A COMPARISON OF RAINFALL ESTIMATION USING HIMAWARI-8 SATELLITE DATA IN DIFFERENT INDONESIAN TOPOGRAPHIES

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Abstract. The Himawari-8 satellite can be used to derive precipitation data for rainfall estimation. This study aims to test several methods for such estimation employing the Himawari-8 satellite. The methods are compared in three regions with different topographies, namely Bukittinggi, Pontianak and Ambon. The rainfall estimation methods that are tested are auto estimator, IMSRA, non-linear relation and non-linear inversion approaches. Based on the determination of the statistical verification (RMSE, standard deviation and correlation coefficient) of the amount of rainfall, the best method in Bukittinggi and Pontianak was shown to be IMSRA, while for the Ambon region was the non-linear relations. The best methods from each research area were mapped using the Google Maps Application Programming Interface (API).

1 INTRODUCTION

Remote sensing is the science of obtaining information about the Earth's surface without having direct contact with it. This is done by sensing and recording the reflected energy and processing, analysing and applying the information (NRC, 2003). Nowadays, remote sensing for the observation of the atmosphere is very important. This is because not all areas on the earth's surface can be covered by in situ observations (Alfuadi, 2016). In addition, remote sensing has contributed greatly to various other fields and led to the development of various sensors (Lillesand et al., 2015). Remote sensing sensors themselves are divided into two types, namely remote sensing with active instruments sensors as found in weather radar and passive instrument sensors found in weather satellites (Stull, 2015).

Weather satellites can be used to identify cloud patterns and structures related to dynamic weather conditions. The development of weather satellite systems has contributed greatly to their use in weather forecasts (Tan, 2014). In fact, observations using weather satellites can provide hourly weather information over a fairly wide area coverage. Such environmental and weather satellite data can be obtained real time, but their use remains very limited in the wider community (Suwarsono et al., 2009).

However, the most recent weather satellite and its data can be used by the wider community, namely the Japanese Himawari-8 satellite, which is a new generation of meteorological satellites with sophisticated optical sensors (Bessho et al., 2016). In addition, precipitation data can be derived from the Himawari-8 satellite data which can be useful in mitigating hydrometeorological disasters (Alfuadi, 2016).

Several studies using the Himawari-8 satellite have also been conducted to estimate rainfall in various areas. For example, Rani, et al. (2016) used the auto estimator method in Pangkalpinang Meteorological Station; the INSAT

189

Multispectral Rainfall Algorithm (IMSRA) method was employed by Alfuadi (2016) in Palangkaraya; and the non-linear relation method with non-linear inversion were used by Alfuadi and Wandala (2016) in Muara Teweh and Palangkaraya.

However, some of these studies only focus on one region topography. In fact, the latitude, slope and altitude in some areas will affect weather activities, such as cloud formation and rain, due to the uneven solar irradiation on the earth's surface (Sucahyono and Ribudiyanto, 2009). Therefore, it is necessary to conduct research into and test the methods used for different topography and weather systems. This study proposes to test the methods that are generally used in various topographies in Indonesia (highlands, lowlands and islands). Apart from testing the methods, the research will display rainfall estimation results into Google Maps Application Programming Interface (API) platform.

The Google Maps API platform allows users to integrate Google Maps into their respective websites by adding their own data points (Davis, 2006). The advantage of the API is that it is possible to modify maps according to user needs and integrate them with the data to be used (Akanbi and Agunbiade, 2013). Therefore, this study will utilise the Google Maps API to add data points in the form of rainfall estimation results (light, moderate, heavy and very heavy rain) into a map which interesting and easy to understand by users

2 MATERIALS AND METHODOLOGY
2.1 Location and Data

The locations of this research were in Bukittinggi (GAW Bukit Kototabang), Pontianak (Supadio Meteorological Station) and Ambon (Pattimura Meteorological Station) (as shown in red on the map in Figure 2-1).

Figure 2-1: Map of the research area

The data used were from Himawari-8 channel IR-1, obtained from ftp://202.90.199.115. IR-1 was used because IR-1 data can be converted into precipitation data (Alfuadi, 2016). The verification of the rainfall estimation was made using rainfall data from the AWS center BMKG. Rainfall date cases were employed in the research are shown in Table 2-1:

Table 2-1: Rainfall date cases (Source - BMKG, 2017 and 2018)

Bukittinggi	
15 April 2017	Heavy rainfall (60.8 mm/day)
25 June 2017	Moderate rainfall (36.9 mm/day)
28 June 2017	Moderate rainfall (46.5 mm/day)
Pontianak	
10 Sept 2017	Heavy rainfall (70.8 mm/day)
11 Nov 2017	Very Heavy rainfall (187.4 mm/day)
13 Oct 2018	Heavy rainfall (76.4 mm/day)
Ambon	
28 May 2018	Very heavy rainfall (100.2 mm/day)
29 June 2018	Very heavy rainfall (111 mm/day)
30 June 2018	Heavy rainfall (75 mm/day)

The tools used in the research were Python 3.7 to extract the value of the cloud top temperature (T) from the IR-1 data. These data are in netCDF (.nc) format, so Python 3.7 extracted the temperature in this format. JavaScript

was also used to prepare the sripct or the mapping of rainfall estimation, and the Google Maps API platform was used for mapping the best method of rainfall estimation result.

