

ANALYSIS OF POVERTY LEVELS IN WEST KALIMANTAN USING GEARY'S C AND LISA SPATIAL AUTOCORRELATION

Annisa Kusuma Dewi¹, Hendra Perdana², Neva Satyahadewi^{3*}

^{1,2,3} Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Tanjungpura
Profesor Dr. H. Hadari Nawawi St., Pontianak, West Kalimantan, 78124, Indonesia

Corresponding author's e-mail: *neva.satya@math.untan.ac.id

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ABSTRACT

Poverty is one of the development issues that is closely related to geographical conditions and regional characteristics. This study aims to analyze the spatial pattern of poverty levels in West Kalimantan in 2020-2024 using the Geary's C global spatial autocorrelation method and the LISA (Local Indicators of Spatial Association) local spatial autocorrelation method. This study uses the queen contiguity approach as a spatial weighting matrix. The results of the Geary's C analysis show that all C values are < 1 and are supported by Zcount values > 1.96 and p-values < 0.05 at a 5% significance level. This means that there is significant positive spatial autocorrelation, so that poverty levels in West Kalimantan form a clustered pattern. The LISA analysis results show that the Sintang and Melawi regions tend to form a High-High cluster, meaning that these regions have high poverty levels and are surrounded by regions that also have high poverty levels. Meanwhile, the Bengkayang, Mempawah, Landak, and Pontianak City regions often appear as Low-Low clusters, meaning that these regions have low poverty levels and are surrounded by regions with low poverty levels. In addition, in certain years, a High-Low pattern emerges, indicating local disparities between neighboring regions. Overall, poverty levels in West Kalimantan are uneven and influenced by spatial relationships between regions, meaning that the conditions of a region cannot be separated from the characteristics of the surrounding regions.



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e-mail: betabarekeng@gmail.com
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1. Introduction

Poverty is a complex and multidimensional problem; therefore, it remains a major priority in national development agendas and local social policy interventions [1], [2]. In general, poverty occurs when individuals or groups lack sufficient resources to meet their basic needs [3]. In Indonesia, the poverty line is commonly operationalized using an expenditure-based approach that covers minimum food and non-food needs [4]. Poverty can hinder development in emerging economies because it limits people's access to adequate education, health services, and nutrition, ultimately affecting the quality of human resources and long-term productivity [1], [3].

Poverty alleviation has been positioned as a key target in Indonesia's long-term and medium-term development planning. The National Medium-Term Development Plan (RPJMN) 2020–2024 sets the target of reducing the poverty rate to around 6–7% by 2024 [5], [6]. Based on Statistics Indonesia (BPS) official releases, the national poverty rate declined to 9.03% in March 2024 and further decreased to 8.57% in September 2024; however, these figures still indicate the need for stronger and more targeted interventions to reach planning targets [7], [8].

In line with national trends, the poverty rate in West Kalimantan Province has also declined over time. According to BPS West Kalimantan, the percentage of poor residents decreased between 2020 and 2024, although the pace of reduction slowed during the 2022–2023 period [9], [10]. This suggests that economic growth has not been fully inclusive, particularly in rural areas where poverty remains relatively higher. Inter-district disparities are also evident. For example, Melawi Regency recorded one of the highest poverty rates in 2024 (10.62%), while Pontianak City showed a much lower rate (4.20%) in the same year [10]. Such differences indicate strong intra-provincial inequality and motivate a spatial perspective to assess whether poverty conditions in one area are statistically related to those in neighboring areas.

Recent spatial poverty studies emphasize that poverty is often geographically concentrated and may exhibit spatial dependence, spatial heterogeneity, and persistent local clustering [11], [12]. International evidence also shows that poverty patterns can be examined through spatial dependence and multi-scale effects [11], and that local clusters may persist even when overall spatial concentration changes over time [12]. Beyond conventional statistics, advances in geospatial data and remote sensing have supported poverty prediction and poverty mapping at finer spatial scales, including applications using satellite imagery and integrated geospatial big data approaches [13], [14], [15], [16]. These findings reinforce the relevance of spatial statistical approaches for understanding poverty distribution and for designing geographically targeted policies.

