The prediction of rainfall events using WRF (weather research and forecasting) model with ensemble technique

I Sofiati\textsuperscript{1} and A Nurlatifah\textsuperscript{1}

\textsuperscript{1}Center of Atmospheric Science and Technology, Indonesian National Institute of Aeronautics and Space (LAPAN), Jl. Dr. Djundjunan No. 133, Bandung 40173, Indonesia

E-mail: sofiati07@gmail.com

Abstract. The research of ensemble technique has become popular in recent years, which can produce probabilistic predictions of rainfall on a short or medium scale. Prediction ensemble is a model formed by combining the predictive system model; the models used was member. This study aims to analyse the ability of the ensemble method in predicting rainfall events in Cilacap (07°45' S, 109°02' E) and Denpasar (08°37' S, 115°13' E). Data processing used ensemble equation; its ensemble member consisted of four members of running model WRF-ARW every cycle (00, 06, 12 and 18 UTC). In general, during the period of July 1 to 20 and February 1 to 20, 2016, the results of the models both single model and ensemble technique show that the model underestimate in predicting rainfall. Nevertheless, the single and three models of ensemble prediction methods estimated dry conditions very well but failed to predict the event of heavy rain. There were supported by the plot curve of the Relative Operating Characteristic (ROC) curve as a completely indicating that the three ensemble techniques performed the same results in all regions, none of them gave many different predictions between ensemble techniques and other ensemble techniques. The usual weighted or ensemble mean method produces almost identical rainfall predictions.

1. Introduction

The last few years of research using numerical prediction models have been much done especially using the WRF-ARW (Advanced Research WRF) model. Efforts to improve the accuracy of model performance in predicting temperature, humidity, wind, rain and other weather variables have also been widely used. \[1\] states that although a very large increase is seen in predictions of temperature, wind, humidity and others, the quantitative prediction of rainfall remains one of the most challenging variables to predict due to the low level of confidence in the predicted results of precipitation.

Prediction of rainfall variables using numerical weather prediction models is one of the most difficult areas to predict accurately. Errors in precipitation are caused by errors occurring in observations and models themselves \[2\]. The model could not adequately represent many parameters and details of the process of rain events. These errors will eventually accumulate into collective error \[3\]. Even sometimes, from models considered very good predictions could have bad results; it is caused by chaos atmosphere conditions \[3\]. Chaos theory is a theory that assumes atmospheric conditions change and evolve very sensitive to very small errors. Very small initial errors (even too small to observe for observers) can cause very large errors with different scales on predicted outcomes, so with the best model, we will never produce perfect conditions \[4\]. Therefore, a method is needed to obtain quantitative information about the uncertainty, let alone for rainfall parameters, which have an unpredictable probability only
with a single forecast [4]. It has led to ensemble research becoming very popular in the recent years to produce probabilistic predictions of rain on a short or medium scale. The ensemble prediction is a model formed by combining predictive system models; the models used are called members of the ensemble. There are various ways to get an ensemble member, either by altering or by disturbing the model’s initial condition and its parameters. Besides using different predictive models (multi models), using a combination of them can also be done.

Related research shows that the greater the number of ensemble members are, the better the predictive ability of the ensemble [5–6] suggests that using more economical ensemble methods of implementation may produce deterministic predictions with higher economic values. Ensemble mean is one form of deterministic prediction that will give better results if it is used in short period. [7] showed that ensemble results using eight different model members resulted in smaller errors than the individual model. However, it is unclear whether the results of the ensemble are good and useful rainfall predictions. The disadvantages of using ensemble approach is the bias of the model members which will also participate in the ensemble predictions so that calibration is required [8]. The results of [9] study suggest that the ensemble method approach with the same weighting of 1.0 on each model member used and possibly also incorporating models with predictive results that tend to be poor can cause the result of the average ensemble also to be less good. Therefore, [9] applies the weighting in the ensemble method. The rainfall prediction produced by ensemble by weighting method shows smaller errors than the ensemble mean ensemble.

In contrast to [9–10] showed that in the tropical regions the usual ensemble mean method produces better predictions whereas in extratropical regions the weighted method produces better predictions. [11] also added that the usual ensemble mean method (same weight in all ensemble members) could be proven to generate better predictions than its members. However, whether the ensemble with weighting method can improve the confidence of the model results is still a debate due to the lack of data set length of the model used by [9, 12] compared ensemble prediction results with different weighting methods in three different areas and showed that weighting. Based on the above reference, this study aims to analyse the ability of the ensemble method in predicting rainfall events by using the output model of WRF-ARW.

