WALAILAK JOURNAL
Applied Sciences
http://wjst.wu.ac.th https://doi.org/10.48048/wjst.2021.9542

Application of the Simple Verification Method to Estimate the Weather at Makassar Maritime Station, Indonesia

Didiharyono DIDIHARYONO[1,*] and Giarno GIARNO[2]

[1]*Andi Djemma University, Palopo, South Sulawesi 91921, Indonesia*
[2]*State College Of Meteorology Climatology and Geophysics, Tangerang 15221, Indonesia*

([*]Corresponding author's e-mail: muh.didih@gmail.com)

Received: 19 February 2020, Revised: 27 June 2021, Accepted: 30 June 2021

Abstract

Verification is used to measure the quality of a weather prediction, improve process performance, and measure the value of weather estimation. Initially, weather verification developed after Finley published his paper on the verification of tornado events. The type of data, objectives, and scale can make a different method in using weather verification. If there are some parameters that can be predicted, a simple question is consequently often asked by the public: how accurate are weather forecasts? Nowadays, the public wants a simple answer in 1 value that is presented quantitatively. The aim of the research is to develop a simple method that can answer the accuracy of weather prediction in a value that is easily understood by the public. Practically, validation comparing between prediction and observation parameters is divided into 2, namely dichotomous and comparing the values. This research tries to combine all weather prediction variables into a dichotomous variable with a threshold. Moreover, this technique is tested on weather predictions for the port of Makassar over a year. The results show that a certain threshold can be used to change the weather variable to be dichotomous. With the application of this method, forecast accuracy and suitability between the predicted parameters can be obtained. Moreover, the weather forecast issued by the Makassar Maritime Station shows the average true value of the forecast to be 69.1 %, and then the capabilities vary by forecasters, which range from 61 to 79 %.

Keywords: Verification, Port, Weather verification, Makassar Maritime Station, Indonesia

Introduction

In atmospheric science, verification of forecasts is often used [1]. This verification is very important because it aims to measure the achievement of the performance of the volunteers, including the institutions that shelter them. In addition, it is also used for the improvement and the development of the forecast methods used that have an impact on increasing economic value and evaluating weather forecasts in the future. The development of weather forecast models goes hand in hand with the development of computational capabilities and the addition of observation networks. Improvements to the weather forecast model have made it even more accurate and have been widely used by weather service centers in making weather forecasts in many countries [2].

Evaluation of weather forecasts scientifically is done by comparing forecasts with observational activities, which is also commonly called meteorological verification [3]. Various references mention there are at least three important objectives of weather forecast verification [4], namely (a) administrative, related to the process of producing weather forecasts and the monitoring of forecast systems; (b) economic, focusing on the value of the influence of economic forecasts, and (c) scientific, relating to the value of forecasts and their observations.

Presenting the accuracy of the weather in 1 value is very important to facilitate public understanding. However, calculating weather accuracy within a single value of many variables and types requires an adjustment of the method. This method must answer a simple question: What is the accuracy of the overall forecast prediction, in 1 variable only? Unfortunately, this issue is still very poorly discussed, especially in Indonesia, where the guidelines for measuring accuracy are not yet formulated. Therefore, we must build a method that will be used to verify forecast parameters before verification. Other problems are the existence of terms or criteria that are used in a variety of ways, tolerance values that have not been made or agreed upon, many forecast formats, and parameters consisting of numeric, non-numerical, and different scale forecasts. This paper aims to create a simple verification format that is easy to understand so that it can be used for weather verification. In particular, it centers on the Makassar port forecast, issued by the Makassar Maritime Station.

The example measurable parameters in meteorology are pressure, temperature, wind direction and speed, and the amount of rain. On the other hand, there are meteorological variables that are observed visually without tools, such as the statement of weather conditions (present/past weather) and visibility horizontally furthest (visibility and resistance). The other condition, meteorological parameters, must be estimated, like wind and waves using the Beaufort scale. Statistical data is divided into non-numeric data (non-numeric), or qualitative data and quantitative data (numeric) [5]. Non-numerical data cannot be carried out in mathematical operations, such as addition, subtraction, multiplication and division. Moreover, the types of qualitative data can be divided into 2: Nominal data and ordinal data. Meanwhile, quantitative data is data in the form of numbers in the real sense, so that it can be operated mathematically. Adding this qualitative data is divided into 2 parts, namely, interval data and ratio data.

