Comparing rainfall estimates derived from rain gages and satellite images at the eastern Mediterranean region

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SUMMARY

This article aims to test a satellite infrared (IR) technique for estimating rainfall over Mediterranean. On that purpose, we use 6hr, 12hr and 24hr cumulative rainfall measurements, obtained from a large set of gages located at the eastern Mediterranean region, during October 2004. Two kinds of comparisons are undertaken. First, rainfall estimates derived from satellite images are projected to the locations of the rain gages and then compared to the actual gage measurements. Results in this case coincide with those reported in Barret (1988): IR satellite observations tend to overestimate precipitation. To obviate this, we seek optimal transformations for the IR satellite data via using statistical tools, namely the Box-Cox method and Linear Mixed models. Next, we perform spatial interpolation to the rain gage measurements and compare the derived surfaces to the ones obtained from satellite images for regions having high spatial density in gages. In both cases the estimation error is positively correlated to the rainfall level; we quantify this dependence using appropriate statistical tools.

KEYWORDS: *Rainfall estimation, satellite based data, ground-based data, spatial interpolation*

INTRODUCTION

The measurement of the near-surface precipitation is very important for studies of the hydrological cycle, water management planning, flash flood identification, input to hydrological and agricultural models, verification of weather modification experiments and the study of convective systems.

Rainfall affects the lives and economies of a majority of the Earth's population. Heavy rain systems are crucial to sustaining the livelihood of many countries. Excess rainfall can cause flood, property and crop damages. A deficiency causes drought and crop failure.

The Mediterranean climate is known for its variety and variability, due to the surrounding orography, to the relative high temperature of the sea and to the different origin and physical characteristics of the air masses. There is a paucity of dense rain gauge networks or precipitation radar networks from which reliable real-time assessments of precipitation can be obtained, due to the presence of the Mediterranean Sea and to the complex topography. In addition, rain gauge observations are not generally available in real time in many regions, and missing reports and grossly erroneous reports occur in cases of extremely heavy rainfall and in regions of steep terrain. Thus remotely sensed information from satellites, having a high spatial coverage and high temporal sampling, can play a key role in monitoring precipitation in flood-prone regions, sea precipitation, and other extreme weather events.

A number of techniques have been developed to indirectly estimate rainfall using visible (VIS) and infrared (IR) satellite data. Most of these methods are based on the notion that deep convective clouds might produce more rain and on operational findings, which show that regions of rainfall tent to be correlated with bright (VIS), cold (IR) clouds. When IR satellite data of high spatial and temporal resolution became available, precipitation was correlated to the cloud-top temperature (CTT) and the relationships used in the satellite techniques were redefined as a function of CTT. Numerous new precipitation estimation algorithms have been developed that use IR data as the only data input; i.e. the Arkin technique (Arkin 1979), the Area Time Integral (ATI) technique (Doneaud et al. 1984, Lopez et al. 1989), the GOES Precipitation Index (GPI) (Arkin and Meisner 1987), the Griffith-Woodley Technique (GWT) (Griffith et al. 1976, 1978, 1981), Negri-Adler-Woodley Technique (NAWT) (Negri et al., 1984), the Convective-Stratiform Technique (CST) (Adler and Negri 1988) and the technique for Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) (Hsu et al. 1997, Hong et al. 2004). One disadvantage of VIS/IR techniques for estimating precipitation rates is that are necessarily inferential (precipitation is inferred from cloud observations). The accuracy of such techniques is not adequately specified and the techniques are not readily transferable from location to location. In contrast, microwave (MW) remote sensing techniques can give direct information on precipitation. Passive MW radiometry from satellite platforms has also the potential to estimate rainfall rates, because the microwave radiation contains direct signals of the cloud and precipitation microphysics. But, the lack of sufficient spatial and temporal coverage of the current polar-orbiting sensors for mid-latitudes as well as the lack of active MW satellite sensors for this area constitutes a major disadvantage for studies of convective rain events. In addition, satellite-measured microwave radiances are also influenced by soil and vegetation effects over land surfaces (including mixed pixel effects in coastal areas).

