Available online at www.iseec2012.com

I-SEEC 2012

Proceeding - Science and Engineering (2013)) 286–293

Proceeding
Science and Engineering

www.iseec2012.com

Science and Engineering Symposium
4th International Science, Social Science, Engineering and Energy Conference 2012

A statistical model for estimating rainfall from satellite data in a tropical environment

P. Nimnuan[a,*] , S. Janjai[a]

[a]Department of Physics, Faculty of Science, Silpakorn University, Nakhon Pathom, 73000, Thailand

Abstract

In this work, a statistical model for estimating rainfall from satellite data was developed. Digital data from visible and infrared channels of the GMS5 satellite collected during an 8-year period (1995-2002) were used in this work. These data displayed as images were transformed to the cylindrical projection and then navigated using the features of coastlines as a reference. The gray levels of the visible images were converted into the earth-atmospheric albedo (ρ_{EA}) whereas the gray levels of the infrared images were converted into the brightness temperatures (T_B) by using calibration tables. The maximum earth-atmospheric albedo ($\overline{\rho}_{EA,max}$) and the average earth-atmospheric albedo ($\overline{\rho}_{EA}$) were derived from the visible images. Additionally, the minimum brightness temperature ($\overline{T}_{B,min}$), the average brightness temperature in the 25-percentile ($\overline{T}_{B,P25}$) and the number of hours with the brightness temperature less than 235K ($N_{T_B<235}$) were calculated from the infrared images. Rainfall data collected from 16 rain gauge stations in a tropical environment of Thailand were used to formulate a statistical model relating monthly rainfall (R_f) with $\overline{\rho}_{EA,max}$, $\overline{\rho}_{EA}$, $\overline{T}_{B,min}$, $\overline{T}_{B,P25}$ and $N_{T_B<235}$. To investigate its performance, the model was used to calculate annual rainfall of 11 areas covering 38 rain gauge stations and the results were compared with the measurements. It was found that the annual rainfall calculated from the model and that obtained from the measurements were in reasonable agreement, with the root mean square difference (RMSD) and mean bias difference (MBD) of 13.6% and -3.6%, respectively.

Keywords: rainfall; tropical environment; satellite data; statistical model

1. Introduction

Rainfall is an important water source for agricultural activities and hydro-electricity generation in tropical countries, including Thailand. Information on rainfall is of importance for water resource management of these

* Corresponding author. *E-mail address:* phenphorn_phys@hotmail.com

countries. In general, the amount of rainfall can be obtained from measurements typically made at ground meteorological stations using rain gauges. This gives accurate estimates of rainfall at a point in a region. With a network of rain gauges, estimation of rainfall can be extended from points to regions by interpolation. Even with a relatively dense network of rain gauges, however such estimates have shortcomings. For example, some areas of rainfall may be undetected because rainfall is a discrete quantity in space. Additionally, in remotes areas, the sparse distribution of rain gauges makes it difficult to estimate reliably the spatial and temporal patterns of rainfall.

As rain is generated from cloud, and cloud is regularly detected by meteorological satellites, scientists in many countries have developed models for calculating rainfall from satellite data [1-2]. Cheng et al. [3] used visible channel and infrared channel from Meteosat to develop the rainfall algorithm. Nunez et al. [2] proposed to estimate rainfall in south-west Tasmania using satellite images. According to their method, data from the infrared channel of NOAA/AVHRR satellite were converted into brightness temperature and multiple linear regression analyses between rainfall and satellite data were carried out to obtain yearly and seasonal averages of rainfall.

Ba and Gruber [4] developed the approach using five channels from GOES satellite data: visible (0.65 μm), near infrared (3.9 μm), water vapor (6.7 μm), and window channels (11 and 12 μm). Data from visible channel were used to identify types of cloud and satellite data in others channels showed brightness temperature, water vapor and droplet effective radius.

A rain-delineation algorithm for night-time based on microphysical considerations was suggested by Lensky and Rosenfeld [5]. The algorithm uses BTD between a 3.7 μm mid-IR channel and an 11 μm thermal IR channel ($T_{3.7-11}$) to detect potentially precipitating cloud.