To address spatial inequality in West Kalimantan, this study applies spatial autocorrelation analysis using Geary's C (global) and Local Indicators of Spatial Association (LISA) (local). Geary's C is often considered more sensitive to local differences because it relies on squared differences between neighboring areas, making it useful for detecting clustering or dispersion patterns [17], [18]. LISA, on the other hand, identifies specific locations that form statistically significant clusters and spatial outliers, providing detailed local insight beyond global indicators [17], [18], [19]. Previous studies have applied Geary's C and LISA in poverty analysis (e.g., Bali Province) [20], as well as in other socioeconomic and health contexts such as educated unemployment, leprosy distribution, and stunting prevalence [21], [22], [23].

However, studies focusing on West Kalimantan poverty patterns across 2020–2024 using the combined Geary's C–LISA approach remain limited, particularly for describing how global clustering relates to local cluster/outlier structures over multiple years [9], [10]. Therefore, this research uses Geary's C to detect overall spatial autocorrelation at the provincial level and LISA to identify local cluster/outlier structures, aiming to describe the spatial distribution pattern of poverty in West Kalimantan during 2020–2024.

2. Research Methods

2.1 Data

This study uses district/city-level poverty rates (percentage of poor population) in West Kalimantan Province for 2020–2024 obtained from BPS West Kalimantan publications and compiled release data [9], [10]. Figure 1 presents the average poverty rate in West Kalimantan during 2020–2024.

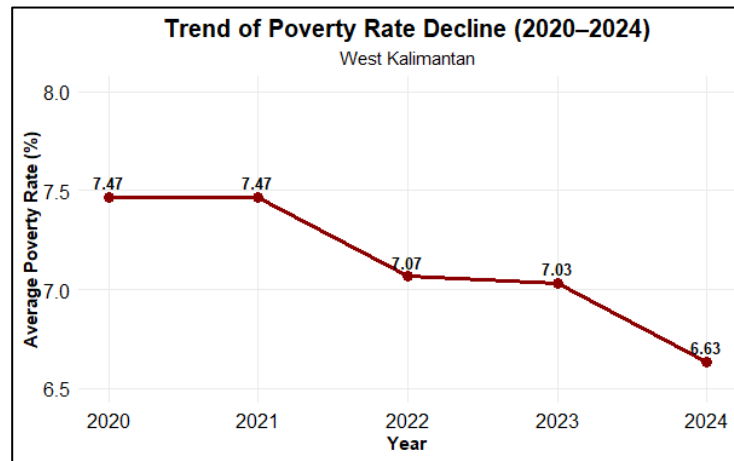


Figure 1. Trend of Poverty Rate Decline in West Kalimantan (2020–2024)

Based on **Fig. 1**, the poverty rate in West Kalimantan shows a consistent downward trend over the period 2020–2024, indicating sustained improvement in poverty reduction, particularly after 2021. In general, poverty in West Kalimantan has declined; however, poverty levels across regions remain uneven, with clear differences between districts/cities, as shown in **Fig. 2**.

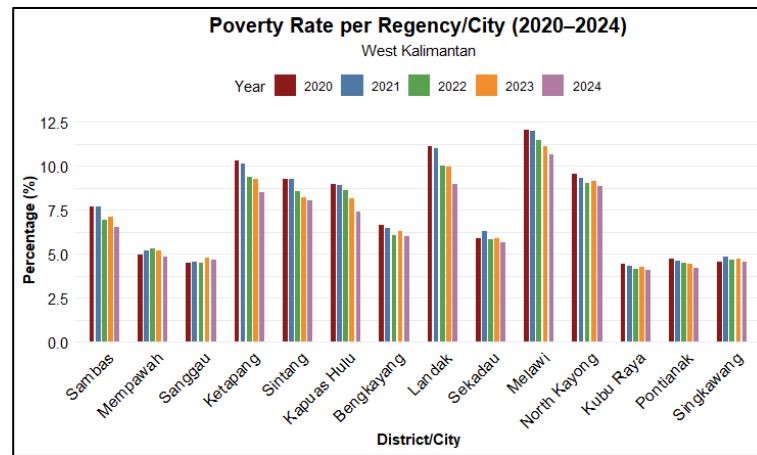


Figure 2. Poverty Rate per District/City in West Kalimantan (2020–2024)

Based on **Fig. 2**, it is evident that the average poverty rate across districts/cities in West Kalimantan is not evenly distributed. Several regions show consistent declines in poverty rates, while others experience year-to-year fluctuations. Melawi and Landak consistently recorded the highest poverty levels compared to other regions throughout the 2020–2024 period. Meanwhile, the lowest poverty rates are dominated by urban areas and urban buffer regions, namely Kubu Raya, Pontianak, and Singkawang [10].

