INFRARED SATELLITE PRECIPITATION ESTIMATE USING WAVELET-BASED CLOUD CLASSIFICATION AND RADAR CALIBRATION

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1. INTRODUCTION

We have developed a methodology to enhance an infrared–based high resolution rainfall retrieval algorithm by intelligently calibrating the rainfall estimates using space-based observations. Our approach involves the following four steps: 1) segmentation of infrared cloud images into patches; 2) feature extraction using a wavelet-based method; 3) clustering and classification of cloud patches; and 4) dynamic application of brightness temperature (T_b) and rain rate relationships, derived using satellite observations.

2. METHODOLOGY

Cloud-top brightness temperature measurements from geostationary satellite (GOES-12), in conjunction with cloud-to-ground lightning data from the National Lightning Detection Networks (NLDN), are used for cloud classification and rain fall estimation. In addition, the 2A12-TMI algorithm, a precipitation product derived from The Tropical Rainfall Measuring Mission's (TRMM) Microwave Imager (TMI), is used for calibration [1]. The results are also evaluated with hourly precipitation from Nexrad Stage IV radar data [2]. The study area in the continental United States covers parts of Louisiana, Arkansas, Kansas, Tennessee, Mississippi, and Alabama. Our methodology for satellite-based rainfall estimation is similar to the PERSIANN approach [3]. However, our algorithms are enriched with lightning data and further enhanced with a wavelet-based feature extraction methodology similar to our previous work but with different reference and calibration [4]. Wavelet transforms is applied in our methodology to extract information from features of cloud texture. In addition, some studies show that lightning is in general correlated to rainfall amounts and cloud top temperatures [5]. So we have used the number of lightning flashes that occur in the respective cloud patch areas during

-15 min to +15 min window of observed infrared data from geostationary platforms. This algorithm has been used to extract cloud features from GEOS-12 (Channel 4) to estimate rain rates at 0.04^o x 0.04^o spatial resolutions every 30 minutes.

The single thresholding technique is used for segmenting clouds from its background (the threshold is 253 K). In addition, morphological image processing techniques are used to remove very tiny clouds as well as to label the clouds connected together as patches. In step 2, besides the feature used by PERSIANN algorithm, we have performed one-scale decomposition 2D wavelet transform on the cloud patches and calculated the mean and the variance of the detail coefficients. Wavelet decomposition and reconstruction are implemented based on Daubechies filters and a sliding window (length-5). In step3, using Self Organizing Map (SOM) neural network classifier [6], we classify the patches into 100 clusters (10x10-size). We have used 400 cloud patches from 2007 for training. In step 4, a proper Temperature-Rainrate (T-R) curve is assigned to each cluster. Based on the coincidental images of top temperature cloud patches (from GOES12) and its corresponding TMI rain rate, we can obtain two vectors of brightness temperature and corresponding rain rate (TMI) samples. Afterward, a nonlinear fitting exponential function is performed to these samples in order to get (T-R) curve for each cluster. In testing mode, once a patch segmented and feature extracted, the SOM indicates the most similar cluster to the patch. Therefore, the rain rate for each pixel of the patch is assigned based on the corresponding (T-R) curve of the cluster. The parameters of (T-R) function are calibrated and optimized whenever the TMI radar passes the area of interest.

3. RESULT

Some results, based on data on July 2008, are shown in Figures 1 - 3. Figure 1 shows the cloud top brightness temperature from the GOES-12 infrared at 08:00 (top-left); an hourly estimate of wavelet-based (with lightning(WL)) cloud classification is shown in top-right; the bottom-left figure shows an hourly estimate of PERSIANN-based cloud classification, The results are qualitatively validated against an estimate of hourly rainfall from Nexrad Stage IV(bottom-right). Figure 2, 3 show the evaluation criteria which are used to validate the results for 6 consecutive hours (from 0300 to 0900) on July 09, 2008. In these figures, the performance of rain/no-rain detection is evaluated by the probability of detection (POD) and the Heidke Skill Score (HSS). The quantitative accuracy of the estimates is evaluated by spacial correlation. The performance of our wavelet-based approach (in terms of HSS), with (WL) and without lightning information (WNL), is comparable to the PERSIANN-like

(P) approach (see Figure 2). However, the wavelet-based methodology has improved the POD (Figure 3) and better spatial correlation (Figure 4). Additional results from extended validation period will be demonstrated and discussed during the conference.

