EVALUATION OF MODIS CLOUD PRODUCT-DERIVED RAINFALL ESTIMATES

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ABSTRACT This study explores the use of infrared and visible bands of the Moderate Resolution Imaging Spectroradiometer (MODIS) to estimate rainfall. Clouds were classified as raining or non-raining using Cloud-top pressure (CTP) and Cloud optical thickness (COT) from the MODIS Cloud Product (MOD06). The cloud classification together with Cloud effective radius (CER), Cloud water path (CWP), Cloud-top temperature (CTT) and COT were employed to estimate rainfall using automatic weather stations (AWS) as ground-truth. Rainfall estimates from the TRMM 3B42 product were also evaluated using the same data set from AWS. Raining and non-raining cloud pixels for the developed MODIS rainfall estimate and TRMM versus AWS were assessed using parameters with the following results: Probability of detection-POD_{MODIS}=0.30 & POD_{TRMM}=0.28; Probability of false detection-$POFD_{MODIS}$=0.11 & $POFD_{TRMM}$=0.05; False alarm ratio-FAR_{MODIS}=0.13 & FAR_{TRMM}=0.44; Bias index-BI_{MODIS}=0.67 & BI_{MODIS}=0.51; Critical success index-CSI_{MODIS}=0.22 & CSI_{TRMM}=0.23; Percentage corrects-PC_{MODIS}=0.76 & PC_{TRMM}=0.83. The R^2 values of the MODIS algorithm and TRMM were 0.137 and 0.136, respectively. Our findings successfully demonstrate that MODIS cloud products can be used to estimate rainfall rate.

1 INTRODUCTION

Rainfall estimates are of utmost importance in the areas of meteorology, climatology and hydrology. Understanding rainfall distribution, amounts and rates are essential in characterizing soil moisture, precision farming, weather forecasting, disaster risk assessment and hazard mapping. Presently, rainfall estimates are done using rain gauges, meteorological radars and satellites. The desire for accurate, high temporal and spatial resolution rainfall estimates prompted researchers to develop new techniques of combining ground and satellite data such as the Global Precipitation Climatology Project (GPCP), GPCP One-Degree-Daily (1DD) and Multi-satellite Precipitation Analysis (TMPA). These techniques are challenged by the methods by which infrared (IR) and microwave are processed and the geography of the area under study (e.g. terrain, latitude, topography) (Scheel et al, 2011). Hence, the latter implies that a rainfall algorithm for a specific area may yield a high skill but when the same is applied to another area may have a poor skill.

Discriminating raining from non-raining clouds is one of the key steps in addressing this problem. At mid-latitude, detection of rain using near IR and visible bands of Terra-MODIS showed promising results (Nauss et al., 2006). The incorporation of microphysical and optical properties of cloud obtained by Meteostat Second Generation (MSG) have greatly improved the algorithm in identifying raining clouds at Mediterranean region (Lazri et al., 2013). In Indian region however, the dependency of rain on cloud effective radius and optical thickness vary in a complex manner (Chakraborty et al., 2013).

In this study, Cloud Products (MOD06) from Moderate Resolution Imaging Spectroradiometer (MODIS), a thirty six (36)-channel (26 IR; 10 visible) instrument onboard Terra Satellite, were used to estimate rainfall. Cloud-top pressure (CTP) and cloud optical thickness (COT) were utilized to classify cloud according to its height and type, which determines whether the cloud is raining or not, based on the International Satellite Cloud Climatology Project (ISCCP) cloud classification. Statistical linear regression on raining clouds was applied to derive relationships between COT, Cloud effective radius (CER), Cloud water path (CWP), and Cloud-top temperature (CTT) and rain.

