Prisma Sains: Jurnal Pengkajian Ilmu dan Pembelajaran Matematika dan IPA IKIP Mataram
https://e-journal.undikma.ac.id/index.php/prismasains/index
e-mail: prismasains.pkpsm@gmail.com

April 2023. Vol. 11, No. 2
p-ISSN: 2338-4530
e-ISSN: 2540-7899
pp. 393-406

Projection of Climate Change on the Probability of Dengue Hemorrhagic Fever in North Sumatra Province

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Received: March 2022; Revised: March 2023; Published: April 2023

Abstract

Climate change is a major threat to global prosperity. The industrial revolution has occurred since 1750 to 2010 where the increase in global air temperature has reached 0.7°C. Rising temperatures and fluctuating rainfall is the identification of climate change, one of the impacts of climate change is changing the distribution of some types of mosquitoes (Aedes Aegypti).Based on the results of the analysis of the main components, a good model uses an accuracy rate of about 85% and passes the test individually and as a whole. Indonesia has a tropical climate where warm temperatures and high rainfall variability are a comfortable habitat for Aedes Aegypti mosquitoes. The breeding and life cycle of the Aedes Aegypti mosquito is directly influenced by climatic conditions. The purpose of this study is to determine the normal rainfall map, an overview of climate projection patterns, identification of characteristics of climate change in the short term (2011 – 2040), medium term (2041 – 2070) and long term (2071-2100) based on rainfall and temperature projections in North Sumatra province. Statistical methods used to determine the effect of climate on health (dengue) include statistical downscaling, delta bias correction, Principal Component Analysis, and ordinal logistic regression. The results of the ordinal logistic regression analysis show that rainfall that is suitable for dengue fever ranges from 100 - 300 mm. For North Sumatra rainfall ranges from 50 - 600 mm. In March and November is the strongest threat because of the peak with high rainfall intensity where the danger of flooding and dengue. The air temperature ranges from 24.5 - 28.5 ^{o}C, this condition is still optimal for the development of the Aedes Aegypti mosquito. The climate change projection index for the short term (2011 - 2040), medium term (2041 - 2070) and long term (2071 - 2100) shows a consistent increase with a range of 0.40C, this value will affect the acceleration of the reproduction of the Aedes aegypti mosquito as the cause of DHF. The projection probability of dengue hemorrhagic fever shows that North Sumatra Province still has a high chance of being categorized as a high risk area for dengue fever with a probability value of 0.82 - 0.99.

Keywords: Climate change, dengue hermologic fever, ordinal logistic regression, probability

How to Cite: Simbolon, T., Frida, E., Sinambela, M., Situmorang, M., Humaidi, S., & Darmawan, Y. (2023). Projection of Climate Change on the Probability of Dengue Hemorrhagic Fever in North Sumatra Province. *Prisma Sains : Jurnal Pengkajian Ilmu dan Pembelajaran Matematika dan IPA IKIP Mataram, 11*(2), 393-406. doi:https://doi.org/10.33394/j-ps.v11i2.7754

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INTRODUCTION

Climate change is a major threat to global prosperity. Solidarity, partnership, cooperation, and collaboration are key in addressing climate change issues globally. Indonesia with its huge natural potential contributes to the handling of climate change. The seventh President of the Republic of Indonesia conveyed Indonesia's commitment to address climate change issues at the Climate Change Conference of the Parties (COP26) at the

Scottish Event Campus, Glasgow, Scotland in 2021. North Sumatra Province was chosen as the location of the Global Covenant of Mayors for Climate and Energy (GCoM) Asia Project program on climate change mitigation and adaptation.

Several areas in North Sumatra Province are industrial areas with high consumption of greenhouse gas (GHG) emissions. The increase of GHG in the atmosphere is the main cause of climate change produced by industrial activities. GHGs have the effect of accelerating the global warming process and increasing the frequency of extreme weather and climate events (Pabalik et al., 2015). The increase in temperature and fluctuating rainfall is an identification of climate change (Putra et al., 2020). According to the United States Environmental Protection Agency (US EPA), several sectors of life that are potentially affected by climate change include health, agriculture, forestry, water resources, infrastructure, coastal areas, fisheries, and other natural environments (Githeko et al., 2003).

Disease transmission is strongly influenced by climatic factors (Brisbois & Ali, 2010). The Intergovernmental Panel on Climate Change (IPCC) states that one of the impacts of climate change is changing the distribution of several mosquito species (Malaria and Aedes Aegypti) and other diseases (IPCC, 2007). Indonesia has a tropical climate where warm temperatures and high rainfall variability provide a comfortable home for the Aedes Aegypti mosquito. The peak incidence of dengue fever occurs at a temperature interval of 27 - 29 oC (Tarmana, 2017). Flooding is very common in North Sumatra due to reduced forest conservation, erosion, and siltation of rivers. Flooding is very supportive of the development of the Aedes Aegypti mosquito. For this reason, this research will discuss climate change that occurs, the need for adaptation and mitigation of dengue hemorrhagic fever by projecting scenarios estimating the amount of greenhouse gas (GHG) emissions in the future.

Future climate change is described through the Radiative Concentration Pathways (RCP) scenario. RCP has 4 scenarios, namely RCP2.6, RCP4.5, RCP6.0 and RCP8.5. The RCP4.5 scenario assumes that all countries in the world take part in mitigation efforts (GHG reduction) simultaneously and effectively (Thomson et al., 2011). This research will project future extreme climate conditions for the short-term (2021 - 2050), medium-term (2051 - 2080), and long-term (2081 - 2100) periods in North Sumatra, so that based on the resulting future extreme climate change projections, adaptation and mitigation actions can be taken by stakeholders in Indonesia, especially North Sumatra for planning in the program to deal with dengue cases.

Climate change has several elements as a reference, the main elements are rainfall and temperature. This research focuses on rainfall and temperature, where if the normal conditions of climate compatibility (rainfall and temperature) with the mosquito's living environment, the normal cycle occurs in the Aedes Aegipty mosquito so that dengue fever cases do not experience significant changes. The existence of climate change issues (changes in rainfall and temperature increase) and according to several studies have an impact on the health sector, especially on dengue fever cases, making changes to the normal cycle of the Aedes Aegipty mosquito. Based on these climate projections, what about the probability of dengue hemorrhagic fever cases in North Sumatra Province.

