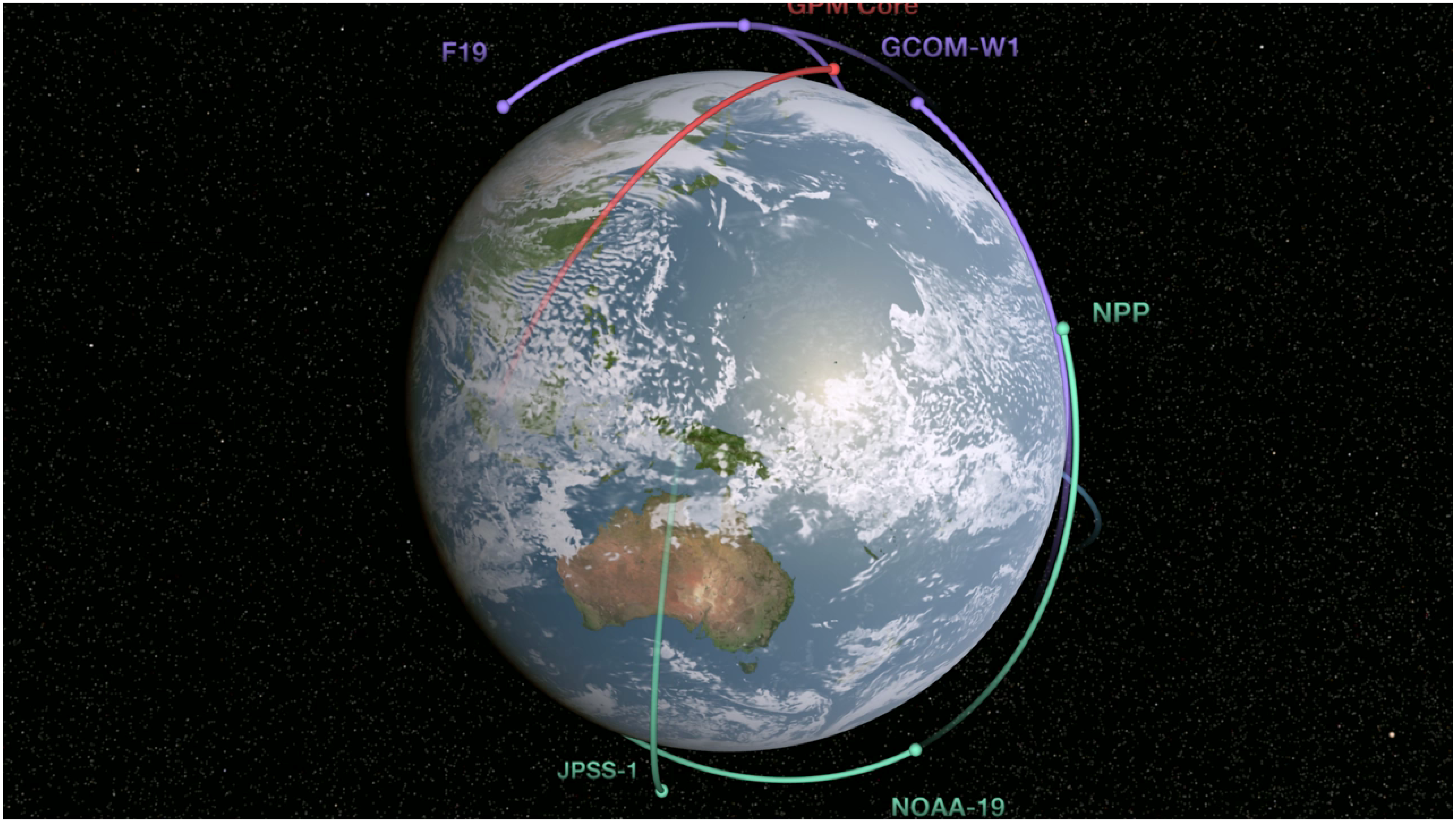
Spatial-Temporal Property of Reference Error



GPM Animation

Courtesy: NASA's ESE



PERSIANN Extensions: Climate-Related

- PERSIANN-CONNECT
- PERSIANN-CDR

PERSIANN-CONNECT

PERSIANN-**CONN**ected precipitation obj**ECT**

EOS

EOS, TRANSACTIONS, AMERICAN GEOPHYSICAL UNION

VOLUME 94 NUMBER 32 6 AUGUST 2013

IN THIS ISSUE:

Computational Earth Science: Big Data Transformed Into Insight

More than ever in the history of science, researchers have at their fingertips an unprecedented wealth of data from continuously orbiting satellites, weather monitoring instruments, ecological observatories, seismic stations, moored buoys, floats, and even model simulations and forecasts. With just an internet connection, scientists and engineers can access atmospheric and oceanic gridded data and time series observations, seismographs from around the world, minute-by-minute conditions of the near-Earth space environment, and other data streams that provide information on events across local, regional, and global scales. These data sets have become essential for monitoring and understanding the associated impacts of geological and environmental phenomena on society.

This increasing amount of data has led us

If such algorithms are run in a computer environment designed to home in on characteristics of objects or events of interest, then the data can be crunched even more efficiently, allowing insights from big data to be revealed at a quicker pace. Such machine learning evolved from artificial intelligence research and focuses on developing models that are based on the behaviors and characteristics of empirical data. Capturing the behaviors and characteristics from data and determining their underlying probability distributions can provide new knowledge regarding the object or characteristic of interest. Typically, the properties or "true" underlying probability distributions of the observed variable of interest are not explicitly known. However, by seeking to define or describe these underlying probability distributions, data mining can help scientists

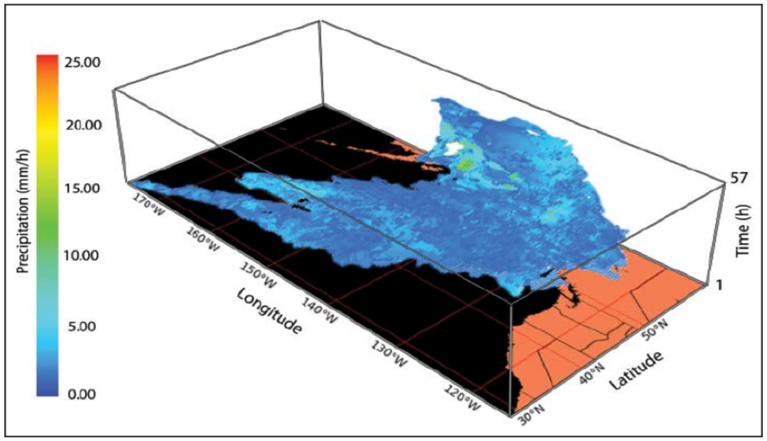
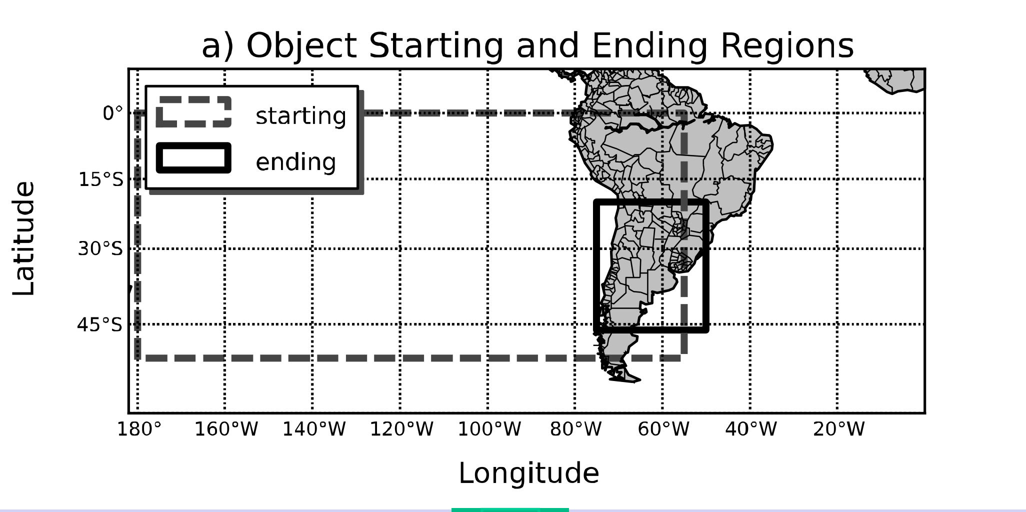
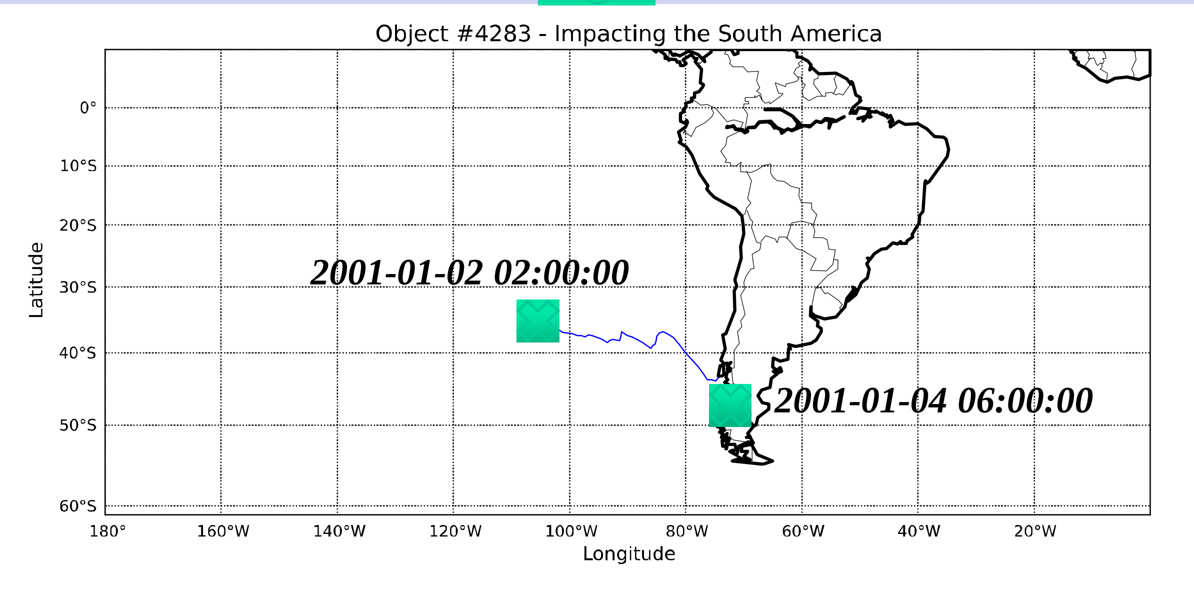


Fig. 1. A connected four-dimensional atmospheric river, or "precipitation object," extracted from the PostgreSQL database. The atmospheric river originated in the eastern Pacific and affected the western United States from 28 to 30 December 2005.

