Forecasting Humidity in Sragen Using Semiparametrik Regression Based on Penalized Fourier Series Estimator

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Abstract. This study examines the use of a semiparametric regression model with a Pe-nalized Least Squares (PLS)-based Fourier Series estimator to analyze the re-lationship between relative humidity and surface temperature in Sragen Re-gency. Combining parametric and nonparametric components, the model ef-fectively addresses complex climate data patterns. A dataset of 100 observa-tions was analyzed under three training data scenarios N = 70, N = 80, and N = 90, yielding optimal Fourier coefficients of 6, 1, and 1. The resulting Mean Absolute Percentage Error (MAPE) values were 1.496268, 1.58244, and 1.627225, with corresponding minimum Generalized Cross Validation (GCV) values of 0.3462398, 0.3863733, and 0.3866026. The model demon-strated its forecasting capability for the next 10 periods using test data sizes of N = 30, N = 20, and N = 10, achieving MAPE values of 1.526222, 1.354613, and 1.055469. These results underscore the model's ability to cap-ture the inverse relationship between humidity and temperature. The study highlights the Fourier-based semiparametric approach's effectiveness in dy-namic scenarios and recommends applying it to other climate variables or re-gions to further evaluate its adaptability and robustness.

Keywords: Semiparametric, Fourier Series Estimator, Relative Humidity, Penalized Least Square.

1. Introduction

Drastic climate change is a phenomenon that we are currently experiencing in various countries in the world, not apart from Indonesia. Climate change in Indo-nesia has a huge impact because it causes several adverse natural phenomena such as natural phenomena such as floods, landslides, fires, earthquakes, volca-noes erupting and many others [1]. Basically, climate change is caused by the greenhouse effect by an increase in the concentration of gases in the air, one of which is carbon dioxide (CO2) [2]. An increase in the concentration of CO2 gas causes the earth's surface temperature to increase drastically [3]. This is because the concentration level of CO2 gas contained in the air plays a role in the per-centage level of air humidity, if the percentage level of humidity in the air is smaller, the temperature of the earth's surface will rise higher [4].

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Facing the challenge of climate change requires a comprehensive and integrat-ed action from various sectors in society. A comprehensive and integrated action in addressing the impacts of climate change depends not only on how to reduce the level of gas emissions due to the greenhouse effect, but also on adaptation to the changes that occur [5]. Adaptations that can be made, such as increasing the resilience of agricultural systems by using plant varieties resistant to high earth surface temperatures, efficient and effective water management so that droughts do not occur, and infrastructure improvements to prepare for natural disaster risk management that may occur [6]. In addition, sustainable environmental manage-ment, such as reforestation and land management in the right way, is highly rec-ommended as a countermeasure, because it can reduce its negative impacts [7]. As we know that tackling before an event occurs is more effective than tackling after an event occurs.

The high temperature of the earth's surface is now a very troubling complaint for the community, because it has an impact on many sectors in Indonesia. Due to the high temperature of the earth's surface, several existing sectors such as the agriculture, health, environment, and so on sectors are affected [8] [9]. The high temperature of the earth's surface in the agricultural sector causes irregular rain-fall patterns so that the level of rainfall is very small. This has an impact on the agricultural sector by disrupting the growing season and potentially reducing crop yields [10]. As a result, local food security has a significant decrease. Fur-thermore, the rise in the earth's surface temperature also affects the health sector because extreme heat causes skin problems. High earth surface temperatures can also cause dehydration and other diseases due to high temperatures [11]. In addi-tion, climate change can affect the spread of diseases such as dengue fever. In terms of the environmental sector, the high temperature of the earth's surface causes prolonged drought which has an impact on fires in several Indonesian districts [12]. The impact of these fires usually occurs in places such as agricul-ture, plantations, settlements, and forestry. The high temperature of the earth's surface is one of the obstacles that must be handled appropriately, and one of the factors that affect the temperature of the earth's surface is the percentage of air humidity level. The relationship between the earth's surface temperature and the percentage of air humidity level is an inverse relationship because the lower the percentage of air humidity level, the higher the earth's surface temperature, and vice versa [13]. On the other hand, the earth surface temperature data obtained is in the form of time sequence data so that the time variable is also chosen as one of the variables in this study.