2.2 Spatial Weight Matrix

A spatial weight matrix represents the proximity relationship between locations based on neighborhood structure (contiguity) or distance. In contiguity-based approaches, spatial interaction is assumed to occur among adjacent regions that share borders or vertices [24], [25], [26]. For an observation area, the matrix element for two areas that share a boundary (or meet at a vertex) is defined as 1, and 0 otherwise [27]. A contiguity matrix is denoted by $\mathbf{W}$, where w_{ij} is the element in row i (location i) and column j (location j).

$$w_i = \sum_{j=1}^n w_{ij} \quad (1)$$

Thus, the matrix form is:

$$\mathbf{W} = \begin{bmatrix} w_{11} & w_{12} & \dots & w_{1n} \\ w_{21} & w_{22} & \dots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \dots & w_{nn} \end{bmatrix}$$

For standardized spatial weights, row-standardization is commonly applied so each row sums to one. The spatial contiguity matrix $\mathbf{W}$ is standardized to obtain $\mathbf{W}^*$ with elements:

$$w_{ij}^* = \frac{w_{ij}}{\sum_{j=1}^n w_{ij}}, \quad i = 1, \dots, n; \quad j = 1, \dots, n \quad (2)$$

Then the form of the matrix W^* is:

$$W^* = \begin{bmatrix} w_{11}^* & w_{12}^* & \dots & w_{1n}^* \\ w_{21}^* & w_{22}^* & \dots & w_{2n}^* \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1}^* & w_{n2}^* & \dots & w_{nn}^* \end{bmatrix}$$

In general, contiguity can be defined in several ways [28]:

1. Rook contiguity: neighbors share an edge (side).
2. Bishop contiguity: neighbors meet at a vertex (corner).
3. Queen contiguity: neighbors share an edge or a vertex.

In this study, queen contiguity is selected because district/city boundaries in West Kalimantan are irregular; this approach can capture adjacency more realistically, which helps the resulting Geary's C and LISA analyses reflect spatial linkages more accurately [24], [25], [26]. Spatial processing and mapping can be supported using GIS software such as QGIS [29].

2.3 Geary's C

Geary's C is a global spatial autocorrelation measure used to identify similarity of a variable across neighboring areas. It is often regarded as more sensitive to local differences because it is based on squared differences between adjacent observations [17], [18]. Geary's C compares values of directly neighboring regions [30]. The Geary's C statistic is formulated as follows [30]:

$$C = \frac{(n-1) \sum_{i=1}^n \sum_{j=1}^n w_{ij}^* (x_i - x_j)^2}{2(\sum_{i=1}^n (x_i - \bar{x})^2)(\sum_{i=1}^n \sum_{j=1}^n w_{ij}^*)} \quad (3)$$

From Eq. (3), Geary's C indicates positive spatial autocorrelation (clustering) when $C < 1$. If $C > 1$, it indicates negative spatial autocorrelation (dispersion), while $C = 1$ suggests no spatial autocorrelation (random pattern). The expected value of Geary's C under the null hypothesis is 1 [30].

The hypotheses for the Geary's C significance test are [30]:

$H_0 : C = 1$, (no spatial autocorrelation at location i)

$H_1 : C \neq 1$, (spatial autocorrelation exists)

The analysis is continued by comparing the p-value to a chosen significance level α . If p-value $< \alpha$, H_0 is rejected, indicating statistically significant spatial autocorrelation.

2.4 Local Indicators of Spatial Association (LISA)

LISA is a local spatial autocorrelation measure used to identify spatial relationships at the individual-area level [17], [18]. LISA helps detect areas that form spatial clusters (similarity with neighbors) and spatial outliers (dissimilarity with neighbors) [17], [19]. A commonly used LISA formulation is [31]:

$$I_i = z_i \sum_{j=1}^n w_{ij} z_j \quad (4)$$

with:

$$z_i = \frac{(x_i - \bar{x})}{\sigma_x} \quad (5)$$

From Equation (4), LISA indicates positive local spatial autocorrelation (local clustering) when $I_i > 0$. If $I_i < 0$, it indicates negative local spatial autocorrelation (local outliers). If $I_i = 0$, it suggests no local spatial autocorrelation.