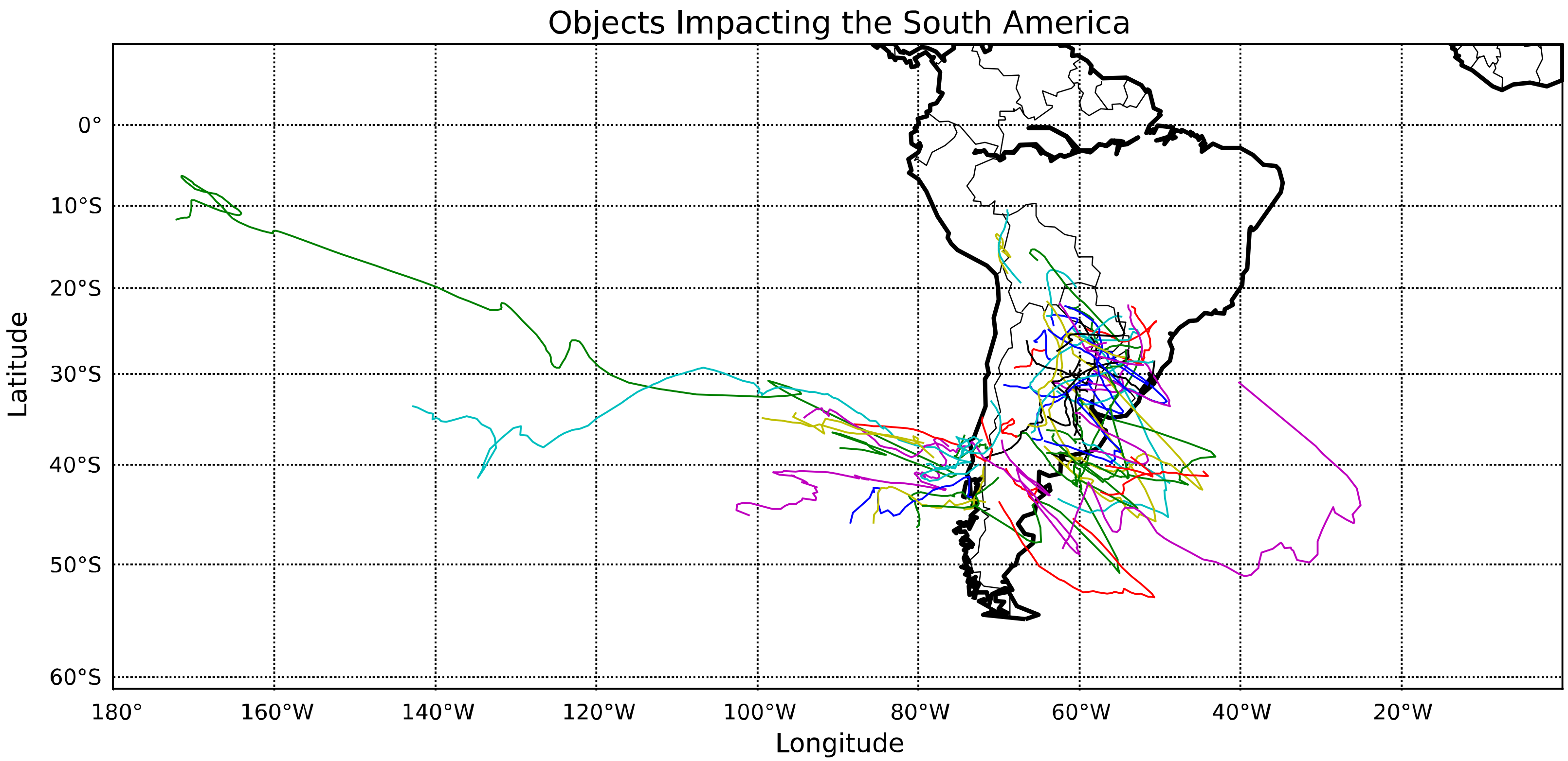
*Sellars, S., P. Nguyen, W. Chu, X. Gao, K. Hsu, and S. Sorooshian (2013), Computational Earth Science: Big Data Transformed Into Insight, EOS Trans. AGU, 94(32),277

Regional Search: Specific Storm

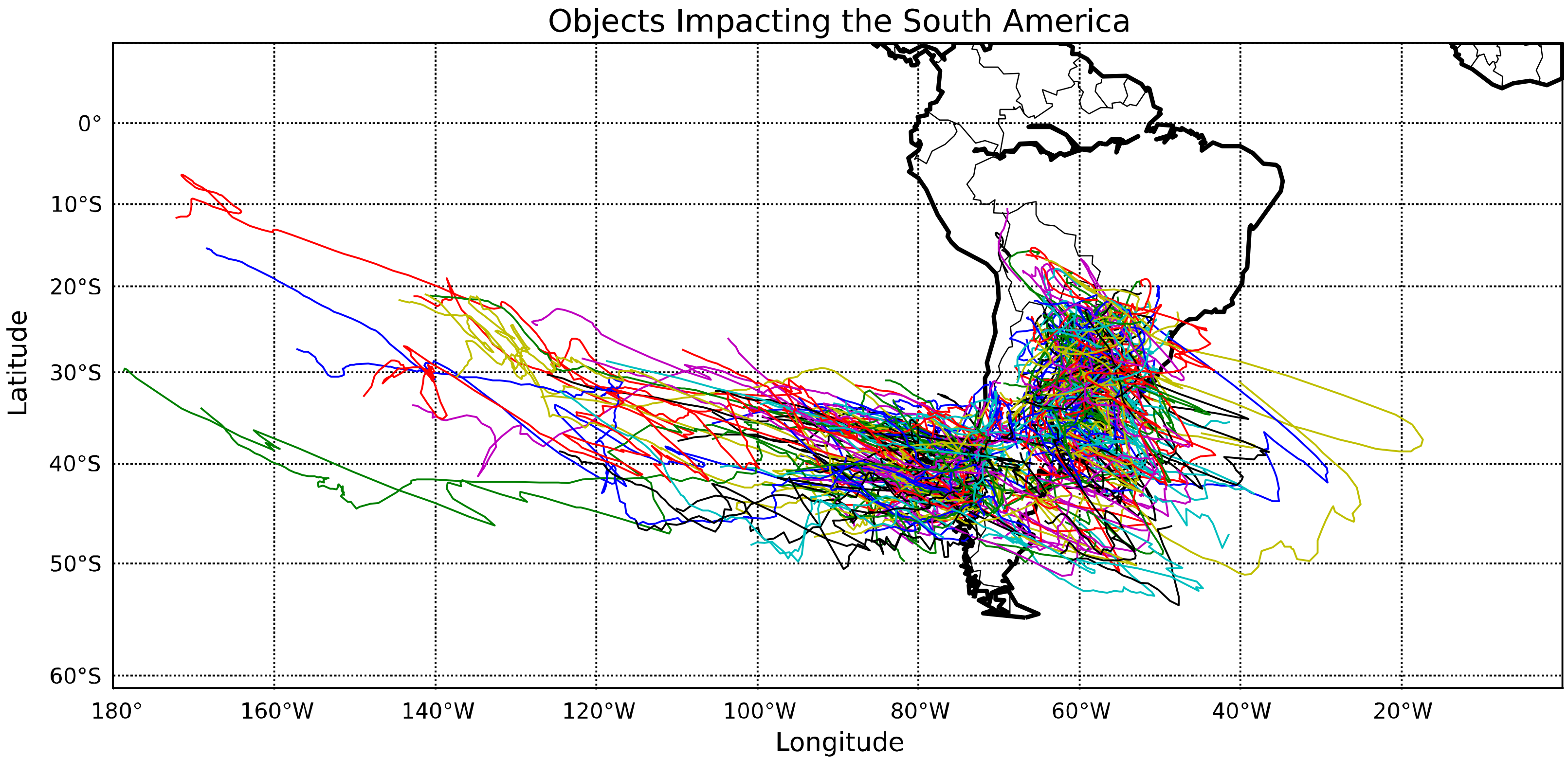




Regional Search: 2001 Storms



Regional Search: All Storms (2000-2010)



Daily precipitation (mm/day) of Typhoon Haiyan

11-11

date

0

9

8

7

6

5

4

3

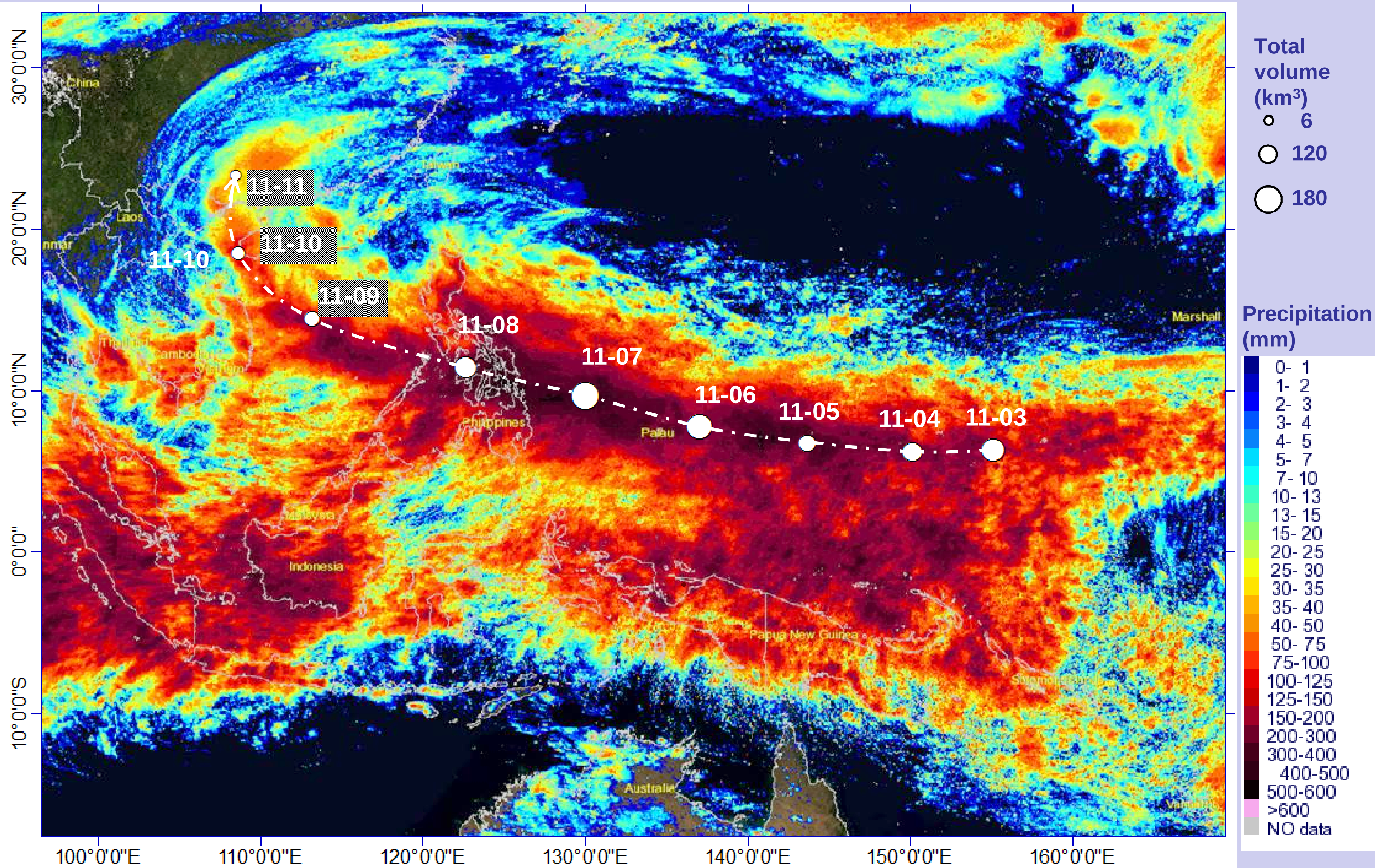
Precipitation (mm/day)

