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MODELING OF SEA SURFACE TEMPERATURE BASED ON PARTIAL LEAST SQUARE - STRUCTURAL EQUATION

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Abstract: Variability of Sea Surface Temperature (SST) is one of the climatic features that influence global and regional climate dynamics. Missing data (gaps) in the SST dataset are worth investigating since they may statistically alter the value of the SST change. The partial least square-structural equation modeling (PLS-SEM) approach is used in this work to estimate the causality relationships between exogenous and endogenous latent variables. The findings of this study, which are significant indicators that have a loading factor value > 0.7 are as follows: i) sea surface temperature (^{o}C) as a measure of the latent variable changes in SST, ii) wind speed (m/s) and relative humidity (%) as a measure of the latent variable of weather, and iii) air temperature (^{o}C), long-wave solar radiation (w/m^2) as a measure of climate latent variables. The size of the Rsquare value is influenced by the number of gaps. The results of the boostrapping show that the latent variables of weather and climate have a significant effect on changes in SST which are indicated by the value of $t_{statistics} > t_{tabel}$. The structural model obtained Changes in SST (η) = -0.330 weather + 0.793 climate + ζ. The model shows that the weather has a negative coefficient, which means that the better the weather conditions, the lower the SST changes. Climate has a positive coefficient, which means that the better the climate, the SST changes will also increase. Rising sea surface temperatures caused by an increase in climate can lead to global warming, impacting El-Nino and La-Nina events.

1. INTRODUCTION

The temperature of waters between 1 millimeter (0.04 inch) and 20 meters (70 feet) below sea level is referred to as sea surface temperature (SST). Water (oceans) covers over 71% of the earth's surface, and seawater makes up 97% of all water on the planet. As a result, the oceans significantly impact the movement and circulation of the atmosphere and weather in any area on the earth's surface (Tjasyono, 2004). SST is closely related to the heat content of the ocean, so it has a relationship with global warming, impacting El Nino and La Nina events. El Nino and La Nina phenomena are temperature deviation events that occur due to global warming and disruption of the climate balance (Safitri, 2015). The westernmost part of Indonesia is Pulau Weh in Aceh Province, located at 6° N, and the ocean adjacent to this province is the Indian Ocean (Julismin, 2013).

Consequently, the Aceh region is a province whose western boundary crosses the Indian Ocean. The vastness of the oceans in the Indian Ocean makes Aceh Province have a significant impact due to changes in SST. One of the studies that analyze SST data (Syaifullah, 2015) examined sea surface temperatures in Indonesia and their relationship with global warming by using temporal-spatial analysis. The analysis results show that for more than 32 years, there has been an increase in sea surface temperature in various parts of Indonesia.

Research on SST has been carried out using various methods such as detecting missing SST data in the Indian Ocean, model fitting of SST by using linear model with interaction (Miftahuddin *et al*, 2021), cross-correlation analysis of SST anomaly with several climate features in the Indian Ocean, specifically for forecasting using SARIMA ARCH/GARCH models (Oktaviani *et al*, 2021), modeling of SST with generalized additive mixed models (GAMM) for risk detection (Humaira *et al*, 2019). Hereinafter, for detection of SSTA phenomena using vector autoregression (Miftahuddin *et al*, 2019), model fitting of SSTA with Generalized Additive Model (GAM), (Ananda and Miftahuddin, 2019) and model fitting of SST through linear model with autocorrelation (Miftahuddin, and Ilhamsyah, 2018). Furthermore, the statistical approach is focused on looking at weather and climate elements in a structure equation through the partial least squares (PLS) model. Through this approach, changes in SST can be seen from the change indicator variables simultanly and relationship between exogenous and endogenous variables. The PLS approach has been applied to the analysis of the relationship of factors that affect the human development index in the Yogyakarta city, (Marwah and Retno, 2016).

The use of a partial least squares (PLS) regression model, essentially modeling without fulfilling the assumption of the distribution of observation variables, can overcome the missing data in time series data with a significant amount of data and the risk of multicollinearity (gaps). It is not uncommon to find missing data in time-series data because the amount of data is not small. Noviyanti (2019) examines the factors that influence the competence of fishermen in Banten bay through Partial Least Square Structural Equation Modeling. The results obtained are the skills of the fishermen as a real influential factor on competence compared to the knowledge and attitudes of the fishermen. Meanwhile, the knowledge aspect has a real influence on the skills and attitudes of fishermen.

