Artigo original

http://dx.doi.org/10.18623/rvd.v22.n2.3141

# POLICY IMPLICATIONS OF THE VILLAGE ECONOMIC RESILIENCE INDEX IN CENTRAL JAVA

## *IMPLICAÇÕES POLÍTICAS DO ÍNDICE DE RESILIÊNCIA ECONÔMICA DAS ALDEIAS EM JAVA CENTRAL*

Article received on: 6/20/2025
Article accepted on: 8/25/2025

**Alizar Isna***
*Faculty of Social and Political Sciences, Jenderal Soedirman University
Purwokerto 53122, Central Java Province, Indonesia
Orcid: https://orcid.org/0009-0009-0113-213X
alizar.isna@unsoed.ac.id

**Andjar Prasetyo****
*Regional Development Planning, Research, and Innovation Agency of Magelang City,
Central Java Province, Indonesia
Orcid: https://orcid.org/0000-0001-5275-0223
studidaerah@gmail.com

The authors declare that there is no conflict of interest

**Abstract**
Village development has become a national priority to reduce inequality and strengthen local independence, yet the effectiveness of the Economic Resilience Index (ERI) as a predictive tool for village economic conditions has not been thoroughly evaluated. This study aims to assess the predictive capacity of ERI in supporting evidence-based village development policies in Central Java, Indonesia. The study uses an ex-post facto quantitative approach based on ERI secondary data 2018–2024. The sample included 7,809 villages, divided into 4,998 trainings, 1,250 validations, and 1,561 tests. The analysis was performed with Decision Tree Regression (DTR) using JASP software. The free variable is ERI 2018–2022, while the bound variable is ERI 2023. The results showed excellent model performance ($R^2 = 0.807$; MAPE = 4.65%). The feature importance analysis confirmed ERI 2023 as the most dominant variable, while the contribution of historical data was lower. The decision tree identifies the value threshold that divides villages into groups with different economic resilience. These findings highlight the importance of recent data in refining the ERI framework and provide practical implications for policymakers in setting village development priorities. Strengthening ERI as a policy instrument may enhance the effectiveness of resource allocation and sustainable village development strategies.

***Resumo***
*O desenvolvimento de aldeias tornou-se uma prioridade nacional para reduzir a desigualdade e fortalecer a independência local, mas a eficácia do Índice de Resiliência Econômica (IRE) como ferramenta preditiva das condições econômicas das aldeias não foi completamente avaliada. Este estudo tem como objetivo avaliar a capacidade preditiva do IRE em apoiar políticas de desenvolvimento de aldeias baseadas em evidências em Java Central, Indonésia. O estudo utiliza uma abordagem quantitativa ex post facto com base em dados secundários do IRE de 2018 a 2024. A amostra incluiu 7.809 aldeias, divididas em 4.998 treinamentos, 1.250 validações e 1.561 testes. A análise foi realizada com Regressão de Árvore de Decisão (DTR) utilizando o software JASP. A variável livre é o IRE de 2018 a 2022, enquanto a variável vinculada é o IRE de 2023. Os resultados mostraram excelente desempenho do modelo ($R^2 = 0{,}807$; MAPE = 4,65%). A análise da importância das características confirmou o IER 2023 como a variável mais dominante, enquanto a contribuição dos dados históricos foi menor. A árvore de decisão identifica o limiar de valor que divide as aldeias em grupos com diferentes resiliências econômicas. Essas descobertas destacam a importância de dados recentes no refinamento da estrutura do IER e fornecem implicações práticas para os formuladores de políticas na definição de prioridades de desenvolvimento das aldeias. O fortalecimento do IER como instrumento político*

**Keywords:** Economic Resilience Index. Village Development. Policy. Prediction. Central Java.

*pode aumentar a eficácia da alocação de recursos e das estratégias de desenvolvimento sustentável das aldeias.*

