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Reconstruction of Rainfall Patterns with the SpVAR Method: Spatial Analysis in DKI Jakarta

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Abstract: Unexpected rainfall is often a challenge for urban areas such as DKI Jakarta. Therefore, this study aims to establish a Spatial Vector Autoregressive (SpVAR) model to analyze rainfall data in DKI Jakarta from 2017 to 2021. This study used three endogenous variables: the amount of rainfall, air temperature and humidity. The use of the SpVAR method with uniform spatial weighting in the DKI Jakarta area was chosen to provide an initial picture of the potential for spatial interactions between various locations in a complex climate context. This method provides valuable insight into the possibility of spatial dependence during climate change in DKI Jakarta. The SpVAR (1.3) model is based on the VAR (p) model by limiting the spatial orders to one. Parameters of the SpVAR model (1.3) were estimated using the FIML method to identify significant factors in the influence of rainfall in the region. The results showed that the SpVAR model (1.3) shows that rainfall, air temperature and humidity in one location are affected by the same variables in other locations. However, not all of them significantly affect five areas in DKI Jakarta Province. This study confirms the effectiveness of the SpVAR method in analyzing spatial patterns of rainfall, provides essential insights for understanding climate, and supports decision-making that is more responsive to urban disasters in the future.

Keywords: Rainfall; Spatial vector autoregressive; Uniform; VAR

Introduction

More than half the world's population lives in urban areas, and estimates indicate that over 66% of cities worldwide will face the threat of flooding in the next three decades. This susceptibility is attributed to a combination of climate change, land subsidence, rising sea levels, and socio-economic factors (Ward et al., 2013). Rainfall is an essential parameter in climate and environmental studies which has a significant impact on various sectors of human life and ecosystems. In urban areas such as DKI Jakarta, rainfall patterns have complex implications for infrastructure, water quality and flood risk. Research on flooding in Jakarta was previously conducted by Sunarharum et al. (2014). The current research aims to enhance community resilience in Jakarta by concentrating on effective engagement strategies for reducing flood risk. Climate change and rapid urbanization have changed rainfall patterns in many urban areas, including Jakarta, which is facing increasingly complex water governance challenges.

The observed rainfall data is time series data and involves regional information (space-time). Rainfall forecasting using air temperature and air humidity variables produces relatively better outcomes (Fadholi, 2013). Air humidity levels have a positive impact on the amount of rain. The higher the percentage of humidity in the air, the higher the chance of rain (Sipayung et al., 2012). Research carried out by Jasmi et al. (2021) shows that the air temperature is rainy with rainfall in DKI Jakarta.

Technological and methodological advances in spatial data analysis have opened new opportunities to understand and manage rainfall patterns more effectively. One method that has attracted attention is the Spatial Vector Autoregressive (SpVAR), which allows the incorporation of spatial and temporal information in the analytical model (Beenstock et al.,

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2007). Spatio-temporal models can be used to study cause-and-effect relationships and patterns in data that includes spatial and temporal dimensions (Longley, 2005). This method can help identify spatial patterns of rainfall that may be difficult to find using traditional analytical methods.

Understanding rainfall patterns and their spatial variability in DKI Jakarta is becoming more urgent with population growth, urbanization and environmental changes. Applying the SpVAR method to rainfall analysis can provide deeper insight into how climate change and urban transformation affect rainfall patterns in this region. Spatial analysis is this study show of interactions and relationships between geographic locations or entities (Lee et al., 2001).

Developing the SpVAR model from the Vector Autoregressive (VAR) (Zivot et al., 2006) model opens the door to understanding the complex relationships between variables in time series data by simultaneously considering the spatial and temporal dimensions. This model allows a deeper analysis of the interrelationships between various weather and environmental variables. In various previous studies, SpVAR has been successfully applied in modeling weather variables such as rainfall, temperature, air humidity, sunshine duration, and wind speed in various geographic areas (Sumarminingsih, 2021).

