Challenges and Limitations of Hydroclimatological Forecasting and the Relative Role of its Three Pillars: Models, Observations and Parameterization

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and many more ...

Climate, Hydrology and Water Resources

• How will Climate effect water Availability?

 Can we predict the future changes which are responsive to "user" needs?





Climate Model Downscaling to regional/watershed Scale



Ensemble Approach

Generation of Future Precipitation Scenarios





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Downscaled Precipitation to Runoff Generation



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Brief Review of Rainfall Runoff modeling:

Progress in Hydrologic Modeling



Hydrologic Modeling: 3 Elements!



Model Selection





Hydrologic Modeling Challenges

Continental Scale: Focus of Hydro-Climate modelers

> Different Scales Different Issues Different Stakeholders

<u>Watershed Scale</u>: Focus of Hydro-Met. Modeling Where hydrology happens





Evolution of Hydrologic R-R Models





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Physically-based

Hydrologic Modeling: "Lumped"



"Semi-distributed" Hydrologic Models



"Semi-distributed" Hydrologic Models



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Example of Distributed Model Appl. in large Basins



Example of Distributed Hydrologic Model



DMIP-1 Findings: In a Nutshell



No Major Difference between the performance of Lumped and distributed models





Model Calibration/ Parameter Estimation





The Identification Problem

- 1. Select a model structure (Input-State-Output equations)
- 2. Estimate values for the parameters





"Automatic" Calibration components

Objective Function Search Algorithm Sensitivity Analysis





Parameter Uncertainty Methods

(1) First-order approximations near global optimum (Kuczera etal)

Limitations

- Assumes Model is Linear
- Assumes Posterior Dist. Guassian



(2) Generalized Likelihood Uncertainty Estimation (GLUE) $^{\Theta_1}$ method (Beven and co-workers)



(3) Markov Chain Monte Carlo (MCMC) methods θ_1 (Vrugt and others) $p(\theta^{t+1}|)$



Multi-Objective Approaches





AGU Monograph – Now Available

Water Science and Application 6



Calibration of Watershed Models presents a state-of-the-art analysis of mathematical methods used in the identification of models for hydrologic forecasting, design, and water resources management. From reviewing advances in calibration methodologies, to describing automated and interactive strategies for parameter estimation, uncertainty analysis, and probabilistic prediction, this book addresses five questions essential to the discipline:

- What constitutes best estimates for watershed model parameters?
- What computational procedures ensure proper model calibration and meaningful evaluation of performance?
- How are calibration methods developed and applied to watershed models?
- What calibration data are needed for reliable parameter values?
- How can watershed modelers best estimate model parameters and assess related uncertainties?

For scientists, researchers and students of watershed hydrology, practicing hydrologists, civil and environmental engineers, and water resource managers.

www.agu.org



Calibration of Watershed Models

> Qingyun Duan Hoshin V. Gupta Soroosh Sorooshian Alain N. Rousseau **Richard Turcotte** Editors











Big Challenge

Adequacy of Hydrologic Observations for model Input, Calibration and Testing



Among the 3 Pillars





A Key Requirement!

Precipitation Measurement is one of the <u>KEY</u>

hydrometeorologic Challenges



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

Radar-Gauge Comparison (Walnut Gulch, AZ)



Uncertainty in Runoff Simulation due to Rainfall Variability

Modeled runoff (KINEROS)

Small scale spatial variability of rainfall (on

the order of ~150 m)

Lucky Hills - 104 Small-Scale Experimental Network



Future Modeling Scenarios (2006-2099)

Western U.S. future model projections





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Dr. Chiyuan Miao - BNU

Future Modeling Scenarios – IPCC AR5

Representative Concentration Pathways (RCP) Scenarios:

RCP2.6: represent 'low' scenarios featured by the radiative forcing of 2.6 W/m² by 2100, the resulting CO₂-equivalent concentrations is 421 ppm in the year 2100.