Sragen Regency, located in Central Java Province, Indonesia, is one of the are-as that feels the direct impact of the high earth's surface temperature [14]. Various sectors in Sragen district, including agriculture, health, and the environment are affected by the high temperature of the earth's surface. Sragen is geographically dominated by agricultural areas, which are very vulnerable to extreme earth sur-face temperatures. This has a direct effect on agricultural productivity and the availability of water for irrigation [15]. Not only that, the people of Sragen face an increased risk of increasing the incidence of weather-related diseases, due to the high temperature of the earth's surface. One of them is dengue fever, which tends to increase during and after the rainy period due to the breeding of the Aedes aegypti mosquito [16]. The impact of high earth surface temperatures is also very visible in the environmental sector in Sragen. One of the impacts on the environ-mental sector is the occurrence of fires in the Sragen area due to the high temper-ature of the earth's surface, so that many plants die and facilitate the occurrence of fires [17].

The above description is the main reference in taking the case to be re-searched, because it really needs to be researched immediately so that the prob-lems that occur can get the right solution. Based on this urgency, an in-depth analysis is needed to model the functional relationship between the earth's sur-face temperature (as the Y response variable) and the percentage level of air hu-midity (as the X predictor variable) using statistical modeling techniques. There are three main types of regression models, namely parametric, nonparametric, and semiparametric regression models that can be used to determine the func-tional relationship between response variables and predictors. The parametric regression model assumes that the functional relationship between the response variable and the predictor follows a certain pattern [18]. In contrast, nonparamet-ric regression models do not assume a specific form of curve pattern on the func-tional relationship between response variables and predictor variables [19] [20]. In the nonparametric regression model, it has high flexibility because the func-tional relationship of the regression curve is considered smooth and can be esti-mated using certain smoothing methods based on data patterns [21]. Furthermore, there is also a semiparametric regression model which is a combination of para-metric and nonparametric models, which has high flexibility in analyzing the functional relationship of the regression curve [22] [23]. In the semiparametric regression model, there are parametric and nonparametric regression where some of the smoothing techniques in nonparametric regression that are often used in-clude kernel estimators [24], linear locals [25], local polynomials [26], splines [27], and fourier series [28].

One of the nonparametric regression approaches used to overcome fluctuating data patterns is to rise high or fall far in the range of values such as the shape of the sine and cosine curve patterns, namely the fourier series estimator [29]. In temperature data where there is a fluctuation around a high value and at a certain time then decreases to a much lower value, it is very suitable for use in a fourier series estimator. The repeating data pattern is very consistent with the fourier series estimator, in the form of repetition of different independent or independent variables [30]. In the optimization of the fourier series estimator, there are several optimization methods that can be used, namely Least Squares (LS) [31], Penalized Least Squares (PLS) [32], Weighted Least Squares (WLS) [28]. PLS is an optimi-zation method that provides smoothing components to the LS method with opti-mization criteria that combine data matching with the smoothness of the curve. PLS estimation is carried out to balance data adjustments and avoid excessive roughness [33]. Basically, PLS is very good to use because in general, General-ized Cross Validation (GCV) cannot select really good parameters because the overfitting effect is ignored in the resulting model [34]. Based on this, penalized in an estimation method is an optimization that can be used to overcome overfit-ting [35].

The application of Fourier series estimators on semiparametric regression us-ing PLS optimization has been applied in various cases and shows significant potential in overcoming the challenges faced by data that have fluctuating pat-terns [36]. PLS optimization is very effective in balancing the need to follow data accuracy by avoiding overfitting [37]. Fourier series estimators, with their ability to model data fluctuations as trigonometric functions, are well suited for data that show repetitive patterns such as the Earth's surface temperature. This capability is particularly relevant for the study of climate change, where parameters such as temperature and humidity have clear seasonal patterns [38].

Further research that integrates the Fourier series approach to semiparametric regression using PLS optimization is expected to provide a more flexible method for understanding and forecasting changes in the earth's surface temperature. This is not only important for academic purposes but also for policymaking, where data-driven decisions and accurate forecasting are urgently needed to plan and implement adaptation and mitigation strategies.

2. Preliminaries

Previous research on estimating semiparametric regression model using fourier series based on PLS has been carried out [14].