2. Data and methods

2.1. Data

Output model data used were WRF-ARW model output [13, 14]. Initialization and information on lateral boundary conditions of the WRF-ARW model used GRIB Global Forecasting System (GFS) data 1. GFS is a model coupling with four models of atmosphere, ocean, surface, and model of sea ice. GFS runs in real-time, for four times a day (00:00, 06:00, 12:00, and 18:00 UTC) and generates predictions every three hours for the next eight days. GFS GRIB1 has a spatial resolution of 0.5°×0.5° (one degree = 111 km), available in 26 elevation levels (1000-10 hPa, excluding surface data). The data came from the National Oceanic and Atmospheric (NOAA); (ftp://nomads.ncdc.noaa.gov/GFS/Grid3). Rainfall data in two study areas, Cilacap (07º45’ S, 109º02’ E) and Denpasar (08º37’ S, 115º13’ E) obtained from Meteorological, Climatological, and Geophysical Agency (BMKG). The rainfall data used were the data with intervals of three hours with a period from July (1-20), and February (1-20) 2016.

2.2. Methods

Estimation of rainfall value used WRF-ARW model. Running models were integrated over the next 24 hours for each cycle. Nested downscaling (nesting) was up to two domains, first domain resolution of 50 km and the smallest domain 5 km. This study used WRF out from WRF-ARW running model with default configuration as presented in table 1.

Data processing in this research used ensemble equation, member ensemble which consisted of four members from the result of running model WRF-ARW. Every cycle was taken hours (00, 06, 12 and 18) UTC. The ensemble equations used consisted of two ensembles with weighted values, and one ensemble mean [15]. The ensemble equations used are:
Ensemble 1 (Mean weighted ensemble using correlation value and RMSE)

\[ Y(\text{en}) = k_1y_1 + k_2y_2 + k_3y_3 + k_4y_4 \]

Where:

\[ Y(\text{en}) = \text{ensemble forecast} \]
\[ k_n = \frac{(C_n + E_n)}{2} \]
\[ k_1 + k_2 + k_3 + k_4 = 0 \]
\[ C_n = \frac{R_n}{\sum R} \]
\[ R = \text{correlation} \]
\[ C_1 + C_2 + C_3 + C_4 = 0 \]
\[ E_n = \frac{(S - \text{RMSE}_n)}{3} \]
\[ E_1 + E_2 + E_3 + E_4 = 0 \]
\[ S = \text{RMSE}_1 + \text{RMSE}_2 + \text{RMSE}_3 + \text{RMSE}_4 \]

Ensemble 2 (Mean weighted ensemble using value of POD/ Hit rate and FAR)

\[ Y(\text{en}) = k_1y_1 + k_2y_2 + k_3y_3 + k_4y_4 \]

where:

\[ Y(\text{en}) = \text{ensemble forecast} \]
\[ k_n = \frac{(C_n + E_n)}{2} \]
\[ k_1 + k_2 + k_3 + k_4 = 0 \]
\[ C_n = \frac{R_n}{\sum R} \]
\[ R = \text{POD} \]
\[ \text{POD} = \frac{\text{hits}}{\text{hits} + \text{misses}} \]
\[ C_1 + C_2 + C_3 + C_4 = 0 \]
\[ E_n = \frac{(S - \text{FAR}_n)}{3S} \]
\[ \text{FAR} = \text{False Alarm Ratio} \]
\[ \text{FAR} = \frac{\text{false alarms}}{\text{hits} + \text{false alarms}} \]
\[ E_1 + E_2 + E_3 + E_4 = 0; \]

\[ S = FAR_1 + FAR_2 + FAR_3 + FAR_4; \]  \hspace{1cm} (14)

Ensemble 3 (\textit{Mean ensemble})

\[ Y(en) = \frac{y_1 + y_2 + y_3 + \ldots + y_n}{n}; \] \hspace{1cm} (15)

\[ Y_n = ch \text{ cycle-}n \] \hspace{1cm} (16)

\[ Y(en) = \text{ensemble forecast} \]

