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DETERMINING RELATIVE HUMIDITY IN SURAKARTA CITY USING SEMIPARAMETRIC REGRESSION BASED ON FOURIER SERIES PENALIZED LEAST SQUARE

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Abstract: This study discusses the use of a semiparametric regression model approach based on Fourier series penalized least square estimator to determine the relationship between relative humidity and dew point in Surakarta city of Indonesia. The proposed method can address complex climate data patterns. A dataset of 100 observations was analyzed under three training data scenarios, for sample sizes of $n = 70$, $n = 80$, and $n = 90$. It yields the optimal Fourier coefficients of 2, 2, and 2, and smoothing parameter values of 0.018, 0.0124, and 0.039, with minimum generalized cross validation values of 4.410572, 4.191036, and 5.989094. The results of this study show

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that the proposed method provided good performance for prediction purpose with Mean Absolute Percentage Error (MAPE) values of 2.471245, 2.270436, and 2.93358. This means that category of the proposed method is highly accurate for prediction purpose. These results underline the ability of the proposed method to capture the inverse relationship between humidity and dew point. In other words, based on these results, this study highlights the effectiveness of the semiparametric regression model approach based on Fourier series penalized least square estimator in dynamic scenarios and recommends its application to other climate variables or regions to further evaluate its adaptability and resilience.

Keywords: relative humidity; dew point; semiparametric regression; Fourier series; penalized least square.

2020 AMS Subject Classification: 62G05, 62G08, 62P99, 65D10.

1. INTRODUCTION

Relative humidity is often a key topic of discussion when addressing weather conditions and the comfort of living environments. In the city of Surakarta, located in Indonesia's tropical region, this phenomenon is particularly relevant, especially during summer when high humidity levels can make the actual temperature feel much hotter than the recorded temperature [1]. This phenomenon not only affects human comfort but also has significant implications for energy consumption, particularly regarding air conditioning systems [2]. High humidity can increase the workload of cooling systems, thereby raising energy consumption and operational costs [3]. By better understanding the impact of relative humidity, interventions can be planned to mitigate its effects on daily life and the environment [4].

Meanwhile, the dew point, which indicates the temperature at which air becomes saturated and water vapor starts to condense, plays an essential role in understanding air moisture conditions [5]. For example, in Surakarta city of Indonesia, high dew point levels often signal the likelihood of heavy rainfall [6]. This information is highly beneficial for agricultural planning and disaster management, enabling early interventions for potential disasters [7]. In agriculture specifically, knowledge about possible rainfall can influence planting and harvesting schedules, as well as irrigation use, thereby enhancing the efficiency of water resource utilization [8].

Understanding the relationship between relative humidity and the dew point is crucial for illustrating climate change [9], where minor changes in these variables can result in significant shifts in weather patterns in Surakarta city [10]. Therefore, this study determines and analyzes this relationship between relative humidity and dew point. The dataset were collected from various geographical locations in Indonesia, including Surakarta city. We evaluated how this relationship varies with seasonal changes and geographical conditions [11]. The study aims to identify patterns or trends that may not be immediately apparent but have long-term impacts on the region's climate and hydro-meteorological conditions [12].

The analysis involves collecting extensive historical data from meteorological stations, including data from the National Aeronautics and Space Administration (NASA) website [13], and data specific to Surakarta. This data is analyzed to assess the relationship between relative humidity and dew point [14], focusing on how these variables interact during extreme weather conditions such as heat-waves or prolonged cold spells [15]. Through this analytical approach, the research aims to develop predictive models that can assist policymakers and the general public in better preparing for and responding to extreme and unpredictable weather phenomena [16]. One of the hypotheses tested in this study is that an increase in the dew point will significantly raise relative humidity, particularly in areas experiencing significant climate change like Surakarta [17]. This hypothesis is based on the principle that warmer air can hold more water vapor [18], which in turn leads to faster air saturation and reaching the dew point at higher temperatures [15]. By understanding this relationship, more effective mitigation strategies can be developed, such as using drought-resistant crops in agriculture or improving infrastructure to counteract the negative effects of increased humidity [19].