The hypotheses for the LISA significance test are [31]:

$H_0 : I_i = 0$, (no local spatial autocorrelation at location i)

$H_1 : I_i \neq 0$, (local spatial autocorrelation exists)

If p-value $< \alpha$, H_0 is rejected and local spatial autocorrelation is considered statistically significant.

A LISA cluster map visualizes local spatial patterns using four standard categories [17], [32]:

Table 1. Cluster Map LISA

Pattern	Description
High–High (HH)	High-value area surrounded by high-value neighbors
Low–Low (LL)	Low-value area surrounded by low-value neighbors
High–Low (HL)	High-value area surrounded by low-value neighbors
Low–High (LH)	Low-value area surrounded by high-value neighbors

HH and LL indicate spatial clustering, while HL and LH indicate spatial outliers. In summary, Geary's C provides a global overview of whether spatial autocorrelation exists at the provincial level, whereas LISA identifies which districts/cities function as cluster centers or deviate locally from the overall pattern.

3. Results And Discussion

3.1 Queen Contiguity

A queen contiguity spatial weight matrix defines neighborhood relationships based on shared edges and vertices (i.e., two regions are neighbors if they share a boundary line or meet at a corner) [17], [30]. This approach is widely used for administrative regions because it can represent adjacency more realistically when boundaries are irregular [17], [18]. **Figure 3** presents the West Kalimantan administrative map to clarify queen contiguity neighborhoods.

**Figure 3.** West Kalimantan Administrative Map

Based on **Figure 3**, **Table 2** summarizes queen contiguity neighborhoods for districts/cities in West Kalimantan.

Table 2. Queen Contiguity Neighborhoods in West Kalimantan

District/City	Neighborhoods
Sambas	Bengkayang, Singkawang
Mempawah	Bengkayang, Landak, Kubu Raya, Pontianak
Sanggau	Ketapang, Sintang, Bengkayang, Landak, Sekadau, Kubu Raya
Ketapang	Sanggau, Sintang, Sekadau, Melawi, North Kayong, Kubu Raya
Sintang	Sanggau, Ketapang, Kapuas Hulu, Sekadau, Melawi
Kapuas Hulu	Sintang
Bengkayang	Sambas, Mempawah, Sanggau, Landak, Singkawang
Landak	Mempawah, Sanggau, Bengkayang, Kubu Raya
Sekadau	Sanggau, Ketapang, Sintang
Melawi	Ketapang, Sintang
North Kayong	Ketapang, Kubu Raya
Kubu Raya	Mempawah, Sanggau, Ketapang, Landak, North Kayong, Pontianak
Pontianak	Mempawah, Kubu Raya
Singkawang	Sambas, Bengkayang

From **Table 2**, the spatial weight matrix W is constructed and then row-standardized so that each row sums to 1 (W^*). Row-standardization improves comparability across areas and is commonly used in global and local spatial autocorrelation analysis [17], [30]. Moreover, the choice and specification of a spatial weight matrix are important because they can influence spatial inference and model results [24], [25], [26].

3.1 Geary's C Analysis

Table 3 presents the global spatial autocorrelation test results using Geary's C computed with RStudio.

Table 3. Geary's C Test

Year	Geary's C	Z _{statistic}	p-value	Decision (H ₀)	Spatial Autocorrelation
2020	0.753	2.293	0.011	Rejected	Positive
2021	0.740	2.355	0.009	Rejected	Positive
2022	0.704	2.531	0.006	Rejected	Positive
2023	0.727	2.410	0.008	Rejected	Positive
2024	0.681	2.636	0.004	Rejected	Positive

All Geary's C values for 2020–2024 satisfy $C < 1$, indicating positive global spatial autocorrelation, meaning poverty tends to be clustered across neighboring districts/cities [17], [18], [30]. The Z-statistics exceed the critical value (1.96 at $\alpha = 0.05$, two-tailed) and all p-values are below 0.05, therefore H₀ is rejected and the global spatial autocorrelation is statistically significant at the 5% level [17], [30].

