A satellite-based rainfall estimation method for the Lake Victoria basin

CARLO DE MARCHI & ARIS GEORGAKAKOS
Georgia Water Resources Institute and School of Civil and Environmental Engineering, Georgia Institute of Technology, Atlanta, Georgia 30332-0355, USA
e-mail: demarchi@ce.gatech.edu

Abstract This article describes a method for estimating precipitation over the Lake Victoria basin in East Africa using Meteosat images. The method identifies infrared and visible signals characteristic of convective storms and associates their features with ground rainfall measurements. These temporal patterns are recognized at the pixel level via a neural network model, while mean areal precipitation (MAP) is estimated at larger spatial scales. The method successfully identifies convective cells and provides reliable MAP for daily time steps, and even better for longer time intervals. The procedure is implemented within the Lake Victoria Decision Support System (LVDSS), which addresses planning as well as operational applications for water resources, agriculture and hydropower management in the Lake Victoria basin. LVDSS is presently used by several water resources agencies in Kenya, Tanzania and Uganda.

Key words bispectral analysis; convective storms; decision support system; East Africa; Lake Victoria; Meteosat; neural networks; rainfall estimation

INTRODUCTION

The Lake Victoria drainage basin extends over an area of 263 000 km², 69 000 km² of which are lake surface, shared among Burundi, Kenya, Rwanda, Tanzania and Uganda. The lake and its basin are vital resources for an increasing population of more than 25 million people.

The purpose of the Lake Victoria Decision Support System (LVDSS) (Georgakakos et al., 1999) is to compile and develop useful information for basin-wide water management, and to facilitate the formulation of mutually agreed strategies for economic development.

A conceptual schematic of the modelling system is shown in Fig. 1. The system integrates hydro-meteorological, geomorphic and socio-economic databases, geographic information systems, models for rainfall estimation using satellite and ground data, hydrological watershed models, agricultural planning models, and models for lake regulation and hydropower scheduling. At the planning level, LVDSS can assess the implications of different basin development scenarios. At the operational level, LVDSS applications are presently focused on streamflow forecasting, irrigation management, lake fluctuation management, and hydropower scheduling. Precipitation estimation is critical for all these applications, with pertinent time scales that vary from daily to interannual.
Fig. 1 Lake Victoria Decision Support System structure and the raingauges used for the calibration and verification of the remote sensing component.

AVAILABLE DATA

The rainfall estimation procedure was calibrated and verified using daily precipitation measurements at the stations indicated in Fig. 1 and contemporaneous Meteosat TIR (10.5–12.5 μm) and VIS (0.5–0.9 μm) images for the period 1 April 1992–10 October 1993.

INFRARED AND VISIBLE SIGNALS OF TROPICAL CONVective STORMS

Figure 2 shows the visible and infrared signals associated with a typical tropical convective storm at the pixel level. Initially, clouds are low (high infrared temperature) and relatively thin (low visible signal). As the convective storm matures, the clouds get thicker (rising visible count), and the cloud top approaches the tropopause becoming colder (falling infrared temperature). As the convective cell dissipates, the visible count decreases while the infrared temperature increases. Rainfall estimation methods exploit different characteristics of this relationship. For example, the rain produced by a cloud system is related to the time the satellite infrared signal is below a threshold (Richards & Arkin, 1981), to the coupled value of the infrared and visible channels (King et al., 1995), or to the coupled value of the infrared channel and of its time derivative (Vincente et al., 1998).
A satellite-based rainfall estimation method for the Lake Victoria basin

LVDSS RAINFALL ESTIMATION METHOD

Identification of convective cells

The method implemented within the LVDSS does not merely look for signal values above or below specific thresholds. Rather, it detects the occurrence of convective rain over a pixel by searching in the daily sequence of TIR and VIS values for complete satellite signal patterns similar to those depicted in Fig. 2. The method uses two feed-forward, 3-layer neural networks for identifying the presence of such rainy patterns: a visible/infrared network for daytime and an infrared-only network for nighttime. The two networks process the satellite signals sequentially throughout the day and night. At every time slot the former network uses 12 consecutive time slots for the TIR signal and eight for the VIS signal, while the latter one uses just the 12 consecutive time slots for the TIR signal.

The capability of the method to recognize convective rainy pixels from stratiform or non-rainy ones is assessed by comparing the rain rate distributions at the pixels identified (by the method) as convective and at the pixels identified as non-convective for the Ngudu region in Tanzania (Fig. 1). Figure 3 shows that rainfall at the convective cells is markedly higher than at the non-convective cells, validating the skill of the method. On the other hand, the rain falling over non-convective pixels accounts for 47% of the total rain, a percentage consistent with that reported in Churchill & Houze (1984).

