3.2 GLOBAL APPLICATION OF THE SELF-CALIBRATING MULTIVARIATE PRECIPITATION RETRIEVAL (SCaMPR)

Robert J. Kuligowski*
NOAA/NESDIS Office of Research and Applications, Camp Springs, MD

Shuang Qiu
QSS Corporation, Lanham, MD

Jung-Sun Im
I.M. Systems Group, Kensington, MD

1. INTRODUCTION

Information about rainfall is critical for a wide variety of applications in the hydrometeorological sciences ranging from flash flood forecasting to water cycle and long-term climate studies. Rain gauges provide accurate point measurements of rainfall but are generally spaced too far apart to capture the full extent of spatial variations in rainfall. Portions of the globe with sufficient financial resources are able to supplement this relatively sparse gauge data with radar-based estimates of rainfall at high spatial and temporal resolution. For oceanic regions and for those nations without sufficient economic resources to implement radar technology, satellites offer an alternative source of precipitation information at fine scales in space and time.

However, the use of satellite data comes with caveats. Infrared (IR) and visible imagery aboard geostationary platforms provide continuous coverage (every 15 or 30 min) from roughly 60°N to 60°S, but since rain clouds are opaque at these frequencies, estimates of rainfall must be based on information about the cloud tops. Consequently, any information about conditions below cloud top must be derived from other sources; e.g., from numerical weather prediction (NWP) models. Rain clouds are semi-transparent at microwave (MW) frequencies, which allows for a more accurate estimation of rainfall based on the bulk quantity of ice or water within the cloud. However, at the present time microwave-based remote sensing of clouds is only possible at low earth orbit, meaning that estimates can only be produced twice per day for a polar orbit, though more frequently for an inclined-orbit instrument such as the Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI).

Numerous efforts have been made to address these complementary strengths and weaknesses by combining IR- and MW- based data in an effort to produce rainfall retrievals with the temporal resolution of IR data but the relative accuracy of IR data. Among these efforts are the Precipitation Estimation using Remotely Sensed Information in Artificial Neural Networks (PERSIANN) algorithm (Sorooshian et al. 2000), the Climate Prediction Center MORPHing (CMORPH) technique (Joyce et al.), the Naval Research Lab-Monterey (NRL) algorithm (Turk et al. 2003), and the Multisatellite Precipitation Analysis (MPA; Huffman et al.2001). This paper describes a technique called the Self-Calibrating Multivariate Precipitation Retrieval (SCaMPR) algorithm (Kuligowski 2002), which previously had been run only over the continental United States (CONUS) using data from a single GOES Imager but is now being expanded to worldwide application.

2. SCaMPR OVERVIEW

2.1 Algorithm Inputs

In theory, the SCaMPR framework (see Fig. 1 for an illustration) is sufficiently flexible to accept any reasonable data field as input. At this point, the real-time version of SCaMPR uses predictor data from the three GOES Imager channels that are not significantly affected by the sun: channel 3 (water vapor), channel 4 (longwave IR), and channel 5 (split-window IR; GOES-10 only) or 6 (CO_2 band; GOES 12 only). In addition to the brightness temperatures from these channels, differences with channel 4 are used, along with two parameters derived from channel 4 that were used in the GOES Multi-Spectral Rainfall

**Corresponding author address:* Dr. Robert J. Kuligowski, E/RA2 RM 712WWBG, 5200 Auth Rd., Camp Springs, MD 20746-4304; e-mail: Bob.Kuligowski@noaa.gov.

