E-Jurnal Matematika Vol. 15(2), Mei 2026, pp. 96-104 ISSN: 2303-1751
DOI: https://doi.org/10.24843/MTK.2026.v15.i02.p508

AN APPLICATION OF GREY MODEL IN MODELLING SOCIO-ECONOMIC VARIABLES WITH LIMITED DATA IN NORTH KALIMANTAN

Ray Sastri[1§], Arbi Setiyawan[2]

[1]Department of Statistics, STIS Polytechnic of Statistics [Email: raysastri@stis.ac.id]
[2]School of Management, Jiangsu University, China [Email: arbies@gmail.com]
[§]*Corresponding Author*

ABSTRACT

New administrative regions often face a severe data scarcity precludes the use of conventional econometric models and data-intensive machine learning techniques. This study evaluates the performance of Grey System Theory, specifically the classical GM(1,1) and the extended model EXGM(1,1) in modeling and forecasting socio-economics variables under limited data conditions. Utilizing official time-series data from 2013–2021, models were developed using an 8-year training set and validated against a 1-year testing set. Performance was measured using the Mean Absolute Percentage Error (MAPE). Mathematical findings reveal that both models achieve highly accurate performance with MAPE under 5% for variables with near-monotonic trends, such as Gross Regional Domestic Product (GRDP) and unemployment rate. While EXGM(1,1) demonstrated superior mathematical fit during the training phase due to optimized background values. The classical GM(1,1) proved more resilient during the testing phase, particularly for volatile indicators like poverty rates. Specifically, EXGM(1,1) exhibited a risk of overfitting to grey noise in non-monotonic datasets, leading to higher forecasting errors compared to the GM(1,1). It concludes that while EXGM(1,1) offers superior flexibility for tracking turning points in stable decaying trends, the classical GM(1,1) remains the more reliable tool for general policy interpolating due to its predictive stability and resistance to stochastic fluctuations.

***Keywords**: Grey System Theory, small sample forecasting, emerging economy, regional planning.*

1. INTRODUCTION

Accurate socioeconomic forecasting is the backbone of effective regional planning Kovshov et al. (2024). For emerging administrative areas, economic modeling is far more than an academic exercise. It is a vital tool for survival and sustainable growth Hariram (2023). North Kalimantan, one of Indonesia's newest provinces, perfectly illustrates the challenges of limited data problem. While established economies can rely on decades of historical records, new provinces must navigate severe data scarcity that renders traditional econometric and machine learning tools hard to use.

Historically, the world of macroeconomic forecasting has been dominated by classical models like Autoregressive Integrated Moving Average (ARIMA). Global literature, spanning from Egypt Adrian (2014) to India Devi et al. (2020), underscores a reliance on ARIMA for Gross Domestic Product (GDP). However, the mathematical validity of these models is predicated on large sample theory. In Indonesia, for instance, a model typically needs between 19 and 52 data points to produce reliable results (Utama & Wirawan, 2014; Silalahi, 2020). Moreover, some statistical model tend to overfit or fail when applied to the small datasets Brigato & Iocchi (2020). This issue creates a methodological gap where ordinary models fail under data scarcity, leaving policymakers to rely on guesswork or biased estimates.

We address the methodological gap by applying Grey System Theory (GST), an approach designed precisely to bridge such data gaps. GST is introduced by Deng in 1982, which provides a sophisticated way to model systems where information is partially known but mostly hidden (Xie, 2017). Unlike standard probability models that demand large samples and normal distribution, Grey models use an Accumulated

Generating Operation (AGO) to smooth out noisy raw data and uncover hidden trends. In fact, the foundational GM(1,1) model can produce remarkably accurate forecasts with as few as four observations (Huang et al., 2014; Wu et al., 2019). Despite this efficiency, the standard model is often criticized for being too rigid to handle the volatility of an emerging economy.

