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The Effect of Population Density, GDP, and Waste Infrastructure on Waste Generation in Bali Province 2021-2024: Panel Data Regression Analysis

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Abstract
Background: Waste generation is an increasingly complex environmental problem along with population growth and increased economic activity, especially in tourism-based areas such as Bali Province.
Objective: This study aims to analyze the influence of population density, Gross Regional Domestic Product (GDP) per capita, and waste management infrastructure on waste generation in all districts/cities in Bali Province in the 2021–2024 period using a panel data regression approach.
Methods: Secondary data was obtained from the National Waste Management Information System (SIPSN), the Central Statistics Agency (BPS) of Bali Province, and the Bali Province One Data Portal. The selection of the best model was carried out through the Chow Test, Hausman Test, and Lagrange Multiplier Test, which resulted in a Random Effect Model (REM) as the selected estimation model.
Results: The results showed that population density and GDP per capita had a significant effect on waste generation with coefficient values of 50.35 and 0.58, respectively, while the variables of waste management infrastructure had no significant effect. The model was able to explain the variation in waste generation by 84.98% (R^2 = 0.8498).
Conclusion: These findings indicate that demographic and economic factors are the main determinants of waste generation in Bali Province, so waste management policies need to consider the dynamics of population growth and regional economic development.

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INTRODUCTION

The problem of waste generation has developed into an increasingly urgent global issue along with the rapid population growth and expansion of economic activities in various countries (Chen et al., 2020; Lebreton & Andrady, 2019; Rodić & Wilson, 2017). Globally, the World Bank estimates that world waste production will reach 3.4 billion tons per year by 2050, an increase of almost double from the current figure of 2.01 billion tons (Kaza et al., 2018). In Indonesia, data from the National Waste Management Information System (SIPSN) of the Ministry of Environment and Forestry noted that in 2023, the total national waste generation will reach more than 68 million tons per year, with the handling rate still in the range of 60–65%, so there is a significant management deficit (KLHK, 2024). Along with Indonesia's increasing population, which is projected to reach 278 million people by 2024, waste production continues to increase and has not been fully balanced with sustainable waste management (Aini et al., 2021). The rapid development, urbanization, and economic activities of the community are not only driving economic growth, but also increasing the need for basic services and the provision of sustainable waste management infrastructure (Napitupulu & Muhyidin, 2021).

Along with population growth and the development of economic activities, the pressure on the environment is also increasing (Zhang et al., 2021). The increase in population and community activities causes an increase in waste generation, so it needs to be balanced with an increase in adequate waste management facilities and infrastructure (Djaelani, 2021; Sharma & Jain, 2020; Supangkat & Herdiansyah, 2020; Voukkali et al., 2024). If not anticipated, the capacity of the existing waste management infrastructure will no longer be able to accommodate the increasing volume of waste (Kaza et al., 2018).

Waste management is one of the main challenges in realizing sustainable development, especially in areas that depend on the tourism sector such as Bali. Based on SIPSN data in 2024, the total waste generation in Bali Province reaches around 1.45 million tons per year, with an average daily waste generation of 0.65–0.70 kg per capita per day. The rapid development of tourism, which is marked by foreign tourist visits to Bali, which reached 5.27 million people in 2023 and increased significantly in 2024, population growth, and increasing public consumption patterns also contribute to an increase in the volume of waste generation from year to year. The increase in the number of people in urban areas also puts pressure on the environment, especially through the increasing volume of waste generated by the community (Abubakar et al., 2022; McGranahan, 2018; Utari et al., 2022). High consumption activities and resource use in areas with high population density cause waste production to tend to increase over time (Lavany & Chandra, 2022). The city of Denpasar as the center of economic and social activity in Bali recorded the highest waste generation with an average of more than 300,000 tons per year, far exceeding other districts, which reflects the high environmental pressure in areas with high population density and economic activity. A number of studies have also shown a positive relationship between population growth and the increasing burden on waste management systems in urban areas. Thus, the population can be one of the important variables in analyzing the tendency of waste generation in districts/cities in Bali Province.

In addition to demographic factors, Gross Regional Domestic Product (GDP) is also often associated with an increase in waste generation. Areas with higher levels of welfare and economic activity generally have larger public consumption patterns so that they have the potential to produce a higher volume of waste as well (Liu et al., 2019). However, these relationships are not always linear because they are influenced by people's consumption patterns, environmental awareness levels, and the availability of waste management infrastructure in each region. Therefore, empirical analysis using district/city panel data is needed to obtain a more comprehensive picture of the relationship between variables.

