"Understanding Climate Change From Data - Perspectives from Hydroclimate Modeling and Data Assimilation."

Soroosh Sorooshian

Center for Hydrometeorology and Remote Sensing - University of California Irvine

NSF Expeditions in Computing:
Understanding climate Change – 2013 Annual workshop
Northwestern Univ. Evanston IL. August 16th, 2013

University of California Irvine (UCI)

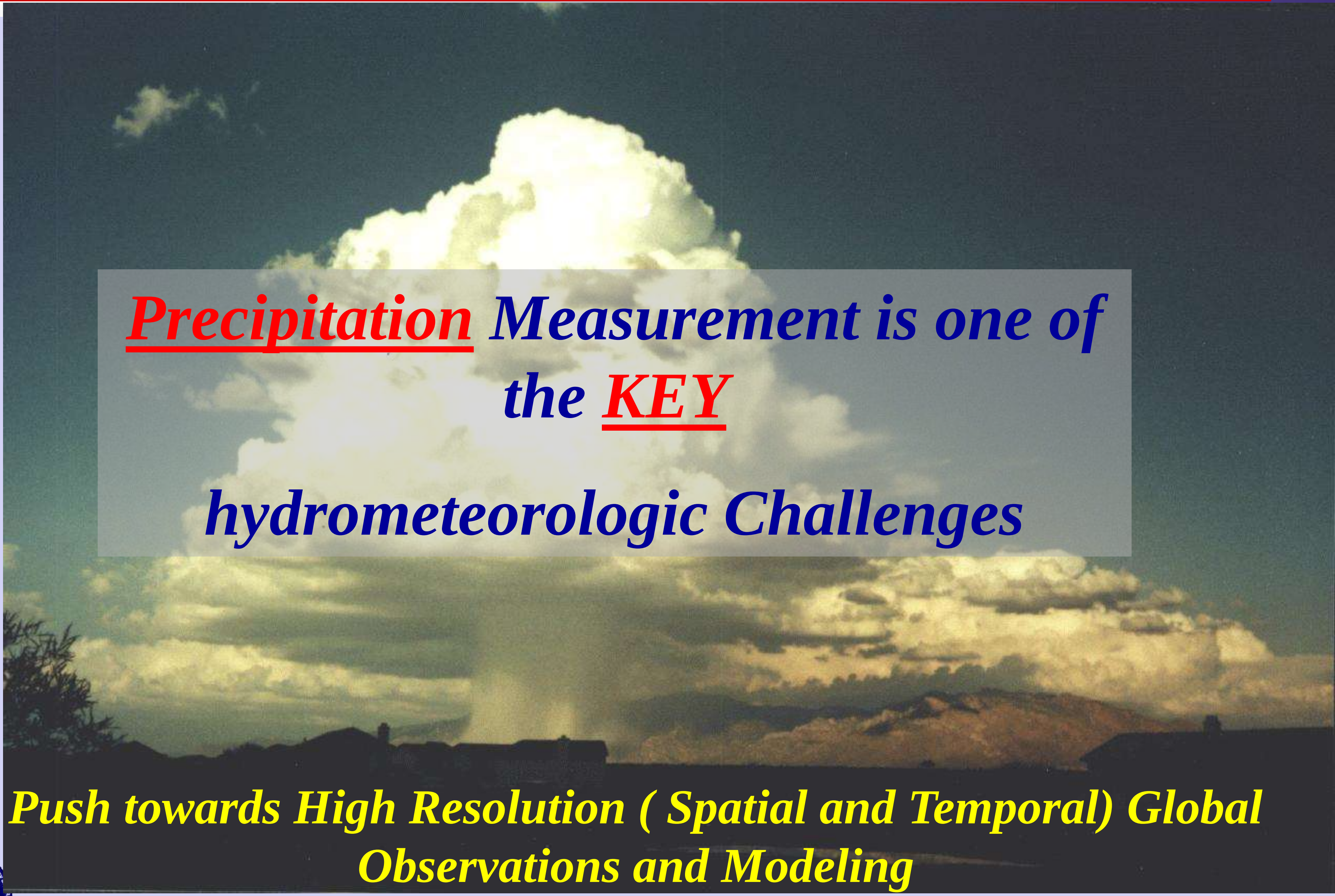
Research Team: Present and Recent Past

and many more ...

Big Challenge

Adequacy of Hydrologic Observations for model input and Validation

A Key Requirement!



Precipitation Measurement is one of the KEY

hydrometeorologic Challenges

Push towards High Resolution (Spatial and Temporal) Global Observations and Modeling

2 Precipitation Scenarios with different Temporal properties

Monthly Total

A

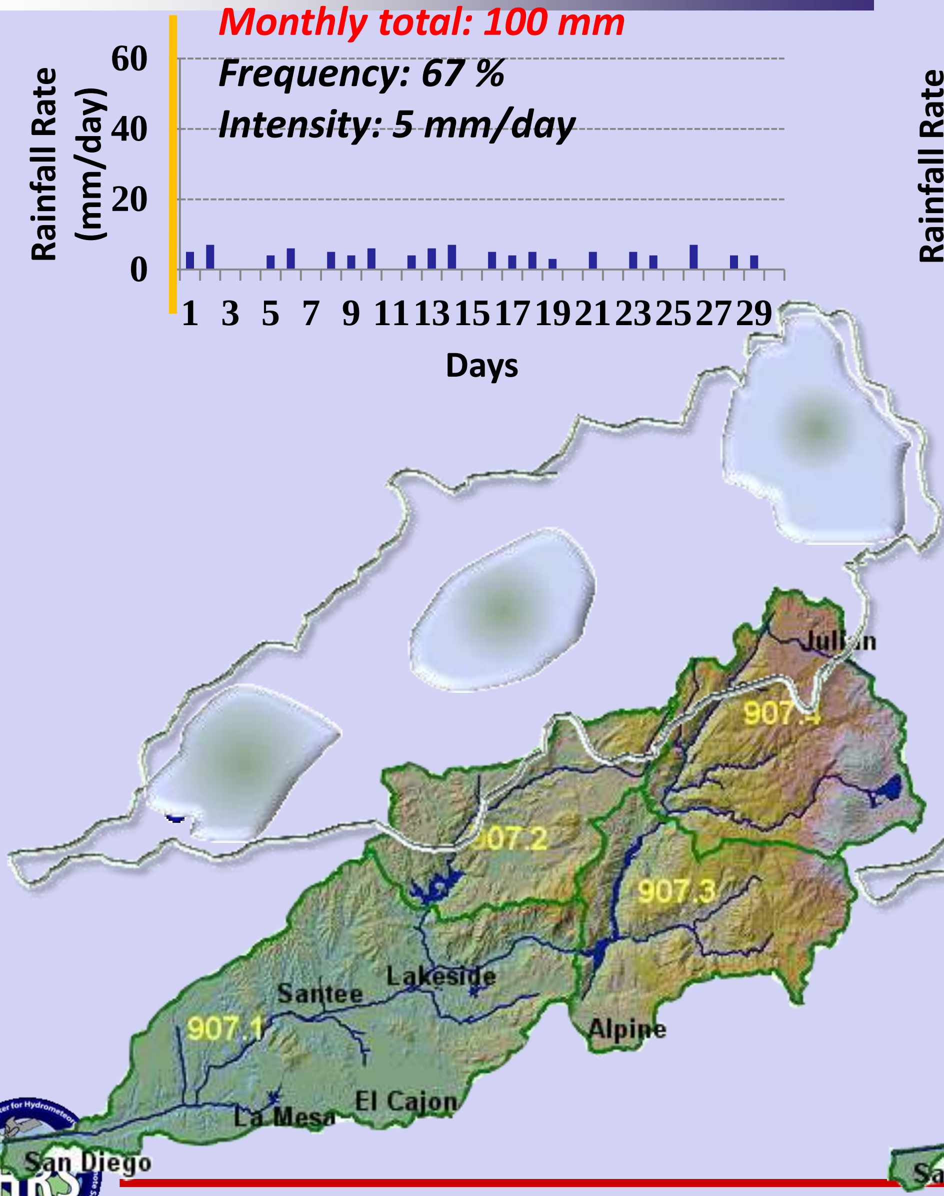
100 mm

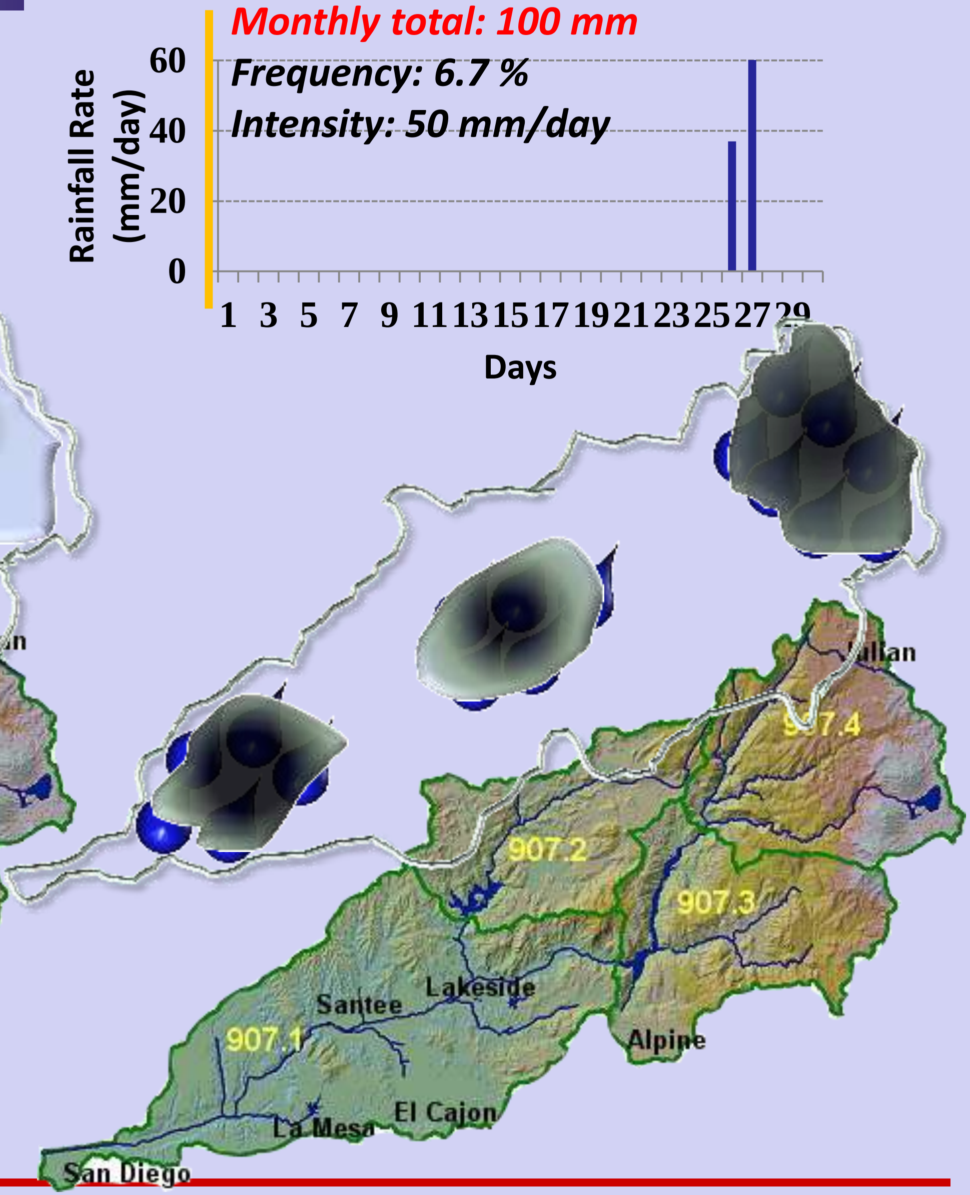
B

100 mm

Idea from: K. Trenberth, NCAR

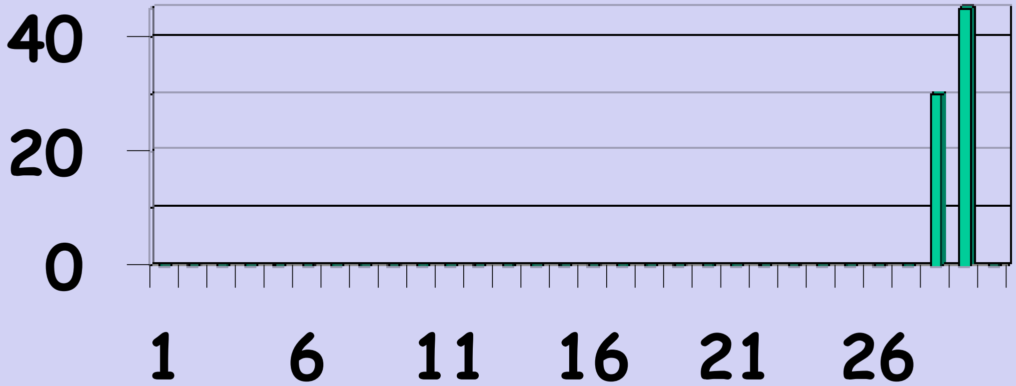
Temporal Scale Importance: *Daily Precip. at 2 stations*





