Journal of Computation Physics and Earth Science
ISSN: 2776-2521 (online)
Volume 1, Number 2, October 2021, Page 48-53
https://journal.physan.org/index.php/jocpes/index

A Review: Information Technology-based Climate Data Dissemination

Syalom Alfa Bazeleel Neonane[1], Adi Bagus Putrantio[2]
[1, 2]Undergraduate Program in Applied of Instrumentation Meteorology, Climatology Geophysics (STMKG)

Article Info

Article history:

Received September 16, 2021
Revised September 26, 2021
Accepted October 01, 2021

Keywords:

Climate,
Information,
Dissemination,
Application.

A B S T R A C T

Changes in climate indicators can cause extreme weather and can trigger disasters, such as floods and droughts and even crop failure. it is difficult to predict because farmers and local governments do not understand the importance of climate information, the solution to the problem is to disseminate and disseminate information, but requires an information system that is also inseparable from software, IoT-based applications, and others. With the method used, namely by classifying the climate based on rainfall. In classifying the climate, the oldeman and schmidt-ferguson classifications are used. Then the dataset is formed to calculate the degree or probability of the rainfall category and the Data Normality test. The test results show that the classification of rainfall categories with light, normal, and heavy categories is 79.5%, 40.9%, and 86.4% respectively. While the precision is 96.4%, 42.6%, and 83.3% respectively. Therefore, in making applications as a medium for disseminating information, it is necessary to understand the process of seasonal occurrence, and how to turn these data into information that can be utilized by the wider community.

Corresponden Author:

Syalom Alfa Bazeleel Neonane,
Undergraduate Program in Applied of Instrumentation Meteorology, Climatology Geophysics (STMKG),
South Tangerang City, Banten, Indonesia.
Email: neonanes4@gmail.com

1. INTRODUCTION

Agroclimate research and analysis often involves time series data with various time scales, ranging from hourly, daily, weekly, decadal, monthly to annual. Analysis is not only temporal but also spatial. Climate research also involves simulation models that are sometimes very complex. Dissemination and dissemination of analyzed information requires an information system that is also inseparable from the use of software, the use of open source software (OSS) is one solution in overcoming the problem of providing software[1]. Changes in climate indicators can lead to extreme weather and can trigger disasters, such as floods and droughts. One of the impacts is crop failure, which is difficult to predict because farmers and local governments do not understand the importance of climate information. One of the adaptive efforts to mitigate the effects of climate change is the holding of a Sekolah lapang Iklim (SLI), where farmers are expected to be able to apply climate information in agricultural activities [2] [3] [4] [5].

Flooding is a natural disaster that greatly disrupts community activities. Floods also cause infrastructure damage and harm economic activities. Current flood detection applications are using sensors and IOT (Internet of Things) with reports in the form of SMS (Short Message Service) gate way (Riny Sulistyowati 2015), All of these applications work in real time by utilizing current data, Machine learning can learn existing historical data patterns to predict rainfall and flooding for the next few days [6] [7]. climate / weather is a very real determinant (significant determinanr) as a factor in the instability of food production management efforts. the availability of existing rainfall data and information can be used to consider water use strategies (irrigation) in the future so that it can be utilized optimally and efficiently [8] [9].

Indonesia is a tropical region with high rainfall intensity. The use of satellite data is a widely used solution in order to reduce the gap in weather and climate information. Based on BMKG data, some data are believed to be parameters or features to be able to determine the state of the weather (rainfall). Some of the features in question include minimum temperature, maximum temperature, average humidity, length of irradiation, and wind speed [10].

Based on some of the journals above, that the application of information system technology is very important in providing climate and weather information, therefore it is necessary to understand the knowledge of current technological developments so that it can support every human activity and activity [11].

2. DATA AND METHOD

The difference in climate on earth is strongly influenced by the location of the earth against the sun, so there are several climate classifications on earth based on the geographical location of the earth, The elements of climate that show a clear pattern of diversity are the basis for climate classification. The climate element that is often used is rainfall. Climate classification is generally very specific based on its intended use, for example for agriculture, plantations, aviation, or marine [12][13].