RCP4.5: represent 'medium' scenarios featured by the radiative forcing of 4.5 W/m² by 2100, the resulting CO₂-equivalent concentrations is 538 ppm in the year 2100.

RCP8.5: represent 'high' scenarios featured by the radiative forcing of 8.5 W/m² by 2100, the resulting CO₂-equivalent concentrations is 936 ppm in the year 2100.





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RCP2.6

Time period: 2006-2099



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RCP8.5

Time period: 2006-2099



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<u>Precipitation Estimation from Remotely Sensed Information</u> <u>using Artificial Neural Networks (PERSIANN)</u>

PERSIANN System

Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks





Kuolin Hsu Algorithm Development



Bisher Imam G-WADI site development

PERSIANN-CCS (Real-time 4 km)



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Reconstruction of 30+ years of Daily, 0.25°

Satellite-Based Precipitation observation

Ashouri et al., BAMS 2014 (to appear)









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PERSIANN-

http://www.ncdc.noa



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- > Development Guidelines
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News

<u>Climate Data and Applications</u> <u>Workshop - A Focus on</u> <u>Precipitation - Dec 3-4, 2013</u>

Congratulations Cheng-Zhi Zou

2013 CDR Annual Meetings Presentations now available

NOAA'S NATIONAL CLIMATIC DATA CENTER

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
- A State of the second s
- INPUTS TO THE PERSIANN CLIMATE DATA RECORD
- GridSat-B1 CDR (IRWIN)
- GPCP 2.5-deg Monthly Data

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

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



ord

vironmental Satellites: Interim 1. The first step in establishing taset itself, and supporting <u>rs Guidelines</u>.

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

Documentation

<u>Algorithm Description</u> <u>Data Flow Diagram</u> <u>Maturity Matrix</u>

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Protecting the past ... Revealing the future

LEO Satellites for Precipitation Estimation



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

PERSIANN-CDR Algorithm









Testing of PERSIANN-CDR: Hurricane Katrina, 2005



Rainfall (mm/day) over land during Hurricane Katrina on 29 August 2005 from PERSIANN-CDR (top row left), Stage IV Radar (top row middle, Lin and Mitchell 2005), and TMPA v7 (top row right, Huffman *et al.* 2007). Black and gray pixels show radar blockages and zero precipitation, respectively. Scatter plots of PERSIANN-CDR and TMPA versus Stage IV Radar data are provided in the bottom row.



Validation of PERSIANN-CDR: Australia Flood Event





Testing of PERSIANN-CDR: Number of Rainy days >= 10 mm/day



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PERSIANN-CDR Evaluation over China





Dr. Chiyuan Miao - BNU

Gauge data: daily precipitation over East Asia (EA) (Xie et al., 2007)

- More than 2200 ground-based stations across China

 -0.5° resolution

– Period 1983-2006

PERSIANN-CDR: up scaled into the same resolution as $EA(0.5^{\circ})$

ID	Definition	Unit
RR95p	The 95th percentile of annual precipitation on wet days (precipitation ≥ 1 mm)	mm/day
R10mmTOT	Annual total precipitation when daily precipitation ≥ 10 mm	mm
R10mm	Annual count of days when precipitation ≥10mm	Days

Extreme precipitation indices used in the analysis



Results: Entire China





Prob. density functions (PDF) of Relative Errors for the Extreme Precipitation Indices: Different Gauge Densities.



PERSIANN-CDR Evaluation: Zooming over the Yellow River Region





PERSIANN-CDR Evaluation: Zooming over the Yellow River Region



The probability density function (PDF) of the relative error for different gauge density



Potential Factors Influencing Agreement Between Gauge Data and PERSIANN-CDR

- Insufficient gauge density most likely leads to Spatial errors: Particularly over the Western and Northwestern Arid Regions.
- The influence of topography on Spatial distribution of precipitation not fully captured by the interpolation process from points to grids.