2 Rain gages with different Temporal properties

A



Monthly

Amount 100 mm

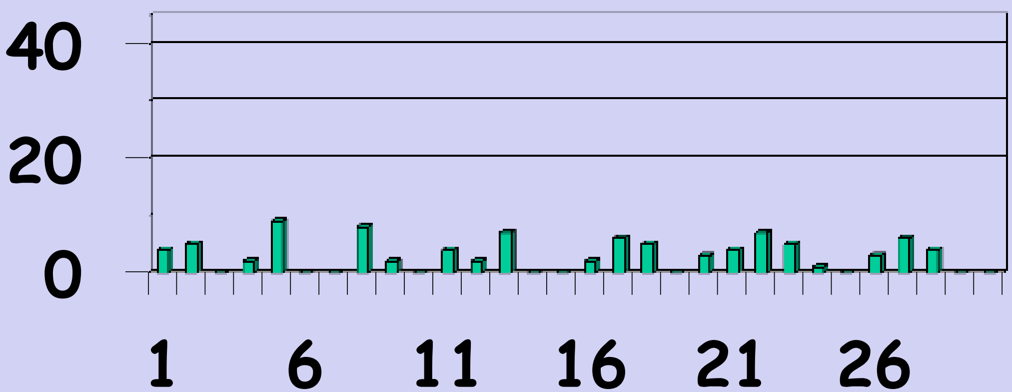
Frequency 6.7%

Intensity 50.0 mm

local Floods

Stream bed Recharge

B



Amount 100 mm

Frequency 67%

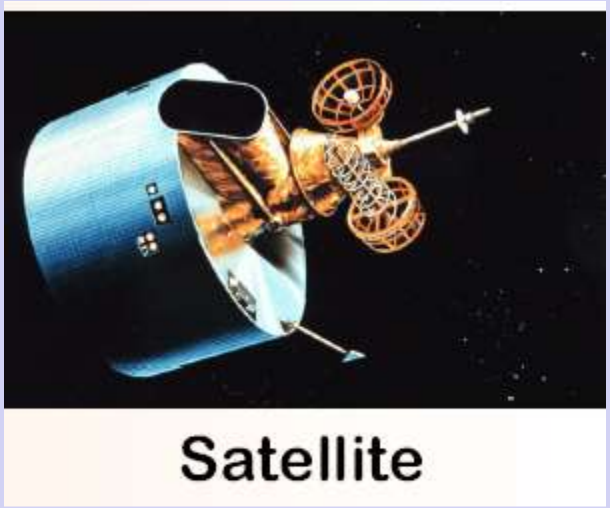
Intensity 5.0 mm

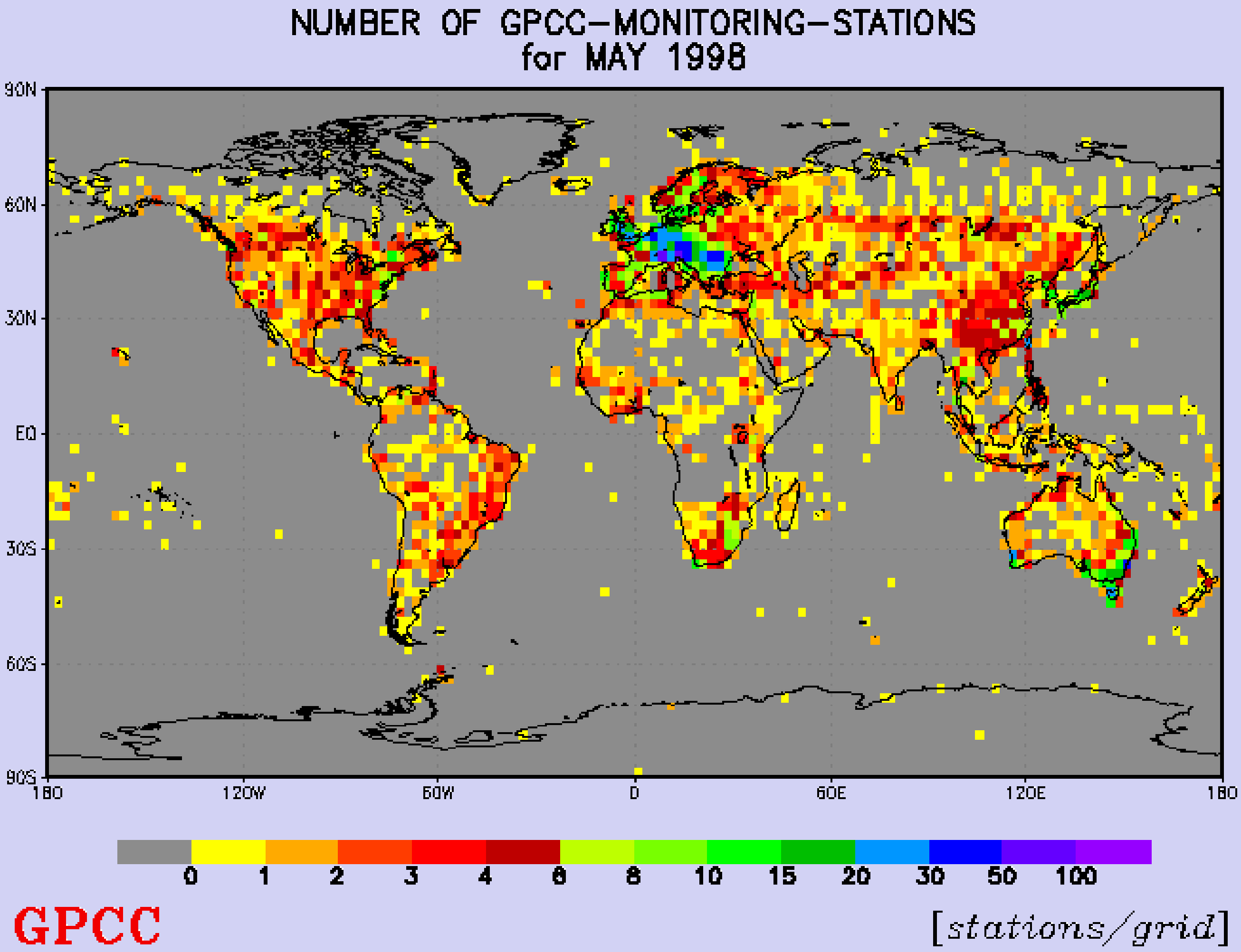
soil moisture replenished

Little or no runoff

Idea from: K. Trenberth, NCAR

Precipitation Observations: Which to trust??

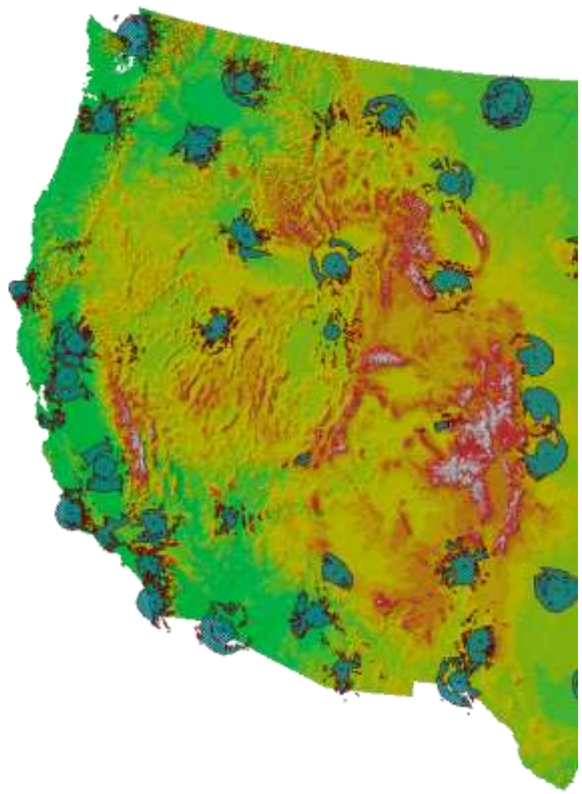




Number of range gauges per grid box**. These boxes are **2x2 degrees

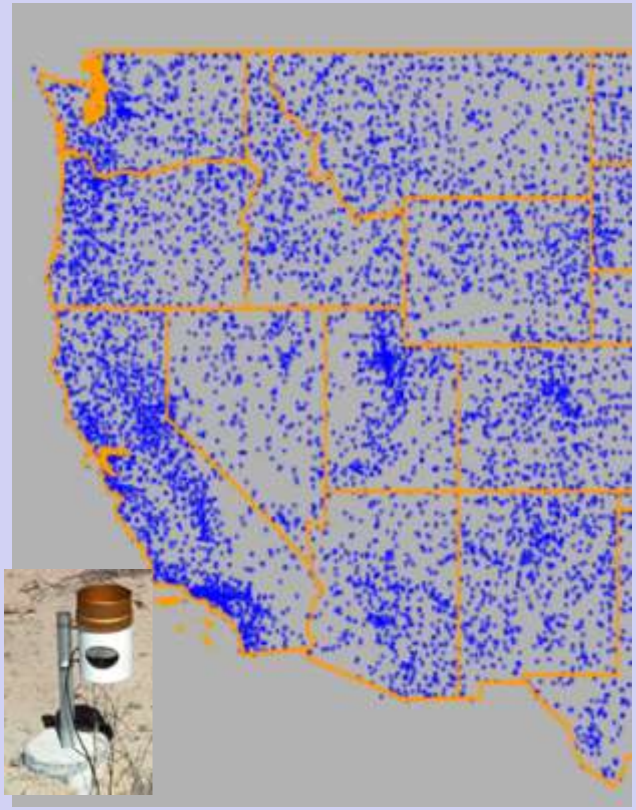
(Source: Global Precipitation Climatology Project)

Coverage of the WSR-88D and gauge networks



1 km AGL

Maddox, et al., 2002

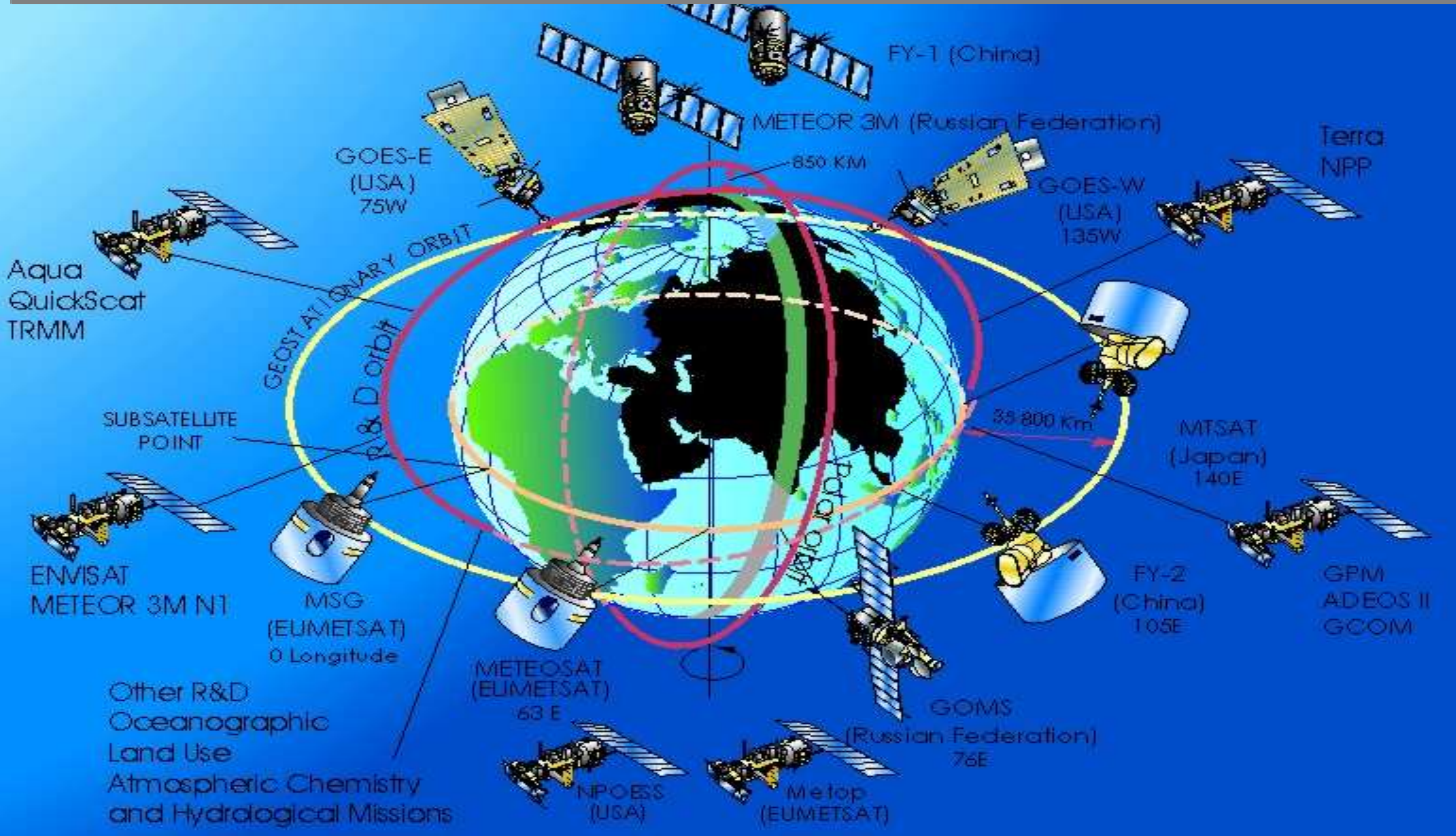


- *Daily precipitation*
- *Gages (1 station per 600 km^2)*
- *Hourly coverage even more sparse*

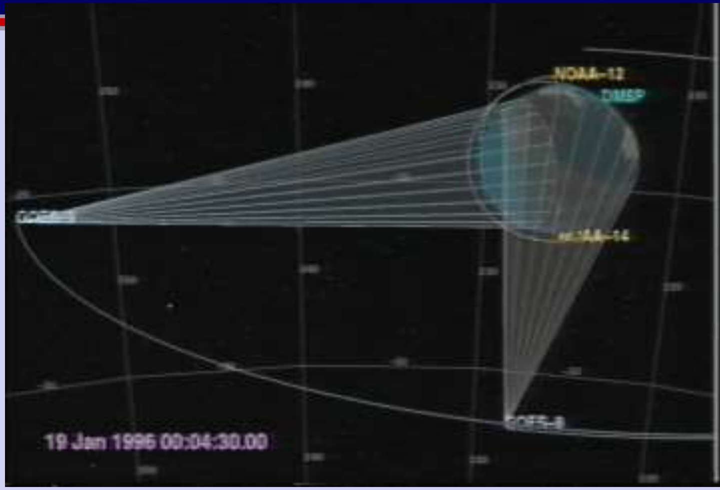
Satellite-Based Precipitation:

Satellite-Based Rainfall Estimation: Promising !

Observations from space: Near-continuous, global coverage,



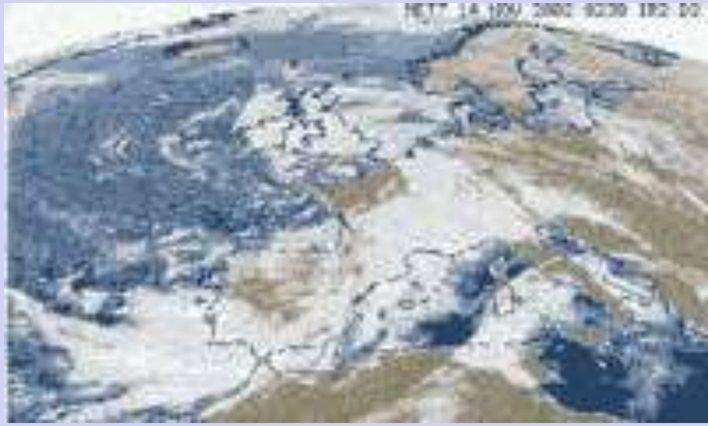
Satellite precipitation retrieval instruments



1) Using GEO satellites (Infrared/Visible channels)

***Advantage*:**

- ***Good temporal and spatial resolution (30 min or less, 4 km)***
- ***very good coverage***



***Disadvantage*:**

-Receives mostly cloud –top information

-Indirect estimation of precipitation.

Problems with IR only algorithm

Assumption: higher cloud → colder → more precipitation

Satellite precipitation retrieval instruments

2) Microwave

Advantage:

- Responds directly to hydrometeors and penetrates into clouds

- More accurate estimates

Disadvantage:

-low temporal and spatial resolution (~5-50km)

-Heterogeneous emissivity over land:
(e.g., problem with warm rainfall over land)