In previous climate classification research used climate classification research using oldeman and schmidt-ferguson classifications. In climate classification using schmidt-ferguson classification is based on the comparison between dry months/ *Bulan Kering* (BK) and wet months/*Bulan Basah* (BB). The provisions for determining wet and dry months follow the following rules:

Dry Month : month with rainfall less than 60mm
Wet Month : months with rainfall greater than 100mm
Humid Month : month with rainfall between 60mm-100mm

Humid months/*bulan Lembab* (BL) are not included in the formula for determining the type of rainfall expressed in Q values, with the following equation:

$$Q = \frac{Rata-rata\ jumlah\ BK}{Rata-rata\ jumlah\ BB} \times 100\%$$

(Schmidt, 1951)

The average number of wet months is the number of wet months of all observation data divided by the number of years of observation data, based on the magnitude of the Q value, the type of rainfall of a place or area is then determined using the Q table:

Table 1. Schmidt-Ferguson Classification of Climate

Climate Types	Description	Criterion
A	Very wet	0<Q<14,3
B	Wet	14,3<Q<33,3
C	Slightly wet	33,3<Q<60
D	moderate	60<Q<100
E	Slightly dry	100<Q<167
F	dry	167<Q<300
G	Very dry	300<Q<700
H	Extremely dry	700<Q

Like the schmidt-ferguson classification, the Oldeman method (1975) also uses rainfall as the basis for climate classification.

Dry Month : rainfall smaller than 100mm
Wet Month : rainfall greater than 200mm
Humid Month : rainfall between 100-200mm

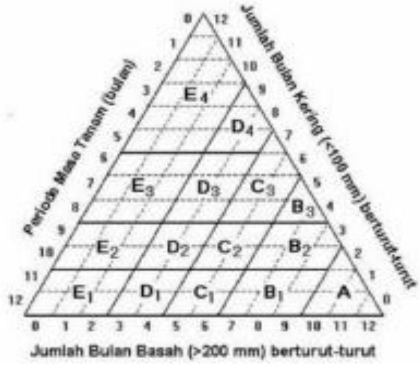

Fig 1. Oldeman's diagram (Oldeman 1975)

From the above review, Oldeman divides 5 agroclimatic regions based on water requirements, namely:

A1: wet month more than 9 consecutive months
B1: 7-9 consecutive wet months and one dry month
B2: 7-9 consecutive wet months and 2-4 dry months
C1: 5-6 consecutive wet months and 2-4 dry months
C2: 5-6 consecutive wet months and 2-4 dry months
C3: 5-6 consecutive wet months and 5-6 dry months
D1: 3-4 consecutive wet months and one dry month
D2: 3-4 consecutive wet months and 2-4 dry months
D3: 3-4 consecutive wet months and 5-6 dry months
D4: 3-4 consecutive wet months and more than 6 dry months
E1: less than 3 consecutive wet months and less than 2 dry months
E2: less than 3 consecutive wet months and 2-4 dry months
E3: less than 3 consecutive wet months and 5-6 dry months
E4: less than 3 consecutive wet months and more than 6 dry months.

3. RESULT AND DISCUSSION

The criteria F1: minimum temperature, F2: maximum temperature, F3: average humidity, F4: length of irradiation, and F5: average wind speeds are determined. In conducting this research, 150 climate data are required, namely climate data from January 2012 to December 2017 which are used as datasets. The dataset is obtained from the site http://dataonline.bmkg.go.id. Based on the dataset obtained, it is then divided into 3 parts according to the rainfall category to be classified with a composition of 50 datasets for each category [10][14].