***Palavras-chave:*** *Índice de Resiliência Econômica. Desenvolvimento de Aldeias. Política. Previsão. Java Central.*

## 1 INTRODUCTION

Village development is one of the main pillars in Indonesia's national development agenda, especially to reduce inequality and strengthen the independence of local communities. The international literature shows that sustainable village development strategies need to be approached multidimensionally. For example, frugal innovation has been shown to be able to strengthen the achievement of the SDGs through resource-efficient entrepreneurship in South Asia (Hossain *et al*., 2023), while rural tourism in Nepal plays an important role in improving socio-economic well-being and preserving local culture (Pokharel & Bhattarai, 2022). In terms of governance, the role of public administration in reducing the rural-urban gap is significant, as shown in the context of Ukraine which emphasizes the importance of equitable access to basic resources and services (Komakha & Koltun, 2024). However, the limitations of decentralized reforms in the country also highlight the major challenges in realizing a decent standard of living for rural communities (Stepanenko *et al*., 2022). In addition, the perspective from China emphasizes the importance of ecological industrialization that transforms the potential of natural resources into village economic strength, thereby increasing the resilience and competitiveness of rural areas (Y. Liu *et al*., 2025). In the framework of village development in Indonesia, the Village Development Index (VDI) and especially the dimension of the Economic Resilience Index (ERI) plays an important role in capturing the actual condition of villages and directing evidence-based policy interventions. The relevance of the use of ERI is even clearer when it is associated with the international literature on rural economic resilience. First, recent research in China emphasizes the importance of integration between urban-village development and rural resilience, which suggests that spatial coordination can strengthen the resilience of villages to economic and social uncertainties (Yu *et al*., 2025a). Second, strengthening digital inclusive financing has been proven to increase village economic resilience through entrepreneurship, improving market access, and reducing the village-city income gap (Shen & Hu, 2024). In addition, green tourism-based economic diversification has great potential in strengthening the resilience of village communities to external shocks, while preserving local culture and the environment (Wijijayanti *et al*., 2025). In the context of natural disasters, studies in Liangshan Yi Autonomous Prefecture show that village transformational capacity greatly determines collective economic resilience to the risk of mountain disasters (Yuan *et al*., 2023). Meanwhile, research in Zhejiang highlights the importance of adaptive capacity, educational infrastructure, and health services in strengthening rural resilience to hydrometeorological threats (F. Liu *et al*., 2025). The integration of these findings with the VDI–ERI framework shows that an effective village development strategy in Central Java needs to emphasize economic diversification, digitalization of financial services, integrated spatial governance, and adaptive capacity building of village communities. This ensures that village development is not only oriented towards economic growth, but also on long-term resilience to various structural and environmental risks.

Although the ERI has been used since 2016 as part of the VDI, its effectiveness as a predictive analysis instrument is still limited to descriptive practices. The main challenge lies in how to utilize multi-year ERI data to produce accurate predictions of village economic resilience, as well as identify key determinants amid the limitations of historical data quality and village development dynamics. The international literature emphasizes the importance of using predictive analysis methods and structural models in understanding the key factors of rural development. For example, a study in Thailand used Structural Equation Modeling (SEM) to identify the dynamic relationship between the five forms of livelihood capital and poverty alleviation outcomes, so that it can guide evidence-based policies (Kaewhanam *et al*., 2025). In the context of technology, the application of Artificial Intelligence (AI) has proven to be effective for predictive modeling in the face of rural demographic and infrastructure challenges, including repopulation strategies and increasing resilience to climate change (Habib *et al*., 2024; Varela, 2024). Furthermore, digital technology-based approaches such as the Internet of Things (IoT) have also been proven to be able to increase the capacity to predict and monitor village development, especially in the agricultural sector and rural infrastructure (Saikia *et al*., 2025). In addition, the application of renewable energy in rural areas has been analyzed through a systematic review to assess its contribution to the SDGs, focusing on scalable models based on predictions of village economic sustainability (Rumbayan *et al*., 2025). Thus, efforts to develop ERI as a predictive instrument require the integration of quantitative approaches (SEM regression modeling, indicator analysis) with the support of digital technologies (AI, IoT, renewable energy). This approach allows local governments, including in Central Java, to overcome the limitations of historical data while producing more reliable predictions about the economic resilience of villages.

Previous research has focused more on describing ERI values and mapping village status, without exploring the potential for predictive analysis from these data. In addition, the literature on village development in Indonesia is still limited in linking the dynamics of economic indicators with advanced statistical methods, such as Decision Tree Regression (DTR). It is this gap that makes this study important: to test the reliability of ERI as a prediction instrument while understanding the evolution of its indicators from 2019 to 2024. This research contributes to two aspects. Academically, the research enriches the literature on measuring village economic resilience and its application in the framework of sustainable development. In practice, the findings provide a basis for local governments, especially in Central Java, to formulate evidence-based village development policies, set more appropriate intervention priorities, and refine ERI instruments to be more adaptive to future rural economic challenges.

## 2 LITERATURE REVIEW

Village economic resilience is understood as the ability of rural communities to maintain and improve their welfare through access to resources, business opportunities, and connectivity to the market. The international literature confirms that economic resilience is not only related to growth, but also the adaptive ability of villages to external changes such as global crises or fluctuations in commodity prices. Diversification of local economies is a key strategy, as shown by a study in Ethiopia that emphasizes the importance of infrastructure, access to credit, and climate-resilient agricultural practices in strengthening sustainable livelihoods (Duale, 2024). Resilience is also strongly influenced by access to finance. Research in China shows that green finance reforms can increase rural household incomes, reduce dependence on traditional agriculture, and encourage productive land use (Yan *et al*., 2025). In line with that, the regional banking system is seen as a fundamental element that supports the local economic infrastructure and strengthens the resilience of the village market (Kosmurzaevich, 2024). Public policy frameworks—whether through infrastructure investment, inclusive financial regulation, or local institutional empowerment—are fundamental instruments in strengthening the foundation of village economic resilience in an era full of uncertainty.