Despite the disadvantages of the rainfall estimates inferred by IR satellite data, interest in making such estimates has not faded. The reason for this is the short duration and high temporal variability of precipitation events and, therefore, the need for high temporal resolution in the observations. Thus, despite the availability of more accurate techniques using microwave (MW) satellite data, the geosynchronous observations (currently limited to IR wavelengths) become extremely important. However, the more physically based MW remote sensing techniques provide enough accurate precipitation estimates to be used as training data in a calibration process of an infrared satellite technique.

Most of infrared techniques provide precipitation estimates that are technique-dependent and change as a function of the particular region. Because of varying rain characteristics according to different climate regimes, any developed infrared method must be validated against appropriate in situ measurements taken over the region of interest before any application is made. Attempts to this direction have been made for Sardinia by Marrocu et al. (1993), for the Korean peninsula by Oh et al. (2002) and for Eastern Africa by Menz (1997).

Therefore, the objective of this work is to test a satellite infrared technique for estimating rainfall over Mediterranean. The parameters of the technique are calibrated using coincident rainfall estimates derived by satellite microwave data. To perform the comparison, we use 6hr, 12hr and 24hr cumulative rainfall measurements, obtained from a large set of gages located at the eastern Mediterranean region, during October 2004. Two kinds of comparisons are undertaken. First, rainfall estimates derived from satellite images are projected to the locations of the rain gages and then compared to the actual gage measurements. Results in this case coincide with those reported in Barret (1988): IR satellite observations tend to overestimate precipitation. To obviate this, we seek optimal transformations for the IR satellite data via using statistical tools, namely the Box-Cox method and Linear Mixed models. Next, we perform spatial interpolation to the rain gage measurements and compare the derived surfaces to the ones obtained from satellite images for regions having high spatial density in gages. In both cases the estimation error is positively correlated to the rainfall level; we quantify this dependence using appropriate statistical tools.

SUMMARY OF METHODOLOGY AND RESULTS

At the first stage of the comparison between the satellite IR technique and ground observations, gage station locations are projected to digital coordinates (line – pixel) of the satellite derived rainfall estimates; then, the corresponding satellite estimates are compared to the actual gage measurements. The projection is performed as follows:

Since gage data coordinates are defined in latitude - longitude on the WGS84 geometry each point is defined as P (θd, φ), where θd, φ stands for geodetic latitude and longitude respectively. The method follows the standard presented by Eumetsat (The Meteosat Archive - User Handbook EUM TD 06 – Issue 2.5)

Step 1. Convert geodetic latitude to geocentric in radians.
Step 2. Calculate the distance from the earth centre to a point on the surface of this latitude.
Step 3. Calculate the equivalent Cartesian co-ordinates of P using a transformation between co-ordinate frames.
Step 4. Drop a perpendicular from P onto the equatorial plane to form point O'.
Step 5. Calculate the angle PSO' and divide this by the line direction angular step 18˚ to calculate the line number of the point.
Step 6. Calculate the angle O'SO and divide this by the pixel direction angular step to calculate the pixel number of the point.

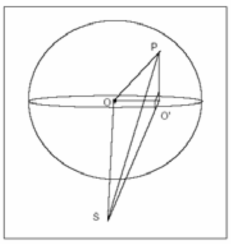

Figure 1: Determining the angular position of point P.

Next, rain depth was calculated by the precipitation algorithm for each pixel *i* of the image, and the corresponding values were added for 12, 24 and 48 successive satellite images corresponding to 6hr, 12hr and 24hr accumulated precipitation, according to:

$$S_i = \sum_{j=1}^{12} D_{ij} \qquad (1)$$

where S_i is the rain depth accumulated over each period (6hr, 12hr and 24hr) and assigned to each pixel i, and D_{ij} is the estimated rain depth in the pixel i of the image j.