This study was conducted with the aim of obtaining the characteristics of future extreme climate change in the North Sumatra region and the probability of Dengue Fever occurrence based on climate change projections in the short term (2011 - 2040), medium term (2041 - 2070) and long term (2071 - 2100) based on the scenario.

METHOD

Statistical methods were used to determine the effect of climate on health (dengue), including statistical downscaling, delta bias correction, Principal Component Analysis, and ordinal logistic regression. The grouping of data modes is Observation Data and Climate Model Data.

Observation Data

1) Observed rainfall data in millimeters (mm) monthly time series from 2006 - 2022 from a network of BMKG stations spread throughout North Sumatra Province in Ms. Excel format;
2) Observed air temperature data in degrees Celsius (oC) monthly time series from 2006 - 2022 from a network of BMKG stations spread throughout North Sumatra Province in Ms. Excel format;
3) Data on the incidence of DHF cases in North Sumatra Province from the North Sumatra Health Office in 2009 – 2022 where classified into 3 (three) risk levels, namely high risk (DHF cases >55), medium risk (20 < DHF cases <55) and low risk (DHF cases <20) based on the Ministry of Health.; and
4) Population data of North Sumatra in 2009 - 2022 from the North Sumatra Central Bureau of Statistics.

Climate Model Data

RCP4.5 scenario model data from IPCC's Fifth Assessment Report (AR5), 2013 stored on APEC Climate Center server (http://adss.apcc21.org). Table 1 shows the description of the rcp scenario. Data in the study includes:

1) Rainfall projection data in units of measurement millimeters (mm) monthly time series from 2011 - 2100 with North Sumatra grid stored in the form of a matrix grid in Netcdf format was converted to Excel;
2) Air temperature projection data in units of degrees Celsius (oC) monthly time series from 2011 - 2100 with North Sumatra grid stored in the form of a matrix grid in Netcdf format converted to Excel; and
3) The model data is then divided into three periods: short-term (2011 - 2040), medium-term (2041 - 2070), and long-term (2071 - 2100). Global model data used ensemble data from CORDEX SEA.

Table 1. RCP Scenario Description

Name	Radiative Forcing	Concentrate (ppm)	Provider
RCP 4.5	4.5 W/m^2 stable after 2100	Equivalent to CO_2 ~ 650 stable after 2100	GCAM

Source: (Wayne, 2013)

RCP4.5 was developed by the GCAM modeling team at the Pacific Northwest National Laboratory JGCRI (Joint Global Change Research Institute), USA. It is a stabilization scenario with stable radiative forcing after 2100, without exceeding the long-term radiative forcing target limit. The research area is shown in Figure 1 and the metadata in Table 2.

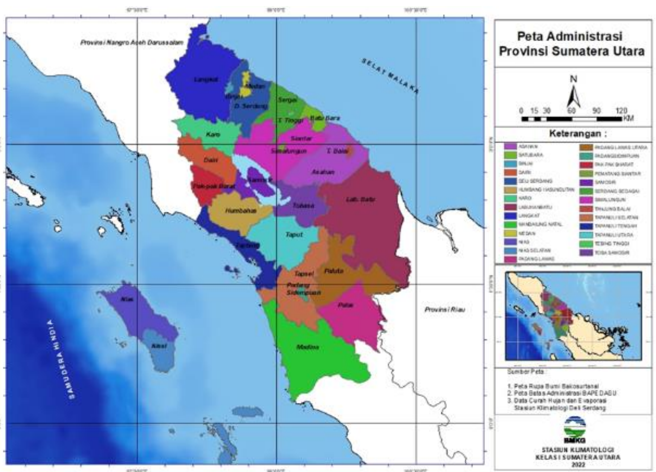

Figure 1. Research area

(Source: North Sumatera Climatology Station)

Table 2. Metadata of BMKG observation stations used in the research (BMKGSoft, 2021)

Station Name	Latitude (°N)	Longitude (°E)	Elevation (m)
Stasiun Klimatologi Deli Serdang	3,62114	98,71485	25
Stasiun Meteorologi Maritim Belawan	3,78824	98,71492	3
Stasiun Meteorologi Kualanamu	3,64573	98,88488	23
Stasiun Geofisika Tuntungan	3,501	98,56	86
Balai Besar MKG Wilayah I Medan	3,5397	98,64	0
Stasiun Meteorologi Binaka	1,1649	97,7036	7
Stasiun Meteorologi Aek Godang	1,55	99,45	281
Stasiun Meteorologi FL Tobing – Sibolga	1,55	98,88	10
Stasiun Geofisika Gunung Sitoli	1,3	97,58	175

This research uses several calculations, namely downscaling statistics, delta bias correction, principal component analysis, weighted distance inverse interpolation and ordinal logistic regression. Statistical downscaling is a technique that uses statistical downscaling to see the relationship between global-scale data and local-scale data. Climate variables in the global model are stored in the form of grid data with a horizontal resolution ranging from 50 - 500 km and then downscaled to a resolution of 25 km as shown in Figure 3. Bias correction with the delta method is used to arrange the correction factor of the model data before testing the accuracy of the model data, illustration of bias correction is shown in Figure 4. The Delta method is a simple downscaling method commonly used to prepare climate change scenarios at the local scale (Faqih, 2017). The formula of the Delta Method calculation is:

$$x_{cor,i} = x_{0,i} + \mu_p - \mu_b \quad \text{(Eq. 1)}$$

$$x_{cor,i} = x_{0,i} \times \frac{\mu_p}{\mu_b} \quad \text{(Eq. 2)}$$

X_(cor,i) is corrected value; μ_p is average in the projection period; X_(o,i) is observation value; μ_b is average in the baseline period.