In the dataset obtained, criteria F1 to F6 are continuous data so that the probability is calculated based on the Gauss decintas. The results of the probability calculation for all criteria are shown in the table:

Table 2. Training Data

Non-Verbal Categories	**Mean value (μ) and standard deviation (δ)**		
	slight	**Normal**	**heavy**
F1:Minimum temperature	$\mu = 24.94$	$\mu = 23.88$	$\mu = 23.69$
	$\delta = 1.35$	$\delta = 0.75$	$\delta = 0.815$
F2:Maximum temperature	$\mu = 31.41$	$\mu = 30.46$	$\mu = 30.15$
	$\delta = 1.289$	$\delta = 1.09$	$\delta = 1.98$
F3: Average humidity	$\mu = 80.38$	$\mu = 84.84$	$\mu = 86.2$
	$\delta = 4.42$	$\delta = 4.15$	$\delta = 4.89$
F4:Duration of irradiation	$\mu = 5.99$	$\mu = 4.21$	$\mu = 2.39$
	$\delta = 3.75$	$\delta = 3.34$	$\delta = 2.74$
F5: Average wind speed	$\mu = 6.92$	$\mu = 7.68$	$\mu = 7.72$
	$\delta = 2.99$	$\delta = 3.99$	$\delta = 3.92$

The results of the calculation of chance statistics in Table 2 are then used to calculate the degree or probability of rainfall categories. As testing, 132 climate data are used that already know the validity of the rainfall category. Tables 3 and 4 show the testing data classification results representing each rainfall category. While table 4 shows the calculation results of light, normal and heavy rainfall classification with Naïve Bayesian [15] [7].

Table 3. The result of calculating the original data of the true category

		CLASSIFICATION RESULT		
		SLIGHT	NORMAL	HEAVY
DATA ORIGINAL	SLIGHT	27	15	2
	NORMAL	16	23	4
	HEAVY	0	4	40

Table 4. The calculation results of the original data of the false category

		CLASSIFICATION RESULT		
		SLIGHT	NORMAL	HEAVY
DATA ORIGINAL	SLIGHT	43	1	0
	NORMAL	1	13	30
	HEAVY	0	8	36

Table 5. Rainfall classification performance result

PARAMETER	CATAGORY		
	SLIGHT	NORMAL	HEAVY
AKURASI	79.5%	40.9%	86.4%
PRESISI	96.4%	42.6%	83.3%
RECALL	61.4%	52.3%	90.9%
ERROR RATE	20.5%	59.1%	13.6%

From testing 132 data, each category of rain, light, normal and heavy 88 data. From the test results, the accuracy value for rain classification with light, normal, and heavy categories is 79.5%, 40.5% and 86.4% respectively. Based on this, the classification in normal rain conditions shows a low accuracy value. This shows the difficulty in determining the detection of normal or non-normal weather. Based on the analysis of the training data, there is no significant difference between the three categories of rain. Thus, it cannot be stated that the naive bayes approach to rainfall classification failed [16].

The Kolmogorov - Smirnov test results for the dry season cycle obtained Asympsig (2 tailed) values Dry season1 = 0.783; Dry season2 = 0.712; Dry season3 = 0.891; Dry season4 = 716; Dry season5 = 0.965; Dry season6 = 0.979; Dry season7 = 0.437; Dry season8 = 0.381. All dry season cycles have Asymp. Sig>0.05, so the residuals of the regression model are normally distributed [17] [18].

Table 6. Kolmogorov-Smirnov normality test results for the dry season cycle

Tabel 1. Hasil uji normalitasKolmogorov -Smirnov untuk siklus musim kemarau

		Kemarau 1	Kemarau 2	Kemarau 3	Kemarau 4	Kemarau 5	Kemarau 6	Kemarau 7	Kemarau 8
N		10	10	10	10	10	10	10	10
Normal Parameters[a]	Mean	139.975	137.240	126.221	97.101	93.276	91.682	83.337	91.808
	Std. Deviation	45.225	49.957	50.868	34.299	34.479	41.413	30.158	36.143
MostExtremeDifferences	Absolute	.207	.221	.183	.221	.158	.149	.275	.287
	Positive	.141	.124	.183	.221	.158	.149	.275	.287
	Negative	-.207	-.221	-.152	-.151	-.092	-.137	-.237	-.204
Kolmogorov-Smirnov Z		.656	.699	.579	.697	.498	.472	.869	.909
Asymp. Sig. (2-tailed)		.783	.712	.891	.716	.965	.979	.437	.381

a. Test distributionis Normal.