Based on the aforementioned, the purpose of this study is to demonstrate the use of Partial Least Square (PLS), which is a modeling technique that uses inference from a significance test to determine exogenous latent variables that affect endogenous latent variables and the significance of indicators on latent variables without the need to test assumptions. The PLS method is an alternative to structural equation modeling (SEM) which still requires assumptions. In its application, the Nonlinear Iterative Partial Least Squares (NIPALS) algorithm is also used in parameter estimation with iterative stages. In addition, this method can predict the relationship between latent variables or variables that cannot be measured directly, where the value can be known through the indicator variables by forming the outer model and inner model of several factors that can affect the SST through its latent variables. Both models are special models found in PLS regression. The outer model is used to see the relationship between indicators and their latent variables, while the inner model is used to predict the relationship between latent variables.

2. LITERATURE REVIEW

2.1. Weather and Climate

Sea surface temperature certainly changes from time to time which is intimately linked to human activities. Sea surface temperature, salinity, and subsea temperature are all indicators that can impact changes in SST. Weather and climate are two elements that can influence SST fluctuations (Minis, 2001). According to Kartasapoetra (2004), the weather is the condition of the atmosphere, sky, or air on earth in a short time. Weather is related to wind speed, precipitation, cloudiness, brightness, atmospheric pressure, and relative humidity. In contrast, the climate is the condition of the atmosphere over a more extended period. Climate includes temperature, summer, rainy season, short wave solar radiation, and longwave solar radiation (Meteorology, Climatology and Geophysics Agency (BMKG), 2020). Sunlight, air temperature, air pressure, humidity, wind, clouds, and rainfall are all elements of weather and climate. The primary distinction is that weather has a fast-changing and abnormal nature with a limited area coverage; meanwhile, the climate has a regular nature and is difficult to change with a more extensive area coverage (Minis, 2001).

2.2. Stuctural Equation Modelling (SEM)

Structural equation modeling (SEM) is a multivariate statistical analysis method in describing the close linear relationship between observed variables (indicators) and variables that cannot be measured directly (latent variables). There are two types of latent variables in SEM, namely endogenous latent variables (η) and exogenous latent variables (ξ) (Haryono, 2012). There are a lot of scenarios where the assumptions in SEM aren't met. One of the SEM approach renewals that can overcome data abnormalities, relatively small sample size, outlier data, and multicollinearity is the partial least square approach.

2.3. Partial Least Square (PLS)

PLS is a model approach with a causal relationship (causation) that aims to maximize the variance of the endogenous latent variable so that it can be explained (explained variance) by the exogenous latent variable. PLS can solve issues with no acceptable solution, such as the singular matrix problem (Jaya & Sumertajaya, 2008). Because PLS is based on a recursive structural model, problems are un-identified, under-identified, or over-identified. Similarly, because the latent variable is a linear combination of indicators, it will always be a combined latent variable when components cannot be determined (factor indeterminacy). PLS can be applied in both reflective and formative measurement models (Kurniawan, 2011). Ghozali (2014), there are two equations in PLS, which include structural equations (inner model) and measurement equations (outer model) with the following explanation.

a. Structural Model (Inner Model)

The structural model in PLS is created for a recursive model, which is a model that demonstrates causality (cause and effect) between exogenous and endogenous latent variables. The recursive model in PLS is formulated as:

$$\boldsymbol{\eta_j = \beta_{ji}\eta_i + \gamma_{jb}\xi_b + \zeta_j} \tag{1}$$

where:

β_{ji} : path coefficient linking endogenous predictor ji

γ_{jb} : path coefficients linking exogenous predictors jb

ζ_j : inner residual variabel j

ξ_b : exogenous latent variable b

η_j : endogenous latent variable j

b. Measurement Model (Outer Model)

The measurement model used in PLS is representing the link between indicators and their latent variables, which is assessed employing confirmatory factor analysis using the equation:

1. Laten Variable with Reflective Indicators

Reflective indicators are factors suspected of influencing latent variables. If the latent variable is an exogenous variable, the equation is:

$$\boldsymbol{x_q} = \boldsymbol{\lambda_{xq}\xi_q} + \boldsymbol{\delta_q} \tag{2}$$

where:

x_q	:	exogenous variable q
λ_{xq}	:	regression coefficient weights of exogenous variables q
ξ_q	:	latent variable of exogenous variable q
δ_q	:	measurement error q