Meteorological observation has tolerance designed by the World Meteorological Organization (WMO), which does not refer to a specific number but is flexible to the magnitude variable [6]. This can be understood based on the fact that the sensitivity of the device will change accuracy as conditions change. Suppose the thermometer changes in terms of intolerance when measuring 26 °C compared to 45 °C. A summary of observational tolerances issued by WMO is shown in **Table 1**.

Table 1 Observation tolerance of weather variables.

NO	Parameter	Tolerance
1	Temperature	± 0.1 °C
2	Humidity	± 1 %
3	Pressure	± 0.1 mb
	Cloud	
4	Number of clouds	± 1/8
	Cloud height	± 10 m
	Wind	
5	Wind direction	± 5 °
	Wind velocity	± 1 knot
6	Precipitation	± 0.1 mm
7	Sun duration	± 1 min
8	Visibility	± 1 m
9	Evaporation	± 0.1 mm

Weather forecast parameters generally combine numeric and non-numeric variables. In numerical form, for example, there are temperature, humidity, pressure, direction and wind speed, while non-numeric form includes the occurrence of rain and clouds [7]. Moreover, the presentation of prediction is also varyiable, using the forms of minimum, maximum, range and averages. Some variables are rounded without digits, and the others are presented with 1 digit behind the comma. The probability terms, such as the chance of rain, are also often used to indicate that the weather conditions on that day are generally cloudy, but the forecaster considers the potential for strong rain.

Verification is very important in developing weather systems; it guides the application and also can help to identify differences between estimates made between models [8]. Verification measures the consistency, quality and value of prediction [9]. Firstly, development of weather verification methods initially developed after Finley verified the occurrence of tornadoes in 1884 in the United States [10]. Using the contingency table 2×2, the correct forecast reaches more than 96 %. Given the pattern of tornado events only in certain months, the high accuracy does not guarantee the skills of a forecaster, so a method of assessing forecast ability is needed. Then, verification is generally carried out for each of the different parameters; for example, verification of rainfall [11-13], heavy rain [14], wind power [15,16], temperature [17], number of clouds [18], tornado [19], administration [20] and others.

The verification method is divided into 4 forms: direct comparison, accumulation of probabilities, relative operating characteristics (ROC) and score [21]. However, because ROC is a combination of probability and score models, and this method is not easily understood by the public. As a result, generally comparing predicted and observed values is widely used for public weather forecast information. This method is calculated based on the number of deviations (JS) measured from the number of differences between forecasts (F) and observations (O), formulated;

$$JS = \sum_{i=1}^{n} \left(O_i - F_i \right) \tag{1}$$

or the average deviation;

$$RJS = \frac{1}{n} \sum_{i=1}^{n} \left(O_i - F_i \right) \tag{2}$$

To overcome the shortage of deviations, the variance used is formulated with;

$$Var = \frac{1}{n} \sum_{i=1}^{n} \left(O_i - F_i \right)^2 \tag{3}$$

or root mean square error (RMSE) with the formula;

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(O_i - F_i \right)^2} \tag{4}$$

Next, the dichotomous method, using the contingency table method. In cases where the requested value is binary data that is true and false, then a contingency table is used, which was originally developed from the Finley contingency table model, developed later. For contingency tables, there are 4 criteria, each of which is entered into a contingency table, such as **Tables 2** and **3**.

Table 2 Contingency table calculation.

		Observation		
		Even	No Even	Total
Forecast	Even	Hits	False alarm	Forecast yes
	No Even	Misses	Correct negative	Forecast No
	Total	Observed no	Observed no	Total

The hits are used when predicted events and observations occur at the same time, and the false alarms are when events occur but observations do not occur. Moreover, the misses are recorded if predictions do not occur but observations do not occur. Finally, if the forecasts and observations of events do not occur, they are recorded in the correct negatives.

Table 3 Contingency table calculation.

		Observation		
		Even	No Even	Total
Forecast	Even	a	B	a + b
	No Even	c	D	c + d
	Total	a + c	b + d	a + b + c + d // (n)

There are many methods to calculate this model, including;

ACC (Accuracy);

$$ACC = \frac{a+d}{n} \tag{5}$$

Accuracy answers the question: Overall, how many forecasts are correct? The value is between 0 until 1, with a perfect score as 1.

BIAS (Bias score);

$$BIAS = \frac{a+b}{a+c} \tag{6}$$

BIAS answers the question: How is the frequency of forecasts of the event starting to occur compared to the frequency of observations of the event starting to occur? The value is between 0 until ∞, with a perfect score as 1.