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Devils are in details ...





How about the testing of all other Remote Sensing Observations and Model Generated Data?



"Observed" vs "Model-Generated" Data

MODIS





MM5R



GLDAS/Noah



Sorooshian et al. 2011 & 2012



Actual ET Estimates From Different Data sets- JJA 2007



2007 JJA Monthly ET (mm)





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Li et al, 2011

Actual ET comparison-spatial distribution – JJA 2007



Monthly ET (mm/month)

An Important Dilemma for the modeling application community will be: Which Remotely Sensed ET Product should be used for model testing and validation??



What is the Message?

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

• Nature is complex and observing and modeling its nonlinear behavior is very challenging. So, "have a will to doubt" the credibility of information "generated" by models.

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

Tibet: Confluence of Lhasa-Tsangpo Rivers August 23rd 2014







Back up slides

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Model historical simulation (1983-2005)



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





PERSIANN-CDR 0.25-deg daily



H. Ashouri

Center for Hydrometeorology and Remote Sensing (CHKS)



Precipitation Observations: Which to trust??



Rain Gauges

TRANSMIT Horizontal Pulse



(B)



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



Maddox, et al., 2002



Daily precipitation gages (1 station per 600 km² for Colorado River basin) hourly coverage even more sparse



Western U.S. historical model simulations



Model historical simulation vs observation



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Model historical simulation



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Space-Based Observations





Satellite Data for Precipitation estimation



Problems with IR only algorithm

Assumption: higher cloud \rightarrow colder \rightarrow more precipitation





Current Microwave Satellite Configurations



PERSIANN Satellite Product On Google Earth


Spatial-Temporal Property of Reference Error



US Daily Precipitation Validation Page

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



	Number of points: # points w/rain: Mean rain rate:	(G) gauge 13828. 4249. 5.55	PERSIANN 13828. 4665. 4.25	(R) radar 13828, 2971, 3,13
	Cond. rain rate:	17.82	12.47	14.46
	Max. rain rate:	181.99	79.07	131.45
	Correlation: Mean Absolute Error: RMSE (mm/day): RMSE (normalized): Probability of Detection False Alarm Ratlo: Bias Ratio (rain:no rain Heidke Skill Score: Hanssen-Kuipers Score	G-S 0.827 3.63 9.44 1.70 : 0.746 0.321 1): 1.098 0.574 : 0.589	G-R 0.726 3.42 11.23 2.02 0.654 0.665 0.699 0.692 0.634	R—S 0.606 3.35 8.66 2.77 0.855 0.455 1.570 0.546 0.546
	Equitable Threat Score:	0.402	0.528	0.376
TETEL LAND				

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











425 36N

365

30N

24N

21N

131

12f1 27N

3018N

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PERSIANN-CDR: PERSIANN Climate Data Record (30-yr, Daily, 25 Km)

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



>

> SEARCH

Environmental Satellites: Interim ted. The first step in establishing dataset itself, and supporting pers Guidelines.

tmospheric, Oceanic, and ratures) that have been improved Rs are geophysical variables pecific to various disciplines. tput.

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GPM Mission: Target Launch Feb. 2014

OBJECTIVES

- 1 Main satellite + 8 Smaller Satellites \
- Provide sufficient global sampling to significantly reduce uncertainties in short-term rainfall accumulations



Future looks bright and will bring more advances for precipitation Estimation



GPM Animation







Hydrologically - Relevant Remote Sensing Missions



SMOS ESA's Soil Moisture and Ocean Salinity (2009)



SMAP Soil Moisture Active Passive Satellite(2014)





TRMM The Tropical Rainfall Measuring Mission



GPM Global Precipitation Measurements (2014)



SWOT Surface Water and Ocean Topography (2020)



GRACE Gravity Recovery and Climate Experiment (2002)



MODIS Moderate Resolution Imaging Spectroradiometer (1999), (2002)