2.2 Methods

Two methods were employed, rainfall estimation equation and statistical verification of the rainfall estimation method

2.2.1 Rainfall Estimation Method
a. Auto Estimator

Based on Vicente et al (1998), the equation for auto estimator is :

$$R = 1.1183 \cdot 10^{11} \, exp(-3.6382 \cdot 10^{-2} \cdot T^{1.2}) \quad (2\text{-}1)$$

where R is the rainfall estimation (mm/hour) and T is the cloud top temperature in Kelvin.

b. IMSRA

The equation used in the research of Gairola et al. (2011) was :

$$R = 8.613098 * exp\left(-(T-197.97)/15.7061\right) \quad (2\text{-}2)$$

where R is the rainfall estimation (mm/hour) and T is the cloud top temperature in Kelvin.

c. Non-Linear Relation

The equation used in the research of Suwarsono et al. (2019) was :

$$R = 2 \cdot 10^{25} \cdot T^{-10.256} \quad (2\text{-}3)$$

Where R is rainfall estimation (mm/hour) and T is the cloud top temperature in Kelvin.

d. Non-Linear Inversion

Based on Octari et al (2015), the equation for non-linear inversion is :

$$R = 1.380462 \cdot 10^{-7} \, e^{3789.518 / T} \quad (2\text{-}4)$$

Where R is rainfall estimation (mm/hour)

and T is the cloud top temperature in Kelvin.

2.2.2 Statistical Verification Method

After obtaining the results of the rainfall estimation described above, we verified the results using RMSE, correlation coefficient and standard deviation and incorporated them into a Taylor diagram. We also calculated the bias of the rainfall estimation.

a. RMSE

Based on Wang and Lu (2018), the RMSE equation is :

$$RMSE = \sqrt{\frac{\sum_{n=1}^{N}(x_i - y_i)^2}{N}} \quad (2\text{-}5)$$

where N is the amount of data, x_i is the rainfall estimation (mm) and y_i is the real observation of rainfall (mm).

b. Correlation Coefficient

In line with Saefuddin et al (2009), the correlation coefficient equation is :

$$r_{xy} = \frac{\Sigma(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\Sigma(x_i - \bar{x})^2}\sqrt{\Sigma(y_i - \bar{y})^2}} \quad (2\text{-}6)$$

where x_i is the rainfall estimation (mm) and y_i is the real observation of rainfall (mm).

c. Bias

Bias is used to establish whether the value of the data is underestimated or overestimated. The equation of bias based on Santos et al (2011) is :

$$Bias = \frac{1}{N}\sum_{i=1}^{n}(x_i - y_i) \quad (2\text{-}7)$$

where x_i is the rainfall estimation (mm) and y_i is the real observation of rainfall (mm).

d. Standard Deviation

Based on Supranto (2008), the equation of standard deviation is:

$$\sigma = \sqrt{\frac{\sum_{n=1}^{N}(xi-\mu)^2}{N}} \tag{2-8}$$

where $(xi-\mu)^2$ is the deviation from the observation to the true mean.

3 RESULTS AND DISCUSSION
3.1 Rainfall Estimation Results

Beside the statistical verification results, the determination of the best method was also based on the Taylor diagram results (the red point closest to the observation point being the best method).

a. GAW Bukit Kototabang Bukittinggi

Based on the statistical verification results (Table 3-1) and the Taylor diagram (Figure 3-1), out of three dates, two (25 and 28 June 2017) indicate that IMSRA is the best method. It has the best rainfall estimation when rain intensity is less than 5-6 mm/hour (Alfuadi, 2016), which

was the case on 25 and 28 June 2017. Furthermore, based on the rainfall bias graph (Figure 3-2), on 15 April 2017 there was an increased in rainfall bias (overestimation) in the auto estimator and non-linear relation methods. This is because of a time lag between the detected cloud top temperature and the real rainfall. On 25 June 2017, there was a drastic reduction (underestimation) at 12.00 UTC. This was due to 22.9 mm/hr of heavy rainfall resulting from cloud top temperature -6.435^0C. In other words, rain comes from cloud with warm cloud top temperature.

On the other hand, on 28 June 2017, the non-linear relation method tended to overestimate and there was a reduction at 13.00UTC, which was due to a time lag (on 12.00 UTC, the cloud top temperature was -52.5^0C, but the rain not falling directly to the earth. The heavy rain fell to the earth on 13.00 UTC when the cloud top temperature had increased).
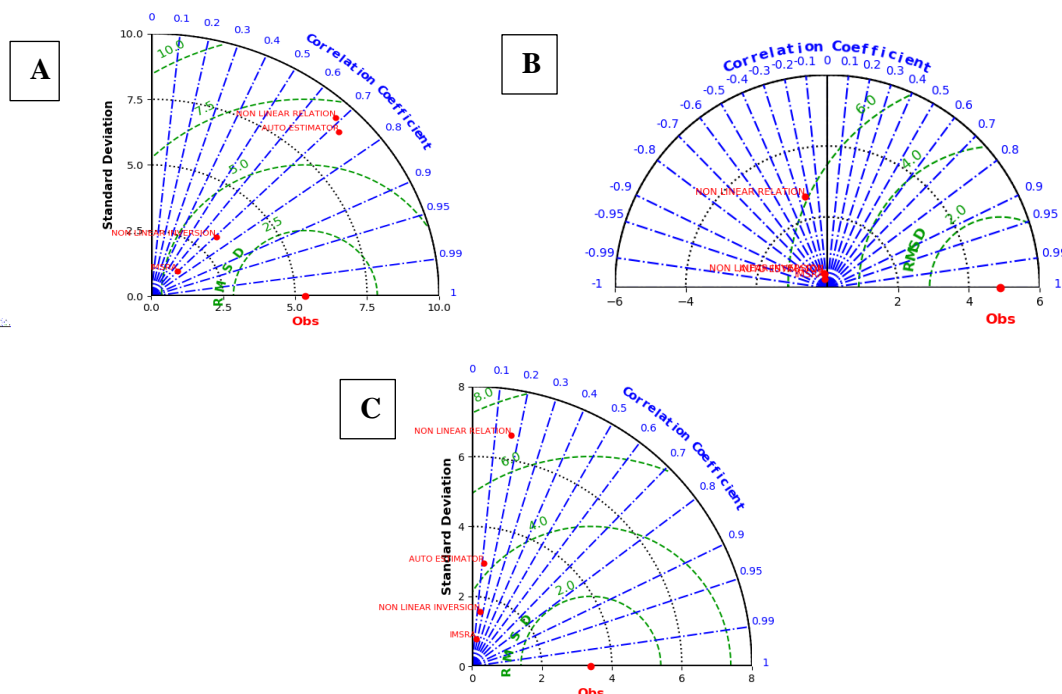

