ANALYSIS OF THE GSTAR-X MODEL WITH CALENDAR VARIATION EFFECTS FOR FORECASTING TOURIST ARRIVALS IN LAMPUNG PROVINCE

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ABSTRACT: At the end of 2023, Lampung Province experienced a significant surge in tourist numbers, reaching 10.28 million people—a 123% increase compared to the previous year. Effective planning and management of this surge require accurate forecasting of tourist arrivals. This study employs the Generalized Space-Time Autoregressive with Exogenous Variables (GSTAR-X) model to forecast tourist numbers in Bandar Lampung City, West Lampung Regency, South Lampung Regency, and Pesawaran Regency. By incorporating an exogenous variable to account for the effects of Idul Fitri calendar variation, the GSTAR-X(1,1) model with cross-correlation normalization weights demonstrates the best performance, yielding the smallest Root Mean Square Error (RMSE) of 2.573. The model's feasibility is confirmed through rigorous testing. This research provides valuable insights for stakeholders in the tourism sector, facilitating more effective and sustainable planning and management strategies for developing the tourism industry in Lampung Province.

Keywords: GSTAR-X; Location Weights; OLS; Forecasting; Calendar Variation Effects.

1. INTRODUCTION

Lampung Province is one of Indonesia's premier tourist destinations, offering significant potential due to its diverse and attractive natural, cultural, and historical attractions [1, 2]. To fully leverage this potential, effective planning is essential, including accurate forecasting of tourist numbers. This has become increasingly crucial given the significant upward trend in tourist arrivals over recent years, especially during extended Eid holidays, when the tradition of "mudik" (returning to hometowns) significantly drives tourist visits to various attractions [3].

According to data from BPS, there was a substantial increase in tourist numbers in 2023, reaching 10.28 million visitors in Lampung Province—a 123% increase compared to the previous year, far exceeding the target of 5 million tourists. This surge has positively impacted Lampung's economy and underscores both the immense potential and the urgent need for effective tourism management. This increase also raises a critical question: How can the influx of tourists be better forecasted and managed? To address this, this study aims to develop an accurate forecasting model using the Generalized Space-Time Autoregressive with Exogenous Variables (GSTAR-X) approach, incorporating calendar variation effects such as Eid al-Fitr.

The focus of this study is on four regions within Lampung Province—Bandar Lampung City, West Lampung Regency, South Lampung Regency, and Pesawaran Regency—which are among the top destinations for tourist visits. The tourist data are time series in nature, reflecting both temporal and spatial interconnections, necessitating comprehensive analysis.

The GSTAR-X model proposed in this study extends the GSTAR model by including exogenous variables [4]. This model excels at capturing heterogeneous temporal and spatial relationships with greater accuracy [5]. The autoregressive parameters vary for each location, allowing the model to more realistically reflect the unique characteristics of each location [6]. These differences are represented through the weight matrix [7].

Incorporating exogenous variables, such as the effect of Eid al-Fitr, allows for a more comprehensive analysis of how such events impact tourist numbers. The Ordinary Least Squares (OLS) method used in the GSTAR-X model ensures efficient and consistent parameter estimation, enhancing the reliability of the data analysis [8][9].

This study utilizes both inverse distance weights and normalized cross-correlation weights to enhance model accuracy and precision. Model evaluation is conducted using the Root Mean Square Error (RMSE) to identify the best model that provides the most accurate forecasts [10].

Previous studies, such as [11] forecasted tourist numbers in the Lake Toba region using the GSTAR model. Furthermore, [12] examined tourist forecasting in Central Java using the GSTAR-SUR model. These studies provide foundational examples for this approach. However, no prior research has specifically focused on forecasting tourist numbers in Lampung Province while considering the influence of Eid al-Fitr through the GSTAR-X model.

This study aims to deliver more accurate forecasts and introduces a novel approach by incorporating the impact of Eid al-Fitr within the GSTAR-X model, which is particularly relevant for the development of creative tourism in Lampung. The findings are expected to significantly contribute to more effective and sustainable tourism planning strategies in the province.

