8.2 IMPROVEMENTS TO THE SELF-CALIBRATING MULTIVARIATE PRECIPITATION RETRIEVAL (SCaMPR) FOR ESTIMATING HIGH-IMPACT RAINFALL EVENTS

Robert J. Kuligowski*
NOAA/NESDIS Center for Satellite Applications and Research (STAR), Camp Springs, MD
Ruiyue Chen and Yaping Li
I. M. Systems Group, Inc., Camp Springs. MD

1. INTRODUCTION

Satellite-based estimates of rainfall can provide critical information to operational forecasters by supplementing data from gauges and radar. Although microwave (MW)-based estimates of rainfall are more accurate than their infrared (IR)-based counterparts, they lack the rapid refresh, high spatial resolution, and short data latency time that are critical for operational forecasters. In response, the Self-Calibrating Multivariate Precipitation Retrieval (SCaMPR; Kuligowski 2002) was developed to provide products that possessed the high spatial resolution and timeliness available from geostationary data but incorporated the higher degree of accuracy available from MW-based estimates.

The SCaMPR algorithm, which has run in real time over the CONUS (20-60°N, 135-60°W) since November 2004, selects and calibrates predictors from the Geostationary Operational Environmental Satellite (GOES) Imager against MW rain rates from the Special Sensor Microwave / Imager (SSM/I; Ferraro 1997) and the Advanced Microwave Sounding Unit (AMSU; Vila et al. 2007). Calibration involves selecting the optimal predictors and optimizing their calibration coefficients, and occurs in two steps: rain / no rain discrimination (via discriminant analysis) and rain rate retrieval (via stepwise linear regression). The currently used GOES predictors are GOES bands 3 (T_3; 6.7 µm on GOES-11 and 6.5 µm on GOES-12); 4 (T_4; 10.7 µm), 5 (T_5; 12.0 µm on GOES-11 and earlier), and 6 (T_6; 13.3µ m on GOES-12 and later), all band-to-band brightness temperature differences (BTD's), and texture variables based on band 4.

2. ALGORITHM CHANGES

A number of enhancements to SCaMPR have been tested and are in the process of being incorporated into the real-time version of the algorithm, including an improved MW calibration data set, a classification scheme based on T_3-T_4, adding visible (VIS) data, and modifying the calibration regions.

2.1. MW Calibration Data Set

As previously noted, the current real-time version of SCaMPR is calibrated against rain rates from the SSM/I and AMSU; however, there is no attempt to intercalibrate or bias-correct these estimates except for a static multiplier of 0.85 applied to the SSM/I rain rates to make their distribution more closely match that of the AMSU.

In a variant of the work of Joyce et al. (2004), the rain rate pixels from these instruments are matched with Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI) rain rates (Kummerow et al. 2001), cumulative distribution functions (CDF's) are constructed for the separate rain rates, and then the CDF's are matched to create a lookup table (LUT) for adjusting SSM/I and AMSU rain rates to have the same statistical distribution as TMI. The LUT is based on the previous 30 days of matched data and is updated daily. In addition, the TMI and TRMM Precipitation Radar (PR) rain rates (Iguchi et al. 2000) were added to the SCaMPR calibration data set.

The new MW calibration data set surprisingly had little overall impact on the accuracy of the SCaMPR estimates. However, preliminary results from the second half of 2007 indicate that while the warm-season wet bias was slightly higher using the new MW calibration data, the bias during the transition and cool season increased significantly; the cause for this is still under investigation.

2.2. Calibration Regions

Other investigators (e.g., Turk et al. 2003) have found that a regional calibration produces better results than a global calibration, so SCaMPR was implemented with separate calibrations for 15x15-degree lat/lon regions. To prevent discontinuities at the seams between

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

regions, SCaMPR overlapped the calibration regions by 10 degrees, leading to 9 separate calibrations and rain rate estimates for each pixel that were then distance-weighted to produce the final result.

However, this choice was not rigorously tested, and studies using Spinning METEOSAT-8 Enhanced Visible Infrared Imager (SEVIRI) data in support of GOES-R development work showed that there was no benefit beyond dividing the coverage area into 30-degree latitude bands. Similar results were found for tests with GOES data, so the real-time algorithm will be modified to use the larger calibration areas (there will actually be four calibration regions, with 105 W as the divider between GOES-West and GOES-East). A comparison of the rain rate estimation skill for July 2007 against microwave rain rates is shown in Fig. 1 (black line vs. red line).

