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A Novel Approach to Evaluate Rice Prices using Bayesian GSTARI (1,1,1) Model

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Abstract

Spatial data refers to the information regarding the price of rice obtained from several regions in East Java, namely Kediri, Blitar, Malang, Probolinggo, Pasuruan, Mojokerto, Madiun, Surabaya and Batu. The data pertainsto rice prices collected throughout the period from January 2019 to July 2023 can be classified as a time series. Thus the rice price data for nine East Java regions from January

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2019 to July 2023 are spatiotemporal. This data can be analyzed using the statistical model Generalized Space Time Autoregressive Integrated (GSTARI). This model is a modification of GSTAR designed for non-stationary data. Numerous previous studies have been conducted regarding the spatial modeling of rice prices. However, the use of Bayesian estimation methodology within a GSTARI model remains unexplored. In estimating model parameters, the Bayesian approach has advantages over the non-Bayesian approach; namely, the small sample size and free distribution of the data. In this paper, we construct the GSTARI $(1, 1, 1)$ model with a Bayesian estimator in order to model East Java's rice prices. The weight used in this investigation is Inverse Distance. According to the findings of this investigation, all GSTARI $(1, 1, 1)$ parameters estimated using the Bayesian estimator are significant at all locations. With the OLS estimator, the GSTARI model parameters $(1, 1, 1)$ were not significant at all locations. The GSTARI $(1, 1, 1)$ model with Bayesian estimator also yields RMSE and AIC values that are much smaller than the OLS estimator.

1 Introduction

The selling price of rice in several locations during a certain period is spatiotemporal data. In reality, the spatiotemporal data that is currently available does not yet satisfy stationary properties. Generalized Space Time Autoregressive (GSTAR) is a statistical technique that can be employed to model such data. The GSTAR model's characteristics are the parameter values at each distinct location [4],[5].

In general, the available spatiotemporal data is not stationary. This condition cannot be depicted using GSTAR because there is no requirement for stationary checking in this model. To counteract this, the GSTARI model was devised for non-stationary data [16]. Numerous researchers have utilized the GSTARI model in the past. Bonar et al. [7] modeled the North Sumatra consumer price index using the GSTARI-ARCH model and Ordinary Least Square (OLS) estimator method. Alawiyah et al. [8] modeled positive Covid patients in Bandung using GSTARI and employed OLS to estimate the parameter model. In the meantime, Monika et al. [16] used the GSTARI-X-ARCH model, which was applied to the West Java climate data and they estimated the model parameters using the Maximum Likelihood (ML) and the Generalized Least Square (GLS) estimator methods.

Problems arise when modeling spatiotemporal data with GSTARI only using small locations. Parameter estimation methods using traditional approaches such as those used by the researchers above will produce poor model performance. To overcome this gap, our idea is using a Bayesian approach for the GSTARI model parameter estimation method as this exhibits excellent accuracy in prediction even with limited sample numbers [9], [10]. The Bayesian approach also has advantages over conventional estimation techniques because the estimator is asymptotically distribution-free and independent of the distribution of the data [11]. In the Bayesian approach, a prior must be determined to estimate the posterior parameter distribution. This is an essential difference between estimators with conventional and Bayesian approaches [12].

Based on the preceding description, we model paddy prices in eight East Java cities using GSTARI and a Bayesian approach.

2 Material and Methods

2.1 Data

The data used in this research from website of Information System for The Availability and Price Developments of Staple Foodstuffs in East Java. The data is bi-weekly rice price in nine cities in East Java; namely, Probolinggo, Mojokerto, Surabaya, Pasuruan, Madiun, Batu, Kediri, Blitar, Mojokerto. The data period starts from January 2019 to June 2023, which was accessed from the website https://siskaperbapo.jatimprov.go.id/.

2.2 GSTARI with Bayesian Estimator

In this article, we explore the GSTARI model using Bayesian parameter estimation. The priors used are Multivariate Normal [19], [20] and Inverse Wishart distributions [21], [22].