Recent breakthroughs have led to the extended model EXGM(1,1), which offers a more flexible evolution of the original theory. By isolating exponential variations and fine-tuning background parameters, the EXGM(1,1) is designed to handle sudden shifts more gracefully than the classical grey model (Bilgil, 2020). While it has shown success in predicting pandemics and population shifts (Tong et al., 2020), its performance in the realm of official regional statistics remains largely unexplored, especially where an administrative transitions and structural shocks are common. In Indonesia, the use of Grey Models for regional planning is still in its infancy. Most local studies still rely on simple descriptive statistics that cannot predict future trends. This study addresses that gap by conducting a systematic evaluation of GM(1,1) versus EXGM(1,1). Using North Kalimantan as a case study, we test whether the methodological adaptability of the EXGM(1,1) can truly overcome the issue of sparse data to provide more resilient model.

The objective of this research is twofold: (1) To evaluate and compare the prediction accuracy of the classical GM(1,1) and optimized EXGM(1,1) models for some important socio-economic variables based on sparse and noisy data. (2) To study the trade-offs between the mathematical complexity and the model parsimony in the volatile and stochastic conditions, considering the risk of overfitting in EXGM(1,1) versus the robustness of GM(1,1). (3) To study the influence of data volatility and non-monotonicity on the predictive divergence of different Grey models, providing a robust methodological benchmarking framework for local governments in new administrative regions. By validating these models against the specific dynamics of North Kalimantan, this study contributes to the global discourse on the adaptability of Grey systems, offering a replicable framework for policy forecasting in data-poor environments worldwide.

2. RESEARCH METHODOLOGY

2.1 Data Source and Variable

This study utilizes three key socio-economic indicators, such as Gross Regional Domestic Product (GRDP), poverty rate, and the open unemployment rate. The data were retrieved from the official website of the Statsitics Indonesia of North Kalimantan (https://kaltara.bps.go.id/). For the GRDP and open unemployment rate variables, the models were developed using a 8 data points of training dataset spanning the 2013–2020 period, with the 2021 data reserved for testing. Meanwhile, the poverty rate model utilized a smaller training set from 2015–2020, with 2021 as the testing year. The use of different data set due to the availability of the official data.

2.2 Grey Model GM(1,1)

The Grey Model GM(1,1) and the Extended Grey Model EXGM(1,1) are employed to model and predict the three socio-economic variables. The GM(1,1) is a mathematical model based on time-series data that is linearly differentiated at the first order, accumulated, and estimated for its exponential trend Tao (2020). The original data series is defined in Equation (1). Where n represents the number of observations and $x^{(0)}(k)$ is the actual data point at index k. To reveal hidden patterns within the data, the First Accumulated Generating Operator (1-AGO) is calculated using the Equation (2), which the background values are determined as Equation (3).

$$X^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)\right)$$
$$n \geq 4, \quad x^{(0)}(k) \geq 0, \; k = 1, 2, \dots, n \tag{1}$$

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)$$
$$k=1,2, .., n \tag{2}$$

$$z^{(1)}(k) = \frac{1}{2}\left(x^{(1)}(k) + x^{(1)}(k-1)\right),$$
$$k = 2, 3, \dots, n \tag{3}$$

The discrete forecasting equation for GM(1,1) is expressed as Liu et al. (2012) in Equation (4). Let $\hat{x}^{0}(k)$ is the predicted value of $x^{(0)}(k)$ and the parameters a (development coefficient) and b

(grey action quantity) are estimated using the Ordinary Least Squares (OLS) method in Equation (5)

$$\hat{x}^0(k) = \left(1 - e^a\right)\left(x^{(0)}(1) - \frac{b}{a}\right)e^{-a(k-1)} \quad (4)$$

$$k = 2, \dots, n$$

$$\begin{pmatrix} a \\ b \end{pmatrix} = \left(\boldsymbol{B^T B}\right)^{-1}\boldsymbol{B^T Y} \quad (5)$$

$$\boldsymbol{Y} = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}, \boldsymbol{B} = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix}$$

2.3 Extended Grey Model EXGM(1,1)

The EXGM(1,1) procedure is an evolution of the GM(1,1) model. While the 1-AGO and background value calculations remain identical, the model equation is extended, as presented in Equation (6) with the background value in Equation (7). Parameters *a, b*, and *c* are estimated via least squares in Equation (8), where B is modified to include the exponential component.