If the latent variable is an endogenous variable, then the equation is:

$$\boldsymbol{y_p} = \boldsymbol{\lambda_{yp}\eta_p} + \boldsymbol{\varepsilon_p} \tag{3}$$

where:

y_p	:	endogenous variable p
λ_{yp}	:	regression coefficient weights of exogenous variables p
η_p	:	latent variable of endogenous variable p
ε_p	:	measurement error p

2. Latent Variables with Formative Indicators

Indicators that are regarded variables that affect latent variables are known as formative indicators. If the latent variable is an exogenous variable, the equation is as follows:

$$\boldsymbol{\xi} = \boldsymbol{\lambda_1 x_1} + \boldsymbol{\lambda_2 x_2} + \cdots + \boldsymbol{\lambda_q x_q} + \boldsymbol{\delta} \tag{4}$$

If the latent variable is an endogenous variable, then the equation is:

$$\boldsymbol{\eta} = \boldsymbol{\lambda_1 y_1} + \boldsymbol{\lambda_2 y_2} + \cdots + \boldsymbol{\lambda_q y_q} + \boldsymbol{\delta} \tag{5}$$

where:

ξ	:	latent variable of exogenous variable
η	:	latent variable of endogenous variable
λ	:	regression coefficient weight of ξ and η
δ , ε	:	measurement error

The estimation of the PLS model is done using the Non-Linear Iterative Partial Least Square (NIPALS) algorithm by performing three iteration stages, namely: i) providing a weight estimate output, ii) providing the path estimate output, and iii) providing the average estimated score (mean) and parameter location (regression constant) (Ghozali, 2014).

3. MATERIAL AND METHOD

3.1. Data Sources and Research Variables

This research focuses on the SST dataset, which is 1 meter below sea level with one location nearest to the Aceh province. Secondary data from the National Oceanic and Atmospheric Administration (NOAA) was used in this study. Monthly data was used with a point position of 8°N90°E, which is close to Aceh Province. There are three latent variables: changes in SST, weather, and climate, with each having three indicators. Data was taken from January 1, 2012 to February 21, 2020 and there were some missing data on each of the variables. The variables used are as shown in Table 1 below:

Table 1. Indicator Variables in Research

Latent Variable	Indicator Variables		Unit	Number of Observations	Number of Missing Data
Change in SST (η)	Y_1	Sea Surface Temperature	^oC	52	4
	Y_2	Salinity	%	40	16
	Y_3	Underwater temperature	^oC	47	9
Weather (ξ_1)	X_1	Rainfall	mm	29	27
	X_2	Wind Speed	m/s	51	5
	X_3	Relative Humidity	%	51	5
	X_4	Air Temperature	^oC	51	5
Climate (ξ_2)	X_5	Shortwave Solar Radiation	w/m^2	52	4
	X_6	Longwave Solar Radiation	w/m^2	56	0

3.2 Research Method

Data analysis was performed using SmartPLS 3.0 software and R 4.1.2. The procedures and stages of data analysis in this study are:

1. Initial identification was carried out, namely descriptive statistical analysis to see the characteristics and initial description of each data variable presented in the form of summary statistics and multicollinearity examination.
2. Inferential analysis was conducted to determine the relationship between exogenous latent variables and endogenous latent variables using the PLS regression model and to estimate the parameters of the model with iterative stages using the NIPALS algorithm with the following steps:
   (1) Forming the outer model and inner model through the following stages:
      a. Designing the model by forming the outer model and inner model in accordance with theoretical studies,
      b. Draw a path diagram,

