



Weather and Climate Extremes over Canada: Science and Adaptation, Winnipeg, Canada, February 7-9, 2011

Application of Remotely Sensed Precipitation Data in Monitoring and Analysis of Extremes: Challenges and Opportunities

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SATELLITE PRECIPITATION DATA



Meteosat 7 (EUMETSAT)



Geostationary IR Cloud top data 15-30 minute temporal resolution

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 (S-35° N-35°)

TRMM PR:(NASA/NASDA)orology & Remote Sensing, University of California, Irvine





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

The algorithm utilizes a neural network classification and approximation approach to derive precipitation estimates based on IR data calibrated with microwave estimates.







GEO (VIS/IR):

- Less accurate estimates
- Good global areal coverage with high temporal sampling



LEO (PMW):

- More accurate and less frequent estimates
- Areal Coverage 3 hour accumulation (Regional gaps)









PERSIANN data Spatial Resolution: 0.25° degree Temporal Resolution: 3-hour Source: HyDIS http://hydis8.eng.uci.edu/hydis-unesco/



PERSIANN-CCS data

Spatial Resolution: 0.04° degree Temporal Resolution: 1-hour Source: GWADI http://hydis.eng.uci.edu/gwadi/





















WHY SATELLITES?

WSR-88D Radar Coverage



Gauge Network



3 km Above Ground Level

Maddox, et. Al., 2002





WHY SATELLITES?

WSR-88D Radar Coverage



Gauge Network



2 km Above Ground Level

Maddox, et. Al., 2002





WHY SATELLITES?

WSR-88D Radar Coverage



Gauge Network



1 km Above Ground Level

Maddox, et. Al., 2002





Drought Analysis Based on Standard Precipitation Index (SPI) Using Remotely Sensed Precipitation Data





SPI Estimates: NCDC Gauge Precipitation Data

1-Month SPI Index; June 2007



3-Month SPI Index; April-June 2007



6-Month SPI Index; January-June 2007







SPI Estimates: PERSIANN Satellite Precipitation Data

1-Month SPI Index; June 2007



SPI Estimates: NCDC Gauge Precipitation Data 1-Month SPI Index; June 2007



3-Month SPI Index; April-June 2007



3-Month SPI Index; April-June 2007



6-Month SPI Index; January-June 2007



6-Month SPI Index; January-June 2007









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SPI Estimates: PERSIANN Satellite Precipitation Data



3-Month SPI Index; April-June 2008



6-Month SPI Index; January-June 2008



SPI Estimates: NCDC Gauge Precipitation Data



3-Month SPI Index; April-June 2008



6-Month SPI Index; January-June 2008





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RECONSTRUCTION OF LONG-TERM DATA

Reconstruction of PERSIANN rainfall data back to 1983 based on the available Inferred (IR) data from GEO



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RECONSTRUCTION OF LONG-TERM DATA

Reconstruction of PERSIANN rainfall data back to 1983 based on the available Inferred (IR) data from GEO



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RECONSTRUCTION OF LONG-TERM DATA

Reconstruction of PERSIANN rainfall data back to 1983 based on the available Inferred (IR) data from GEO



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3-Month Forecast

~ 30 Years Satellite-Based Rainfall







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3-Month Forecas

~ 30 Years





1950





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Application of Satellite Precipitation Data to Flood Warning





High Resolution Data from Satellites

Radar Observation (2 km AGL)

PERSIANN-CCS Estimates



4km x 4km, 3-hour accumulated precipitation

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High Resolution Data from Satellites

Radar Observation (2 km AGL)

PERSIANN-CCS Estimates



4km x 4km, 3-hour accumulated precipitation

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SATELLITE VS. GAUGE



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SATELLITE VS. GAUGE





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FLOOD WARNING



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FLOOD WARNING







FLOOD WARNING







QPOD



$$QPOD = \frac{\sum_{i=1}^{n} \mathbf{I}\left(P_{sat}|P_{sat} \geq t\&P_{ref} \geq t\right)}{\sum_{i=1}^{n} \mathbf{I}\left(P_{sat}|P_{sat} \geq t\&P_{ref} \geq t\right) + \sum_{i=1}^{n} \mathbf{I}\left(P_{ref}|P_{sat} < t\&P_{ref} \geq t\right)}$$

- P_{sat} = satellite estimates
- P_{ref} = reference measurements (e.g., STIV data)
- t = extreme threshold (e.g., 75, 90, 95 percentiles of data)
- n =number exceedances

Period of Analysis: 2005-2008

Reference data: Stage IV radar-based gauge adjusted data





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QFAR

Quantile False Alarm Ration (QFAR)

$$QFAR = \frac{\sum_{i=1}^{n} \mathbf{I} \left(P_{sat} | P_{sat} \ge t \& P_{ref} < t \right)}{\sum_{i=1}^{n} \mathbf{I} \left(P_{sat} | P_{sat} \ge t \& P_{ref} \ge t \right) + \sum_{i=1}^{n} \mathbf{I} \left(P_{ref} | P_{sat} \ge t \& P_{ref} < t \right)}$$

- P_{sat} = satellite estimates
- P_{ref} = reference measurements (e.g., STIV data)
- = extreme threshold (e.g., 75, 90, 95 percentiles of data)
- n =number exceedances

Period of Analysis: 2005-2008

Reference data: Stage IV radar-based gauge adjusted data





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MONTHLY QUANTILE BIAS

Monthly Quantile Bias

$$MQB = \frac{\sum_{i=1}^{n} \left(P_{sat} | P_{sat} \ge t \right)}{\sum_{i=1}^{n} \left(P_{ref} | P_{ref} \ge t \right)}$$

- P_{sat} = satellite estimates
- P_{ref} = reference measurements (e.g., STIV data)
- = extreme threshold (e.g., 75, 90, 95 percentiles of data)
- n =number exceedances

Period of Analysis: 2005-2008

Reference data: Stage IV radar-based gauge adjusted data





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ADAPTING ALGORITHMS FOR CLIMATE REGIONS



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ERROR DECOMPOSITION



Total MSE	Systematic MSE	Random MSE
$\sum_{i=1}^{n} \left(P_{sat} - P_{ref} \right)^2 =$	$\sum_{i=1}^{n} \left(P_{sat}^{*} - P_{ref} \right)^{2} +$	$\sum_{i=1}^{n} \left(P_{sat} - P_{sat}^{*} \right)^2$
n	n	п

$$P_{sat}^* = a P_{ref} + b$$

 P_{sat}^* : Linear regression to reference measurements
 $a:$ Slope
 $b:$ Intercept

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ERROR DECOMPOSITION



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ERROR DECOMPOSITION





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HYDROLOGIC APPLICATIONS

Distributed Model Intercomparison Project (DMIP)

Hydrologic Modeling

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HYDROLOGIC APPLICATIONS

Distributed Model Intercomparison Project (DMIP)

Hydrologic Modeling







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THANK YOU FOR YOUR ATTENTION

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