Satellite precipitation retrieval instruments

3) Active Radar

***Advantage*:**

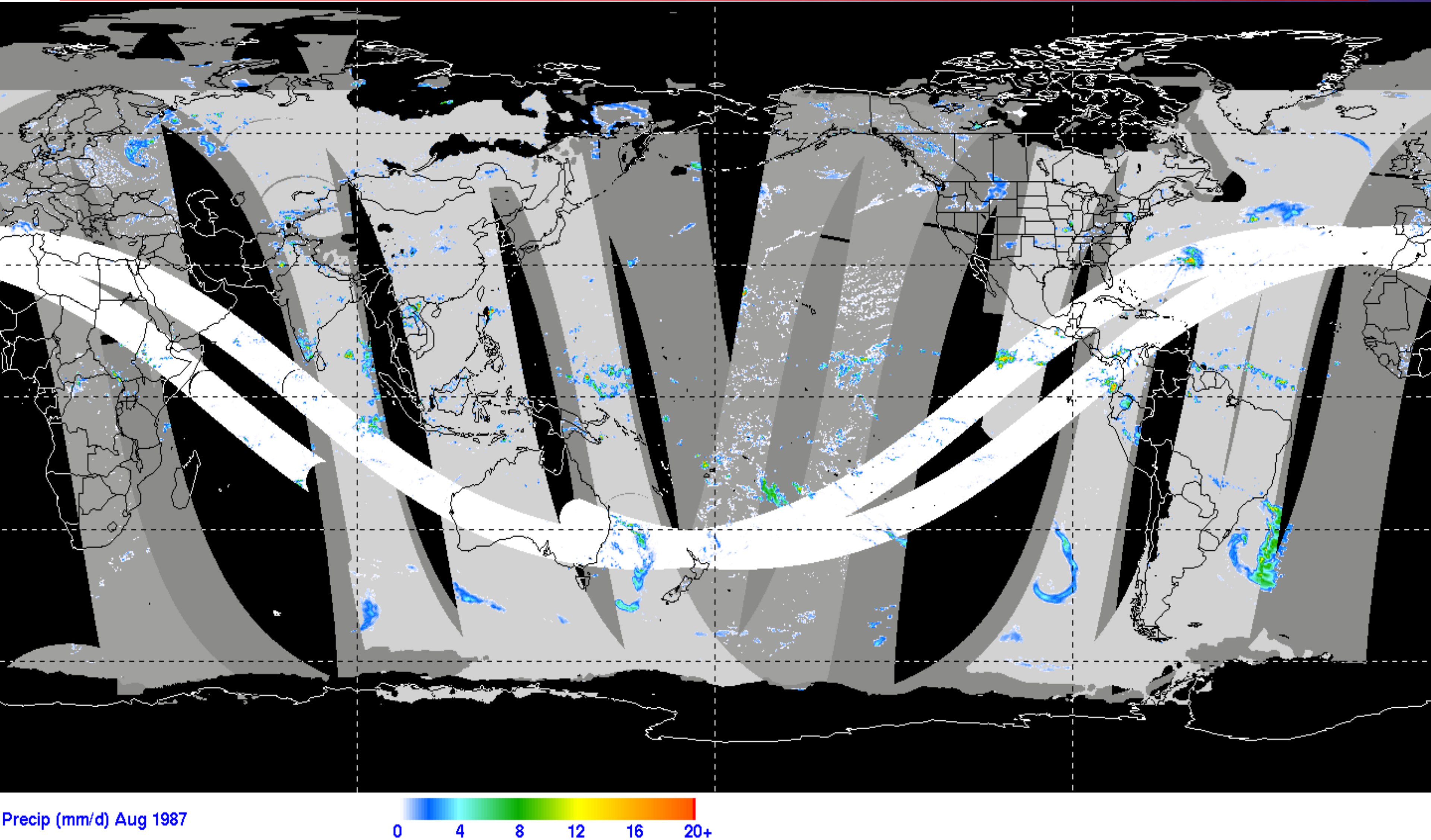
-More accurate

- good spatial resolution

***Disadvantage*:**

- Poor temporal resolution

Current Microwave Satellite Configurations



Source: Huffman et al. 2007

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

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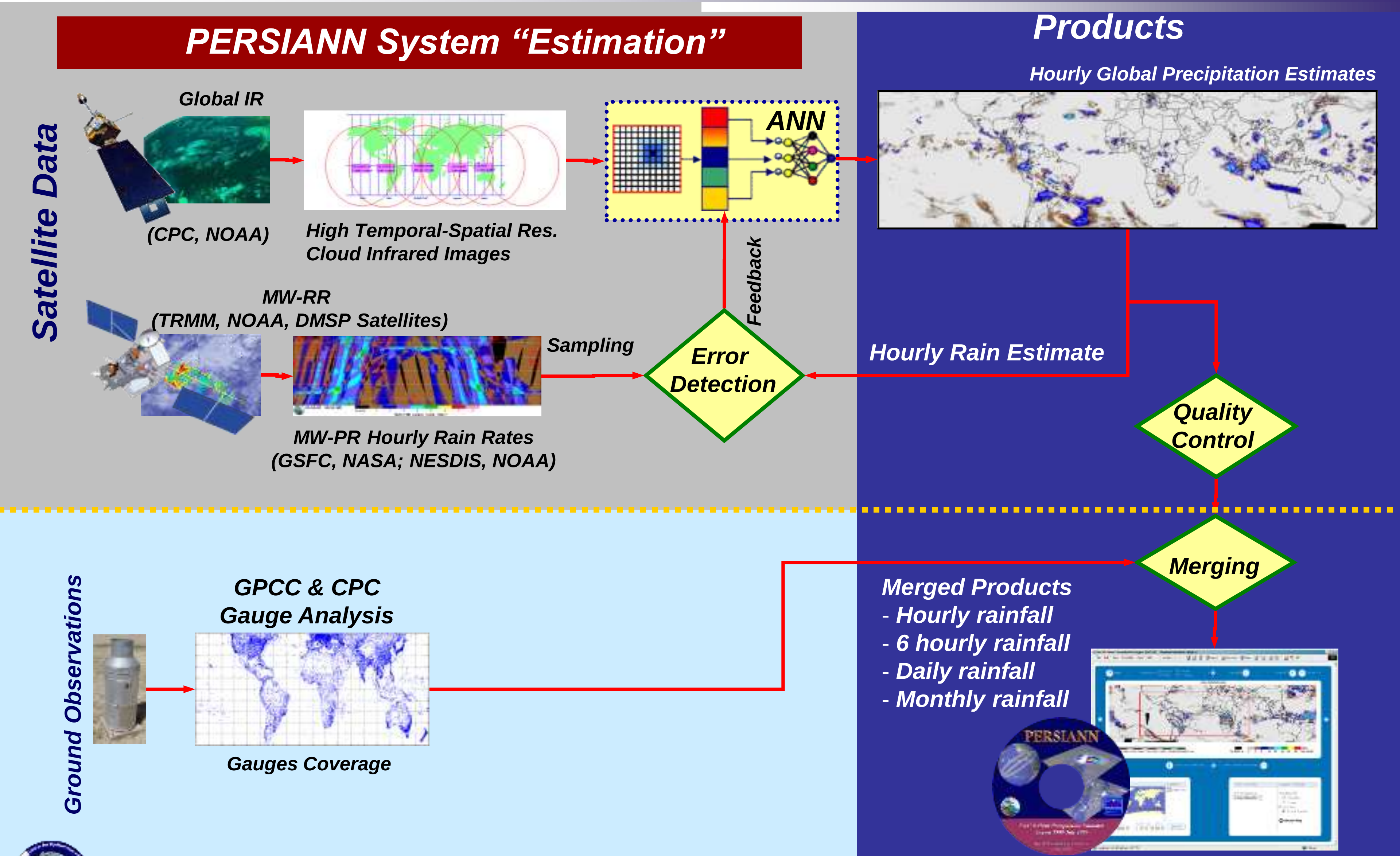


Center for Hydrometeorology and Remote Sensing, University of California, Irvine

High Resolution Precipitation Estimates

PERSIANN-CCS

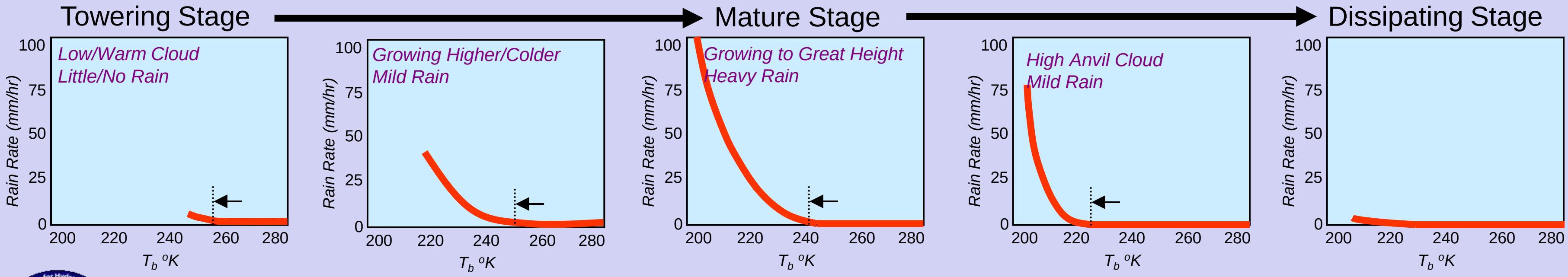
Center for Hydrometeorology and Remote Sensing, University of California, Irvine

Stages of a Convective Storm and Rainfall Distribution

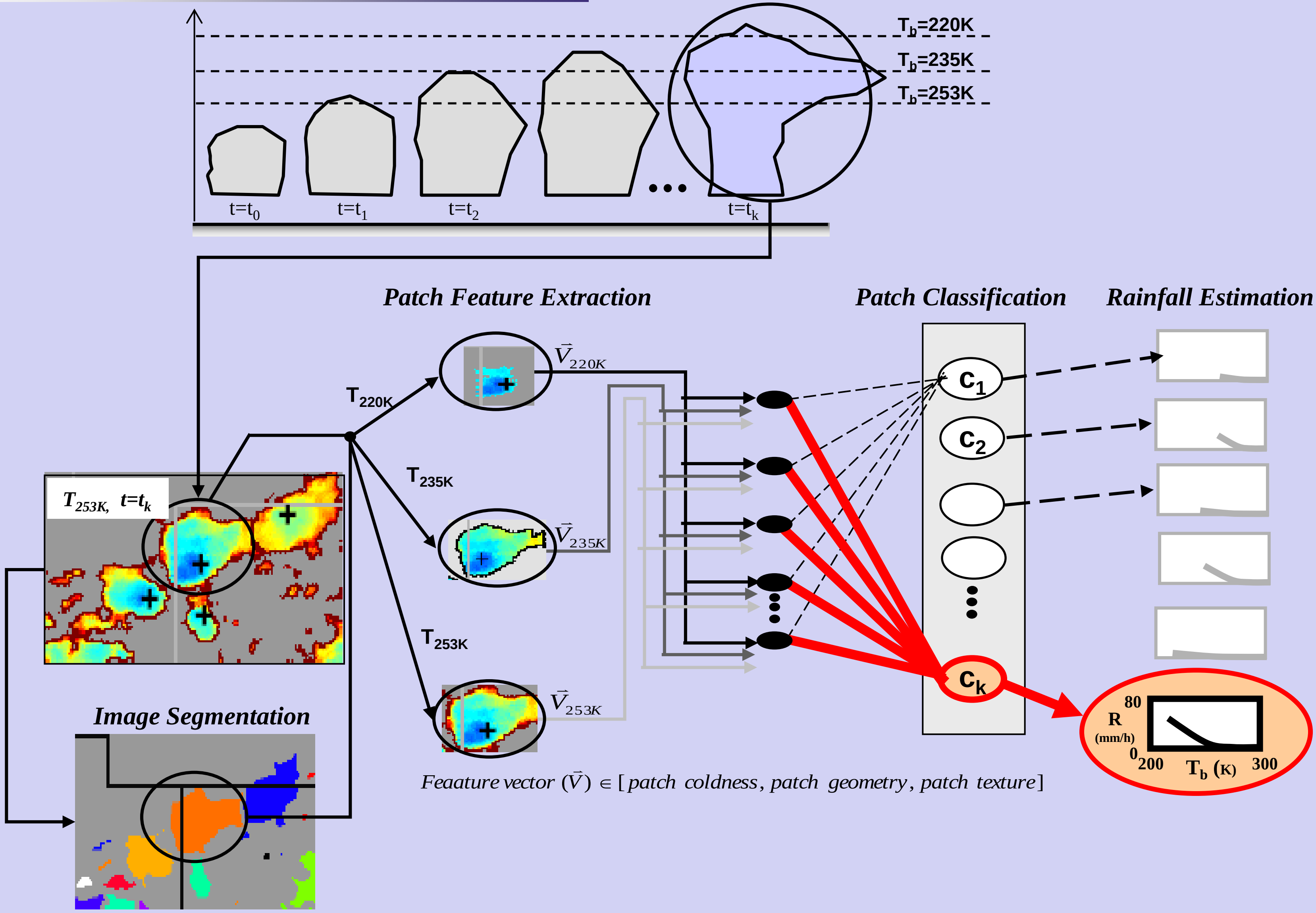
TOWERING CUMULUS STAGE

MATURE STAGE

DISSIPATING STAGE

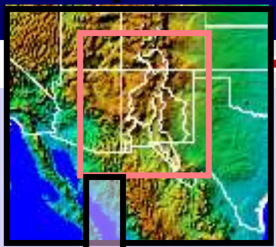


Cloud Segmentation Algorithm



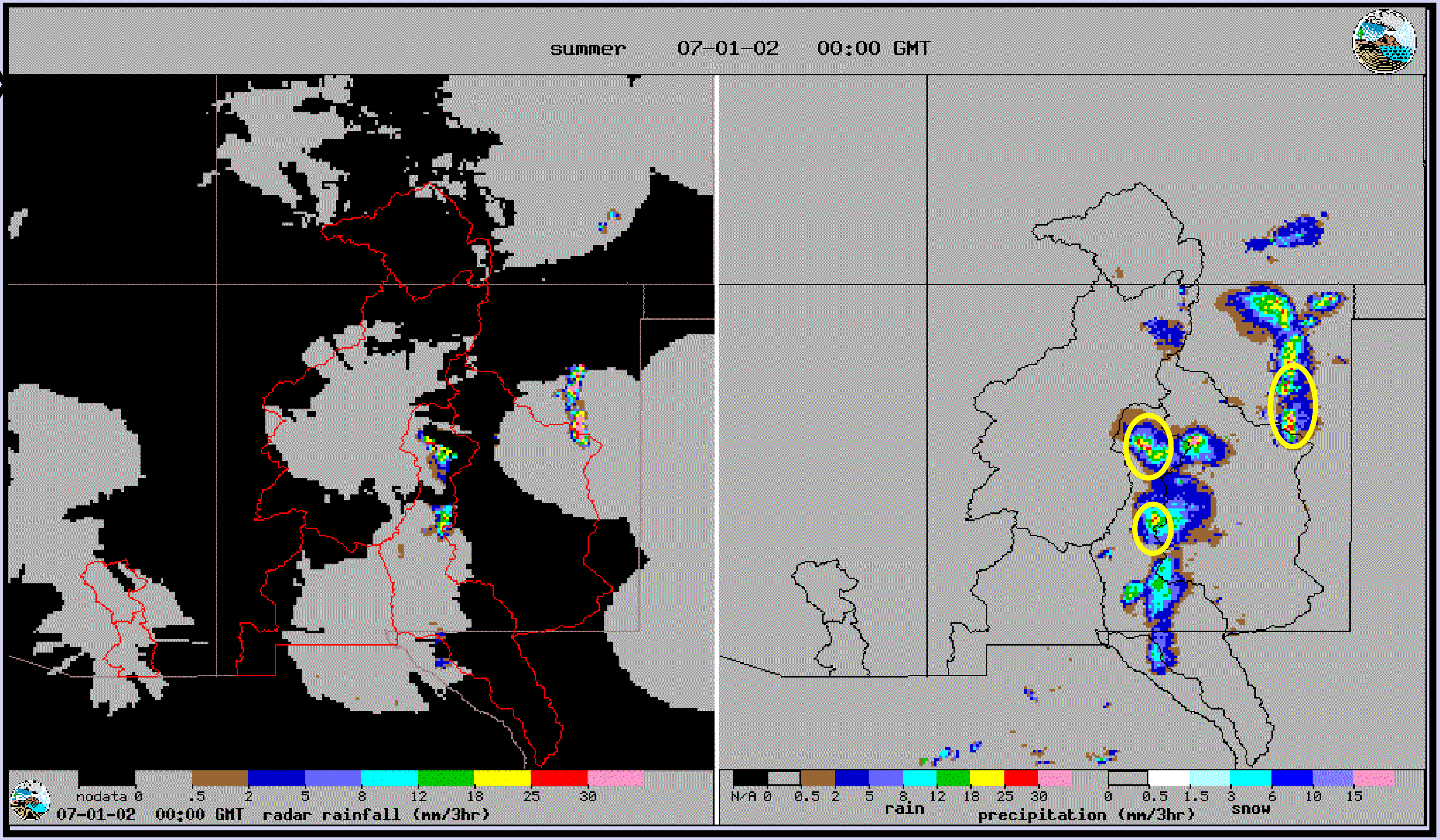
High Resolution Precipitation Estimates from PERSIANN-Cloud Classification System

Study Area



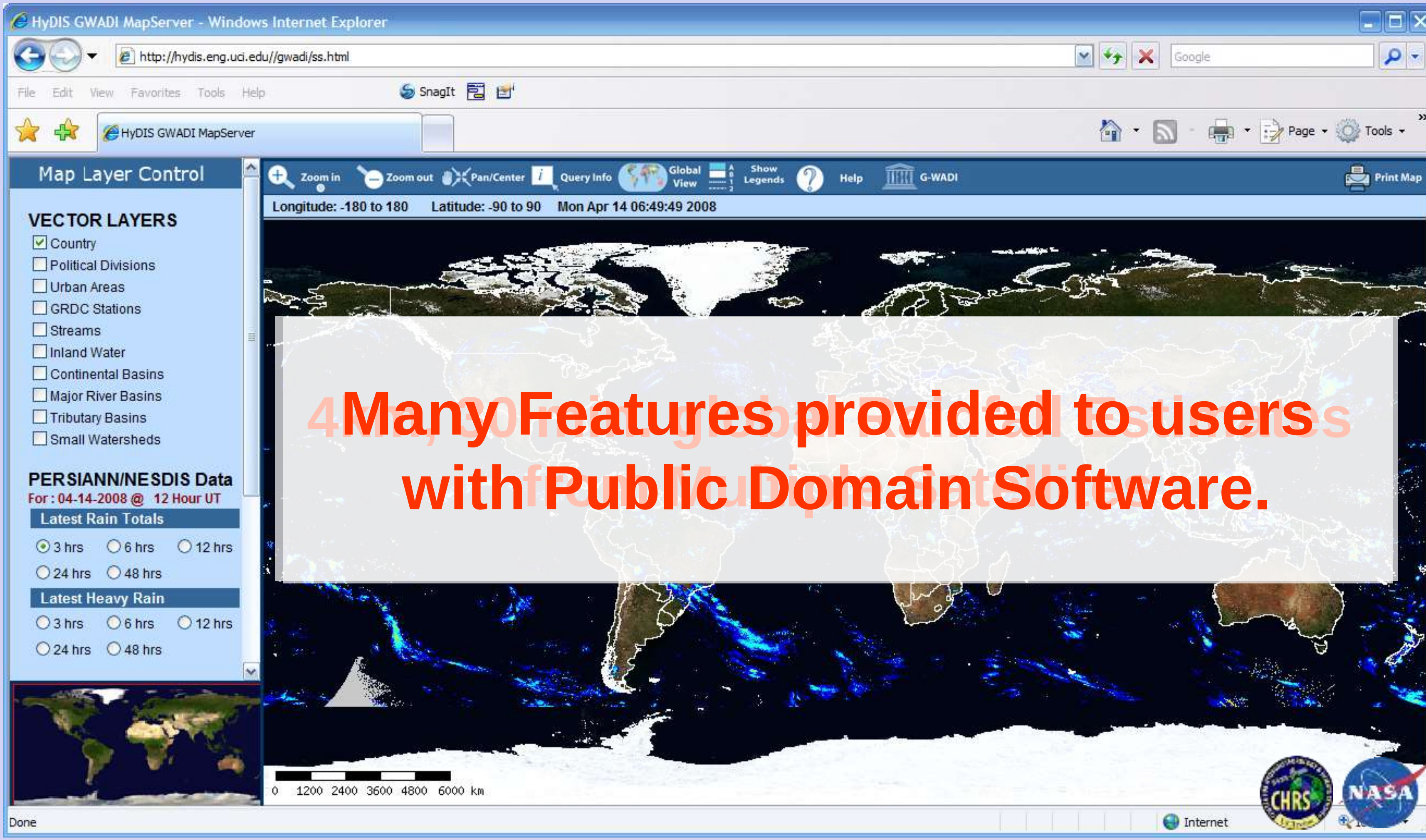
Radar Observation (2 km AGL)