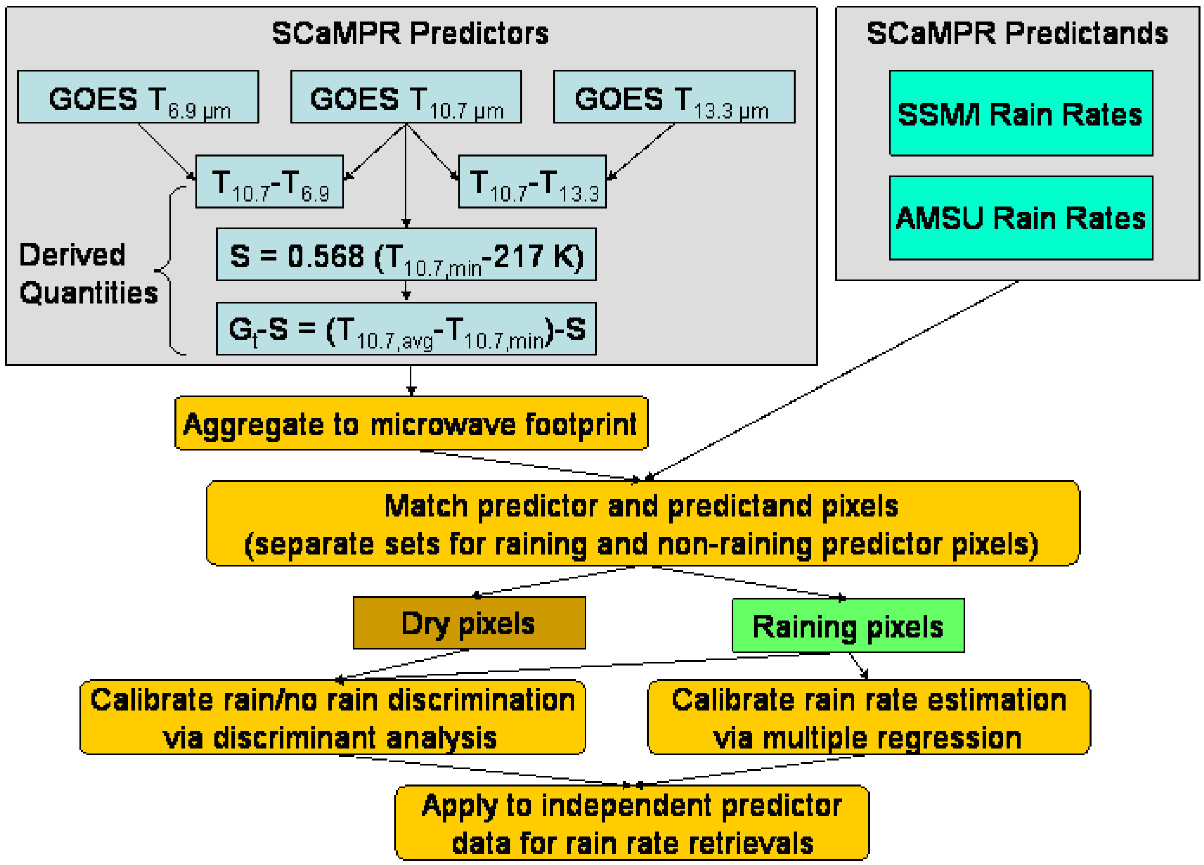

Figure 1. Schematic diagram of the SCaMPR algorithm.

Algorithm (Ba and Gruber 2001) and modified from the Convective-Stratiform Technique (CST) of Adler and Negri (1988).

The target data are rainfall rates from the Defense Meteorological Satellite Program (DMSP) Special Sensor Microwave/Imager (SSM/I) using the algorithm of Ferraro (1997) and the NOAA Polar Orbiting Environmental Satellite (POES) Advanced Microwave Sounding Unit-B (AMSU-B), using the Ferraro et al. (2004) algorithm.

Since the MW rainfall rates are at a coarser spatial resolution than the GOES data, the GOES data are aggregated onto the MW footprints prior to calibration.

2.2 Rain/no rain calibration

Calibration is performed once a suitable amount of data has is available in the training data set. The exact definition of a "suitable" amount remains undetermined, and is a balance between the desire for large amounts of data to assure a statistically significant calibration, and short calibration periods to maximize the ability of the algorithm to adapt to changes in weather system types, season, etc. The determination of the amount of training data to use has been done in different manners by different investigators—some have a fixed period of time for accumulating calibration data, while others require a specific number of matched data points to be available. In this particular case, experiments by the authors have shown that optimal calibration is achieved with a minimum of 250 pixels with MW rain rates of at least 5 mm/h.

The first step of rain/no rain calibration is to separate the matched predictor and predictand data into separate sets of raining and non-raining pixels. Because of significant differences in the depiction of light rainfall by the SSM/I and AMSU-B, the thresholds for rain versus no rain are 0.25

mm/h for the SSM/I and 2.0 mm/h for the AMSU-B.

Discriminant analysis is then used to determine which of the predictors best separates raining from nonraining pixels, and a threshold value is then selected to guarantee an unbiased separation. In its current real-time configuration, SCaMPR will select up to two predictors for rain/no rain separation, but the program can easily be modified to select additional predictors if desired.