It was observed that research works on satellite-rainfall modelling in the tropics are very limited. Therefore, the objective of this work is to develop a statistical model for estimating rainfall satellite data in a tropical environment.

2. Methodology

To fulfill the objective of this work, a satellite-rainfall model was formulated and validated using satellite and ground-based data in tropical areas of Thailand. The following research activities were carried out. These were acquisition and processing of satellite data, provision of ground-based rainfall data, formulation of rainfall estimation model and model validation. This procedure is schematically shown in Fig. 1 and the details are explained as follows.

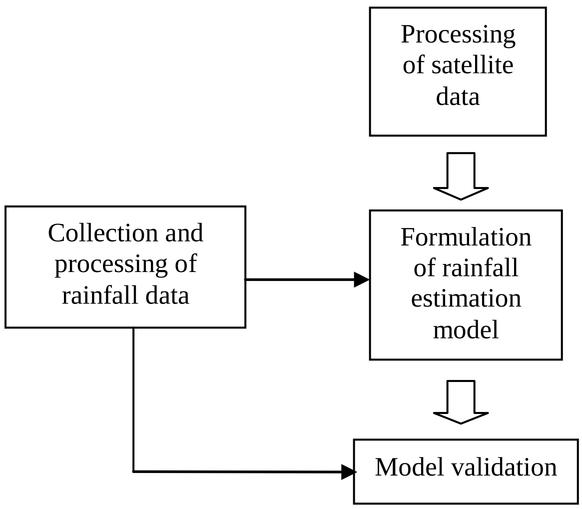

Fig. 1. Schematic diagram of the esearch procedure

2.1 Processing of satellite data

An eight-year period (1995-2002) of data from visible channel (0.55-0.90 μm) and infrared channel (10.5-11.5 μm) from GMS5 satellite was acquired. Digital hourly data taken at 8:30, 9:30,10:30, 11:30, 12:30, 13:30, 14:30 and 15:30 h local time were used. These data displayed as image cover the entire area of Thailand with a spatial resolution of 3 x 3 km^2 and 5 x 5 km^2 for visible channel and infrared channel, respectively. In the original satellite map projection, the satellite images show the curvature of the earth's surface, creating difficulty in the navigation process. These images were transformed into cylindrical projection with the distance in the images being linear in latitude and longitude. Then, the images were navigated to identify the coordinate of all satellite pixels by using coastlines as references. After the navigation, the rectified images which are linear in latitude and longitude were obtained. Example of the rectified image is shown in Fig. 2. The gray levels of the visible images were converted into the earth-atmospheric albedo) ρ_{EA}) whereas the gray levels of the infrared images were converted into the brightness temperatures (T_B) by using calibration tables supplied by the satellite data agency.

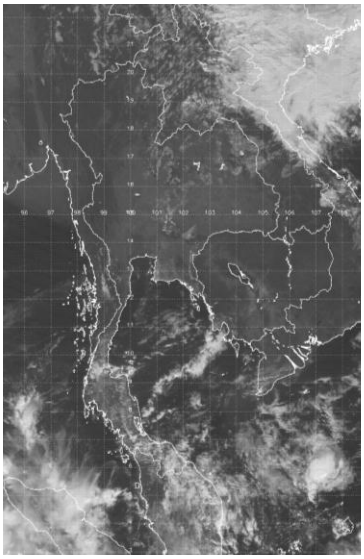

Fig. 2. Example of a rectified image from the visible channel

2.2 Collection and processing ground-based meteorological data

In order to develop the rainfall estimation model, it is necessary to use ground-based rainfall data. As the study areas of this research include the entire areas of Thailand, ground-based rainfall data were collected from 50 meteorological stations across the country. The positions of the stations are shown in Fig 3 and their names and coordinates are given Table 1. Prior to the utilization, these data were subjected to the quality control by removing the outlier that could unduly affect the statistics [6]. After the quality control, the rainfall data were separated into 2 sets, one set from 16 stations for the model formulation, the other 34 stations for model validation.