PERSIANN-CCS Estimates



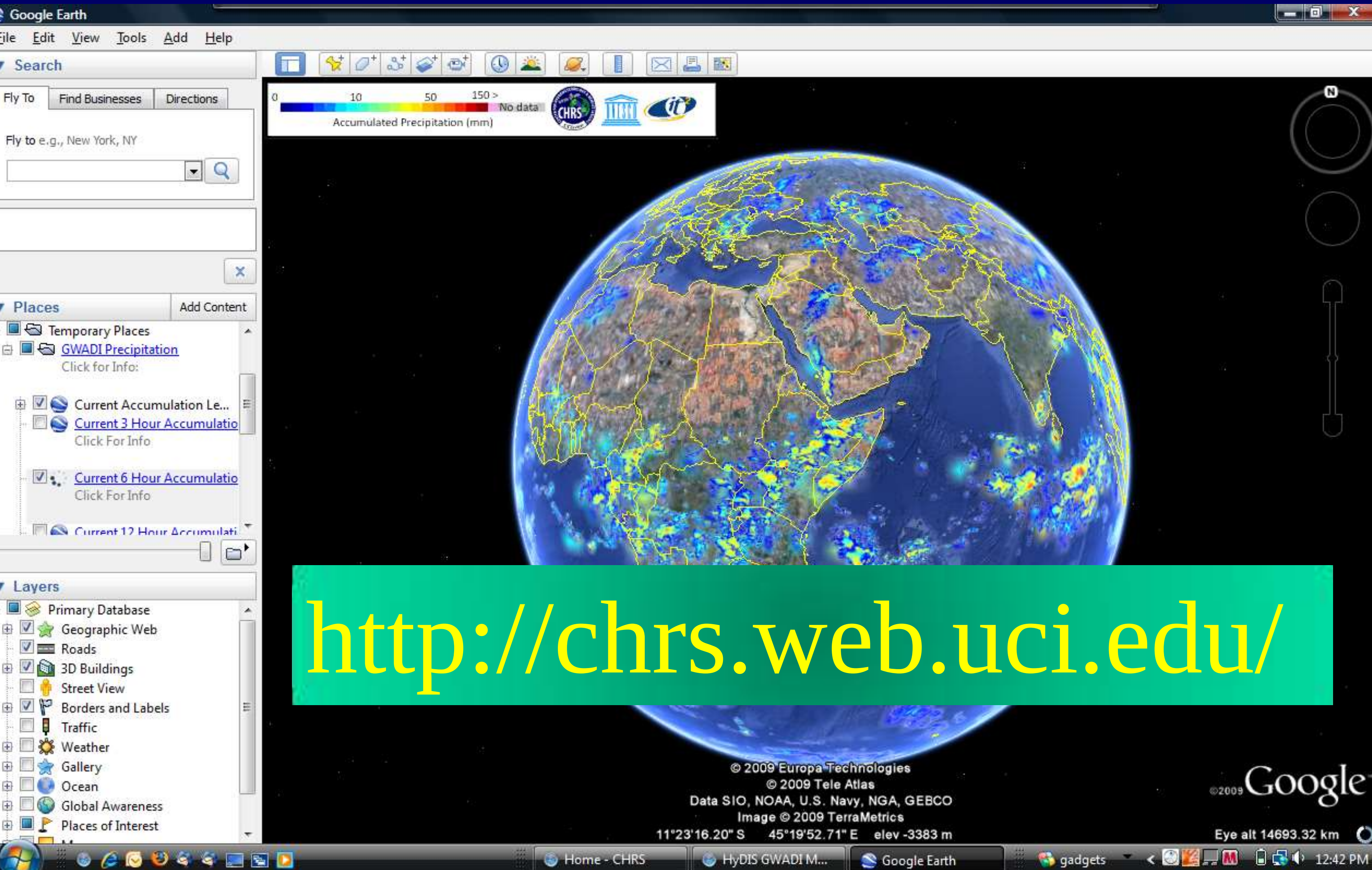
4km x 4km, 3-hour accumulated precipitation

Real Time Global Data: Cooperation With UNESCO



Many Features provided to users with Public Domain Software.

PERSIANN Satellite Product On Google Earth



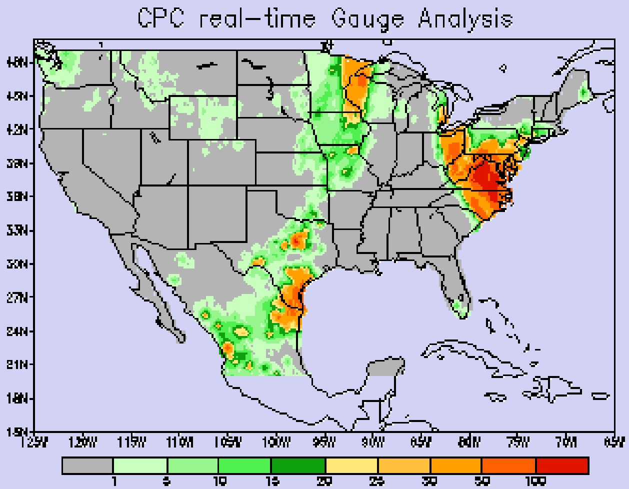
http://chrs.web.uci.edu/

Validation and Application of Satellite Products

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)

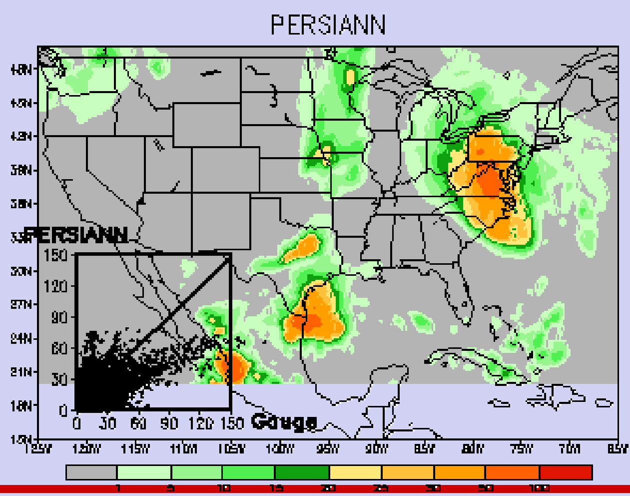


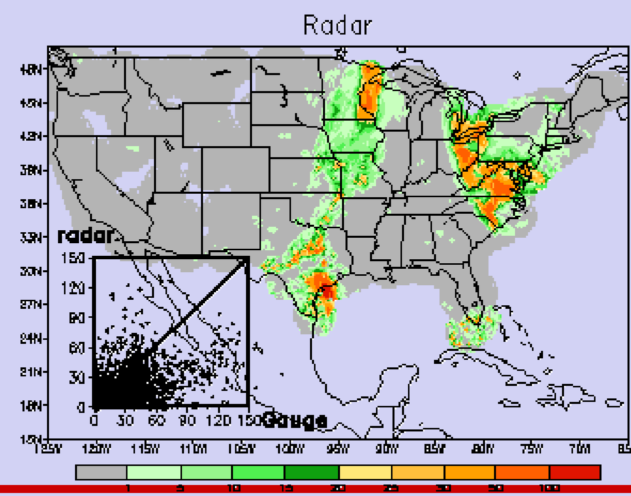
	(G) gauge	(S) PERSIANN	(R) radar
Number of points:	13828.	13828.	13828.
# points w/rain:	4249.	4665.	2971.
Mean rain rate:	5.56	4.25	3.13
Cond. rain rate:	17.82	12.47	14.46
Max. rain rate:	181.99	79.07	131.45

	G−S	G−R	R−S
Correlation:	0.827	0.726	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.





Multi–spectral images:

Will combining LEO(PMW) and GEO (VIS/IR) Satellite Imagery improve Precipitation Estimates?

The ABI (Advanced Baseline Imager) on GOES-R

- *Currently many sensors provide multi-spectral images with high spatial and temporal resolution.*

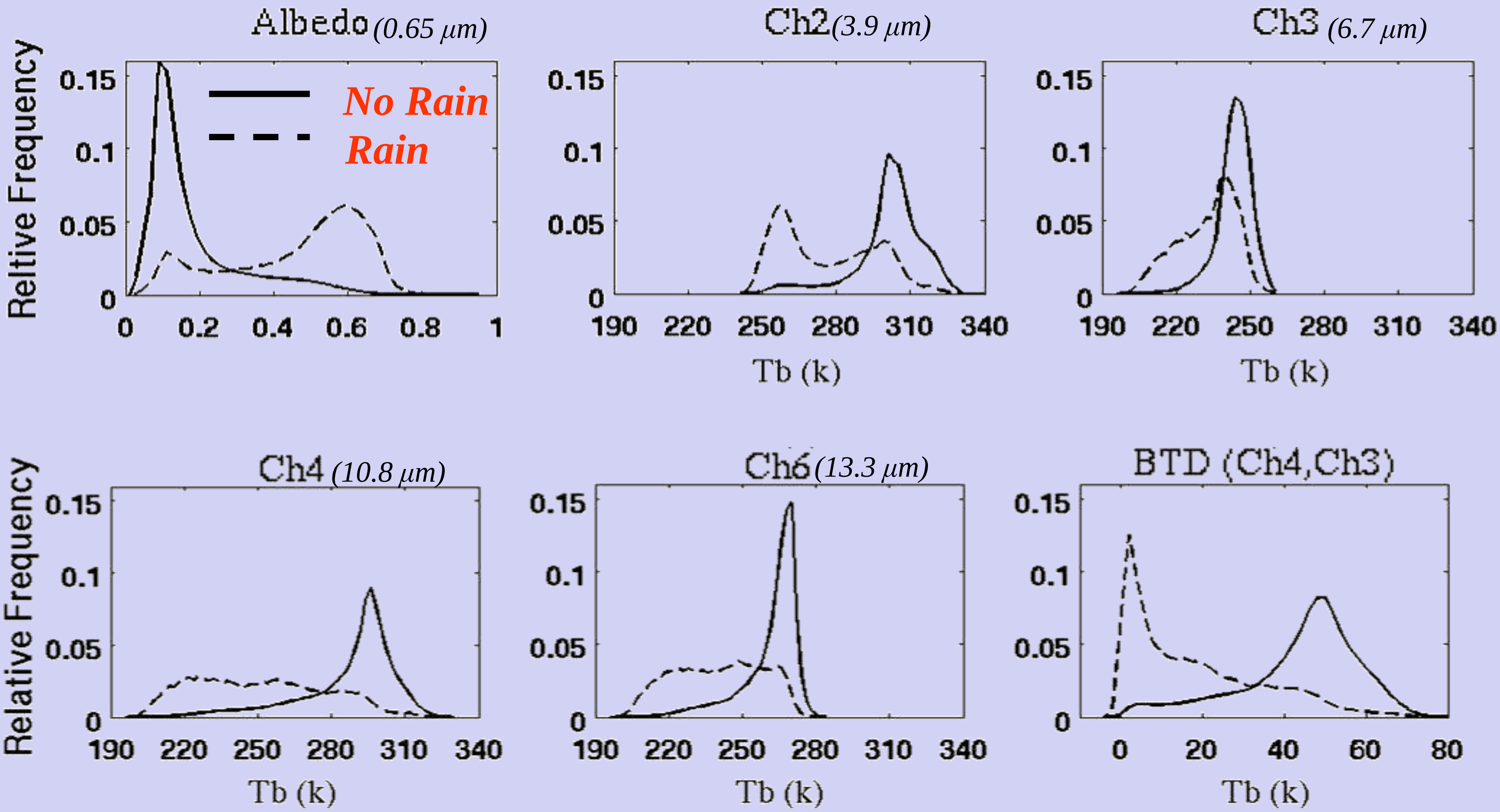
- *SEVIRI is a sensor on Meteosat Second Generation (MSG) satellite that has 12 spectral bands.*

- *In Approx. 2015, ABI sensor on GOES-R will provide 16 spectral bands.*

Figure courtesy of ITT Industries

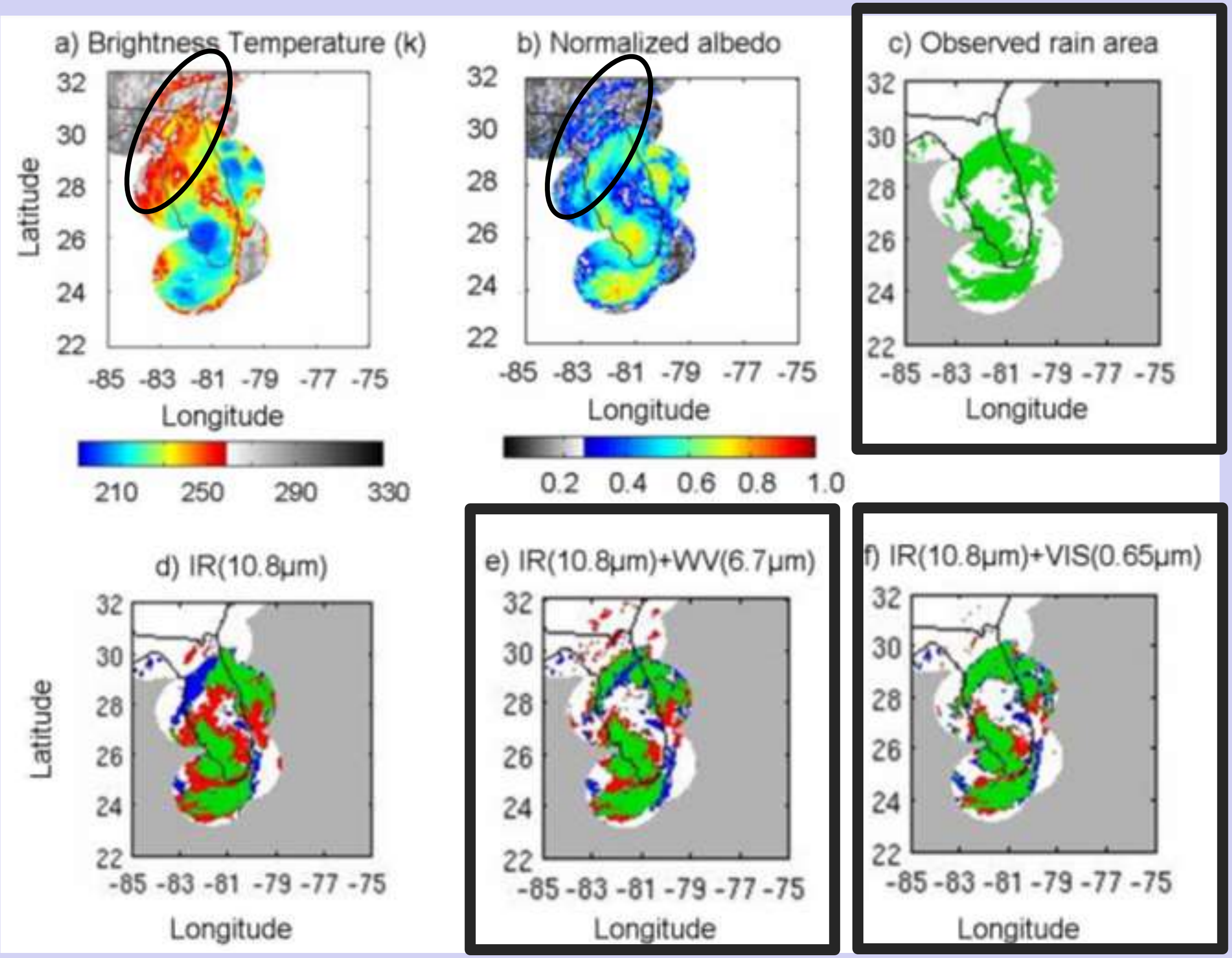
- ***Together a great opportunity to investigate the role of multi-spectral data for precipitation estimation***