In this study, the spatial weighting matrix is central in describing the spatial interactions between adjacent locations. Approaches using uniform location weights provide a relevant way to describe spatial dependencies. Considering these spatial factors, the SpVAR model is expected to provide better accuracy in predicting rainfall patterns in the DKI Jakarta area. With a better understanding of rainfall patterns and their spatial interactions, this research can significantly contribute to developing flood mitigation strategies, sustainable spatial planning, and managing water resources in growing urban areas such as DKI Jakarta. In addition, the results of this research can be the basis for making smarter decisions in dealing with the risks of climate change and its impact on cities in the future.

The results of this research not only have the potential to provide a better understanding of rainfall patterns and their spatial interactions but also directly contribute to planning and policies that are more effective in dealing with climate change and its impacts on urban areas. By implementing the findings from this study, governments and other stakeholders can take more appropriate steps to build disaster-resilient infrastructure, manage flood risk, and mitigate the negative impacts of extreme weather changes. Therefore, this research has high relevance and urgency in responding to the challenges of climate change and flood mitigation in DKI Jakarta.

Method

This research is based on secondary data originating from the official publication of the DKI Jakarta Province Central Statistics Agency (BPS) from January 2017 to December 2021. The data used in this study were obtained from five regions in DKI Jakarta Province: South Jakarta, East Jakarta, Central Jakarta, West Jakarta, and North Jakarta. The SpVAR model with uniform locations on rainfall data in the DKI Jakarta area is obtained based on the following steps:

1. Calculate of descriptive statistics will be applied to each variable included in the study according to (Johnson et al., 2019). This includes calculating the average value according to Equation 1.

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{1}$$

Which is:

$\bar{x}$: arithmetic mean

n : number of observation

x_i : value of the i-th data

The variability of the data is calculated according to Equation 2.

$$s^2 = \frac{\sum_{i=1}^{n} (x_i - \bar{\bar{x}})^2}{(n-1)} \tag{2}$$

Then, determining the minimum and maximum values, and identifying particular patterns in the data according to (Makridakis et al., 1999).

2. The unit root panel stationarity test will be run on the data according to Equation 3. The unit root panel test, introduced by Levin et al. (2002) is a method used to test data stationarity. The test hypothesis used is as follows.

$H_0 : \delta = 0$ (data is not stationary)

$H_1 : \delta < 0$ (data is stationary)

$$t_{\delta}^{*} = \frac{t_{\delta} - N\tilde{T}\hat{S}_N \hat{\sigma}_{\tilde{\varepsilon}}^{-2} STD(\hat{\delta}) \mu_{m\tilde{T}}^{*}}{\sigma_{m\tilde{T}}^{*}} \tag{3}$$

Which is:

$\hat{S}_N$: standard deviation ratio

$\hat{\sigma}_{\tilde{\varepsilon}}^{2}$: error variance

When the value of the adjusted t-test statistic is greater than the value of Table t ($t_{\delta}^{*} > t_{\alpha,n}$) it is concluded that the data is stationary.

3. The VAR model is multivariate time series (Wei, 2006) has the order p with the variable K expressed in the Equation 4 (Lütkepohl, 2005).

$$\boldsymbol{y}_t = \mathbf{A}_1\boldsymbol{y}_{t-1} + \cdots + \mathbf{A}_p\boldsymbol{y}_{t-p} + \boldsymbol{u}_t \tag{4}$$

where $\boldsymbol{y}_t$ is a random vector at time t and k-th variable$(y_{1t}, y_{2t}, \dots, y_{Kt})'$, $\mathbf{A}_i$ is a coefficient matrix of size (K×K) of i-th lag$-i$ $(i = 1, 2, \dots, p)$, $\boldsymbol{y}_{t-p}$ s a vector of variable observations at the previous time point $(y_{t-1}, y_{t-2}, \dots, y_{t-p})'$, and $\boldsymbol{u}_t$ s a vector of errors at time t and k $(u_{1t}, u_{2t}, \dots, u_{Kt})'$. Identification of the temporal order (autoregressive) will be carried out by referring to the most optimal lag in the VAR (p) model use the Akaike Information Criteria (AIC) (Brockwell et al., 2002) according to equation 5.