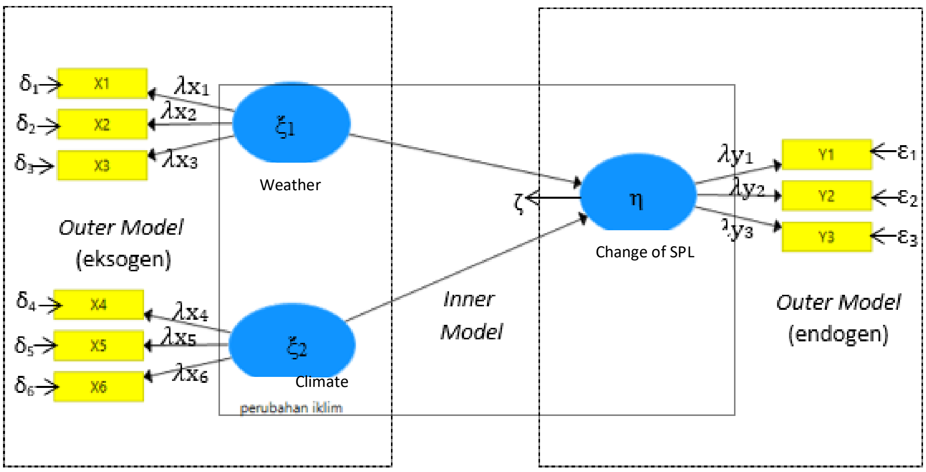

Figure 1. Path Diagram

c. After completing the path diagram as shown in Figure 1, the next step is to convert the path diagram into a system of equations for the outer model and inner model:

Outer model

$X_1 = \lambda x_1 \xi_1 + \delta_1$	$X_4 = \lambda x_4 \xi_2 + \delta_4$	$Y_1 = \lambda_{y1} \eta_1 + \varepsilon_1$
$X_2 = \lambda x_2 \xi_1 + \delta_2$	$X_5 = \lambda x_5 \xi_2 + \delta_5$	$Y_2 = \lambda_{y2} \eta_1 + \varepsilon_2$
$X_3 = \lambda x_3 \xi_1 + \delta_3$	$X_6 = \lambda x_6 \xi_2 + \delta_6$	$Y_3 = \lambda_{y3} \eta_1 + \varepsilon_3$

Inner model

$$\eta_1 = \gamma_{11}\xi_1 + \gamma_{21}\xi_2 + + \zeta_1$$

d. Estimation of PLS model parameters using the NIPALS algorithm, namely estimates on a weight estimate, path estimate, and parameter location,
e. Proceed to the inner model evaluation if the indicators and indicator blocks are valid and reliable (for the outer model with reflective indicators) and the estimated weight value is substantial (for the outer model with formative indicators).
f. If not, then have to re-design the path diagram,
g. Obtain the factor score from the model.

(2) Evaluating the model
By examining the validity and reliability of the indicators, the outer model is evaluated to see if they can be claimed to reflect the latent variables. Evaluation of the inner model is carried out to describe the relationship between latent variables, which is carried out through R^2, f^2, Q^2, goodness of fit index (GFI).

(3) Performing hypothesis tests
Using a nonparametric technique with a bootstrapping procedure and a t statistic test.

(4) Draw conclusions from the results and discussion of points 1 to 3.

4. RESULTS AND DISCUSSION

4.1. Statistics Summary

The variables used in the study are summarized statistically in the table below:

Table 2. Statistics Summary of SST Dataset with Gap in 2012-2020 Period

Variable	Missing	Mean	Median	Min	Max	Standard Deviation	Quartile 1	Quartile 3
Y_1	4	29.043	29.030	26.200	31.100	0.908	28.590	29.460
Y_2	16	33.529	33.550	32.597	34.327	0.415	33.300	33.710
Y_3	9	21.893	22.281	17.820	25.295	2.073	20.430	23.330
X_1	27	0.126	0.100	0	0.510	0.116	0.030	0.190
X_2	5	5.714	5.900	2.500	9.200	1.693	4.450	6.700
X_3	5	79.298	79.790	73.170	84.130	2.815	77.390	81.280
X_4	5	28.417	28.270	27.460	30.310	0.659	27.910	28.770
X_5	4	224.724	226.300	169.180	284.040	30.979	202.400	248.900
X_6	0	413.801	419.690	369.600	444.890	24.389	391.400	435.900

Table 3. Statistics Summary of SST Dataset withhout Gap in 2012-2020 Period

Variable	Mean	Median	Min	Max	Standard Deviation	Quartile 1	Quartile 3
Y_1	28.990	29.080	26.200	31.070	1.034	28.550	29.460
Y_2	33.570	33.590	32.597	34.327	0.453	33.310	33.860
Y_3	22.690	22.980	18.130	25.295	1.968	22.100	23.860
X_1	0.130	0.100	0	0.510	0.118	0.030	0.190
X_2	5.600	5.700	2.500	9.200	1.890	4.000	7.200
X_3	79.130	79.780	73.170	84.130	3.131	76.760	81.610
X_4	28.320	28.120	27.560	30.120	0.609	27.860	28.730
X_5	228.100	230.600	169.500	282.500	30.120	210.500	247.200
X_6	408.800	413.600	369.600	444.700	16.249	387.600	435.800