**2.1 The VDI: history, regulation, and application**

Since its introduction in 2015, the VDI has transformed from a mere categorization tool to a public policy instrument for planning, budg*et al*location, and evaluation of village development. The change in the ERI indicator from a general definition (2019–2020), integration with the Village SDGs (2021–2022), to the preparation of technical and strategic indicators (2023–2024), shows that there are efforts to improve the accuracy of data and its relevance to national targets. The international literature on rural development and resilience indices provides an important context for this evolution. The study on the implementation of SDGs indicators emphasizes that the integration of global indicators with local development indices needs to consider social, economic, and ecological dimensions to be in line with the needs of local governments (Faishal Mahdy *et al*., 2023). This is in line with methodological studies that use the sustainable development window model to measure the socio-ecological-economic balance in regional development (Fomina, 2022). Research on the coordination of village-urban integration in China shows that village resilience indexes need to be designed spatially and temporally to assess the adaptability of villages to regional dynamics (Yu *et al*., 2025b). Meanwhile, longitudinal studies found that rural resilience measurement frameworks are still diverse and not yet uniform, so there is a need for more consistent indicators to support evidence-based policies (Zhu *et al*., 2025). The application of the index in extreme environmental contexts, such as in the Heihe River Valley, China, proves that the integration of socio-economic data with ecology-based spatial data can strengthen the capacity to predict the resilience of villages to environmental risks (Huang *et al*., 2025). More broadly, the Latin American regional report emphasizes the importance of sustainable development indicators that are sensitive to health and climate issues, to ensure alignment between local policies and the global agenda (Hartinger *et al*., 2024). The evolution of VDI and especially ERI in Indonesia reflects a global trend in the sustainable development literature: the need for increasingly detailed, measurable, spatial, and integrated indicators with the SDGs. This ensures that VDI is not only an instrument for measuring the status of villages, but also an adaptive policy tool to respond to village development challenges within national and international frameworks.

## 2.2 Previous research on village economic development

A number of international studies confirm that village economic development is influenced by a combination of structural and social factors, ranging from governance, access to finance, to community participation. Household financial management in the agricultural sector plays an important role in rural development, where limited resource allocation and financial management can hinder local economic growth (Nurliza, 2023). In Malaysia, the Islamic banking system contributes to the economic empowerment of the poor, although the challenges of financial literacy are still significant (Abdul Rahman & Yamaludin, 2025). Access to financial technology (FinTech) in Africa is expanding financial inclusion, especially for vulnerable groups, although exploitative business models still create new economic inequities (Hsin-Hao & Yu-Kang, 2025). At the institutional level, cooperative banking frameworks for MSMEs in developing countries have been proven to support village economic resilience through a more inclusive financial system (Thelma Chibueze, 2024). Village infrastructure remains the main driving factor for connectivity with regional markets. A study in Cameroon highlights a water resource governance crisis that hampers basic services, showing how weak infrastructure can undermine village resilience (Toumba *et al*., 2025). Meanwhile, the digitalization of villages in China shows that effective digital configuration can boost economic growth in rural areas, although it still faces the challenges of the digital divide (Xie *et al*., 2025). The dimensions of governance and community participation are also crucial. Analysis of village fund allocation policies in Indonesia shows that governance based on transparency, financial literacy, and public participation strengthens the effectiveness of village development (Ardiputra *et al*., 2025). Village economic development cannot rely on just one factor, but requires multi-layered interventions: physical infrastructure, inclusive financial regulation, participatory governance, and financial technology innovation. The integration of these four dimensions provides direction for public policies to strengthen village independence and competitiveness.

Although the literature points to many determinants of rural economic resilience, there is an important gap: the lack of predictive analysis based on VDI longitudinal data that examines relationships between years. Most studies stop at descriptive mapping, without utilizing advanced statistical methods to see which variables are truly determining. In addition, there has been no study that explicitly links the evolution of the ERI concept in official documents to its empirical performance as a predictive instrument. Against this background, this study seeks to fill this gap through the application of Decision Tree Regression (DTR) to analyze the role of ERI in predicting village economic resilience in Central Java. The main questions of the study are: To what extent can ERI in previous years predict the economic resilience of villages in 2023, which factors are the most dominant, and what are the implications for village development policies?