$$AIC = -2l(\boldsymbol{\beta}) + 2P \tag{5}$$

Which is:
$l(\boldsymbol{\beta})$: maximum value of the likelihood function.
P : number of parameters in the model

4. A uniform location weighting matrix is created using Equation 6, which is based on the assumption that the observation locations in the study are consistent and similar (Qu et al., 2015).

$$w_{ij} = \frac{1}{n_i} \tag{6}$$

5. Parameter estimation of the SpVAR (1,p) will be carried out by applying the FIML approach (Sumarminingsih et al., 2018). The SpVAR model is included in the multivariate time series model, which analyzes space-time data with more than one variable. This model was developed by Di Giacinto (2010) as follows Equation 7.

$$\boldsymbol{y_t} = \boldsymbol{B_1}\,\boldsymbol{y_{t-1}} + \cdots + \boldsymbol{B_p}\,\boldsymbol{y_{t-p}} + \boldsymbol{\eta_t} \tag{7}$$

There is $\mathbf{y_t}$ adalah $[y_{11t}, y_{21t}, \dots, y_{N1t}, y_{12t}, y_{22t}, \dots, y_{N2t}, \dots, y_{1Kt}, y_{2Kt}, \dots, y_{NKT}]'$, N is the number of observation locations, K is the number of endogenous variables, T is the number of observations, y_{nkt} is the value of the kth variable observed at the nth location at the tth time,$\boldsymbol{\eta_t}$ ais the error vector of the observation of the kth variable observed at the nth location at time t or$[\eta_{11t}, \eta_{21t}, \dots, \eta_{N1t}, \eta_{12t}, \eta_{22t}, \dots, \eta_{N2t}, \dots, \eta_{1Kt}, \eta_{2Kt}, \dots, \eta_{NKT}]'$.

In estimating parameters using the FIML method, there are assumptions that must be met, namely that the error is assumed to spread multivariate normally (Sumarminingsih et al., 2020). $(\boldsymbol{\xi} \sim \mathbf{N}(\mathbf{0}, \boldsymbol{\Omega}))$ where $\boldsymbol{\Omega} = \mathbf{I_T} \otimes \boldsymbol{\Sigma}$ hence $\mathbf{y} \sim \mathrm{N}(\mathbf{Z\theta}, \boldsymbol{\Omega})$. The natural log function of the likelihood is written in Equation 8.

$$\ln L(\boldsymbol{\theta}, \boldsymbol{\Sigma}_\xi) = -\frac{NKT}{2}\ln(2\pi) + \frac{T}{2}\ln\left|\boldsymbol{\Sigma}_\xi{}^{-1}\right| - \frac{1}{2}(\boldsymbol{y} - \mathbf{Z}\boldsymbol{\theta})'(\mathbf{I_T} \otimes \boldsymbol{\Sigma}_\xi^{-1})(\boldsymbol{y} - \mathbf{Z}\boldsymbol{\theta}) \tag{8}$$

The equation is solved by differentiating θ and equating to zero.

Result and Discussion

Descriptive statistical analysis in this study aims to provide a comprehensive capture of rainfall, air temperature and humidity data in five areas in DKI Jakarta from January 2017 to December 2021. The descriptive statistical calculation method involves an average value according to Equation 1, the variance according to Equation 2, the minimum value, and the maximum value. More detailed information regarding this calculation is available in Table 1 to Table 3.

Table 1. Descriptive Statistics of Rainfall (mm)

Location	Average	Variance	Min	Max
South Jakarta	193.02	31,375.73	1.00	1,043.20
East Jakarta	214.97	32,451.23	2.20	768.80
Central Jakarta	174.58	33,728.14	0.50	1,043.20
West Jakarta	175.83	33,406.03	0.80	1,043.20
North Jakarta	136.87	19,563.92	1.00	627.90

Table 2. Descriptive statistics of air temperature (℃)

Location	Average	Variance	Min	Max
South Jakarta	28.47	0.77	26.10	31.50
East Jakarta	28.38	1.16	26.70	30.90
Central Jakarta	28.49	0.79	23.50	29.60
West Jakarta	28.50	0.68	24.00	29.60
North Jakarta	28.75	0.33	27.30	29.80