2. METHOD

The steps used in this study are as follows:

- 1. **Data Collection**: Monthly tourist data from 2019–2023 for Bandar Lampung, West Lampung, South Lampung, and Pesawaran were obtained from the Lampung Tourism Office.
- 2. Research Variables:
- The study utilizes the following variables:
- BDL : Tourist numbers in Bandar Lampung
- *LB*: Tourist numbers in West Lampung
- *LS* : Tourist numbers in South Lampung
- PSW : Tourist numbers in Pesawaran
- The exogenous variable represents the calendar variation effect of Eid al-Fitr, using a combined dummy variable:
- D(t): Dummy variable equal to 1 during the Eid al-Fitr month, 0 otherwise
- D(t-1): Dummy variable equal to 1 in the month preceding Eid al-Fitr, 0 otherwise.

These two dummy variables were combined into a single dummy variable to represent the overall Eid effect, simplifying the model and avoiding potential multicollinearity.

- 3. Stationarity Test: The Augmented Dickey-Fuller (ADF) test is conducted to assess data stationarity. Differencing is applied if necessary [13][14].
- 4. Spatial Correlation: Pearson correlation is performed to test spatial relationships between locations.
- 5. Spatial Heterogeneity: The Gini Index is used to assess spatial heterogeneity.
- 6. Model Identification: The temporal order is identified using Akaike's Information Criterion corrected (AICC) [15], while the spatial order is limited to 1.
- 7. Location Weight Calculation: Inverse distance weights and cross-correlation normalization weights are computed for spatial modelling.
- 8. Model Estimation: Estimate parameters using Ordinary Least Squares (OLS) [16].
- 9. Diagnostics: Evaluate residuals with Ljung-Box and Kolmogorov-Smirnov tests [17].
- 10. Model Validation: The best GSTAR-X model is selected based on the smallest Root Mean Square Error (RMSE).

3. RESULTS AND DISCUSSION

This section presents an analysis of monthly tourist data for Bandar Lampung, West Lampung, South Lampung, and Pesawaran, covering the period from January 2019 to December 2023. The dataset consists of 240 observations obtained from the Lampung Tourism Office. A summary of the descriptive statistics is provided in Table 1.

Location	Mean	StDev	Min	Max	
BDL	84.176	83.993	0	283.210	
LB	69.194	60.838	0	193.110	
LS	43.667	29.241	0	146.681	
PSW	79.980	83.031	0	558.300	

Bandar Lampung recorded the highest mean monthly tourist numbers at 84,176, accompanied by considerable variability (StDev = 83,993). Conversely, South Lampung had the lowest mean at 43,667 and the smallest variation (StDev = 29,241), indicating a more stable tourist flow. Maximum tourist numbers also varied significantly, with Pesawaran peaking at 558,300, while Bandar Lampung and West Lampung reached 283,210 and 193,110, respectively. Periods of zero tourist numbers correspond to the closure of tourist sites during the COVID-19 pandemic.

Model Identification

The modelling process begins with testing the stationarity of the data using the Augmented Dickey-Fuller (ADF) test. At a 5% significance level, the test results indicate that all data from the four locations are stationary.

Table 2. Results of the ADF Test for Tourist Data Stationarity

_	Location	P-Value	Decision
_	BDL	84.176	Reject H_0
	LB	69.194	Reject H_0
	LS	43.667	Reject H_0
_	PSW	79.980	Reject H_0

Next, Correlation tests were conducted to identify significant spatial relationships between locations, using the Pearson Product-Moment Correlation test at a 5% significance level, as shown in Table 3. The p - values < 0.05 confirm significant correlations and spatial dependence.

Table 3. Pearson Product Moment Correlation Test Results				
Lokasi	BDL	LB	LS	PSW
BDL	1	0.722	0.461	0.709
p-value	0.000	0.000	0.000	0.000
LB	0.722	1	0.624	0.726
p-value	0.000	0.000	0.000	0.000
LS	0.461	0.624	1	0.558
p-value	0.000	0.000	0.000	0.000
PSW	0.709	0.726	0.558	1
p-value	0.000	0.000	0.000	0.000

Next, spatial heterogeneity was tested using the Gini Index. Table 4 shows that all locations have a Gini Index greater than 1, confirming spatial heterogeneity for GSTAR-X modelling.

	Table 4. Gini Index	
Lokasi	Indeks Gini	Keputusan
BDL	1,00208333	Tolak H ₀
LS	1,00208333	Tolak H ₀
LB	1,00208333	Tolak H_0
PSW	1,00208333	Tolak H_0

The final step is to determine the optimal time lag for the GSTAR-X model using the VAR-X approach, selecting the smallest Akaike Information Criterion Corrected (AICC) value, as shown in Table 5.