Research on waste generation in districts/cities in Bali Province requires an analytical approach that is able to accommodate differences in characteristics between regions as well as data changes from time to time. Therefore, panel data regression analysis was chosen because it is able to combine cross section and time series dimensions so that it can produce more informative, efficient, and able to explain the dynamics of the relationship between variables more accurately than ordinary regression (Baltagi, 2008). The use of panel data also allows the identification of the influence of factors such as population, GDP, and Human Development Index on waste generation in each district/city more comprehensively.

This study has the following objectives: (1) to analyze the influence of population density on waste generation in districts/cities of Bali Province in the period 2021–2024; (2) analyzing the influence of GDP per capita on waste generation in districts/cities of Bali Province in the 2021–2024 period; (3) analyzing the influence of waste management infrastructure on waste generation in districts/cities of Bali Province in the 2021–2024 period; and (4) determine the best panel data regression model that can comprehensively and efficiently explain the relationship between these variables.

This research has a novelty that distinguishes it from previous studies in several aspects. First, in terms of regional coverage and data period, this study uses the latest panel data covering all nine districts/cities in Bali Province in the period 2021–2024, which is the post-COVID-19 pandemic period where there was an economic recovery and a significant surge in tourist visits. This latest data has not been widely used in empirical studies of waste generation in Bali. Second, this study explicitly includes the variable of waste management infrastructure (number of waste management facilities) as an independent variable along with population density and GDP, thus allowing an integrated analysis between demand-side (population and economy) and supply-side (infrastructure capacity) factors in a single model framework. Third, the use of a systematic panel data model selection approach through a series of statistical tests (Chow, Hausman, and Lagrange Multiplier Tests) resulted in a more accurate Random Effect model in accommodating heterogeneity between districts/cities in Bali. Thus, this research makes a more comprehensive empirical contribution in understanding the determinants of waste generation in tourism-based areas, which can be the basis for the formulation of more adaptive and data-based waste management policies.

METHOD

This study uses a descriptive quantitative approach to analyze the influence of population density, GDP per capita, and waste management infrastructure on waste generation in Bali Province in 2021–2024. The data used is secondary data obtained from the Central Statistics Agency of Bali Province, district/city statistics publications, the Ministry of Environment and Forestry through the National Waste Management Information System (SIPSN), and the Bali Province One Data Portal. The research data covers all districts/cities in Bali Province so as to form a data panel that combines time series data and cross-section data.

The research variables consist of one dependent variable, namely annual waste generation, and three independent variables, namely population density, GDP per capita, and waste management infrastructure. The use of panel data regression is considered appropriate because it is able to produce more efficient estimates, increase the degree of freedom, and control heterogeneity between regions that cannot be observed directly (Gujarati & Porter, 2012). The research variables are stated in accordance with the following Table 1.

Table 1.
Research Variables

Variable	Variable Name	Units	Data Source
Y	Annual Waste Generation	Tons/Year	SIPSN/One Data of Bali Province Year 2021-2024
X1	Population Density	Soul/km2/year	BPS Year 2021-2024
X2	GDP Per Capita	Rupiah/Year	BPS Year 2021-2024
X3	Waste infrastructure	Amount/Year	SIPSN/One Data of Bali Province Year 2021-2024

Source : bps.go.id ,sipsn.kemenlh.go.id, and balisatudata.baliprov.go.id

The analysis technique uses panel data regression through *the Common Effect Model* (CEM), *Fixed Effect Model* (FEM), and *Random Effect Model* (REM) approaches. The selection of the best model is made using the Hausman test. The entire analysis process was carried out using Stata.

Stages of Data Analysis

The stages of data analysis in this study are carried out systematically through several interrelated steps. The research flow is generally presented in the following flowchart.

