6th Workshop on Water Resources in Developing Countries: Hydroclimate Modeling, Information Tools and Simulation Techniques May 20-31, 2024

Satellite precipitation estimation at CHRS UCI: Algorithm Development & Challenges



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Floods caused by extreme precipitation are the most widespread nature disasters

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





Remote Sensing Precipitation

Hydrologic

Predictions

CIrvin

Hydrologic Education

Develop state-of-the-art systems to estimate rainfall from satellite observations at global scale and high spatial and temporal resolutions

Information Technology to provide world-wide access to real-time global precipitation products: http://hydis.eng.uci.edu/gwadi/



Goal:

High spatial and temporal resolution of precipitation measurements at global scale for hydrological applications:

- Short-term operational applications
 - Flood forecasting
 - Data assimilation in numerical weather models
 - Long-term climate extreme event analysis
- Hydro-climate studies
- Validation of GCM models

Precipitation Observation



Rain Gauges



WSR-88D Radar



Satellite

Multiple Sources for Rainfall Estimation



Precipitation Observation



Distance from nearest gauge





Source: Kidd et al. 2016

Precipitation Observation



Source: Walker and Western



NEXRAD Radar coverage

Satellite Precipitation Monitoring



Geostationary IR Cloud top heights only 15-30 minute data

Passive Microwave (SSM/I)Some characterization 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)

TRMM)

Observations from Satellites



TRMM, NOAA-15, -16, -17, DMSP F-13, F-14, F-15 (Six-Hour Sample Counts)



Global Precipitation Measurement (GPM)



The GPM spacecraft collects information that unifies data from an international network of existing and future satellites to map global rainfall and snowfall every three hours.





Tanegashima Space Center, Japan

Friday, Feb. 28, 2014

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



Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Cloud Classification System (PERSIANN-CCS)



PERSIANN-CCS (Real-time 4 km)



Cloud Feature Extraction









Multiple vs. Single Curve Fitting Models





- Cloud Segmentation (Cloud Patch vs. Pixel Window)
- Cloud Feature Extraction
- Cloud Patch Classification
- Cloud Coverage and Rainfall Distribution

Cloud Segmentation Algorithm







Features Extraction



IR-RR Relationship of Various Cloud Patches



IR-RR Relationship of Various Cloud Patches



Six-Hour Accumulated Rainfall: Hurricane Ivan September 2004



Thailand Flood 2011



Hsu, Sellars and Nguyen et al. 2013

iRain: http://irain.eng.uci.edu/





The dynamic cloud-top brightness temperature (T_b)-rain rate (RR) model



The workflow of PDIR from input to output



Average annual rainfall in mm/year for the validation period (2008-2013) for the baseline product Stage IV (ST4), the near real-time Stage II

(ST2), the three satellite-based precipitation products (CMORPH (CMO), TRMM, and PERSIANN-CCS (CCS)) and the new product, PDIR.



Continuous comparison metrics for daily rainfall



Volumetric categorical indices for daily rainfall



Rainfall during the period November 28th, 2012 to December 7th, 2012 associated with an extreme AR event over California



Rainfall during the period March 20, 2018 to March 25, 2018 associated with an extreme AR event over California

PERSIANN Precipitation Climate Data Record

Reconstruction of 30-year+ Daily Precipitation Data



PERSIANN Precipitation Climate Data Record

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

NOAA's NATIONAL CLIMATIC DATA CEN NOAA's Climate Data Record (CDR) Program

PRECIPITATION ESTIMATION FROM REMOTE SENSING INFORMATION USING ARTIFICIAL NEURAL NETWORK



CLIMATE DATA RECORD PROGRAM INFORMATION http://www.ncdc.noaa.gov/cdr/index.html

PERSIANN CLIMATE DATA SOME USES OF THE PERSIANN **RECORD SPECIFICATIONS** CLIMATE DATA RECORD 0.25-deg * 0.25-deg (60°S-60°N · Climatologists can perform long-term climate studies at latitude and 0°-360° longitude) a finer resolution than previously possible. Hydrologists can use PERSIANN-CDR for rainfall-runoff Daily Product 1980-present modeling in regional and global scale, particularly in Updated Monthly remote regions. Performing extreme Event Analysis (intensity, frequencies, and duration of floods and droughts). Water Resources Systems Planning and Management INPUTS TO THE PERSIANN **PERSIANN CLIMATE DATA RECORD** http://www.ncdc.noaa.gov/cdr/operationalcdrs.html **CLIMATE DATA RECORD**

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

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

• Daily Precipitation Data

- Data Period: 1983~2023
- Coverage: 60°S ~ 60°N
- Spatial Resolution: 0.25°x0.25°

Historical GEO Satellite Data



Source: NOAA NCDC

PERSIANN-CDR

- PERSIANN estimation at 0.25° every 3-hr from GridSat B1 IRWIN
- Monthly accumulation and bias adjusted using GPCP monthly estimation at 2.5°
- Bias adjustment of short-term 3-hr estimation



Ashouri et al, BAMS, 2015



Daily Precipitation: Hurricane Katrina, 2005



Center for Hydrometeorology and Remote Sensing (CHRS)

Sierra-Nevada Mountain Region

Area: 63,100 square kilometers (24,370 sq mi)

Length: 400 mile, Width: 64 mile.