Figure 3-1: A. Taylor diagram on 15 April 2017; B. Taylor diagram on 25 June 2017; C. Taylor diagram on 28 June 2017

Table 3-1: Rainfall Estimation Results for GAW Bukit Kototabang, Bukittinggi

| Dates	Methods	RMSE (mm/day)	Correlation	STDEV (mm/day)
15 April 2017	Auto Estimator	6.36	0.72	9.03
	IMSRA	4.54	0.69	1.32
	Non-Linear Relation	6.88	0.68	9.35
	Non-Linear Inversion	3.83	0.70	3.18
25 June 2017	Auto Estimator	4.98	-0.19	0.40
	IMSRA	4.95	-0.24	0.25
	Non-Linear Relation	6.08	-0.23	2.64
	Non-Linear Inversion	5.01	-0.23	0.43
28 June 2017	Auto Estimator	4.24	0.11	2.97
	IMSRA	3.37	0.15	0.79
	Non-Linear Relation	6.99	0.16	6.71
	Non-Linear Inversion	3.53	0.14	1.58
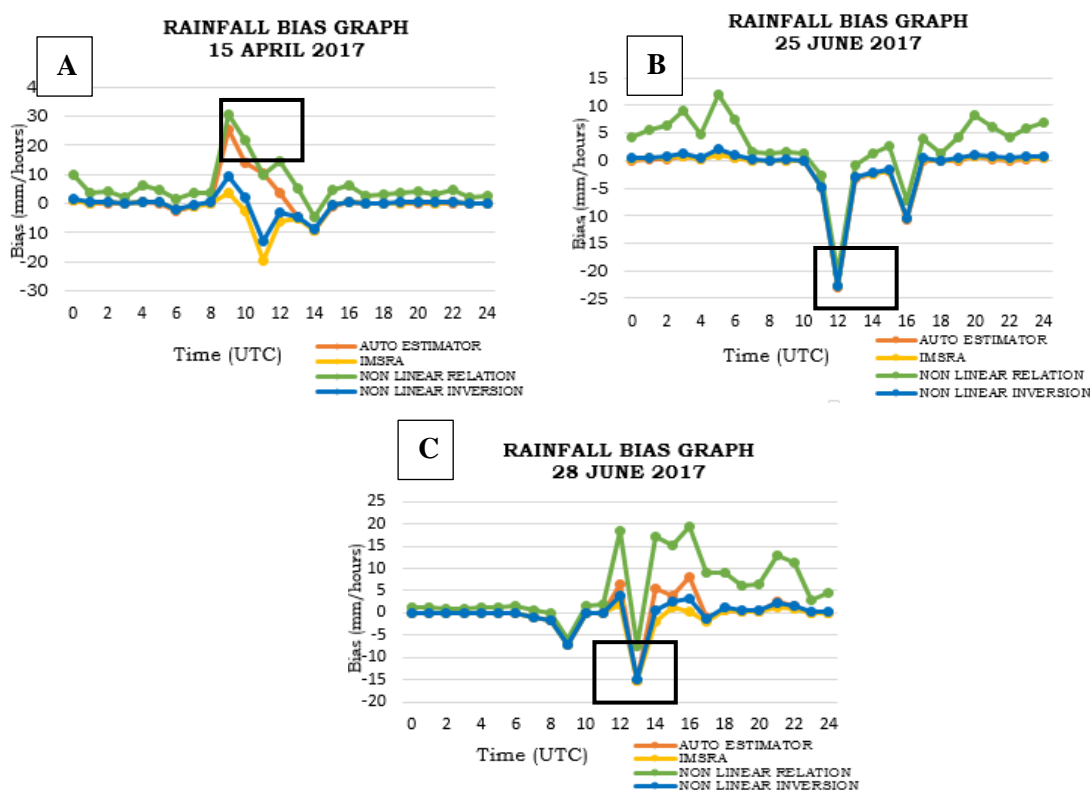
Figure 3-2: Rainfall Bias Graph for GAW Bukit Kototabang Bukittinggi (A. 15 April 2017; B. 25 June 2017; C. 28 June 2017)

b. Supadio Meteorological Station Pontianak

The statistical verification results (Table 3-2) and the Taylor diagrams (Figure 3-3) shows that IMSRA was the best method for the Supadio Meteorological Station. On 10 September 2017, 11 November 2017 and 13 October 2018, the method produced the best results because the dominant hourly rainfall (from AWS) had an intensity of less than 5-6 mm / hour (Alfuadi, 2016). This was the same case as Bukittinggi, where the dominant hourly rainfall was also less than 5-6 mm / hour, so Bukittinggi and Pontianak have the same best rainfall estimation method. Moreover, one of the reasons why Bukittinggi and Pontianak have the same best rainfall estimation method is because both regions arein the equatorial rainfall category.