Table 5. Lag AICC						
Lag 1 2 3 4 5						
AICC	85.204*	85.454	86.201	86.841	87.486	

The smallest AICC value is found at lag 1, so the autoregressive order (p) for the GSTAR-X model is p = 1, with a spatial order of $\lambda_S = 1$. Thus, the GSTAR-X model used in this study is GSTAR-X(1,1).

Model Estimation

After specifying the GSTAR-X(1,1) model, the next step is to calculate the location weight matrices for parameter estimation. The GSTAR-X model uses distance inverse weights and normalized cross-correlation weights.

The distance inverse weights, which represent the geographic distances between the locations, are presented in **Table 6.**

Table 6. Geographic Coordinates for Study Locations

T intono	
Lintang	Bujur
-5,39637	105,2668
-5,10970	104,1465
-5,56226	105,5472
-5,49342	105,079
	-5,39637 -5,10970 -5,56226

Based on the coordinates in Table 6, the distance inverse weight matrix between locations is given by:

	ΓO	0,100	0,354	0,546
<i>W</i> =	0,341	0	0,268	0,391
	0,524	0,116	0	0,361
	0,604	0,127	0,270	0

Next, the normalized cross-correlation weights are computed from the cross-correlation values between locations at corresponding time lags. The results for these weights in the GSTAR-X(1,1) model are as follows:

	ΓO	0,652	0,349 0,341 0 -0,128	-0,002
147	0,660	0	0,341	-0,001
vv =	0,527	0,525	0	-0,051
	0,720	0,407	-0,128	0

After obtaining the location weighting matrix, the next step is the parameter estimation of the GSTAR-X model using both inverse distance weights and normalized crosscorrelation weights.

At a significance level of $\alpha = 5\%$, the parameter estimates for the GSTAR-X model with inverse distance weights, using the OLS method, are presented in Table 7 below.

 Table 7. Parameter Estimation of GSTAR-X(1,1) with Inverse

 Distance Location Weights

Parameter	Estimated Value	t-Value	P-Value
$\Phi_{10^{(1)}}$	0.82498	11.60	< 0.0001
$\Phi_{11^{(1)}}$	0.65910	4.91	0.0001
γ_1	0.20062	2.18	0.0336
$\Phi_{10^{(2)}}$	0.83021	10.64	< 0.0001
$\Phi_{11^{(2)}}$	0.18921	2.42	0.0189
γ_2	0.19840	2.15	0.0364
$\Phi_{10^{(3)}}$	0.39104	2.77	0.0076
$\Phi_{11^{(3)}}$	0.03452	2.46	0.6492
γ ₃	0.19826	2.13	0.0379
$\Phi_{10^{(4)}}$	0.49348	4.27	< 0.0001
$arPhi_{11^{(4)}}$	-0.17479	-0.77	0.4453
γ_4	0.19014	2.09	0.0414

Based on the significant parameter values in Table 7, the final form of the GSTAR-X model with inverse distance location weights is as follows:

 $+\varepsilon_{BDL}(t).$

 $LB = 0.830214_{LB}(t-1) + 0.06452061_{BDL} (t-1)$ $+ 0.05070828_{LS} (t-1) + 0.0739111_{PSW} (t-1)$ $+ 0.19840 X_{LB} (t) + \varepsilon_{LB}(t).$

GSTAR-X(1,1) Inverse Distance Weight for South Lampung: $LS = 0.391049_{LS} (t-1) + 0.19826 X_{LS} (t) + \varepsilon_{LS}(t).$ **GSTAR-X(1,1)** Inverse Distance Weight for Pesawaran: $PSW = 0.493486_{PSW} (t-1) + 0.19014 X_{PSW} (t)$

+
$$\varepsilon_{PSW}(t)$$
.

Next, the parameter estimation for the GSTAR-X model with normalized cross-correlation weights was computed using the OLS method. At a significance level of $\alpha = 5\%$, the estimated parameters for the GSTAR-X model with normalized cross-correlation location weights are as follows: Table 8. Parameter Estimation for GSTAR-X(1 1) with

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Nom	alized Croc	o Correlati	n I contion	Weighte