Relative-frequency dist. of different channels (rain / no-rain) conditions



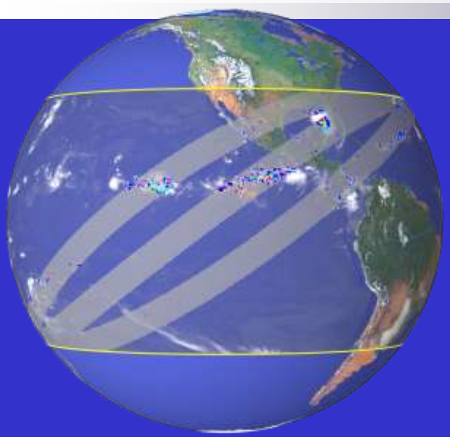
By counting satellite pixels under rain and no-rain conditions we can plot the relative frequency curves for each spectral band. These curves indicate that different spectral channels show different capabilities to distinguish between rain and no-rain pixels

Case Study: Hurricane Ernesto August 30, 2006



Hit *Under Estimation* *Over Estimation*

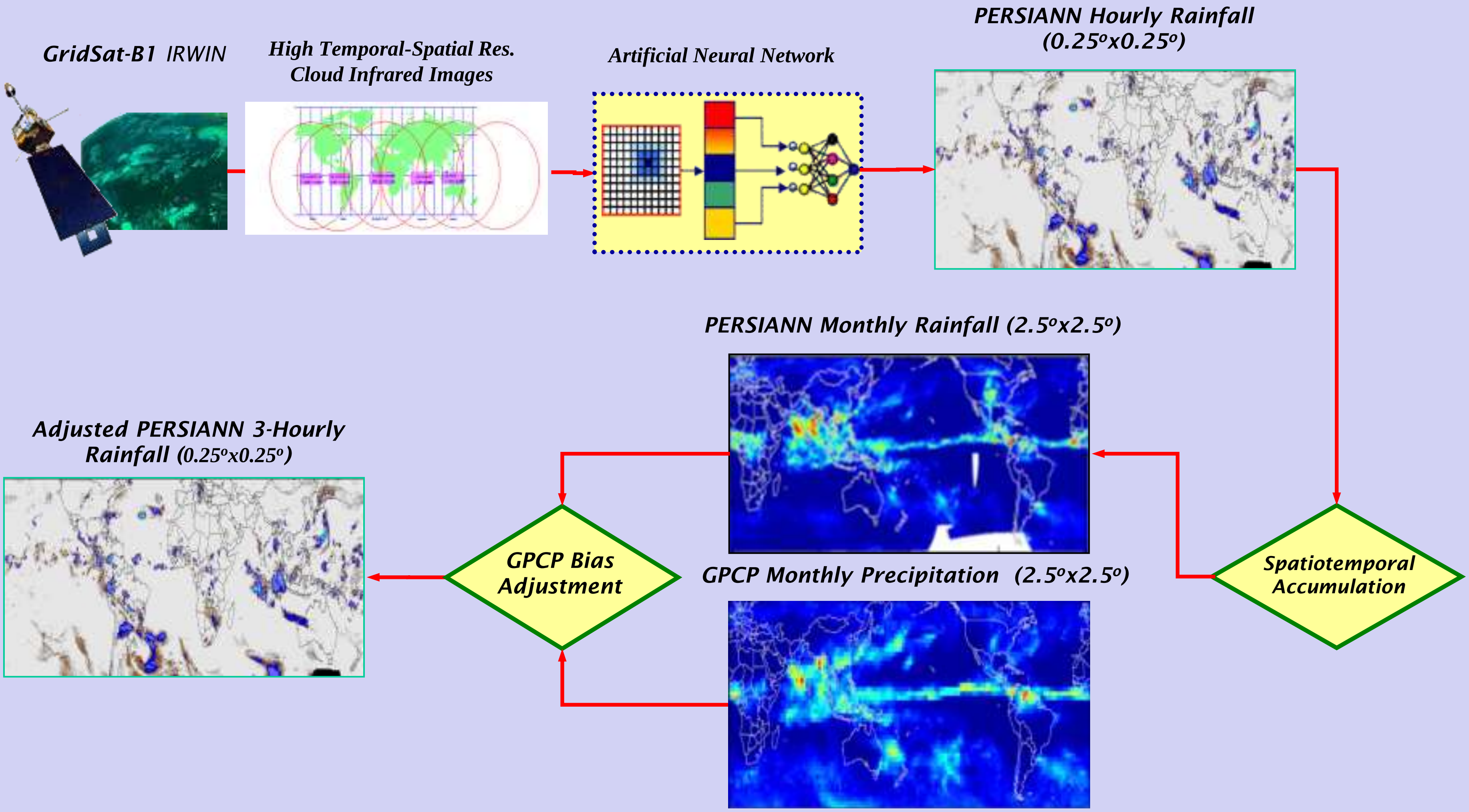
Behrangi et al (2009 a & b)



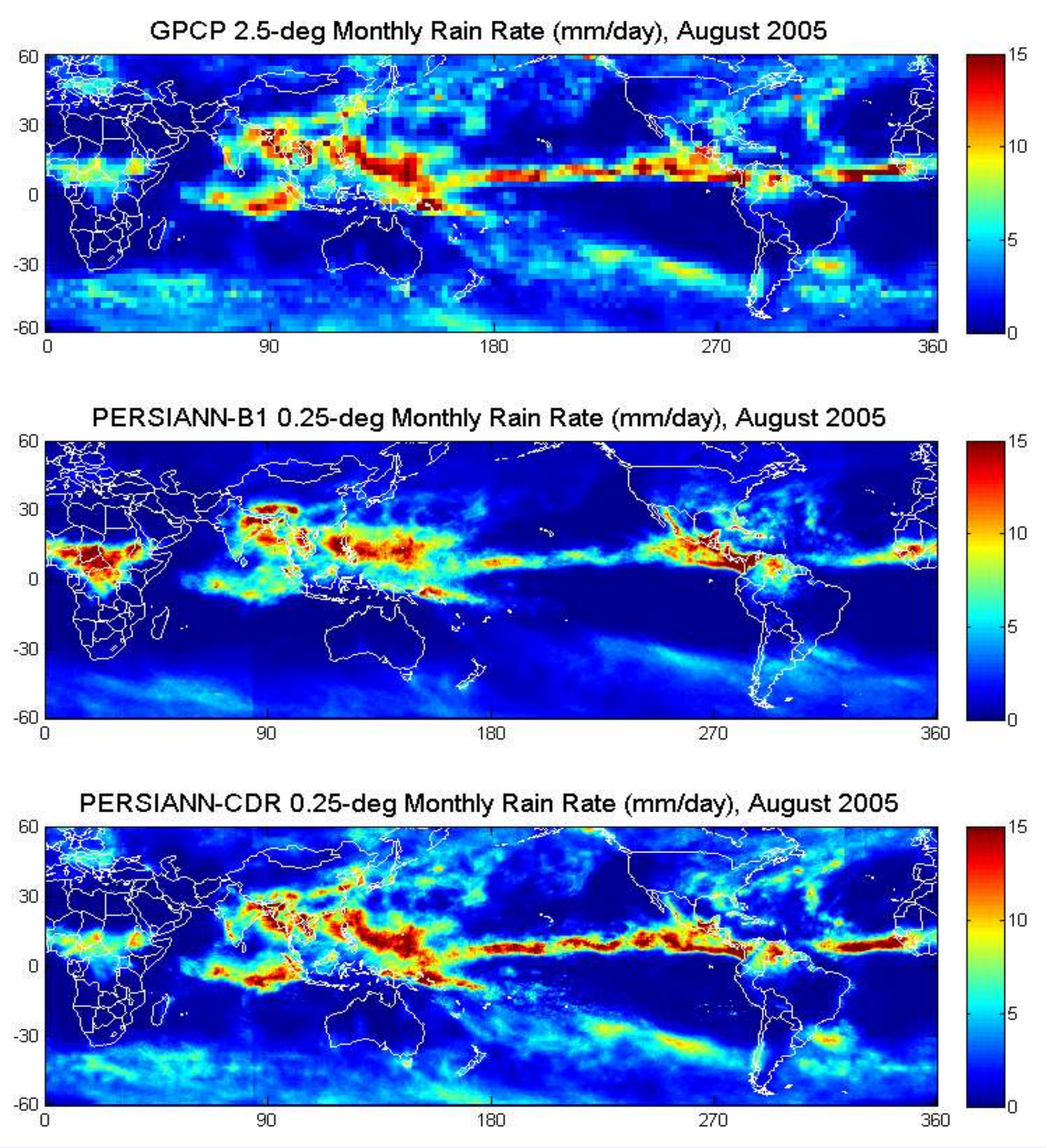
PERSIANN Climate Data Record (PERSIANN-CDR)

33 Years of Multi-Satellite, High-Resolution, Near-Global, Daily Precipitation Data Record

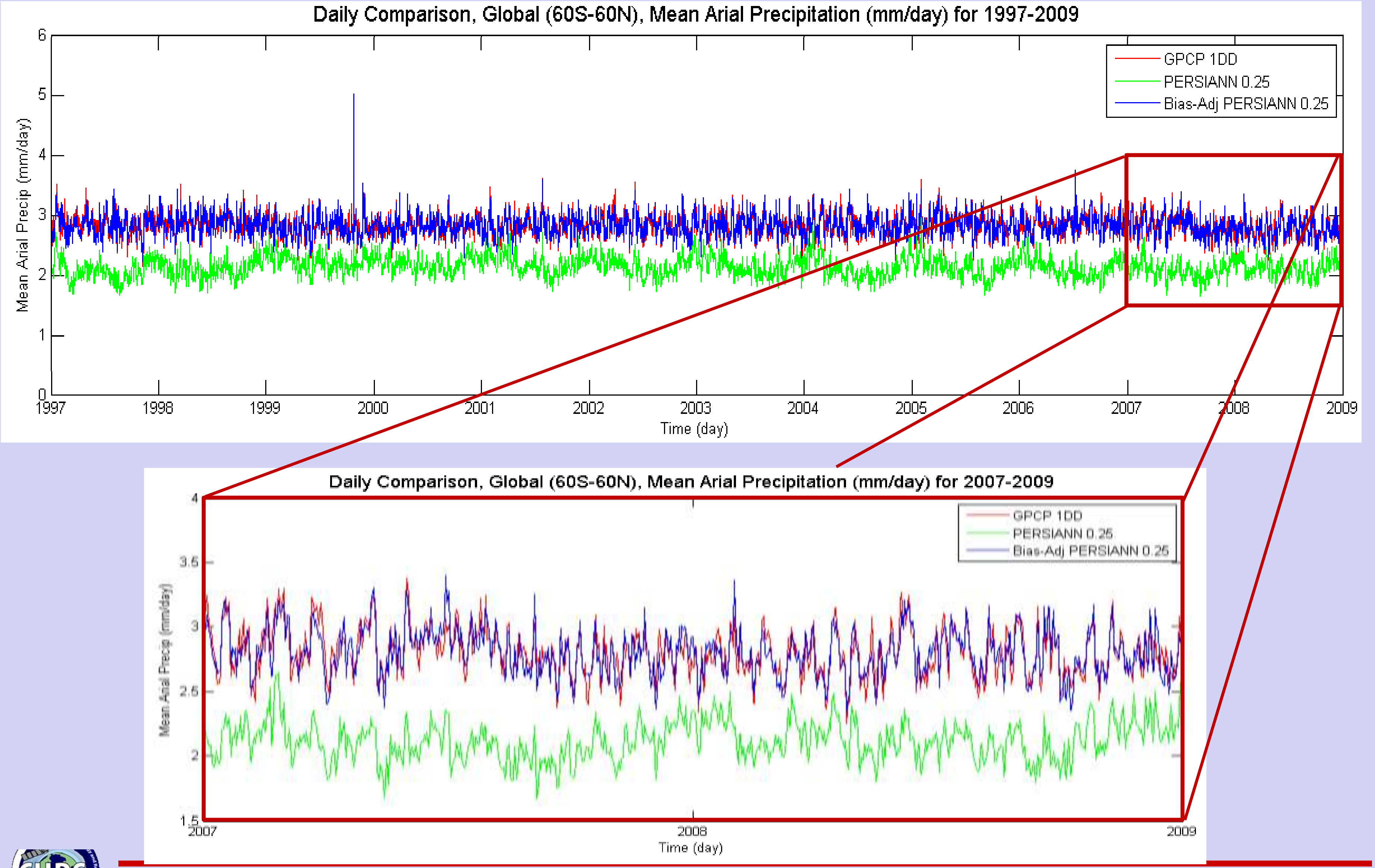
PERSIANN-CDR Algorithm



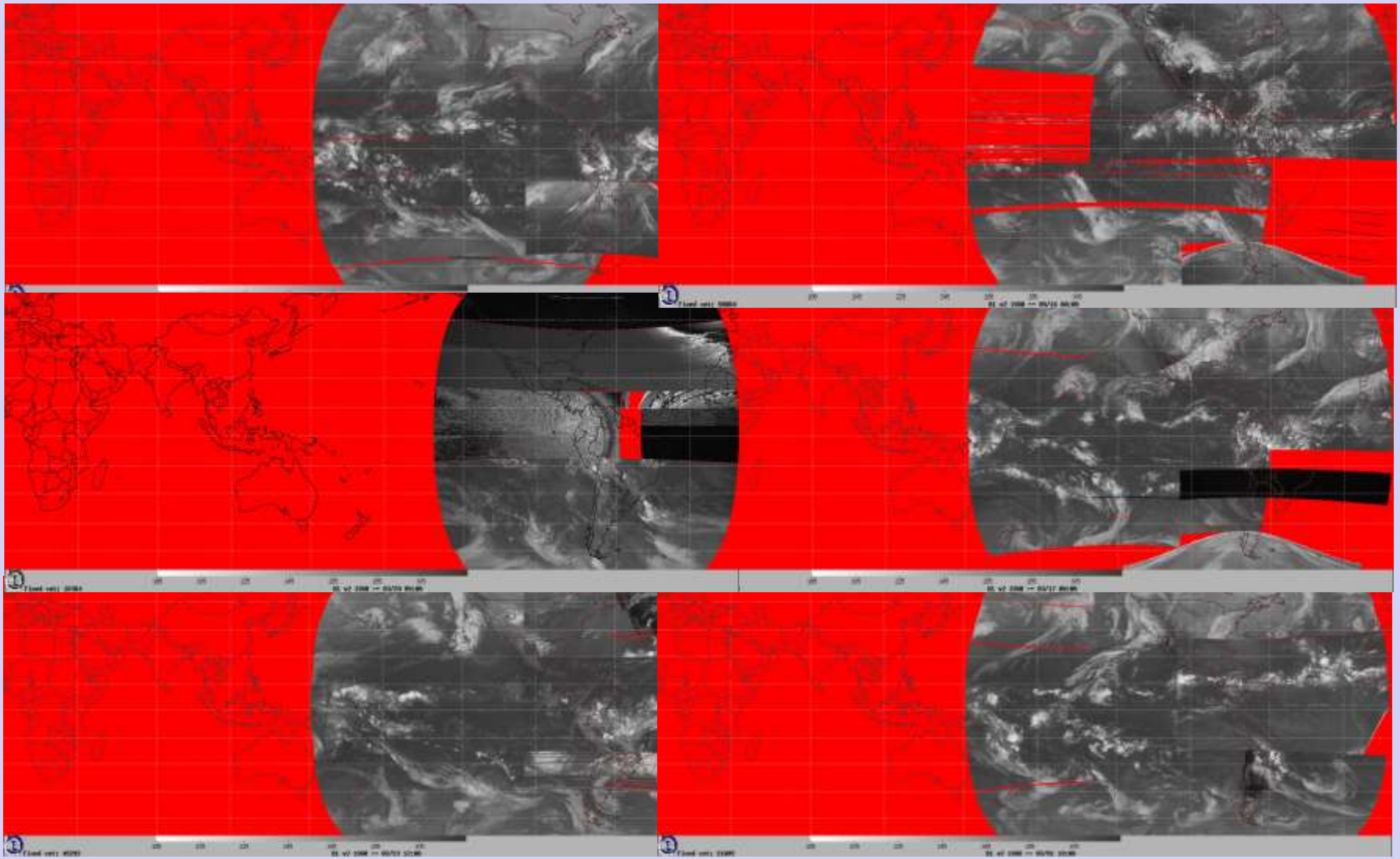
Preliminary Tests (Aug. 2013)