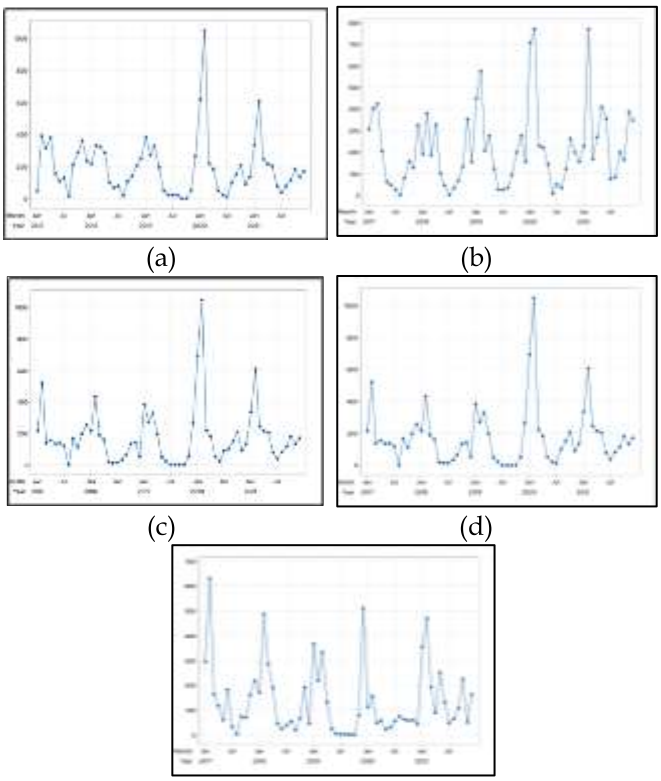
Table 3. Descriptive Statistics of Humidity (%)

Location	Average	Variance	Min	Max
South Jakarta	76.91	26.76	68.50	94.00
East Jakarta	75.50	36.49	61.00	87.00
Central Jakarta	75.28	18.08	67.00	84.00
West Jakarta	74.36	31.69	53.00	83.00
North Jakarta	75.33	19.68	66.00	84.00

Based on Table 1 to Table 3, there are climate patterns that can be concluded. The average annual rainfall in South Jakarta is around 193.02 mm, while in East Jakarta, it reaches 214.97 mm. On the other hand, North Jakarta recorded a lower average rainfall, namely

136.87 mm. Regarding air temperature, Jakarta demonstrates a minimal range, fluctuating from 28.38°C to 28.75°C on average. However, South Jakarta stands out with less daily temperature variation, with temperatures spanning from 26.10°C to 31.50°C. Examining air humidity, Jakarta maintains an average range of 74.36% to 76.91%. Notably, South Jakarta records the highest humidity levels, potentially linked to urban factors and the proximity to water bodies. Jakarta displays diverse rainfall patterns across its regions, while air temperature and humidity tend to remain relatively stable.

Identifying patterns in time series data is a crucial step in time series analysis. Patterns can provide insights into the underlying structure of the data, helping analysts and data scientists make predictions or better understand the behavior of the time series (Bandt et al., 2007). The identification of data patterns in this study involved the creation of plots and the presentation of a summarized overview of rainfall data in five regions within DKI Jakarta Province. Specific details of this graphical representation can be referenced in Figure 1 below.



(a) (b) (c) (d) (e)

Figure 1. Plot of Rainfall Data for the period January 2017 to December 2021 in the areas of (a) South Jakarta, (b) East Jakarta, (c) Central Jakarta, (d) West Jakarta, and (e) North Jakarta

Rainfall data for five areas in DKI Jakarta Province from January 2017 to December 2021 show significant weather fluctuations and a clear rainy season pattern. Each location shows variations in rainfall intensity each year, with varying intensity peaks. The pattern of the rainy and dry seasons is visible, where certain months tend to have higher rainfall while others are drier. High monthly fluctuations also indicate weather uncertainty and fluctuations from month to month. Although there is no clear trend in changes in rainfall over these five years, this analysis provides a complete picture of the rainfall characteristics in each region within DKI Jakarta Province.

