Rainfall Estimation over the Nile Basin using Multi-Spectral, Multi-Instrument Satellite Techniques

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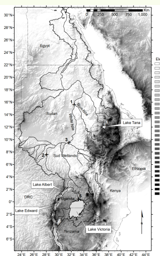
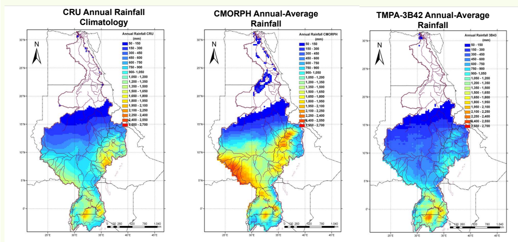
Background, Earlier Results & Research Need

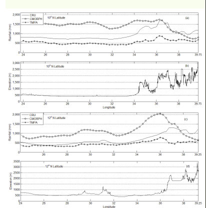
- Management of Egypt's Aswan High Dam is critical for flood control and for ensuring adequate water supplies for most of Egypt. However, reservoir inflow is driven by rainfall over Sudan, Ethiopia, Uganda, and several other countries from which routine rain gauge data are sparse. Alternatively, satellite techniques for rainfall estimation offer a much more detailed and timely set of data to form a basis for decisions on the operation of the dam.
- Currently, a single-channel infrared (IR) algorithm is in operational use at the Egyptian Nile Forecast Center (NFC). This algorithm doesn't take advantage of recent advances in satellite data and techniques (e.g., increasing availability of Microwave (MW) information)
- Examination of existing global satellite products (e.g. TMPA, CMORPH, others; see figures below) reveal serious biases over the Nile Basin domain and thus highlight the need for regional-focused algorithm development and local calibration and adaptation.
- In this study, the authors report on the application and adaptation of a multi-spectral, multi-instrument satellite rainfall estimation algorithm (Self-Calibrating Multivariate Precipitation Retrieval, SCaMPR) for operational application by NFC over the Nile Basin.
- The adapted algorithm uses a set of rainfall predictors from multi-spectral IR observations and self-calibrate them to a set of predictands from the more accurate, but less frequent, MW rain rate estimates.



Nile Basin Topography



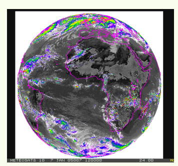
Mean annual rainfall distribution (mm) over the Nile Basin based on: CRU 2.0 climatology, CMORPH product, and TPMA-3B42 product.



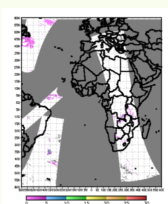
Cross sectional plots of mean annual rainfall (mm) and elevation (m) along two latitudes: 10º N and 12º N

Methodology

- Overview: Uses MW-derived rain rates to calibrate an algorithm based on IR data in real time
- Objective: optimal calibration for a particular geographic area, cloud type, and season.
- Basic steps:
  - Create a matched predictor / target data set
  - Calibrate using the matched data
  - Apply to current (independent) SEVIRI data
- Calibration data: half-hourly, 1/8° lat/lon combined SSMIS, AMSU/MHS, AMSR-E, TMI
- IR bands used in the algorithm:
  - WV 6.2mm
  - WV 7.3mm
  - IR 8.7mm
  - IR 10.8mm
  - IR 12.0mm
- SEVIRI data are matched with MW data by aggregating to MW footprint
- Matched data are divided into 3 classes
  - One Latitude band
  - Three Cloud types
- Two calibration steps:
  - Rain / no rain separation—calibrate using discriminant analysis (linear predictors only)
  - Rain rate—calibrate using stepwise forward linear regression for all available predictors (pick best pair)
- Update calibration whenever new MW data become available

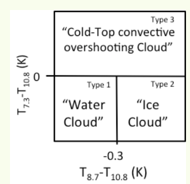


Example: Full disk 10.8- µm color-enhanced image from SEVIRI for 1200 UTC on January 7, 2005



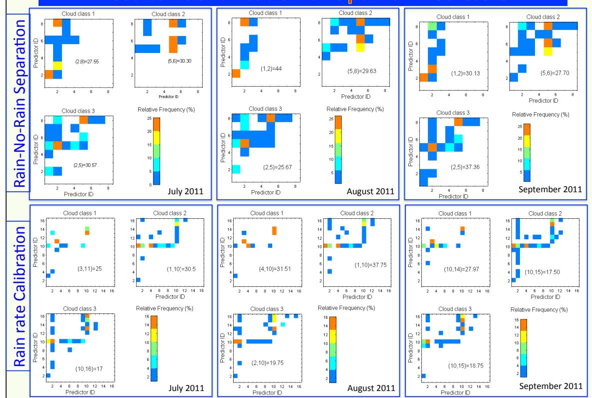
Example: Blended MW rainfall rates covering 1230-1300 UTC 7 January 2005