Generally, rainfall bias on 10 September 2017 showed that there was time lag between the detected cloud top temperature and the actual rainfall in Pontianak, which as shown in Figure 3-4 A. This was because the low temperature of the cloud tops, which in the mature phase does not immediately produce heavy rainfall that falls to the Earth's surface. In addition, the influence of rapid cloud and wind movement affected the accuracy of rainfall in Pontianak and thus influencing the rainfall bias.
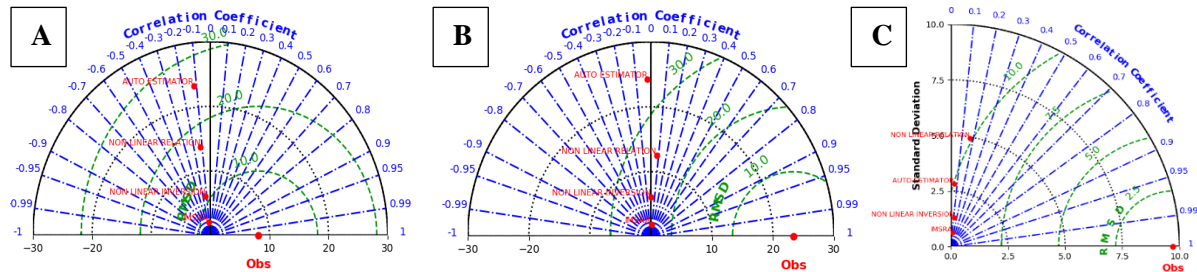

Figure 3-3: A. Taylor Diagram on 10 September 2017; B. Taylor Diagram on 11 November 2017; C. Taylor Diagram on 13 October 2018

Table 3-2 : Rainfall Estimation Results for Supadio Meteorological Station Pontianak

| Dates	Methods	RMSE (mm/day)	Correlation	STDEV (mm/day)
10 Sept 2017	Auto Estimator	25.61	-0.12	23.31
	IMSRA	8.68	-0.13	2.09
	Non-Linear Relation	16.87	-0.12	13.82
	Non-Linear Inversion	10.84	-0.12	6.17
11 Nov 2017	Auto Estimator	34.06	-0.02	24.25
	IMSRA	23.36	0.04	1.92
	Non-Linear Relation	25.70	0.07	12.56
	Non-Linear Inversion	24.09	0.006	6.04
13 Okt 2017	Auto Estimator	9.97	0.05	2.83
	IMSRA	9.64	0.14	0.62
	Non-Linear Relation	10.12	0.16	4.94
	Non-Linear Inversion	9.65	0.11	1.30
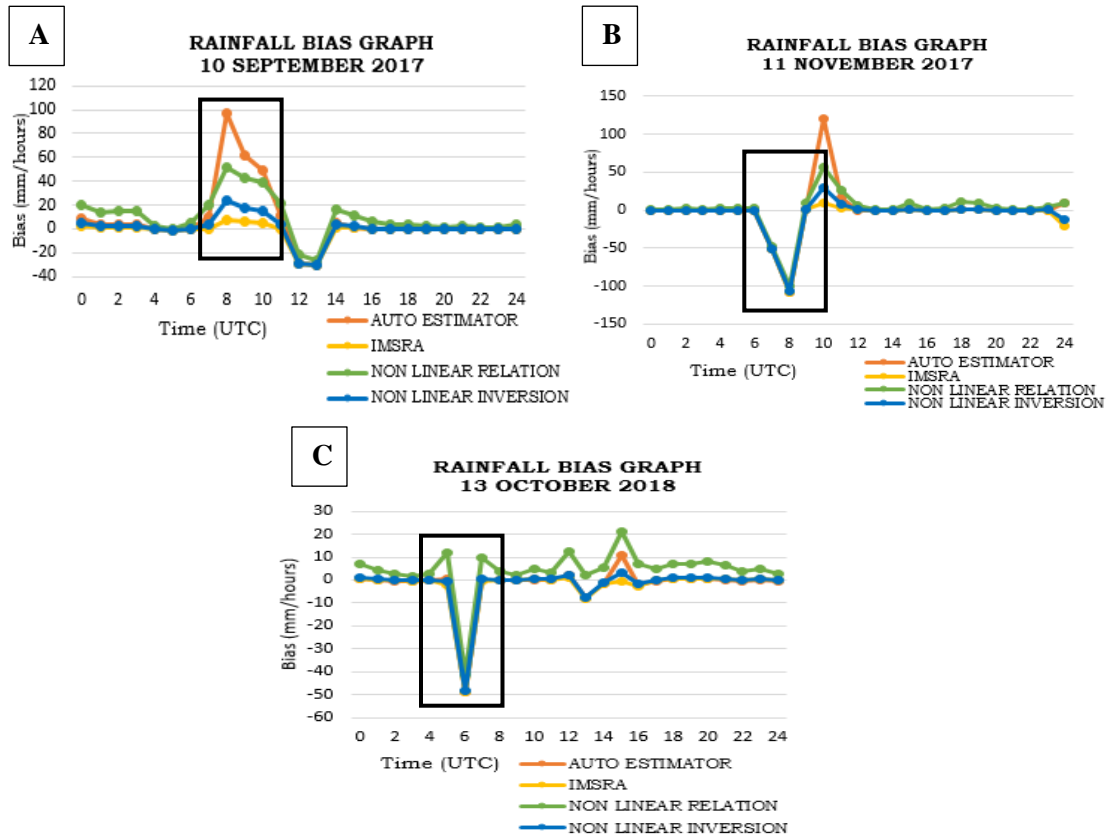
Figure 3-4: Rainfall Bias Graph for Supadio Meteorological Station Pontianak (A. 10 September 2017; B. 11 November 2017; C. 13 October 2018)