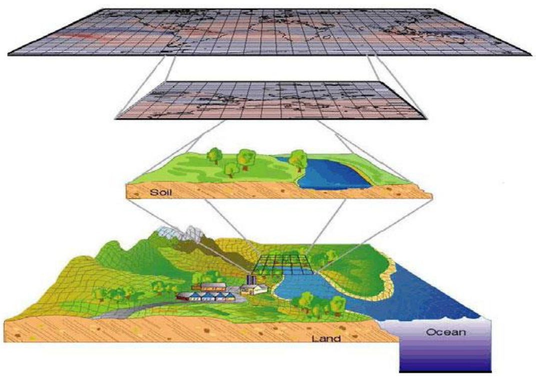

Figure 3. Downscaling scheme
(Source: Khan and Pilz, 2018)

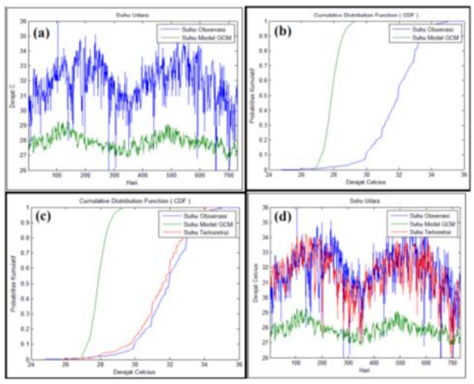

Figure 4. Bias correction illustration
(Source: Jadmiko dkk, 2017)

Principal Component Analysis (PCA) can be used to reduce the dimension of data without significantly reducing the characteristics of the data (Cahyadi, 2007). PCA is a form of linear transformation projection of variable data. The formula of PCA calculation is:

$$KU_1 = \mathbf{a}_1\mathbf{x} = a_{11}x_1 + \ldots + a_{1p}x_p \quad \text{(Eq. 3)}$$

If the origin variable group {X1, X2, …, Xp} has a variance matrix **Σ** then the variance of the principal component is :

$$\sigma^2 KU_1 = a^{1'}\Sigma a1 = \sum_{l=1}^{p} \sum_{j=1}^{p} a_{1i}a_{1j}\sigma ij \quad \text{(Eq. 4)}$$

Vector $\mathbf{a}_1$ is matrix feature vector Σ which corresponds to the root of the largest feature. Linear combination of {X1, X2, …, Xp} form $KU_1 = a_1x = a_{11}x_1 + \ldots + a_1pXp$ known as first KU and has a variance of λ_1 = largest characteristic root. Form $KU_2 = a_2x = a_{21}x_1 + \ldots + a_2pXp$. Searching for vectors a_2 so the variety maximum of KU_2, and KU_2 not correlated with KU_1. a_2 is none other than the feature vector that corresponds to the second largest feature root of the matrix Σ. Example $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_p > 0$ is the feature vector that corresponds to the feature vector $a_1, a_2, \ldots, a_p$ by matrix Σ, and the length of each of the vectors is 1, or $a_i'a_i = 1$ for $i = 1, 2, \ldots, p$. So, $KU_1 = a_1'x$, $KU_2 = a_2'x$, …, $KU_p = a_p'x$ onsecutive is first main component, second, …, by-p to x. More $var(KU_1) = \lambda_1$, $var(KU_2) = \lambda_2$, …, $var(KU_p) = \lambda_p$, or the characteristic root of the variance matrix Σ is variety of major components.

Dengue hemorrhagic fever is It is an infectious disease caused by the dengue virus of the flavivirus genus that is transmitted through the bite of the Aedes Aegypti mosquito. There are several climatic parameters that can affect the incidence of Dengue hemorrhagic fever. (Wirayoga, 2013) through his research discusses the relationship between climate parameters (temperature, rainfall, humidity and wind speed) and the incidence of DHF in Semarang City.

The weighted distance inverse interpolation method is an interpolation method by making the distance between the predicted point and the measured point a weighting factor. The formula for this method is:

$$Z_0 = \sum_{i=1}^{n} \lambda_i z_i \qquad \text{(Eq. 5)}$$

Z_0 = Value of the predicted point, Z_i = Measured value of the surrounding point elements, λi = Possible weights to use, n = Number of points with measured values
The formula for calculating self-weight is:

$$\lambda_i = \frac{di_0^{-p}}{\sum_{i=1}^{n} d_i o^{-p}} \qquad \text{(Eq. 6)}$$

$$\sum_{i=1}^{n} \lambda_i = 1 \qquad \text{(Eq. 7)}$$

d_{io} = Distance between the point whose value is predicted and the neighboring points, p = inverse power of weighted distance

Categorical data on response variables can be nominal or ordinal, for the case of ordinal response variables, the regression model that can be used is the ordinal logistic regression model. In this logistic model (logit link), the ordinal nature of the response variable Y is expressed in cumulative odds so that the cumulative logit model is a model obtained by comparing the cumulative odds, namely the odds of being less than or equal to-j response category on the p predictor variables expressed in the X vector ($P[Y \leq j|X]$), with a probability greater than the response category to-j ($P[Y \geq j|X]$) (Hosmer dan Lemeshow, 2000). Cumulative probability $P(Y \leq j|X)$ is defined as follows:

$$P(Y \leq j|X) = \frac{exp(\alpha_j + \sum_{k=1}^{p} \beta_k X_k)}{1 + exp(\alpha_j + \sum_{k=}^{p} \beta_k X_k)} \qquad \text{(Eq. 8)}$$

with j = 1,2,…,J is response category (Agresti, 1990)

In terms of classification, the cumulative logit model is a classification function. The classification function formed when there are J response categories is a number of J - 1. If (X) = P(Y = j I X) π j = states the probability of response category to-j at p the predictor variable expressed in vector X and P ($Y \leq j|X$) states the cumulative probability at p predictor variables expressed in vector X then the value of (X) π j obtained by the following equation :

$$\gamma_j = P(Y \leq j)X = \pi_1(X) + \pi_2(X) + \cdots + \pi j(X)$$

with j = 1,2, …, J. For five response categories where j = 1, 2, 3, 4, 5 then the value of the response category probability to – j is :

$$\gamma_1 = P(Y \leq 1IX) = \frac{exp(\alpha_1 + \sum_{k=1}^{P} \beta_k X_k)}{1 + exp(\alpha_1 + \sum_{k=1}^{p} \beta_k x_k)}$$

$$\gamma_2 = P(Y \leq 2IX) = \pi_1(X) + \pi_2(X) = \frac{exp(\alpha_2 + \sum_{k=1}^{P} \beta_k X_k)}{1 + exp(\alpha_2 + \sum_{k=1}^{p} \beta_k x_k)} \quad \text{(Eq. 9)}$$