2 DATA and METHODS

2.1 Data Collection and Description

The study used two (2) Terra-MODIS Products namely, MOD03 (Geolocation) and MOD06 (Cloud) Collection 5.1, Tropical Rainfall Measurement Mission (TRMM) 3B42 Product and automatic weather station (AWS) rain dataset. MODIS data were collected from Level 1 and Atmospheric Archive and Distribution System

(LAADS) of the National Aeronautic and Space Administration (NASA) Goddard Space Flight Center (GSFC). The data covers the Philippines (4^0-22^0 N, 116^0-127^0 E) at observation time 0205-0240 UTC (10:05-10:40 AM local time) from January to December 2013. The corresponding TRMM and ground-based AWS rain data were obtained from NASA and Department of Science and Technology-Advanced Science and Technology Institute (DOST-ASTI), respectively.

2.1.1 Geolocation Product. MOD03 or the Geolocation Data Set is a level 1 product which is being used for geolocation. Although MOD06 also contains this information at 5 km resolution, the study made use of MOD03 which provides more accurate coordinates at 1 km resolution.

2.1.2 Cloud Product. MOD06 or the Cloud Product is a level 2 product that contains the following scientific data sets (SDS) used in this study:

1. Cloud Optical Thickness (COT) is a dimensionless SDS at 1 km spatial resolution that tells the opaqueness of the atmosphere (figure 1a). A value of zero (0) means a clear atmosphere and a value of 100 means a completely opaque atmosphere (King et al., 1997). COT can be used to delineate raining from non-raining regions (Nauss et al., 2006) and threshold value can be determined locally for precipitation formation (Chakraborty et al., 2013).
2. Cloud Effective Radius (CER) is a cloud microphysical property with a unit of microns (10^{-6} m) that estimates the radius of cloud droplets (figure 1b). This SDS is given at 1 km resolution. CER together with COT can be used to delineate raining from non-raining clouds (Nauss et al., 2006). Large cloud droplets may coalesce with other droplets to form rainfall droplets (Ahrens, 2004). CER can be a determining factor in estimating the amount of rain (Chakraborty et al., 2013).
3. Cloud Water Path (CWP) is a SDS with 1 km resolution and a unit of gram per square meter (g/m^2). It is a measure of the total mass of a square meter water column from the top of the atmosphere to the surface of the earth (figure 1c). CWP represents the liquid water content of the cloud which is one of most crucial factors in the raindrop formation (Ahrens, 2004)
4. Cloud-Top Temperature (CTT) with a unit of Kelvin (K) gives the estimated temperature at the top of the cloud at 5 km spatial resolution (figure 1d). Generally, thicker clouds have colder CTT which may result to heavy surface rainfall (Miller et al, 2001).
5. Cloud-Top Pressure (CTP) with a unit of hectoPascal (hPa) estimates the pressure at the top of the cloud. It is given at 5 km spatial resolution (figure 1e). Low CTP is associated with high clouds.