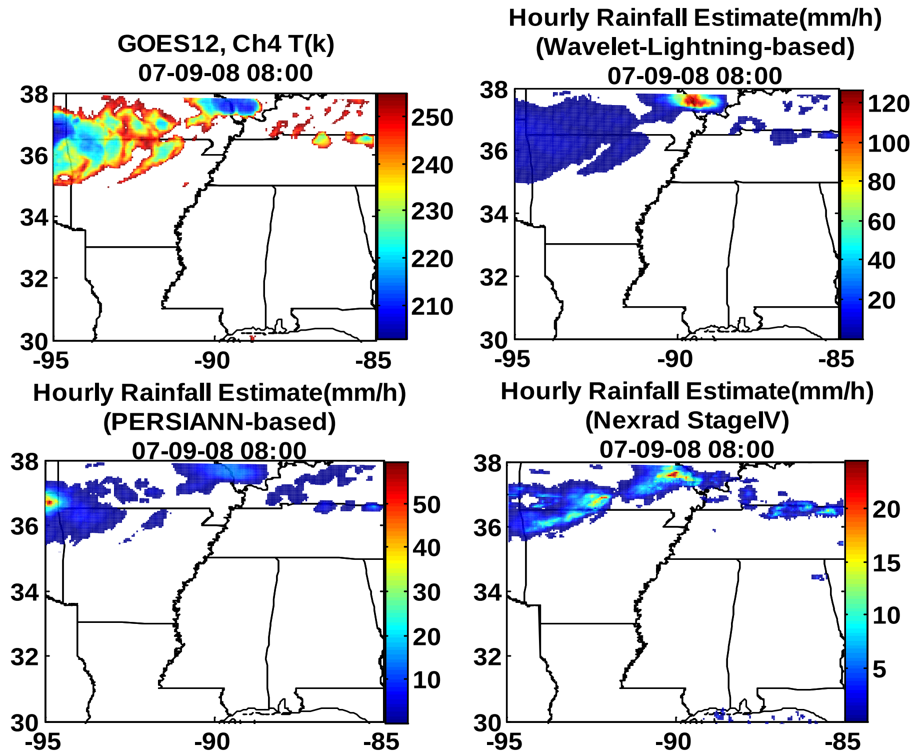

Figure1– Cloud-top brightness temperature (top-left),One hour Wavelet-based rainfall estimate (top-right), One hour PERSIANN-based Rainfall Estimate (bottom-left), and hourly Nexrad Stage IV rainfall estimate (bottom-right) on July 09, 2008 for 8 am

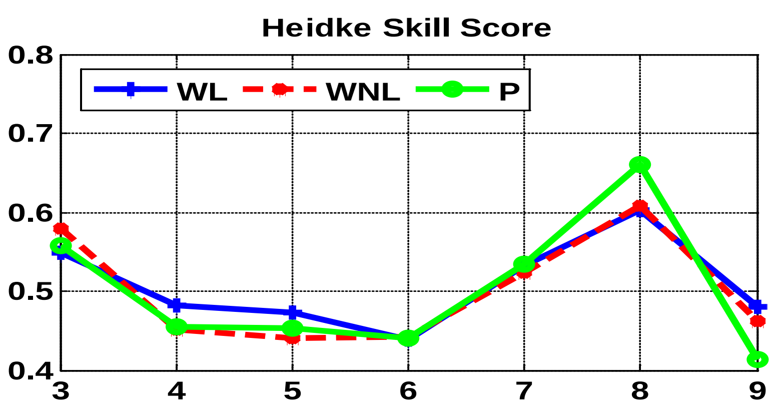

Figure 2– Heidke Skill Score for wavelet- based (with (WL) or without (WNL) and PERSIANN-based (P)