4. CONCLUSION

The test results show that the classification of rainfall categories with light, normal, and heavy categories is 79.5%, 40.9%, and 86.4% respectively. While the precision is 96.4%, 42.6%, and 83.3% respectively. Classification in light and heavy rainfall categories, the system can classify well. The possibility of low results in the normal rain category lies in the data, there should be no significant difference between the three classes. It is necessary to retest with more data [10].

The t-test results show that the dry season H0 is accepted in periods 4,5,6 and 7, meaning that there has been a change in rainfall patterns in the dry season since the period 1987 - 1996. For the wet season cycle began to be seen in the period 1995 - 2004. Although in the rainy season cycle of 1999 - 2008 t hit < t 0.975 but the value of the difference is very thin so it can be concluded that at the study site, climate change began to occur in the year of the dry season 1987 and the rainy season 1995 [17].

In understanding climate change predictions, exascale computing combined with advances in mathematical modeling and parallel algorithms will lead to new insights into the impacts of climate, including the prevalence of storms, droughts, wildfires, and more [19] [20].

From the results and discussion of several journals above, it can be concluded that in utilizing information system technology, as a determinant of seasonal rainfall data is very influential. Therefore, in making applications as a medium for disseminating information, it is necessary to understand the process of seasonality, and how to make these data into information that can be utilized by the wider community.

REFERENCE

[1] Y. Sarvina, "Pemanfaatan Software Open Source ' R ' Untuk Penelitian Agroklimat ' R ' Open Source Software for Agroclimate Research," *Inform. Pertan.*, vol. 26, no. 1, pp. 23–30, 2017.

[2] H. Subyantara *et al.*, "Penggunaan Mqtt Sebagai Optimasi Pengiriman Data Aaws Sebagai Sarana Sekolah Lapang Iklim Berbasis Internet of Things (Iot)," *J. Meteorol. Klimatologi dan Geofis.*, vol. 5, no. 1, pp. 1–10, 2018, [Online]. Available: www.mqtt.org

[3] D. Tarmana and A. Ulfah, "Peningkatan Pemahaman Informasi Iklim Melalui Sekolah Lapang Iklim (Sli) Bagi Petani," *JMM (Jurnal Masy. Mandiri)*, vol. 5, no. 2, pp. 798–809, 2021.

[4] I. L. Mranoto, "PERANCANGAN SISTEM INFORMASI DATA PENGAMATAN AGROKLIMAT BERBASIS WEBSITE," 2019.

[5] N. Singh, S. Chaturvedi, and S. Akhter, "Weather Forecasting Using Machine Learning Algorithm," *2019 Int. Conf. Signal Process. Commun. ICSC 2019*, pp. 171–174, 2019, doi: 10.1109/ICSC45622.2019.8938211.

[6] I. Fitriyaningsih, Y. Basani, and L. M. Ginting, "Machine Learning: Prosperity of Rainfall, Water Discharge, and Flood With Web Application in Deli Serdang," *J. Penelit. Komun. Dan Opini Publik*, vol. 22, no. 2, 2018, doi: 10.33299/jpkop.22.2.1752.

[7] C. J. Huang, M. C. Liu, S. S. Chu, and C. L. Cheng, "Application of machine learning techniques to Web-based intelligent learning diagnosis system," *Proc. - HIS'04 4th Int. Conf. Hybrid Intell. Syst.*, pp. 242–247, 2005, doi: 10.1109/ichis.2004.25.