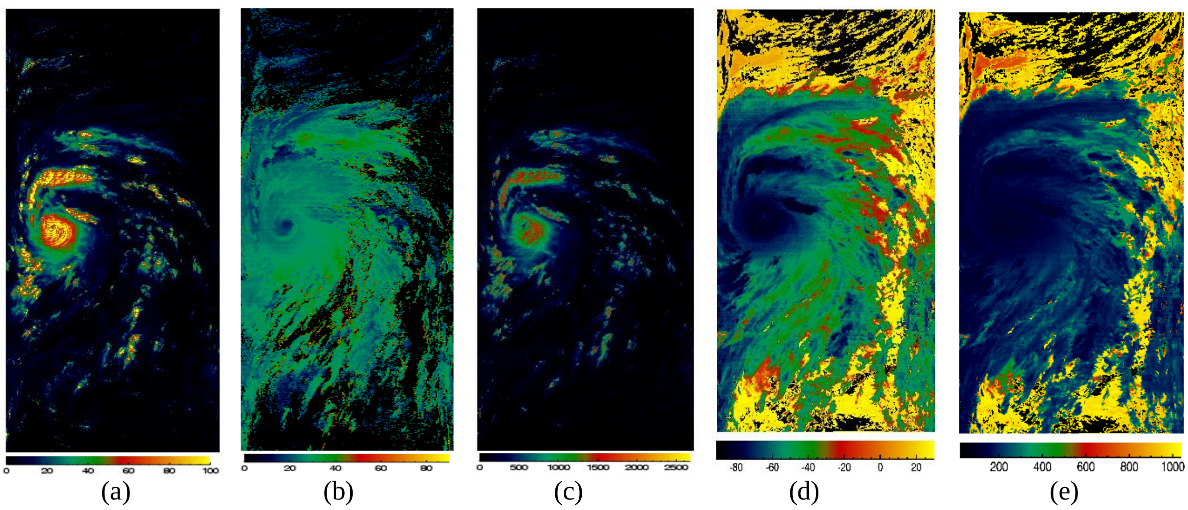

Figure 1. Cloud Properties of Typhoon Haiyan. (a) Cloud optical thickness *(dimensionless; 0-clear;100-can't see through)*; (b) Cloud effective radius *(microns)*; (c) Cloud water path *(g/m^2)*; (d) Cloud-Top temperature *(^0C)*. (e) Cloud-Top Pressure *(hPa)*. Data used are dated 08 November 2013 0205-0210 UTC.

2.1.3Tropical Rainfall Measuring Mission (TRMM) 3-Hour 0.25 TRMM and Other-GPI Calibration Rainfall Data or TRMM 3B42. This product is a 3-hour rainfall rate with 0.25x0.25 degree spatial resolution (figure 2).

2.1.4. Automatic Weather Station (AWS) Rainfall Dataset. Rainfall data from AWS were used as ground-truth. As of the study time, there were about 480 AWS used and their geolocations were utilized as centers of the 10 x 10 km areas that served as boundaries of latitude and longitudes of the regions of interest.

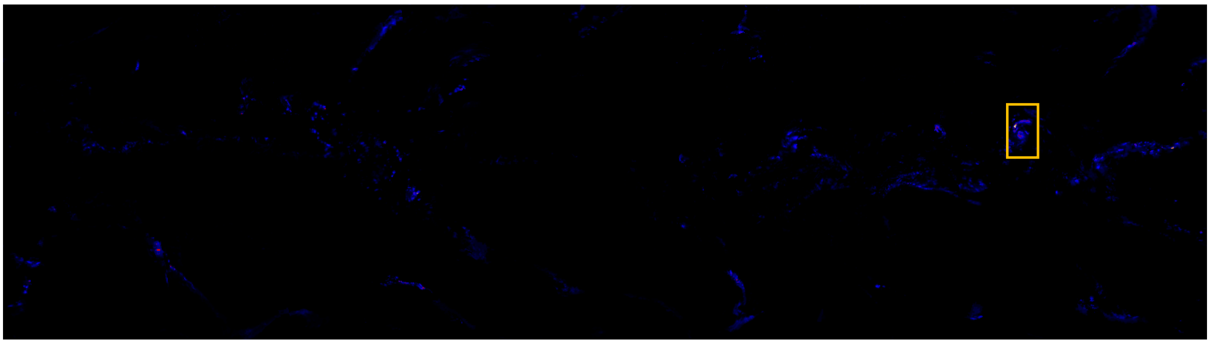

Figure 2. TRMM 3B42. The orange rectangle shows the area under consideration. Data used are dated 08 November 2013 0130 UTC.