## 3 METHODS

This study uses a quantitative design with an ex-post facto approach based on secondary data. The analysis model chosen is DTR (Gosiewska & Biecek, 2020), because it is able to identify dominant predictor variables while producing rule-based classifications that are easy to interpret. The research was conducted on villages in Central Java Province, with diverse development contexts, ranging from very disadvantaged villages to independent villages. The data analyzed came from the results of the update of the VDI for the 2018–2023 period compiled by the Ministry of Villages, Development of Disadvantaged Regions, and Transmigration (Dirjen Pemdes dan Perdesaan, 2024). The research variable consists of the value of the ERI in 2018–2022 as an independent variable, while the ERI in 2023 is used as a bound variable. Operationally, ERI is defined as a composite index that reflects the economic resilience of the village through five main indicators: 1) economic facilities and infrastructure, 2) market and logistics access, 3) access to financial institutions, 4) the existence of village economic institutions (BUMDes/cooperatives), and 5) regional openness. The ERI score was obtained from the VDI questionnaire using a scale of 0–5, then normalized to an index value according to official guidelines.

The instrument used is the VDI questionnaire, which is filled out by the village head and verified by the village local assistant, village assistant, and experts at the district and provincial levels. This instrument produces quantitative data related to village economic conditions. The research sample covers all villages in Central Java Province with complete data from 2018–2023. The amount of data analyzed consisted of 4,998 villages for training, 1,250 villages for validation, and 1,561 villages for testing. The census selection was carried out so that the results of the research could take a picture of the condition of the village as a whole. Data analysis was carried out using JASP software with a Decision Tree Regression model. In general, decision tree regression serves to map non-linear functions:

$$\hat{Y} = f(X) + \in \quad (1)$$

where $\hat{Y}$ is the prediction value ($ERI_{2023}$), X={$X_{2018}$, $X_{2019}$, $X_{2020}$, $X_{2021}$, $X_{2022}$} is the predictor vector (the previous year's ERI value), and ε is the residual error. In DTR algorithms, the *f(X)* function is constructed through if-then rules that are formed from splitting based on specific variables and threshold points. The separation process is guided by impurity reduction measurements (e.g. deviance or variance reduction). The optimal separation is selected by the following criteria:

$$\Delta I = I(S) - \left(\frac{N_L}{N} I(S_L) + \frac{N_R}{N} (IS_R)\right) \quad (2)$$

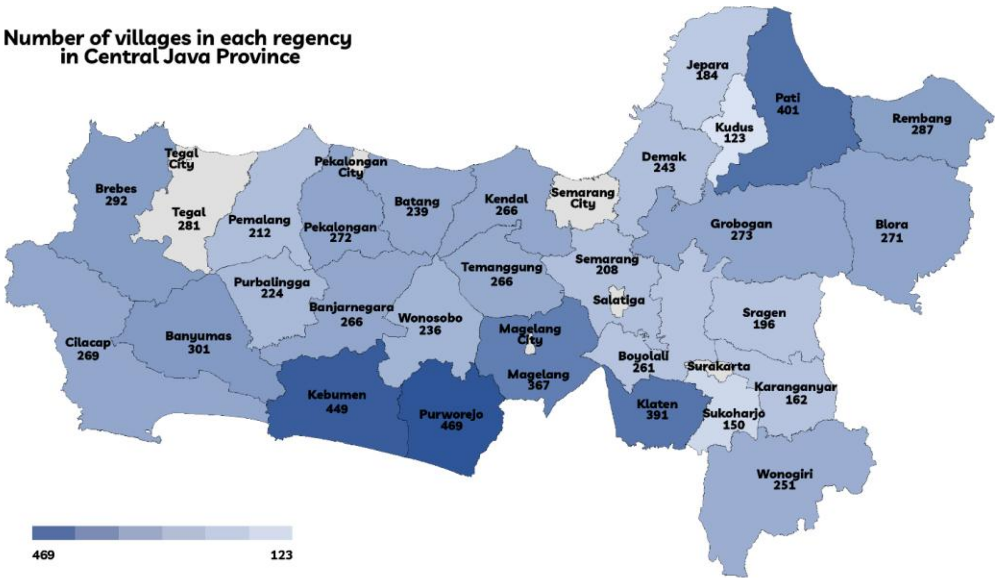
with *ΔI* is the impurity improvement, I(S) impurity before split, $I(S_L)$ and $I(S_R)$ impurity on the left and right branches, and NL,NR is the number of observations on each branch. The analysis stages in this study include evaluation of model performance through MSE, RMSE, MAE, MAPE, and $R^2$; feature importance analysis to assess the relative contribution of each variable; additive explanations to see the contribution of features to individual predictions; and visualization of tree structure to identify village classification patterns based on ERI 2023 values. The use of DTR is based on three considerations: 1) it produces an easy-to-interpret model to support public policy, 2) it can capture the pattern of non-linear relationships between variables, and 3) it allows the identification of threshold values that separate villages with different levels of economic resilience, thus facilitating the determination of development intervention priorities.