In the weighted ensemble weighted ensemble equation, the weighted values were calculated based on RMSE and POD-FAR correlations compared with the observed data in each study point. There are many methods to verify the predicted results from the model. For rainfall variables, yes or no verification is required. It is because rain is a non-probabilistic variable. Verification was done with a contingency table, so there were four possible outcomes. If both model and observation results show rain, the simulation is considered Hit. If the model does not show rain but the observation shows rain, the simulation is considered Miss. The opposite of Miss's condition is False Alarm, meaning that simulation shows rain while observation is not. Finally, if simulation and observation do not show rain, the simulation is Correct Negative (table 2).

| Prediction | Observation | Prediction Total |
|------------|-------------|-----------------|
| Yes        | Yes         | A + B           |
| No         | Yes         | C + D           |
| Observ. total | Yes        | A + B + C + D = N |

| Observation | Yes | No | Total |
|-------------|-----|----|-------|
| Hit         |     |    |       |
| False Alarm |     |    |       |
| Correct Negative | | |       |
| Prediction Yes |    |    |       |
| Prediction No |    |    |       |
| Observ. total | Yes | No | Total |

In the determination of rain or not in the verified area, a threshold value for rainfall was required. Threshold refers to the rainfall category BMKG taken one mm threshold to see the model which shows rain or not at the time of the incident, and 10 mm to see how well the model is in showing more dense rain (table 3).

| Rainfall category | Intensity of rainfall |
|-------------------|-----------------------|
|                   | (mm/hour)             | (mm/day)             |
| Light             | 1.0 – 4.9             | 0.1 – 19.9           |
| Medium            | 5.0 – 9.9             | 20.0 – 49.9          |
| Heavy             | 10.0 – 19.9           | 50.0 – 99.9          |
| Very dense        | > 20.0                | > 100                |

Table 2. Table of Contingency.

Table 3. Rainfall threshold according to BMKG.

After grouping based on contingency table (table 2), then the accuracy of the model was calculated. There are a lot of methods to calculate the accuracy and verification of model results. The present study used some standard methods for verification of rainfall cases, namely:

- POD shows the number of parts of the predicted rain event correctly, while the FAR shows the number of parts of the rain event that misses its prediction. Almost the same as FAR, the POFD
shows how many events are not rain that misses predictions. The value of POD gets better as it approaches one, while the FAR and POFD values will be better if it gets closer to zero.

Probability of Detection (POD) or

\[ \text{Hit rate} = \frac{\text{hits}}{\text{hits} + \text{misses}} \]  

Range: 0 until 1; Perfect score 1

Probability of False Detection (POFD) or

\[ \text{False Alarm Rate} = \frac{\text{false alarms}}{\text{correct negatives} + \text{false alarms}} \] \hspace{1cm} (18)

False Alarm Ratio (FAR) = \[ \frac{\text{false alarms}}{\text{hits} + \text{false alarms}} \] \hspace{1cm} (19)

Range: 0 until 1; Perfect score: 0

• Accuracy is a value that shows the level of trust between prediction and observation. The difference between the value of observation and prediction is the value of error. The lower the error, the greater the accuracy of the model of observation data. The range of accuracy values is from zero to one, and one is the best value. For example, if the accuracy of the model is known to be 0.83 it means that 83% of the predicted results are true.

\[ \text{Accuracy (Fraction Correct)} = \frac{\text{hits} + \text{correct negatives}}{\text{total}} \] \hspace{1cm} (20)

Range: 0 until 1; Perfect score: 1 (PC score)

• Bias is the frequency ratio of the prediction to the frequency of observation data. The biased value shows the model trend for under forecast (bias <1) or over forecast when the biased value> 1. Nevertheless, BIAS has a drawback because it cannot measure well how the prediction response to an observation. It can only measure its relative frequency.

\[ \text{Score (Frequency bias)} = \frac{\text{hits} + \text{false alarms}}{\text{hit} + \text{misses}} \] \hspace{1cm} (21)

Range: 0 to ∞ Perfect score : 1

• SR (Success Ratio) provides information about the probability of the observed event from the predicted result. The value of the success ratio is sensitive to the FA but it ignores the occurrence of the misses. The SR value is calculated by 1-FAR. If the value of SR is 0.68, indicating in 68% of the predicted rain event, the actual rainfall is observed.