$$\hat{x}^1(k) = \left(x^{(0)}(1) - \frac{b}{a} - \frac{c}{a-1}e^{-1}\right)e^{a(1-k)} + \frac{b}{a} + \frac{c}{a-1}e^{-k} \quad (6)$$

$$\hat{x}^0(k) = \hat{x}^1(k) - \hat{x}^1(k-1) \quad (7)$$

$$\begin{pmatrix} a \\ b \\ c \end{pmatrix} = \left(\boldsymbol{B^T B}\right)^{-1}\boldsymbol{B^T Y} \quad (8)$$

$$\boldsymbol{Y} = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}$$

$$\boldsymbol{B} = \begin{bmatrix} -z^{(1)}(2) & 1 & (e-1)e^{-2} \\ -z^{(1)}(3) & 1 & (e-1)e^{-3} \\ \vdots & \vdots & \vdots \\ -z^{(1)}(n) & 1 & (e-1)e^{-n} \end{bmatrix}$$

2.4 Model Evaluation

Model accuracy is measured using the Mean Absolute Percentage Error (MAPE). A lower MAPE value indicates superior predictive performance. Following the criteria established by [15], model performance is categorized as excellent (MAPE < 1%), good (1%< MAPE < 5%), qualified (5% <MAPE < 10%), and unqualified (MAPE > 10%). The MAPE is calculated using Equation (9).

$$MAPE = \frac{1}{n}\sum_{k=1}^{n}\left(\left|\frac{\hat{x}^0(k) - x^0(k)}{x^0(k)}\right| \times 100\%\right) \quad (9)$$

3. RESULT AND DISCUSSION

A research by Bilgil (2020) found that EXGM(1,1) was better than GM(1,1) due to the improvement equation. However, prior research use general case. In this research, we want to test, whether EXGM(1,1) better than GM(1,1) in all case. The evaluation of Grey Model's performance will use three different variables. We construct a model and calculate the MAPE for each of the data set.

3.1 GRDP Model Analysis

In this specific visualization in Figure 1, the GRDP of North Kalimantan exhibits a consistent positive trend. Meanwhile, the GM(1,1) and EXGM(1,1) lines are almost perfectly superimposed on each other. This finding suggests that for this specific dataset, the extended parameters of the EXGM model did not significantly deviate from the classical GM model. Both models maintain a relatively smooth and upward trajectory. In the first half of the series, both the GM(1,1) in red line and EXGM(1,1) in blue line appear to be nearly identical. They track the actual data in the black line with high precision during this period. The models successfully capture the steady, linear growth trend of the economy between 2013 and 2015. In 2016, both models slightly overestimate the actual data, but they quickly realign by 2017–2018. The critical difference between the models and the real-world data emerges after 2018, where the actual data exhibits significant fluctuations. In 2019, there is a sharp spike in actual GRDP. In this situation, both models fail to reach this peak, suggesting that the Grey mechanism prioritizes smoothing the overall trend rather than reacting to short-term anomalies or sudden economic surges.

Moreover, the actual data drops significantly in 2020, likely due to the global economic impact of the COVID-19 pandemic. In the periode of recovery in 2021, the actual data begins to recover, but at a slower rate than the models predicted. The results indicate that while both Grey models are excellent at identifying the long-term underlying trend of North Kalimantan's economy with limited data. However, they are less sensitive to structural shocks like the 2020 economic downturn.

Based on the model evaluation in Table 1, the predicted values from both models are nearly identical, causing their respective curves to overlap. In the training phase in 2013–2020, the primary metric for evaluating Grey Models is the Mean Absolute Percentage Error (MAPE). The GM(1,1) achieves a training MAPE of 1.41%, while the EXGM(1,1) achieves 1.40%. These scale is considered highly accurate. Both models indicates that they are exceptionally well-suited for North Kalimantan's GRDP data. The negligible difference (0.01%) suggests that while the extended model EXGM(1,1) offers a theoretical refinement, the classical model GM(1,1) is already highly efficient at capturing the province's economic trajectory. In testing phase in 2021, the error increased slightly to 3.26% for GM(1,1) model and 3.32% for EXGM(1,1) model.