Finally, punctual 6hr, 12hr and 24hr accumulated precipitation (G_i) for each of the pluviometric station processed, versus the rainfall ($\bar{S}_i$) retrieved from satellite data for the corresponding pixel location. For each station, the total precipitation $\bar{S}_i$ was calculated as the average value of 3 by 3 pixels, centred over each pixel corresponding to the station. That was done to reduce the effect of the error arisen by the uncertainty of ±1 pixel in the co-location of the pluviometric stations on the Meteosat images.

Both ground and satellite data appear to be highly skewed –far from normally distributed. For the efficient implementation of the statistical models that will follow, similar to Hutchinson (2003), we employ the square root transformation (the log transformation was tested too but leaded to inferior results). Bivariate correlations for the variables of interest, that is square roots of satellite estimates for cumulative 6hr, 12hr and 24hr rainfall at 18.00 and square roots of the corresponding rain gage observations, range between 0.25 and 0.35 which is not satisfactory for predictive purposes. To improve the predictive power of satellite IR data we seeked optimal Box-Cox transformations for ground measurements. Box-Cox transformations are optimal transformations of the response variable in a regression model, that linearize the regression relationship and stabilize its variance; results indicate that no other transformation than the square root is better suited for the regression problem. Then we run separate regressions for the rain gage-IR satellite relationship for each day of the study; we observed that the fit of the regression line tends to be worse as average rainfall increases. The correlation coefficients between the goodness of fit indices (R^2) and average rainfall are negative but not statistically significant. Next, to evaluate how variable the rain gage-IR satellite relationship is with respect to measurement location, we implemented linear mixed models with random effects having spatially dependent covariance matrices (see Verbeke and Molenberghs 1997 and Diggle et al 1996). Results indicate that the intercepts at the rain gage-IR satellite relationship are much more volatile than the corresponding slopes.

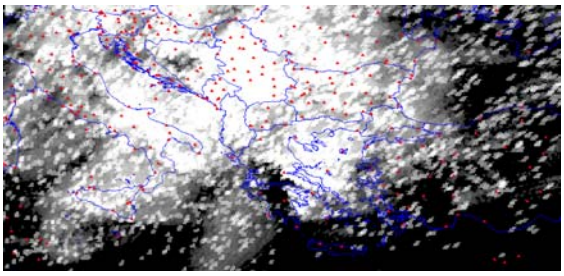

Figure 2: Satellite derived rainfall estimations over the study area for 16 October 2004. Bright tones indicate high rainfall amounts. The positions of the rain gauge stations (red triangles) as well as the coastlines and country borders are overlaid.

At the second stage of the comparison between satellite-derived rainfall estimates and rain-gage measurements we performed spatial interpolation for the rain gage measurements and compared the derived surfaces to the ones obtained from satellite images for regions having high spatial density in gages. The adopted spatial interpolation scheme was, similar to Sun et al (2003), isotropic kriging based on an exponential variogram. The reader should note that we compare regions with high density in rain gages so that kriging estimates have less error; moreover different interpolation schemes tend to give similar results in this case. Again, estimation error is positively correlated to the rainfall level; we quantify this dependence using spatial regression techniques. Figure 2 shows the satellite derived rainfall estimations over the study area for 16 October 2004 and Figure 3 displays the spatial distribution of the difference between the satellite derived rainfall estimations and the krigged rain gauge measurements for 22 October 2004. We elaborate on the statistical methodology and derived results in a forthcoming article.

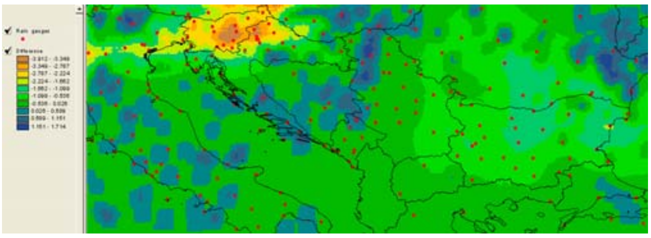

Figure 3: Spatial distribution of the difference between the satellite-derived rainfall estimations and the krigged rain gauge measurements for a part of the study area where high density of in-situ stations exists for 22 October 2004.

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