SR (Success score);

$$SR = \frac{a}{a+b} \tag{7}$$

Equation (7) mean that SR answers the question: what is the frequency of forecasts for events to occur and actually occur? The value of the score is between 0 until 1, with a perfect score as 1.

Although there are other methods, such as the probabilistic method, reliability charts, brier scores, ranked probability skill scores and ROC [22]. These are more difficult for many people to understand. Because this work, simplicity is a priority, so only 3 techniques are used in this study to verify the weather at the Makassar port. these methods are combined into one value that is easy to understand when specifying the accuracy of a weather forecast.

Materials and methods

The weather forecasting for the Makassar port is released by the Paotere Maritime Station. This work used data from 2012, comparing observation data at the same location on the same day, month and year. For the non-numerical weather forecast parameters such as rain event, verification was done by contingency table and then by calculating the desired scores, especially the ACC-score. Moreover, other parameters were determined by tolerance, as in **Table 4**, where an average of forecast weather parameters was considered to be still true compared to 2 times than tolerance of the observations. Then, the comparison results is divided into 2 categories; overestimate, to declare predictions higher than the observations, and underestimate, to declare predictions lower than the observations. In order to verify the corresponding rainfall parameter (3 categories), the negative hits and corrections were accurate, while false alarms were categorized as overestimating, and misses as underestimating.

Table 4 Weather forecast tolerance.

Tolerance	
Average wind speed	2.5 knots
Maximum wind speed	5.0 knots
Average temperature	1 °C
Maximum temperature	2 °C
Average relative humidity	2.5 %
Maximum relative humidity	5.0 %
Average pressure	1 mb
Maximum pressure	2 mb

The considerations for choosing a threshold in **Table 4** are as follows. First, the statistics of estimated parameter values. Since the average parameter is usually smaller than the maximum and minimum fluctuations, then, the maximum/minimum tolerance is twice as large as the average. Also, the behavior of the parameter has characteristics of fluctuation. For example, pressure with a maximum range and minimum daily is smaller than temperature and wind speed. Therefore, the tolerance for pressure calculates as smaller than the temperature and wind speed. Second, rounding off the forecast parameters. The maximum temperature parameter is generally an integer; however, tolerance without a digit will occur and create bias. Moreover, in this verification, the parameters of direction and wave height and wind direction are not included, due to technical considerations. Finally, an estimated forecast value (NP) is formulated;

$$NP = \left(\frac{\sum_{1}^{n} acurate}{n} \right) \times 100\% \tag{8}$$

Estimated values range from 0 to 100 %. A value of 100 % means all forecasts are perfect. With this method, it can also be calculated how many number of overestimate and underestimate that are very useful for evaluation.

Results and discussion

Estimated value total

From the calculation with Eq. (8), shown in **Table 5**, the overall weather forecast value for Makassar port in the February to December period is 69.1 %. However, for estimated maximum and average wind speed, average temperature, humidity, and average pressure, the value is below 69.1 %. This means that the prediction of these parameters needs to be evaluated by the method of determining its value, because it is still below average. Specifically, the average humidity must receive serious attention, because the value is very low, at 35.9 %. This points to 2 problems: First, there is the possibility of a mismatch in the forecast rain and humidity. For example, if the predictor predicts rain tomorrow, he must be able to describe whether the rain is for all day, or partly cloudy, partly rain, or generally cloudy, and if the rain is only brief, or if the intensity is of heavy, moderate, or light rain, which certainly affects the humidity value. Therefore, this depiction should have implications for the average humidity value. Second, the ability to predict the value of humidity itself. Each season or month and place has a different character that must be studied, and this affects each parameter, especially humidity.

Table 5 The total value of the port weather forecast for each parameter.

Parameter	True	False	% True
Rain /no rain	222	93	70.5
Average wind speed	218	97	69.2
Maximum wind speed	206	109	65.4
Average temperature	206	109	65.4
Maximum temperature	282	33	89.5
Average relative humidity	113	202	35.9
Maximum relative humidity	236	79	74.9
Average pressure	184	131	58.4
Maximum pressure	293	22	93.0
Total	1738	782	69.1

Other striking parameters are average pressure and maximum pressure. The accuracy of the maximum pressure forecast reached 93.0 %, where the average was only 58.4 %. However, this error may be caused by rounding. In the Indonesian region, pressure has small fluctuations, and 1 mb was chosen as a threshold for verification. Moreover, caused rounding can also mean caused errors. To reduce the mistake, the prediction of the average pressure changed in 1 digit behind the comma, adjusting its tolerance. On the other hand, small relative humidity accuracy values and overestimate and underestimate values are summarized in **Table 6**.