The study also highlights the importance of a better understanding of the relationship between relative humidity and dew point for more accurate weather and climate modeling [14]. This is particularly crucial for scientists and meteorologists to predict extreme weather conditions and plan effective interventions in response to climate change in Surakarta. The models developed can aid in designing more reliable early warning systems, thus enabling preventive actions before extreme weather events occur [20]. Additionally, the results of this analysis are expected to aid in developing more robust climate models, which can better predict and mitigate the impact of climate change on natural resources and society [21]. This includes water resource planning, agricultural strategies, and public health, particularly in areas vulnerable to extreme climate variability such as Surakarta city. Improved accuracy in these models can also facilitate more efficient and effective resource allocation, reduce economic losses, and enhance community resilience to climate change [22].

This study also includes an analysis of diurnal and seasonal variations in the relationship between relative humidity and dew point [23]. This provides in-depth insights into how the interaction between these two variables changes throughout the day and across different seasons, allowing for a better understanding of atmospheric processes in Surakarta. Such analysis is highly valuable for sectors heavily dependent on weather conditions, such as agriculture, tourism, and natural resource management, as it provides the necessary information to adapt their activities to changing weather conditions [24]. Thus, this study is not only relevant to atmospheric science and climatology but also has broad implications for environmental policy and adaptation strategies to climate change [25]. Understanding the complex relationship between relative humidity and dew point is key to addressing some of the most significant challenges faced by climate science and society today [14], particularly in Surakarta city. Through comprehensive and focused research, this study aims to generate knowledge that can be applied to help mitigate risks and improve quality of life in the face of increasingly complex weather and climate challenges [26].

Therefore, careful analysis and the use of cutting-edge technology in data collection and analysis in this study aim to provide answers to key questions that will help design more effective and sustainable solutions for adapting to and mitigating global climate change. This research hopes to make a valuable contribution to science and practice in managing natural resources and reducing disaster risks related to weather and climate in Surakarta city, ensuring that the adaptation and mitigation strategies developed are not only scientific but also practical and sustainable in the long term.

2. PRELIMINARIES

Previous research on estimating the semiparametric regression model using penalized least square (PLS) method has been carried out by [27–29]. Also, estimating semiparametric regression model using PLS method based on Fourier series has been carried out by [30–33]. Suppose that given a paired dataset $\left(y, t, u_1, u_2, \ldots, u_p\right)$ that follows a semiparametric regression model as follows [32]:

(1) $$y = \beta_0 + \beta_1 u_1 + \beta_2 u_2 + \ldots + \beta_p u_p + g(t) + \varepsilon.$$

Next, based on equation (1), for $i = 1,2, \ldots, n$, the paired observations $(y_i, t_i, u_{1i}, u_{2i}, \ldots, u_{pi})$ follows the following semiparametric regression model:

(2) $$y_i = \beta_0 + \beta_1 u_{1i} + \beta_2 u_{2i} + \ldots + \beta_p u_{pi} + g(t_i) + \varepsilon_i,\ \ i = 1, 2, \ldots, n.$$

We may write the equation (2) into a matrix notation as follows:

(3) $$\boldsymbol{y} = \mathbf{U}'\boldsymbol{\beta} + \boldsymbol{g}(\boldsymbol{t}) + \boldsymbol{\varepsilon}$$

where $\boldsymbol{y}$ represents a vector of response variables, $\boldsymbol{U}$ represents a matrix of predictor variables for parametric component, $\boldsymbol{\beta}$ is a vector of parameter for parametric component, $\boldsymbol{g(t)}$ is a vector of nonparametric regression functions, and $\boldsymbol{\varepsilon}$ is a vector of random errors that is Normally distributed, namely $\boldsymbol{\varepsilon} \sim \boldsymbol{N_n}(\mathbf{0}, \sigma^2\mathbf{I})$.