Source: Google Earth

Center for Hydrometeorology and Remote Sensing (CHRS)

Sierra-Nevada Mountain (California and Nevada)



Center for Hydrometeorology and Remote Sensing (CHRS)

Applications

HiResFlood-UCI model and near real-time PERSIANN-CCS for flood forecasting

Nguyen, P., A. Thorstensen, S. Sorooshian, K. Hsu, A. AghaKouchak, B. Sanders, V. Koren, Z. Cui, and Michael Smith, 2015. A high resolution coupled hydrologic-hydraulic model (HiResFlood-UCI) for flash flood modeling. Journal of Hydrology. 2015. DOI:10.1016/j.jhydrol.2015.10.047.

Nguyen, P., A. Thorstensen, S. Sorooshian, K. Hsu, and A. AghaKouchak, 2015: Flood Forecasting and Inundation Mapping Using HiResFlood-UCI and Near-Real-Time Satellite Precipitation Data: The 2008 Iowa Flood. J. Hydrometeor, 16, 1171–1183. DOI http://dx.doi.org/10.1175/JHM-D-14-0212.1.

HiResFlood-UCI model

Coupling HL-RDHM with BreZo



Development of HiResFlood-UCI

Model Heritage

HL-RDHM

HL-RDHM involves four main components: snow-17, SAC-SMA, Continuous API and Overland and Channel Routings (Rutpix7, Rutpix9).

HL-RDHM was designed and implemented for the entire CONUS at two spatial resolutions of 1 HRAP (~4km) and 1/2 HRAP (~2km).



HL-RDHM model: (a) SAC component, (b) Routing scheme

Development of HiResFlood-UCI

Model Heritage

BreZo (Sanders & Begnudelli)

Hydraulic model solving the shallowwater equations using a Godunov-type finite volume algorithm that has been optimized for wetting and drying applications involving natural topography and runs on an unstructured grid of triangular cells.





Demo of BreZo simulation

Iowa Flood 2008

Cedar River 2008 Flood Some areas flooded beyond 500-year flood level

- 20,000 evacuated
- 3,900 homes under water



Model implementation



Near real-time precipitation data



Total precipitation during the event from 29 May 00:00 to 25 June 23:00 2008



Flooded map



Cleaned flooded maps of pre-flood and flood over the extended Cedar Rapids area

Flooded map



Modeled flood depth maps with Stage 2 and PERSIANN-CCS precipitation data



Validations of flooded maps from the model (with STAGE2 and PERSIANN-CCS precipitation) using AWiFS areal imagery

Nguyen, P., A. Thorstensen, S. Sorooshian, K. Hsu, and A. AghaKouchak, 2015: Flood Forecasting and Inundation Mapping Using HiResFlood-UCI and Near-Real-Time Satellite Precipitation Data: The 2008 Iowa Flood. J. Hydrometeor, 16, 1171–1183. DOI http://dx.doi.org/10.1175/JHM-D-14-0212.1.

Global Rainfall Trend Analysis

Nguyen, P., A. Thorstensen, S. Sorooshian, H. Ashouri, H. Tran, K. Hsu and A. AghaKouchak. Global precipitation trends across spatial scales. 2016. Under preparation.

Mann-Kendall Test

We test the null hypothesis H_0 that there is no significant trend in the data at significance level α =0.05 (or 95% confidence level)

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn(x_j - x_k) \qquad z = \begin{cases} \frac{S-1}{\sqrt{\frac{n(n-1)(2n+5)}{18}}} & \text{if } S > 0\\ 0 & \text{if } S = 0\\ \frac{S+1}{\sqrt{\frac{n(n-1)(2n+5)}{18}}} & \text{if } S < 0\\ \frac{S+1}{\sqrt{\frac{n(n-1)(2n+5)}{18}}} & \text{if } S < 0\\ 0 & \text{if } (x_j - x_k) = 0\\ -1 & \text{if } (x_j - x_k) < 0 & p = 0.5 - \frac{1}{\sqrt{2\pi}} \int_0^{|Z|} e^{-t^2/2} dt \end{cases}$$



Annual mean precipitation in mm (a) and pixel-based precipitation trends (b, c) from 1983 to 2015 from PERSIANN-CDR



Monthly Nino3.4 (a) Changes in precipitation volume (b, c) and precipitation volume trends (d) over continents and oceans.



Precipitation trends from 1983 to 2015 over climate zones (60°N - 60°S)



Precipitation trends from 1983 to 2015 over 201 countries (60°N - 60°S) and state/province political divisions of US, Saudi Arabia and China



Precipitation trends from 1983 to 2015 over 237 global major basins

Thank you for your attention!

Questions?

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