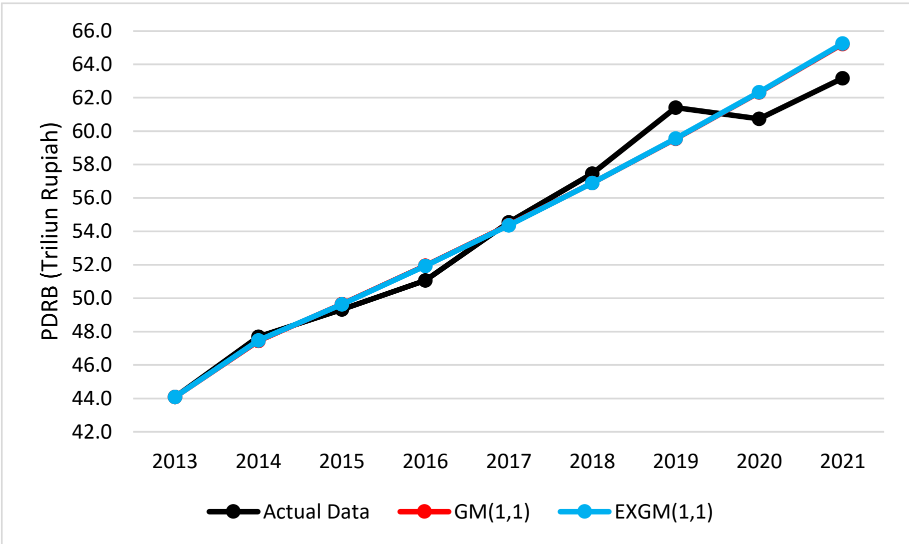

Figure 1. North Kalimantan GRDP Modeling Results Using Grey Models

Table 1. Model Evaluation for GRDP Model

Year		GRDP (Triliun Rp)	Predicted Value		Absolute Percentage Error (%)	
			GM(1,1)	EXGM(1,1)	GM(1,1)	EXGM(1,1)
Training Data	2013	44.09	44.09	44.09		
	2014	47.70	47.44	47.48	0.55	0.46
	2015	49.32	49.64	49.63	0.66	0.64
	2016	51.06	51.95	51.93	1.74	1.70
	2017	54.54	54.37	54.35	0.30	0.34
	2018	57.46	56.90	56.89	0.97	0.99
	2019	61.42	59.55	59.55	3.04	3.04
	2020	60.75	62.32	62.34	2.59	2.62
				MAPE (%)	1.41	1.40
Testing Data	2021	63.16	65.22	65.26	3.26	3.32

E-Jurnal Matematika Vol. 15(2), Mei 2026, pp. 96-104
DOI: https://doi.org/10.24843/MTK.2026.v15.i02.p508 ISSN: 2303-1751

3.2 Poverty Rate Model Analysis

Unlike the previous GRDP chart where the models were nearly identical, the chart for poverty rate reveals a significant divergence between the two models, as presented in Figure 2. The GM(1,1) in the red line acts as a smoother, ignoring the year-to-year volatility and establishes a steady. However, the model fails to capture the sharp peak in 2017 or the dip in 2019. This model assumes that poverty in North Kalimantan is following a long-term structural climb. While it has higher error rates for specific years, it provides a more stable, conservative estimate that isn't easily swayed by temporary data fluctuations.

On the other side, the EXGM(1,1) in the blue line attempts to track the actual data much more aggressively. It successfully captured the bump between 2017 and 2018 where the GM(1,1) model failed. However, after 2019, the model crashed downward while the actual poverty rate climbed sharply back up in 2021. Overall, the EXGM(1,1) shows high local responsiveness and better at following turning points in the short term, but in this specific case, it suffered from what looks like a lagged reaction to the 2019 point, leading to a very large forecast error in 2021.