The nonparametric component $\boldsymbol{g(t)}$ can be approached by a Fourier series estimator. The Fourier series estimator has high flexibility, so that it is really good to use for volatile data. The function for Fourier series in previous study was introduced by [30–33]. It can be presented as follows:

(4) $$g(t_i) = \alpha_0 + \sum_{j=1}^{J}\left[c_j(cos(2\pi j t_i)) + d_j(sin(2\pi j t_i))\right].$$

According to [34], the PLS is a good optimization method to avoid over-fitting effect. Based on [30–33] the PLS method in the semiparametric regression based on Fourier series estimator is provided by the optimization function as follows:

(5) $$\min_{\beta \epsilon R^{r+1}, g \epsilon C(0,1)} \left[n^{-1}(\boldsymbol{y}^* - \boldsymbol{g(t)})'(\boldsymbol{y}^* - \boldsymbol{g(t)}) + \lambda \int_0^1 \left(\boldsymbol{g}^{(2)}(\boldsymbol{t})\right)^2 dt\right].$$

Based on equation (5), we obtain estimation of the semiparametric regression model (3) as follows:

$$\hat{\mathbf{y}}(\boldsymbol{u}, \boldsymbol{t}) = \mathbf{U}'\hat{\boldsymbol{\beta}} + \hat{\boldsymbol{g}}(\boldsymbol{t})$$

where $\hat{\boldsymbol{\beta}} = [\mathbf{U'VU}]^{-1}\mathbf{U'Vy}$; $\hat{\boldsymbol{g}}(\boldsymbol{t}) = \mathbf{H}(\mathbf{I} - \mathbf{HU}[\mathbf{U'VU}]^{-1}\mathbf{U'V})\mathbf{y}$; $\mathbf{y} = (y_1 \quad y_2 \quad \cdots \quad y_n)'$; $\mathbf{H} = \mathbf{F}(n^{-1}\mathbf{F'F} + \lambda^*\mathbf{D})^{-1}n^{-1}\mathbf{F}'$; $= (\mathbf{I} - \mathbf{H})'(\mathbf{I} - \mathbf{H})$; and

$$\mathbf{U}' = \begin{bmatrix} 1 & u_{11} & u_{21} & \cdots & u_{p1} \\ 1 & u_{12} & u_{22} & \cdots & u_{p2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & u_{1n} & u_{2n} & \cdots & u_{pn} \end{bmatrix}.$$

To get the best estimation, one of the most important things is to select an optimal bandwidth with associated Kernel function. This can be performed by using Generalized Cross-Validation (GCV) criterion with formula as follows [35]:

(6) $$\text{GCV} = \frac{n^{-1}\|(\mathbf{I} - \mathbf{UK} - \mathbf{L})\mathbf{y}\|^2}{\left(n^{-1}trace(\mathbf{I} - \mathbf{UK} - \mathbf{L})\right)^2}$$

where $= [\mathbf{U}'\mathrm{V}\mathbf{U}]^{-1}\mathbf{U'V}$; $\mathbf{L} = \mathbf{H}(\mathbf{I} - \mathbf{HU}[\mathbf{U}'\mathrm{V}\mathbf{U}]^{-1}\mathbf{U'V})$, and $\|.\|$ is a norm of a vector.

The error rate measurement to compare the best estimator is based on the value of the following Mean Absolute Percentage Error (MAPE) [36]:

(7) $$MAPE = \frac{1}{T}\sum_{t=1}^{T}\frac{|y_t - \hat{y}_t|}{y_t} \times 100\%$$

where T is the size of the sample, $\hat{y}_t$ is the value predicted by the model for time point t , and y is the value observed at time point t. The criteria for MAPE values are shown in Table 1 [36].

Table 1. MAPE Value Criteria

MAPE	**Definition**
< 10	Highly Accurate
10 – 20	Accurate
20 – 50	Reasonable
>50	Inaccurate

Hereinafter, the steps of statistical analysis in this study are as follows: (1). Collecting the data of relative humidity and dew point as the main variables; (2). Inputting the relative humidity data at time t and dew point data at time t for further analysis; (3). Creating the scatter plots between relative humidity at time t and dew point at time t, as well as between relative humidity at time t and time t, to understand the relationship patterns among variables; (4). Selecting a suitable semiparametric regression model to represent the relationship between relative humidity, dew point, and time t; (5). Applying the semiparametric regression model to analyze the relationship between relative humidity at time t, dew point at time t, and time t; (6). Optimizing the model using the GCV technique to select the best model parameters; (7). Using the MAPE criteria to assess accuracy of the model in predicting relative humidity; (8). Selecting the model with the best performance based on the MAPE evaluation results; (9). Using the selected model to make future predictions of relative humidity and validate the results using additional data; (10). Analyzing the prediction results and report the identified patterns in the relationship between relative humidity and dew point from the model.