2.2 Methods

Five (5) Terra-MODIS MOD06 SDS (COT, CER, CWP, CTT and CTP) were employed in this study. Processing these data involves the consideration of offset value (OV_{COT} = 0.0; OV_{CER} = 0.0; OV_{CWP} = 0.0; OV_{CTT} = -15000; OV_{CTP} = 0.0) and multiplication of scale factor (SF_{COT} = 0.01; SF_{CER} = 0.01; SF_{CWP} = 1.0; SF_{CTT} = 0.01; SF_{CTP} = 0.1). Pixels that contain fill value (FV_{COT} = -9999; FV_{CER} = -9999; FV_{CWP} = -9999; FV_{CTT} = -32768; FV_{CTP} = -32768;) were not included in this study. Using the 10 x 10 km area defined by the geolocations of AWS, the corresponding values of the SDS were averaged and extracted. Only daytime data from 0205-0240 UTC were considered in this study during which, the Terra satellite passes over the Philippines.

In this study, the cloud classification of The International Satellite Cloud Climatology Project (ISCCP) (figure 3) was extensively utilized to infer the cloud type and consequently discriminate raining and non-raining clouds. CTP was used to sort the cloud as low (1000-681 MB), middle (680-441 MB) or high (440-50 MB). COT further classified the cloud according to its depth. The cloud type names presented in the figure are strongly supported by the climatological comparison between satellite-borne cloud properties measurements and surface-based observations (ISCCP-NASA).

According to the classical morphological cloud types, cumulonimbus (Cb) or deep convection is associated with heavy torrential rain, nimbostratus (Ns) produces continuous heavy rain, stratus (St) may be accompanied by drizzle and stratocumulus (Sc), which may be present in all types of weather, may yield light rain. Hence, they are classified as raining clouds. For Sc, the study made use of COT threshold value of 9.4. Cumulus (Cu) cloud should be large enough and requires certain thickness or depth to yield surface rain making it hard to predict. Cu together with cirrus (Ci), cirrostratus (Cs), altocumulus (Ac) and altostratus (As) were classified as non-raining clouds as they lack certain thickness and are high enough that their precipitation often do not reach the earth's surface.

The TRMM 3B42 rainfall dataset were obtained by extracting the corresponding pixel that contains the latitude and longitude of the AWS. The study made use of the 0130-0459 UTC (9:30 AM-2:59 PM local time) time window.

Two (2) AWS rainfall dataset were collected in this study. The first dataset made use of the time window of the Terra-MODIS. Three (3)-hour accumulated rain were extracted from 0206-0241 to 0506-0541 UTC. As an example, if Terra-MODIS data were collected at 0205 UTC, rainfall data from 0206-0506 UTC were totaled. The second dataset exactly adopted the time window of the TRMM 3B42 precipitation dataset which is from 0130 to 0459 UTC.

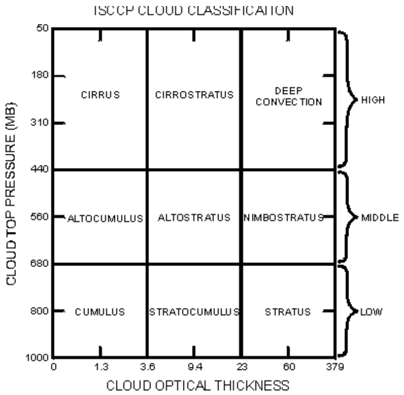

Figure 3. The ISCCP Cloud Classification. Copyright @ http://isccp.giss.nasa.gov/cloudtypes.html

Table 1 shows the contingency table used in this study. The four (4) combinations of MODIS/TRMM predictions and AWS observations are (a) *hit* if MODIS/TRMM classified it as raining cloud and it is raining, (b) *miss* if MODIS/TRMM said it as non-raining cloud and it is raining, (c) *false alarm* if MODIS/TRMM identified it as raining cloud but it is not raining, and (d) *correct negative* if MODIS/TRMM forecasted it as non-raining cloud and it did not rain.

The dichotomous (raining or non-raining cloud) dataset were evaluated using standard evaluation parameters such as probability of detection (POD = a/[a+c]), probability of false detection (POFD = b/[b+d]), false alarm ratio (FAR = b/[a+b]), bias index (BI = [a+b]/[a+c]), critical success index (CSI = a/[a+b+c]) and percentage of corrects (PC = [a+d]/n). Statistical linear regressions were also done to MODIS Cloud properties such as COT, CER, CWT and CTT vs AWS and TRMM vs AWS.