By utilizing the two cumulative opportunities above, the opportunities for each response category will be obtained as follows:

$$\pi_1(X) = P(Y \leq 1IX) = \frac{exp(\alpha_1 + \sum_{k=1}^{P} \beta_k X_k)}{1 + exp(\alpha_1 + \sum_{k=1}^{p} \beta_k x_k)} \quad \text{(Eq. 10)}$$

$$\pi_2(X) = P(Y \leq 2IX) - \pi_1(X) = \frac{exp(\alpha_2 + \sum_{k=1}^{P} \beta_k X_k)}{1 + exp(\alpha_2 + \sum_{k=1}^{p} \beta_k x_k)} - \frac{exp(\alpha_1 + \sum_{k=1}^{P} \beta_k X_k)}{1 + exp(\alpha_1 + \sum_{k=1}^{p} \beta_k x_k)} \quad \text{(Eq. 11)}$$

$$\pi_3(X) = 1 - P(Y \leq 2IX) = \frac{exp(\alpha_3 + \sum_{k=1}^{P} \beta_k X_k)}{1 + exp(\alpha_3 + \sum_{k=1}^{p} \beta_k x_k)} \quad \text{(Eq. 12)}$$

For value classification $\pi_1(X)$ at equation 1 to 3 will be used as a guideline for classification. An observation will fall into the response category *j* based on the largest $\pi_j(X)$ (Wibowo, 2002).

RESULTS AND DISCUSSION

The air temperature for North Sumatra Province at BMKG stations ranges from 24.5 - 28.5 ^{0}C, with the highest temperature occurring in May and the lowest occurring in November. The overall temperature allows for the growth of Aedes Aegypti mosquitoes can be seen in Figure 5. The rainfall pattern at BMKG stations is a climate element that is discussed in this study. The normal monthly rainfall (1991 - 2020) for North Sumatra Province generally ranges from 50 mm - 600 mm can be seen in Figure 7. In general, the seasonal period in the North Sumatra region can be categorized into periods of December - January - February (DJF), March - April - May (MAM), June - July - August (JJA) and September - October - November (SON). DJF and JJA are dry periods, while MAM and SON are wet periods. Based on the monthly normal distribution of rainfall, the North Sumatra region is included in the Equatorial rainfall type, which means that it has each of the two peaks and two valleys rainfall patterns. The first rain peak is generally in March, while the second rain peak is generally in November. The second rainy peak has a higher rainfall accumulation than the first rainy peak. The first dry peak is generally in February, while the second dry peak is generally in July as shown in Figure 6.

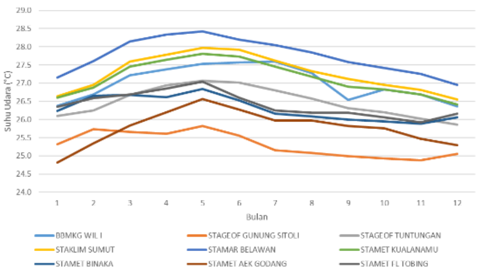

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Figure 5. Average Monthly Air Temperature(^{0}C)

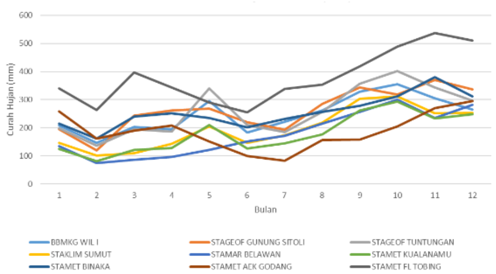

Figure 6. Average Monthly Precipitation (mm)

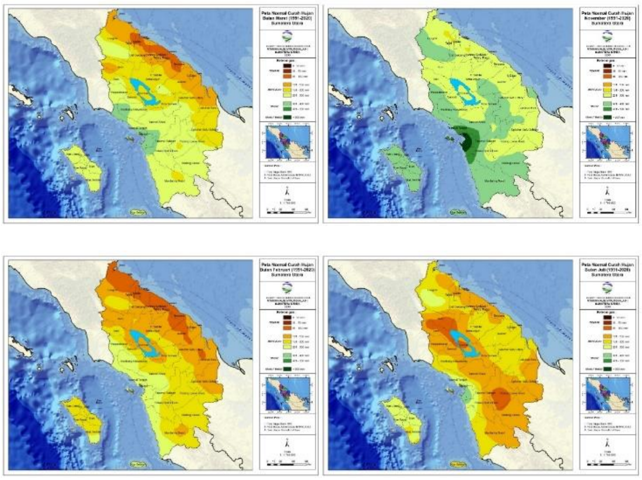

Figure 7. Spatial map of normalized rainfall during peak rainy and peak dry periods.

When viewed from climatological factors, namely rainfall and air temperature are theoretically the optimum factors for the development of the aedes aegypti mosquito, plus supporting rainfall puddles as a breeding ground, so North Sumatra has a vulnerability in the health sector as a result of climate change.