## 4 RESULT

As one of the provinces with the largest number of villages in Indonesia, Central Java Province plays an important role in the dynamics of national rural development. The variation in the number of villages between districts/cities in this province reflects the diversity of socio-economic contexts, infrastructure, and institutional capacity, which has direct implications for the strategy of strengthening the VDI and especially the ERI. Therefore, spatial mapping of the number of villages is an important foundation for understanding the framework for analyzing village economic resilience. Figure 1 shows the distribution of the number of villages in each district/city in Central Java. The district with the largest number of villages is Purworejo (469 villages), followed by Kebumen (449 villages), Pati (401 villages), and Klaten (391 villages). On the other hand, the areas with the least number of villages are Kudus City (123 villages), Sukoharjo (150 villages), and Karanganyar (162 villages). This difference in the number of villages illustrates the heterogeneity of the burden of development in each region, which can affect the effectiveness of VDI-based interventions. Districts with large village numbers have the potential to face more complex challenges in data consolidation and development program implementation, while areas with small village numbers have opportunities to focus on deepening the quality of village development.

**Figure 1.**

*Number of villages in each district/city in Central Java Province*




Source: results analysis, 2025

This section presents the main findings of the research related to the prediction of the 2023 ERI of villages in Central Java Province using the DTR model. The presentation of the results was carried out in stages to provide a comprehensive picture of the model's performance, the most influential factors, and the pattern of village classification based on the ERI value. The results presented can answer the formulation of research problems while supporting the discussion of the implications of village development policies.

**Table 1.**

*Decision Tree Regression Model Performance Summary*

| Metric | MSE | MSE (scaled) | RMSE | MAE | MAP | $R^2$ |
|---|---|---|---|---|---|---|
| Value | 0.002 | 0.203 | 0.048 | 0.031 | 4.65% | 0.807 |

*Source: results analysis, 2025*

Table 1 shows that the Decision Tree Regression model has a high degree of accuracy. The MSE (0.002) and RMSE (0.048) values show a relatively small average prediction error. Relative error is also low, with a MAPE of only 4.65%, so the prediction is considered precise. In addition, an $R^2$ of 0.807 indicates that the model is able to explain 80.7% variation in village economic resilience, which shows excellent performance for village development data-driven research.

**Table 2.**

*Feature Importance Variable ERI (2018–2023)*

| Variable | Relative Importance | Mean Dropout Loss |
|---|---|---|
| ERI 2023 | 31.602 | 0.152 |
| ERI 2022 | 22.502 | 0.047 |
| ERI 2021 | 15.99 | 0.047 |
| ERI 2020 | 13.523 | 0.047 |
| ERI 2019 | 9.454 | 0.047 |
| ERI 2018 | 6.928 | 0.047 |

Source: results analysis, 2025

The feature importance results (table 2) show that ERI 2023 is the most dominant variable in the model, with a relative contribution of 31,602 and the highest mean dropout loss (0.152). Variables from previous years continued to contribute, but their value declined over time, with the 2018 ERI accounting for only 6,928. This pattern confirms that the current economic conditions of the village are more relevant in determining economic resilience than historical data.