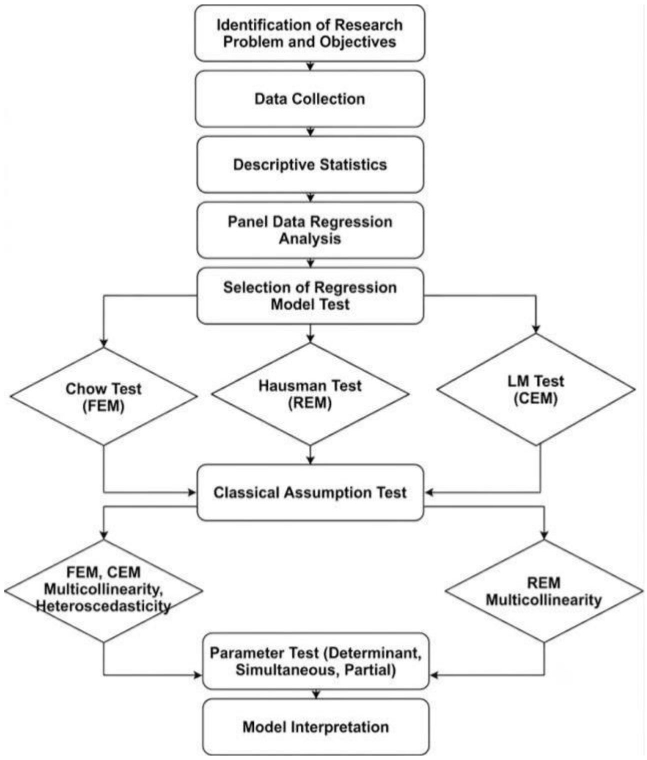

Figure 1. Research Flow Diagram

This research began with the identification of problems related to the increase in waste generation in Bali Province and the determination of the research objectives, namely analyzing the influence of population density, GDP per capita, and waste management infrastructure on waste generation. Furthermore, secondary data was collected sourced from the National Waste Management Information System (SIPSN), the Central Statistics Agency, and the Bali Province One Data Portal. The data used consisted of annual waste generation as a dependent variable, while population density, GDP per capita, and waste management infrastructure were used as independent variables.

Descriptive Analysis

The data obtained was then analyzed descriptively through the calculation of mean values, minimum, maximum, and standard deviation to describe the characteristics and distribution of research data.

Model Selection

In the panel data regression analysis, the selection of the best model is carried out to determine the most appropriate approach between *the Common Effect Model* (CEM), *Fixed Effect Model* (FEM), and *Random Effect Model* (REM). Model selection was carried out through the Chow test, Hausman test, and Lagrange Multiplier test (Gujarati & Porter, 2012).

1. Chow Test

The Chow test is used to determine the best model between the Common Effect Model (CEM) and the Fixed Effect Model (FEM). The hypotheses used are:
H0 : CEM model is more appropriate to use than FEM
H1 : FEM model is more appropriate to use than CEM
Test decisions are made based on probability values (p-value). If the p-value < 0.05, H0 is rejected so that the FEM model is more suitable to be used.

2. Hausman Test

The Hausman test is used to determine the best model between the Fixed Effect Model (FEM) and the Random Effect Model (REM). The hypotheses used are:
H0 : REM model is more appropriate to use than FEM
H1 : FEM model is more appropriate to use than REM

If the p-value < 0.05, H0 is rejected so that the FEM model is chosen as the best model.

3. Lagrance Multiplier Test (LM Test)

The Lagrange Multiplier test is used to determine the best model between the Common Effect Model (CEM) and the Random Effect Model (REM). The hypotheses used are:
H0 : CEM model is more appropriate to use than REM
H1 : the REM model is more appropriate to use than CEM
If the p-value < 0.05, H0 is rejected so that the REM model is more suitable to be used.

Table 2

Testing	Results	Conclusion
Chow Test	Prob > 0.05	CEM
	Prob < 0.05	FEM
Hausman Test	Prob > 0.05	REM
	Prob < 0.05	FEM
Lagrange Multiplier Test (LM Test)	Prob > 0.05	CEM
	Prob < 0.05	REM

Source: (Baltagi, 2008; Gujarati & Porter, 2012))

Classic Assumption Test

In panel data regression analysis, classical assumption testing is performed to ensure the regression model produces good estimates. The classical assumption test used in this study includes the multicollinearity test and the heteroscedasticity test (Gujarati & Porter, 2012).

1. Multicollinearity Test

   The multicollinearity test was performed to determine the relationship or correlation between independent variables in the regression model. A good regression model should not have a high correlation between independent variables. The test was carried out using *the Variance Inflation Factor* (VIF) value. The model is declared free of multicollinearity if the VIF value is < 10. Multicollinearity tests were performed on all regression models used in the study.

