Remote Sensing Precipitation Using GEO Satellite Information

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New and emerging remote-sensing technologies for precipitation data sets and their applications and validation

The IPWG7 Training Course Program
17-20 November 2014
Tsukuba International Congress Center, Tsukuba, Japan
Outline

• Precipitation Measurement
• GEO Satellite Information for Precipitation Retrieval
• Precipitation Estimation from Remote Sensing Information using Artificial Neural Networks (PERSIANN)
• PERSIANN-Climate Data Record (PERSIANN-CDR)
• Summary
Extreme Precipitation & Flash Flooding

Floods caused by extreme precipitation are the most widespread nature disasters

High spatial and temporal resolution of precipitation measurement is needed for operational hydrology
Precipitation Observation

WSR-88D Radar

Rain Gauges

Satellite
Coverage of the WSR-88D and gauge networks

1 km AGL
**Satellite Precipitation Monitoring**

- **Geostationary IR**
  - Cloud top heights only
  - 15-30 minute data

- **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
  - (35°N-35°S only)
“Instantaneous” rain rate from TRMM

http://trmm.gsfc.nasa.gov/
Typical Microwave Coverage in 3 Hr

http://trmm.gsfc.nasa.gov/

- TMI – white
- AMSR-E – medium grey
- SSM/I – light grey
- AMSU-B – dark grey
Mission Elements:
- **GPM Core Satellite**
- **Constellation Satellite Members**
- **Precipitation Processing System (PPS)**
- **International Ground Validation (GV) Network & Research Program**
- **International Body of Science and Engineering Teams**

Building on the Rich Heritage of the Tropical Rainfall Measuring Mission (TRMM), the GPM Mission is:

- the Flagship Mission for Global Water and Energy Cycle (GWEC) research.
- an International Partnership Constellation Mission—Potential missions by ESA (E-GPM) and CNES-ISRO (Megha-Tropiques) are currently under consideration.
- an important contribution to the U.S. Climate Change Science Program (CCSP) and the U.S. Weather Research Program (USWRP).
- an outstanding example of peaceful uses of space, according to the United Nations, enabling important societal applications involving fresh water resources and environmental forecasting.
- a prototype for the emerging Global Earth Observation System of Systems (GEOSS), a coordinated international effort to provide comprehensive, long-term, and systematic observations of Earth.

**GPM**

An International Partnership Mission to Understand Global Precipitation and Its Impact on Humankind

**NASA**

[www.nasa.gov](http://www.nasa.gov)

**Science Mission Directorate**

[http://science.hq.nasa.gov](http://science.hq.nasa.gov)

**GPM**


One of the next generation of systematic measurement missions that will measure global precipitation, a key climate factor, with improved time resolution and spatial coverage.

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**Global Precipitation Measurement**

**NASA**

[www.nasa.gov](http://www.nasa.gov)

**JAXA**

[www.jaxa.jp](http://www.jaxa.jp)
Interpolation of 3-hour Precipitation

Rain started between 3-hr period

Missed the peak

Rain ended between 3-hr period

Short-life event
Advantages:
• Good space and time resolution (half-hour, 4 km)
• Observations in near real time
• Near global coverage

Disadvantages:
• Measures cloud-top properties instead of rain
• May mistake cirrus for rain clouds
• May not capture rain from warm clouds
VIS/IR Rainfall Estimates

- **IR brightness temperature**
  - Deeper clouds ≠ colder ≠ heavier rainfall
  - Low clouds ≠ Warm ≠ no rain

- **VIS reflectivity**
  - Thicker clouds ≠ brighter: heavier rainfall
  - Light clouds ≠ Dark: no rain
VIS-IR Image vs. Rainfall
**VIS-IR Image vs. Rainfall**

**Infrared Imagery: (0400 UTC, 6/5/89)**

A. **Cold-Thin clouds**

B. **Warm-Thick clouds**

**Visible Imagery: (0400 UTC, 6/5/89)**

**(c) Ground-based Rainfall Measurement**

**Rain Rate (mm/hr)**

- 0 to 15
- Visible: 0.6 to 0.8
- Infrared (K): 210 to 300

- NaN: 0
- 0.5
- 3
- 7 (mm/hr)
Multi-spectral Image for Rain Classification

Ali et al., J. Hydrometeorology, 2009
Florida: Hurricane Ernesto August 30 2006

Ch 1: 0.6 µm  Ch2: 3.9 µm  Ch3: 6.5 µm  Ch4: 10.7 µm  Ch5: 13.3 µm

ETS=25  POD=74  FAR=45
ETS=29  POD=77  FAR=42
ETS=27  POD=78  FAR=44
ETS=36  POD=76  FAR=35
ETS=30  POD=80  FAR=42
ETS=30  POD=78  FAR=39
ETS=35  POD=79  FAR=37
ETS=48  POD=75  FAR=22
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ETS=37  POD=78  FAR=35
ETS=37  POD=80  FAR=36
ETS=48  POD=75  FAR=22
ETS=49  POD=79  FAR=24
ETS=37  POD=78  FAR=35
ETS=37  POD=80  FAR=36
ETS=48  POD=75  FAR=22
ETS=49  POD=79  FAR=24

Ali et al., J. Hydrometeorology, 2009
A Strategy for Satellite Precipitation Estimation

Nonlinear multivariate function

f(.)