2.3 Rain rate calibration

Only those pixels that are exhibiting rain rates above the aforementioned rain/no rain thresholds are used for rain rate calibration. The predictor/predictand set is calibrated using stepwise forward linear regression to both select and calibrate the rain rate predictor(s). The real-time version of SCaMPR selects only a single rain rate predictor, but the code can easily be modified to select additional predictors if desired.

Since the relationship between IR window brightness temperature and rain rate is known to be highly nonlinear (e.g., Vicente et al. 1998), simple linear regression will not sufficiently capture the relationships between predictor(s) and target data. Consequently, SCaMPR performs a regression of each predictor against the target data in log-log space to produce a power-law fit. Since a pure power-law equation (i.e., $y=ax^b$) contains only a multiplier (a) and an exponent (b), nonlinearities can occur in log-log space if an intercept is involved. Thus, the value of the predictor is increased in increments (in linear space) until the fit in log-log space is optimized. This last improvement was just recently made in SCaMPR and has significantly improved its ability to fit nonlinear functions.

The resulting rain/no rain and rain rate calibration relations are then applied to independent predictor data to produce the rain rate estimates, and the calibration is updated when new training data become available (i.e,. when a new SSM/I or AMSU-B overpass is received and processed).

2.4 Regional Calibration and Blending

The original version of SCaMPR used a single calibration for the entire region of interest; when the real-time version began running in November 2004 it used GOES-12 data over the CONUS only. However, SCaMPR was found to exhibit a diurnal variation in rainfall that was determined not to be physical but to be the result in differences in the relationships between the predictors and the MW rain rates over different portions of the CONUS. For instance, the threshold IR window brightness temperature for rain/no rain discrimination was found to be much lower in the central portion of the CONUS (where cold-top convection is dominant) than over the western and eastern portions of the US (where stratiform and warm-top convection are common).

In response, SCaMPR was modified to perform separate calibrations for overlapping 15x15-degree regions, and then the rain rate for a particular pixel is a weighted average of the rain rates derived for the 15x15-degree regions that overlap over the pixel. This is similar to the regional calibrations used by the other IR/MW rain rate algorithms mentioned in Section 1. This approach has the advantage of accounting for regional differences induced by differences in predominant rainfall systems.

An additional advantage to this approach is that it paves the way for SCaMPR to be applied globally without concerns about the differences in the channels used by various satellites in the global geostationary satellite constellation: the GOES Imager, the EUMETSAT Meteosat Imager and Meteosat Second Generation (MSG) Spinning Enhanced Visible and Infra-Rared Imager (SEVIRI), and the Japan Meteorological Agency (JMA) Multi-functional Transport Satellite (MTSAT)-1R Imager. SCaMPR simply makes use of the channels available for calibrating each particular 15x15-degree area. This capability has already been demonstrated over the CONUS, where GOES-10 and GOES-12 have different bandwidths for their water vapor (channel 3), and GOES-10 has a 12.0-micron “split window” channel while GOES-12 has a 13.2-micron channel in the CO_2 absorption band.

3. EXAMPLE

Examples of the real-time SCaMPR products can be found on the Internet at http://www.orbit.nesdis.noaa.gov/smcd/emb/ff/scampr.html. Figure 2 shows a 1-hour SCaMPR total rainfall accumulation over the CONUS and nearby regions compared with the corresponding Stage IV radar/rain gauge product for 0800-0900 UTC 1 November 2005. The superior coverage of

SCaMPR compared to the radar is obvious, and SCaMPR does well at capturing the general precipitation features. However, in this particular example the heaviest areas of rainfall are generally not depicted well in the SCaMPR retrieval.

a)