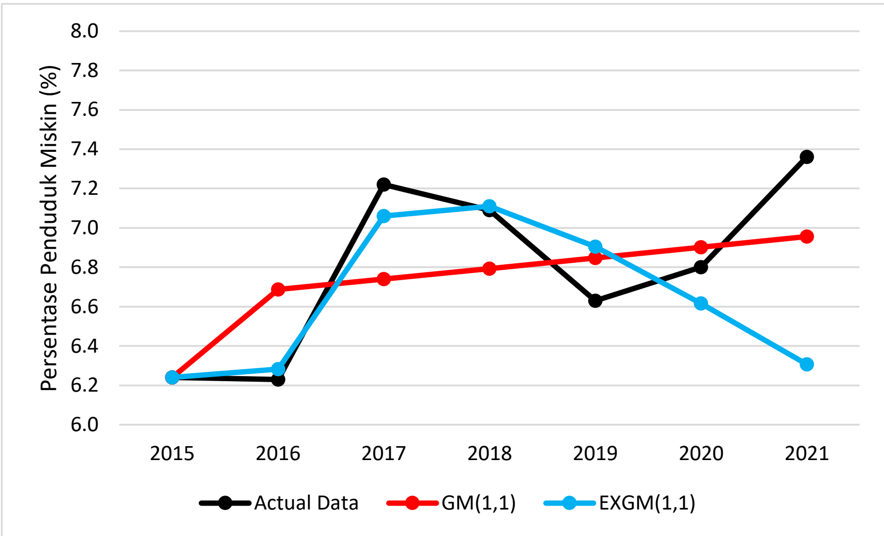

Figure 2. North Kalimantan Poverty Rate Modeling Results Using Grey Models

The results in Table 2 shows that in the training phase, the EXGM(1,1) model demonstrated superior fit, tracking the actual data closely. EXGM(1,1) have a lower MAPE of 2.04%, compared to 4.59% for the GM(1,1) model. However, this high level of accuracy did not extend to the forecasting phase. the EXGM(1,1) model failed to accurately predict the 2021 testing data, resulting in a significant error of 14.30%. In contrast, the GM(1,1) model proved more robust for forecasting, yielding a lower error of 5.49%. Because the EXGM(1,1) was so sensitive to the fluctuations in the training data between 2017 and 2019, it became too tuned to those specific past noises. When the actual poverty rate jumped to 7.36% in 2021, the EXGM was unable to pivot, leading to a significant forecasting failure.

The classical model GM(1,1) is more simple and resilient. Even though its training MAPE was higher, it stayed closer to the actual trend during the testing phase. It is the more reliable choice for long-term poverty forecasting in North Kalimantan. Whereas, EXGM(1,1) model is mathematically more sophisticated, but highly sensitive to grey noise. In environments with limited data and high volatility like poverty rates, its sensitivity can lead to a loss of predictive power when new, unexpected data points appear.

Table 2. Model Evaluation for Poverty Rate Model

Year		Poverty rate (%)	Predicted Value		APE (%)	
			GM(1,1)	EXGM(1,1)	GM(1,1)	EXGM(1,1)
Training Data	2015	6.24	6.24	6.24		
	2016	6.23	6.68	6.28	7.34	0.83
	2017	7.22	6.74	7.06	6.64	2.22
	2018	7.09	6.79	7.11	4.18	0.28
	2019	6.63	6.85	6.90	3.28	4.14
	2020	6.80	6.90	6.62	1.49	2.71
				MAPE (%)	4.59	2.04
Testing Data	2021	7.36	6.96	6.31	5.49	14.30

3.3 Unemployment Rate Model Analysis

The unemployment rate shows a downward trend with minor fluctuations, as visualized in Figure 3. The modeling of the unemployment rate in North Kalimantan reveals a high degree of convergence between the observed data and both Grey model. Unlike the high volatility observed in poverty indicators, the unemployment rate follows a relatively smooth negative exponential decay from its 2013 peak of 8.6%. Because Grey models are mathematically optimized to extract exponential signals from sparse datasets, both GM(1,1) and EXGM(1,1) demonstrated exceptional fit, maintaining close alignment with the actual values throughout the study period.