The following flow-chart (see Figure 1) outlines the process for determining and analyzing relative humidity and dew point data. The process begins with data collection and input, followed by scatter plot creation to visualize the relationships between relative humidity, dew point, and time. A semiparametric regression model is then selected, optimized using GCV, and evaluated with MAPE. The best-performing model is applied for future predictions, and the results are analyzed to identify patterns in relative humidity and dew point data.

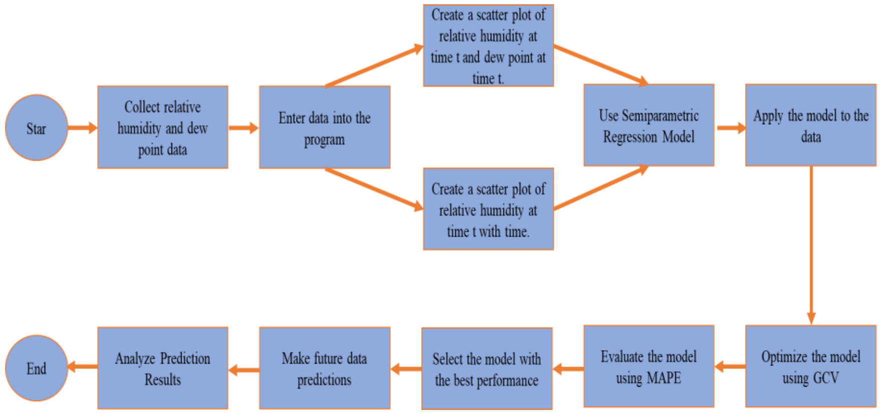


Figure 1. Flow-chart of Determining Relative Humidity Variations in Surakarta City.

3. Main Results

The data used in this study consists of 100 observations which are divided into training data and testing data. The distribution of training data is sequentially divided into 70, 80, and 90 data points. Meanwhile, the testing data is sequentially distributed into 30, 20, and 10 data points. The first step in this study is to examine the relationship between relative humidity at 2 meters and dew point at 2 meters for the three sets of training data. This examination is conducted using correlation statistical analysis, which aims to determine the strength and direction of the relationship between of two variables: relative humidity at 2 meters, denoted as RH2M, and dew point at 2 meters, denoted as T2MDEW. To measure the correlation, the Pearson correlation coefficient is used, providing values between -1 and 1. A positive value indicates a positive correlation, while a negative value indicates a negative correlation. The following figure (see Figure 2) illustrates the correlation between RH2M and T2MDEW.

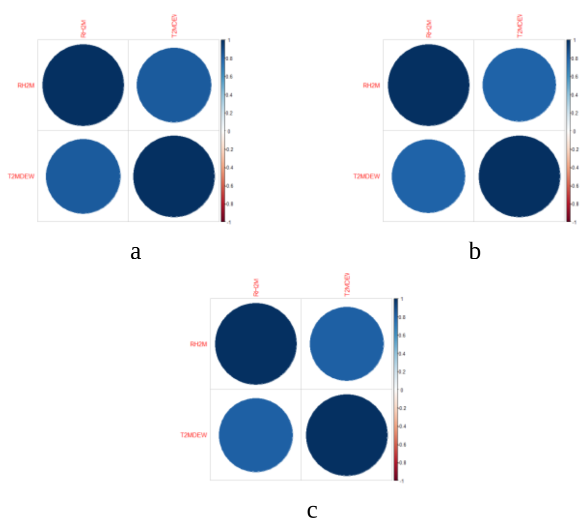


Figure 2. Correlation Plots of : (a). 70 Training Data; (b). 80 training data. (c) 90 training data.