Generally, weather port forecasts by the Makassar Maritime Station were underestimated by a total of 17.1 %. Evaluation of average and maximum wind speed needs special treatment since underestimation forecasts can reduce the anticipation of adverse high winds. The underestimate forecast had a high score of 30.5 %, compared to 0.3 % overestimate. The imbalance score needs special attention. Likewise, the forecast does not rain but in reality obtain rain, only 20% events. This suggests the anticipation of bad conditions before fair weather. It should be noted that overestimate values at average temperatures and average pressures also need special attention because of the huge difference.

Table 6 Over/underestimate value (%) weather forecast for each parameter.

Parameter	Accurate	False	% True
Rain	70.5	9.5	20.0
Average wind speed	69.2	0.3	30.5
Maximum wind speed	65.4	10.2	24.4
Average temperature	65.4	22.2	12.4
Maximum temperature	89.5	1.9	8.6
Average relative humidity	35.9	35.9	28.3
Maximum relative humidity	74.9	10.2	14.9
Average pressure	58.4	30.8	10.8
Maximum pressure	93.0	2.9	4.1
Total true	69.1	13.8	17.1

Figure 3 shows the worst forecast values almost evenly in each season, namely March, May, July, August and December, for 5 months out of 11 months by contributing 54 % of errors. Interestingly, a major mistake occurs both in the rainy season period such as December, and also in the dry season such as July and August. Therefore, this method shows that the error of the forecaster does not depend on the season, because major mistakes can occur in the rainy, dry, and transitional seasons.

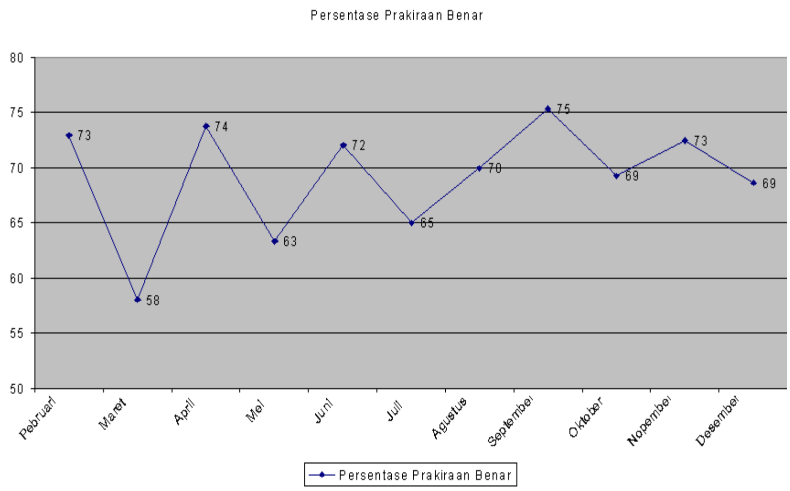

Figure 1 Graph of forecast values true to the month.

Accuracy of estimate forecasters

Based on **Table 7**, the accuracy of estimation between forecasters ranges from 61 to 79 %. Moreover, the best prediction, with a very good value of 80 % and above, was for maximum temperature and maximum pressure. This means the ability of forecasters to predict the maximum temperature parameters and maximum pressure must be maintained, while other parameters need to be increased in accuracy again, especially the relative humidity. Almost all forecasters had low accuracy, below 50 %, except for the first forecaster (F01). However, although the first forecaster could predict weather parameters with more than 70 % accurate, he had low rainfall event prediction.

The weather parameter estimates were not synchronous with the other, especially in relative humidity prediction. Normally, if one can predict rain correctly, this will be directly proportional to the average relative humidity and temperature. The depicted weather condition was still not exactly the relationship between the parameters, as desired. Therefore, the prediction could not describe whether there would be rain throughout the day, or partly cloudy, partly rain, or generally cloudy, and if the rain is only brief, or with an intensity of heavy, moderate, or light rain, all of which certainly affect the value of humidity and temperature.