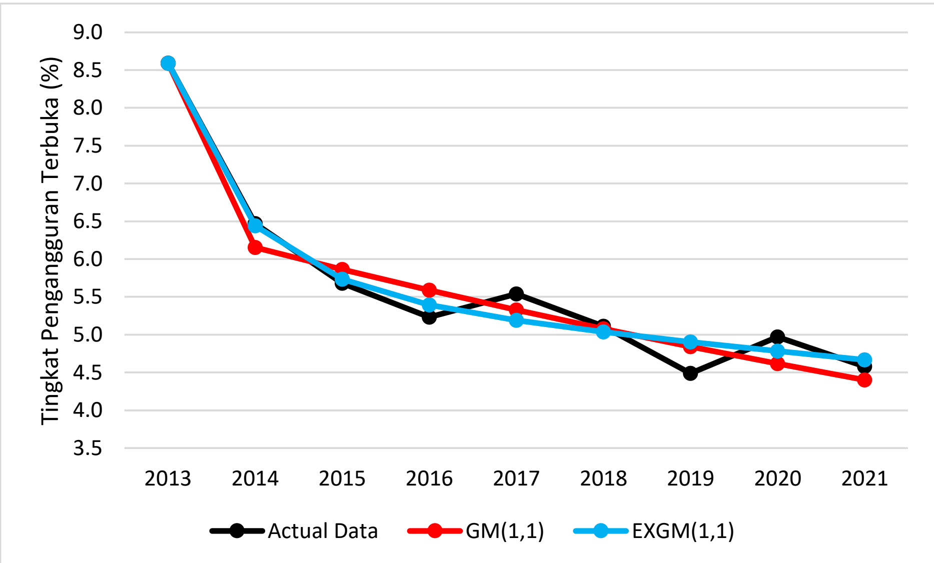

Figure 3. North Kalimantan Unemployment Rate Modeling Results Using Grey Models

While both models successfully captured the structural decrease in unemployment, their response to short-term fluctuations varied. In the initial 2013–2014 period, both models precisely mapped the steep decline in the unemployment rate. Between 2016 and 2017, the actual data experienced a minor spike. The EXGM(1,1) demonstrated superior flexibility by tracking this fluctuation more closely, whereas the GM(1,1) maintained a more rigid. In 2019, unemployment dipped sharply to 4.5%. While both models initially overshot this outlier, they demonstrated strong self-correction capabilities in the subsequent 2020–2021 period.

The evaluation results in Table 3 indicate that the Grey models successfully captured the trends in the unemployment rate data, with all MAPE values remaining below 5%. During the training

E-Jurnal Matematika Vol. 15(2), Mei 2026, pp. 96-104
DOI: https://doi.org/10.24843/MTK.2026.v15.i02.p508 ISSN: 2303-1751

phase, the EXGM(1,1) model achieved a superior fit with a MAPE of 3.62%, compared to 4.92% for the standard GM(1,1). Notably, EXGM(1,1) also demonstrated exceptional forecasting performance. As shown in Table 3, The testing error of EXGM(1,1) was significantly lower at 1.90%, whereas the GM(1,1) model recorded a 3.92% error.

The evaluation of the final testing year (2021) highlights a critical distinction in predictive accuracy. The EXGM(1,1) forecast converged almost perfectly with the actual data point with MAPE of 1.90%. Whereas, the GM(1,1) marginally underestimated the rate with the MAPE of 3.92%. This performance suggests that for variables following a fluctuating decline trend, the background value optimization inherent in the EXGM(1,1) provides a significant advantage. While the classical GM(1,1) is effective as a smoothing tool, the EXGM(1,1) exhibits superior adaptability to the turning points of the labor market. These findings imply that for lagging indicators like unemployment, the mathematical agility of the Extended Grey Model offers a more robust framework for regional policy forecasting under conditions of data scarcity.