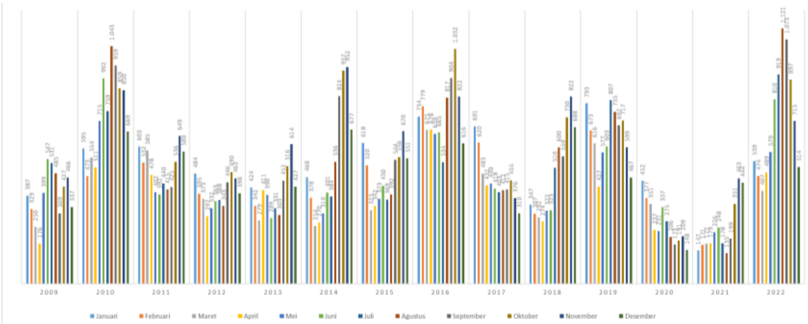

Figure 8. Monthly dengue cases 2019 - 2022 in North Sumatra Province

The results of descriptive analysis of data on the number of DHF cases in North Sumatra Province shown in Figure 8 show that it varies greatly. The number of monthly cases with the period 2019 - 2022 shows that October is the highest total number of dengue cases at 8694 cases and the lowest in April at 5201 cases. In Table 3 based on the Ministry of Health which divides 3 (three) levels of risk, from the dengue hemorrhagic fever data in general, North Sumatra is in the medium to high risk category.

Table 3 Classification into 3 (three) risk levels

Month	**Classification of Dengue Cases Monthly Average**													
	2009	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
January	Med	Med	Med	Med	Med	Med	Med	High	High	Med	High	Med	Low	Med
February	Med	Med	Med	Med	Med	Med	Med	High	Med	Med	High	Med	Low	Med
March	Med	Med	Med	Med	Med	Med	Med	High	Med	Med	Med	Med	Low	Med
April	Low	Med	Med	Med	Med	Med	Med	High	Med	Med	Med	Low	Low	Med
May	Med	High	Med	Med	Med	Med	Med	High	Med	Med	Med	Low	Low	Med
June	Med	High	Med	Med	Med	Med	Med	High	Med	Med	Med	Med	Low	High
July	Med	High	Med	Med	Med	Med	Med	Med	Med	Med	High	Med	Low	High
August	Med	High	Med	Med	Med	Med	Med	High	Med	Med	High	Low	Low	High
September	Med	High	Med	Med	Med	High	Med	High	Med	Med	High	Low	Low	High
October	Med	High	Med	Med	Med	High	Med	High	Med	High	High	Low	Med	High

Month	Classification of Dengue Cases Monthly Average													
	2009	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
November	Med	High	High	Med	Med	High	High	High	Med	High	Med	Low	Med	High
December	Med	High	Med	Med	Med	High	Med	Med	Med	High	Med	Low	Med	Med

Description: Low = Low Risk, Med = Medium Risk, High = High Risk

Principal component analysis can produce more optimal values to represent all variations. Problems that commonly occur in a large variety of data include a large number of variables that make analysis difficult and multicollinearity that invalidates conclusions.

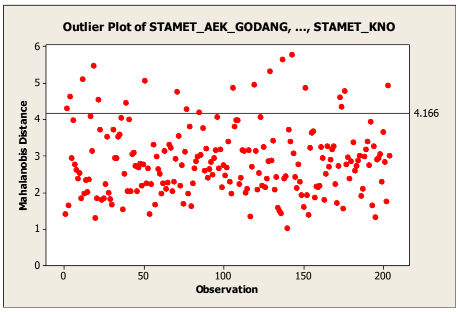

Figure 9. Outlier Plot of Precipitation

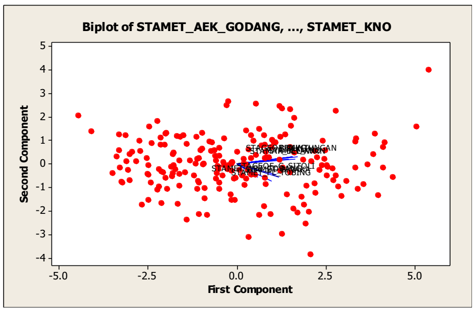

Figure 10. Biplot of Precipitation

In Figure 9, the rainfall outlier plot aims to identify outliers. Any point that is above the reference line is an outlier. Outliers can significantly affect the results of the analysis. Therefore, if an outlier is identified in the data, one should examine the observations to understand why they are unusual. Correct any measurement or data entry errors. Consider removing data related to special causes and repeating the analysis. In these results, there are several outliers. The rainfall biplot in Figure 10 aims to assess the structure of the data and the load of the first two components on one graph. Minitab plots the value of the second principal component versus the value of the first principal component, as well as the loadings for both components. This biplot shows the following: The overall data has a large positive loading on component 1, the point in the bottom right corner may be an outlier.

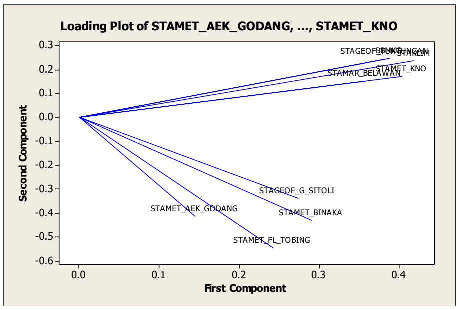

Figure 11. Loading Plot of Precipitation

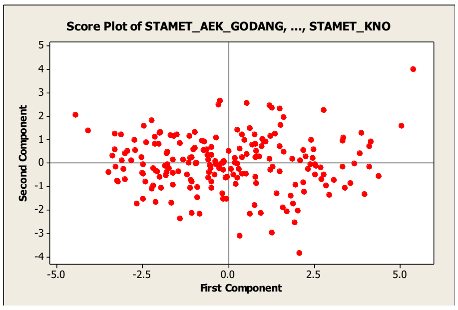

Figure 12. Score Plot of Precipitation

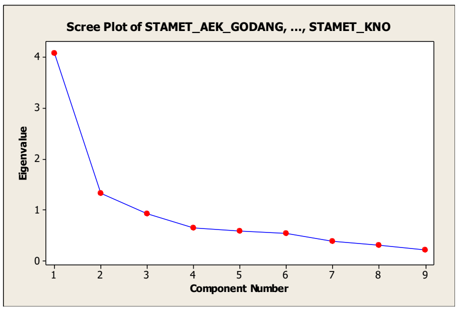

Figure 13. Scree Plot of Precipitation

In figure 11 Loading plots of rainfall aim to identify which variables have the greatest effect on each component. Loadings can range from -1 to 1. Loadings close to -1 or 1 indicate that the variable strongly influences the component. Loadings close to 0 indicate that the variable has a weak influence on the component. Loading plots can also help characterize each component in terms of variables. This plot has a large positive loading on component 1, so this component primarily measures stability. Stamet Aek Godang, Stamet FL Tobing, Stageof Gunung Sitoli and Stamet Binaka have large negative weights on component 2. In Figure 12 the Score plot of rainfall aims to assess the structure of the data and detect clusters, outliers and trends. Data grouping on the plot can indicate two or more separate distributions in the data. If the data follows a normal distribution and there are no outliers, the points will be randomly distributed around zero. In this scree plot, the point in the bottom corner may be an outlier. In figure 13 this Scree plot of rainfall shows that the eigenvalues start to form a straight line after the second principal component. Therefore, the remaining principal components account for a very small proportion of the variability (close to zero) and may not be important.