2. Heteroscedasticity Test

   The heteroscedasticity test was performed to determine whether there was an unevenness of residual variance between observations in the regression model. A good regression model should have a constant residual variance (*homocedasticity*). The test was carried out by looking at the probability value (*p-value*) at a significance level of 5% ($\alpha = 0.05$). If the probability value is < 0.05, then the model experiences heteroscedasticity. Heteroscedasticity tests are generally carried out on models using *the Ordinary Least Squares* (OLS) approach, such as *the Common Effect Model* (CEM) and *Fixed Effect Model* (FEM), while in *the Random Effect Model* (REM) using *the Generalized Least Squares* (GLS) approach, heteroscedasticity tests are not mandator.

Test Model Parameters

The model parameter test was carried out to determine the level of significance and ability of the regression model in explaining the relationship between independent variables and dependent variables. The tests used included a determination coefficient test, a simultaneous significance test (*F test*), and a partial significance test (*t test*) (Gujarati & Porter, 2012).

1. Coefficient Determination Test

   The determination coefficient is used to determine the ability of independent variables to explain dependent variables together. The value of the determination coefficient is shown through the *Adjusted* R^2 value which is in the range of 0 to 1 The *Adjusted* R^2 *value* which is getting closer to 1 indicates that the independent variable is able to better explain the variation of the dependent variable.

2. Simultaneous Significance Test (F Test)

   Simultaneous significance tests are used to find out whether all independent variables

together have an effect on dependent variables. The hypotheses used are:
H0 : all independent variables simultaneously have no effect on dependent variables
H1 : all independent variables simultaneously affect the dependent variables
Test decisions are made based on probability values (*p-value*). If the *p-value* < 0.05, H0 is rejected so that the independent variable simultaneously has a significant effect on the dependent variable.

3. Partial Significance Test (t-test)

The partial significance test is used to determine the influence of each independent variable on the dependent variable individually. The hypotheses used are:
H0 : the independent variable partially has no effect on the dependent variable
H1 : independent variables partially affect dependent variables

If the probability value (*p-value*) < 0.05, then H0 is rejected so that the independent variable partially has a significant effect on the dependent variable.

RESULTS AND DISCUSSION

Results

Data Collection

In the initial stage, secondary data collection was carried out whose sources came from SIPSN, BPS, and the Bali Province One Data Portal which was collected in the form of aggregate data as shown in Table 2 below.

Table 3
Data Overview

Districts	Year	Waste Generation/Ton/Year	Population Density/ Km2/ Year	GDP/ Rupiah/ Year	Total Waste Infrastructure/ Year
Jembrana	2021	59.395.72	382	42.382	56
Tabanan	2021	84.247,48	459	47.573	50
Badung	2021	116.731.24	1.312	81.198	80
Gianyar	2021	141.337.13	1.412	49.810	54
Klungkung	2021	34.221.57	667	41.163	31
Bangli	2021	40.479.96	535	26.319	116
Karangasem	2021	96.912	597	33.353	16
Buleleng	2021	123.771.50	591	41.893	98
Denpasar	2021	349.519.44	5.686	67.754	17
Jembrana	2022	59.72.92	389	45.249	44
Tabanan	2022	849.23.09	463	50.978	43
Badung	2022	119.474.58	1.313	99.076	105
Gianyar	2022	196.698.50	1.424	53.645	96
Klungkung	2022	376.43.55	679	44.269	43
Bangli	2022	408.36.05	544	28.182	196
Karangasem	2022	113.711.83	609	35.519	54

Buleleng	2022	143.283.67	605	44.603	110
Denpasar	2022	316.312.65	5.688	73.732	78
Jembrana	2023	597.65.28	381	48.270	44
Tabanan	2023	849.22.73	549	54.774	43
Badung	2023	195.222.49	1.413	121.414	105
Gianyar	2023	196.698.50	1.438	58.259	96
Klungkung	2023	40.239.61	665	48.260	43
Bangli	2023	41.195.36	496	30.256	196
Karangasem	2023	102.643.48	596	37.953	54
Buleleng	2023	150.562.50	612	121.414	110
Denpasar	2023	357.984.70	5.946	80.305	78
Jembrana	2024	60.106.92	383	51.730	72
Tabanan	2024	86.571.07	551	59.123	58
Badung	2024	199.810.15	1.426	132.027	157
Gianyar	2024	205.129.64	1.447	62.693	233
Klungkung	2024	40.829.45	667	52.628	73
Bangli	2024	41.557.88	498	32.275	306
Karangasem	2024	102.643.48	599	40.233	45
Buleleng	2024	150.779.68	616	50.796	118
Denpasar	2024	366.806.75	6003	86.425	89