Table 7 Over/underestimate value (%) weather forecasts for each parameter. F01, F02, F03, F04, F05 and F06 are the 1st, 2nd, 3rd, 4th, 5th, and 6th forecaster.

True Parameter (%)	F01	F02	F03	F04	F05	F06
Rain	33	62	77	63	76	74
Average wind speed	100	53	93	94	23	92
Maximum wind speed	80	74	70	80	68	54
Average temperature	50	53	85	70	60	68
Maximum temperature	100	88	96	92	82	93
Average relative humidity	70	24	37	38	27	44
Maximum relative humidity	90	71	78	88	71	72
Average pressure	90	68	78	44	46	65
Maximum pressure	80	94	100	90	94	94
Total true	77	65	79	73	61	73

Another note to consider is Forecaster 06, with the estimated maximum wind speed of only 54 %. Because of the harmful effects of this maximum wind speed, if the predicted value was lower, it would reduce people's caution. The ability to predict wind speed by forecasters 02 and 05 of below 60 % also needs to be considered. The forecast value of forecaster 01, which is 33 %, must also be considered, because it is very low.

Table 8 Over/underestimate value (%) weather forecasts for each parameter.

	Parameter	Accurate	False	% True
Forecaster 1 (10)	Rain	33	11	56
	Average wind speed	100	0	0
	Maximum wind speed	80	10	10
	Average temperature	50	40	10
	Maximum temperature	100	0	0
	Average relative humidity	70	20	10
	Maximum relative humidity	90	10	0
	Average pressure	90	10	0
	Maximum pressure	80	20	0
	Parameter	**Accurate**	**False**	**% True**
Forecaster 2 (34)	Rain	62	10	21
	Average wind speed	63	0	47
	Maximum wind speed	74	3	24
	Average temperature	53	41	6
	Maximum temperature	88	3	9
	Average relative humidity	24	65	12
	Maximum relative humidity	71	6	24

	Parameter	Accurate	False	% True
	Average pressure	68	29	3
	Maximum pressure	94	3	3
Forecaster 3 (27)	**Parameter**	**Accurate**	**False**	**% True**
	Rain	77	8	15
	Average wind speed	93	0	7
	Maximum wind speed	70	19	11
	Average temperature	85	11	4
	Maximum temperature	96	0	4
	Average relative humidity	37	22	41
	Maximum relative humidity	78	0	22
	Average pressure	78	15	7
	Maximum pressure	100	0	0
Forecaster 4 (50)	**Parameter**	**Accurate**	**False**	**% True**
	Rain	63	10	27
	Average wind speed	94	0	6
	Maximum wind speed	80	6	14
	Average temperature	70	14	16
	Maximum temperature	92	0	8
	Average relative humidity	38	26	36
	Maximum relative humidity	88	4	8
	Average pressure	44	42	14
	Maximum pressure	90	4	6
Forecaster 5 (84)	**Parameter**	**Accurate**	**False**	**% True**
	Rain	76	8	15
	Average wind speed	23	0	77
	Maximum wind speed	68	14	18
	Average temperature	60	25	15
	Maximum temperature	82	4	14
	Average relative humidity	27	46	26
	Maximum relative humidity	71	15	13
	Average pressure	46	48	6
	Maximum pressure	94	2	4
Forecaster 6 (108)	**Parameter**	**Accurate**	**False**	**% True**
	Rain	74	8	18
	Average wind speed	92	1	7
	Maximum wind speed	54	7	39
	Average temperature	68	19	13
	Maximum temperature	93	2	6
	Average relative humidity	44	26	30
	Maximum relative humidity	71	13	16
	Average pressure	65	19	17
	Maximum pressure	94	1	6

Almost all the weather predictions showed errors due to underestimating, which comprised 15 % in total, where the forecast was lower than the observation (**Table 8**). This condition needs serious attention. Based on weather variable characteristics, wind speed and rain are 2 parameters that need to be considered because of their impact. If, for example, a maximum wind forecast is only 10 knots, but in reality it is up to 30 knots, then it might be detrimental to the community.

Discussion

Compared to the contingency method for evaluating non-numerical weather forecasts [9,23] or using correlation, RMSE or MAE [24,25], the simple method in this research can be used to evaluate all estimated parameters as a whole. Separate evaluation can cause bias and be less comprehensive, where the results of the assessment cannot describe the relationship between parameters to weather conditions. Prediction parameter synchronization cannot be demonstrated if the evaluation is carried out unilaterally.