In Principal Component Analysis (principal component analysis) can be seen in table 4, eigenvalues (also called characteristic values or latent roots) are variants of the principal components. Measure the eigenvalues to determine the number of principal components. Keep the principal component with the largest eigenvalue. For example, using the Kaiser criterion, only use principal components with eigenvalues greater than 1. Proportion is the proportion of variability in the data explained by each principal component, determining which principal component explains most of the variability in the data. The higher the proportion, the more variability is explained by the principal component. The proportion measure can help decide whether the principal component is important enough to retain. The principal component with a proportion of 0.452 explains 45.2% of the variability in the data. Therefore, this component is important to include. Another component has a proportion of 0.034, and thus explains only 3.4% of the variability in the data. These components may not be important enough to include. Cumulative is the cumulative proportion of the sample variability explained by the successive principal components. Use the cumulative proportion to assess the total amount of variance explained by the successive principal components. The cumulative proportion can help determine the number of principal components to use. Keep the principal components that explain an acceptable level of variance. The acceptable level depends on the application. 70% of the variance explained by the principal components is required if only using them for descriptive purposes. However, if you want to perform other analyses on the data, perhaps at least 85% of the variance explained by the principal components.

Table 4. Principal Component Analysis of Rainfall

Principal Component Analysis: STAMET_AEK_G, STAMET_BINAK, STAKLIM, STAMET_FL_TO (CURAH HUJAN)

Eigenanalysis of the Correlation Matrix

Eigenvalue	4.0710	1.3204	0.9310	0.6491	0.5809	0.5351	0.3843	0.3059
Proportion	0.452	0.147	0.103	0.072	0.065	0.059	0.043	0.034
Cumulative	0.452	0.599	0.702	0.775	0.839	0.899	0.941	0.975

Eigenvalue	0.2222
Proportion	0.025
Cumulative	1.000

Variable	PC1	PC2	PC3	PC4	PC5	PC6	PC7
STAMET_AEK_GODANG	0.145	-0.414	-0.801	0.088	-0.365	0.055	0.087
STAMET_BINAKA	0.290	-0.433	0.253	0.383	-0.003	-0.611	-0.364
STAKLIM	0.418	0.236	-0.022	-0.165	0.158	-0.142	0.249
STAMET_FL_TOBING	0.242	-0.546	-0.007	-0.237	0.693	0.302	0.045
BBMKG	0.387	0.246	0.024	0.408	0.071	0.306	0.067
STAGEOF_TUNTUNGAN	0.382	0.244	-0.102	0.337	0.013	0.350	-0.422
STAGEOF_G_SITOLI	0.273	-0.339	0.521	-0.110	-0.566	0.359	0.258
STAMAR_BELAWAN	0.358	0.151	-0.070	-0.685	-0.188	-0.094	-0.497

STAMET_KNO	0.404	0.171	-0.085	-0.024	0.024	-0.398	0.547
Variable	PC8	PC9					
STAMET_AEK_GODANG	0.097	-0.071					
STAMET_BINAKA	0.095	-0.039					
STAKLIM	0.254	-0.755					
STAMET_FL_TOBING	-0.072	0.094					
BBMKG	0.609	0.385					
STAGEOF_TUNTUNGAN	-0.581	-0.180					
STAGEOF_G_SITOLI	-0.080	-0.073					
STAMAR_BELAWAN	0.135	0.257					
STAMET_KNO	-0.424	0.403					

In Table 4, the cumulative proportion is 85 %, so the regression analysis is the first 5 principal components, namely PC1, PC2, PC3, PC4 and PC5. The constant value is associated with rainfall at each station. The scores for the first principal component can be calculated from the standardized data using the coefficients listed below:

PC1 = (0.145*Stamet Aek Godang) + (0.29*Stamet Binaka) + (0.418*Staklim Sumut) + (0.242*Stamet FL Tobing) + (0.387*BBMKG) + (0.382*Stageof Tuntungan) + (0.273*Stageof Gunung Sitoli) + (0.358*Stamar Belawan) + (0.404*Stamet Kualanamu).
PC2 = (-0.414* Stamet Aek Godang) + (-0.433* Stamet Binaka) + (0.236* Staklim Sumut) + (-0.546* Stamet FL Tobing) + (0.246* BBMKG) + (0.244* Stageof Tuntungan) + (-0.339* Stageof Gunung Sitoli) + (0.151* Stamar Belawan) + (0.171* Stamet Kualanamu)
PC3 = (-0.801* Stamet Aek Godang) + (0.253* Stamet Binaka) + (-0.022* Staklim Sumut) + (-0.007* Stamet FL Tobing) + (0.024* BBMKG) + (-0.102* Stageof Tuntungan) + (0.521* Stageof Gunung Sitoli) + (-0.07* Stamar Belawan) + (-0.085* Stamet Kualanamu)
PC4 = (-0.088* Stamet Aek Godang) + (0.383* Stamet Binaka) + (-0.165* Staklim Sumut) + (-0.237* Stamet FL Tobing) + (0.408* BBMKG) + (0.337* Stageof Tuntungan) + (-0.11* Stageof Gunung Sitoli) + (-0.685* Stamar Belawan) + (-0.024* Stamet Kualanamu)
PC5 = (-0.365* Stamet Aek Godang) + (-0.003* Stamet Binaka) + (0.158* Staklim Sumut) + (0.693* Stamet FL Tobing) + (0.071* BBMKG) + (0.013* Stageof Tuntungan) + (-0.566* Stageof Gunung Sitoli) + (-0.188* Stamar Belawan) + (0.024* Stamet Kualanamu)