Normalized Cross-Correlation Location Weights					
Parameter	Estimated Value	t-Value	P-Value		
$\Phi_{10^{(1)}}$	0.60182	4.79	< 0.0001		
$\Phi_{11^{(1)}}$	0.57047	2.91	0.0052		
γ_1	0.14835	1.87	0.0669		
$\Phi_{10^{(2)}}$	0.72179	7.94	< 0.0001		
$\Phi_{11^{(2)}}$	0.26210	2.81	0.0068		
γ_2	0.12783	1.68	0.0989		
$\Phi_{10^{(3)}}$	0.50258	4.00	0.0002		
$\Phi_{11^{(3)}}$	0.14781	2.38	0.0208		
γ_3	0.18261	2.13	0.0374		
$\Phi_{10^{(4)}}$	0.50952	4.45	< 0.0001		
$\Phi_{11^{(4)}}$	0.15823	1.30	0.1990		
γ_4	0.17829	2.04	0.0465		

Based on the significant parameter values in Table 8, the final form of the GSTAR-X model with normalized cross-correlation location weights is as follows:

GSTAR-X(1,1) Normalized Cross-Correlation Weights for Bandar Lampung:

$$BDL = 0.601824_{BDL} (t-1) + 0.371952308_{LB} (t-1) - 0.001_{PSW} (t-1) + \varepsilon_{BDL} (t).$$

GSTAR-X(1,1) Normalized Cross-Correlation Weights for West Lampung:

$$LB = 0.721798_{LB} (t-1) + 0.1729_{BDL} (t-1) + 0.0894_{LS} (t-1) - 0.0003_{PSW} (t-1) + \varepsilon_{LP} (t).$$

GSTAR-X(1,1) Normalized Cross-Correlation Weights for South Lampung:

$$LS = 0.502589_{LS} (t-1) + 0.0779_{BDL} (t-1) + 0.776_{LB} (t-1) - 0.0075_{PSW} (t-1) + 0.18261 X_{LS} + \varepsilon_{LS} (t).$$

GSTAR-X(1,1) Normalized Cross-Correlation Weights for Pesawaran:

$$PSW = 0.509521_{PSW} (t-1) + 0.17829 X_{PSW} (t) + \varepsilon_{PSW} (t).$$

Model Diagnosis

Model diagnosis is a stage aimed at determining whether the white noise and multivariate normality assumptions of the GSTAR-X(1,1) model for the four locations have been met. If the GSTAR-X(1,1) forecasting model with both location weights satisfies the diagnostic assumptions, then the model is considered suitable for use in forecasting tourist numbers. The white noise test evaluates potential correlations among the model's residuals. The Ljung-Box-Pierce test results, at a 5% significance level, are as follows:

Table 9. White Noise Test Results		
Location Weight	P – value	
Invers Distance	0.0814	
Normalized Cross-Correlation	0.0672	

Based on Table 9, all p-values are greater than $\alpha = 0.05$, indicating that the GSTAR-X(1,1) model with both location weights meets the white noise assumption, as its residuals are independent. Thus, the model is suitable for forecasting. The next step is to test for multivariate normality using the Kolmogorov-Smirnov test. At a 5% significance level, the results are as follows:

Table 10. Multivariate Normality Test Results		
Location Weight	P – value	
Inverse Distance	0.1593	
Normalized Cross-Correlation	0.1309	

Based on Table 10, it can be concluded that all p-values are greater than $\alpha = 0.05$, meaning that the GSTAR-X(1,1) model with both location weights satisfies the multivariate normality assumption, making it suitable for forecasting.

The results of the white noise and multivariate normality tests confirm that the GSTAR-X(1,1) model with both inverse distance and normalized cross-correlation weights meets the diagnostic assumptions, making it appropriate for forecasting tourist numbers.

Model Validation

After the diagnostic assumptions of the model have been met, the next step is to select the best GSTAR-X(1,1) model based on the smallest RMSE value. RMSE is used to assess how well the model forecasts tourist numbers. The RMSE calculation results for the GSTAR-X(1,1) model with both location weights are presented in Table 11 below.

Table 11. RMSE of the GSTAR-X(1,1) Model		
Location Weight	P – value	
Inverse Distance	2.1892	
Normalized Cross-Correlation	2.0736	

Table 11 shows that the GSTAR-X(1,1) model with normalized cross-correlation weights has the lowest RMSE of 2.0736, compared to 2.1892 for the inverse distance weights model. Thus, the model with normalized cross-correlation weights is the most effective for forecasting tourist numbers in Lampung Province.

4. CONCLUSION

This study developed a GSTAR-X(1,1) model to forecast tourist numbers in Lampung Province, incorporating Idul Fitri calendar variations. Tests confirmed the data's suitability for GSTAR-X modelling. Both inverse distance and normalized cross-correlation weight models were significant, with white noise and multivariate normality tests validating their forecasting capability. The GSTAR-X(1,1) model with normalized cross-correlation weights performed best, making it a valuable tool for tourism planning and policy-making.

