



Model for estimating rainfall from meteorological geostationary satellite data over southern China

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Abstract

In this work, a model for calculating rainfall from satellite data in the southern China was developed. Digital data from the visible and infrared channels of FY-2D meteorological geostationary satellite during a 5-year period (2008-2012) were used. The satellite - derived quantities namely, the maximum earth-atmospheric albedo ($\bar{\rho}_{EA,max}$), the average earth-atmospheric albedo ($\bar{\rho}_{EA}$), the minimum brightness temperature ($\bar{T}_{B,min}$), the average brightness temperature in the 25-percentile ($\bar{T}_{B,P25}$) and the number of hours with the brightness temperature less than 235 K ($N_{T_B < 235}$) were used as dependent variables in the model. Rainfall data acquired from 68 rain gauge stations were used, 36 stations for model formulation and 32 stations for model validation. To establish a model relating monthly rainfall (R_f) with $\bar{\rho}_{EA,max}$, $\bar{\rho}_{EA}$, $\bar{T}_{B,min}$, $\bar{T}_{B,P25}$ and $N_{T_B < 235}$, the multiple linear regression was used to estimate the coefficients of the model. For model validation, the rainfall calculated from the model was compared to that obtained from rain gauge and the discrepancy in terms of root mean square difference (RMSD) and mean bias difference (MBD) was found to be 14.4% and -6.0%, respectively.

Keywords: rainfall, satellite data, southern China

1. Introduction

Rainfall is an important water source of southern China. It is very essential for agricultural activities and hydro-electricity generation in this region. Information on rainfall is of importance for water resource management because several dams have been planned to construct in southern China. To manage the water resource, two case studies are proposed for water resources system study using mathematical modeling for flood and draught problems reduction [1]. However, rainfall mapping is also essential for water resource management. In general, the amount of rainfall can be obtained from measurements 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. However, rainfall is a discrete quantity in space and time and difficult to be reliably estimated by interpolation, for example, some areas of rainfall may be undetected.

As rain is generated from cloud and cloud is regularly detected by meteorological satellites [2], it is possible to estimate rainfall from satellite data [3]. Many researchers proposed the algorithm to estimate rainfall from satellite data. Ba and Gruber combined five channels from GOES satellite in the multispectral

rainfall algorithm [4]. Lensky and Rosenfeld suggested a rain-delineation algorithm for nighttime based on microphysical considerations using infrared satellite data [5]. Delgado et al. [6] used geostationary infrared and visible data for daily rainfall estimation in South America. Nunez et al. [7] proposed to estimate rainfall in south-west Tasmania using satellite images. Cheng et al. [8] used visible channel and infrared channel from Meteosat satellite to develop a rainfall algorithm. According to their method, the data from the infrared channel from NOAA/AVHRR satellite were converted into brightness temperature. Then, multiple linear regression analysis between rainfall and satellite data were carried out to obtain yearly and seasonal averages of rainfall.

Janjai et al. [9] have developed a model for estimating rainfall from 4 geostationary satellites and compared with rainfall from TRMM and CMORPH. Then, the model was used to calculate climatology rainfall for Thailand. The use of geostationary satellite data has advantages in terms of good spatial resolution and simplicity of the approach. However, the use of these data is still very limited. Therefore, in this work, we propose to develop a simple model for estimation of rainfall for southern China from FY-2D geostationary satellite.

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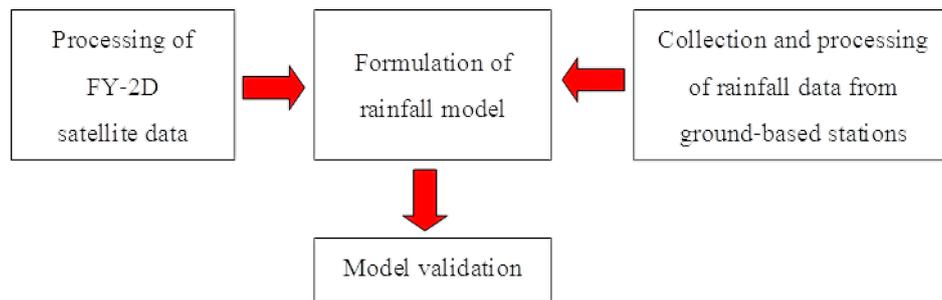


Figure 1 Schematic diagram of research work



Figure 2 Locations of the stations for model formulation and model validation

2. Materials and methods

In this study, the model for estimating rainfall from satellite data were formulated and validated using satellite data and ground-based data in southern China. To fulfill the objective of this study, the following research activities were carried out. These were acquisition and processing of satellite data, collection and processing of ground-based rainfall data, formulation of rainfall model and model validation. This procedure is schematically shown in Figure 1. The details for each activity are as follows.