Source : bps.go.id ,sipsn.kemenlh.go.id, and balisatudata.baliprov.go.id

Descriptive Analysis

Descriptive analysis was carried out to provide an overview of the characteristics of the research data on each variable used. The results of the descriptive analysis of each variable are presented in the form of a table to facilitate the interpretation of the research data.

Table 4

Variable	Remarks	Maximum	Minimum	Average
Y	Waste Generation/Ton/Year	366806.8	5972.92	127470.6
X1	Population Density/Km2/Year	381	6003	1323.361
X2	GDP per capita/Rupiah/Year	132027	26319	57653.69
X3	Number of Waste Management Facilities/Year	306	16	89.08333

Source: STATA Software Output Results

Estimation Model Selection

There are three methods that can be used for panel data in this study, namely *Common Effect (CE), Fixed Effect (FE),* and *Random Effect (RE) regression models.* To determine the best estimation model in this study, the Chow Test, the Lagrance Multiplier Test and the Hausman Test were carried out.

Table 5
Model Test Results

Chow Test Results	
Effect Test	**Prob.**
F(8, 29)	14.94
Prob. >F	**0.0000**
Hausman Test Results	
Effect Test	**Prob.**
Chi-Square (3)	1.62
Prob>Chi2	**0.6551**
Lagrance Multiplier *Test Results*	
Effect Test	**Prob.**
chibar2(01)	30.33
Prob chibar2>F	**0.0000**

Source :STATA Software Output Results

Recap of Model Test Results

Testing	**Results**	**Conclusion**
Chow Test	Prob>0.05	CEM
	Prob<0.05	**FEM**
Hausman Test	**Prob>0.05**	**REM**
	Prob<0.05	FEM
Lagrange Multiplier Test	Prob>0.05	CEM
(LM Test)	**Prob<0.05**	**REM**

Source : Recap of Stata Output Test Results

Based on table 3 of the results of the Chow Test, it is known that the Prob>F value in the Fixed Effect model (FEM) estimate shows the number 0.0000 which means (Prob>F) < 5% if H0 is rejected. Based on the results of the Chow test, the best estimation model is the *Fixed Effect Model* (FEM). Then continued with the Hausman Test showing the number 0.6551 which means (Prob>chi2) > 5% so that H0 is accepted. Based on the results of the Hausman Test, the best estimation model is *the Random Effect Model* (REM). Finally, *the Lagrange Multiplier Test* was carried out, it was known that the Prob>chibar2 value on the results *of the Lagrange Multiplier Test* showed the number 0.0000 which means (Prob>chibar2) < 5% so that H0 was rejected. Based on the results of the *Lagrance Multiplier* Test, the best estimation model is *the Random Effect Model*. Based on the three tests above, it can be concluded that the selection of the best estimation model is *the Random effect Model*.

Classic Assumption Test

According to Gujarati (2012) The estimation method in the *Random Effect Model* (REM) uses the *Generalized Least Squares* (GLS) approach, while *the Common Effect Model* (CEM) and *Fixed Effect Model* (FEM) use the *Ordinary Least Squares* (OLS) approach. One of the advantages of the GLS method is that it does not require the fulfillment of all classical assumptions. Based on the results of the selection of the best model, this study uses *a Random Effect model* so that the classical assumption test that is focused on is the multicollinearity test. The multicollinearity test was carried out to determine the correlation between independent variables in the regression model by looking at *the value of the Variance Inflation Factor* (VIF). The model is declared free of multicollinearity if the VIF value < 10.

Table 6
Multicollinearity Test Results

Variable	VIF	1/VIF

X1	3.61	0.276965
X2	2.43	0.412130
X3	1.96	0.510626
Mean VIF	**2.67**	

Source: STATA Software Output Results

Based on table 4, it is known that the VIF value of the mean value is as large as showing that the data used in this model is free from the symptoms of multicollinearity because it has a VIF value that is not greater than 10, thus the classical assumption of multicollinearity is fulfilled.

