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

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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

Monthly total: 100 mm
Frequency: 67%
Intensity: 5 mm/day

Monthly total: 100 mm
Frequency: 6.7%
Intensity: 50 mm/day
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??

Rain Gauges

Satellite

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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

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

Maddox, et al., 2002
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 $\rightarrow$ colder $\rightarrow$ more precipitation
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)
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)

PERSIANN System “Estimation”

Satellite Data
- Global IR
  (CPC, NOAA)
- High Temporal-Spatial Res. Cloud Infrared Images
- MW-RR
  (TRMM, NOAA, DMSP Satellites)
- MW-PR Hourly Rain Rates
  (GSFC, NASA; NESDIS, NOAA)

Ground Observations
- GPCC & CPC
  Gauge Analysis
- Gauges Coverage

Error Detection

Feedback

Merging

Products
- Hourly Global Precipitation Estimates

Hourly Rain Estimate
- Quality Control

Merged Products
- Hourly rainfall
- 6 hourly rainfall
- Daily rainfall
- Monthly rainfall

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High Resolution Precipitation Estimates

PERSIANN-CCS
Stages of a Convective Storm and Rainfall Distribution

**TOWERING CUMULUS STAGE**
- Low/Warm Cloud
- Little/No Rain

**MATURE STAGE**
- Growing Higher/Colder
- Mild Rain
- Growing to Great Height
- Heavy Rain

**DISSIPATING STAGE**
- High Anvil Cloud
- Mild Rain

Rain Rate (mm/hr) vs. Temperature (K)

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Cloud Segmentation Algorithm

Patch Feature Extraction

Patch Classification

Rainfall Estimation

Image Segmentation

Patch Classification

Rainfall Estimation

Feature vector (\( \vec{V} \)) \( \in \) [patch coldness, patch geometry, patch texture]

\( T_b = 220 \text{K} \)

\( T_b = 235 \text{K} \)

\( T_b = 253 \text{K} \)

\( t = t_0 \)

\( t = t_1 \)

\( t = t_2 \)

\( t = t_k \)
High Resolution Precipitation Estimates from PERSIANN-Cloud Classification System

Radar Observation (2 km AGL)  PERSIANN-CCS Estimates

4km x 4km, 3-hour accumulated precipitation

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Many Features provided to users with Public Domain Software.
PERSIANN Satellite Product On Google Earth

http://chrs.web.web.uci.edu/
Validation and Application of Satellite Products
US Daily Precipitation Validation Page

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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.

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

Figure courtesy of ITT Industries
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

Behrangi et al (2009 a & b)

Hit Under Estimation Over Estimation
PERSIANN Climate Data Record (PERSIANN-CDR)

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

**GridSat-B1 IRWIN**

High Temporal-Spatial Res. Cloud Infrared Images

Artificial Neural Network

**PERSIANN Hourly Rainfall (0.25°x0.25°)**

**Adjusted PERSIANN 3-Hourly Rainfall (0.25°x0.25°)**

**GPCP Bias Adjustment**

**GPCP Monthly Precipitation (2.5°x2.5°)**

**PERSIANN Monthly Rainfall (2.5°x2.5°)**

**Spatiotemporal Accumulation**
Preliminary Tests (Aug. 2013)
Daily Comparisons

Daily Comparison, Global (60S-60N), Mean Arial Precipitation (mm/day) for 1997-2009

Daily Comparison, Global (60S-60N), Mean Arial Precipitation (mm/day) for 2007-2009
Devils are in details …
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.

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

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?
- Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN)
- Hourly bias corrected PERSIANN w/GPCP data
- 0.25 degree
- 60° North - 60° 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
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 et 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)
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

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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.
Back Up
Uncertainty of Estimates
Error Analysis
Spatial-Temporal Property of Reference Error

Reference Error: $\sigma_\varepsilon \sim (1/\Delta T)^{c_1}$

Reference Error: $\sigma_\varepsilon \sim (1/\Delta A)^{c_2}$

Spatial Resolution

Temporal Resolution
Reference Error: $\Delta T = 24$-hour, $\Delta A = 0.25^\circ \times 0.25^\circ$
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)

Rain gauge data:

Precipitation event: Aug. 11, 2000

Storm depth (mm)

Radar data:

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

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-hourly track of the typhoon provided by IBTrACS.
Interpolation of 3-hour Precipitation