Given data pairs $(y, g(t), u_1, u_2, \ldots, u_p)$ follow regression model [18]

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

based on Eq. (1) i with observation then variable as $(y_i, t_i, u_{1i}, u_{2i}, \ldots, u_{pi})$ and the regression model follow

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

Eq. 2 can be written to matrix

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

where _y is vector respon variable with i observation, $\boldsymbol{U}$ is matric predictor variable for parametric component, $\underline{\beta}$ is vector parameter for parametric component, $\underline{g}(t)$ is vector nonparametric regression function and $\underline{\varepsilon} \sim \boldsymbol{N_n}(\mathbf{0}, \sigma^2\mathbf{I})$.

Parametric component _g (t) can be approach by fourier series estimator. The fourier series estimator have high fleksibelity, then really good to use in volatile data. The function for fourier series in previous study introduced by [8], and can be written as:

$$\hat{g}(t_i) = \gamma t_i + \frac{\alpha_0}{2} + \sum_{k=1}^{K} (\alpha_k \cos kt_i + b_k \sin kt_i) \tag{4}$$

Because the goal is for prediect, we use Mean Absolute Percentage Error (MAPE) for looking the best model:

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\frac{|y_t - \hat{y}_t|}{y_t} \quad (5)$$

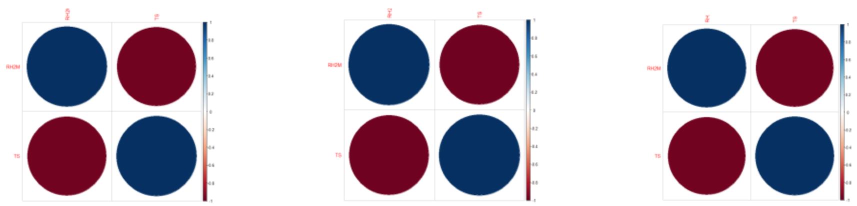
where T is the size of the sample, $\hat{y}_t$ is the value predicted by the model for time point t and y is the value observed at time point t. The criteria for MAPE values are shown in the following Table 1 [29].

Table 1. MAPE Value Criteria.

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

3. Results and Discussions

The data used in this study is 100 data, which is divided into training data and data testing. For the distribution of training data, it was divided consecutively, namely 70, 80, and 90 data. As for the distribution of testing data, it is divided consecutively, namely 30, 20, and 10 data. The first thing in this study is to check the relationship or correlation between temperature and relative humidity on the three training data. This check was carried out using statistical analysis of correlation which aims to determine the strength and direction of the relationship between the two temperature variables symbolized by TS and relative humidity symbolized by RH2M. To measure correlation, the Pearson correlation coefficient is used, which gives a value between -1 to 1. Positive values indicate a positive correlation, while negative values indicate negative correlations. Here is a picture showing the correlation between relative humidity and temperature:



a b c

Figure 1. (a) Correlation image of relative humidity and temperature training data 70. (b) Correlation image of relative humidity and temperature training data 80. (c) Correlation image of relative humidity and temperature training data 90.

Based on figure 1 The following are the results of the correlation values in the form of a table based on the confusion matrix between temperature variables and relative humidity:

Table 2. Confusion Matrix for each N.

	N =70		**N = 80**		**N = 90**	
	RH2M	TS	RH2M	TS	RH2M	TS
RH2M	1.0000000	-0.9700351	1.0000000	-0.9656242	1.0000000	-0.9640268
TS	-0.9700351	1.0000000	-0.9656242	1.0000000	-0.9640268	1.0000000

In table 2, it can be seen that the image tends towards blue and red, with the correlation values shown in the matrix -0.9700351, -0.9656242, and -0.9640268, which show a correlation between temperature and relative humidity. A negative correlation value means that the relationship between temperature and relative humidity is inversely proportional, that is, when the temperature rises, the relative humidity value will decrease and vice versa.