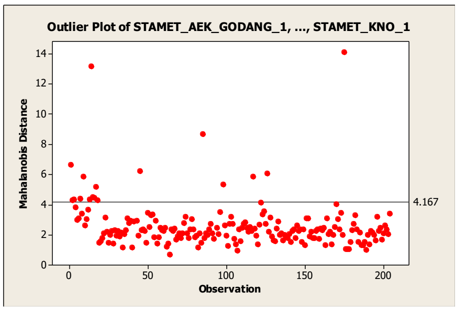

Figure 14. Outlier Plot of Air Temperature

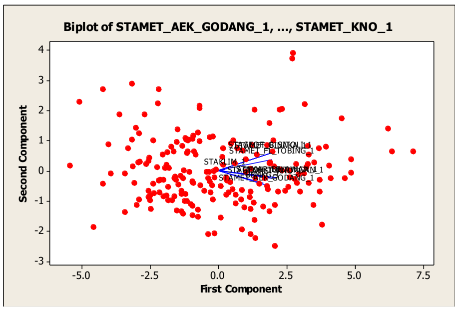

Figure 15. Biplot of Air Temperature

In Figure 14, the air temperature outlier plot aims to identify outliers. Any point that is above the reference line is an outlier. Outliers can significantly affect the results of the analysis. Therefore, if you identify an outlier in the data, you should examine the observation to understand why it is unusual. Correct any measurement or data entry errors. Consider removing data related to special causes and repeating the analysis. In these results, there are several outliers. In figure 15 this Biplot shows the following: The overall data has a large positive load on component 1, the point in the bottom right corner may be an outlier.

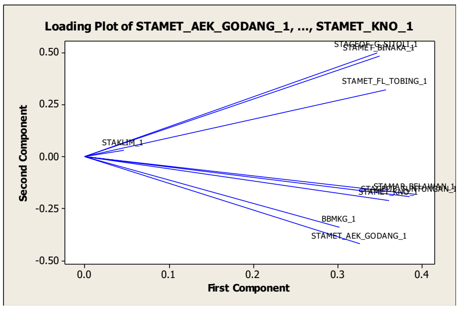

Figure 16. Loading Plot of Air Temperature

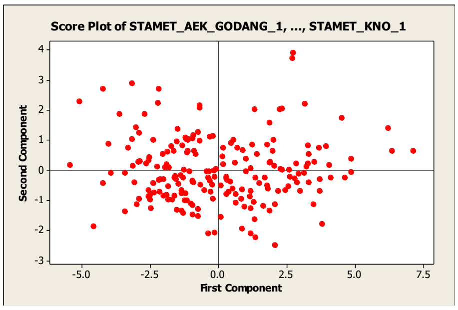

Figure 17. Score Plot of Air Temperature

In figure 16 Loading plots of air temperature aim to identify which variables have the greatest effect on each component. Loadings can range from -1 to 1. Loadings close to -1 or 1 indicate that the variable strongly influences the component. Loadings close to 0 indicate that the variable has a weak influence on the component. Loading plots can also help characterize each component in terms of variables. This plot has a large positive loading on component 1, so this component primarily measures stability. BBMKG Wil I, Stamet Aek Godang, Stamar Belawan and Stamet Kualanamu have a large negative weight on component 2 of around (-0.25) to (-0.5). In Figure 17, the Score plot of air temperature aims to assess the structure of the data and detect clusters, outliers, and trends. The clustering of data on the plot may indicate two or more separate distributions in the data. If the data follows a normal distribution and there are no outliers, the points will be randomly distributed around zero. In this score plot, the point in the bottom corner may be an outlier.

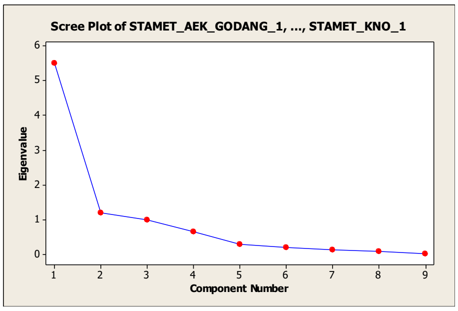

Figure 18. Scree Plot of Air Temperature

In Figure 18 this Scree plot of air temperature shows that the eigenvalues start to form a straight line after the second principal component. Therefore, the remaining principal components account for a very small proportion of the variability (close to zero) and may not be important.

Table 5. Principal Component Analysis Air Temperature

Principal Component Analysis: STAMET_AEK_G, STAMET_BINAK, STAKLIM_1, STAMET_FL_ (SUHU UDARA)

Eigenanalysis of the Correlation Matrix

Eigenvalue	6.2826	1.2373	0.6962	0.2872	0.2079	0.1281	0.0764	0.0508
Proportion	0.698	0.137	0.077	0.032	0.023	0.014	0.008	0.006
Cumulative	0.698	0.836	0.913	0.945	0.968	0.982	0.991	0.996
Eigenvalue	0.0335							
Proportion	0.004							
Cumulative	1.000							

Variable	PC1	PC2	PC3	PC4	PC5	PC6	PC7
STAMET_AEK_GODANG_1	0.307	-0.335	0.404	-0.569	-0.523	0.178	-0.019
STAMET_BINAKA_1	0.317	0.504	0.061	0.214	-0.299	0.112	-0.018
STAKLIM_1	0.364	-0.230	-0.290	0.097	-0.076	-0.139	0.356
STAMET_FL_TOBING_1	0.320	0.378	0.095	-0.586	0.544	-0.319	0.016
BBMKG_1	0.279	-0.229	0.715	0.485	0.257	-0.234	-0.030
STAGEOF_TUNTUNGAN_1	0.367	-0.166	-0.172	0.050	0.367	0.645	-0.497
STAGEOF_G_SITOLI_1	0.310	0.534	0.036	0.172	-0.271	0.094	-0.016