Furthermore, on 11 November 2017, there was a decrease in the bias value (Figure 3-4 B) at 08.00 UTC due to actual rainfall (from AWS) reaching 108.6 mm/hour, but the cloud top temperature was only -37.571^{0}C. In addition, there is an increase in the bias value at 10.00 UTC due to the low temperature of the top cloud of -75.289^{0}C, although the actual rainfall (from AWS) is 0 mm/hour. This was contrary to the principles that the lower the cloud top temperature, the higher it's potential to produce a rainfall. Rain events on this date indicate that low cloud top temperatures do not always produce heavy rains, and vice versa (Nurasniyati et al., 2018)

The rainfall bias graph of 13 October 2018 (Figure 3-4 C) shows that there was a significant decrease in the bias value at 06.00 UTC. This was because the cloud top temperature at 06.00 UTC was only -35.47^{0} C, but produces heavy rainfall up to 49.6 mm/hour (from AWS). This further reinforces the notion that the cloud top temperature only played a minor role in the rainfall process on this date. The rainfall process is not only influenced by the cloud top temperatures, but can also be influenced by the conditions and composition of the atmosphere, circulation and local atmospheric dynamics (Avia & Haryanto, 2013) as well as by local convection currents (Marpaung, 2010) in Pontianak.

c. Pattimura Meteorological Station Ambon

The statistical verification results (Table 3-3) and Taylor diagrams (Figure 3-5) show that the non-linear relation method was the best for Pattimura Meteorological Station Ambon.

The best dominant rainfall estimation method for the Ambon region is therefore different to that of the Pontianak and Bukittinggi areas. This could be a result of the topographical conditions of Ambon, which affect the process of rainfall formation. In addition,

Ambon has a local type of rainfall pattern characterised by the extent of the influence of local conditions, such as the presence of mountains, oceans, other water landscapes, and the occurrence of intensive local warming (Tukidi, 2010). The condition of Ambon, which has a local type of rainfall pattern and is heavily influenced by local characteristics (Tjasyono and Harijono, 2013) will affect the distribution of rain. The distribution of rain will affect the characteristics of rainfall in an area, .meaning the estimation results will be affected

There was very intense rainfall reaching 100.2 mm / day on 28 May 2018. Rainfall bias graph at Figure 3-6 A shows that at 13.00, 14.00 and 16.00 UTC, the rainfall bias had decreased quite

dramatically (underestimated). This was because the rainfall fell to the earth's surface came from cloud tops with the temperatures of -36.279, -42.25 and -35.67^0 C. The hours of 13.00, 14.00 and 16.00 UTC are the time when peak rainfall occurs, with an intensity of 23, 17.4 and 16.4 mm/hour (from AWS). This shows that the cloud top temperature only makes a small contribution to the process of very heavy rain. This process can be influenced by local factors such as wind, humidity and water vapour (Nurasniyati et al., 2018). There is a gap in the rainfall bias data at 22.00 UTC, because the Himawari-8 satellite could not detect the cloud top temperature, so it could be converted into rainfall by the four methods.
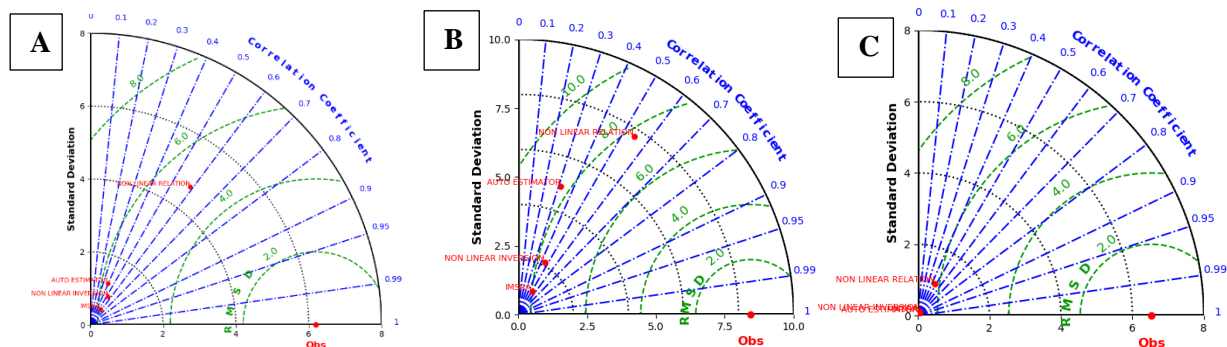

Figure 3-5: A. Taylor Diagram on 28 May 2018; B Taylor Diagram on 29 June 2018; C. Taylor Diagram on 30 June 2018