Substantively, this indicates a persistent clustering structure: high-poverty districts/cities tend to be located near other high-poverty areas, while low-poverty areas tend to be adjacent to other low-poverty areas. This reflects spatial interdependence, where regional poverty conditions are not isolated but associated with neighboring contexts [11], [12].

3.1 LISA Analysis

Table 4 reports the local spatial autocorrelation (LISA) statistics for each district/city and year.

Table 4. LISA Test

District/City	LISA Value (Ii)				
	2020	2021	2022	2023	2024
Sambas	-0.064*	-0.054*	0.047*	-0.015*	0.034
Mempawah	0.274	0.309	0.297*	0.303	0.359*
Sanggau	-0.203	-0.201	-0.125	-0.126	-0.115
Ketapang	0.056	0.066	0.082	0.089	0.159
Sintang	0.226*	0.255*	0.250*	0.194*	0.250*
Kapuas Hulu	0.399	0.411	0.428	0.269	0.260
Bengkayang	0.112*	0.126	0.151*	0.107	0.112*
Landak	-1.248*	-1.272*	-1.137*	-1.162*	-0.991*
Sekadau	-0.125	-0.097	-0.096	-0.088	-0.102
Melawi	1.537*	1.575*	1.562*	1.429*	1.580*
North Kayong	-0.034	-0.067	-0.114	-0.127	-0.184
Kubu Raya	-0.021	0.004	-0.031	-0.059	-0.023
Pontianak	1.116*	1.212*	1.140*	1.240*	1.288*
Singkawang	0.130	0.163	0.264	0.171	0.188

*significant ($p\text{-value} < 0.05$)

A positive Ii indicates local similarity with neighbors (spatial clustering), while a negative Ii indicates local dissimilarity (spatial outliers) [18], [19], [31]. Sintang, Melawi, and Pontianak show relatively consistent positive and significant Ii values, suggesting stable local clustering structures during 2020–2024 [18], [19]. Mempawah and Bengkayang show positive Ii values in several years but are not always significant, indicating that local autocorrelation is year-dependent in those areas.

In contrast, Landak exhibits consistently negative and significant Ii values across all years, indicating a stable local outlier pattern. Sambas also shows negative and significant values in some years (2020, 2021, 2023), reflecting local dissimilarities during those periods. Overall, LISA results confirm that local spatial autocorrelation patterns are heterogeneous across areas: some locations show persistent significance, while others are fluctuating or statistically insignificant over time [17], [18].

3.1 Mapping (LISA Cluster Map)

Mapping is used to visualize how poverty clustering forms geographically and to confirm the LISA results for 2020–2024. **Figure 4** shows the LISA cluster maps, which were produced with GIS support (e.g., QGIS) [29].