0- 1
1- 2
2- 3
3- 4
4- 5
5- 7
7- 10
10- 13
13- 15
15- 20
20- 25
25- 30
30- 35
35- 40
40- 50
50- 75
75-100
100-125
125-150
150-200
200-300
300-400
400-500
500-600
>600
NO data

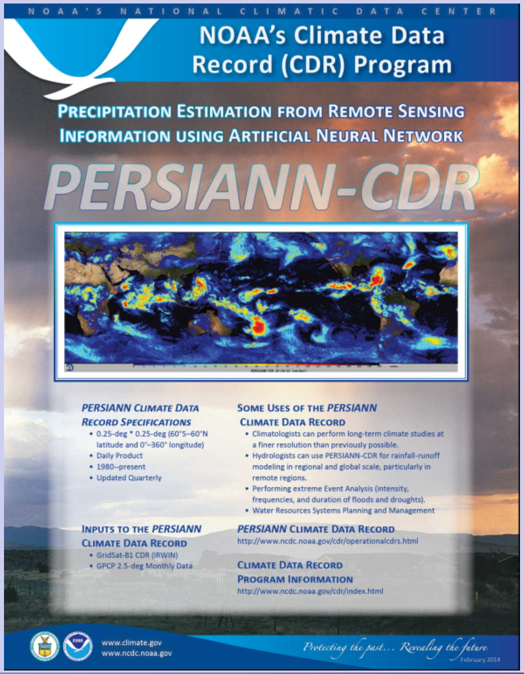
Tracking characteristics of Typhoon Haiyan

Date	Max Precip. Intensity (mm/d)	Total Volume (km3)
11/3/2013	243.67	143.254
11/4/2013	265.65	114.829
11/5/2013	332.88	108.398
11/6/2013	328.25	150.658
11/7/2013	360.94	184.89
11/8/2013	320.47	126.253
11/9/2013	220.7	53.126
11/10/2013	130.69	24.673
11/11/2013	70.27	6.233

Typhoon Haiyan – Total Accumulated Precipitation (mm)



Evaluation of PERSIANN-CDR in Rainfall-Runoff Modeling



PERSIANN-C… ord

http://www.ncdc.noa…

NOA…

Home | Operational CDRs | D…

SEARCH NCDC

CLIMATE DATA RE…

- Serving the Public
- Data
- Development Guidelines
- Contact Us

News

Climate Data and Applications Workshop - A Focus on Precipitation - Dec 3-4, 2013

Congratulations Cheng-Zhi Zou

2013 CDR Annual Meetings Presentations now available

…vironmental Satellites: Interim …d. The first step in establishing …taset itself, and supporting …rs Guidelines.

…ospheric, Oceanic, and …tures) that have been improved … are geophysical variables …cific to various disciplines. …ut.

Documentation
Algorithm Description Data Flow Diagram Maturity Matrix
Algorithm Description Data Flow Diagram Maturity Matrix
Algorithm Description Data Flow Diagram Maturity Matrix
Algorithm Description Data Flow Diagram Maturity Matrix
Algorithm Description Data Flow Diagram Maturity Matrix

Paper submitted to BAMS, Ashouri et al. 2014

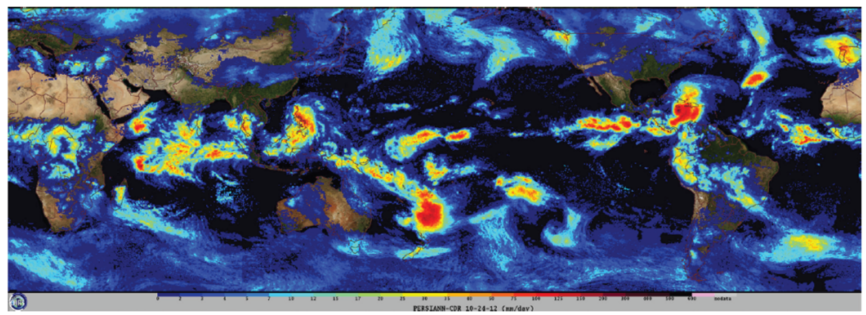
Center for H…

N O A A ' S N A T I O N A L C L I M A T I C D A T A C E N T E R

NOAA's Climate Data Record (CDR) Program

Precipitation Estimation from Remote Sensing Information using Artificial Neural Network

PERSIANN-CDR



PERSIANN Climate Data Record Specifications

- 0.25-deg * 0.25-deg (60°S–60°N latitude and 0°–360° longitude)
- Daily Product
- 1980–present
- Updated Quarterly

Some Uses of the *PERSIANN* Climate Data Record

- Climatologists can perform long-term climate studies at a finer resolution than previously possible.
- Hydrologists can use PERSIANN-CDR for rainfall-runoff modeling in regional and global scale, particularly in remote regions.
- Performing extreme Event Analysis (intensity, frequencies, and duration of floods and droughts).
- Water Resources Systems Planning and Management

Inputs to the *PERSIANN* Climate Data Record

- GridSat-B1 CDR (IRWIN)
- GPCP 2.5-deg Monthly Data

PERSIANN Climate Data Record

http://www.ncdc.noaa.gov/cdr/operationalcdrs.html

Climate Data Record Program Information

http://www.ncdc.noaa.gov/cdr/index.html

www.climate.gov
www.ncdc.noaa.gov

Protecting the past… Revealing the future

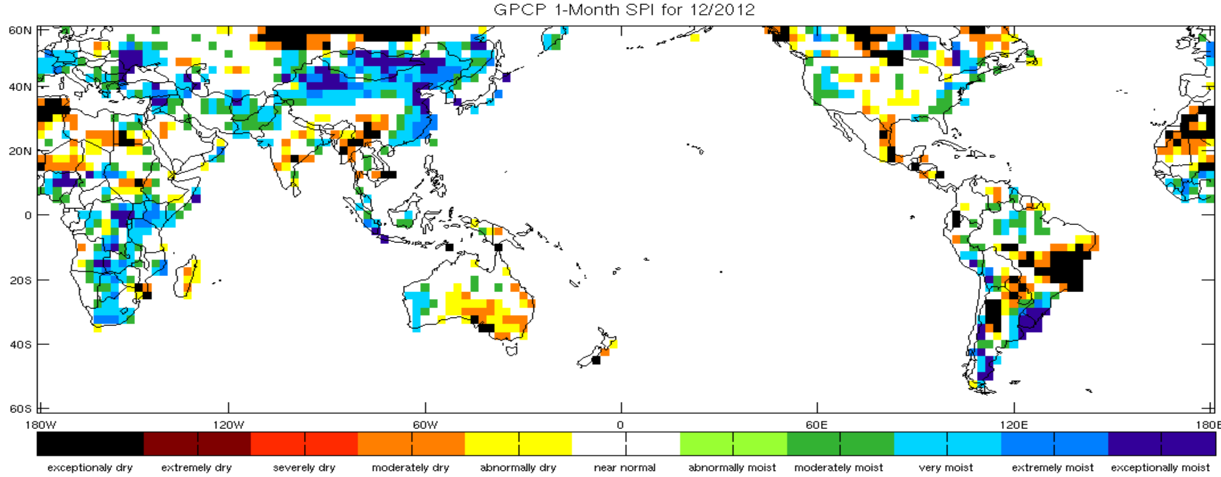
February 2014

Global Drought Monitoring

Monitoring global "abnormal" wetness and dryness conditions using Standard Precipitation Index (SPI) method from GPCP 2.5-deg monthly (top) and PERSIANN-CDR 0.25-deg daily (bottom) for the period of 1983-2012. NOTICE the difference in spatial resolution

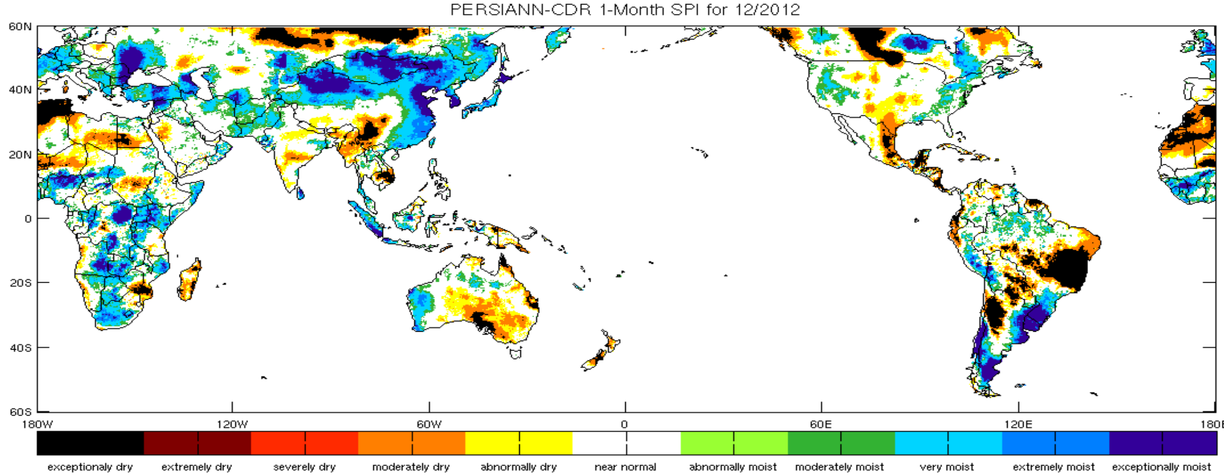
GPCP 2.5-deg monthly

GPCP 1-Month SPI for 12/2012



PERSIANN-CDR 0.25-deg daily

PERSIANN-CDR 1-Month SPI for 12/2012



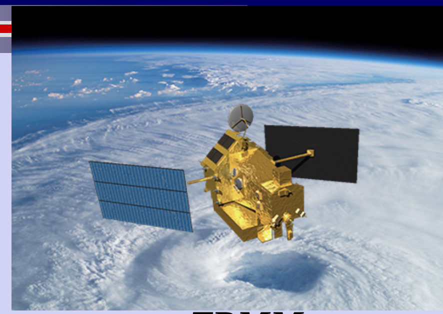
H. Ashouri

So:
What about all the Remote Sensing Observations and Model Generated Data??