GOES
IR
VIS
...

Location
Topography
Wind flow
Water Vapor
.
.
.

Other Information

Rainfall Intensity

error

High quality Rainfall sampling data

Rain gauge, radar, SSM/I, and TRMM
Some IR based Algorithms

- **Global Precipitation Index (GPI):** Arkin and Meisner, 1987
- **Negri-Adler-Wetzel (NAW) technique:** Negri et al., 1984
- **Convective Stratiform Technique (CST):** Adler & Negri, 1988
- **AutoEstimator:** Vicente et al., 1998
- **Hydro-Estimator:** Scofield and Kuligowski, 2003
- **Tropical Applications of Meteorology using SATellite data (TAMSAT):** Grimes et al., 1999
- **PERSIANN/PERSIANN-CCS.PERSIANN-MSA:** Hsu et al., 1997; Sorooshian et al., 2000; Hong et al., 2004; Behrangi et al., 2009
- **and many more ...**
PERSIANN System
Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks
Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks

PERSIANN System “Estimation”

Satellite Data

- Global IR
- MW-RR (TRMM, NOAA, DMSP Satellites)
- High Temporal-Spatial Res. Cloud Infrared Images
- MW-PR Hourly Rain Rates

Products

- Hourly Global Precipitation Estimates

Ground Observations

- Radar Coverage
- Gauges Coverage

HyDIS WEB

Sorooshian et al., BAM, 2000
Designing the PERSIANN System

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

Input Variables
- satellite cloud features
- geophysical features

SOFM Algorithm

Linear Classifier

Rainfall Rate

Output Variable

Switch

Error Detection-Correction

Input feature Classification

other sources of observations

Feedback for adaptivity
Input Variables

- Surface Type: Land, Coast Ocean
- $T_b$ at the central pixel
- $T_b$ and $T_b$-SD in the 3 x 3 window
- $T_b$ and $T_b$-SD in the 5 x 5 window

$w = 2$

RR(c)
Comparing the rain rate distribution on the output layer with the weight distributions of input variables on the SOFM layer.
Daily Rainfall: January 23, 2005

Verification statistics for 20050123, n=9835, Verif. grid=0.25°, Units=mm/d

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<th>PERSIANN</th>
<th>Analysed PERSIANN</th>
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<tr>
<td>≥1</td>
<td>653</td>
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Daily fraction by occurrence:

- Obs
  - % Areal fraction 100%
  - Daily fraction of total rain
  - Rainfall accumulation by amount

PERSIANN estimates for 20050123
IPWG Validation of Precipitation (US)

http://cics.umd.edu/ipwg/us_web.html

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

<table>
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<tr>
<th></th>
<th>(G)</th>
<th>(S)</th>
<th>(R)</th>
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<tbody>
<tr>
<td>Number of points</td>
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<td>13828</td>
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<tr>
<td># points w/rain</td>
<td>4248</td>
<td>4605</td>
<td>2971</td>
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<tr>
<td>Mean rain rate</td>
<td>5.86</td>
<td>4.26</td>
<td>3.13</td>
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<tr>
<td>Cond. rain rate</td>
<td>17.62</td>
<td>12.47</td>
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<td>Max. rain rate</td>
<td>181.99</td>
<td>79.07</td>
<td>131.45</td>
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<table>
<thead>
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<th>G-S</th>
<th>G-R</th>
<th>R-S</th>
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<tr>
<td>Correlation</td>
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<td>Mean Absolute Error</td>
<td>3.63</td>
<td>3.42</td>
<td>3.35</td>
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<td>RMSE (mm/day)</td>
<td>9.44</td>
<td>11.23</td>
<td>8.66</td>
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<td>RMSE (normalized)</td>
<td>1.70</td>
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<td>Probability of Detection</td>
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<td>0.654</td>
<td>0.655</td>
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<tr>
<td>False Alarm Ratio</td>
<td>0.321</td>
<td>0.065</td>
<td>0.455</td>
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<tr>
<td>Bias Ratio (rainfall)</td>
<td>1.098</td>
<td>0.689</td>
<td>1.570</td>
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<tr>
<td>Heidke Skill Score</td>
<td>0.574</td>
<td>0.692</td>
<td>0.546</td>
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<tr>
<td>Hanasso–Kuipers Score</td>
<td>0.589</td>
<td>0.634</td>
<td>0.680</td>
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<tr>
<td>Equitable threat score</td>
<td>0.402</td>
<td>0.528</td>
<td>0.376</td>
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<tr>
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<th>PERSIANN</th>
<th>Rodar</th>
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<tr>
<td>≥ 1</td>
<td>1147</td>
<td>2778</td>
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Rainfall Estimation Using Satellite-Based Cloud Classification Maps
Satellite Image Feature Extraction