Based on this evaluation, it can also be shown which parameters are accurate compared to other parameters with an equivalent comparison. It is different if the verification uses a different measure; for example, a contingency table on one of the parameters, such as rain and using RMSE for temperature. The results of these 2 evaluations cannot be added up to 1 answer value for how accurate the weather prediction is. Generally, a researcher uses these 2 types of evaluation separately [26].

Weather prediction in the tropics sometimes experiences difficulties in estimating some parameters such as rainfall events, but the fluctuation of variables in this area, such as average temperature or air pressure, is often not too large accordingly. Evaluation of several weather models used in Indonesia shows the accuracy of predicted rainfall is less than 70 %, even on average around 40 % [27]. Time, place, and topography greatly affect the accuracy of rain predictions [26,28]. This condition also occurs in the estimation of rainfall from remote sensing results, such as satellites and radar [26,29-31]. There are still a lot of things to be done about adjustments of models or radar and weather satellites for rain predictions.

Ideally, forecast service providers and users understand each other's form of prediction models and variables and understand the needs of weather variables. It is very important to conduct dissemination and consultation through on-line questionnaires, interviews, visits, and open workshop discussions [32]. The results of these consultations highlights significant deficiencies in the methodology and communication of the assessment of the quality of the forecasts. The open dialogue and transparency needed to set mutually agreed standards within the users such as company and individual purpose are lacking. In addition, a comprehensive review of the existing forecast verification methodologies and metrics has been carried out.

Conclusions

The method used by making tolerance limits on numerical parameters can be used to verify weather forecasts quite well. This method can obtain forecast accuracy and suitability between the predicted parameters. Its application to the port weather forecast issued by Makassar Maritime Station shows the average true value of the forecast is 69.1 % and the different capabilities of each forecaster, which range from 61 to 79 %. The influence of the season is less visible in this study, where major mistakes can occur in the rainy season, dry season and transition season. In general, forecasters are not able to describe the weather conditions comprehensively between predicted parameters. This can be seen from the low average humidity value, which is much lower than the other parameters. Likewise, this simple method can show differences in abilities between the forecasters on different parameters, which vary in predictions for certain parameters, the maximum value of parameters and the average predictions.

Acknowledgements

We are profoundly thankful to the head of the Meteorology, Climatology and Geophysics Agency (BMKG) Paotere Maritime Station in Makassar, and the chair of the Institute for Research and Community Service (LP2M), Andi Djemma University, for their help and support in the process of completing this research.

References

[1] IT Jolliffe and DB Stephenson. *Forecast verification: A practitioner's guide in atmospheric science*. John Wiley & Sons, New Jersey, 2003.

[2] I Gustari, TW Hadi, S Hadi and F Renggono. Akurasi prediksi curah hujan harian operasional di jabodetabek: Perbandingan dengan model WRF. *Jurnal Meteorologi dan Geofisika* 2012; **13**, 119-30.

[3] P Nurmi. *Meteorological forecast verification: Scope and method*. Workshop on Space Weather Verification Universidad de Alcala, 2011.

[4] S Mariani and M Casaioli. *Forecast verification: A summary of common approaches and examples of application*. Università degli Studi di Trento, Trento, 2008.

[5] SS Steven. On the theory of scale of measurement. *Science* 1946; **103**, 677-80.

[6] World Meteorological Organization. *Guide to meteorological instruments and methods of observation*. World Meteorological Organization, Geneva, 1983.

[7] BMKG. Prakiraan Cuaca Pelabuhan Makassar Februari - Desember 2012. *Stasiun Meteorologi Maritim Paotere Makassar*, 2012.

[8] JL Mahoney, JK Henderson, BG Brown, JE Hart, A Loughe, C Fischer and B Sigren. The Real-Time Verification System (RTVS) and its application to aviation weather forecasts. *In*: Proceedings of the 10th Conference on Aviation, Range, and Aerospace Meteorology, Portland, OR. 2002; **9**, 323-6.

[9] AH Murphy. What is a good forecast? An essay on the nature of goodness in weather forecasting. *Weather Forecast.* 1993; **8**, 281-93.

[10] AH Murphy. The Finley affair: A signal event in the history of forecast verification. *Weather Forecast.* 1996; **11**, 1-20.

[11] V Mandal and UK De. Precipitation forecast verification of the Indian summer monsoon with intercomparison of three diverse regions. *Weather Forecast.* 2006; **22**, 428-43.