Hydrologically - Relevant Remote Sensing Missions

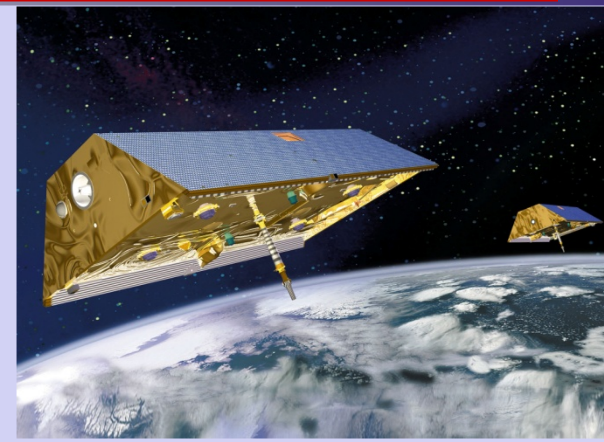
SMOS

ESA's Soil Moisture and Ocean Salinity (2009)



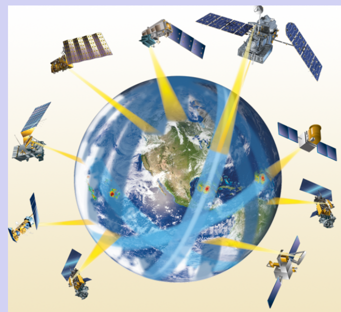
TRMM

The Tropical Rainfall Measuring Mission



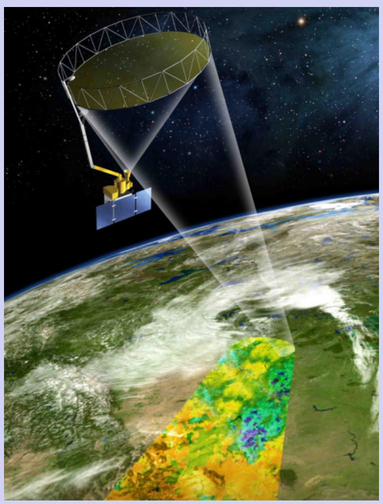
GRACE

Gravity Recovery and Climate Experiment (2002)



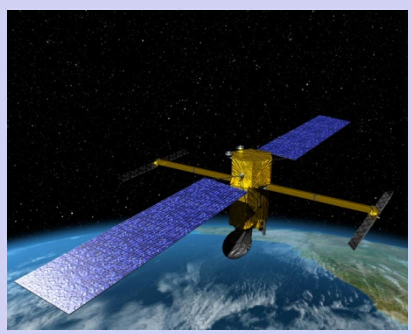
GPM

Global Precipitation Measurements (2014)



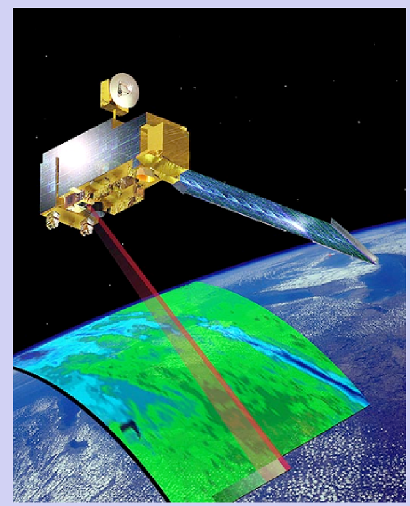
SMAP

Soil Moisture Active Passive Satellite(2014)



SWOT

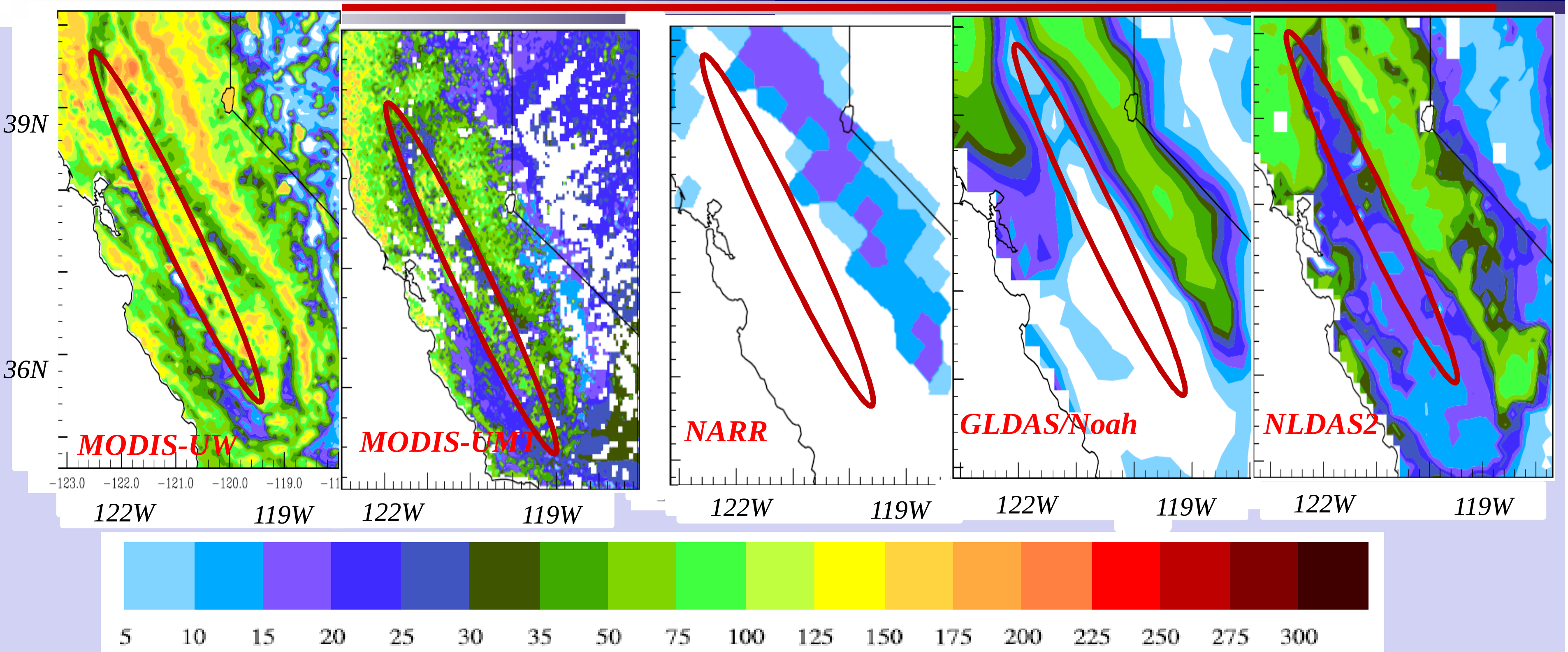
Surface Water and Ocean Topography (2020)



MODIS

Moderate Resolution Imaging Spectroradiometer (1999) , (2002)

Actual ET Estimates From Different Data sets– JJA 2007

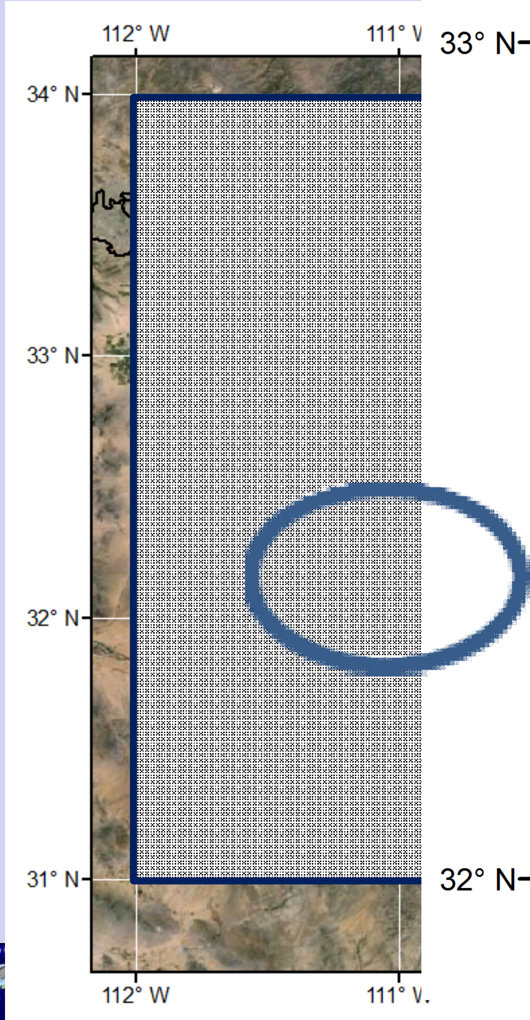


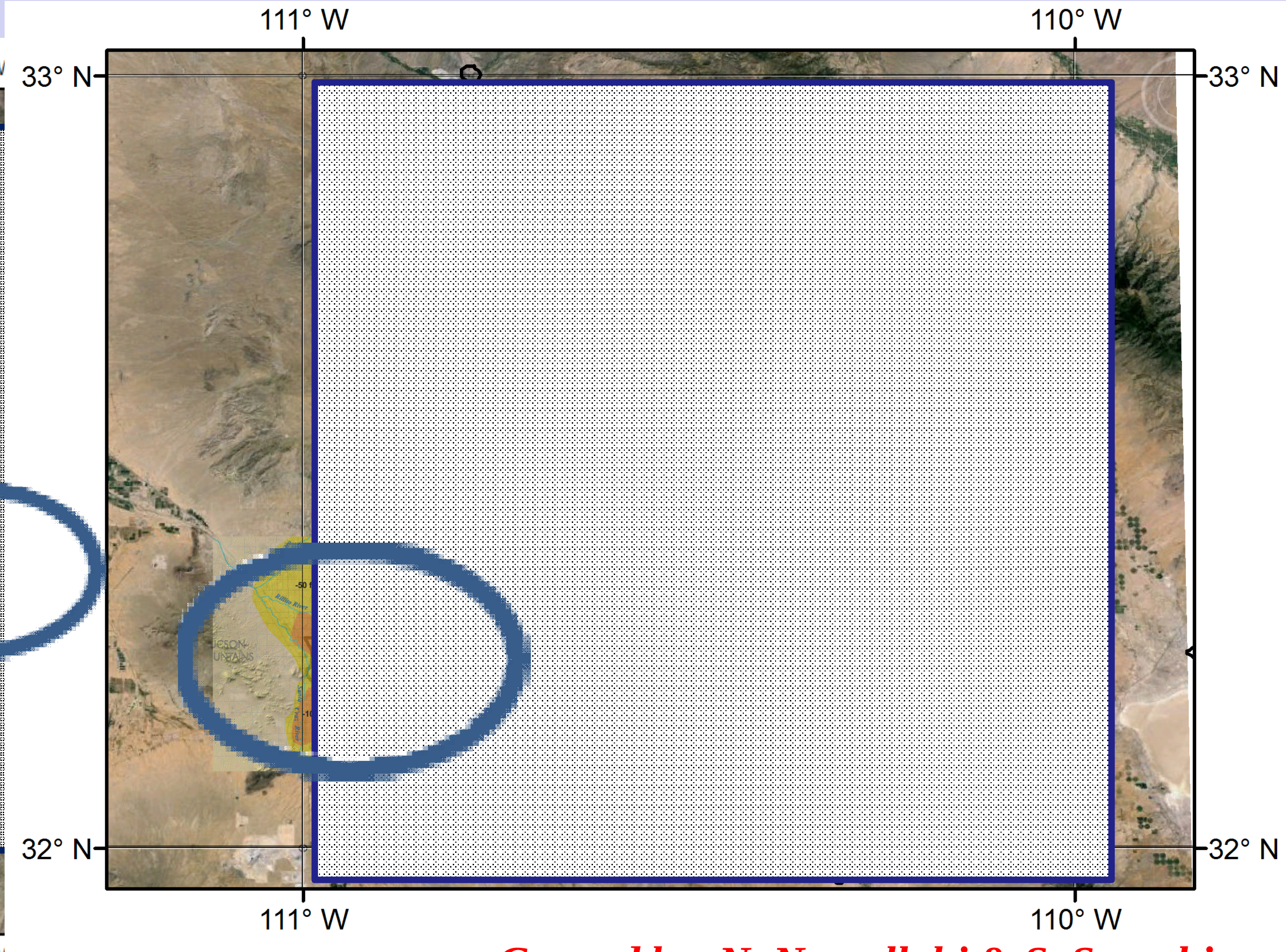
2007 JJA Monthly ET (mm)