- $T_b$: IR temperature of calculation pixel
- $\mu_{3\times3}$: Mean temperature of 3x3 pixels
- $\sigma_{3\times3}$: Standard deviation temperature of 3x3 pixels
- $\mu_{5\times5}$: Mean temperature of 5x5 pixels
- $\sigma_{5\times5}$: Standard deviation temperature of 5x5 pixels

Cloud information

Pixel information

200 225 250 275 300 325
Cloud Types and Rainfall Distribution

Cloud Type Classification

Tb–R relationship

Convective Cloud

Cirrus Cloud

Cloud Top Temperature Tb (°K)

Rainfall Rate (mm/hr)
Patch-based Approach (PERSIANN-CCS)

Feature vector \( \mathbf{v} \) ∈ \{patch coldness, patch geometry, patch texture\}
Multiple vs. Single Curve Fitting Models

400 $T_b$-R curves from PERSIANN-CCS model

(1) simple threshold
(2) Linear: single line
(3) Nonlinear: single curve
Features Extraction

\[ V \in \{ \text{patch coldness, patch geometry, patch texture} \} \]
Near Real Time Global Precipitation Data

http://hydis.eng.uci.edu/gwadi/
Global PERSAINTN-CCS Hourly Estimates

[Map showing global precipitation estimates.]
Continue Development

- Adjust PERSIANN-CCS precipitation estimates using passive microwave rainfall

- Improve rain estimation from warm clouds
Change Threshold from 253K to 280K
PERSIANN Precipitation Climate Data Record

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

- **Daily Precipitation Data**
- **Data Period:** 1983~2014
- **Coverage:** 60°S ~ 60°N
- **Spatial Resolution:** 0.25°x0.25°
Limited PMW Samples
Before year 2000

Equator–Crossing Times (Local)
1987–2010, Ascending Passes (F08, MetOp–A Descending)

Thickest lines denote GPCP calibrator.

Image by Eric Nelkin (SSAI), 20 October 2010, NASA/Goddard Space Flight Center, Greenbelt, MD.
Historical GEO Satellite Data

- International Satellite Cloud Climatology Project (ISCCP)
  1979 to present
  10-km and 3-hour intervals

1. U.S. Geostationary Operational Environmental Satellite (GOES)
2. European Meteorological satellite (Meteosat) series
3. Japanese Geostationary Meteorological Satellite (GMS)
4. The Chinese Fen-yung 2C (FY2) series

Source: NOAA NCDC
Bias Adjustment of PERSIANN Estimates

PERSIANN structure in a simple scheme

Satellite Data
- Global IR
- TRMM, DMSP, NOAA Satellites
- High Temporal-Spatial Res. Cloud Infrared Images
- Instantaneous PMW Rain Estimates

Parameter Adjustment

Products
- PERSIANN Hourly Rainfall (0.25°x0.25°)
- PERSIANN Monthly Rainfall (2.5°x2.5°)
- GPCP Monthly Precipitation (2.5°x2.5°)

PERSIANN Adjusted (Monthly Scale)
- Adjusted PERSIANN Hourly Rainfall (0.25°x0.25°)
- Bias Adjustment
Daily Precipitation: Hurricane Katrina, 2005

PERSIANN w/o GPCP adjustment

a) PERSIANN-B1

b) PERSIANN-CDR

c) Stage IV Radar
d) TMPA V7 3B42

Rain rate (mm/day)
Satellite Precipitation Data for Hydrologic Applications

Algorithm

Web Services

Applications

Drought Management  Flood Forecasting  Water Resources
Advantages of GEO-based precipitation retrieval:

• Good space and time resolution
• Observations in near real time
• Near global coverage

Improve IR-based estimation by:

• Extending from pixel to texture based classification
• Extending from single IR band to multi-spectral bands
• Integrating information with LEO satellite PMW measurements
• Merging estimation with ground measurements
• Applying advanced machine learning methods to learn cloud-rain system
Thanks !!