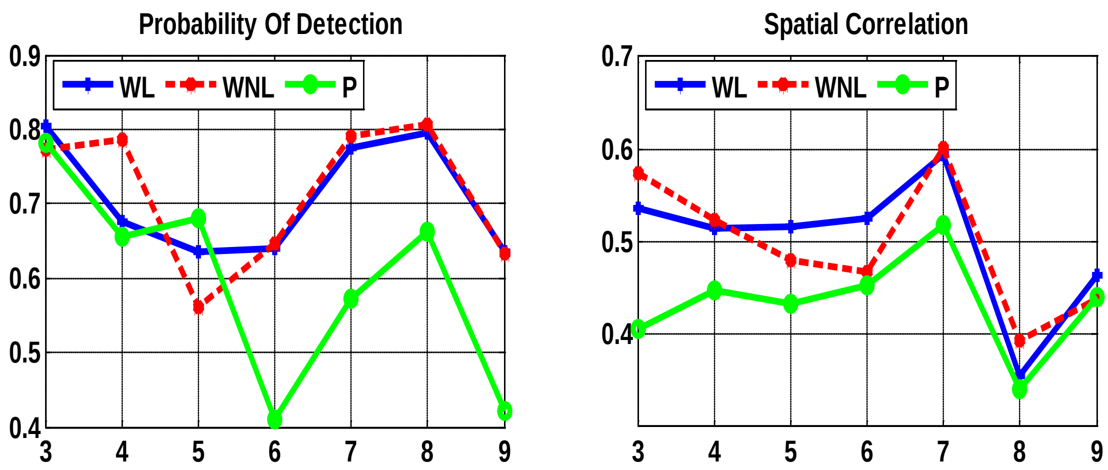

Figure 3– Probability of Detection and Spatial Correlation evaluation for wavelet- based (with (WL) or without (WNL) lightning) and PERSIANN- based (P)

4. REFERENCES

[1] C. Kummerow, Y. Hong, W. S. Olson, S. Yang, R. F. Adler, J. McCollum, R. Ferraro, G. Petty, D. B. Shin, and T. T. Wilheit, "The evolution of the Goddard profiling algorithm (GPROF) for rainfall estimation from passive microwave sensors", *J. Appl. Meteor., 4*0, 1801-1820, 2001

[2] Y. Lin, and K. E. Mitchell "The NCEP Stage II/IV hourly precipitation analyses: development and applications. Preprints", 19th *Conf. on Hydrology*, American Meteorological Society, San Diego, CA, 9-13 January 2005, Paper 1.2., 2005

[3] Y. Hong, K. L. Hsu, S. Sorooshian, and X. G. Gao, "Precipitation Estimation from Remotely Sensed Imagery using an Artificial Neural Network Cloud Classification System," *Journal of Applied Meteorology, 43*, 1834-1852, 2004

[4] M. Mahrooghy, V. G. Anantharaj, N. H. Younan, W. A. Petersen, and F. J. Turk, "An Adaptive Methodology To Enhance Infrared Satellite Precipitation", 34th *Conf. on Radar Meteorology*, AMS, Williamsburg, VA, Paper 14.26., 4-9 October, 2009.

[5] T. Chronis, E. Anagnostou, and T. Dinku, "High frequency estimation of thunderstorms via Satellite Infrared and a long-range lightning network in Europe", *Quarterly Royal Meteorological Society Vol.130* No. 599, 2004.

[6] T. Kohonen, "Self-organized formation of topologically correct feature maps". *Biol. Cybernetics ,43*, 59–69, 1982