Li et al, 2011

GRACE Satellite Footprint

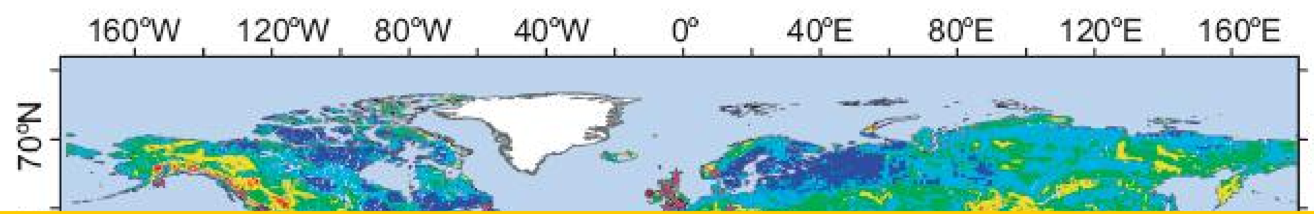
1 Degree (~100 Km) resolution



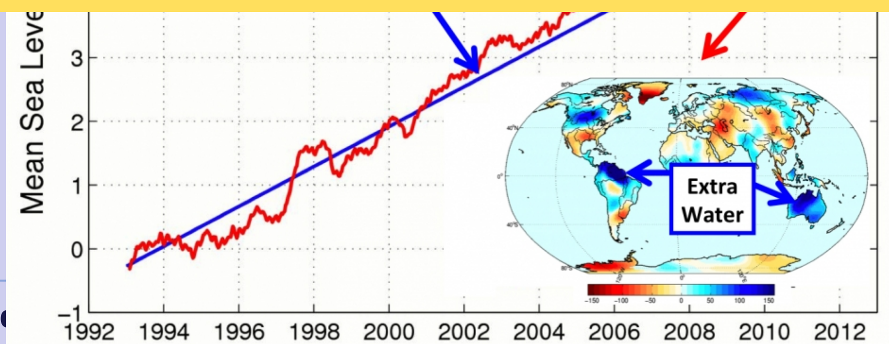


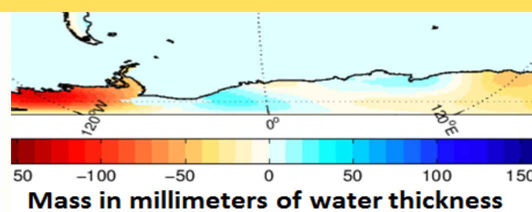
Created by: N. Nasrollahi & S. Sarachi

Landslide Risk map:



Will to Doubt: Always good to question the credibility of information reported !





What is the Message?

- ***Despite advances to date, predicting the future Hydro-Climate variables will remain a major challenge:***

Factoring in Resiliency in water resources system's design and planning is still the safest approach!

- ***Long-term and sustained observation programs are critical, especially for model verification. Without some degree of verifiability, hard to expect their use***

Thank you for the Invitation

Somewhere in New Mexico, USA - Photo: J. Sorooshian

Back up slides

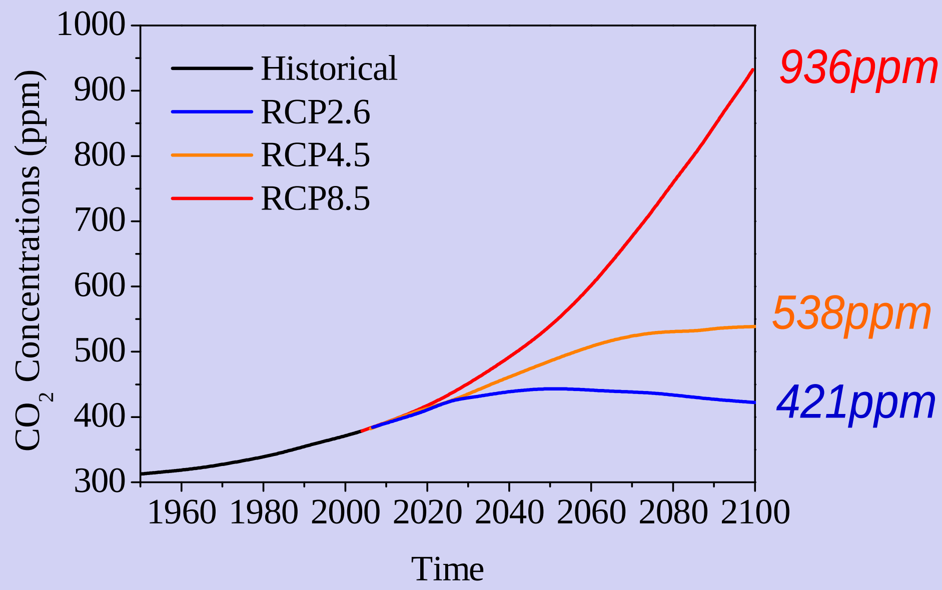
Future Modeling Scenarios

Representative Concentration Pathways (RCP) Scenarios:

RCP2.6: represent 'low' scenarios featured by the radiative forcing of 2.6 W/m^2 by 2100, the resulting CO_2-equivalent concentrations is 421 ppm in the year 2100 .

RCP4.5: represent 'medium' scenarios featured by the radiative forcing of 4.5 W/m^2 by 2100, the resulting CO_2-equivalent concentrations is 538 ppm in the year 2100 .

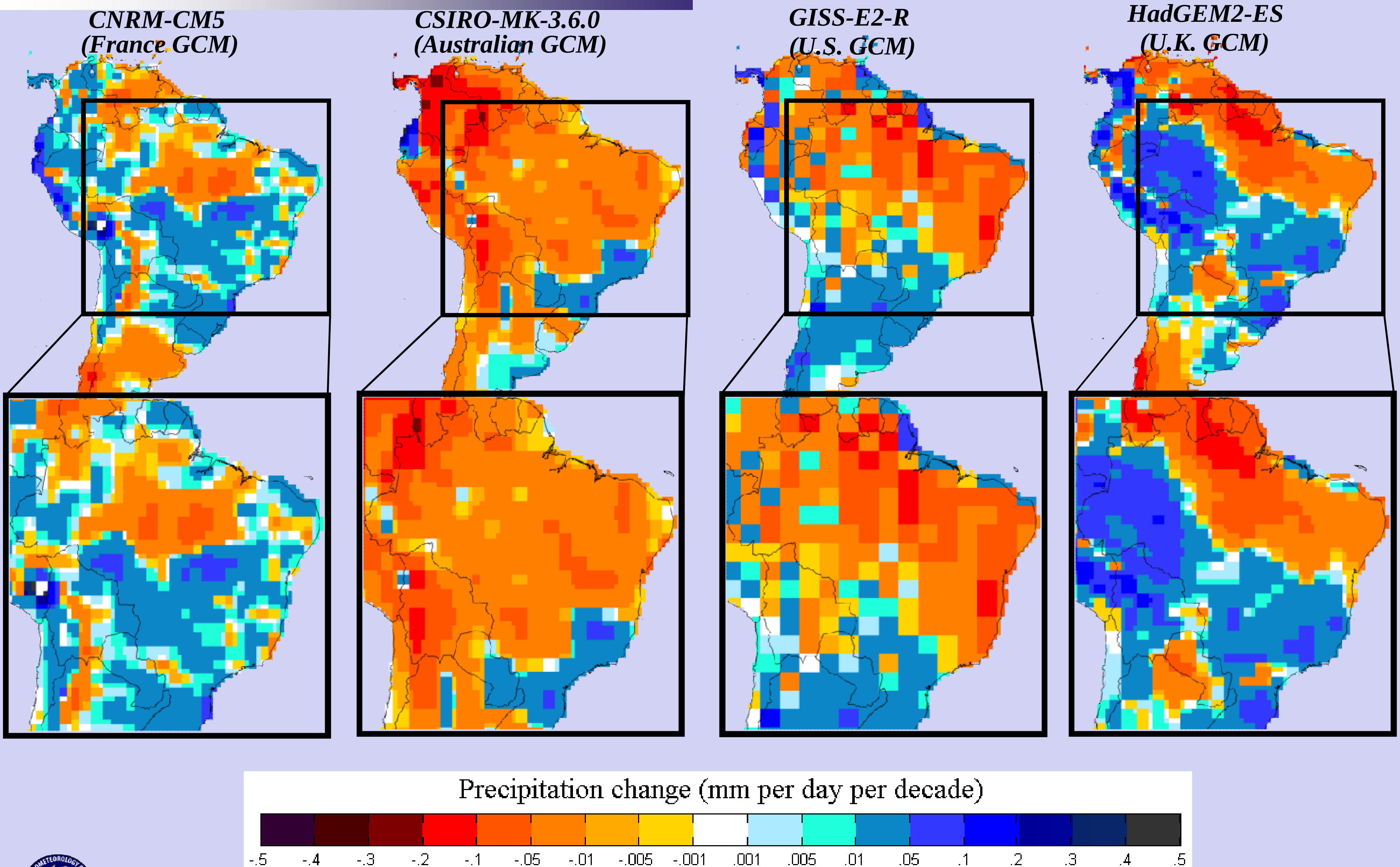
RCP8.5: represent 'high' scenarios featured by the radiative forcing of 8.5 W/m^2 by 2100, the resulting CO_2-equivalent concentrations is 936 ppm in the year 2100 .



IPCC AR5 Scenarios

Time period: 2006-2099

RCP4.5 (“Medium”: 4.5 W/m^2, Equivalent CO_2 conc. 538 ppm by 2100)