Table 3.3 Rainfall Estimation Result at Pattimura Metetorological Station Ambon

| Dates	Methods	RMSE (mm/day)	Correlation	STDEV (mm/day)
28 May 2018	Auto Estimator	5.81	0.39	1.23
	IMSRA	5.93	0.55	0.50
	Non-Linear Relation	5.13	0.58	4.67
	Non-Linear Inversion	5.77	0.52	0.91
29 June 2018	Auto Estimator	8.33	0.31	4.90
	IMSRA	7.99	0.50	0.98
	Non-Linear Relation	7.73	0.54	7.70
	Non-Linear Inversion	8.33	0.31	4.90
30 June 2018	Auto Estimator	6.52	0.30	0.04
	IMSRA	6.50	0.43	0.07
	Non-Linear Relation	6.13	0.47	1.00
	Non-Linear Inversion	6.48	0.43	0.12
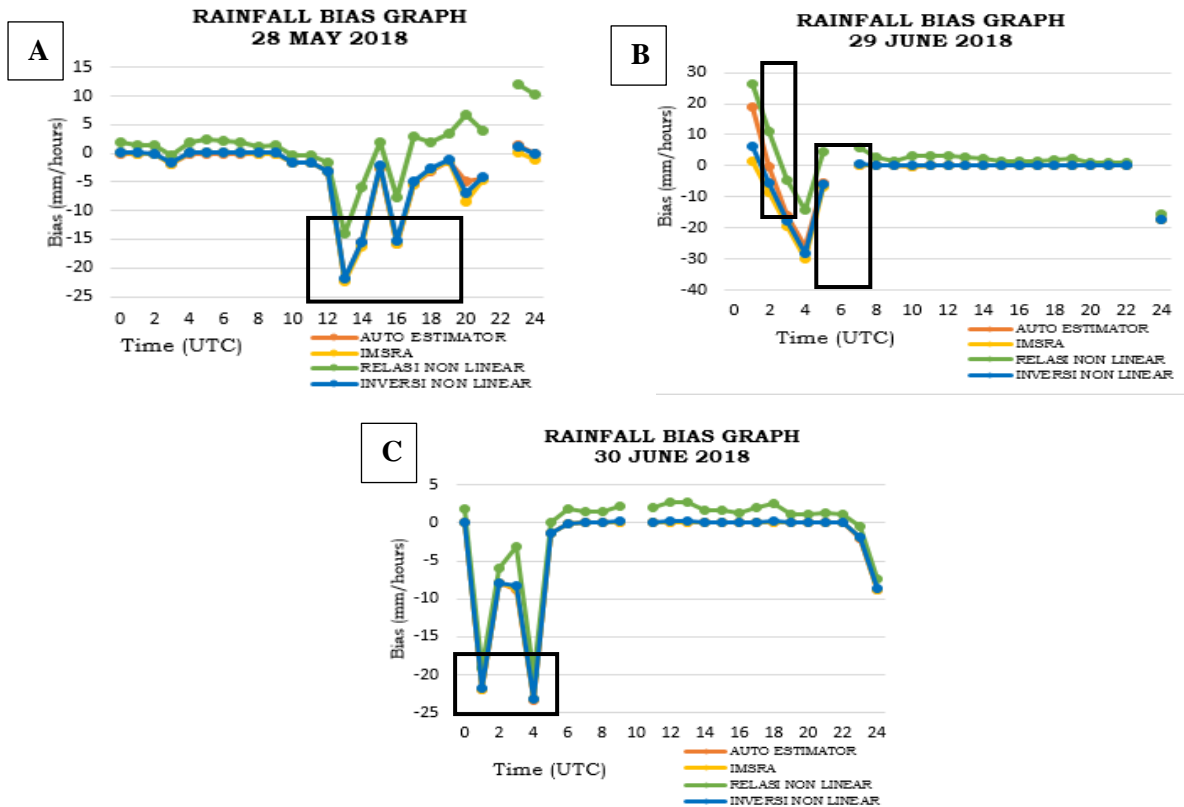
Figure 3-6: Rainfall Bias Graph in Pattimura Meteorological Station Ambon
(A. 28 May 2018; B. 29 June 2018; C. 30 June 2018)

Furthermore, based on Figure 3-6 B, the time lag influenced the rainfall bias. There was an increase in this bias (overestimation) at 01.00 UTC, especially for the auto estimator and non-linear relation method. The different results in the bias were caused by the estimated rainfall results due to the low cloud top temperature (-61.53998^0C), whereas the actual rainfall (based on AWS data) was only 2 mm/hour. In other words, this shows that a low cloud top temperature does not always produce heavy rain at that time. Likewise, at 04.00 UTC, there was a decrease in the rainfall bias (underestimation), because the rain fell heavily when the cloud top temperature gradually rose to -51.70801^0 C from -61.53998^0C. There are a data gaps in the rainfall bias data at 00.00, 06.00 and 23.00 UTC, because the Himawari-8 satellite could not detect the temperature of the cloud tops, so it cannot be converted into rainfall by the four methods.

The rainfall bias graph on Figure 3-6 C shows that there was a decrease in the rainfall bias (underestimation). This was caused by heavy rainfall (22 and 23.4 mm/hour) at 01.00 and 04.00 UTC, although the detected cloud top temperatures were only -8.64404 and -12.21997^0 C. The cloud observations at Pattimura Meteorological Station showed Cumulus (Cu) clouds at 01.00 and 04.00 UTC. In other words, heavy rain is generated from Cu clouds, not Cumulunimbos (Cb) ones with low cloud top temperatures.