Table 3. Model Evaluation for Unemployment Rate Model

Data	Year	Unemployment rate (%)	Predicted Value		APE (%)	
			GM (1,1)	EXGM (1,1)	GM (1,1)	EXGM (1,1)
Training Data	2013	8.59	8.59	8.59		
	2014	6.47	6.15	6.44	4.91	0.44
	2015	5.68	5.86	5.74	3.26	0.97
	2016	5.23	5.59	5.39	6.90	3.14
	2017	5.54	5.33	5.19	3.80	6.33
	2018	5.11	5.08	5.04	0.58	1.43
	2019	4.49	4.84	4.91	7.86	9.25
	2020	4.97	4.62	4.78	7.12	3.75
	MAPE (%)				4.92	3.62
Testing Data	2021	4.58	4.40	4.67	3.92	1.90

3.4 Discussion

The empirical results demonstrate that both GM(1,1) and EXGM(1,1) are highly capable of modeling economic variables in North Kalimantan, even under the structural constraints of a limited data environment. However, a nuanced evaluation reveals a critical divergence in model behavior. While the EXGM(1,1) consistently outperformed the classical model during the training phase, evidenced by its superior MAPE values, this high fitting accuracy did not universally translate into superior forecasting power. This phenomenon highlights a classic challenge in predictive modeling. In the testing phase, the classical GM(1,1) proved more resilient for predicting GRDP and poverty rates. This result suggests that while the EXGM(1,1) is mathematically adept at hugging historical data points through background value optimization, it may become overly sensitive to localized the fluctuation, thereby losing its generalizability when applied to out-of-sample data.

The predictive performance of both models was significantly dictated by the underlying nature of the time-series data. For variables exhibiting near-monotonic behavior, such as GRDP and the unemployment rate, both models yielded errors below 5%, confirming their robustness in capturing long-term economic momentum. Conversely, for highly volatile indicators like poverty rates, the models produced divergent results with larger error margins. This confirms a fundamental limitation of Grey models: their efficacy is inherently tied to the strength of the underlying exponential signal. When a system is subjected to frequent fluctuations, the Accumulated Generating

Operation (AGO) may struggle to filter out stochastic interference, leading to less reliable forecasts.

These findings extend the foundational conclusions of Huang et al. (2014) and Wu et al. (2019) regarding the efficiency of the GM(1,1) in data-sparse environments. By validating these models against a new autonomous region's data, this study provides empirical evidence that the classical model often maintains superior parsimony and predictive stability over more complex variants. Furthermore, our results refine the application of the EXGM(1,1) proposed by Bilgil (2020), suggesting that its use should be reserved for systems where the exponential variation is highly pronounced and relatively free from erratic structural shocks.

4. CONCLUSION

This study evaluated the efficacy of the classical model GM(1,1) and the extended model EXGM(1,1) in forecasting key socioeconomic indicators within the data-poor environment of North Kalimantan, Indonesia. As a new administrative region, North Kalimantan presents a unique small data challenge that renders traditional econometric models like ARIMA and modern machine learning techniques statistically unreliable. Our findings provide robust evidence that GST effectively bridges this methodological vacuum. The empirical results lead to three primary conclusions. First, both Grey Models demonstrated highly accurate predictive capabilities (MAPE < 5%) for variables with strong underlying exponential trends, such as GRDP and the unemployment rate. This validates the use of the AGO as a powerful tool for extracting structural momentum from sparse, noisy datasets. Second, while the EXGM(1,1) consistently achieved superior fit during the training phase due to its optimized background values, it exhibited a higher risk of overfitting in volatile scenarios. In the case of poverty rates, the classical GM(1,1) proved more resilient, suggesting that model parsimony often yields better generalizability than mathematical complexity when dealing with stochastic fluctuations. Third, the research highlights that the accuracy of Grey models is intrinsically linked to the monotonicity of the data. As volatility increases, the predictive divergence between model variants becomes more pronounced.

This research establishes performance parameters and provides a clear methodological benchmark for local governments in new administrative regions with data scarcity. The result shows that Grey models can be used as a reliable tool to inform policy and planning in case of limited data. For decision-making framework,ocal planners should take advantage of EXGM(1,1) for accurate tracking of stable, trending socio-economic indicators, and revert to the classical GM(1,1) for robustness in forecasting highly volatile or stochastic metrics.