Variable	PC1	PC2	PC3	PC4	PC5	PC6	PC7
STAMAR_BELAWAN_1	0.374	-0.163	-0.216	0.071	0.151	0.166	0.633
STAMET_KNO_1	0.349	-0.213	-0.389	0.073	-0.198	-0.572	-0.472

Variable	PC8	PC9
STAMET_AEK_GODANG_1	-0.034	-0.009
STAMET_BINAKA_1	0.037	0.701
STAKLIM_1	0.753	-0.045
STAMET_FL_TOBING_1	0.064	0.034
BBMKG_1	0.003	-0.026
STAGEOF_TUNTUNGAN_1	0.091	-0.010
STAGEOF_G_SITOLI_1	-0.040	-0.709
STAMAR_BELAWAN_1	-0.574	0.029
STAMET_KNO_1	-0.295	0.017

In table 5, the cumulative proportion is 85 %, so the regression analysis is the first two principal components, PC1 and PC2. The score for the first principal component can be calculated from the standardized data using the coefficients listed below:

PC1 = (0.307* Stamet Aek Godang) + (0.317* Stamet Binaka) + (0.364* Staklim Sumut) + (0.32* Stamet FL Tobing) + (0.279* BBMKG) + (0.367* Stageof Tuntungan) + (0.31* Stageof Gunung Sitoli) + (0.374* Stamar Belawan) + (0.349* Stamet Kualanamu)
PC2 = (-0.335* Stamet Aek Godang) + (0.504* Stamet Binaka) + (-0.23* Staklim Sumut) + (0.378* Stamet FL Tobing) + (-0.229* BBMKG) + (-0.166* Stageof Tuntungan) + (0.534* Stageof Gunung Sitoli) + (-0.163* Stamar Belawan) + (-0.213* Stamet Kualanamu)

Table 6. *Regresi Logistic Ordinal*

REGRESI ORDINAL DBD TERHADAP PCT1, PCT2, PC1, PC2, PC3, PC4, PC5 (OBSERVASI)

Ordinal Logistic Regression: DBD versus PCT1, PCT2, ...

Link Function: Logit

Response Information

Variable	Value	Count
DBD	1	17
	2	111
	3	40
	Total	168

Logistic Regression Table

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	Upper
Const(1)	0.479196	11.5910	0.04	0.967			
Const(2)	4.00140	11.5965	0.35	0.730			
PCT1	-0.0259634	0.140007	-0.19	0.853	0.97	0.74	1.28
PCT2	0.273918	0.288864	0.95	0.343	1.32	0.75	2.32
PC1	-0.0006404	0.0008043	-0.80	0.426	1.00	1.00	1.00
PC2	0.0011183	0.0011304	0.99	0.323	1.00	1.00	1.00
PC3	0.0004959	0.0015812	0.31	0.754	1.00	1.00	1.00
PC4	0.0004095	0.0019992	0.20	0.838	1.00	1.00	1.00
PC5	-0.0035318	0.0016322	-2.16	0.030	1.00	0.99	1.00

In Table 6 Rainfall (PC1, PC2, PC3, P4 and PC5), Temperature (PCT1 and PCT2) and dengue fever classification using ordinal logistic regression equations at each station with the division of the short term (2011 - 2040), medium term (2041 - 2070) and long term (2071 - 2100) obtained chance equations:

$$P(Y=1) = \frac{e^{0.479196+(-0.0259634)PCT1+0.273918PCT2+(-0.0006404)PC1+0.0011183PC2+0.0004959PC3+0.0004095PC4+(-0.0035318)PC5}}{1+e^{0.479196+(-0.0259634)PCT1+0.273918PCT2+(-0.0006404)PC1+0.0011183PC2+0.0004959PC3+0.0004095PC4+(-0.0035318)PC5}}$$

$$P(Y=2) = \frac{e^{4.00140+(-0.0259634)PCT1+0.273918PCT2+(-0.0006404)PC1+0.0011183PC2+0.0004959PC3+0.0004095PC4+(-0.0035318)PC5}}{1+e^{4.00140+(-0.0259634)PCT1+0.273918PCT2+(-0.0006404)PC1+0.0011183PC2+0.0004959PC3+0.0004095PC4+(-0.0035318)PC5}}$$

$$P(Y=3) = 1 - P(Y=2)$$

CONCLUSION

Based on the results of the analysis and discussion: (1) The normal rainfall characteristics of North Sumatra Province generally range from 50 mm - 600 mm. The first rain peak is generally in March, while the second rain peak is generally in November. The second rain peak has a higher rainfall accumulation than the first rain peak. The first dry peak is generally in February, while the second dry peak is generally in July. Air temperature characteristics generally range from 24.5 ^{0}C - 28.5 ^{0}C, with the highest temperature occurring in May and the lowest occurring in November; (2) Analysis of the climate change index for the short-term (2011 - 2040), medium-term (2041 - 2070) and long-term (2071 - 2100) periods showed a consistent increase with a range of 0.4^{0}C, this value will affect the acceleration of the reproduction of the aedes aegypti mosquito as the cause of DHF. For rainfall projections, the changes are not consistent, there are months that experience an increase in rainfall and some that experience a decrease; (3) For the projected probability of DHF incidence in the future, there is still a high chance of belonging to the category of DHF high risk areas with a probability value of 0.82 - 0.99.

RECOMMENDATION

Based on the findings described, the recommendations are: (1) It is necessary to carry out quality control of dengue fever data continuously in North Sumatra Province; (2) Climate change (rainfall and air temperature) increases the chance of dengue fever. This research is basic information that in the future there needs to be appropriate policies to be able to minimize the incidence of dengue hemorrhagic fever, so that mitigation measures need to be taken to withstand the rate of climate change, and adaptation in dealing with the impacts that will occur, especially in the health sector; (3) It is necessary to conduct further research on the breeding parameters of Aedes Aegpty mosquitoes with more case studies so as to characterize the mitigation system in the regions in North Sumatra Province.

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