Discussion

Best Model Parameter Test

Panel Data Regression Analysis

Hypothesis testing was carried out on the best model selected, namely *the Random Effect Model* (REM). The tests in this study include a determination coefficient test, a simultaneous significance test, and a partial significance test to determine the model's capabilities and the influence of independent variables on dependent variables.

1. Determination coefficient test

   Determination coefficient analysis was carried out to find out how much independent variables are able to explain the simultaneous variation of dependent variables.

Table 7

Coefficient of Determination

	Overall R-Square
Random Effect Model	0.8498

Source : STATA Software Output Results

From the results of the random effect model estimation, an adjusted R-squared value of 0.8498 was obtained, meaning that the independent variable was able to explain the dependent variable by 84.98%

2. Simultaneous significance test

   Simultaneous tests were performed to determine whether all independent variables together had a significant influence on the dependent variables.

Table 8

Simultaneous Tests

	Prob > Chi2
Random Effect Model	0.0000

Source : STATA Software Output Results

Based on the results of simultaneous testing in the table, a probability value (F Statistic) p value of 0.000 was obtained, which is less than $\alpha = 0.05$, then it causes H0 to be rejected, meaning that there is an influence of independent variables together on dependent variables.

3. Independent Variable Partial Significance Test

   Partial tests are used to find out if each variable is independent have a significant or not effect on the individual dependent variables.

Table 9

Partial Significance Test

Variable	**Variable Description**	**Coefficients**	**Prob.**
C	Kostanta	17017.6	0.424
X1	Population Density	50.35014	0,000
X2	GDP Per Capita	0.5772225	0.009
X3	Number of Waste Management Facilities	118.3453	0.151

Source : STATA Software Output Results

From the table above, the hypothesis results of each independent variable are obtained as follows

1. Variable X1 (Population Density)

   The probability value of the p value of the variable X1 (Population Density) is 0.000 less than α = 0.05 causing H0 to be rejected, then the independent variable Variable (Population Density) has a significant effect on the dependent variable of Waste Generation.
2. Variable X2 (GDP per capita)

   The probability value of Variable X2 (GDP Per Capita) is 0.009 less than α = 0.05 causing H0 to be rejected, then the independent variable Variable X2 (GDP Per Capita) has a significant effect on the dependent variable of Waste Generation.
3. Variable X3 (Number of Waste Management Facilities)

   The probability value of the p value of Variable X3 (Waste Management Facility) is 0.151 more than α = 0.05 causing H0 not to be rejected, then the independent variable X3 (Waste Management Facility) does not have a significant effect on the dependent variable of Waste Generation.

Based on the above analysis, a Random Effect Model equation model was obtained with 2 independent variables that have a significant effect on the Sampa Generation variable, namely: variables X1 (Population Density), and X2 (GDP per capita).

$$\hat{Y}it = 17017.6 + 50.350X1it + 0.57\ X2it$$

Description :

$\hat{Y}it$ = Generated Waste (tons)
X1it = Population Density (population/km^2)
X2it = GDP per capita (rupiah)

Interpretation :

1. The constant of 17017.6 shows that if population density and GDP per capita are considered constant, then waste generation is estimated at 17,017.6 tons.
2. The population density coefficient of 50,350 shows that every increase in population density by 1 person/km^2 will increase waste generation by 50,350 tons.
3. The GDP coefficient per capita of 0.57 shows that every increase in GDP per capita of 1 rupiah will increase waste generation by 0.57 tons.

CONCLUSION

The best estimation model in this study is the Random Effect Model (REM), where there are two independent variables that have a significant effect on the dependent variables of waste generation, namely population density and GDP per capita. The population density variable has a positive relationship with waste generation, which shows that an increase in the number of people in an area tends to increase the amount of waste generated by it. The GDP per capita variable also has a positive relationship with waste generation, which indicates that an increase in economic activity and the level of community welfare also increases waste generation. The results of this study show that population and economic factors have an important role in increasing waste generation in Bali Province. Therefore, waste management needs to consider the dynamics of population growth and economic development in each district/city. For further research, other independent variables related to environmental aspects and waste services can be added, such as the level of public consumption, the number of waste management facilities, or the level of waste transportation services so that the results of the analysis can provide a more comprehensive picture.

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