Table 2 shows that a statistical summary of monthly SST dataset from 2012 to 2020 period, with missing data in each variable. The sea surface temperature variable (Y_1) has four missing data points, with a minimum value of 26.2^{o}C, a maximum value of 31.1^{o}C, and an average of 29.043^{o}C. There are 16 missing data points for salinity (Y_2), with the lowest salinity of 32.597 %, the average seawater salinity of 33.529 %, and the highest salinity of 34.327 %. Underwater temperature (Y_3) has nine missing data points, with the lowest temperature of 17.82°C, the average of 21.893°C, and the highest temperature of 25.295°C. There are 27 missing data in the rainfall (X_1) variable, with the lowest rainfall is 0 mm (no rain), the average is 0.126 mm, and the highest rainfall is 0.51mm. In the wind speed (X_2) variable, there are five missing data points: the lowest wind speed is 2.5 m/s, the average is 5.714 m/s, and the maximum speed is 9.2 m/s. The relative humidity (X_3) variable has 5 data missing; the lowest relative humidity is 73.17%, with an average of 79.298% and a maximum of 84.13%. Air temperature (X_4) has five missing data, with the lowest air temperature is 27.46^{o}C, the average is 28.417^{o}C, and the highest air temperature is 30.31^{o}C. There are four missing data variables in short wave solar radiation (X_5), with the lowest radiation value is 169.18 w/m^2, the average is 224.724 w/m^2, and the highest value is 284.04 w/m^2. Longwave solar radiation (X_6) has no missing data; the lowest value is 369.6 w/m^2, the average is 413.801 w/m^2, with the highest value is 444.89 w/m^2.

4.2 Identification of Multicollinearity

In a data study that requires assumptions, multicollinearity is a common issue. The high correlation between exogenous variables in data might generate multicollinearity. However, by using SEM-PLS, the presence or absence of multicollinearity is not a problem. Even SEM-PLS can overcome the multicollinearity that exists between exogenous variables. Meanwhile, before moving on to the PLS analysis stage, the data to be used is checked for multicollinearity.

Table 4. VIF Data Value

Variable	Name	VIF Score
X_1	Rainfall	1.138
X_2	Wind Speed	1.615
X_3	Relative Humidity	1.643
X_4	Air Temperature	1.465
X_5	Shortwave Solar Radiation	1.095
X_6	Longwave Solar Radiation	1.375

Table 4 indicates no multicollinearity in the data utilized from 2012 to 2020 because the VIF value obtained for all variables is less than 10.

4.3 SEM-PLS Analysis

4.3.1.Measurement Model Test (Outer Model)

Furthermore, the SmartPLS 3.0 program with the PLS Algorithm is used to execute the structural diagram path (path) model (as shown in Figure 1), resulting in the standard values of model estimates such as loading factor, path coefficient, and R^2 (as in Figure 2).

Convergent Validity

Convergent validity is a method for measuring the validity of reflexive indicators as a measure of variables determined from the outer loading using indicators on latent variables. All loading factor values have a value $\lambda > 0.7$, indicating that the value is genuine or may be utilized as data in the model (see Figure 2). The Average Variance Extracted (AVE) value, which illustrates the link between indicators that serve in creating constructs or latent variables, can also be used to see convergent validity values, with AVE formula as follow,

$$\boldsymbol{AVE} = \frac{\sum \boldsymbol{\lambda_i}^2}{\sum \boldsymbol{\lambda_i}^2 + \sum_i \left(\mathbf{1} - \boldsymbol{\lambda_i}^2\right)}$$

Discriminant Validity

A high discriminant validity value indicates that a latent variable is unique. The way to measure discriminant validity is to compare the correlation between constructs (latent variables) with the roots of AVE. The results of discriminant validity can be shown in Table 5.

Reliability Test

Composite Reliability is used to calculate reliability. The reliability criteria can be seen if the latent variable has a composite reliability value > 0.7.