**Figure 2.**

*Mean Squared Error Plot and Decision Tree*

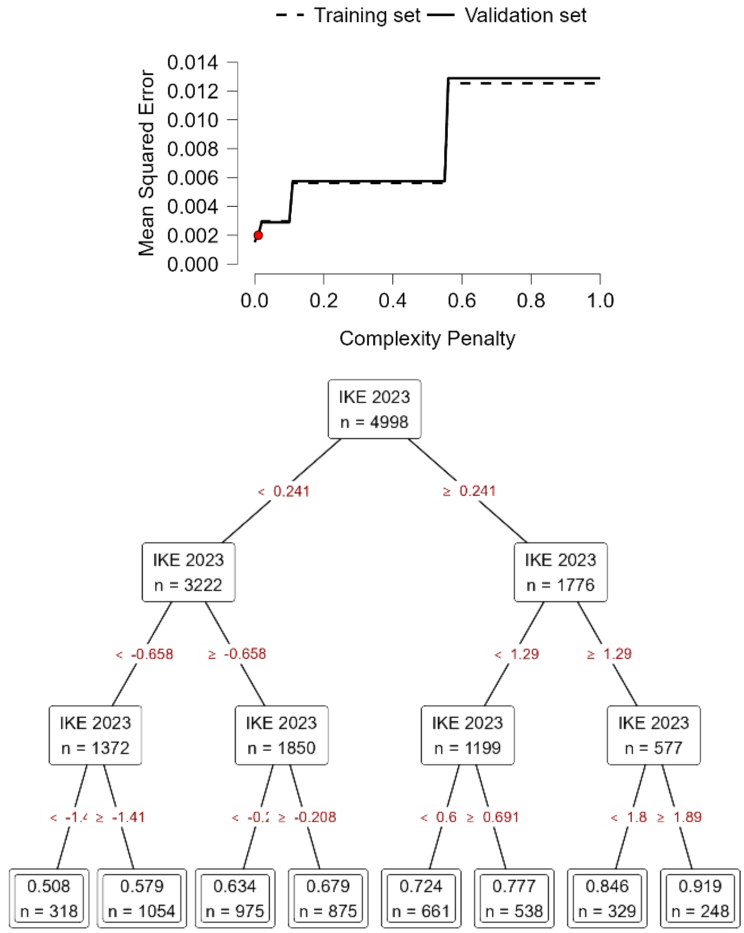



Figure 2 shows two important things: the accuracy of the model through the Mean Squared Error (MSE) curve and the decision structure through the Decision Tree. The graph on the left shows that the MSE in the training set (dotted line) and validation set (full line) is consistently low at the complexity penalty point of about 0.01 (marked in red), indicating that the optimal model is achieved at that complexity with minimal prediction error. Meanwhile, the tree diagram on the right illustrates that the entire major branching is determined by the ERI 2023 variable, with the first node separating the data at the 0.241 cut-off point. The next branching is also based on the 2023 ERI score with different thresholds (e.g. -0.658, -0.208, 0.691, 1.290), which results in village groups with varying average ERI scores, ranging from 0.508 to 0.919. This pattern confirms that the latest data (ERI 2023) is the dominant predictor in determining the variation in target values, while the previous year's data is not included in the main decision tree. Thus, the model shows two things: (1) good performance stability due to low and consistent MSE, and (2) strong reliance on current village economic conditions to predict outcomes, which is relevant to the needs of the latest data-driven policies.

**Table 3.**

*Additive Explanations for Test Cases*

| Case | Predicted | Base | ERI 2018–2022 | ERI 2023 |
|---|---|---|---|---|
| 1 | 0.679 | 0.678 | 0 | 0.001 |
| 2 | 0.634 | 0.678 | 0 | -0.04 |
| 3 | 0.634 | 0.678 | 0 | -0.04 |
| 4 | 0.579 | 0.678 | 0 | -0.1 |
| 5 | 0.634 | 0.678 | 0 | -0.04 |

Source: results analysis, 2025

The results of additive explanations in the test set (table 3) show how each ERI variable from 2018 to 2023 contributes to the model's predictive value. The Base column represents the base value of the prediction without considering the feature, which is about 0.678. In most cases (1–5), the contribution from ERI 2018 to ERI 2022 is 0.000, meaning that historical variables do not have an additional influence on the predicted results for these observations. On the other hand, the 2023 ERI is the main factor that shifts the prediction value: in Case 1, the contribution is positive by 0.001, so the prediction increases to 0.679; while in other cases, the contribution is negative, for example -0.044 (Case 2, 3, 5) or -0.098 (Case 4), so that the prediction decreases from the base value. This pattern confirms that the most recent data (ERI 2023) is the main determinant of prediction variation, while the previous year's data does not add significant information in these test cases. Thus, the model is more sensitive to current village economic conditions than to long-term historical trends.

## 4 DISCUSSION

The results of the study show that Decision Tree Regression (DTR) is able to predict the 2023 ERI of villages in Central Java with high accuracy (MSE = 0.002; $R^2$ = 0.807). The dominance of the 2023 ERI variable in feature importance indicates that current economic conditions are more relevant than historical data. These findings are consistent with the international literature on machine learning-based predictive modeling in the context of rural economic development. Studies in the United States show that machine learning models, including DTR, are effective in predicting the formation of new businesses in rural areas, with high accuracy in distinguishing dominant factors from historical variables (Hand *et al*., 2023). In the Philippines, random forest and DTR algorithms have successfully predicted the poverty rate of indigenous communities with >90% accuracy, confirming the importance of up-to-date data in supporting evidence-based policies (Onsay & Rabajante, 2025). In the context of climate adaptation, ML multimodel based predictive modeling can optimize climate and socio-economic data to strengthen food security in Uganda (Atuhaire *et al*., 2024). Another study introduced a resilience inference measurement framework with the support of decision trees to identify the most influential socio-economic factors, demonstrating the relevance of cutting-edge local data integration (Mandal *et al*., 2024). Furthermore, research in China shows that the application of ML, including feature attribution methods such as SHAP, is able to identify the dominant factors that affect household economic resilience, confirming the limitations of using historical data alone (Chen *et al*., 2025). At the level of public policy in the European Union, decision tree regression is used to analyze the relationship between economic indicators and migration, proving the added value of explainability in supporting prediction-based policy interventions (Dragomir-Constantin *et al*., 2025). This discussion shows that the dominance of the 2023 ERI variable in the DTR model is not an anomaly, but is consistent with the global literature, where cutting-edge data more strongly explains resilience variations than historical data. Implicitly, ML-based predictive models can be a strategic instrument for evidence-based village planning, although they need to be balanced with long-term data validation to remain relevant to the dynamics of village development.