2.1 Processing of FY-2D satellite data

A five-year period (2008-2012) of data from visible channel (0.5 μm -0.75 μm) and infrared channel (10.3 μm -11.3 μm) from FY-2D satellite were collected. Digital hourly data displayed as image covering the area of southern China with a spatial resolution 1.25 x 1.25 km^2 and 5 x 5 km^2 for visible channel and infrared channel, respectively, were used. The gray level of visible channel were converted to the earth-atmospheric albedo (ρ_{EA}) whereas the gray level of infrared channel were converted to the brightness temperatures (T_B)

using calibration tables retrieved from the satellite data agency.

2.2 Collection and processing of rainfall data

In order to formulate the rainfall model, it is necessary to use ground-based rainfall data. The five-year period (2008-2012) of rainfall data from 68 stations were collected and then separated into two groups. The first group from 36 stations was used for model formulation whereas the other from 32 stations was used for model validation. The names and coordinates of the stations are listed in Table 1 and the locations of the stations are shown in Figure 2.

2.3 Formulation of rainfall model

In this work, we propose to estimate rainfall from satellite - derived quantities, namely the maximum earth-atmospheric albedo ($\bar{\rho}_{EA,max}$), the average earth-atmospheric albedo ($\bar{\rho}_{EA}$), the minimum brightness temperature ($\bar{T}_{B,min}$), the average brightness temperature in the 25-percentile ($\bar{T}_{B,P25}$) and the number of hours with the brightness temperature less than 235K ($N_{T_B < 235}$). $\bar{\rho}_{EA,max}$ and $\bar{\rho}_{EA}$ were calculated

Table 1 Names and coordinates of meteorological stations used for formulation and validation

Name of station	Coordinate		Name of station	Coordinate	
	Latitude	Longitude		Latitude	Longitude
1. NANJING	32.00	118.80	35. GANZI	31.62	100.00
2. SHANGHAI	31.41	121.46	36. CHANGDU	31.15	97.17
3. ANQING	30.53	117.05	37. HEFEI	31.87	117.23
4. JIUJIANG	29.45	115.59	38. HANGZHOU	30.23	120.17
5. ZHOUNGXIANG	31.17	112.57	39. HANKOU	30.62	114.13
6. YICHANG	30.70	111.30	40. YUEYANG	29.38	113.08
7. NINGBO	29.86	121.56	41. CHANGDE	29.05	111.68
8. WENZHO	28.02	120.67	42. QUXIAN	28.97	118.87
9. FUZHOU	26.08	119.28	43. PUCHENG	27.92	118.53
10. GUIXI	28.30	117.21	44. YONGAN	25.97	117.35
11. GUANGCHANG	26.85	116.33	45. NANCHANG	28.60	115.92
12. GANZHOU	25.85	114.95	46. JIAN	27.12	114.97
13. HENGYANG	26.90	112.60	47. CHANGSHA	28.12	113.04
14. LINGLING	26.14	111.36	48. BINZHOU	25.45	112.59
15. XIAMEN	24.48	118.08	49. ZHIJIANG	27.45	109.68
16. SHANTOU	23.40	116.68	50. MEIXIAN	24.30	116.12
17. HEYUAN	23.73	114.68	51. QUJIANG	24.80	113.58
18. YANGJIANG	21.87	111.97	52. GUANGZHOU	23.08	113.19
19. HAIKOU	20.03	110.35	53. ZHENJIANG	21.22	110.40
20. LIUZHOU	24.22	109.23	54. GUILIN	25.33	110.30
21. NANNING	22.82	108.35	55. WUZHOU	23.29	111.18
22. BAISE	23.90	106.60	56. ZUNYI	27.70	106.88
23. GUIYANG	26.58	106.72	57. BIJIE	27.30	105.23
24. XINGREN	25.43	105.18	58. RONGJIANG	25.97	108.53
25. ENSHI	30.28	109.47	59. DAXIAN	31.20	107.50
26. YOUYANG	28.83	108.77	60. CHONGQING	29.52	106.48
27. NANCHONG	30.80	106.08	61. NEIJIANG	29.58	105.05
28. MIANYANG	31.47	104.68	62. CHENGDU	30.67	104.02
29. YIBING	28.80	104.60	63. XICHANG	27.90	102.27
30. KANGDING	30.05	101.97	64. LIJIANG	26.83	100.47
31. HUILI	26.65	102.25	65. BAOSHAN	25.13	99.22
32. DALI	25.70	100.18	66. LINCANG	23.95	100.22
33. KUNMING	25.02	102.68	67. JINGHONG	22.02	100.80
34. MENGZI	23.38	103.38	68. DEQIN	28.50	98.90