3.2 Visual Comparison Map of the Rainfall Estimation

In the rainfall estimation map, the blue colour shows light intensity rain, green shows moderate rain intensity, purple colour shows heavy intensity rain and red very heavy/ extreme rain. Mapping using Google Maps API only takes one date and a certain hour of rain events as an example.
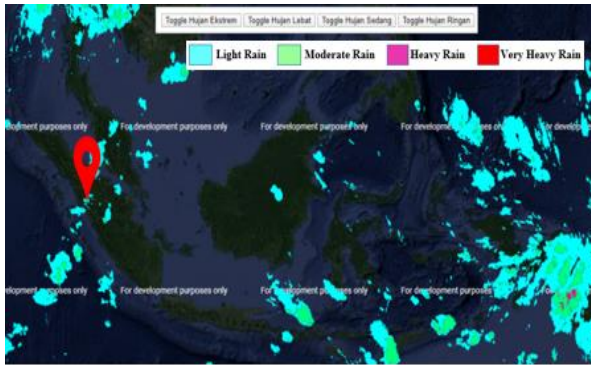
a. GAW Bukit Kototabang Bukittingi

Figure 3-7: Mapping of Rainfall Estimation Results on 28 June 2017 at 12.00 UTC using Google Maps API

As the IMSRA method is the best method in Bukittinggi based on the results and discussion in section 3.1, the rainfall estimation result from the IMSRA method were mapped using Google Maps API for 28 June 2017. Based on the rainfall estimation results in Figure 3-7, it can be seen that the IMSRA method produced an estimate of light rainfall in GAW Bukit Kototabang at 12.00 UTC. In addition, the rainfall estimation from the IMSRA method produced the lowest amount of rainfall in comparison to the other three methods, but this was closer to the actual rainfall levels.
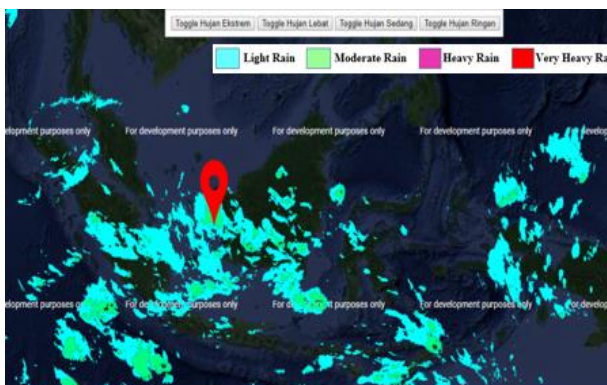
b. Supadio Meteorological Station Pontianak

Figure 3-8 : Mapping of Rainfall Estimation Results on 10 September 2017 at 10.00 UTC using Google Maps API

As the IMSRA method is the best method in Pontianak based on the results and discussion in section 3, the rainfall estimation results from the IMSRA method were mapped using Google Maps API for 10 September 2017. Based on the the rainfall estimation results in Figure 3-8, it can be seen that the IMSRA method produced an estimate of moderate rainfall at the Supadio Meteorological Station at 10.00 UTC.
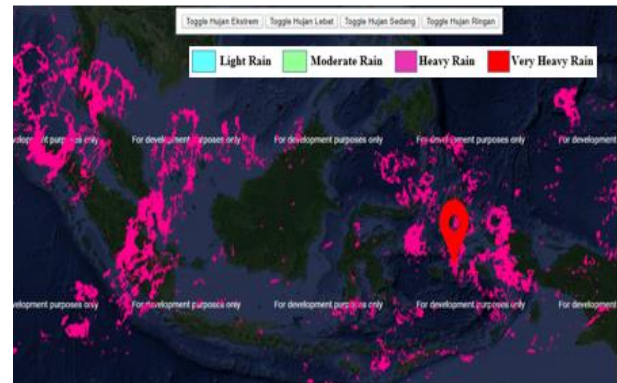
c. Pattimura Meteorological Station Ambon

Figure 3-9 : Mapping of Rainfall Estimation Results on 29 June 2018 at 05.30 UTC using Google Maps API

As the non-linear relation method is the best method for Ambon based on results and discussion on section 3.1, the rainfall estimation results from non-linear relation method were mapped using Google Maps API for 29 June 2018. Based on Figure 3-9, it can be seen that the non-linear relation method produced as heavy rainfall estimation for Pattimura Ambon Station. Rainfall estimation using this method produced a high level of rainfall compared to the other three methods. This was influenced by the ability of the algorithm in the four methods to estimate rainfall.

4 CONCLUSION

Based on the results and discussion above, we can conclude that :

a. The best method for estimating rainfall in Bukittinggi is the IMSRA method, with an RMSE of 3.37 to 4.95 mm/day, a correlation coefficient of -0.24 to 0.15 and a

standard deviation of 0.25 to 0.79 mm/day.

b. The best method for estimating rainfall in Pontianak is the IMSRA method, with an RMSE of 8.68 to 23.36 mm/day, a correlation coefficient of -0.13 to 0.14 and a standard deviation of 0.62 to 2.09 mm/day.

c. The best method for estimating rainfall in Ambon is the non-linear relation method, with an RMSE of 5.13 to 7.73 mm/day, a correlation coefficient of 0.47 to 0.58 and a standard deviation of 1.0 to 7.7 mm/day.

d. The conclusion from the visual comparison map of the rainfall estimation shows that it can clearly describe the types of cloud and the results of the estimated rainfall.

e. The physiographical conditions of Indonesian territory, such as its latitude, altitude, wind patterns (trade and monsoon winds), distribution of land and waters, and mountains have an effect on variations and types of rainfall in the country (equatorial, monsoon and local types), including rainfall estimation.

f. In further research, it will be necessary to process satellite data and considerable rainfall data (1-5 years), because this study investigates whether different topographies affect the results of rainfall estimation in each region.