GSTARI(1,1,1) model can be represented as:

$$\mathbf{Y} = \mathbf{\Phi} X + \varepsilon, \tag{2.1}$$

where $\mathbf{Y} = \mathbf{y_t}, \mathbf{X} = \mathbf{y_{t-1}}, \mathbf{\Phi^{(i)}_{10}} + \mathbf{\Phi^{(i)}_{11}} \mathbf{W^{(1)}}, \mathbf{\Phi} = \mathbf{\Phi^{(i)}_{10}} + \mathbf{\Phi^{(i)}_{11}} \mathbf{W^{(1)}}, \varepsilon = \mathbf{e(t)}$. In case of $\mathbf{Y_i} \sim \mathrm{MN}(\mathbf{\Phi} X_i, \mathbf{\Omega})$, the probability function of $\mathbf{Y}$ is

$$f(y_1, y_2, \ldots, y_N) = (2\pi)^{-\frac{1}{2}} |\Omega|^{-\frac{1}{2}} \exp\left\{-\frac{1}{2}(\mathbf{y} - \mathbf{\Phi} x)' \Omega^{-1} (\mathbf{y} - \mathbf{\Phi} x)\right\}. \tag{2.2}$$

Hence, the probability function of the joint probability $\mathbf{Y}$ is

$$f(\mathbf{Y}|\mathbf{\Phi}, \mathbf{\Omega}) \propto |\Omega|^{-\frac{t}{2}} \exp\left\{-\frac{1}{2}(\mathbf{y} - \mathbf{\Phi x})' \mathbf{\Omega}^{-1} (\mathbf{y} - \mathbf{\Phi x})\right\}. \tag{2.3}$$

Prior joint probability is expressed as follows

$$f(\mathbf{\Phi}, \mathbf{\Omega}) \propto |\mathbf{\Omega}|^{-\frac{-(f_0+n+1)}{2}} \exp\left\{-\frac{1}{2}\mathrm{tr}\left(\mathbf{\Omega}^{-1}\mathbf{G_0^{-1}}\right)\right\} |\mathbf{V_0}|^{-\frac{n}{2}} |\mathbf{\Omega}|^{-\frac{n}{2}}. \tag{2.4}$$

The joined posterior distribution can be expressed as follows:

$$f(\mathbf{\Phi}, \mathbf{\Omega}|\mathbf{Y}) \propto f(\mathbf{Y}|\mathbf{\Phi}, \mathbf{\Omega}) f(\mathbf{\Phi}, \mathbf{\Omega}) \tag{2.5}$$

In other terms, Equation 2.5 is proportional to the product of Equations 2.3 and 2.4.

3 Results and Discussion

3.1 Checking Stationarity of Data

In space time modelling, the initial stage of analysis involves assessing whether the data exhibits stationary qualities. Initially, a time series graphic is deployed at each single area.

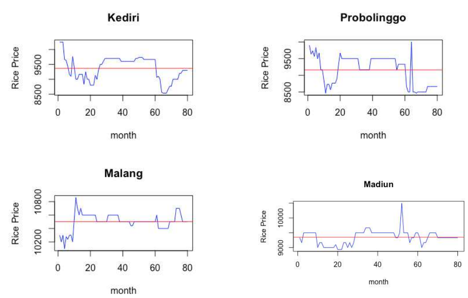

Figure 1: Timeseries Plot

The rice price data plot in nine distinct towns has not yet attained stationarity. For instance, figure 1 above depicts a stationary plot of four regions. To enhance this data, the Augmented Dickey-Fuller (ADF) value was examined. The ADF test for the unit root is used to assess the stationarity of the data at $\alpha = 0,05$ the confidence level, where H_0 indicates that the data have a unit root and are not stationary. H_1 demonstrates that the data lack a unit root and are stationary [26], [27].

Table 1: ADF Test of The Differencing Data

Location	P-Value	Location	P-Value	Location	P-Value
Kediri	0.028	Probolinggo	0.01	Madiun	0.01
Blitar	0.01	Pasuruan	0.01	Surabaya	0.01
Malang	0.01	Mojokerto	0.01	Batu	0.01

Table 1 contains P-values in all locations are all less than 0.05. This implies that the data at all regions have satisfied the requirements for stationary conditions, allowing for the progression of data analysis to the following step.

3.2 GSTARI using Bayesian Estimator

The following table presents the results of estimating the GSTARI parameters $(1, 1, 1)$ using Ordinary Least Square and Bayesian estimators, respectively.