The next stage is to form a time series plot on each training data, namely relative humidity with temperature to check the distribution of data. Here's a scatter of the temperature plot symbolized by TS and the relative humidity symbolized by RH2M:

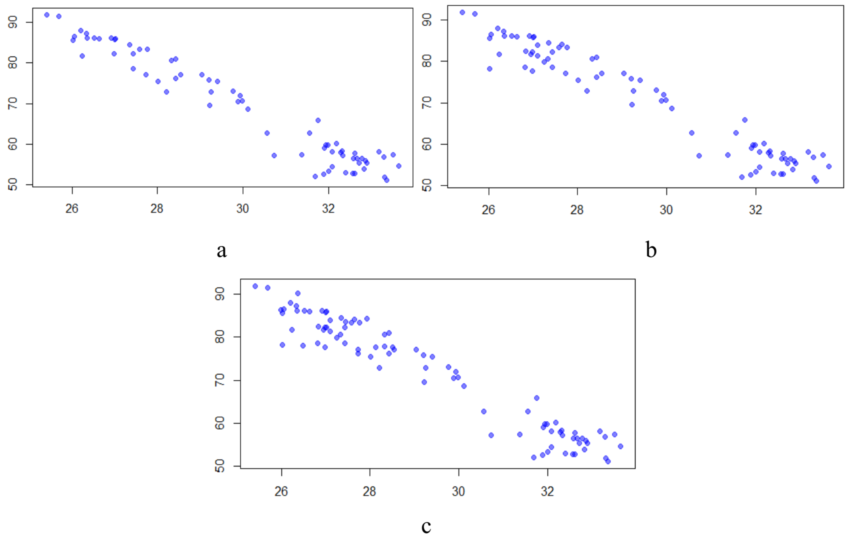


Figure 2. (a) Scatter plot plots of relative humidity and temperature training data 70. (b) Scatter plot plot of relative humidity and temperature training data 80. (c) Scatter plot of relative humidity and temperature training data 90.

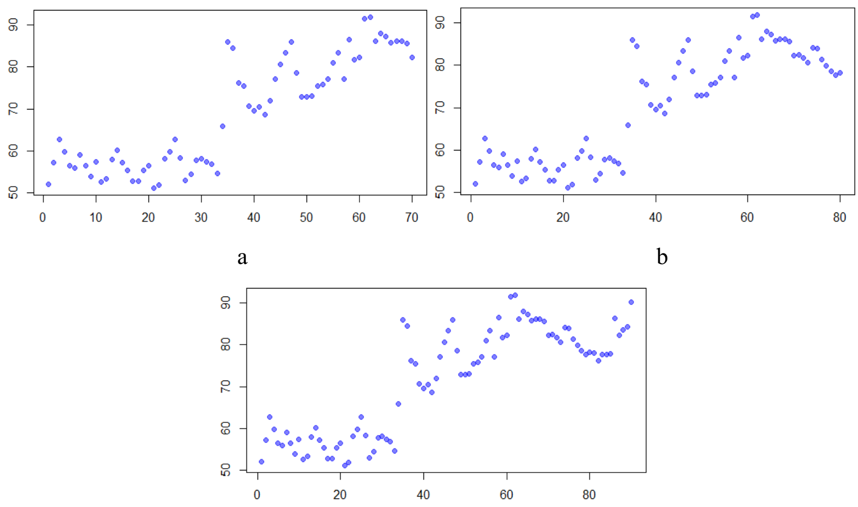
The results of the scatter plot in figure 2 show that the three training data have a pattern that follows a linear assumption with a descending line which means showing the parametric negative relationship between the three training data between relative humidity and temperature. To strengthen the assumption, a linearity test was carried out by following a linear regression model and the following results were obtained:

Table 3. Linear model parameter significance test.

	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 ***

It can be seen in the table above for each training data competition that the coefficient value is less than α=0.05 the meaning of the significant linear model coefficient. It can be concluded that the variables between relative humidity and temperature have a linear relationship.

Next, we create a scatter plot between relative humidity and time, and the scatter plot is shown in the image below:

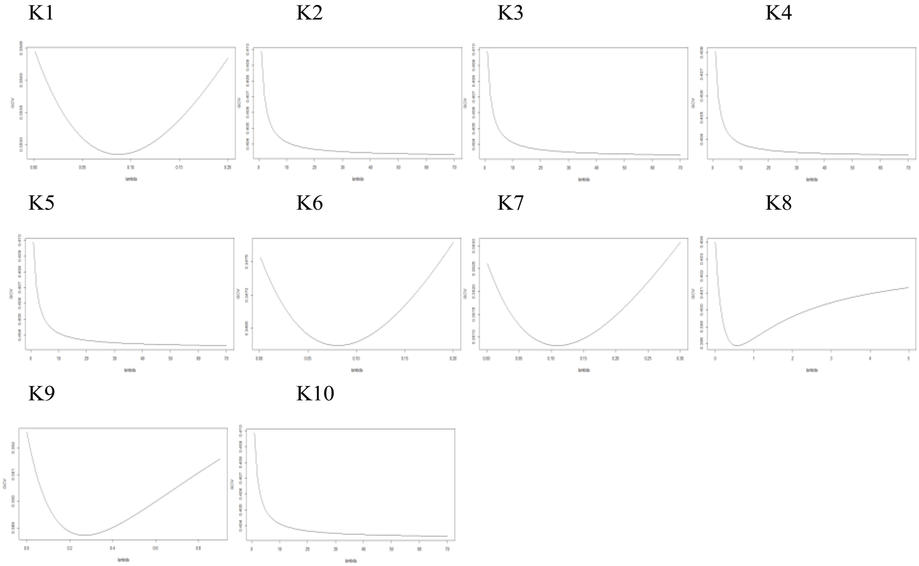


c

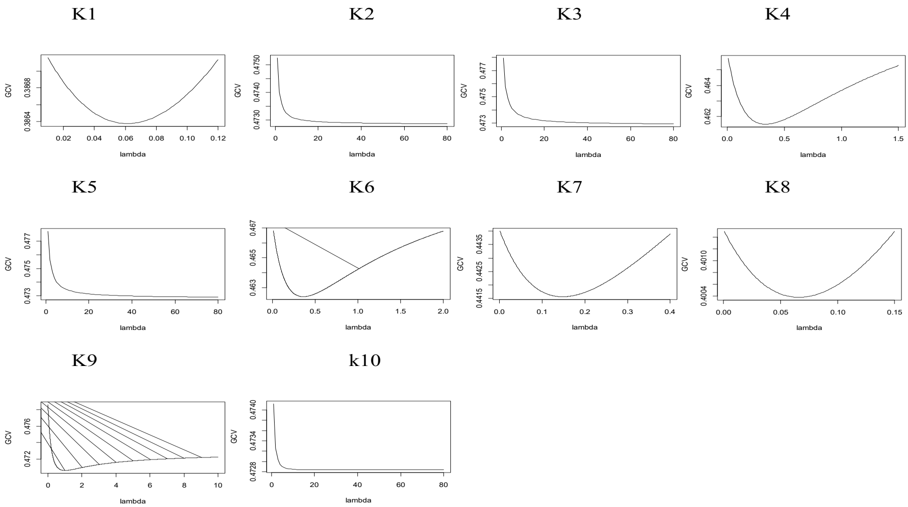
Figure 3. (a) Scatter plots of relative humidity and time data training 70. (b) Scatter plots of relative humidity and time data training 80. (c) Scatter plots of relative humidity and time training data 90.

Based on Figure 3, the scatter plot between relative humidity and time does not seem to form a specific pattern. This indicates that a nonparamteric regression approach can be used. Therefore, knowing that the functional relationship between relative humidity and temperature is linear while the functional relationship between relative humidity and time does not form a specific pattern, the semi-parametric regression approach is used in this case. This approach involves finding the minimum Generalized Cross Validation (GCV) value using a Fourier series estimator. In this study, the limit for the

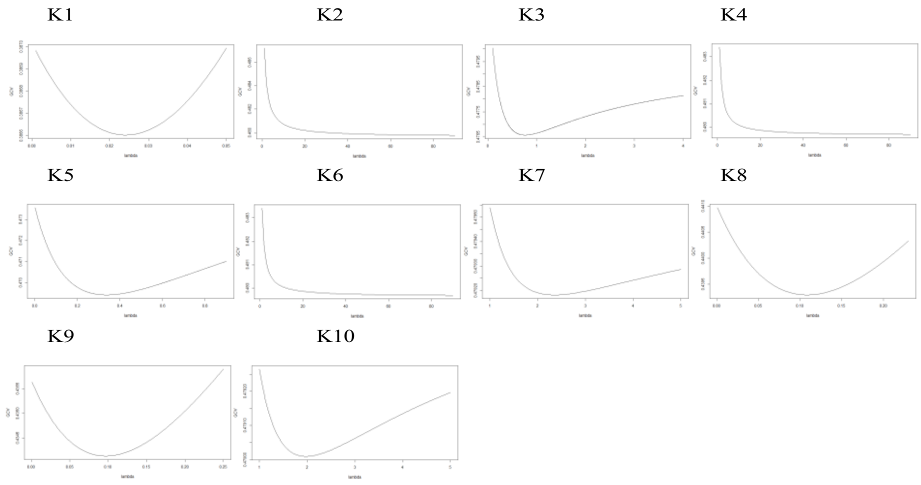
Fourier series coefficient is used as much as 10. Below is the GCV plot for each Fourier coefficient of all three training data:



(a)



(b)



(c)

Figure 4. (a) Plot GCV N=70. (b) Plot GCV N=80. (c) GCV plot N=90 for K=1 until K=10

Based on figure 4 it can be seen that each fourier coefficient has its minimum GCV value and the corresponding lambda respectively. Here are the values of each GCV and lambda on each of the fourier coefficients:

Table 4. GCV and Lambda values K = 1 to K = 10 for N each.

N = 70			**N = 80**			**N = 90**		
K	GCV	Lambda	K	GCV	Lambda	K	GCV	Lambda
1	0.352845	0.087	1	0.3863733	0.061	1	0.3866026	0.024
2	0.4033435	69	2	0.4728692	79	2	0.4797619	89
3	0.4032046	69	3	0.4729304	79	3	0.4765743	0.762
4	0.4032947	69	4	0.4615144	0.34	4	0.4796852	89
5	0.4032578	69	5	0.4729242	79	5	0.4694168	0.336
6	0.3462398	0.081	6	0.4623881	0.36	6	0.4797452	89
7	0.3608138	0.109	7	0.4415578	0.148	7	0.479182	2.4
8	0.3978887	0.561	8	0.4003805	0.066	8	0.4392967	0.109
9	0.3887199	0.27	9	0.4706223	0.999	9	0.4341334	0.097
10	0.4033518	69	10	0.4728427	79	10	0.4790095	1.98

Based on the Figure and Table above, that the GCV value for each Fourier coefficient in the training data has a minimum GCV value at the sixth fourier coefficient for N=70, then the fourier coefficient one for and the fourier coefficient one for .N=80N=90 It can be concluded that the best semiparametric model to lie in is the sixth Fourier coefficient with a minimum GCV value N=70 of 0.3462398 and lambda 0.081. Then to lie in the first fourier coefficient with a minimum GCV value N=80of 0.3863733 and lambda 0.061. As for the first fourier coefficient with a minimum GCV value N=90 of

0.3866026 and lambda 0.024. The best semiparametric model based on the minimum GCV characteristics using a Fourier series estimator can be written as follows:

$$N = 70$$

$$\begin{aligned} y_i = 8.998 + 0{,}182\, u_{1i} + 45.327 + 42{,}581 + 0.313018\, cos\,(2t_i) \\ + 0.003381742\, sin(2t_i) + 0.004513696\, cos\,(4t_i) \\ + 0.000971543\, sin(4t_i) + 0.000704646\, cos\,(6t_i) \\ + 0.001002052\, sin(6t_i) + 0.100582\, cos\,(8t_i) \\ + 0.01050146\, sin(8t_i) + 0.009831979\, cos\,(10t_i) \\ + 0.001528712\, sin(10t_i) + 0.00070959\, cos\,(12t_i) \\ + 0.001124252\, sin(12t_i) \end{aligned}$$

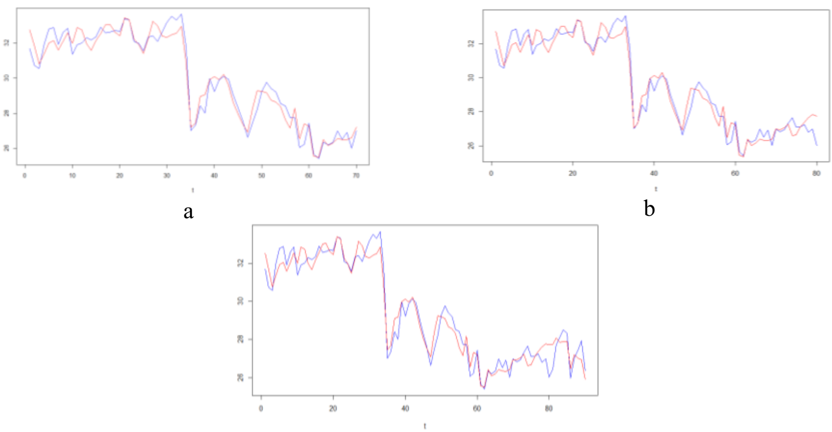
$$N = 80$$

$$y_i = 3.146 + 0.191\, u_{1i} + 44.863 + 43.060 + 0.3651031\, cos\,(2t_i) + 0.1051078\, sin(2t_i)$$