[12] ME Baldwin. Verification of the time evolution of precipitation systems in numerical weather forecasts. *In*: Proceedings of the 18th World IMACS/ MODSIM Congress, Cairns, Australia. 2009; 4177-83.

[13] E Gilleland, TCM Lee, JH Gotway, RG Bullock and BG Brown. Computationally efficient spatial forecast verification using baddeley's delta image metric. *Monthly Weather Rev.* 2008; **136**, 1747-57.

[14] M Jaroensutasinee, W Pheera, R Ninlaeard, K Jaroensutasinee and S Choldumrongkul. Weather affecting Macro-Moth diversity at Khao Nan National Park, Thailand. *Walailak J. Sci. Tech*. 2011; **8**, 21-31.

[15] N Chen, Z Qian, IT Nabney and X Meng. Wind power forecasts using Gaussian processes and numerical weather prediction. *IEEE. Trans. Power Syst.* 2013; **29**, 656-65.

[16] Y Zhang, P Wang, T Ni, P Cheng and S Lei. Wind power prediction based on LS-SVM model with error correction. *Adv. Electr. Comput. Eng.* 2017; **17**, 3-9.

[17] DT Myrick and JD Horel. Verification of surface temperature forecasts from the national digital forecast database over The Western United States. *Weather Forecast.* 2006; **21**, 869-92.

[18] M Jaroensutasinee, P Sangarun, W Pheera and K Jaroensutasinee. Tropical montane cloud forest characteristics in Southern Thailand. *Walailak J. Sci. & Tech*. 2011; **7**, 103-13.

[19] JP Finley. Tornado predictions. *J. Am. Meteorol.* 1884; **1**, 85-8.

[20] SJ Mason and AP Weigel. A generic forecast verification framework for administrative purposes. *Mothly Weather Rev.* 2009; **137**, 331-49.
[21] H Zhang and T Casey. Verification of categorical probability forecasts. *Weather Forecast.* 2002; **15**, 891-97.
[22] K Kadarsah. Aplikasi ROC untuk uji kehandalan model hybmg. *Jurnal Meteorologi dan Geofisika* 2010; **11**, 32-42.
[23] Fatkhuroyan, T Wati, A Sukmana and R Kurniawan. Validation of satellite daily rainfall estimates over Indonesia. *Forum Geografi* 2018; **32**, 170-80.
[24] Q Ran, W Fu, Y Liu, T Li, K Shi and B Sivakumar. Evaluation of quantitative precipitation predictions by ECMWF, CMA, and UKMO for flood forecasting: Application to two basins in China. *Nat. Hazards Rev.* 2018; **19**, 05018003.
[25] G Wang, D Wang, J Yang and L Liu. Evaluation and correction of quantitative precipitation forecast by storm-scale NWP model in Jiangsu, China. *Adv. Meteorol.* 2016; **3**, 1-13.
[26] Giarno, MP Hadi, S Suprayogi and SH Murti. Distribution of accuracy of TRMM daily rainfall in Makassar Strait. *Forum Geografi* 2018; **32**, 38-52.
[27] Kiki and F Alam. Verifikasi parameter Presipitasi Akumulasi 24 jam pada model Cuaca Numerik Tahun 2017. *Buletin BBMKG Wilayah II* 2019; **9**, 1-5.
[28] Giarno, Didiharyono, AA Fisu, and A Mattingaragau. Influence rainy and dry season to daily rainfall interpolation in complex terrain of Sulawesi. *IOP Conference Series: Earth and Environmental Science*. 2020: **469**, 012003.
[29] Giarno, MP Hadi, S Suprayogi and SH Murti. Bias correction of radar and satellite rainfall estimates and increasing its accuracy using modified merging. *Mausam* 2020; **71**, 376-90.
[30] Giarno, MP Hadi, S Suprayogi and SH Murti. daily quantitative precipitation estimates use weather radar reflectivity in South Sulawesi. *IOP Conf. Ser. Earth Environ. Sci*. 2019: **256**, 012042.
[31] Giarno, MP Hadi, S Suprayogi and SH Murti. Impact of rainfall intensity, monsoon and MJO to rainfall merging in the Indonesian maritime continent. *J. Earth Syst. Sci.* 2020; **129**, 164.
[32] JDW Kahl, KA Horowitz, CA Berg and MC Gruhl. The quest for the perfect weather forecast. *Sci. Scope* 2004; **27**, 24-7.