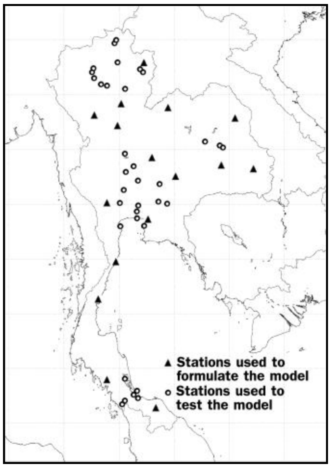

Fig. 3. Position of 50 meteorological stations whose rainfall data were used in this study

Table 1. Names and coordinates of meteorological stations whose rainfall data were employed in this work

Name of Station	Coordinate		Data period
	Latitude	Longitude	
1. Tha Wang Pha*	19.12	100.80	1995-2002
2. Uttaradit*	17.62	100.10	1995-2002
3. Bhumibol Dam*	17.23	99.05	1995-2002
4. Kamphang Phet*	16.80	99.88	1995-2002
5. Wichian Buri*	15.65	101.12	1995-2002
6. Sakon Nakhon*	17.15	104.13	1995-2002
7. Tha Tum*	15.32	103.68	1995-2002
8. Ubon Ratchathani*	15.25	104.87	1995-2002
9. Loei*	17.45	101.73	1995-2002
10. Nakhon Ratchasima*	14.97	102.08	1995-2002
11. Kanchanaburi*	14.02	99.53	1995-2002
12. Chon Buri*	13.37	100.98	1995-2002
13. Prachuap Khiri Khan*	11.83	99.83	1995-2002
14. Chumphon*	10.48	99.18	1995-2002
15. Trang (Airport)*	7.52	99.53	1995-2002
16. Yala Agromet*	6.52	101.28	1995-2002

* For model formulation

** For model validation

Name of Station	Coordinate		Data period
	Latitude	Longitude	
17. Nakhon Sawan**	15.80	100.17	1995-2002
18. Tak Fa Agromet**	15.35	100.50	1995-2002
19. Chai Nat Agromet**	15.15	100.18	1995-2002
20. Lop Buri**	14.80	100.62	1995-2002
21. Suphan Buri**	14.47	100.13	1995-2002
22. Kamphaeng Saen Agromet**	14.02	99.97	1995-2002
23. Pak Chong Agromet**	14.70	101.42	1995-2002
24. Prachin Buri**	14.05	101.37	1995-2002
25. Kabin Buri**	13.98	101.70	1995-2002
26. Don Muang Airport**	13.92	100.60	1995-2002
27. Bangkok Metropolis**	13.73	100.57	1995-2002
28. Bang Na Agromet**	13.67	100.62	1995-2002
29. Pilot Station**	13.37	100.60	1995-2002
30. Phetchaburi**	13.15	100.07	1995-2002
31. Ko Sichang**	13.17	100.80	1995-2002
32. Phatthalung Agromet**	7.58	100.17	1995-2002
33. Songkhla**	7.20	100.60	1995-2002
34. Kho Hong Agromet**	7.02	100.50	1995-2002
35. Pattani Airport**	6.78	100.15	1995-2002
36. Satun**	6.65	100.08	1995-2002
37. Hat Yai Airport**	6.92	100.60	1995-2002
38. Mae Jo Agromet**	18.92	99.00	1995-2002
39. Chiang Mai**	18.78	98.98	1995-2002
40. Lamphun**	18.57	99.03	1995-2002
41. Lampang Agromet**	18.32	99.28	1995-2002
42. Lampang**	18.28	99.52	1995-2002
43. Phayao**	19.13	99.90	1995-2002
44. Chiang Rai**	19.92	99.83	1995-2002
45. Phrae**	18.17	100.17	1995-2002
46. Nan**	18.78	100.78	1995-2002
47. Nan Agromet**	18.87	100.75	1995-2002
48. Kosum Phisai**	16.25	103.07	1995-2002
49. Roi Et Agromet**	16.07	103.62	1995-2002
50. Roi Et**	16.05	103.68	1995-2002