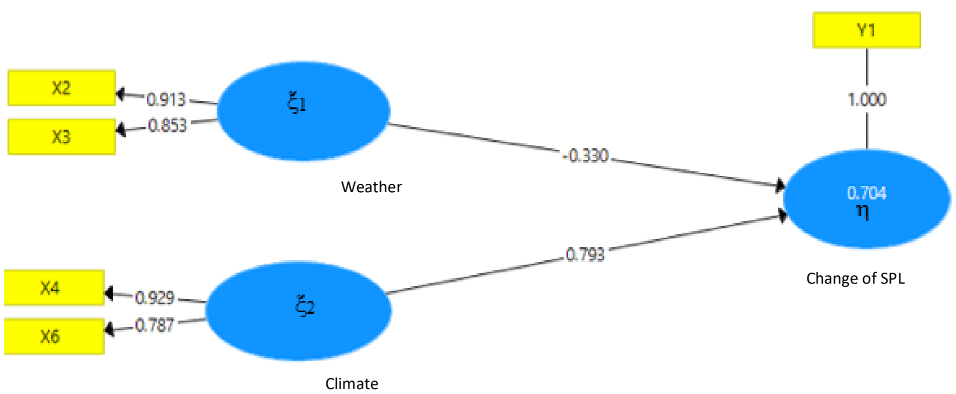

Figure 2. Value of Loading Factor, Trajectory Coefficient, and R^2

Measurement Model (Outer Model)

$Y_1 = 1$ sea surface temperature + ε_1,
$X_2 = 0.913$ wind speed + δ_2,
$X_3 = 0.853$ relative humidity + δ_3,
$X_4 = 0.929$ air temperature + δ_4,
$X_6 = 0.787$ longwave solar radiation + δ_5

Table 5. Average Variance Extracted (AVE) Value

Variable	Before Elimination AVE	After Elimination AVE
Change of SST	0.514	1
Weather	0.512	0.781
Climate	0.525	0.741

Table 6. AVE Root Value

Before Elimination			
Variable	Change of SST	Weather	Climate
Change of SST	**0.725**		
Weather	-0.364	**0.717**	
Climate	0.715	-0.075	**0.715**
Elimination			
Variable	Change of SST	Weather	Climate
Change of SST	**1**		
Weather	-0.277	**0.884**	
Climate	0.771	0.067	**0.861**

Table 7. Composite Reliability Value

Variable	*Composite Reliability*	
	Before Elimination	After Elimination
Change of SST	0.075	1
Weather	0.642	0.877
Climate	0.740	0.850

In the measurement models, there are nine initial indicators. The output of the Smart-PLS application output reveals that multiple indicators have a loading factor value (λ) < 0.7. Following the deletion of the indicators, the loading factor (λ) value is recalculated to see if it meets the reliability indicator > 0.7.

After the indicators are deleted, the loading factor (λ) value is recalculated, whether it meets the reliability indicator > 0.7. Figure 2 shows that the loading factor value (λ) < 0.7 is no longer present, indicating that the measuring indicator obtained is good. Following the elimination of various indicators, the three latent variables have AVE values consistent with the measurement model (see table 4). As a result, it can be concluded that the convergent validity of each indicator is good or that each indicator can measure the latent variables of changes in SST, weather, and climate. Table 6 shows that the discriminant validity results prior to elimination are insufficient since the root value of AVE of a latent variable is identical to the value between constructs. The indicators that do not fulfill the loading factor (λ) criteria are thus eliminated, resulting in an AVE root value greater than the value between constructs after being excluded. Table 7 demonstrates that before being removed, the composite reliability value described the indicators of the three latent variables unable to measure each latent variable (construct) accurately. After dropping these indicators, the five measurement models produced were found to be reliable.

4.3.2.Structural Model Test (Inner Model)

A model representing the relationship between latent variables utilizing path coefficients, R^2, f^2, Q^2 and GFI is referred to as an inner model. The structural model that is formed is based on Figure 2, namely:

$$\text{Change of SPL } (\eta) = -0.330 \text{ weather} + 0.793 \text{ climate} + \zeta$$

The weather has a negative coefficient in the model, which means that the better the weather, the lower the SST changes. Climate has a positive coefficient, which means that if the climate improves, so will the SST changes.

a. R-square

The calculated R^2 value is used to explain the diversity that exogenous latent variables may explain compared to endogenous latent variables. The SPL change has an R^2 value of 0.704. This suggests that the variance in SST that can be explained by weather and climatic variables accounts for 0.704 % variation.

b. f-square (f^2)

The f-square value is used to determine how an exogenous latent variable affects the endogenous latent variable. Based on the output of the *smartPLS* 3 program, the f-square value is as follows.