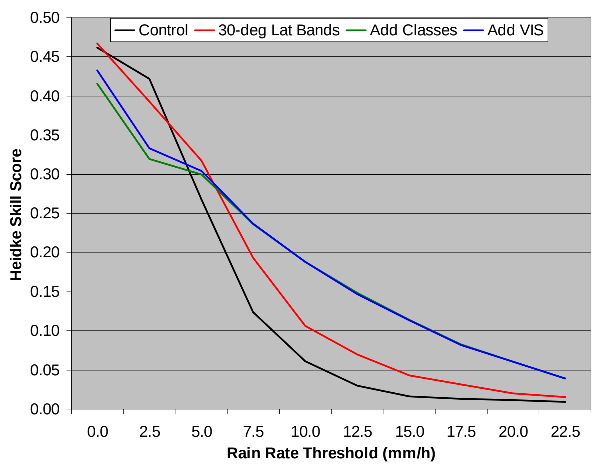

Fig 1. Heidke Skill Score as a function of rain rate threshold for the current version of SCaMPR (black line), with the region boundaries at 30 N and 105 W (red), with the T3-T4 classification scheme added (blue), and with visible data added to a separate daytime calibration (green).

2.3. Classification Scheme

Previous authors (e.g., Tjemkes et al. 1997) have showed that water vapor band (~6.7 µm) brightness temperatures exceeding the IR window band (~11 µm) brightness temperature indicate regions of deep convection. A comparison of the best-fit regression line of T_4 against rain rate for various values of T_3-T4 show that the relationship between T_4 and rain rate is very weak for low values of T_3-T_4 and stronger for higher values of T_3-T_4 (Fig. 2), as expected. The transition region is rather broad, but a demarcation line of -3 K for

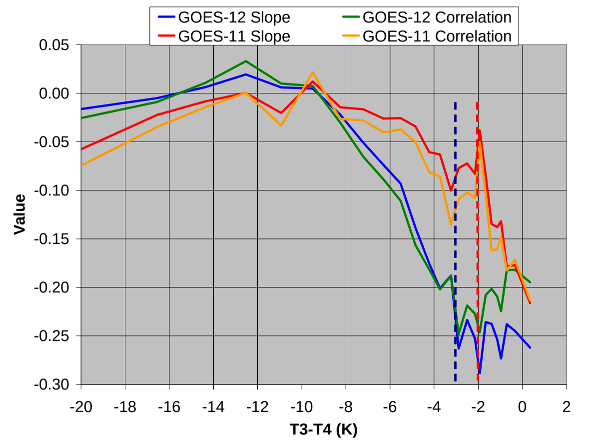

Fig. 2. Slope (and correlation) of the best-fit regression line between T_4 and microwave rain rate as a function of T_3-T_4. Vertical blue and red dashed lines indicate the selected threshold values for GOES-12 (-3 K) and GOES-11 (-2 K), respectively.

GOES-12 and -2 K for GOES-11 produces the best results during testing. Using separate calibrations for these two BTD regimes produced additional improvement in the retrievals for moderate to heavy rain rates, but some degradation for very light rain rates (Fig. 1). However, the higher rain rates are more critical for flood forecasting, so this is an acceptable compromise.

2.4. Visible data

Numerous authors (e.g., Griffith et al. 1978) have demonstrated the utility of visible data in discriminating raining cumulonimbus clouds from nonraining cirrus clouds, both of which appear cold in IR imagery. Tests on SEVIRI for GOES-R development work showed an improvement in SCaMPR skill when VIS data were added, even though this required separate calibrations for the daytime and nighttime (the latter used data from both day and night for calibration but did not include any bands with significant solar components). Related tests on GOES data also revealed some improvement for rain / no rain separation and very light rain events.

In light of the work by Rosenfeld and Gutman (1994) relating the reflectance at 3.9 µm to cloud-top properties, the impact of using this band in SCaMPR was tested, first on SEVIRI data and then on GOES data. However, there was no additional impact beyond that from using the VIS data in SCaMPR.

3. FUTURE WORK

These modifications are in the process of being implemented into the real-time version of SCaMPR and should be in place by the spring of 2009. Tests are also being performed to test the potential utility of using precipitable water (PW) and / or relative humidity (RH) data from numerical weather models to correct for subcloud evaporation and moisture availability as is done in the operational Hydro-Estimator (H-E) algorithm at NESDIS (Scofield and Kuligowski 2003). The new version of SCaMPR will be tested against the operational H-E to determine if it might be suited for operational implementation at NESDIS.

4. ACKNOWLEDGMENTS

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