2.3 Formulation of the rainfall estimation model

As a lot of satellite data are required for the development of the rainfall estimation model, the model should not be too complicated and require heavy calculation. Therefore, we propose to develop a statistical model relating rainfall and satellite-derived atmospheric parameters. We used two derivative variable derived from visible images and three derivative variable derived from infrared images. The following variables used in the statistical model designed to estimate monthly rainfall for each station. :

1. Maximum earth-atmospheric albedo ($\rho_{EA\,max}$). The highest reflectivity for each station in the visible channel was obtained daily and then averaged over the entire month forming $\overline{\rho}_{EA\,max}$. This variable is sensitive to cloud cover and increases with cloud thickness.
2. Average earth atmospheric albedo ρ_{EA} . The daily average reflectivity at each station was calculated and then averaged over the entire month to form $\overline{\rho}_{EA}$. This term responded to the climatology for a particular location.
3. Minimum brightness temperature $T_{B\,min}$. The lowest brightness temperature was obtained on a daily basis for each station and then averaged over the entire month to obtain $\overline{T}_{B,min}$.
4. Average brightness temperature in 25 percentile band T_{B25}. The variability of each station was examined daily and all brightness temperatures equal to or lower than the 25 percentile value were averaged. This procedure was repeated for all days and further averaged so as to obtain a monthly average $\overline{T}_{B25}$. This parameter responds to thick rain-bearing clouds.
5. Number of hours with brightness temperatures less than 235K ($N_{TB<235}$). The number of brightness temperature in which each station was equal to or less than 235 K was counted on a daily basis. This value, expressed in hours was summed over the entire month to produce a monthly total.

The statistical regression had the form:

$$R_f = C_0 + C_1\overline{\rho}_{EA,max} + C_2\overline{\rho}_{EA} + C_3\overline{T}_{B,min} + C_4\overline{T}_{B,P25} + C_5 N_{T_B<235} \quad (1)$$

where R_f = monthly rainfall (mm/month)

$\overline{\rho}_{EA,max}$ = maximum earth-atmospheric albedo (-)

$\overline{\rho}_{EA}$ = average earth-atmospheric albedo (-)

$\overline{T}_{B,min}$ = average minimum brightness temperature (K)

$\overline{T}_{B,P25}$ = average brightness temperature in the 25-percentile (K)

$N_{T_B<235}$ = number of hours with the brightness temperature less than 235K

C_1, C_2, C_3, C_4 and C_5 are regression coefficients of the model.

The regression between rain gauge and 5 variables from satellite was established to achieve the regression coefficients. The coefficients and the square of the relation coefficient (R^2) of the model are shown in Table 2.

Table 2. The coefficients and the square of the correlation coefficient (R^2) of the model

Coefficient	Coefficient value
C_0	-965.63
C_1	1092.60
C_2	-532.079
C_3	-5.474
C_4	8.25508
C_5	1.13441
Regression R^2 = 0.80	

2.4 Model validation

Although the model was rigorously developed using both satellite data and ground-based measurements, it is necessary to validate its performance prior to the utilization. To accomplish this, the model was used to estimate rainfall from satellite data at the position of 34 rain gauge stations over Thailand. These stations were divided into 10 regions (Fig. 5). Each region composed of 3-4 stations. For a given region, the values of rainfall from all stations inside the region were averaged and the average value was used to represent the rainfall of that region. This procedure was carried out, both for the rainfall from the model and that obtained from the measurements. Then values of the average rainfall from the measurements and those from the model were compared (Fig. 6). Two statistical parameters namely, root mean square difference (RMSD) and mean bias difference (MBD) were used to indicate the model performance.