Using OLS to estimate the parameters of the GSTARI model $(1, 1, 1)$ yields p-values that are greater than 0.05. This means that none of the parameters from

Table 2: GSTARI$(1,1,1)$ Parameters Using OLS Estimator

Location	Φ_{10}	**P-Value**	Φ_{11}	**P-Value**
Kediri	-0.098	0.991	-0.004	1
Blitar	0.077	0.992	0.430	0.995
Malang	-0.125	0.998	-0.065	0.999
Probolinggo	-0.343	0.925	0.966	0.996
Pasuruan	-0.472	0.956	0.017	1
Mojokerto	-0.173	0.973	-0.033	1
Madiun	-0.321	0.966	0.129	0.999
Surabaya	-0.498	0.984	0.089	0.999
Batu	-0.248	0.998	-0.212	0.996

GSTARI $(1,1,1)$ are significant at any location as seen in Table 2. Therefore, researchers are interested in estimating the GSTARI parameters $(1,1)$ using a Bayesian approach. The Bayesian method for estimating the GSTARI parameters

Table 3: GSTARI$(1,1,1)$ Parameters Using Bayesian

Location	**Mean** Φ_{10}	**Credible Int**	**Mean** Φ_{11}	**Credible Int**
Kediri	-0.012	[-0.0119;-0.0115]	0.454	[0.4537;0.4538]
Blitar	0.073	[0.0723;0.0727]	0.434	[0.4337;0.4339]
Malang	-0.012	[-0.0119;-0.0115]	0.454	[0.4537;0.4538]
Probolinggo	0.039	[0.0389;0.0393]	0.422	[0.4217;0.4219]
Pasuruan	0.023	[0.0226;0.0230]	0.470	[0.4699;0.4700]
Mojokerto	0.199	[0.1992;0.1995]	0.359	[0.3587;0.3589]
Madiun	0.048	[0.0475;0.0478]	0.427	[0.4265;0.4266]
Surabaya	0.028	[0.0276;0.0280]	0.436	[0.4358;0.4360]
Batu	0.061	[0.0610;0.0614]	0.476	[0.4765;0.4767]

$(1,1,1)$ indicates that the parameter values Φ_{10} and Φ_{11} are significant at all locations. This is evident from the fact that none of the credible interval values contain 0 as seen in Table 3. The performance of the GSTARI $(1,1,1)$ model will then be evaluated by contrasting the RMSE of the OLS and Bayesian estimators [28], [29]. In this research, AIC was additionally utilized to evaluate the validity of the model [30, 31, 32] The outcome was compared to the RMSE value. The following table shows the RMSE and AIC values for the two estimators of GSTARI $(1,1,1)$.

Table 4 displays that the GSTARI $(1,1,1)$ model with OLS estimator exhibits dropped RMSE and AIC values compared to the GSTARI $(1,1,1)$ model with Bayesian estimator, which is solely generated by the Mojokerto location. In contrast, the GSTARI $(1,1,1)$ model using Bayesian estimators at eight sites yields

Table 4: Comparing OLS and Bayesian GSTARI $(1,1,1)$

Location	**RMSE**		**AIC**	
	OLS	**Bayesian**	**OLS**	**Bayesian**
Kediri	17.904	2.126*	457.823	121.218*
Blitar	15.195	14.350*	433.913	424.873*
Malang	10.311	0.966*	374.647	0.515*
Probolinggo	99.522	11.355*	734.859	391.883*
Pasuruan	89.839	4.338*	720.687	241.846*
Mojokerto	44.645*	51.402	612.200*	634.469
Madiun	65.414	9.729*	674.555	373.475*
Surabaya	55.696	3.108*	651.147	195.164*
Batu	34.428	8.489*	557.141	355.927*

much lower RMSE and AIC values compared to GSTARI $(1,1,1)$ with OLS. These findings highlight that the GSTARI $(1,1,1)$ model with Bayesian estimator outperforms the GSTARI $(1,1,1)$ model with OLS estimator.

4 Conclusion

The rice prices of nine cities in East Java province can be considered as spatiotemporal data. A potential statistical model for modeling this data is GSTARI which involves the Bayesian parameter estimation method. The GSTARI $(1,1,1)$ model, which follows a Bayesian estimator, demonstrates statistically significant parameter values across all areas when used to model rice prices in East Java. This contrasts with the condition when using the OLS estimator in which none of the parameter values at any position exhibit significance. In addition, the GSTARi $(1,1,1)$ model offers better performance in terms of value when working with the Bayesian estimator compared to OLS. The RMSE and AIC values of the GSTARI $(1,1,1)$ model relying on the Bayesian estimator at eight locations are significantly lower than those of the OLS model. Therefore, it can be inferred that the GSTARI $(1,1,1)$ model with the Bayesian estimator outperforms the OLS model.