SEVIRI Predictor ID	
1	$T_{6.2}$
2	0.568-($T_{min,10.8}$-217 K)
3	$T_{avg,10.8}$ - $T_{min,10.8}$ - S
4	$T_{7.3}$ - $T_{6.2}$
5	$T_{8.7} - T_{7.3}$
6	$T_{10.8} - T_{7.3}$
7	$T_{8.7} - T_{10.8}$
8	$T_{10.8} - T_{12}$
9-16	Non-linear transformation of 1-8



Criteria for three cloud types used in the algorithm

Results: Identification of Optimal Predictors



Optimal pairs of parameters identified for (1) rain/no-rain separation, and (2) rain rate estimation within a dynamic calibration setting for three months of analysis: July-August-September of 2011. The displayed 2D histograms present frequencies of identification of each pair parameters

Static vs. Dynamic Calibration

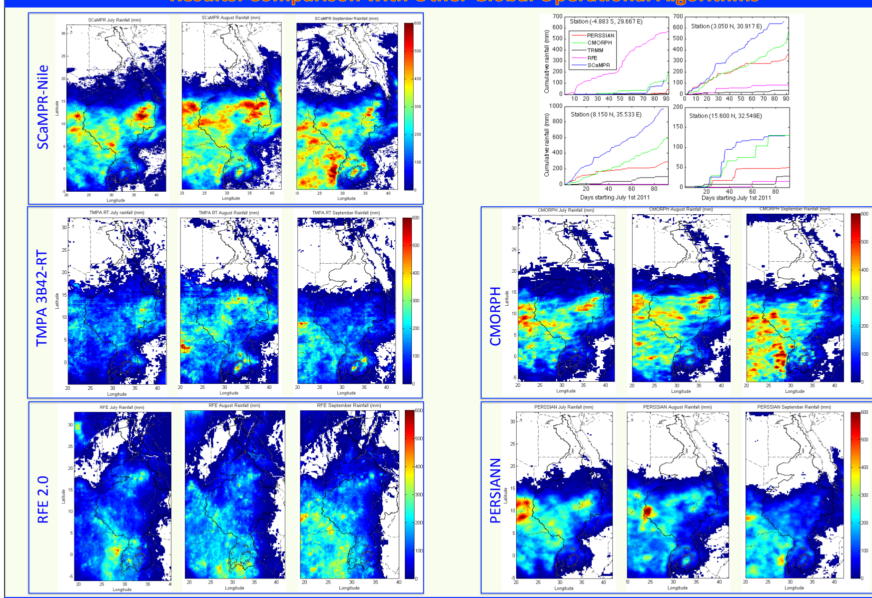
The study tested two modes of algorithm calibration:

- Dynamic (real-time) calibration with continuous updates of coefficients with newly coming MW rain rates, and
- Static calibration using fixed coefficients that are derived from IR-MW data from past observations.

		Rain/no Rain Predictors			Rain Rate Predictors		
		Cloud Type (1)	Cloud Type (2)	Cloud Type (3)	Cloud Type (1)	Cloud Type (2)	Cloud Type (3)
July 2011	Static	(2,8)	(5,8)	(2,5)	(3,11)	(10,1)	(10,16)
	Dynamic	(2,8),(2,1),(2,3)	(5,6),(5,8),(5,5)	(2,5),(5,8),(2,8)	(3,11),(10,13),(10,14)	(10,1),(10,4),(10,15)	(10,16),(10,13),(10,2)
Aug 2011	Static	(2,8)	(5,8)	(2,7)	(10,14)	(10,1)	(10,1)
	Dynamic	(2,1),(2,8),(2,3)	(5,8),(5,6),(5,1)	(2,5),(5,8),(5,1)	(10,4),(11,3),(10,14)	(10,1),(10,4),(10,15)	(10,2),(10,13),(10,1)
Sep 2011	Static	(2,1)	(5,3)	(2,5)	(10,14)	(10,15)	(10,13)
	Dynamic	(2,1),(2,3),(2,8)	(5,6),(5,8),(5,5)	(2,5),(5,8),(4,5)	(10,14),(11,3),(10,4)	(10,15),(10,1),(10,4)	(10,15),(10,13),(10,2)

Optimal pairs of parameters identified for (1) rain/no-rain separation, and (2) rain rate estimation under static and calibration setting. The Table also shows the three pairs of predictors with highest frequencies identified with the dynamic calibration experiment.

Results: Comparison with Other Global Operational Algorithms



Acknowledgment

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