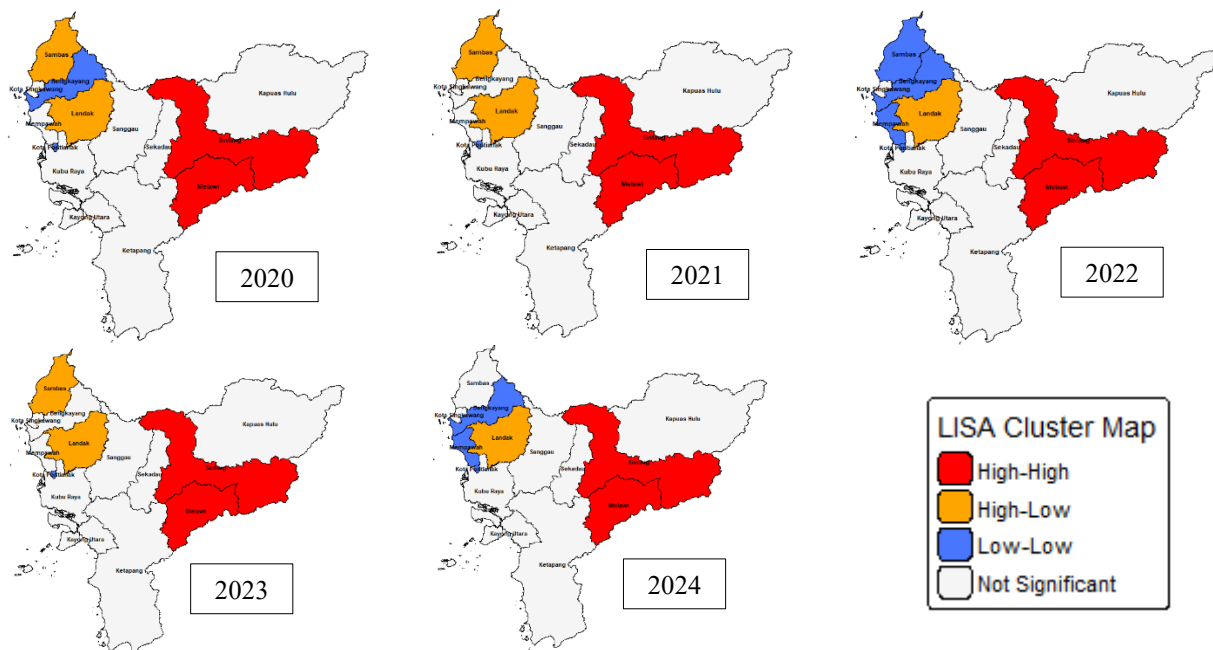


Figure 4. LISA Cluster Map of Poverty in West Kalimantan

The cluster maps indicate a relatively consistent spatial pattern over time. Sintang and Melawi frequently appear in High–High (HH) clusters, indicating persistent high-poverty clustering in the central inland part of the province [10]. This pattern aligns with broader evidence that poverty can display spatial dependence and persistent local clustering [11], [12]. It is also consistent with West Kalimantan-related studies that link poverty to development dimensions, including human development indicators and structural conditions [2], [33], [34].

Conversely, Bengkayang, Mempawah, Landak, and Pontianak often appear in Low–Low (LL) clusters, indicating contiguous low-poverty areas. More developed areas with better connectivity and more diversified economic activities are generally associated with lower poverty and may reinforce neighboring low-poverty patterns through spatial spillovers [11], [12]. The appearance of High–Low (HL) patterns in certain years (e.g., Sambas in some periods) indicates local disparities, high-poverty areas adjacent to lower-poverty neighbors, often interpreted as uneven local development conditions that require targeted interventions at sub-provincial scales [11], [12].

Not all regions form clusters; some are statistically non-significant. These areas show no strong local spatial autocorrelation with their neighbors and therefore cannot be classified into High–High, Low–Low, High–Low, or Low–High clusters. Overall, Geary’s C and LISA results suggest that poverty dynamics in West Kalimantan are spatially structured: geographic proximity can strengthen both inequality and progress across neighboring districts/cities. Therefore, spatially targeted policies and coordinated cross-border development programs are important, particularly for persistent High–High cluster cores [1], [11], [12].

4. Conclusions

Geary’s C results for 2020–2024 indicate that poverty in West Kalimantan exhibits significant positive global spatial autocorrelation, meaning poverty tends to be clustered across neighboring districts/cities. LISA results show that local spatial autocorrelation is significant in several districts/cities, although significance patterns vary by year. Areas such as Sambas, Sintang, Bengkayang, Landak, Melawi, Mempawah, and Pontianak frequently appear as significant locations. Most significant areas indicate positive local autocorrelation (spatial clustering), while Sambas in 2020, 2021, and 2023 and Landak across all years show negative local autocorrelation (spatial outliers).

The LISA cluster maps for 2020–2024 reveal a relatively consistent poverty distribution pattern over time. High–High clusters are commonly found in inland areas such as Sintang and Melawi, while Low–Low clusters are dominant in relatively more developed areas such as Bengkayang, Mempawah, Landak, and Pontianak. The presence of High–Low patterns in certain years (e.g., Sambas) reflects local disparities between neighboring regions. These results imply that poverty reduction strategies should incorporate spatial linkages and focus interventions on persistent cluster cores while strengthening inter-district coordination to enhance positive spatial spillover effects.

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Conflict of Interest

The authors declare that he/she has no conflicts of interest to report study.

Declaration of Generative AI and AI-assisted technologies

Generative AI tools were used solely for language refinement (grammar, spelling, and clarity). The scientific content, analysis, interpretation, and conclusions were developed entirely by the authors. The authors reviewed and approved all final text.

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