$$N = 90$$

$$y_i = 1.339 + 0.171\, u_{1i} + 37.779 + 41.631 + 0.24974\, cos\,(2t_i) + 0.5651011\, sin(2t_i)$$

After obtaining the best semiparametric regression model on each training data, the next step in this study is to measure the accuracy and performance of the semiparametric regression model using a Fourier series estimator. This is done using the Mean Absolute Percentage Error (MAPE) for each of the best semiparametric regression models obtained. MAPE measures forecasting error in the form of percentages, with smaller values indicating higher accuracy. Here's a plot of the best model accuracy of each N along with the Fourier Coefficient:

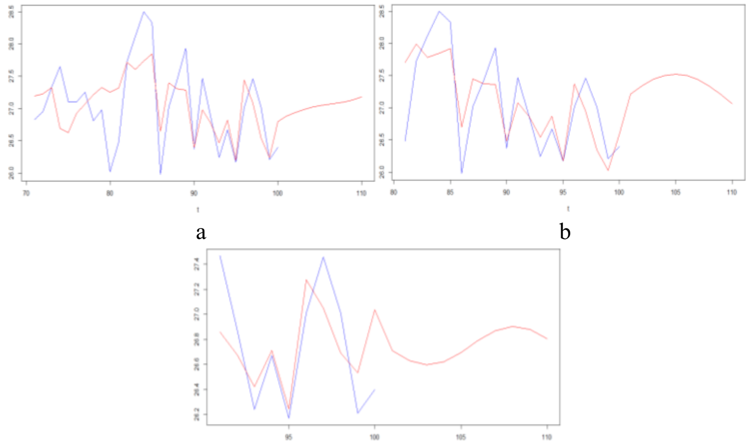


a b

c

Figure 5. Plot of the Actual and Forecasting Data for (a) N = 70. Plot of the Actual and Forecasting Data for (b) N = 80. Plot of the Actual and Forecasting Data for (c) N = 90

Based on Figure 5, it can be seen that the accuracy of the model in forecasting data demonstrates good performance. For each N with the best Fourier coefficient, the model shows a strong ability to explain data variability and forecasting error rates. Therefore, the semiparametric regression model using the Fourier series estimator can be used for forecasting by comparing forecasted data with testing data as well as forecasted data for the subsequent period. Here is a plot of forecasted data with testing data based on the best model of semiparametric regression using the Fourier series estimator:



a b

c

Figure 6. Plot forecasting and testing data for (a) N = 30. Plot forecasting and testing data for (b) N = 20. Plot forecasting and testing data for (c) N = 10

It can be seen in Figure 6 that the forecasting data is not much different from the actual data, where this assumption is strengthened by obtaining the MAPE values in Table 5:

Table 5. MAPE values of training data for each N.

N30	N20	N10
MAPE	MAPE	MAPE
1.526222	1.354613	1.055469

4. Conclusions

This study applied a semiparametric regression model with a PLS-based Fourier Series estimator to examine the relationship between surface relative humidity and temperature in Sragen Regency. By combining parametric and nonparametric components, the model effectively handled fluctuating data patterns across three training scenarios N = 70, 80, 90 with optimal Fourier coefficients of 6, 1, and 1, respectively. Forecasting results showed minimal discrepancies between actual and forecasted values, demonstrating reliable performance. The model success-fully forecasted the next 10 periods, with MAPE values of 1.526222, 1.354613, and 1.055469 for test data sizes of 30, 20, and 10. These results highlight the effectiveness of the Fourier-based semiparametric approach in modeling the in-verse relationship between humidity and temperature while maintaining accuracy in analyzing complex data. Future research could extend this approach to other regions or variables, enhancing its applicability for climate-related studies and policy development.

Disclosure of Interests

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