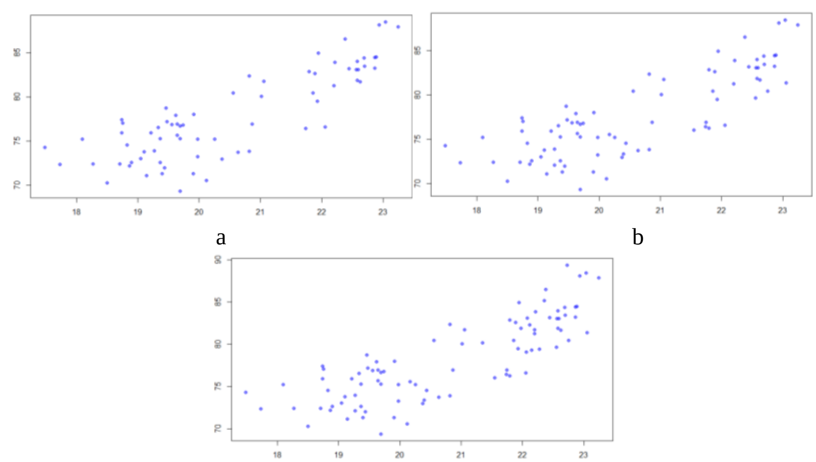
Based on Figure 2, the following table presents the correlation values derived from the correlation matrix between RH2M and T2MDEW.

Table 2. Correlation Matrix For Each N.

	N =70		**N = 80**		**N = 90**	
	RH2M	T2MDEW	RH2M	T2MDEW	RH2M	T2MDEW
RH2M	1.0000000	**0.8341989**	1.0000000	**0.8072026**	1.0000000	**0.8140003**
T2MDEW	0.8341989	1.0000000	0.8072026	1.0000000	0.8140003	1.0000000

In Table 2, correlation values of 0.8341989, 0.8072026, and 0.8140003 present the correlation between T2MDEW and RH2M. These values indicate that the relationship between T2MDEW and RH2M is positive, meaning that the higher the humidity, the more the dew point increases.

The next step is to create a time-series plot for each training dataset, which includes relative humidity and dew point, to examine the data distribution. The scatter-plots of relative humidity and dew point are given in Figure 3.



a b c

Figure 3. Scatter-plots of Relative Humidity Versus Dew Point for: (a). 70 training data, (b). 80 training data, and (c). 90 Training data.

The scatter-plots in Figure 3 indicate that all three training datasets exhibit a pattern following a linear assumption, with a downward-sloping line, suggesting a negative parametric relationship between RH2M and T2MDEW in the three datasets. To reinforce this assumption, a linearity test was conducted using a linear regression model, and the results are presented in Table 3.

Table 3. Significance Test of Linear Model Parameters.

	N = 70	**N = 80**	**N = 90**
	Pr(>|t|)	Pr(>|t|)	Pr(>|t|)
(Intercept)	<2e-16 ***	<2e-16 ***	<2e-16 ***
RH2M	<2e-16 ***	<2e-16 ***	<2e-16 ***

From the Table 3, for each training data comparison, the coefficient values are less than significance level value ($\alpha = 0.05$). This indicates that the linear model coefficients are significant. It can be concluded that there is a linear relationship between the variables of RH2M and T2MDEW. Next, we create a scatter-plot between RH2M and time, and the results are given in Figure 4.

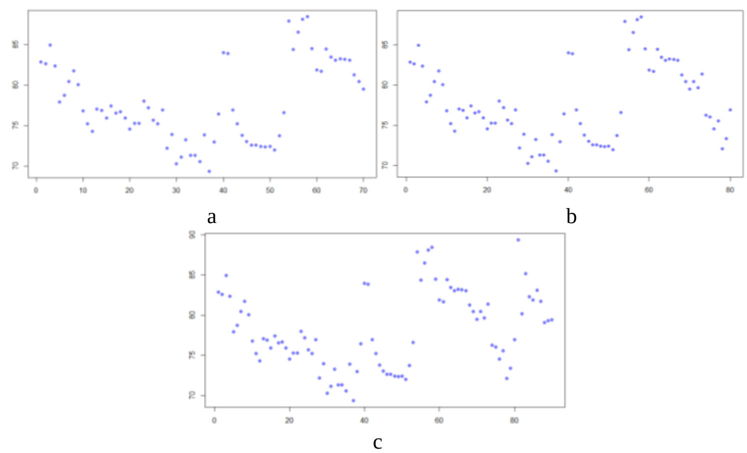


Figure 4. Scatter-Plots of RH2M versus Time for : (a). 70 training data, (b). 80 training data, and (c). 90 training data.