\[ \text{Success Ratio (SR)} = \frac{\text{hits}}{\text{hits} + \text{false alarms}} \] \hspace{1cm} (22)

Range: 0 until 1; Perfect score: 1

• Threat Score (TS) or Critical Success Index calculates observed events or predicted predictions correctly. The TS value is considered as an accuracy value if it removes the correct negatives from the analysis. In the other words, TS only takes into account the prediction of the right occurrence. However, TS is highly dependent on the hits value, so it does not take into account the source of error in the prediction, because sometimes the hits event can occur due to the random factor only. The value of TS = 0.57 indicates that about more than half of predicted or observed rain events have been predicted correctly.

\[ \text{Threat Score (TS)} = \frac{\text{hits}}{\text{hits} + \text{misses} + \text{false alarms}} \] \hspace{1cm} (23)

Range: 0 until 1; 0 indicates no skill, perfect score 1
Another method often used to verify probabilistic predictions is the Relative Operating Characteristic (ROC) curve. According to Kadarsah [16], the ROC curve is a method recommended by the World Meteorological Organization (WMO) as a method that can indicate the probabilistic ability of weather and climate prediction. Besides, this method is also applied to the HyBMG model. The ROC curve is made by comparing the hit rate (POD) value with the false alarm rate (POFD). Hit rate and false alarm rate is calculated for each range of probabilities. Then the result is plotted on a graph with a hit rate as the vertical axis and false alarm rate on the horizontal axis. Predictions that do not have skills are marked with a diagonal line (when the hit rate is always equal to the false alarm rate). The bigger skill marked by a curve that is above the no-skill line and the negative skill is shown if the curve line is below the no-skill line.

3. Results and discussion

3.1. Results

Time series rainfall in the Cilacap and Denpasar areas show the model and ensemble prediction underestimated when compared with observed data that was much higher in rainfall (figure 1).

![Figure 1. Time series rainfall in the two study areas (a) Cilacap and (b) Denpasar. Observation data is rainfall data per 3 hours, rainfall cycle 00, 06, 12 and 18 is the output of WRF-ARW model run and is a member of the ensemble. Ensembles 1 and 2 are a weighted ensemble, while ensemble 1 with correlation and RMSE, ensemble 2 calculates POD and FAR, and ensemble 3 is a regular ensemble mean.](image)

It can be seen from the low yield curves of the ensemble results when compared with the observed data. These conditions are likely caused by the selection of schemes from the WRF in this study. The underestimated results occurred both in the ensemble in Cilacap (figure 1a) and Denpasar (figure 1b). However, from these results it can still be concluded whether the ensemble could improve the accuracy of predicted results. It can be seen clearly that at the Cilacap study point, rainfall between each member with ensemble prediction was not much different, the condition was indicated by overlap curves. While in the area of Denpasar, prediction results more visible rainfall varies, especially the prediction results from cycle 18.

To quantify the performance of each model and ensemble results in predicting rainfall in both areas which required verification and validation, this study used standard methods of rainfall verification and ROC curve. From the verification parameter of rainfall, figure 2 shows the model and the ensemble technique tends to fail in predicting rainfall in case of heavy rain in Cilacap region. It is seen from the values of SR, TS, POD, FAR and POFD which almost all have no value (figure 2a, 2b). At the same time, the value of FC (Fraction Correct) shows a high enough value, almost all reaching 0.8. Such circumstances suggest that although the ensemble model and techniques fail to predict the occurrence of heavy rainfall, the ensemble models and predictions estimate dry or non-rainy conditions very well (figure 2a and 2b). In other words, the accuracy of the model is good enough in predicting dry days or not rainy as shown in figures 2a and 2b. Similarly, it happened in the area of Denpasar as shown
in figure 3. The model and ensemble techniques tended to fail in predicting rainfall in the case of heavy rain in the area of Denpasar. It is seen from SR, POD, FAR, and POFD (figure 3a and 3b). The value of FC (Fraction Correct) shows a high value, with the value of everything almost reached 0.8. Such circumstances indicate that the ensemble model and technique fail to predict the occurrence of heavy rain, but the ensemble model and prediction is very good at predicting dry or non-rainy conditions with (figure 3a and 3b). Overall, the accuracy of the model is good enough in predicting dry or non-rainy days as shown in figures 2a and 3a. Similarly, it is also shown in the case of light rain, high FC values in both regions, and all WRF predictions and ensemble methods used. The parameter of rainfall verification showed FC value or high accuracy level of 0.8 in both regions meaning that the level of trust between prediction and observation reached 80% with an error about observation data about 20% (figure 2 and figure 3).