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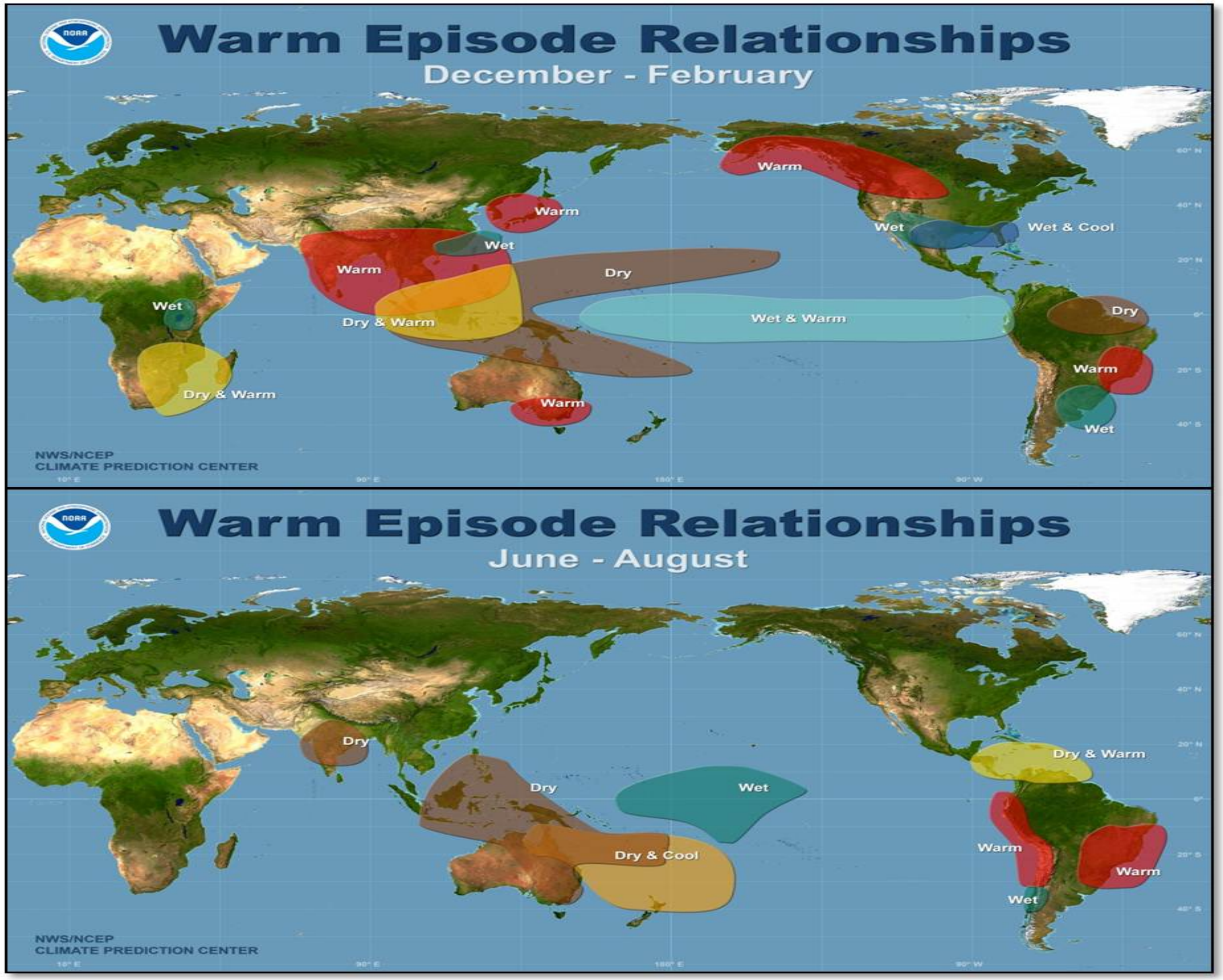
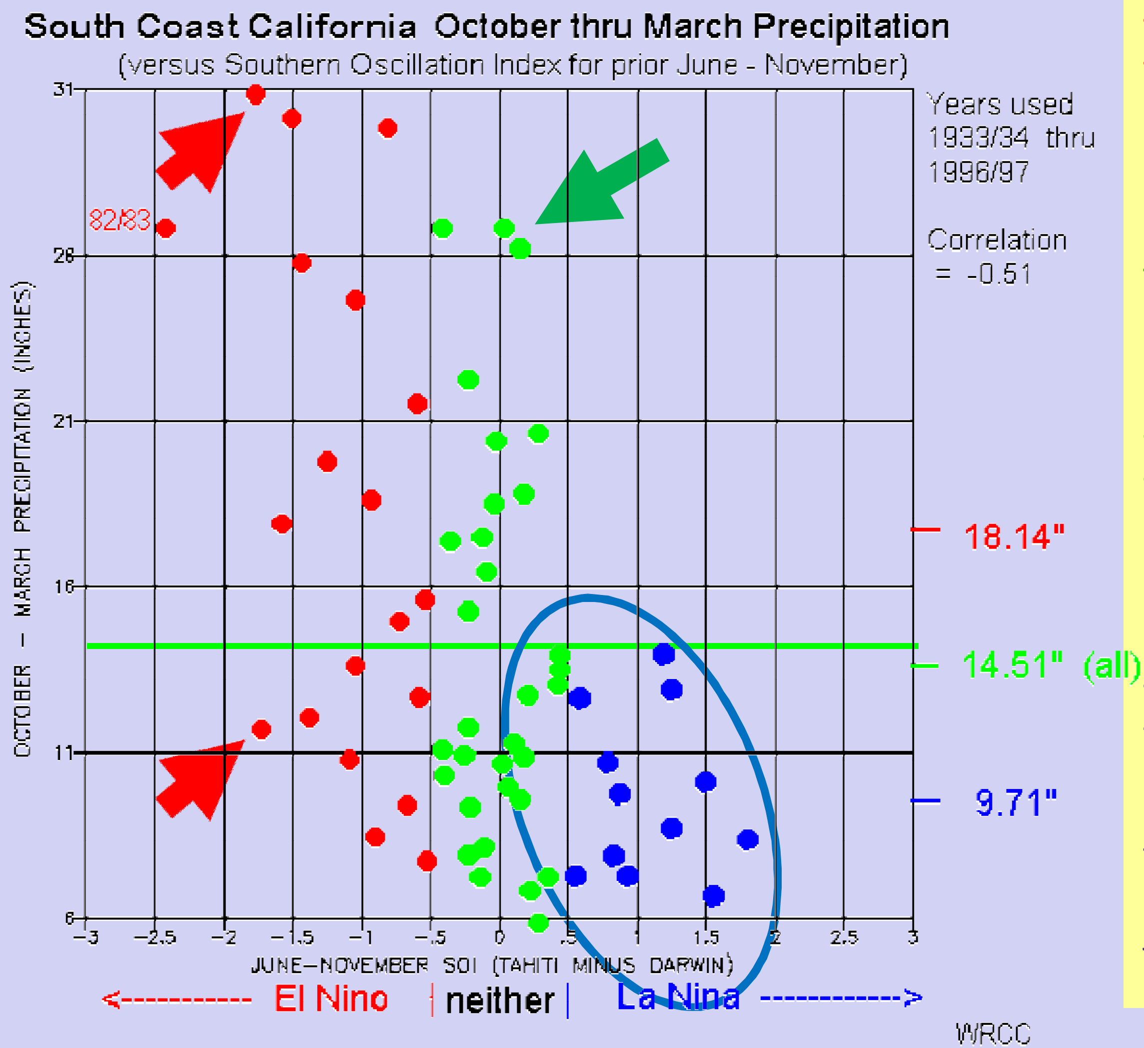
El Nino: Known Regional Influences



High Resolution Images can be found at:
http://www.cpc.ncep.noaa.gov/products/precip/CWlink/ENSO/ENSO-Global-Impacts/

ENSO Example: South Coast California



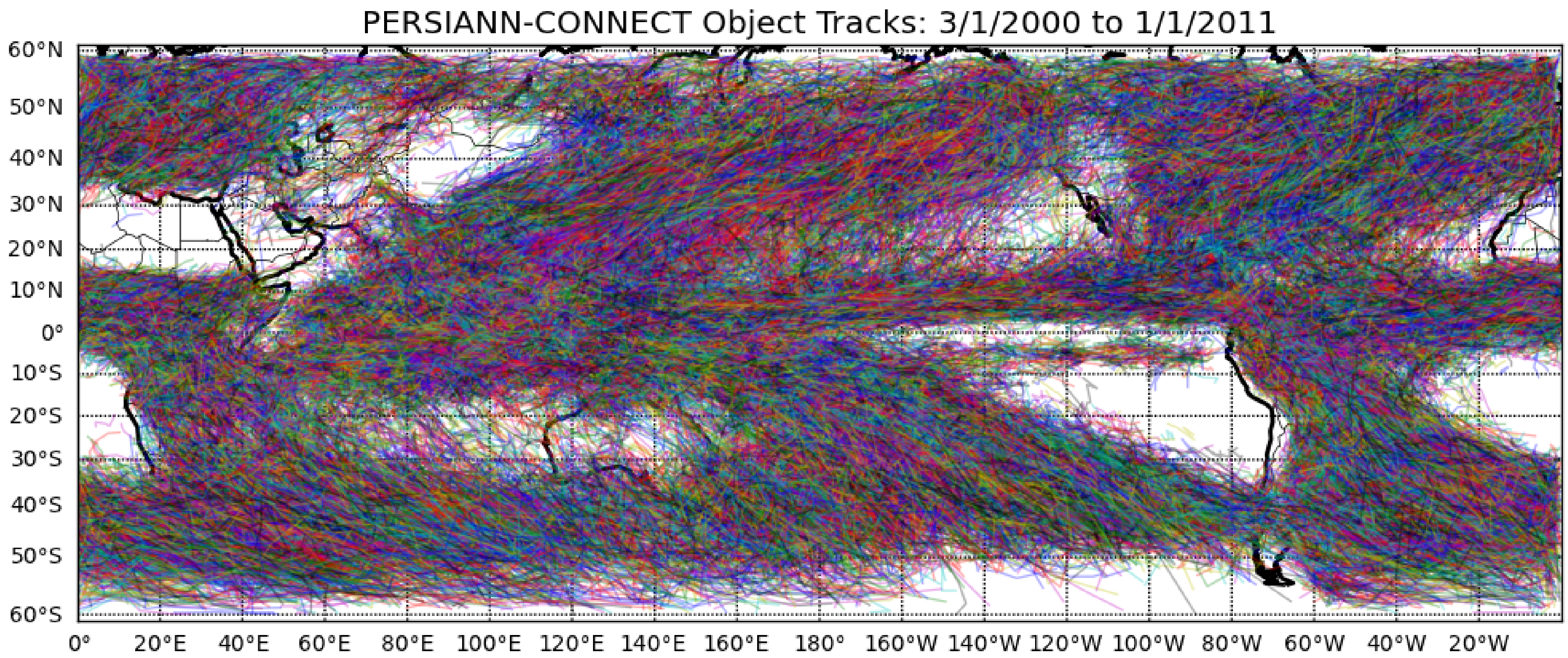
El Nino winters may be very wet.

Very wet winters are typically El Nino winters, but not always...

La Nina winters are typically dry, but reliably not wet.

* *Redmond and Koch 1991, Methodology*

Global Search: All Storms (2000-2010)



*Sellars, S., P. Nguyen, W. Chu, X. Gao, K. Hsu, and S. Sorooshian (2013), Computational Earth Science: Big Data Transformed Into Insight, EOS Trans. AGU, 94(32),277

Validation and Application of Satellite Products

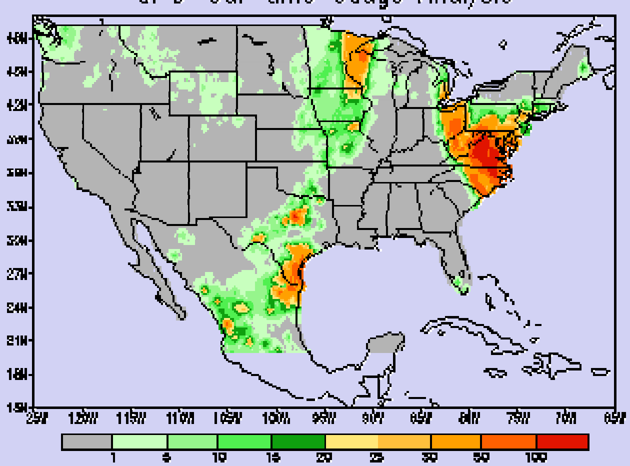
Center for Hydrometeorology and Remote Sensing, University of California, Irvine

US Daily Precipitation Validation Page

http://www.cpc.ncep.noaa.gov/products/janowiak/us_web.html

13Z 19Sep2003 thru 12Z 19Sep2003
Data on 0.25 deg grid (UNITS are mm/day)

CPC real-time Gauge Analysis



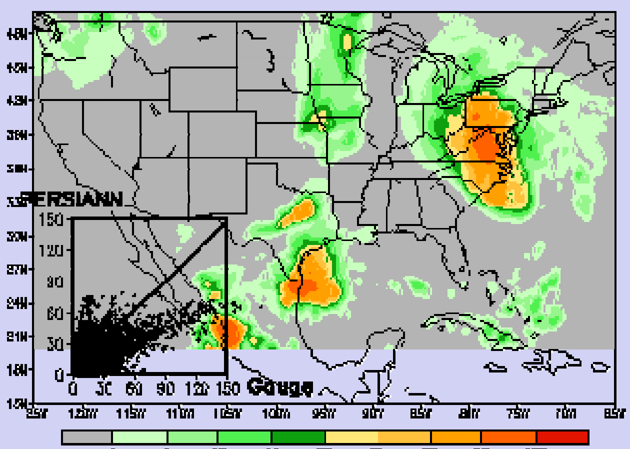
	(G) gauge	(S) PERSIANN	(R) radar
Number of points:	13828.	13828.	13828.
# points w/rain:	4249.	4665.	2971.
Mean rain rate:	5.56	4.25	3.13
Cond. rain rate:	17.82	12.47	14.46
Max. rain rate:	181.99	79.07	131.45