Based on Figure 4, the scatter plot between RH2M and Time does not appear to form a specific pattern. This indicates that a nonparametric regression approach can be utilized. Therefore, knowing that the functional relationship between RH2M and T2MDEW is linear, while the functional relationship between RH2M and time does not exhibit a specific pattern, a semi-parametric regression approach is used in this case. This approach involves finding the minimum value of GCV using the Fourier series estimator. In this study, the Fourier series coefficient limit is set to 15. The GCV plots for each Fourier coefficient for the three training dataset are given in Figure 5.

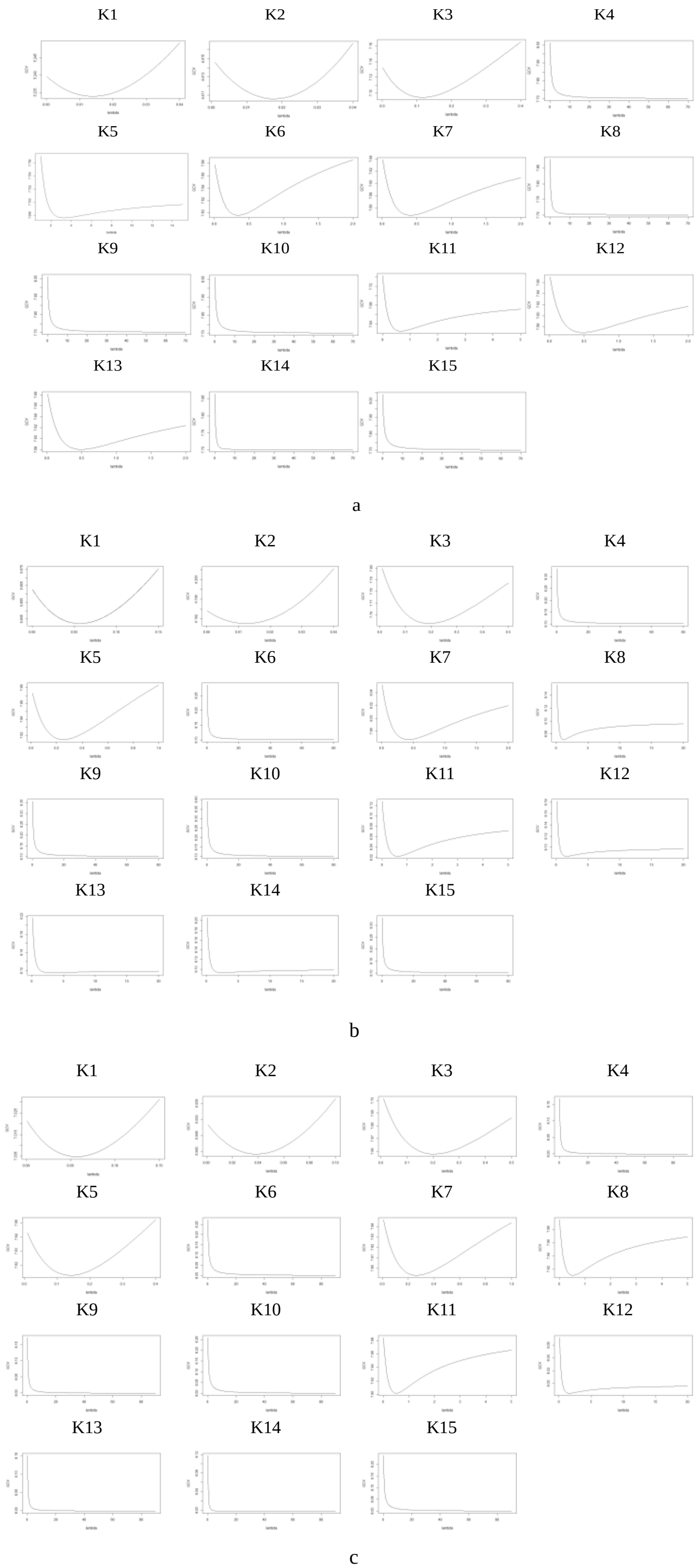


Figure 5. Plots of GCV Values for : (a). $n = 70$, (b). $n = 80$, and (c). $n = 90$.

Based on Figure 5, it can be observed that each Fourier coefficient has a minimum GCV value and the corresponding lambda for each other. The GCV and lambda values for each Fourier coefficient are presented in Table 4.