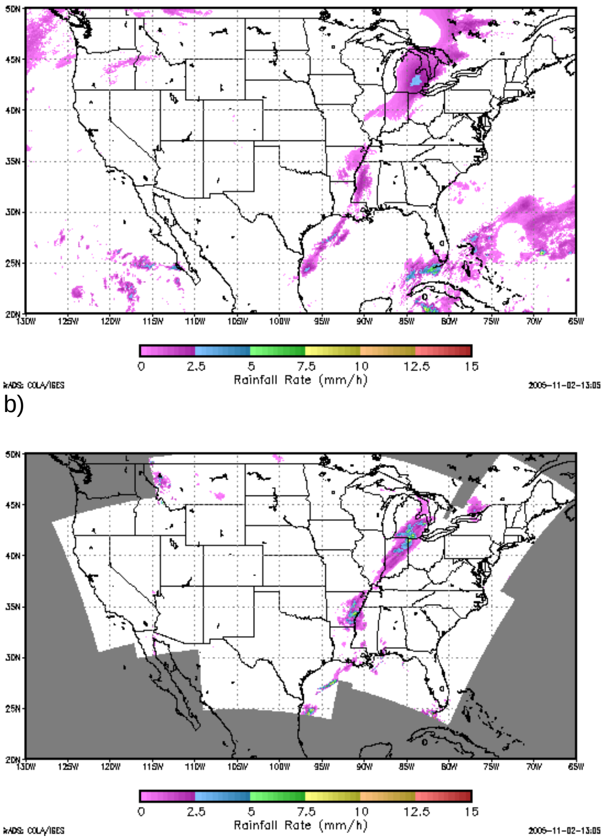

Figure 2. Sample SCaMPR 1-h total rainfall field (a) and corresponding Stage IV radar/rain gauge field (b) for 0800-0900 UTC 1 November 2005.

4. ONGOING AND FUTURE WORK

SCaMPR is being validated in real time in comparison to other experimental and operational satellite rainfall algorithms at NESDIS at http://www.orbit.nesdis.noaa.gov/smcd/emb/ff/validation/validation.html, and is also being evaluated as part of the International Precipitation Working Group (IPWG) evaluation of high resolution precipitation products. Improvements to SCaMPR will be explored based on the results of these findings.

5. ACKNOWLEDGMENTS

This work was partially supported by the GOES I-M Product Assurance Plan (GIMPAP) of the NOAA/NESDIS Office of Systems Development.

6. REFERENCES

Adler, R. F., and A. J. Negri, 1988: A satellite technique to estimate tropical convective and stratiform rainfall. *J. Appl. Meteor.*, **27**, 30-51.

Ba, M. B., and A. Gruber, 2001: GOES Multispectral Rainfall Algorithm (GMSRA). *J. Appl. Meteor.*, **40**, 1500-1514.

Ferraro, R. R., 1997: Special Sensor Microwave Imager derived global rainfall estimates for climatological applications. J. Geophys. Res., 102, 16715-16736.

-----, F. Z. Weng, N. C. Grody, L. M. Zhao, H. Meng, C. Kongoli, P. Pellegrino, S. Qiu, and C. Dean, 2005: NOAA operational hydrological products derived from the Advanced Microwave Sounding Unit. *IEEE Trans. Geosci. Remote Sens.*, **43**, 1036-1049.

Huffman, G. J., R. F. Adler, M. M. Morrissey, D. T. Bolvin, S. Curtis, R. Joyce, B. McGavock, and J. Susskind, 2001: Global precipitation at one-degree daily resolution from multisatellite observations. *J. Hydrometeor.*, **2**, 36-50.

Joyce, R. J., J. E. Janowiak, P. A. Arkin, and P. P. Xie, 2004: CMORPH: A method that produces global precipitation estimates from passive microwave and infrared data at high spatial and temporal resolution. *J. Hydrometeor.*, **5**, 487-503.

Kuligowski, R. J., 2002: A self-calibrating GOES rainfall algorithm for short-term rainfall estimates. *J. Hydrometeor.*, **3**, 112-130.

Sorooshian, S., K.-L. Hsu, X. Gao., H. V. Gupta, B. Imam, and D. Braithwaite, 2000: Evaluation of PERSIANN system satellite-based estimates of tropical rainfall. *Bull. Amer. Meteor. Soc.*, **81**, 2035-2046.

Turk, F. J., E. E. Ebert, H.-J. Oh, B.-J. Sohn, V. Levizanni, E. A. Smith, and R. Ferraro, 2003: Validation of an operational global precipitation analysis at short time scales. Preprints, *12th Conf. on Satellite Meteorology and Oceanography*, Long Beach, CA, Amer, Meteor. Soc., CD-ROM, JP1.2.

Vicente, G. A., R. A. Scofield, and W. P. Menzel, 1998: The operational GOES infrared rainfall estimation technique. *Bull. Amer. Meteor. Soc.*, **79**, 1883-1898.

7. DISCLAIMER

The contents of this conference preprint are solely the opinions of the authors and do not constitute a statement of policy, decision, or position on behalf of NOAA or the United States Government.