	G–S	G–R	R–S
Correlation:	0.877	0.776	0.606
Mean Absolute Error:	3.63	3.42	3.35
RMSE (mm/day):	9.44	11.23	8.66
RMSE (normalized):	1.70	2.02	2.77
Probability of Detection:	0.746	0.654	0.855
False Alarm Ratio:	0.321	0.065	0.455
Bias Ratio (rain:no rain):	1.098	0.699	1.570
Heidke Skill Score:	0.574	0.692	0.546
Hanssen–Kuipers Score:	0.589	0.634	0.660
Equitable Threat Score:	0.402	0.528	0.376

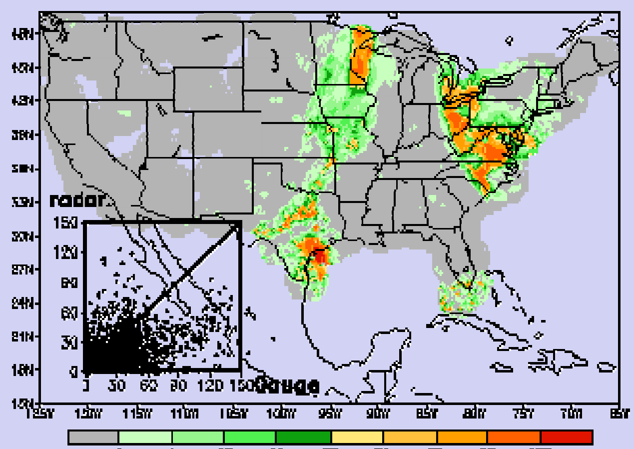
gauge \ PERSIANN	< 1	≥ 1
< 1	8082.	1497.
≥ 1	1081.	3168.

gauge \ radar	< 1	≥ 1
< 1	9386.	193.
≥ 1	1471.	2778.

PERSIANN



Radar



Required Hydrometeorological Predictions

Short Range – · – · – · – · – · – · – · – · – · – · – · – · – · Long Range

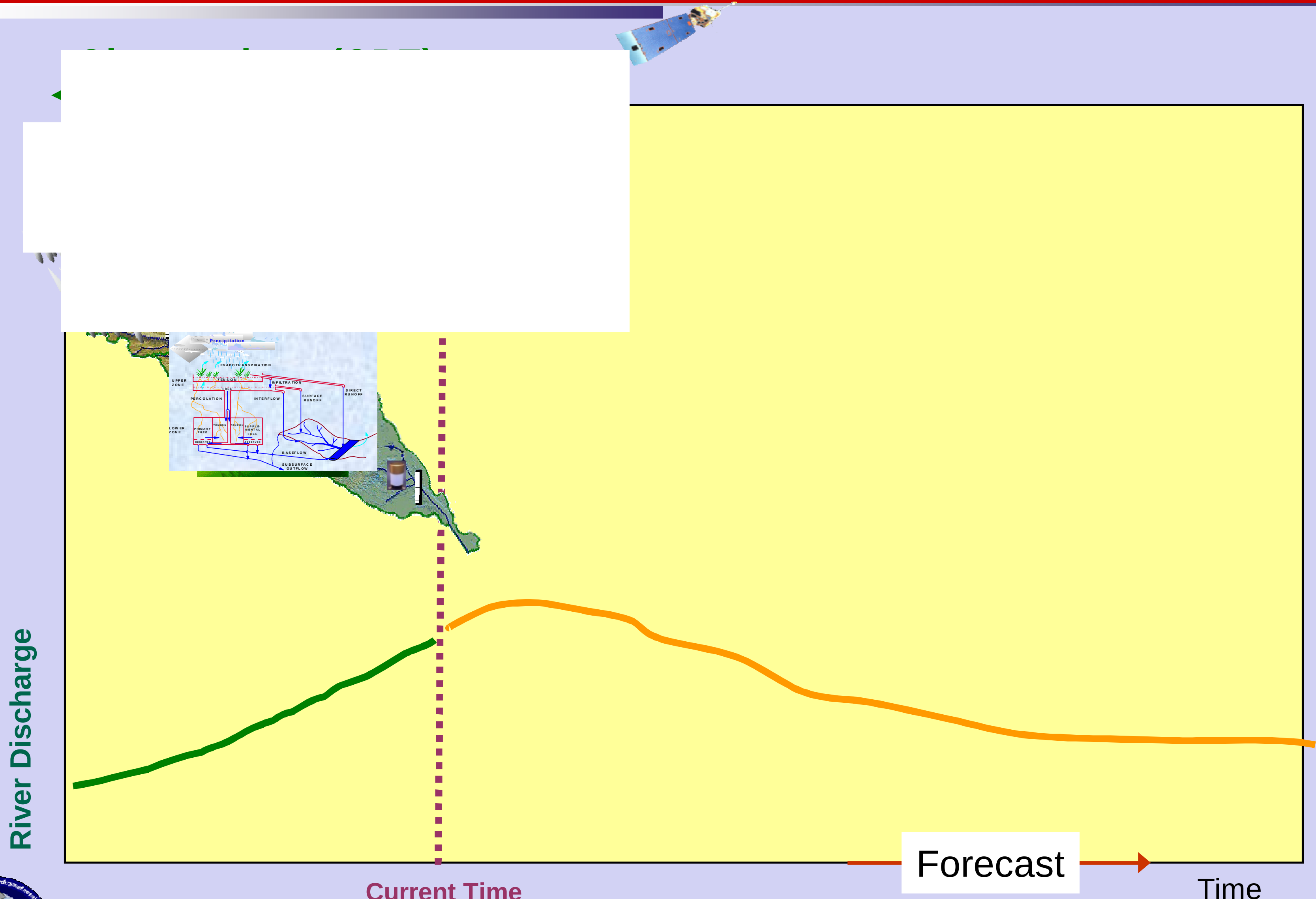
hours – – – – > days – – – – > weeks – – – > months – – > seasons – – > years – – – – – – > decades

arning

•*Weather Scale:*

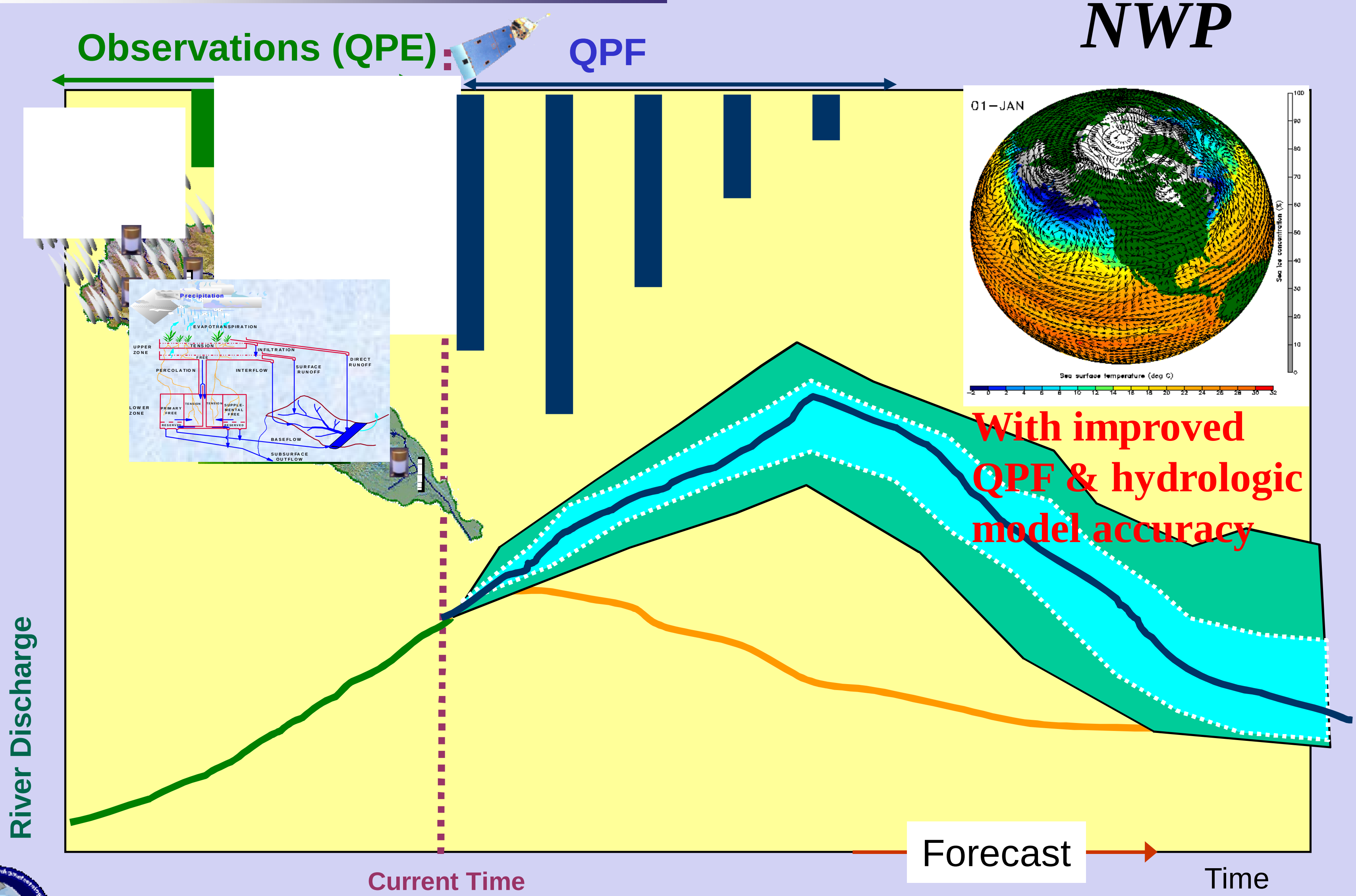
➢ ***flood and River flow forecasting***