Table 4. GCV and Lambda values K = 1 to K = 10 for each sample size (n).

	***n* = 70**			***n* = 80**			***n* = 90**	
K	GCV	Lambda	K	GCV	Lambda	K	GCV	Lambda
1	5.233924	0.0139	1	6.842198	0.0563	1	7.004737	0.057
2	4.410572	0.018	2	4.191036	0.0124	2	5.989094	0.039
3	7.094387	0.116	3	7.752289	0.19	3	7.65772	0.2
4	7.704155	69	4	8.101509	79	4	7.999226	89
5	7.697598	3.3	5	7.81449	0.25	5	7.512814	0.14
6	7.496283	0.34	6	8.100980	79	6	8.000358	89
7	7.547716	0.41	7	7.967005	0.43	7	7.793134	0.27
8	7.701461	69	8	8.071495	1.2	8	7.910492	0.53
9	7.703256	69	9	8.101751	79	9	7.999180	89
10	7.703289	69	10	8.102196	79	10	8.000171	89
11	7.625082	0.67	11	8.022154	0.62	11	7.901593	0.51
12	7.569197	0.48	12	8.084105	1.6	12	7.984896	1.7
13	7.580269	0.49	13	8.095577	3.2	13	7.998925	89
14	7.701049	69	14	8.092627	2.5	14	7.998550	89
15	7.703692	69	15	8.101425	79	15	7.999927	89

Based on the Figure 5 and Table 4, it can be seen that the GCV value for each Fourier coefficient in the training data reaches its minimum for the first Fourier coefficient for $n = 70$, the second Fourier coefficient for $n = 80$, and the second Fourier coefficient for $n = 90$. It can be concluded that the best semiparametric model for $n = 70$ is found at the second Fourier coefficient with a minimum GCV value of 4.410572 and lambda of 0.018. For $n = 80$, the best model is at the second Fourier coefficient with a minimum GCV value of 4.191036 and lambda of 0.0124. For $n = 90$, the best model is at the second Fourier coefficient with a minimum GCV value of 5.989094 and lambda of 0.039. The best semi-parametric model based on the minimum GCV characteristics using the Fourier series estimator can be written as follows:

For $n = 70$, we have:

$$\begin{aligned} y_i = 1.086104\mathrm{E} - 15 + 2.612595\, u_{1i} + 24.22774 + 0.01392463 \cos(2\pi t_i) \\ + 0.0003796424 \sin(2\pi t_i) + (-0.001884484) \cos(4\pi t_i) \\ + 0.001011526 \sin(4\pi t_i) \end{aligned}$$

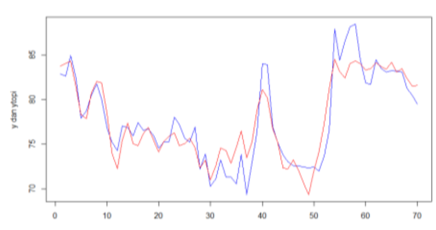
For $n = 80$, we have:

$$y_i = -1.461667\mathrm{E} - 16 + 2.62754\, u_{1i} + 23.48827 + 0.009920683 \cos(2\pi t_i) + 0.0005859833\, \sin(2\pi t_i) + 0.004703738 \cos(4\pi t_i) + 0.0008128012 \sin(4\pi t_i)$$

For $n = 90$, we have:

$$y_i = -2.160557\mathrm{E} - 15 + 2.767361\, u_{1i} + 20.63976 + 0.008129007 \cos(2\pi t_i) + 0.0003912754\, \sin(2\pi t_i) + 0.004112282 \cos(4\pi t_i) + 0.000621312 \sin(4\pi t_i)$$

After obtaining the best semi-parametric regression model for each training dataset, the next step is to evaluate the model's accuracy and performance. This evaluation uses the Fourier series estimator with the Mean Absolute Percentage Error (MAPE) as the metric. MAPE measures the percentage prediction error, where lower values indicate higher accuracy. This analysis aims to ensure that the resulting model effectively captures the relationship between variables. Additionally, the Fourier coefficients from the best model will be included to demonstrate the contribution of each component in improving accuracy. Plots of actual and prediction values using the best Fourier coefficients are given in Figure 6.