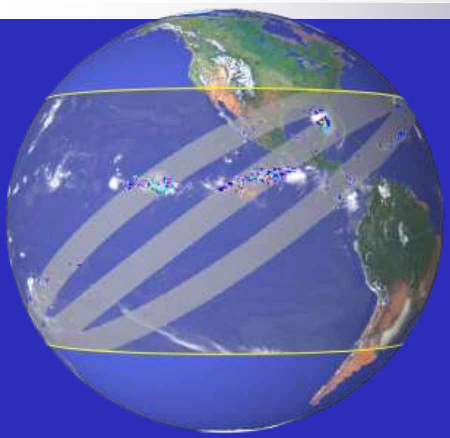


Daily Comparisons



Devils are in details …





PERSIANN-CONNECT
8-13-2013
University of California, Irvine

Last Chance: Present at the 2013 Fall Meeting Exploration Station.
Deadline 12 Aug. http:/bit.ly/FMExplore

EOS

IN THIS ISSUE:

EOS, TRANSACTIONS, AMERICAN GEOPHYSICAL UNION

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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

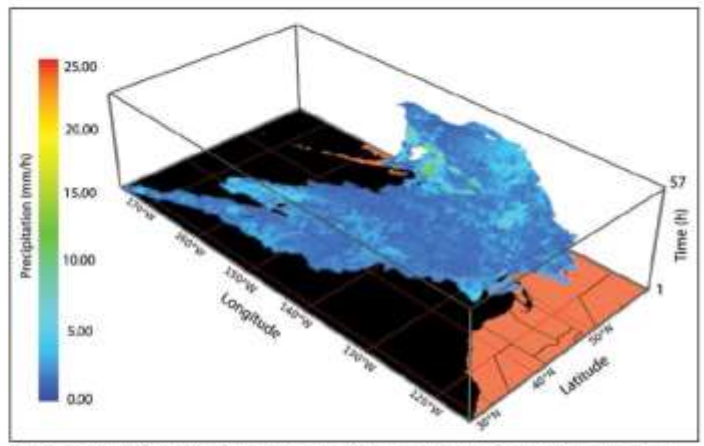
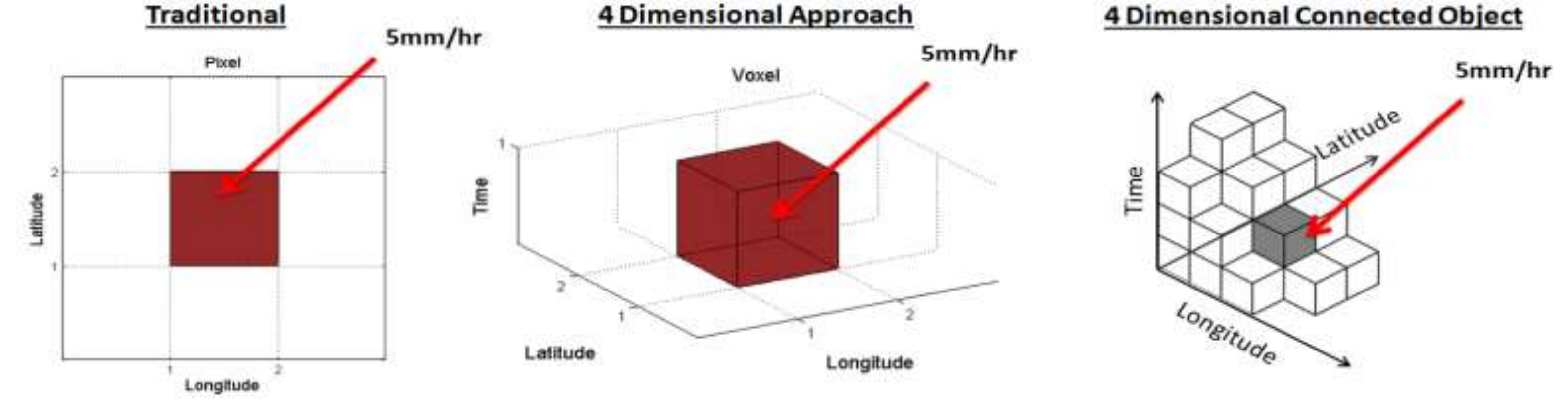


Fig. 1. A connected four-dimensional atmospheric river, or "precipitation object," extracted from the PostgreSQL database. The atmospheric river originated in the eastern Pacific and affected the western United States from 28 to 30 December 2005.

**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*

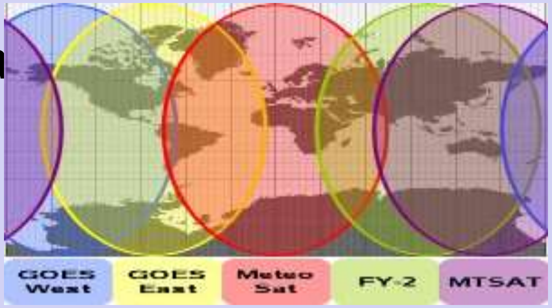
Transforming Big Data Into Insight

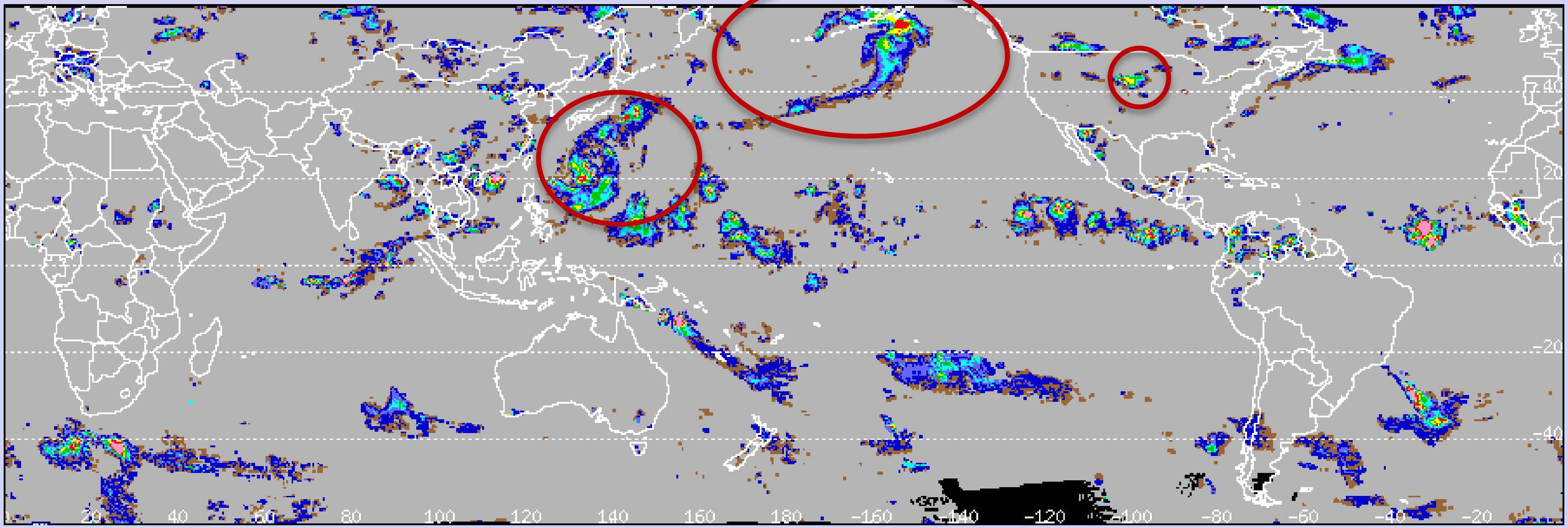
- PERSIANN CONNected precipitation objECT
  - PERSIANN-CONNECT
- Connectivity algorithm transforms data into 4D “objects” in time and space
  - Latitude, Longitude, Time and Intensity
- Allows “object” population statistics to be discovered and analyzed – Teleconnections with Climate Indices?



PERSIANN

- Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN)
- Hourly bias corrected PERSIANN w/GPCP data
- 0.25 degree
- 60^0 North - 60^0 South
- 01 March 2000 – 1st January 2011





4D Object Characteristics

Physical Based Characteristics:

- Duration (hr)
- Max Intensity (mm/hr)
- Speed (km/hr)
- Centroid (lat/lon)
- Volume (m^3)
- and many more…

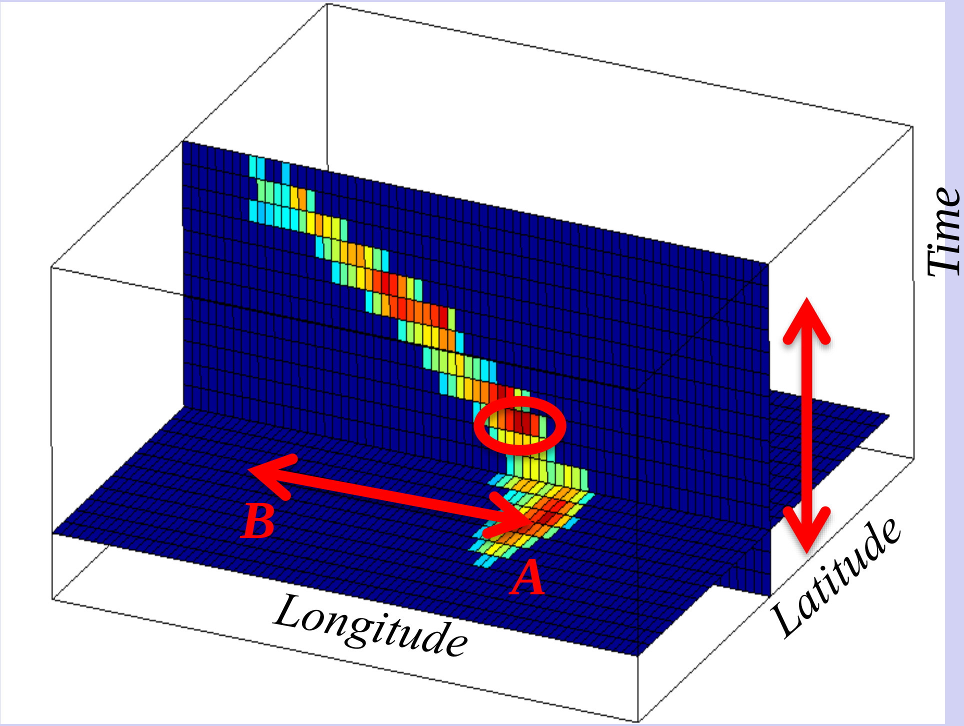
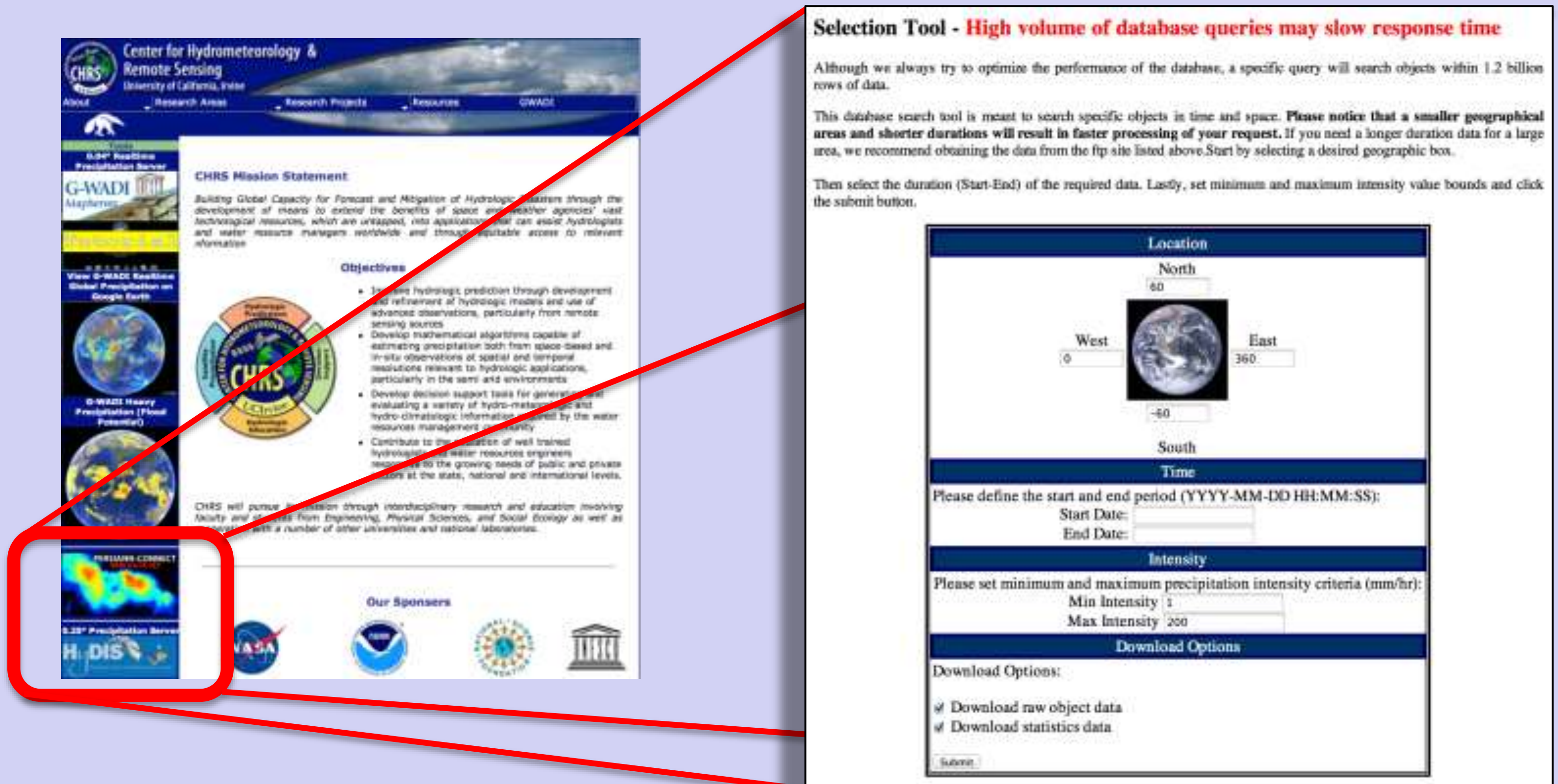


*Image courtesy of Dr. Wei Chu (CHRS)

Online PERSIANN-CONNECT Database Access

- All objects and characteristics are stored in a publically available PostgreSQL database
  - http://chrs.web.uci.edu/research/voxel/index.html



Impact of Irrigation

Previous studies:

1) Based on temperature variation

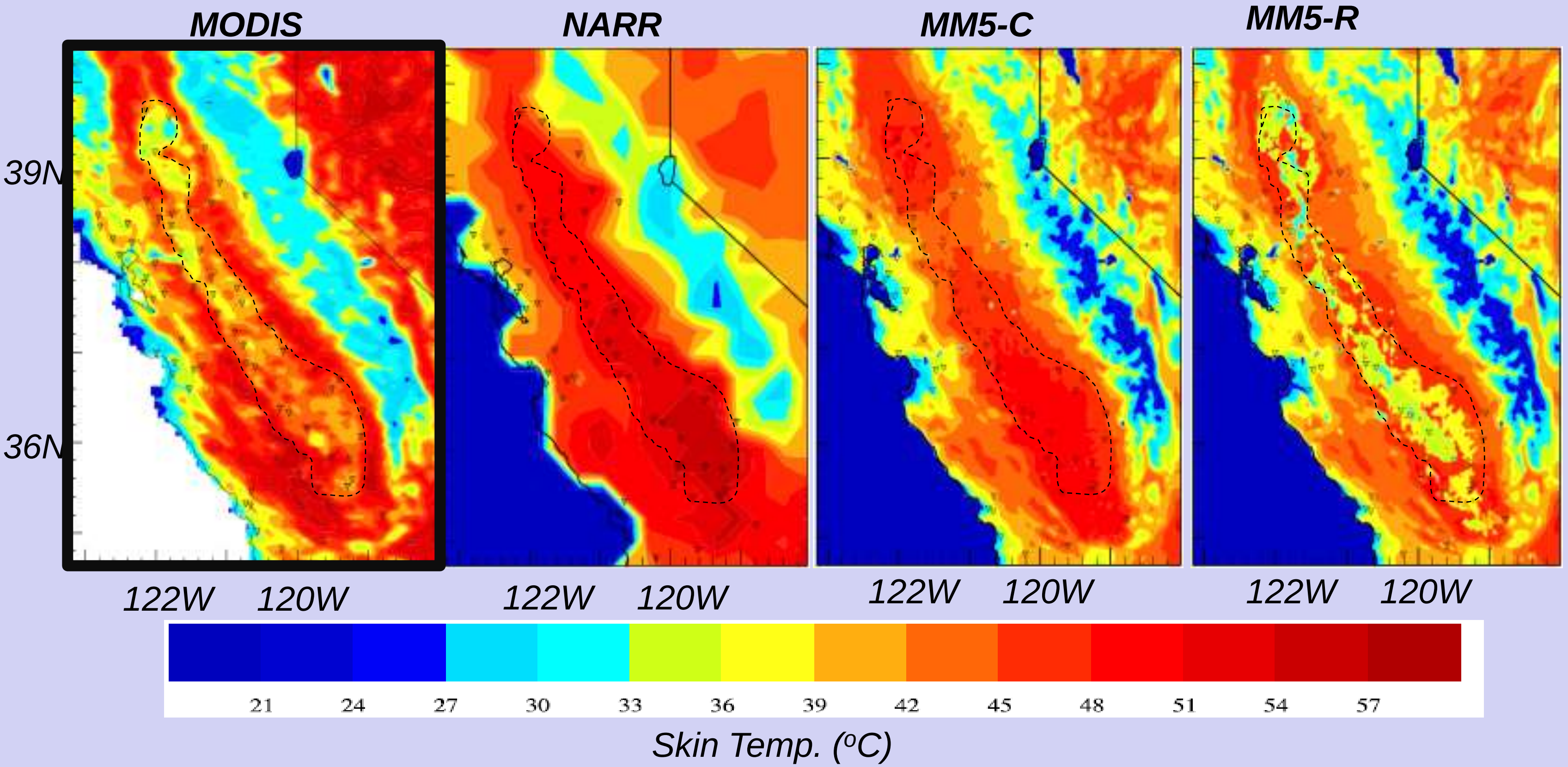
2) Assuming soil water at field capacity (saturation)

- *the modeled soil layers are kept at field capacity or at full saturation during the simulation runs (e.g.Adegoke, et al. 2003; Haddand et al. 2006; Kueppers at al. 2007)*

Our study

Implementing a more realistic irrigation method recommended by Hanson et al. (2004)

Mean skin surface temp. at daytime in June, July and August, 2007.

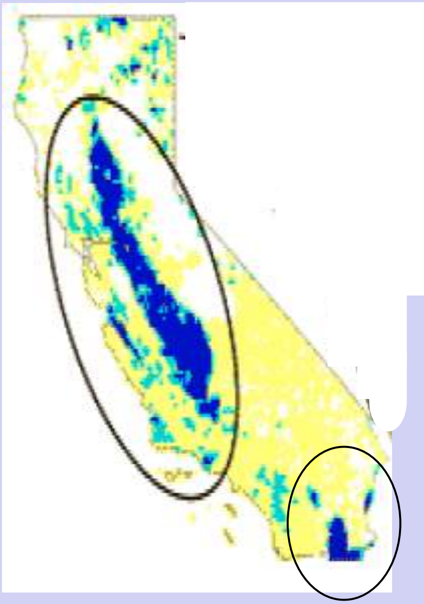


Adding irrigation into RCM (MM5), Improves the model's ability to simulate, more closely, the temperature patterns observed by MODIS

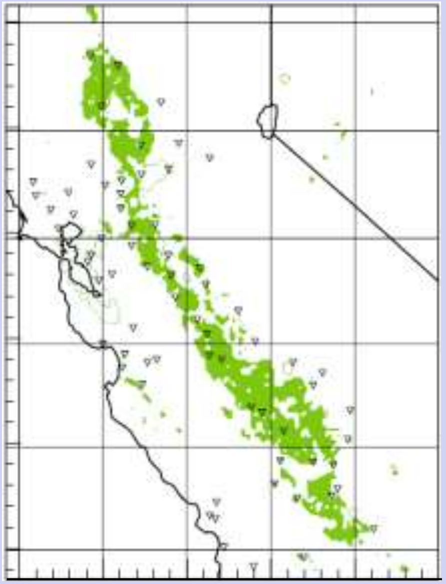
Sorooshian et al, (JGR 2011)

"Observed" vs "Model-Generated" Data

Irrigation areas



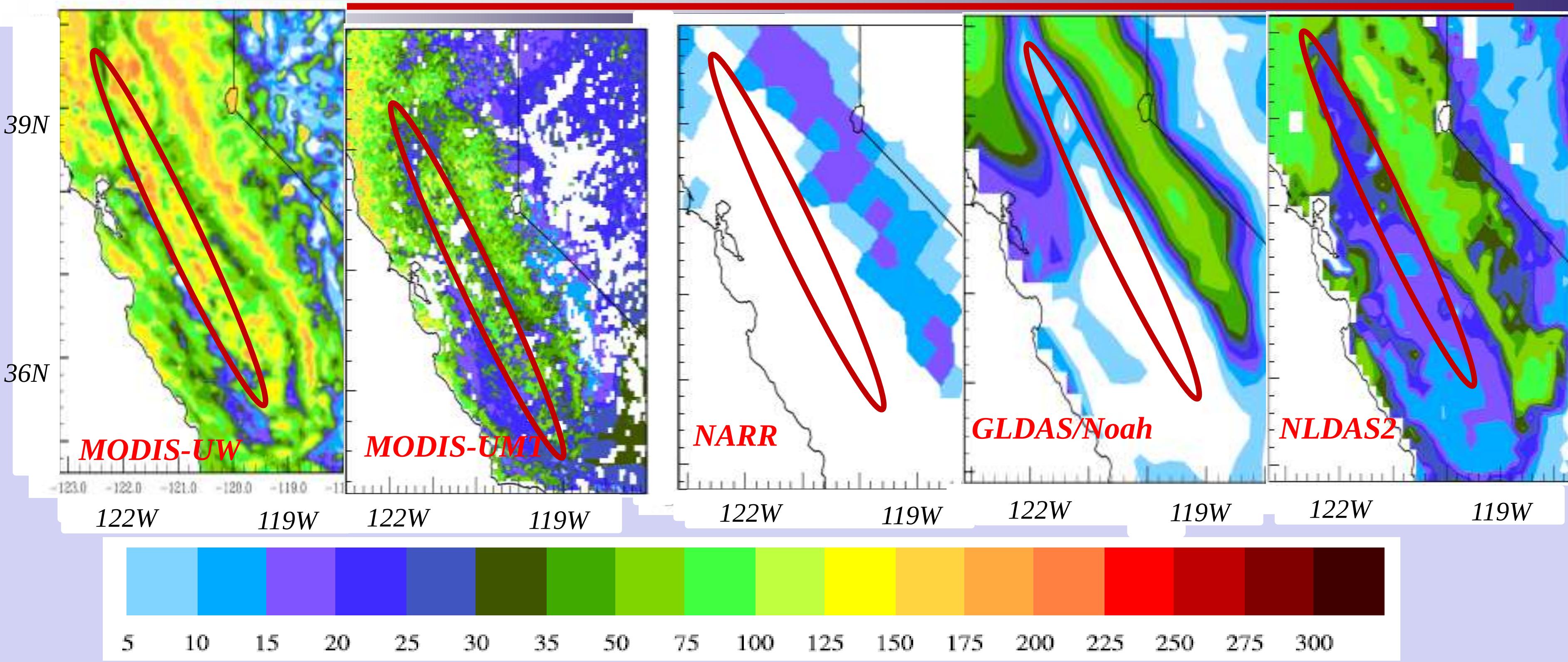
CIMIS stations



Studies over California's Central Valley Irrigation Region

Sorooshian et al. 2011 & 2012

Actual ET Estimates From Different Data sets– JJA 2007



2007 JJA Monthly ET (mm)

Li et al, 2011

In a nutshell!

- ***ET Underestimation by MM5 control run is roughly about 10 million Ac-Ft of water/yr***
- ***ET Overestimation by MM5 with "full-saturation" irrigation is about 6.5 Million Ac-Ft/yr***
- ***Use of the realistic irrigation scheme results in only 1.5 Million Ac-Ft/yr of overestimation.***

placed in Societal context :

Roughly speaking, the amount of ET underestimation equals supply requirement of 13 million households and the overestimation covers the needs of 9 million households per year.

Thank You For the Invitation

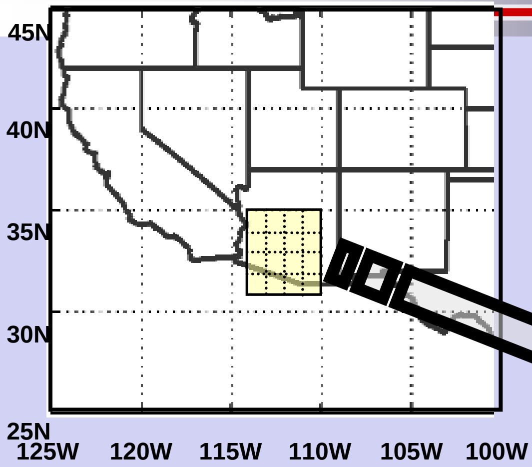
Somewhere in New Mexico, USA - Photo: J. Sorooshian