Common practice in Flood and River Flow Forecasting



Animation Assisted by: Q. Xia & Gi-H. Park

Efforts in Extending the Forecast Lead Time

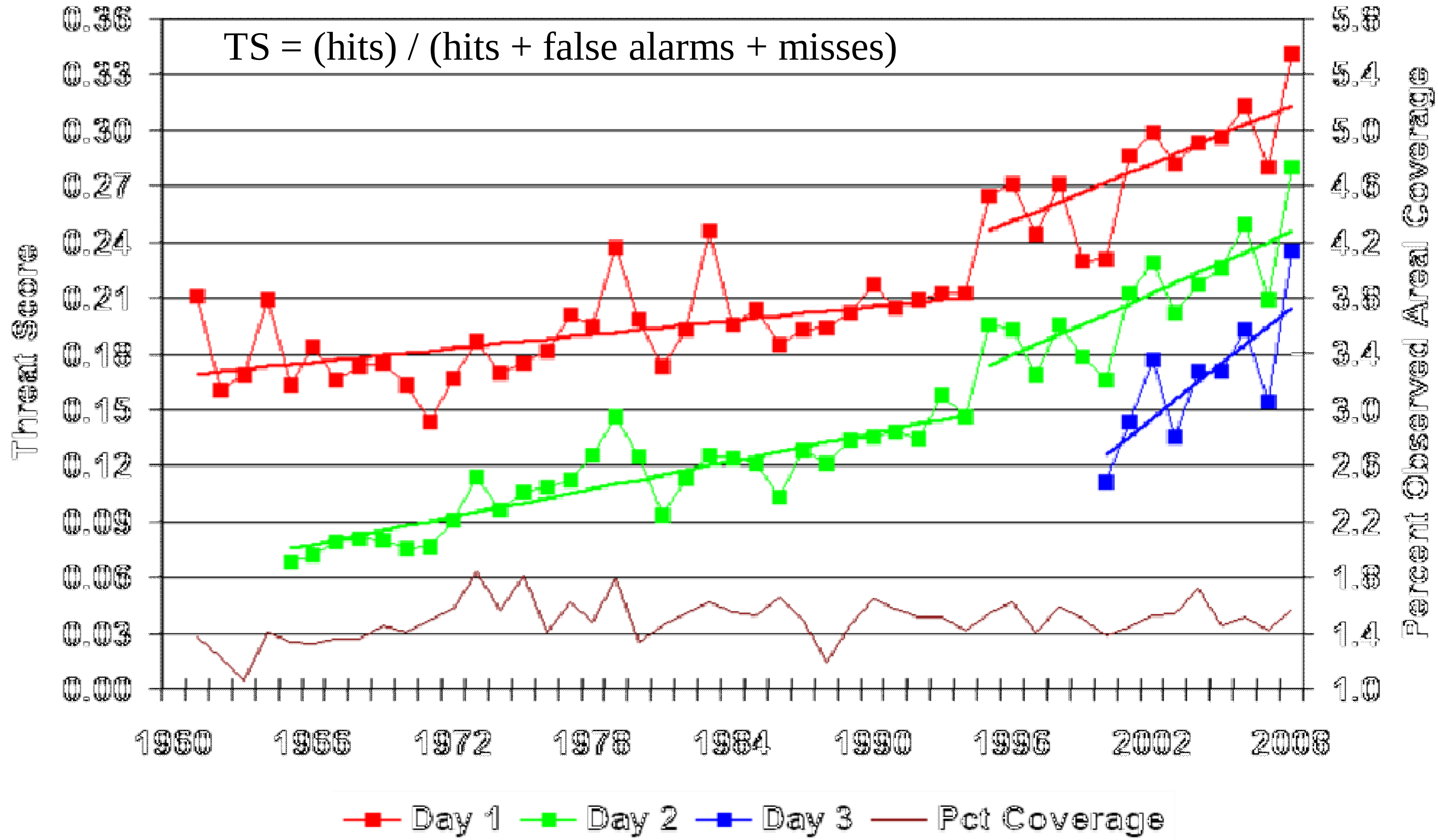


Animation Assisted by: Q. Xia, Gi-H. Park & L. Bastidas

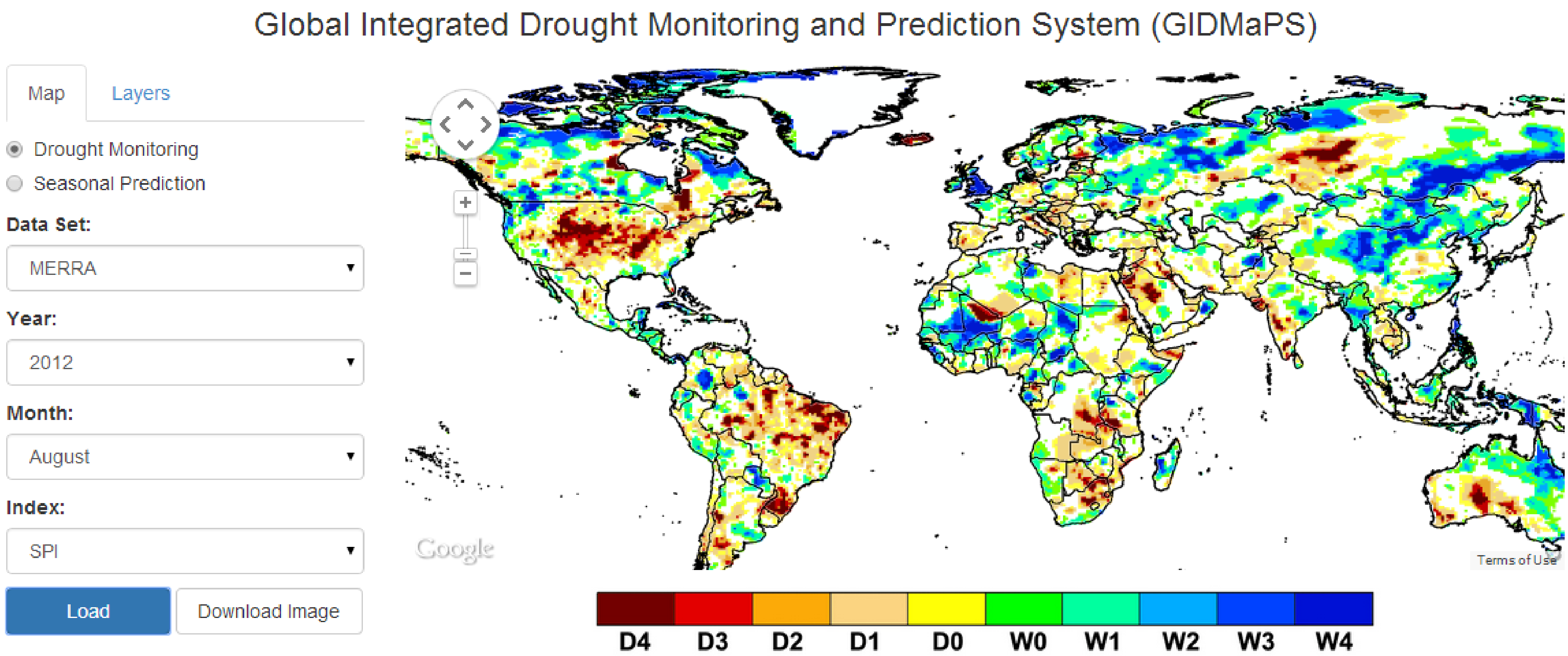
Center for Hydrometeorology and Remote Sensing, University of California, Irvine

Provided by: J. Hoke

HPC QPF verification
1-inch threat score



UC-I Global Drought Monitoring System



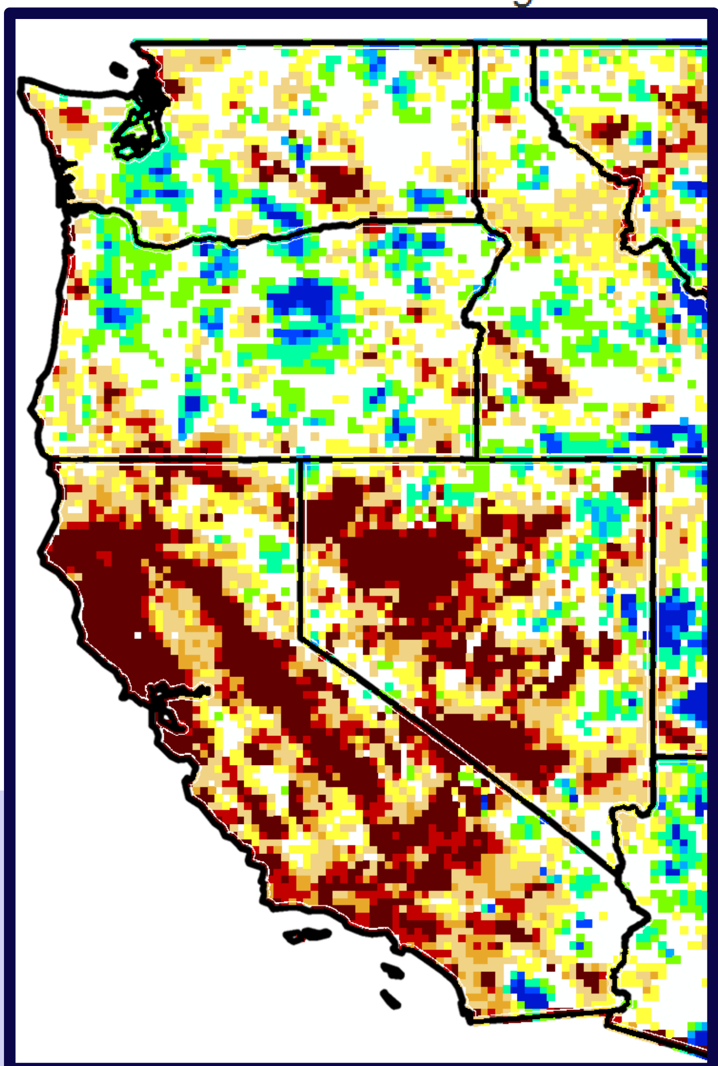
http://drought.eng.uci.edu/

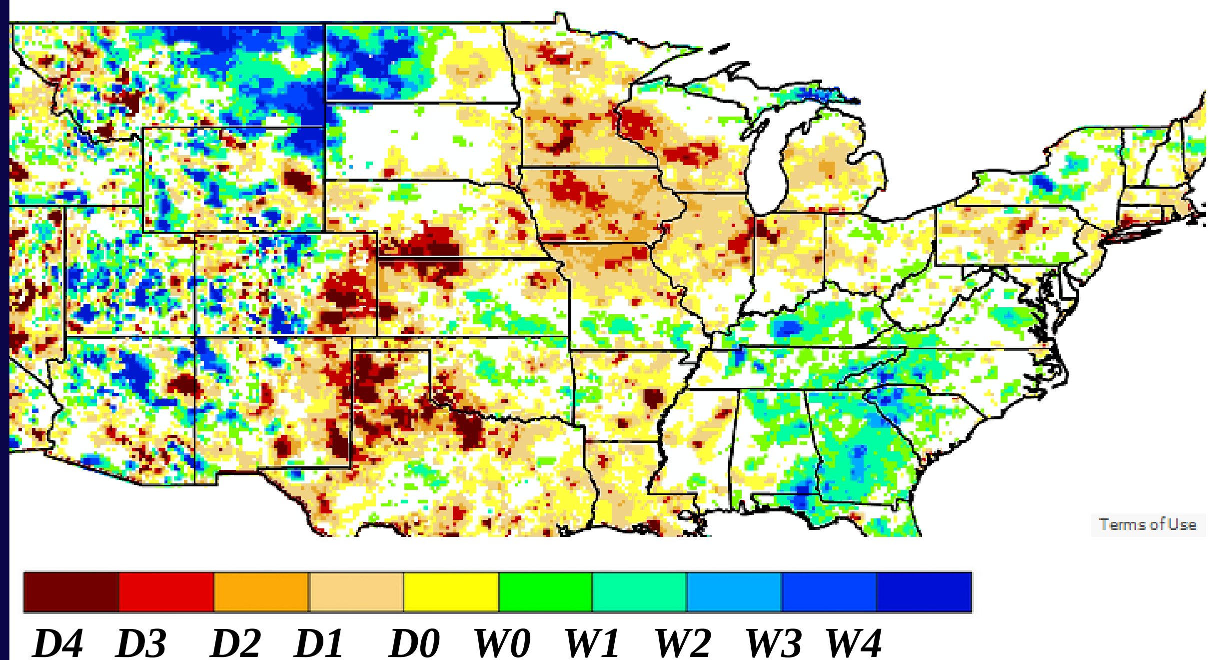
A. AghaKouchak Group

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

UC-I Global Drought Monitoring System

Global Integrated Drought Monitoring and Prediction System (GIDMaPS)





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

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