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References

[1] Ruspayandi, Topan, Tajuddin Bantacut, Bustanul Arifin, Idqan Fahmi, "Market-Approach-Based Policy to Achieve Rice Price Stability in Indonesia—Can It Be a Complement?" Economies, **10,** no. 12, (2022), 296.

[2] Feryanto, Harianto, Herawati, "Retail trader pricing behavior in the traditional rice market: A micro view for curbing inflation", Cogent Economics and Finance, **11,** no. 1, (2023), 2216036.

[3] Deski, Sri Wahyuni, Sartiyah Sartiyah, Chenny Seftarita, "Investigating the Effect of Rice Commodity Price Volatility on Provincial Capital Poverty: An Evidence from Indonesi", International Journal of Global Optimization and Its Application, **1,** no. 2, (2022), 90-99.

[4] Prastyo, Dedy Dwi, Feby Sandi Nabila, Suhartono, Muhammad Hisyam Lee, Novri Suhermi, Soo-Fen Fam. "VAR and GSTAR-based feature selection in support vector regression for multivariate spatio-temporal forecasting", In Soft Computing in Data Science: 4th International Conference, Bangkok, Thailand, August 15-16, 2018, Proceeding, **4,** (2019), 46-57, Springer Singapore.

[5] Abdullah, Atje Setiawan, Setiawan Matoha, Deltha Airuzsh Lubis, Annisa Nur Falah, I. G. N. M. Jaya, Eddy Hermawan, Budi Nurani Ruchjana, "Implementation of Generalized Space Time Autoregressive (GSTAR)-Kriging model for predicting rainfall data at unobserved locations in West Java", Applied Mathematics and Information Science, **12,** no. 3 (2018), 607–615.

[6] Putri Monika, Budi Nurani Ruchjana, Atje Setiawan Abdullah, "GSTARI-X-ARCH Model with Data Mining Approach for Forecasting Climate in West Java", Computation, **10,** no. 12 (2022), 204.

[7] Hot Bonar, Budi Nurani Ruchjana, Gumgum Darmawan, "Development of generalized space time autoregressive integrated with ARCH error (GSTARI–ARCH) model based on consumer price index phenomenon at several cities in North Sumatera province", In AIP Conference Proceedings, 1827, no. 1. AIP Publishing, 2017.

[8] M. Alawiyah, D. A. Kusuma, B. N. Ruchjana, "Application of Generalized Space Time Autoregressive Integrated (GSTARI) model in the phenomenon of covid-19", Journal of Physics: Conference Series, 1722, no. 1, (2021), 012035.

[9] Steffen Zitzmann, Oliver Lüdtke, Alexander Robitzsch, Martin Hecht, "On the performance of Bayesian approaches in small samples: A comment on Smid, McNeish, Miocevic, and van de Schoot", Structural Equation Modeling: A Multidisciplinary Journal, **28,** no. 1 (2021), 40–50.

[10] Mitzi Morris, Katherine Wheeler-Martin, Dan Simpson, Stephen J. Mooney, Andrew Gelman, Charles DiMaggio. "Bayesian hierarchical spatial models: Implementing the Besag York Mollié model in stan", Spatial and spatio-temporal epidemiology, **31,** (2019), 100301.

[11] Asim Ansari, Kamel Jedidi, "Bayesian factor analysis for multilevel binary observations", Psychometrika, **65,** (2000), 475–496.

[12] Prathiba Natesan, Ratna Nandakumar, Tom Minka, Jonathan D. Rubright. "Bayesian prior choice in IRT estimation using MCMC and variational Bayes." Frontiers in Psychology, **7,** (2016), 214660.

[13] Erma Suryani, Rully Agus Hendrawan, Isnaini Muhandhis, Rarasmaya Indraswari, "A simulation model to improve the value of rice supply chain (A case study in East Java–Indonesia)", Journal of Simulation, **16,** no. 4 (2022), 392–414.

[14] Mutiarra Ridyo Arum, Arini Wahyu Utami, Irham Irham. "Climate Change and Rice Production in East Java Province, Indonesia", In 3rd International Conference on Smart and Innovative Agriculture (ICoSIA 2022), Atlantis Press, (2023), 400–413.