Note: Station 1-36 for model formulation and station 37-68 for model validation

from the visible data of FY-2D satellite whereas $\bar{T}_{B,\min}$, $\bar{T}_{B,P25}$ and $N_{T_B < 235}$ were estimated from infrared data of this satellite. Based on rainfall from the ground and these satellite-derived variables, a model for estimating rainfall for southern China was formulated as follows.

$$R_f = a_0 + a_1 \bar{\rho}_{EA,\max} + a_2 \bar{\rho}_{EA} + a_3 \bar{T}_{B,\min} + a_4 \bar{T}_{B,P25} + a_5 N_{T_B < 235} \quad (1)$$

where

R_f = monthly rainfall (mm/month)

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

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

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

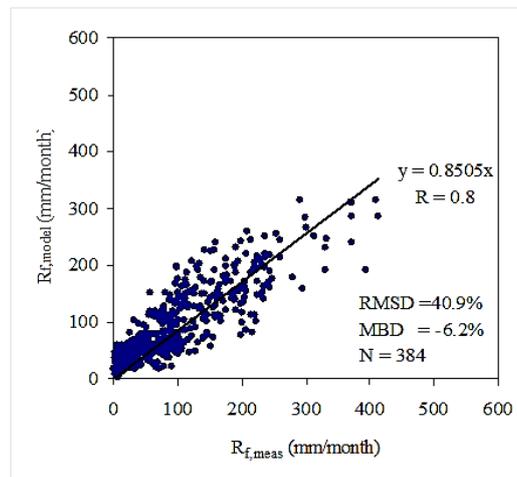
$\bar{T}_{B,P25}$ = average brightness temperature in the 25-percentile (K)

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

a_0, a_1, a_2, a_3, a_4 and a_5 are regression coefficients of the model.

Table 2 Coefficient values and t-statistic of coefficient

Coefficient	a_0	a_1	a_2	a_3	a_4	a_5
Coefficient value	-726.677	-776.487	1089.501	-7.904	10.570	2.129
t-statistic	-4.7	-4.5	5.2	-5.1	11.8	6.4

**Figure 3** Comparison between values of monthly rainfall calculated from the model ($R_{f,model}$) and those obtained from the measurement ($R_{f,meas}$)

A multiple linear regression was used to obtain the values of the empirical coefficients in Equation (1) and the results are shown in Table 2.

After the model was formulated, the monthly rainfall from other 32 rain gauge stations were calculated using the model. Then, the values of monthly rainfall were summed to obtain annual rainfall ($R_{f,mod}$) and then compared with those from the measurements in the term of root mean square difference (RMSD) and mean bias difference (MBD). The equations of RMSD and MBD were shown in Equation (2) and Equation (3), respectively.

$$RMSD = \frac{\sqrt{\frac{(R_{f,mod} - R_{f,meas})^2}{N}}}{\bar{R}_{f,meas}} \times 100\% \quad (2)$$

$$MBD = \frac{\frac{(R_{f,mod} - R_{f,meas})}{N}}{\bar{R}_{f,meas}} \times 100\% \quad (3)$$

where

$R_{f,meas}$ = yearly rainfall from the measurements (mm/year)

$R_{f,mod}$ = yearly rainfall from the model (mm/year)