Table 8. Value of Effect Size f-Square (f^2)

	Change of SST	Effect
Weather	0.366	Strong
Climate	2.114	Strong

Table 8 illustrates that the indicators contained in each exogenous construct (latent variable) have a strong effect on sea surface temperature.

c. Goodness of Fit Index (GFI)

The GFI value derived by manual calculations is also used in the structural model evaluation in SEM-PLS. These calculations show that the GFI value of SST changes is 0.788, which is greater than 0.38. Thus, based on the criteria, the GFI value of SST changes has a sizeable structural model.

4.4. Hypothesis Testing

The *Smart-PLS* software's bootstrapping technique uses a subsample of 56 with = 0.05 and a t_{tabel} value of 2.003. When testing the hypothesis on the measurement and structural model, the null hypothesis is rejected if the absolute value of $t_{hitung} > t_{tabel}$ (2.003). This indicates that these indicators are useful for measuring and explaining latent variables. It signifies that the exogenous latent variable significantly influences the endogenous latent variable in the inner model.

Table 9. Relationship between Indicators and Exogenous Latent Variables

	t statistics	*p-values*
X_2 <- Weather	13.424	0
X_3 <- Weather	7.439	0
X_4 <- Climate	64.523	0
X_6 <- Climate	11.603	0

Table 10. Relationship between Exogenous and Endogenous Latent Variables

	Coefficient Path	*t statistics*	*p-values*
Weather $\rightarrow$ change of SST	-0.330	4.246	0
Climate $\rightarrow$ change of SST	0.793	15.503	0

The increase in SST in two decades has an impact on climate change, such as extreme weather, changes in marine ecosystems, and human socities (Pastor, F. (2021). This change is a result of global warming with an average temperature increase of 1.1ºC. The sixth assessment report of the IPCC Working Group I shows that the world could achieve or exceed 1.5ºC of warming in just two decades. Only by reducing emissions ambitiously will the world be able to limit global temperature rise to 1.5ºC levels, the limit scientists set to prevent the worst climate impacts. Under the high emission scenario, the IPCC found that global warming could reach 4.4ºC by 2100, which would have dire consequences (IPCC, 2021). Referring to the report that there is a tendency for SST changes of 0.793 in 2021 to approach the point of 1.1ºC to 1.5ºC (the upper limit of global climate change calculations) in the span of 79 years, when it can reach 4.4ºC.

As shown in Table 8, wind speed and relative humidity are the indicators that significantly affect the latent variables of the weather. Meanwhile, in the climate latent variables, significant indicators are air temperature and long-wave solar radiation. Weather and climate are the ones that have a significant effect on changes in SST, as seen in Table 9. The value of the path coefficient parameter obtained from the relationship between weather variables and SST changes is -0.33 with a *t-statistic* value of 4.246 > 2.003 (t-table) at a significance level of α = 0.05. It can be concluded that there is a significant influence between weather and changes in SST. The path parameter coefficient value obtained from the relationship between climate variables and SST changes is 0.793 with a t-statistic value of 15.503 > 2.003 ($t_{\text{-tabel}}$) at a significance level of α = 0.05 (5%). Hence there is a significant influence between climate and SST changes, as shown in Table 9.

5. CONCLUSION

There is a tendency for SST changes of 0.793 in the Indian Ocean in period reserach to approach the point of 1.1ºC to 1.5ºC. It was found that five significant indicators of modeling of sea surface temperature by using partial least square (PLS) that have a loading factor value > 0.7 are i) sea surface temperature (ºC) as a measure of the latent variables of SST changes, ii) wind speed (m/s), iii) relative humidity (%) as a measure of the latent variable of weather, and iv) air temperature (ºC), v) longwave solar radiation (w/m^2) as a measure of the latent variable of climate. The model shows that the better the weather conditions, the SST changes will decrease while the better the climate conditions, the SST changes will increase. Latent variables that have a significant effect on changes in SST are weather and climate. This implies that if there is an increase or decrease in weather and climate, it can cause significant changes to the SST. Rising sea surface temperatures caused by increasing climate with indicators of air temperature and longwave solar radiation can result in global warming, impacting El-Nino and La-Nina events.

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