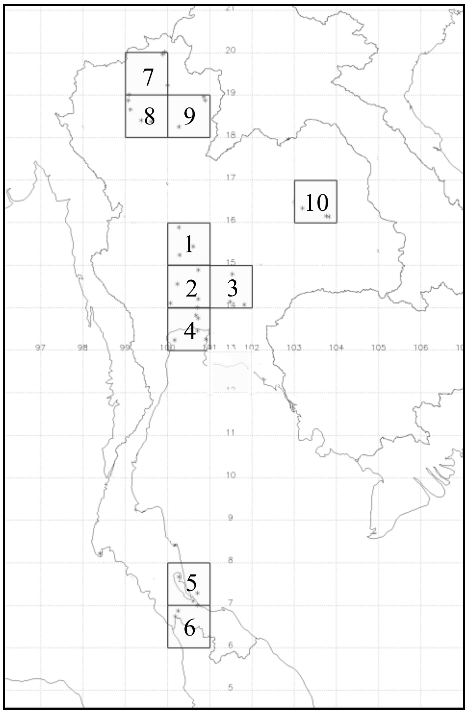

Fig. 5. Position of 10 regions and rain gauges in the regions

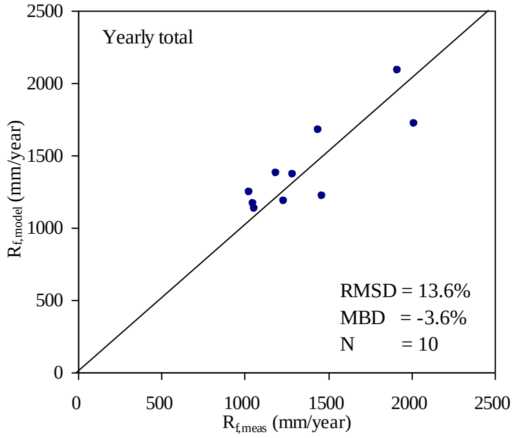

Fig. 6. Comparisons between measured ($R_{f,meas}$) and calculated ($R_{f,model}$) yearly rainfall over 10 regions

From fig. 6, it showed that the values of RMSD and MBD from 10 regions are 13.6% and -3.6%, respectively. This result indicated that values of yearly rainfall estimated from this model agreed well with those obtained from the measurement.

3. Conclusion

A statistical model for estimating monthly rainfall from satellite data in Thailand has been proposed. Rainfall from rain gauge and satellite at 16 stations were used to formulate a model relating rain gauge data to 5 variables from visible and infrared channel of GMS5 satellite. The square of the relation coefficient (R^2) of the model is 0.80. From the rainfall model, monthly rainfall over 10 regions was calculated and summed to obtain yearly rainfall. The yearly rainfall from model was compared with that from the ground-base measurements. It was found that the estimated and measured rainfalls were in reasonable agreement.

Acknowledgements

We would like to thank Development and Promotion of Science and Technology Project (DPST) for giving a scholarship to the first author. The authors are grateful to National Research Council of Thailand for providing a financial support to this research work.

References

[1] Levizzani V, Amovati R. *A review of satellite-based rainfall estimation methods*. Technical Report. Institute of Atmospheric Science and Climate. Bologna, Italy; 2002.

[2] Nunez M, Kirkpatrick JB, Nilsson C. Rainfall estimation in south-west Tasmania using satellite images and photosociological calibration. *Int. J. Remote Sensing* 1996;**17(8)**:1583-1600.

[3] Cheng M, Brown R, and Collier CG. Delineation of precipitation areas using METEOSAT infrared and visible data in the region of the United Kingdom. *J. Appl. Meteorol.* 1993;**32**: 884-898.

[4] Ba MB, Gruber A. GOES Multispectral Rainfall Algorithm (GMSRA). *J. Appl. Meteorol*. 2001;**40**: 1500-1514.

[5] Lensky IM, Rosenfeld DA. Night-Rain Delineation Algorithm for Infrared Satellite Data Based on Microphysical Considerations. *J. Appl. Meteorol*. 2003;**42**: 1218-1226.

[6] Gonzalez-Rouco JF, Jimenez JL, Quesada V, Valero, F. Quality Control and Homogeneity of Precipitation Data in the Southwest of Europe. *J. Climate* 2001;**14**: 964–978.