The evolution of the definition and indicators of the ERI from 2019 to 2024 (table 4) shows a shift from descriptive instruments to strategic policy tools. In the early stages (2019–2020), the focus is still on local potential, financial access, and trade facilities. Significant changes have emerged since 2021–2022 when ERI began to be integrated with the Village SDGs, although the challenge of data consistency is still large. In the 2023–2024 period, the ERI indicator will be more technical and detailed, directly linked to the national target (10,000 disadvantaged villages, 5,000 independent villages). The international literature shows that these dynamics are in line with global trends. Studies in Indonesia underline that the success of village development measurement is highly determined by the integration of SDGs indicators with local policies, including village governance (Faishal Mahdy *et al*., 2023). Accountability mechanisms and incentives have also been proven to increase the effectiveness of village development indices in measuring social and economic resilience (Furqan, 2023).

**Table 4.**

*Development of the Definition and Indicators of the ERI*

| Year of Document | Definition of ERI | Key Indicators | Position in VDI | Evaluation Notes |
|---|---|---|---|---|
| 2019 | ERI measures the economic resilience of villages based on local potential, economic access, and availability of economic institutions. | Access to finance, trade facilities, distribution/logistics, availability of economic institutions. | One of 3 composite indexes. | The focus is still general, not yet detailed related to household welfare. |
| 2020 | Similar to 2019, emphasizing the resilience of the village economy to limitations. | Similar indicators: access to finance, economic means, territorial openness. | Combined with social and ecological to become VDI. | It has not included the issue of inequality between regions. |
| 2021 | ERI is positioned closer to the Village SDGs, related to poverty alleviation and a sustainable economy. | Access to banking, markets, distribution, and the involvement of BUMDes. | Integral part of VDI. | Starting with integration with the SDGs, but the challenge is the consistency of village data. |
| 2022 | ERI as the basis for village economic development for independence. | Economic infrastructure, access to finance, village economic institutions. | It remains as a component of VDI. | There is an emphasis on the accuracy of field data, the role of PLD is greater. |
| 2023 | ERI is associated with economic facilities/ infrastructure, market access, logistics, and financial institutions. | Economic infrastructure, access to trade centers, territorial openness, economic institutions. | Integrated in the VDI questionnaire. | More detailed & technical, guiding field data filling. |
| 2024 | ERI assesses the economic resilience of villages based on community participation in strengthening village autonomy. | Availability of economic facilities, market connectivity, financial institutions, logistics. | One of the three pillars of VDI. | It is more strongly associated with national targets (10,000 disadvantaged villages, 5,000 independent villages). |

*Source: SOP VDI 2019-2024*

At the global level, the economic resilience index has been applied to the agricultural sector in England and Wales to map spatial economic vulnerabilities, demonstrating the importance of a spatio-economic approach in strengthening the relevance of indicators (Berry *et al*., 2022). The study in India added a dimension of multi-stakeholder participation in the preparation of micro-level indicators to ensure the sustainability of evidence-based policies (Nandanan *et al*., 2025). The DPSIR (driving force–pressure–state–impact–response) framework used in China has proven effective in measuring rural resilience by balancing social, economic, and ecological indicators (Wei & Wang, 2025). Meanwhile, research in Spain developed a holistic index framework based on a diversity of indicators, which emphasizes the importance of the dimensions of governance, social justice, and innovation in increasing resilience (Suárez *et al*., 2024). Resilience indicators are integrated into the Food Systems Countdown 2030 architecture, highlighting the need for multidimensional indicators that link food, ecology, and economic aspects (Schneider *et al*., 2023). Other research in China on rural multifunctionality emphasizes the importance of indicators that are flexible to local needs (production, ecology, and social), according to the complexity of village functions (Tang *et al*., 2025). The development of ERI indicators in the VDI document reflects international trends, from general indicators to technical, spatial, multi-dimensional, and integrated indices with the SDGs and national targets. This transformation strengthens ERI's position as a public policy instrument that not only measures, but also guides the direction of sustainable village development.

Theoretically, these results enrich the understanding of village economic resilience in the context of sustainable development. The findings show that economic resilience is dynamic, so relevant indicators must always be updated according to current conditions. This supports the theory of resilience in development studies, which emphasizes the importance of adaptation to changes in the social, economic, and political environment. In addition, the integration of ERI with the Village SDGs since 2021 reinforces the conceptual foundation that measuring economic resilience should be linked to global development goals, such as poverty alleviation and inclusive economic development. The results of this study strengthen the understanding that village economic resilience is dynamic, so the indicators used to measure it need to be updated according to the latest socio-economic conditions. This is in line with the theory of resilience in development studies, which emphasizes the ability of communities to adapt to changes in the social, economic, and political environment. The international literature suggests that indicator-based resilience frameworks can more accurately capture the dynamics of rural development. For example, in China, the DPSIR (driving force–pressure–state–impact–response) framework is used to measure the dynamics of rural resilience, emphasizing the need to regularly update indicators to be relevant to changes in external conditions (Tang *et al*., 2025). A similar approach was also developed in Spain through a holistic index framework that integrates social, economic, ecological, and governance dimensions to assess the resilience of regions in layers (Suárez *et al*., 2024). The integration of ERI with the Village SDGs since 2021 shows the direction of globalization of development indicators. Studies in India emphasize the importance of a multi-stakeholder-based bottom-up approach to the localization of SDGs indicators, to better suit the local context (Nandanan *et al*., 2025). Similarly, research in Thailand shows how community tourism-based indicators can be directly linked to sustainable development goals, such as poverty alleviation and strengthening local identity (Suriyankietkaew *et al*., 2025).