	Identified by AWS		
Classified by MODIS/TRMM	Raining	Non-raining	
Raining	***(a) hits***	***(c) false alarm***	*Forecast Yes (a+c)*
Non-raining	***(b) misses***	***(d) correct negatives***	*Forecast No (b+d)*
	Observed Yes (a+b)	*Observed No (c+d)*	*(n) Total (a+b+c+d)*

Table 1. The contingency table.

3 RESULTS and DISCUSSION

The study made use of more than thirty thousand (30,000) data points both for MODIS and TRMM (table 2). The standard evaluation parameters and the R-squares for MODIS vs AWS and TRMM vs AWS are given on table 3.

MODIS is slightly better than TRMM in correctly identifying raining clouds as shown by the POD values (POD_{MODIS} = 0.30; POD_{TRMM} = 0.28). However, MODIS has incorrectly identified more areas than TRMM as indicated by its higher POFD value ($POFD_{MODIS}$ = 0.11; POD_{TRMM} = 0.05). The FAR value of MODIS (FAR_{MODIS} = 0.13) which measures the fraction that MODIS identified as raining but the AWS says otherwise, is far too superior compared to TRMM (FAR_{TRMM} = 0.44). This suggests that TRMM incorrectly identified more non-raining pixels and flagged them as raining pixels. Both TRMM and MODIS underestimated the events as shown by their Bias indices (BI_{MODIS} = 0.67; BI_{TRMM} = 0.51). The MODIS and TRMM critical success indices (the fraction of observed and/or estimated events that were correctly diagnosed) are almost equal (CSI_{MODIS} = 0.22; CSI_{TRMM} = 0.23). TRMM can correctly better estimate the events than MODIS as values of PC indicate (PC_{MODIS} = 0.76; PC_{TRMM} = 0.83). Based on the six (6) evaluation parameter values, MODIS and TRMM have almost the same skill in discriminating raining and non-raining areas. These results are further confirmed by the values of the R-squares of MODIS (R^2_{MODIS}=0.137) and TRMM (R^2_{TRMM}=0.136), respectively.

	MODIS	TRMM
a	2075	1930
b	2597	1535
c	4883	4902
d	21832	29239
n	31387	37606

Table 2. Summary of the contingency tables.

Categorical Statistics	MODIS	TRMM	Optimal Value
POD	0.30	0.28	1
POFD	0.11	0.05	0
FAR	0.13	0.44	0
BI	0.67	0.51	1
CSI	0.22	0.23	1
PC	0.76	0.83	1
R-Square	0.137	0.136	1

Table 3. Results of evaluation parameters and R-squares of MODIS/TRMM vs AWS.

4 CONCLUSION and RECOMMENDATIONS

The evaluation parameters and R-square values of MODIS show that it can perform at par with TRMM. MODIS bested the TRMM in three (3) out of six (6) evaluation parameters and it has a slightly higher R-square value. This suggests that cloud properties obtained by satellite-borne can be used in discriminating raining and non-raining clouds. Further, the study implies that the use of the cloud properties derived by visible and infrared channels is a potential proxy in estimating rainfall amount and rate.

Poor skill of TRMM and MODIS in discriminating raining and non-raining cloud and estimating rainfall may arise from several issues such as the perpetual problem in validating remotely sensed data, which has coarse spatial resolution, with ground observations, which are significantly point representatives. Increasing the quantity and quality of the dataset may lessen this issue. Data filtering using uncertainties and quality assurance and continuous calibration of ground and satellite instruments are essential measures in improving data quality. Finally, rainfall is not solely dependent on cloud properties. Incorporating other factors that affect rainfall rate and amount such as vertical updraft and surface temperature will improve the algorithm.

5 ACKNOWLEDGMENT

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