The SR (Success Ratio) scores in both regions were below 0.5 indicating that of nearly 50 percent of the predicted rainfall events, the actual rainfall observed. Between two areas, the SR values in Cilacap (figure 2) were higher than in Denpasar (figure 3). The value of POD or hit rate in the two study areas showed a maximum value of about 0.45, meaning that only a maximum of 45% of precipitated rain events were correctly predicted. Otherwise, this was supported by FAR values indicating a high enough value; this value means rain event missed a high enough predictable and some even reach 80% (figure 2 and figure 3).

The parameter verification of rainfall variables in Cilacap region in detecting light rain events (threshold >= 1mm) and heavy rain (threshold >= 10mm). (a) Cilacap with threshold CH >= 1mm, (b) Cilacap with threshold CH >= 10 mm. FC is Fraction Correct, SR = Success Ratio, TS = Threat Score, POD = Probability of Detection, FAR = False Alarm Ratio and POFD = Probability of False Detection or also called False Alarm Rate. ENS1 = ensemble 1, ENS2 = ensemble 2, ENS3 = ensemble 3.

The parameter verification of rainfall variables in the study area to detect light rain events (threshold >= 1mm) and heavy rain (threshold >= 10mm). (a) Denpasar with threshold CH >= 1 mm, and (b) Denpasar with threshold CH >= 10 mm. FC is Fraction Correct, SR = Success Ratio, TS = Threat Score, POD = Probability of Detection, FAR = False Alarm Ratio and POFD = Probability of False Detection. ENS1 = ensemble 1, ENS2 = ensemble 2, ENS3 = ensemble 3.
When compared between each member ensemble with predictions their ensemble could not concluded if the ensemble prediction results always provide better performance than its members do. The graphs of the rainfall variable verification method (figure 2 and figure 3) do not always indicate a higher ensemble than its member at POD, FC and SR or lower than its FAR value. It means that in some cases, the performance of each model is better than the prediction of the ensemble. Furthermore, from the comparison between the ensemble prediction method with weighting or by the usual mean method (without weighting), it was discovered that weighting did not give a significant impact on the increase of rainfall prediction. This can be seen from figure 2 and figure 3 which shows values that are not much different between gray, yellow, and blue bar tables (ENS 1, ENS 2 and ENS 3).

![Figure 4](image1.png) ROC curve for threshold (a) Cilacap light rain\(> = 1\) mm, and (b) Cilacap heavy rain\(> = 10\) mm

In this study, the ROC curve is analyzed as shown in figure 4 and figure 5. This ROC value can illustrate the reliability of the ensemble method to increase rainfall prediction in both areas of observation. From both areas of study it can be seen that the two regions show the ability of the model and the ensemble technique that is good enough to predict rainfall, as can be seen from figure 4 and figure 5, it is seen that the graph of ROC curve is above the diagonal line no skill (broken line).

All of the ROC curves as a whole show that the three ensemble techniques performed yield similar results in both areas, none of which provide many different predictions between an ensemble technique with other ensemble techniques (figure 4 and figure 5). It is seen from the graph of the ROC curve of each method that almost coincides. The ensemble prediction produces almost the same predicted rainfall, either using weighting method or ordinary ensemble mean (figure 4 and figure 5).

![Figure 5](image2.png) ROC curve for threshold (a) Denpasar light rain\(> = 1\) mm, and (b) Denpasar heavy rain\(> = 10\) mm.
3.2 Discussion
Compared with other studies [17], using the WRF Double-Moment 6-class (WDM6) microphysics scheme is known to simulate the warm rain process very well. The selection of microphysics scheme has a very significant role in determining the surface rain-rates. Most of the WRF microphysics scheme missed the warm rain process over the humid region, especially over Indonesia where the warm rain process is dominant over land [18].