In addition, the integration of ERI with the SDGs is also consistent with the international framework in food system transformation, where the bioeconomy is used as a policy tool to encourage economic growth as well as social inclusion (Trigo *et al*., 2023). In Romania, the implementation of the SDGs in the agricultural sector confirms that resilience indicators must be able to capture structural challenges such as water efficiency, infrastructure modernization, and the impact of climate change (Nistoroiu *et al*., 2024). The global study of the Food Systems Countdown 2030 architecture also emphasizes the need for multidimensional indicators that link food, ecology, and economic aspects, reinforcing the view that resilience indicators must be constantly updated to remain relevant to global development goals (Schneider *et al*., 2023). The findings of this study not only support the theory of resilience, but also show the relevance of the integration of village economic resilience indicators with the global agenda of the SDGs. This emphasizes that ERI as part of VDI needs to be continuously adjusted in order to be able to capture local dynamics while supporting the achievement of the world's sustainable development goals.

Operationally, these findings confirm the need for evidence-based policies by prioritizing the use of the latest ERI data. This is in line with studies that show that village economic development must rely on real-time data to formulate adaptive strategies to local dynamics (Ma *et al*., 2025). The classification of decision trees can be a practical instrument for setting policy intervention priorities. Villages with low ERI should be directed to strengthening infrastructure and market access, while villages with high ERI can be encouraged to develop productive businesses and digitalize the economy. This is consistent with research on the development of digital villages which has been proven to increase regional economic resilience through strengthening the local financial system (Sun & Chen, 2025). The improvement of ERI indicators must continue to be carried out by including aspects of the digital economy and technology-based financial inclusion. Recent studies show that digital inclusive finance increases rural resilience through improved transportation infrastructure and technological innovation (Shen & Hu, 2024).

In addition, research on the role of the digital economy in food systems confirms the importance of new indicators that capture resilience to global crises, highlighting the role of digital technology, digital finance, and human capital as key channels for adaptation (Wang *et al.*, 2023). Institutional support is also very important, such as the development of an effective cooperative banking framework in strengthening MSMEs and building financial inclusion in areas that are difficult for formal banks to reach (Thelma Chibueze, 2024). The direction of reform of the ERI indicator needs to move towards a multi-dimensional direction that combines aspects of basic infrastructure, digital innovation, financial inclusion, and systemic resilience. This will strengthen the function of VDI as a public policy instrument that is responsive to global changes as well as contextual for village development in Indonesia. This study answers the main question that the ERI of previous years can predict the economic resilience of villages in 2023 with high accuracy ($R^2 = 0.807$; MAPE = 4.65%), although the contribution of variables is different. ERI 2023 is the most dominant factor, while the 2018–2022 data plays a smaller role. This dominance reflects the improvement of the indicators in the latest VDI document, which is more detailed and technical than in the previous period. Implicitly, annual data updates are crucial to support evidence-based village development policies, with different intervention priorities according to the conditions of village economic resilience.

## 5 CONCLUSION

This study confirms that ERI in previous years can predict the economic resilience of villages in 2023 with high accuracy ($R^2 = 0.807$; MAPE = 4.65%), but the role is not equal. The 2023 ERI emerged as the most dominant variable, while the 2018–2022 historical data contributed only a little. These results are in line with the evolution of VDI, where the 2023 indicators are more comprehensive and technical. This finding implies that village development policies in Central Java must be based on the latest data and utilize the results of model classification to develop intervention strategies, ranging from strengthening infrastructure to developing BUMDes and the digital economy. The ERI indicator needs to be enriched with new dimensions such as the digital economy, technology-based financial inclusion, and resilience to global crises to be more adaptive to modern rural dynamics. In addition, cross-provincial research and other methods of analysis such as Random Forest or Gradient Boosting can be used to strengthen the validation of these findings.

The next direction of research needs to be focused on enriching ERI indicators by incorporating new aspects such as the digital economy, technology-based financial inclusion, and resilience to global crises to be more adaptive to modern rural dynamics. In addition, it is necessary to conduct comparative analysis between provinces or across time to assess the consistency of the prediction model, as well as the integration of other analytical methods such as Random Forest or Gradient Boosting to improve prediction performance. Qualitative research is also needed to complement quantitative findings, especially in understanding the socio-political context that affects the validity of VDI data at the village level.

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