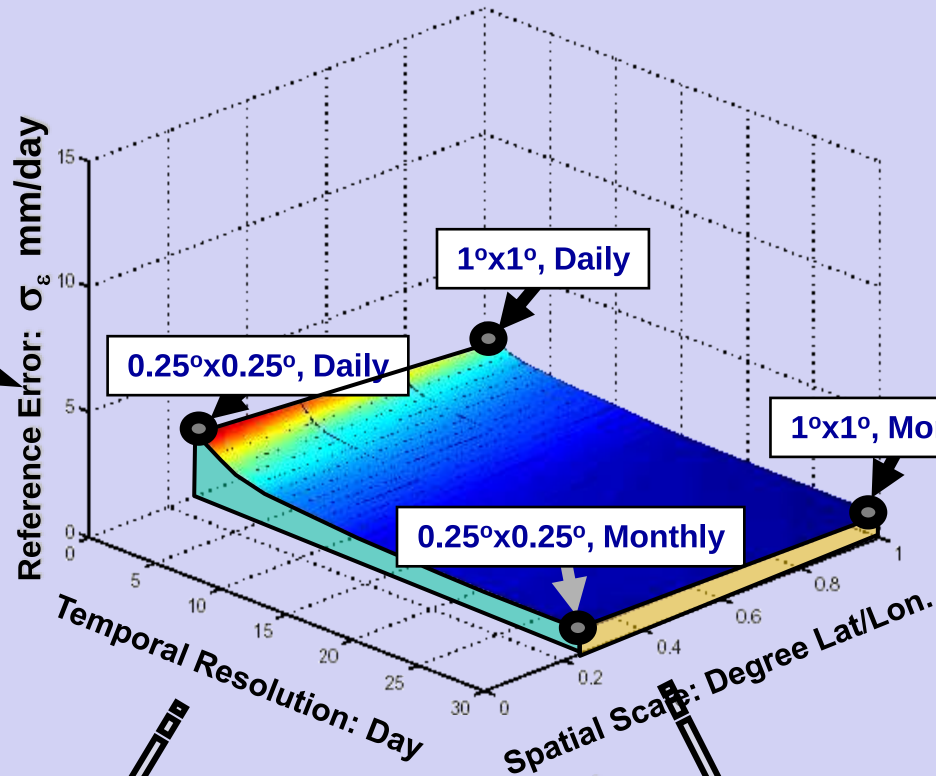
Back Up

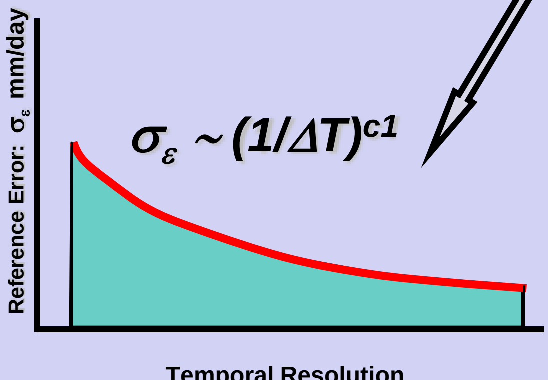
➢*Uncertainty of Estimates*

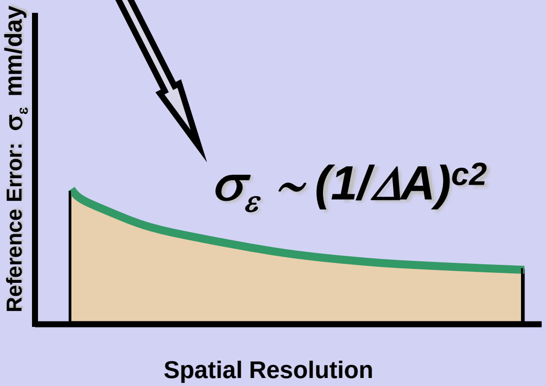
Error Analysis

Spatial-Temporal Property of Reference Error

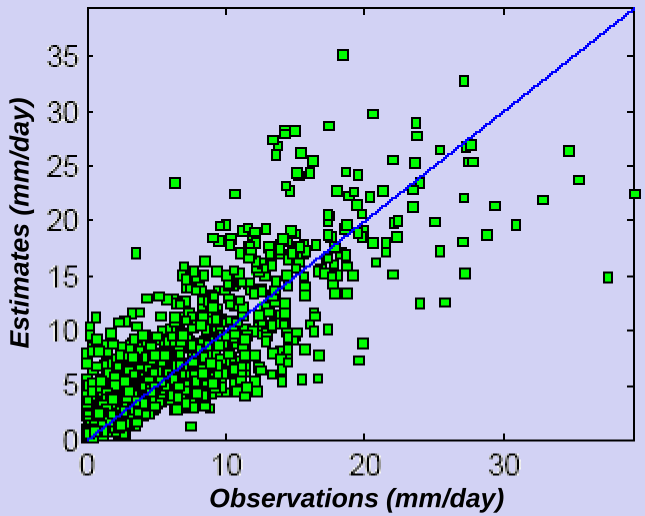


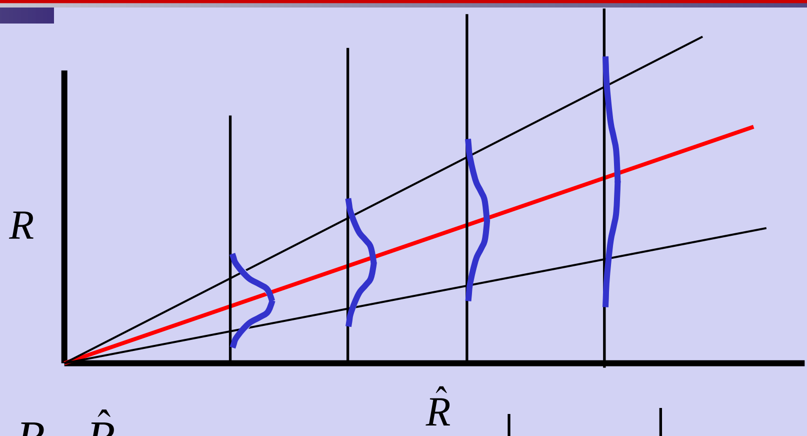


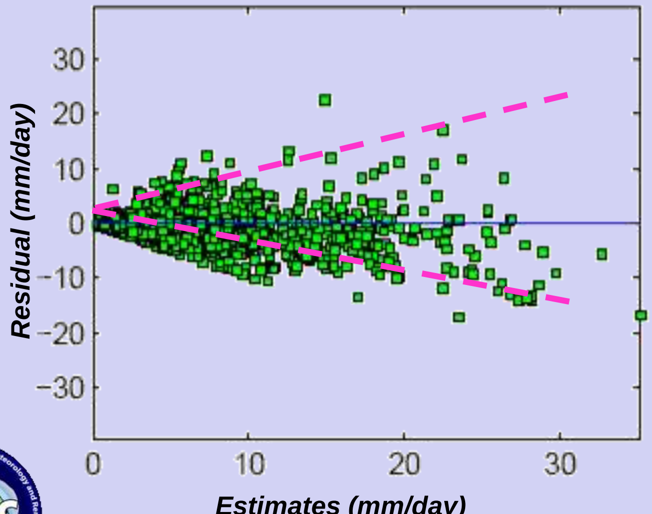


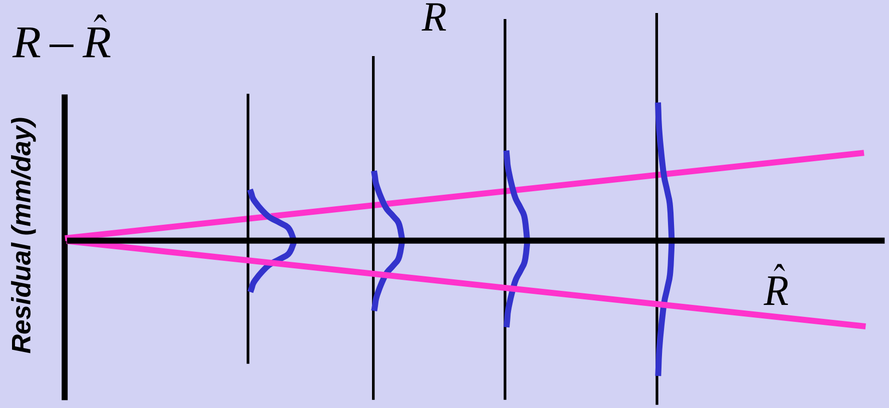


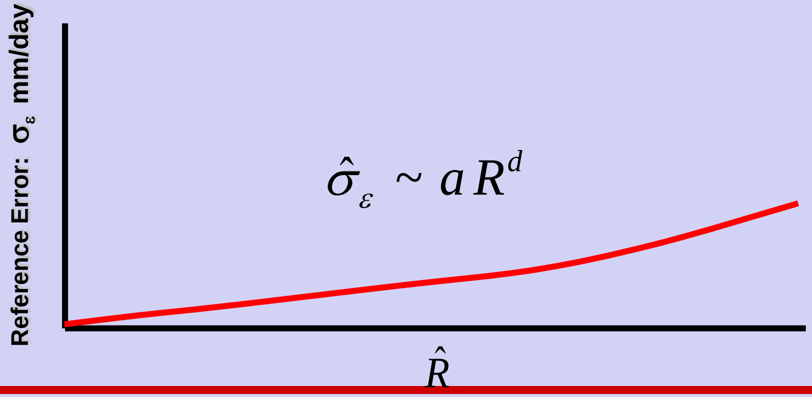
Reference Error: ΔT = 24-hour, ΔA = 0.25ºx0.25º





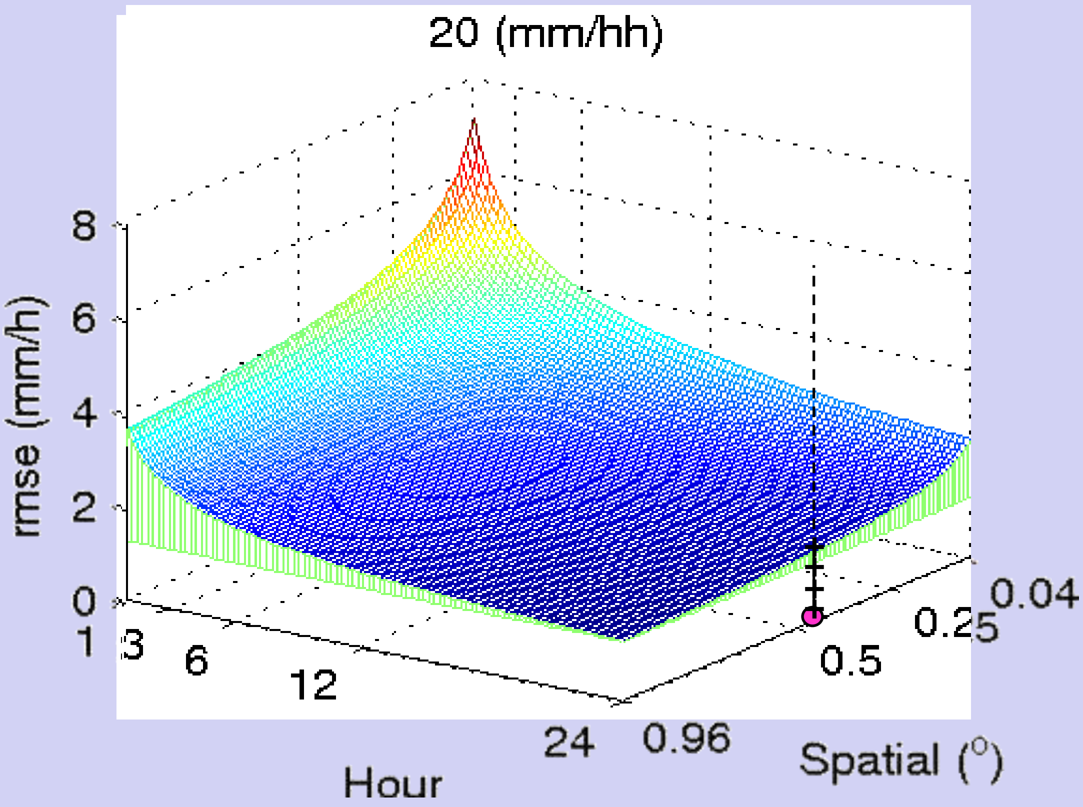






Scaling Property of PERSIANN-CCS Reference Error

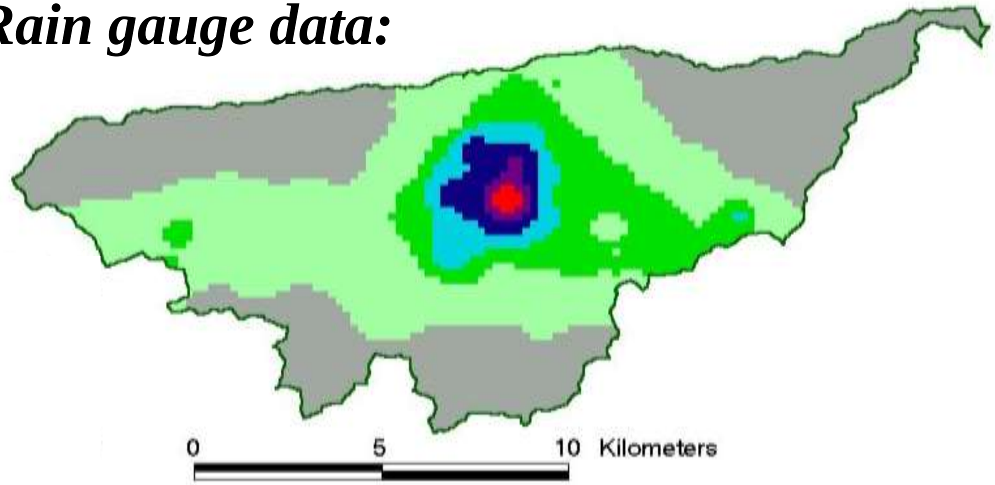
$$\hat{\sigma}_{\varepsilon} = a_1 . \left(\frac{1}{\Delta A}\right)^{b_1} \left(\frac{1}{\Delta T}\right)^{c_1} \left(\hat{R}\right)^{d_1}$$



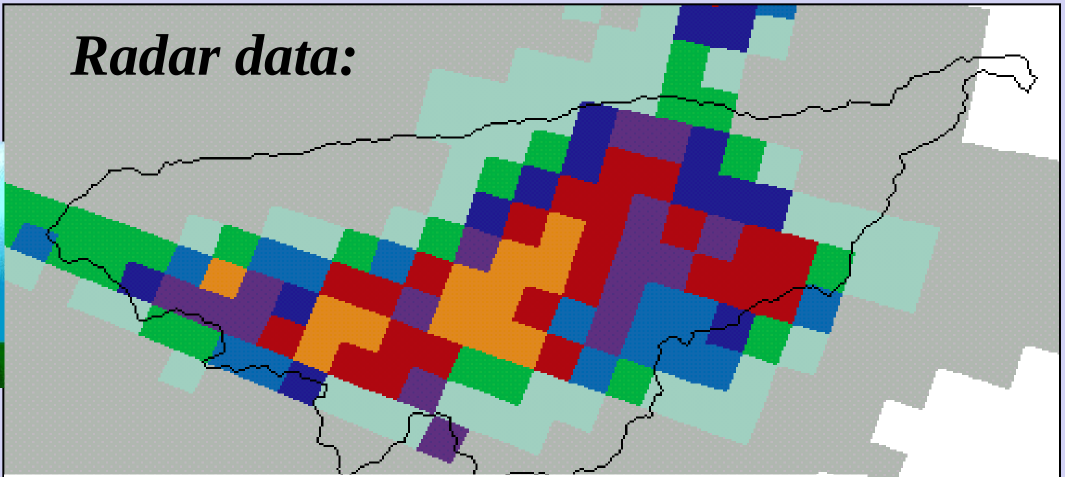
Radar-Gauge Comparison (Walnut Gulch, AZ)

Precipitation event:
Aug. 11, 2000

Rain gauge data:

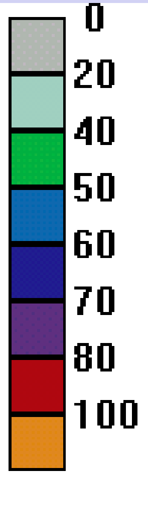


Radar data:



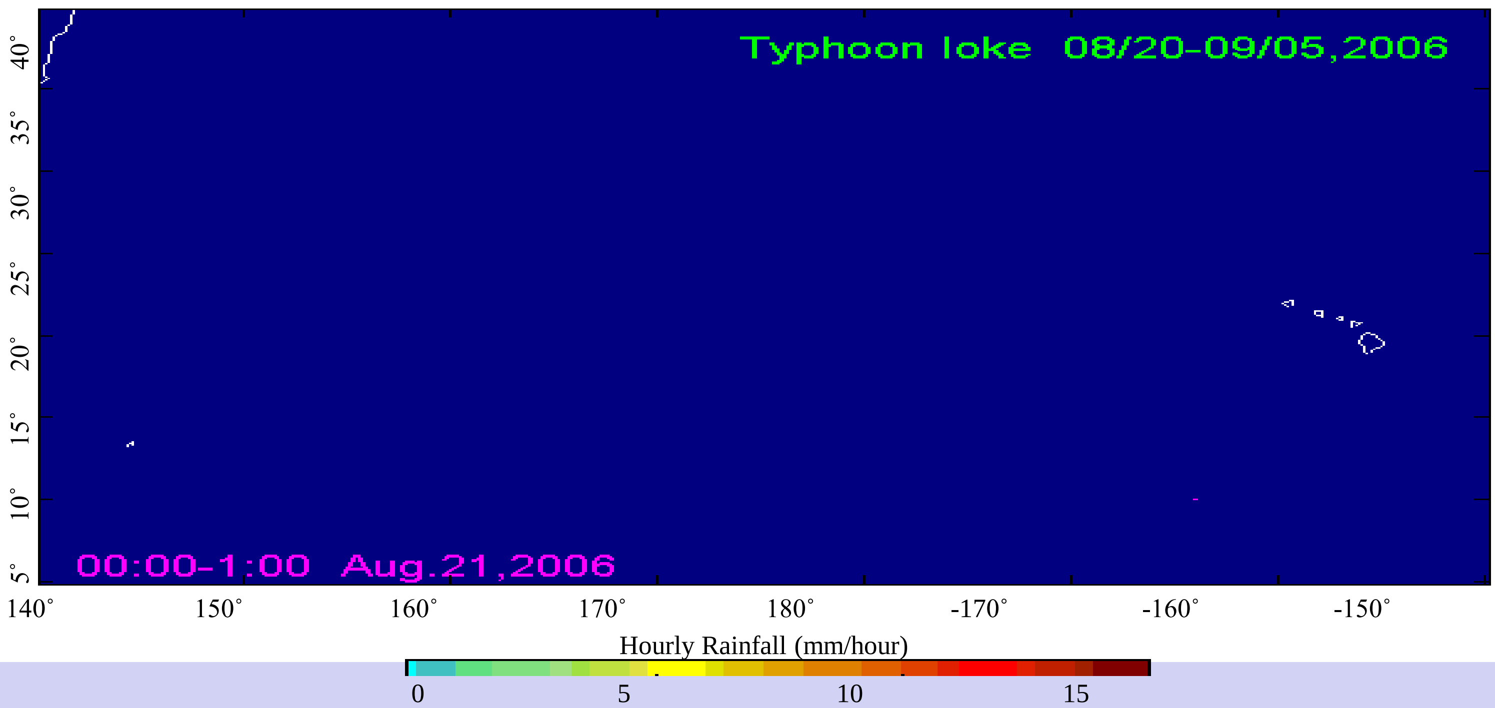
Z=300R$^{1.4}$, 2.4º elevation, HailThresh=56 dbz

Storm depth (mm)

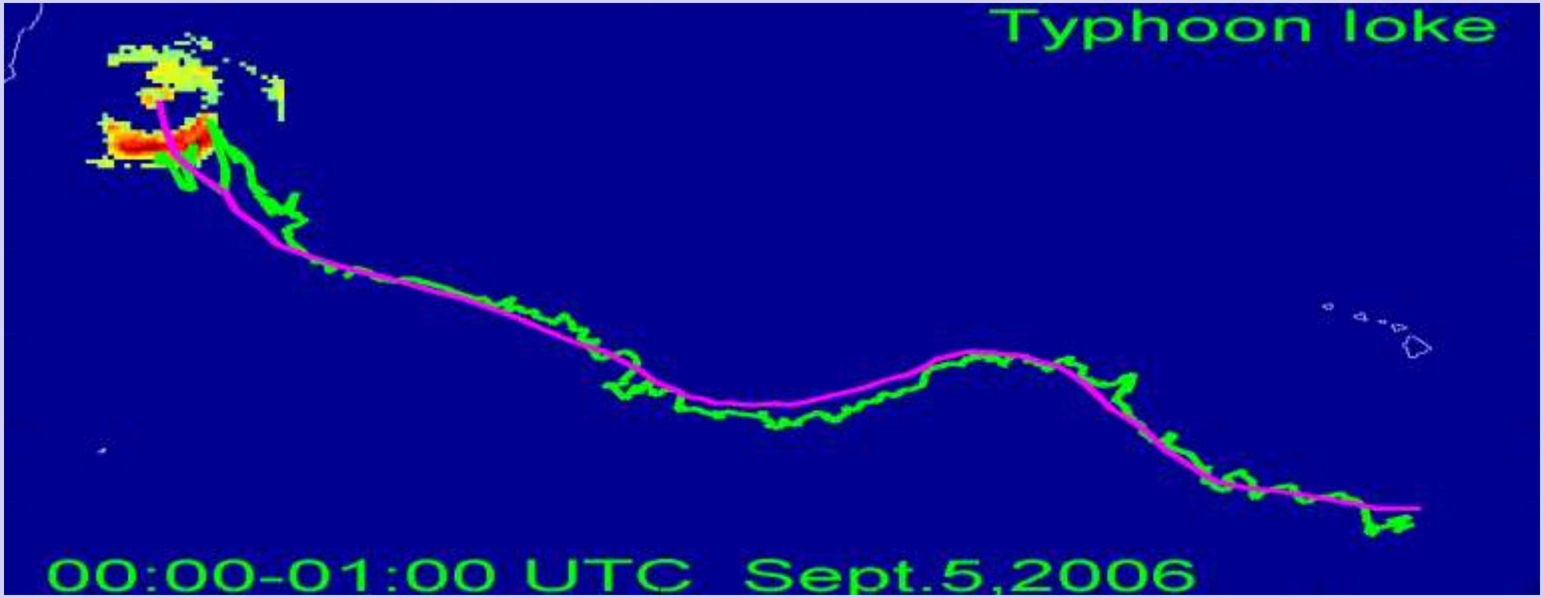


70% overestimation by the radar!

Morin et al ADWR 2005



Magenta line: Tracks of the location of the peak rainfall rate pixel



Green line: the 6-hourly track of rainfall volume centroid
Magenta line: the 6-houly track of the typhoon provided by IBTrACS.

Interpolation of 3-hour Precipitation