[15] Toni Toharudin, Rezzy Eko Caraka, Hasbi Yasin, Bens Pardamean, "Evolving Hybrid Generalized Space-Time Autoregressive Forecasting with Cascade Neural Network Particle Swarm Optimization", Atmosphere, **13,** no. 6 (2022), 875.

[16] Putri Monika, Budi Nurani Ruchjana, Atje Setiawan Abdullah. "GSTARI-X-ARCH Model with Data Mining Approach for Forecasting Climate in West Java", Computation, **10,** no. 12 (2022), 204.

[17] Chen Zhu, Chien-Chiang Lee, "The effects of low-carbon pilot policy on technological innovation: Evidence from prefecture-level data in China", Technological Forecasting and Social Change, **183,** (2022), 121955.

[18] Andrew Gelman, John B. Carlin, Hal S. Stern, Donald B. Rubin, Bayesian data analysis, Chapman and Hall/CRC, 1995.

[19] Joseph M. Northrup, Brian D. Gerber, "A comment on priors for Bayesian occupancy models", PLoS One, **13,** no. 2 (2018), e0192819.

[20] Andrea Carriero, Todd E. Clark, Massimiliano Marcellino, "Large Bayesian vector autoregressions with stochastic volatility and non-conjugate priors", Journal of Econometrics, **212,** no. 1 (2019), 137–154.

[21] Xiaoyan Li, Jinwen Ma, "Non-central Student-t mixture of Student-t processes for robust regression and prediction", In Intelligent Computing Theories and Application: 17th International Conference, Shenzhen, China, August 12–15, 2021, Proceedings, Part I, Springer International Publishing, (17), 2021, 499–511.

[22] Zhiyong Zhang, "A note on wishart and inverse wishart priors for covariance matrix", Journal of Behavioral Data Science, **1,** no. 2 (2021), 119–126.

[23] Andi Asmawati Azis, Aswi Aswi, "Spatial clustering of stunting cases in Indonesia: A Bayesian approach", Communications in Mathematical Biology and Neuroscience, 2023, no. 8, 1–11.

[24] Tomaz Back Carrijo, and Alan Ricardo da Silva, "Modified Moran's I for small samples", Geographical Analysis, **49,** no. 4 (2017), 451–467.

[25] A. Aswi, S. M. Cramb, Paula Moraga, K. Mengersen, "Bayesian spatial and spatio-temporal approaches to modelling dengue fever: a systematic review", Epidemiology and Infection, **147,** (2019), e33.

[26] Petrônio Cândido de Lima e Silva, Carlos Alberto Severiano Junior, Marcos Antonio Alves, Rodrigo Silva, Miri Weiss Cohen, Frederico Gadelha Guimarães, "Forecasting in non-stationary environments with fuzzy time series", Applied Soft Computing, **97,** (2020), 106825.

[27] Feng Jin, Yongwu Li, Shaolong Sun, Hongtao Li, "Forecasting air passenger demand with a new hybrid ensemble approach", Journal of Air Transport Management, **83,** (2020), 101744.

[28] Thendiyath Roshni, Madan K. Jha, Ravinesh C. Deo, A. Vandana, "Development and evaluation of hybrid artificial neural network architectures for modeling spatio-temporal groundwater fluctuations in a complex aquifer system", Water Resources Management, **33,** (2019), 2381–2397.

[29] Allan C. Just, Kodi B. Arfer, Johnathan Rush, Michael Dorman, Alexandra Shtein, Alexei Lyapustin, Itai Kloog, "Advancing methodologies for applying machine learning and evaluating spatiotemporal models of fine particulate matter (PM2. 5) using satellite data over large regions", Atmospheric Environment, **239,** (2020), 117649.

[30] Jarbou Bahrawi, Abdulaziz Alqarawy, Anis Chabaani, Amro Elfeki, Mohamed Elhag, "Spatiotemporal analysis of the annual rainfall in the Kingdom of Saudi Arabia: predictions to 2030 with different confidence levels", Theoretical and Applied Climatology, **146,** (2021), 1479–1499.

[31] Muhammad Faiz Amir Aththufail, Sindy Devila, Fevi Novkaniza, "Forecasting Indonesia mortality rate using beta autoregressive moving average model", Commun. Math. Biol. Neurosci., (2023).

[32] Wei Zhou, Kaihua Ding, Peng Liu, Guanghong Lan, Zutao Ming, "Spatiotemporal filtering for continuous GPS coordinate time series in mainland China by using independent component analysis", Remote Sensing, **14,** no. 12, (2022), 2904.