4. Conclusion
This research analyses the performance of single model and ensemble technique in predicting the light and heavy rainfall in the area of Cilacap and Denpasar. In general, from July 1 to 20 and February 1 to 20, 2016, the results show that both of single model and ensemble techniques underestimated the prediction of rainfall. Nevertheless, the single model and the three ensemble prediction methods estimated very well for dry conditions or no rain. In contrast, a single model and the three models of ensemble techniques were considered failing to predict the event of heavy rain. When testing performance, the ensemble technique is deemed incapable of better than its constituent models, both the usual ensemble technique and the ensemble technique with mean weights. It is supported by the plot curve of the ROC curve indicating that the three ensemble techniques performed give almost the same results in both areas of observation, none of which provides many different predictions between ensemble techniques with other ensemble techniques. It means that in this case, the weighted method or ensemble mean method produces almost identical rainfall predictions.

Acknowledgments
The author would like to thank Mrs. Rachmawati Syahdiza S.Si, BPPT, alumni of the Faculty of Earth Science and Technology, Department of Earth Science, Bandung Institute of Technology (ITB) for her help.

5. References
[1] Stensrud D.J. and N. Yussouf. 2007. Reliable probabilistic quantitative precipitation forecasts from a short-range ensemble forecasting system. Wea. and Forecast., 22, 3-17
[2] Permana, Gilang. 2009. Ensemble prediction using CCAM (Conformal-Cubic Atmospheric Model) to predict rain probability in Java island (in Indonesian). Undergraduate Thesis, Institut Teknologi Bandung
[3] Lorenz, E.N. 1969. The predictability of a flow which possesses many scales of motion. Tellus, 11 (3), 289-307
[4] Goo, Tae-Young, M. Kyouda, and H.B. Cheong. 2007. Evaluation of the calibrated probability of precipitation forecast from the medium range ensemble prediction system. Asia Pacific J. of Atm. Sci., 44, 25-35
[5] Buizza, R. and T.N. Palmer. 1998. Impact of ensemble size on ensemble prediction. Mon. Wea. Rev., 126, 2503-2518
[6] Zhu, Y., Z. Toth, R. Wobus, D. Richardson, and K. Mylne. 2002. The economic value of ensemble-based weather forecasts. Bull. Amer. Meteorol. Soc., 83, 73-82
[7] Ebert, E.E. 2001. Ability of a poor man’s ensemble to predict the probability and distribution of precipitation. Mon. Wea. Rev., 129, 2461-2480
[8] Hamill, T.M., and S.J. Colucci. 1997. Verificaiton of ETA-RSM short range ensemble forecasts. Mon. Wea. Rev., 125, 1312-1327
[9] Khrisnamurti,T.N., C.M. Kishtawal, Zan Zhang, T. LaRow, D. Bachiochi, and E. Williford. 2000. Multimodel ensemble forecast for weather and seasonal climate. J. of Clim., 13, 4196-4216
[10] Kharin, V.V., and F.W. Zwiers. 2002. Climate predictions with multimodel ensembles. J. of Clim., 15, 793-799
[11] Pena, M., and H. Van den Dool. 2008. Consolidation of multimodel forecasts by ridge regression: application to pacific sea surface temperature. J. of Clim., 21, 6521-6538
[12] Marrocu, M., and P.A. Chessa. 2008. A multimodel /multianalysis limited-area ensemble: calibration issues. Meteor. Appl., 15, 171-179
[13] Skamarock, W. C., and Coauthors. 2008. A description of the advanced research WRF version 3. NCAR Tech. Note NCAR/TN-4751STR, 113
[14] Burakowski E.A., Ollinger S.V., Bonan G.B., Wake C.P, Dibb J.E., and Hollinger D.Y. 2016. Evaluating the climate effects of reforestation in new england using weather research and forecasting (WRF) model multiphysics ensemble, J. of Clim., 29, 5141-5156
[15] Wanders, N., and Wood. E.F. 2016. Improved sub-seasonal meteorological forecast skill using weighted multi-model ensemble simulations. Environ. Res. Lett., 11 1748-9326
[16] Kadarsah. 2010. ROC application for HyBMG reliability test (in Indonesian). Jurnal Meteorologi dan Geofisika, 11 (2), 33-43.
[17] Song H J, Sohn B J, and Hashino T. 2017. Idealized numerical experiments on the microphysics evolution of warm-type heavy rainfall, J. Geos. Rea. 1685-1699
[18] Sekaranom A. B., and Masunaga H. 2017. Comparison of trmm-derived rainfall products for general and extreme rains over the maritime continent. J. of App. Meteor. and Clim. 1867-1881