While this study establishes a benchmark for Grey modeling in Indonesian regional statistics, it is limited by the short-term nature of the time series analyzed. Future research should explore the integration of rolling mechanism Grey models or fractional Hausdorff Grey models to further enhance predictive accuracy in the presence of extreme structural shocks, such as global pandemics or sudden shifts in fiscal policy. Furthermore, applying these models across other newly formed provinces in Indonesia would help generalize the findings and strengthen the regional statistical framework nationwide.

REFERENCES

Adrian, M. (2014). Developing a simple predictive model for job growth in the tertiary and quaternary sectors: Predicting employment based upon anticipated population growth. *Journal of Economic Development Studies*, *2*(3), 49–59. https://doi.org/10.15640/jeds.v2n3a4

Bilgil, H. (2020). New grey forecasting model with its application and computer code. *AIMS Mathematics*, *6*(2), 1497–1514. https://doi.org/10.3934/math.2021091

Brigato, L., & Iocchi, L. (2021). A close look at deep learning with small data. *2020 25th International Conference on Pattern Recognition (ICPR)*, 2490–2497. https://doi.org/10.1109/ICPR48806.2021.9412492

Devi, R., Agrawal, K. K., Dhar, J., & Tripathi, P. K. (2020). Scientifically forecasting the growth of Indian GDP (Gross Domestic Products) using ARIMA model. *Journal of Critical Review*, *7*(14), 2816–2824. https://jcreview.com/archives/volume-7/issue-14/4651

Hariram, N. P., Mekha, K. B., Suganthan, V., & Sudhakar, K. (2023). Sustainalism: An integrated socio-economic-environmental model to address sustainable development and sustainability. *Sustainability*, *15*(13), 10682. https://doi.org/10.3390/su151310682

Huang, C., Lu, C., & Chen, C. (2014). Application of grey theory to the field of economic forecasting. *Journal of Global Economics*, *3*(1), 1–3. https://doi.org/10.4172/2375-4389.1000131

Kovshov, V., Stovba, E., Lukyanova, M., et al. (2024). Foresight and forecasting of socio-economic development of rural territories. *Environment, Development and Sustainability*, *26*, 28219–28237. https://doi.org/10.1007/s10668-023-03808-7

Lin, L. C., Wu, S. Y., & Huang, Y. F. (2014). Forecasting the output values of Taiwan bicycles and spare parts with Fourier modified grey model. In E. Qi, J. Shen, & R. Dou (Eds.), *Proceedings of the 2013 4th International Asia Conference on Industrial Engineering and Management Innovation (IEMI2013)* (pp. 989–997). Springer. https://doi.org/10.1007/978-3-642-40060-5_95

Liu, S., Forrest, J., & Yang, Y. (2012). A brief introduction to grey systems theory. *Grey Systems: Theory and Application*, *2*(2), 89–104. https://doi.org/10.1108/20439371211260081

Silalahi, D. K. (2020). Forecasting of poverty data using seasonal ARIMA modeling in West Java province. *JTAM (Jurnal Teori dan Aplikasi Matematika)*, *4*(1), 76. https://doi.org/10.31764/jtam.v4i1.1888

Tao, L. (2020). Prediction model of financial income of listed companies based on grey model. *2020 IEEE International Conference on Industrial Application of Artificial Intelligence (IAAI)*, 374–378. https://doi.org/10.1109/IAAI51705.2020.9332821

Tong, M., Yan, Z., & Chao, L. (2020). Research on a grey prediction model of population growth based on a logistic approach. *Discrete Dynamics in Nature and Society*, *2020*, 2416840. https://doi.org/10.1155/2020/2416840

Utama, M. S., & Wirawan, I. G. P. N. (2014). Model Box-Jenkins dalam rangka peramalan. *Buletin Studi Ekonomi*, *19*(1), 92–104. https://api.semanticscholar.org/CorpusID:156918343

Wu, W., Zhang, T., & Zheng, C. (2019). A novel optimized nonlinear grey Bernoulli model for forecasting China’s GDP. *Complexity*, *2019*, 1731262. https://doi.org/10.1155/2019/1731262

Xie, N. (2017). Explanations about grey information and framework of grey system modeling. *Grey Systems: Theory and Application*, *7*(2), 179–193. https://doi.org/10.1108/GS-05-2017-0012