ACKNOWLEDGEMENTS

REFERENCES

Akanbi A.K., & Agunbiade, O.Y. (2013), Integration of a city GIS data with Google Map API and Google Earth API for a web-based 3D Geospatial Application. *International Journal of Science and Research (IJSR)* 2(11), 200-203.

Alfuadi N. (2016). Interkomparasi Teknik Estimasi Curah Hujan. *Prosiding Seminar Nasional Sains Atmosfer*, 151-162.

Alfuadi, N., & Wandala, A. (2016). Comparative Test of Several Rainfall Estimation Methods Using Himawari-8 Data. *International Journal of Remote Sensing and Earth Science 3(2)*, 95-104.

Avia, L.Q., & Haryanto, A. (2013). Penentuan Suhu Threshold Awan Hujan di Wilayah Indonesia Berdasarkan data satelit MTSAT dan TRMM. *Jurnal Sains Dirgantara* 10(2), 82-89.

Bessho, K., Date K., Hayashi M., Ikeda A., Imai T., Inoue H., …Yoshida, R. (2016). An Introduction to Himawari-8/9-Japan's New-Generation Geostationary Meteorological Satellites. *Journal of the Meteorological Society of Japan* 94(2), 151-183.

Gairola, R.M., Varma A.K., Prakash, S., Mahesh, C., Pal, P.K. (2011). Development of Rainfall Estimation Algorithms for Monitoring Rainfall Events over India Using KALPANA-IR Measurements on Various Temporal and Spatial Scales. *38th Meeting of the Coordination Group of Meteorological Satellites (CGMS)*, New Delhi, India, 8–12 November.

Lillesand, T.M., Kiefer R.W., & Chipman J.W. (2015). *Remote Sensing and Image Interpretation* (7th ed), USA: John Wiley & Sons, Inc.

Marpaung, S. (2010). Pengaruh Topografi Terhadap Curah Hujan Musiman dan Tahunan di Provinsi Bali Berdasarkan data Observasi Resolusi Tinggi. *Prosiding Seminar Penerbangan dan Antariksa*, 104-110.

NRC (2003). Fundamentals of Remote Sensing, A Canada Centre for Remote Sensing Remote Sensing Tutorial, Canada.

Nurasniyati, Muliadi, & Adriat R. (2018). Estimasi Curah Hujan di Kota Pontianak Berdasarkan Suhu, Ketebalan dan Tekanan Puncak Awan. *Jurnal Prisma Fisika* 6(3), 184-189.

Octari, G.R., Suhaedi D., & Noersomadi, (2015). Model Estimasi Curah Hujan Berdasarkan Suhu Puncak Awan Menggunakan Inversi Nonlinear. *Prosiding Penelitian SPeSIA 2015 Bid. Matematika* 1(1), 23-29.

Rani, N.A., Khoir, A.N., & Afra S.Y. (2016). Rainfall Estimation Using Auto-Estimator Based On Cloud-Top Temperature Of Himawari 8 Satellite Compared To Rainfall Observation In Pangkalpinang Meteorological Station. *Proceedings The 6th International Symposium for Sustainable Humanosphere*, 1(1), 93-98.

Saefuddin, A., Notodiputro K.A., Alamudi A., & Sadik, K. (2009). *Statistika Dasar*. Jakarta: PT Grasindo.

Santos, C.A.C.D., Silva B.B.D., Rao T.V.R.R., Satyamurti P., & Manzi A.O. (2011). Downward Longwave Radiation Estimates For Clear Sky Conditions Over Northeast Brazil. *Revista Brasileira de Meteorologia* 26(3), 443-450.

Supranto, J. (2008). Statistik Teori dan Aplikasi. Jakarta: Penerbit Erlangga.

Stull, R. (2015). *Practical Meteorology-An Algebra-based Survey of Atmospheric Science*. University of British Columbia, Canada.

Sucahyono, D., & Ribudiyanto, K. (2009). Cuaca dan Iklim Ekstrim di Indonesia. Puslitbang, Badan Meteorologi Klimatologi dan Geofisika.

Suwarsono, P., Kusumaning A.D.S., & Kartasamita M. (2009). Penentuan Hubungan Antara Suhu Kecerahan dangan MTSAT dengan Curah Hujan Data QMORPH. *Jurnal Penginderaan Jauh* 6(1), 32-42.

Tan, S.Y., (2014), *Meteorological Satellite Systems*. France : Springer.

Tjasyono, B.H.K., & Harijono S.W.B. (2013). Atmosfer Ekuatorial, Puslitbang, Badan Meteorologi Klimatologi dan Geofisika.

Tukidi (2010). Karakter Curah Hujan di Indonesia, *Jurnal Geografi* 7(2), 136-145.

Wang, W., & Lu Y. (2018). Analysis of the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) in Assessing Rounding Model. *IOP Conference Series: Materials Science and Engineering*, 324(1), 1-10.