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REFERENCE

- R. S. Aminda and E. Rahmawati, "The Effect of the Number of Tourism Attractions and Restaurants on Local Own-Source Revenue in the Regency/City of Lampung Province," *Media Ekon.*, vol. 31, no. 1, pp. 97–114, 2023, doi: 10.25105/me.v31i1.18298.
- [2] S. Ali and L. Maharani, "Development of Religious Tourism in Bandar Lampung, Indonesia," *African J. Hosp. Tour. Leis.*, vol. 8, no. 5, pp. 1–8, 2019.
- [3] H. P. Jesica, D. Ispriyanti, and T. Tarno, "Peramalan Jumlah Wisatawan Yang Berkunjung Ke Objek Wisata Di Jawa Tengah Menggunakan Variasi Kalender Islam Regarima," *J. Gaussian*, vol. 8, no. 3, pp. 305–316, 2019, doi: 10.14710/j.gauss.v8i3.26676.
- [4] E. Setyowati, Suhartono, and D. D. Prastyo, "A Hybrid Generalized Space-Time Autoregressive-Elman Recurrent Neural Network Model for Forecasting Space-Time Data with Exogenous Variables," *J. Phys. Conf. Ser.*, vol. 1752, no. 1, 2021, doi: 10.1088/1742-6596/1752/1/012012.
- [5] A. Aprianti, M. Usman, and N. Faulina, "Generalized Space Time Autoregressive (GSTAR) Model for Air Temperature Forecasting in the South Sumatera, Riau, and Jambi Provinces," *Inpr. Indones. J. Pure Appl. Math.*, vol. 6, no. 1, pp. 1–13, 2024, doi: 10.15408/inprime.v6i1.36049.
- [6] P. Pfeifer and S. . Deutrch, "A Three-Stage Iterative Procedure for Space-Time Modeling," *Technometrics*, no. 22, pp. 35–47, 1980.
- B. Ruchjana, "Pemodelan Kurva Produksi Minyak Bumi Menggunakan Model Generalisasi S-Tar," Semin. Nas. Stat., 2002.
- [8] B. Ruchjana, S. A. Borovkova, and H. . Lopuhaa, "Least squares estimation of Generalized Space Time AutoRegressive (GSTAR) model and its properties," *AIP Conf. Proceedings.*, 2012.
- [9] R. S. Tsay, Analysis of Financial Time Series. Chicago:

John Wiley & Sons, Inc., 2002.

- [10] W. W. S. Wei, *Multivariate Time Series Analysis and Application*. New York: John Wiley and Sons, Inc, 2019.
- [11] I. Fitriyaningsih, M. Solikhin, Y. Basani, I. T. Del, J. Sisingamangaraja, and S. Utara, "Pemodelan Jumlah Wisatawan Tiga Tempat Wisata di Kawasan Danau Toba," *Pros. SNIP*, pp. 286–293, 2018.
- [12] I. Adella, D. Ispriyanti, and H. Yasin, "Pemodelan Jumlah Wisatawan di Jawa Tengah Menggunakan Metode Generalized Space Time Autoregressive -Seemingly Unrelated Regression (GSTAR-SUR)," J. Gaussian, vol. 11, no. 2, pp. 258–265, 2022, doi: 10.14710/j.gauss.v11i2.35473.
- [13] J. D. Cryer and K.-S. Chan, *Time Series Analysis with Applications in R*. New York: Springer, 2008.
- [14] S. Makridakis, S. C. Wheelwright, and R. J. Hyndman, *Forecasting Methods And Applications*. Wiley, 2008.
- [15] G. Kirchgassner and J. Wolters, Introduction to Modern Time Series Analysis, 1st ed. Heidelberg: Springer Berlin, 2007. doi: https://doi.org/10.1007/978-3-540-73291-4.
- [16] S. Borovkova, H. P. Lopuhaä, and B. N. Ruchjana, "Consistency and asymptotic normality of least squares estimators in generalized STAR models," *Stat. Neerl.*, vol. 62, no. 4, pp. 482–508, 2008, doi: 10.1111/j.1467-9574.2008.00391.x.
- [17] G. E. P. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, *Time Series Analysis Forecasting and Control*, 5th ed. New Jersey: Wiley, 2016.