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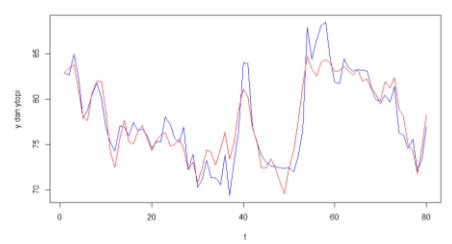

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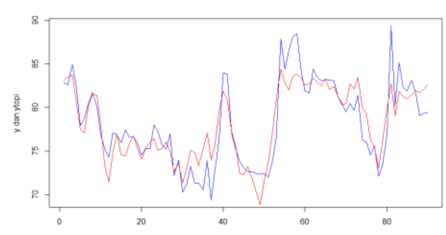

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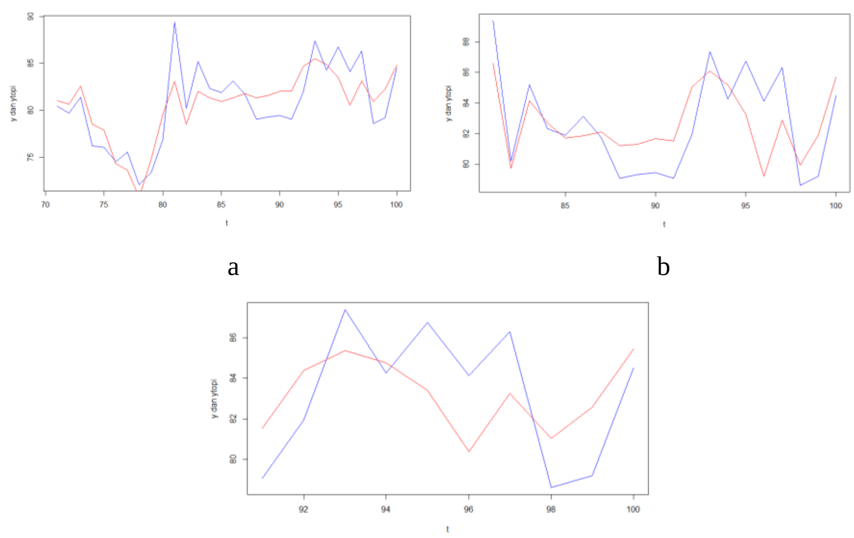
Figure 6. Plots of Actual and Prediction Values for: (a). $n = 70$, (b). $n = 80$, and (c). $n = 90$.

Based on Figure 6, it can be seen that the plots of prediction model provide good performance. For each n with the best Fourier coefficients, the model shows a strong ability to explain data variability and a low error rate in the testing data. Therefore, the semiparametric regression model approach based on Fourier series penalized least square estimator can be used to evaluate predicting performance by comparing the actual and prediction values. Plots of the actual and prediction values are given in Figure 7.



a b

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Figure 7. Plots of Actual and Prediction Values for: (a). $n = 30$, (b). $n = 20$, and (c). $n = 10$.

It can be seen in Figure 7 that the prediction values do not much different from the actual values, where this assumption is also reinforced by obtaining the MAPE values as presented in Table 5.

Table 5. MAPE Values for Each n.

$n = 30$	$n = 20$	$n = 10$
2.471245	2.270436	2.93358

4. CONCLUSIONS

In this study we propose a new method that can address complex climate data patterns by using a semiparametric regression model approach based on Fourier series penalized least square estimator to determine the relationship between surface relative humidity represented by RH2M and dew point represented by T2MDEW in Surakarta city of Indonesia. By combining parametric and nonparametric components, the model effectively handles fluctuating data patterns in three training scenarios ($n = 70, 80, 90$). The estimation results show minimal differences between the actual and predicted values, indicating reliable performance. This model successfully made good predictions for testing data sizes of 30, 20, and 10, with MAPE values of 2.471245, 2.270436, and 2.93358, respectively. These results highlight the effectiveness of the semiparametric regression model approach based on Fourier series penalized least square estimator in modeling the inverse relationship between humidity and dew point while maintaining accuracy in analyzing complex data. Future research could extend this approach to other regions or variables, enhancing its application for climate-related studies and policy development.

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CONFLICT OF INTERESTS

The authors confirm that there is no conflict of interests.

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