Estimation of MAP

In view of the noisy relationship between the rain rate over a pixel and its visible brightness or infrared temperature, LVDSS estimates daily mean areal precipitation (MAP) over larger areas. It was found that the highest correlation between the
Carlo De Marchi & Aris Georgakakos

Fig. 3 Daily rain rate distribution for pixels where the neural network method indicates convective storm activity (convective cells) and for all the other pixels (non-convective cells) in the Ngudu area for a period of six months.

remotely-sensed characteristics of a cloud system and the observed MAP occurs over a square of $7 \times 7$ pixels (roughly $35 \times 35$ km). However, the relative scarcity of rain gauges and their clustering in small areas may have been a factor in this evaluation.

The estimation of the rain over convective cells is done separately from that of the rain over non-convective pixels. The daily rainfall volume over the convective pixels of the $7 \times 7$ square is a linear regression function of the sum of the products of the neural network value and the time integral of the TIR channel below a threshold of 290 K. The values of the regression coefficient, regression offset, and TIR threshold were calibrated for October and November 1992, and May 1993. The months of May, August and September in 1992, and February, March and April in 1993, are used for verification purposes. Table 1 reports the comparison between computed convective rain volume and rain gauge volume in the two periods. The correlation and coefficient of explanation ($COE$) during the verification period are not appreciably different from the values of the calibration period. Overall, the method is unbiased and captures the variability and trend of the rain measured on the ground.

<table>
<thead>
<tr>
<th>Table 1 Estimation of daily precipitation over Ngudu.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rainfall volume over convective cells:</td>
</tr>
<tr>
<td>Correlation</td>
</tr>
<tr>
<td>Calibration</td>
</tr>
<tr>
<td>Verification</td>
</tr>
</tbody>
</table>

| Daily MAP over the $7 \times 7$ square:              |
| Correlation | $MSE$ (mm) | $COE$ |
| Calibration | 0.73        | 1.80  | 0.54 |
| Verification| 0.69        | 1.77  | 0.44 |

As mentioned, non-convective cells roughly account for half of the total rain falling over a $7 \times 7$ pixel square and cannot be neglected. In LVDSS, the rain over the non-convective pixels of a $7 \times 7$ square is calculated only if at least one convective cell is present within the square or the adjacent neighbouring squares. In this case, rain is
expressed as a linear regression function of the integral of the difference between the TIR temperature and a temperature threshold of 275 K. This procedure essentially accounts for the stratiform rain falling on the area surrounding convective cells. Overall, the previous procedure for stratiform rain estimation is expected to be less effective, mainly due to: (a) the weak infrared and visible satellite signals associated with non-convective rain, and (b) the noisy raingauge observations in the available dataset. Convective and stratiform rainfall estimates are summed to estimate the total MAP over the square with satisfactory results for both the calibration and verification periods as shown in Table 1.

To assess the method performance over the longer time periods relevant to water resources planning and management, satellite- and raingauge-based estimates of daily MAP are summed over 10-day and monthly intervals. Table 2 reports the results of this comparison, indicating that model performance is excellent. In particular the correlation, COE and mean square error (MSE) for the monthly time scale are 0.98, 0.95 and 6.11 mm month\(^{-1}\), while the bias during the verification months is only 7%.

Table 2 Estimation of daily precipitation over Ngudu and Kisumu (all months).

<table>
<thead>
<tr>
<th></th>
<th>10-day MAP:</th>
<th>Monthly MAP:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Correlation</td>
<td>Correlation</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ngudu</td>
<td>0.90</td>
<td>0.81</td>
</tr>
<tr>
<td>Kisumu</td>
<td>0.79</td>
<td>0.60</td>
</tr>
</tbody>
</table>

The method was also tested in Kisumu, western Kenya, without re-calibration using local data. Because few raingauges are available in the Kisumu area, the MAP estimates at the daily resolution are marginal. Thus, only the 10-day and monthly comparison is conducted. At the 10-day resolution (Table 2), agreement between satellite-based and ground-based MAP estimates is good and improves further at the monthly resolution. However, more ground-based data are needed to better assess the performance of the method.

CONCLUSIONS AND ON-GOING RESEARCH

The satellite-based rainfall estimation method described provides an effective means of identifying convective and non-convective rain areas and captures the variability and trend of MAP at daily time intervals. At longer time scales, the performance of the method improves, and the differences between satellite-based estimates and ground-based estimates are very small. Thus, the information contained in the infrared and visible satellite signals can be used to provide useful precipitation estimates over the Lake Victoria basin. The satellite-based rainfall estimation module is integrated within the Lake Victoria Decision Support System (LVDSS) and is used in preliminary assessments of watershed response, crop yield, and lake level fluctuations.

The LVDSS rainfall estimation method is being tested and re-calibrated with data from other ground stations and from TRMM (Tropical Rainfall Measuring Mission) precipitation radar.
Acknowledgements Funding for the work described was provided by the Food and Agriculture Organization (FAO) of the United Nations and by the Georgia Water Resources Institute and Georgia Tech. LVDSS has been developed for the Governments of Kenya, Tanzania and Uganda.

REFERENCES