$\bar{R}_{f,meas}$ = yearly average rainfall from the measurements (mm/year)

N = number of yearly rainfall data

3. Results and discussion

To validate the model, the model was used to calculate the monthly rainfall of other 32 rain gauge stations across the region. The comparison between monthly rainfall calculated from the model and those obtained from the measurement is shown in Figure 3. Additionally, the histogram of monthly rainfall from the model and rain gauge were plotted to show the trend of low rainfall and high rainfall in Figure 4. From the figure shown the similar patterns which high frequency rainfall is between 100–150 mm/month. The annual rainfall obtained from the summation of monthly rainfall was plotted against the yearly rainfall from rain gauge and the result is shown in Figure 5. The discrepancy between the calculated and measured annual rainfall in terms of root mean square difference (RMSD) and mean bias difference (MBD) was found to be 14.4% and -6.0%, respectively. This result implies that the model can be used to estimate rainfall in southern China with reasonable accuracy [9].

4. Conclusions

A statistical model for estimating monthly rainfall using satellite data over southern China has been proposed. Rainfall from 36 rain gauge stations was used to formulate the model. For model validation, the rainfall calculated from the model was compared with that from the ground-based measurements at 32 independent stations. It was found that the estimated and measured rainfall was in reasonable agreement.

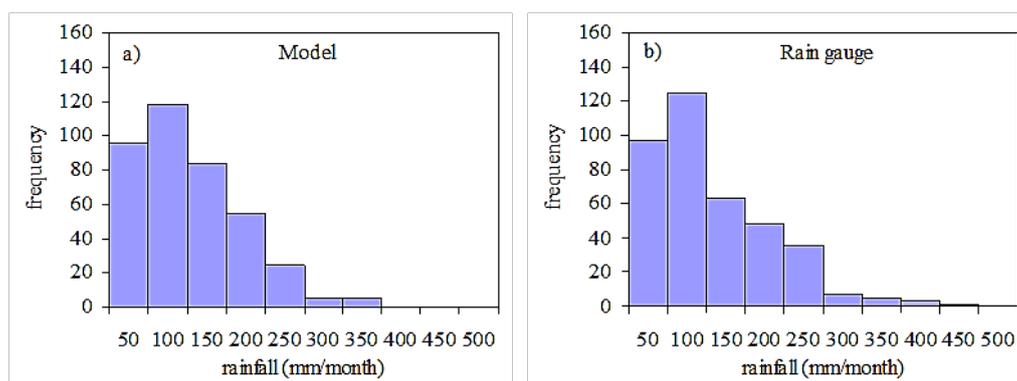


Figure 4 Frequency histogram of monthly rainfall in southern China from a) model and b) rain gauge

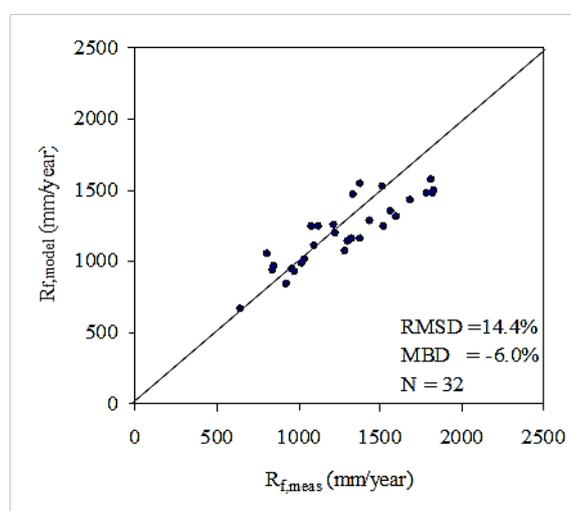


Figure 5 Comparison between values of annual rainfall calculated from the model ($R_{f,model}$) and those obtained from the measurement ($R_{f,meas}$)

From the model which formulated in this study, monthly rainfall map over southern China can be generated from meteorological geostationary satellite. Moreover, this model can be developed to obtain climatology rainfall map from satellite data for other countries in the future.

Acknowledgements

The authors would like to thank Thailand Research Fund and National Natural Science Foundation of China for providing a financial support to this research work. The authors also thank Rajamangala University of Technology Rattanakosin for other support.

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