[8] I. G. E. Gunartha, "APLIKASI METODE KEKERINGAN PADA PENDUGAAN DATA IKLIM/CUACA'," 1995.

[9] F. Irsyad, E. G. Ekaputra, and A. Assyaukani, "Kajian Perubahan Iklim Pada Penentuan Jadwal Tanam Cabai Di Kabupaten Agam," *J. Teknol. Pertan. Andalas*, vol. 23, no. 1, p. 91, 2019, doi: 10.25077/jtpa.23.1.91-102.2019.

[10] i gede aris gunadi, "Klasifikasi Curah Hujan di Provinsi Bali Berdasarkan Metode Naïve Bayesian," *Wahana Mat. dan Sains J. Mat. Sains, dan Pembelajarannya*, vol. 12, no. 1, pp. 14–15, 2018, [Online]. Available: https://ejournal.undiksha.ac.id/index.php/JPM/article/view/pril2018-2

[11] E. A. Hussein, M. Ghaziasgar, C. Thron, M. Vaccari, and A. Bagula, "Basic statistical estimation outperforms machine learning in monthly prediction of seasonal climatic parameters," *Atmosphere (Basel).*, vol. 12, no. 5, 2021, doi: 10.3390/atmos12050539.

[12] E. Gumilanggeng, "Visualisasi Informasi Klasifikasi Iklim Koppen Menggunakan Metode Polygon Thiessen (Studi Kasus Provinsi Jawa Tengah)," pp. 6–22, 2013.

[13] A. Mihai, G. Czibula, and E. Mihuletc, "Analyzing Meteorological Data Using Unsupervised Learning Techniques," *Proc. - 2019 IEEE 15th Int. Conf. Intell. Comput. Commun. Process. ICCP 2019*, pp. 529–536, 2019, doi: 10.1109/ICCP48234.2019.8959777.

[14] A. Zakir, "Analisis dan Pengembangan Sistem Metode Prakiraan Cuaca di Bidang Informasi Meteorologi," p. 1, 2005.

[15] Doreswamy, I. Gad, and B. R. Manjunatha, "Performance evaluation of predictive models for missing data imputation in weather data," *2017 Int. Conf. Adv. Comput. Commun. Informatics, ICACCI 2017*, vol. 2017-Janua, pp. 1327–1334, 2017, doi: 10.1109/ICACCI.2017.8126025.

[16] N. Giarsyani, "Komparasi Algoritma Machine Learning dan Deep Learning untuk Named Entity Recognition : Studi Kasus Data Kebencanaan," *Indones. J. Appl. Informatics*, vol. 4, no. 2, p. 138, 2020, doi: 10.20961/ijai.v4i2.41317.

[17] D. Susilokarti, S. S. Arif, S. Susanto, and L. Sutiarso, "IDENTIFIKASI PERUBAHAN IKLIM BERDASARKAN DATA CURAH HUJAN DI WILAYAH SELATAN JATILUHUR KABUPATEN SUBANG, JAWA BARAT (Identification of Climate Change Based on Rainfall Data in Southern Part of Jatiluhur, Subang District, West Jawa)," *J. Agritech*, vol. 35, no. 01, p. 98, 2015, doi: 10.22146/agritech.13038.

[18] C. He, J. Wei, Y. Song, and J. J. Luo, “Seasonal prediction of summer precipitation in the middle and lower reaches of the yangtze river valley: Comparison of machine learning and climate model predictions,” *Water (Switzerland)*, vol. 13, no. 22, 2021, doi: 10.3390/w13223294.

[19] K. Yelick, “Computing and Data Challenges in Climate Change,” pp. xix–xix, 2021, doi: 10.1109/hipc50609.2020.00009.

[20] F. Sains and U. Diponegoro, “Klasifikasi Curah Hujan di Kota Semarang Menggunakan Machine Learning Rainfall Classification in the Semarang City Using Machine Learning,” vol. 1, no. 1, pp. 1–5, 2022.