Testing for stationarity is important in data analysis because many statistical methods and analytical models, especially in time series analysis, require the assumption of stationary data (Anderson, 2011) also (Montgomery et al., 2015). Then the calculation results of unit root panel stationarity is presented in Table 4.

Table 4. Stationarity Test Results

Variable	Statistics LLC	*p*-value
Rainfall	17.696	< 0.01**
Air Temperature	10.739	< 0.01**
Humidity	17.799	< 0.01**

Based on the outcomes of Levin, Lin, & Chu's (LLC) test presented in Table 4, it was observed that the results for the three variables, namely Rainfall, Air Temperature, and Humidity, were statistically significant. Specifically, for the Rainfall variable, the LLC statistic registered at 17.696 with a p-value below 0.01 ($p < 0.01$**), indicating that the Rainfall data is characterized by stationarity. Similarly, the LLC statistic for the Air Temperature variable yielded a value of 10.739 with a p-value less than 0.01 ($p < 0.01$**), suggesting that the Air Temperature data also exhibits stationarity. In the case of the Humidity variable, the LLC statistic recorded a value of 17.799, and the associated p-value is less than 0.01 ($p < 0.01$**), signifying that the Humidity data is stationary as well.

Overall, the outcomes of the Levin, Lin, & Chu's (LLC) test indicate that the data for Rainfall, Air Temperature, and Air Humidity fulfill the stationarity assumption. These findings hold significance for subsequent analyzes as they can influence the accuracy and interpretation of the chosen model or method in the data analysis process.

In selecting the autoregressive order in the SpVAR (1,p) model, the approach used is similar to the VAR (p) model, namely using the smallest AIC value criterion to determine the optimum lag in the VAR (p) model, according to Equation 5. Further information regarding the possible autoregressive orders in this model can be found in Table 5, which briefly presents the various autoregressive order options.

Table 5. AIC Value on VAR (p) Tentative Model

Model	AIC Value
VAR (1)	1.1044
VAR (2)	1.0950
VAR (3)	1.0475

Table 5 displays the preliminary AIC values for the VAR (p) models. The AIC value serves the purpose of determining the optimal autoregressive order for the analysis. From the results listed, it can be observed that the VAR (3) model has the lowest AIC value of 1.0475. This shows that the VAR model with autoregressive order 3 has a better level of accuracy in explaining variations in the data compared to the VAR (1) and VAR (2) models. So in this study, the model that will be used in predicting rainfall, air temperature, and air humidity in DKI Jakarta is SpVAR (1.3).

Grasa (2013) stated that the fundamental element in forming a spatial model is the existence of a weighting matrix, which reflects the relationship between one region and other regions. Spatial analysis offers various methods for establishing the spatial weighting matrix, and two common approaches are point weights and area weights, determined based on the proximity between regions (LeSage et al., 2009). Forming uniform spatial weights in the DKI Jakarta area involves giving equal weight to each region, regardless of each area's distance or special characteristics. This approach assumes that all regions have the same influence or relationship in spatial analysis without significant variation based on geographical position or other attributes. Thus, each region is treated evenly or uniformly in calculating spatial weight, regardless of the differences in characteristics between these areas. The uniform spatial weighting matrix $\boldsymbol{W_u}$ elements, which describe the relationship between the five regions in DKI Jakarta Province, are presented in a matrix according to Equation 9.

$$\boldsymbol{W_u} = \begin{array}{c} \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} \begin{array}{c} \begin{array}{ccccc} 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{bmatrix} 0 & 0.25 & 0.25 & 0.25 & 0 \\ 0.25 & 0 & 0.25 & 0 & 0.25 \\ 0.25 & 0.25 & 0 & 0.25 & 0.25 \\ 0.25 & 0 & 0.25 & 0 & 0.25 \\ 0 & 0.25 & 0.25 & 0.25 & 0 \end{bmatrix} \end{array} \quad (9)$$

The estimation results of the SpVAR model (1.3) using uniform weights on matrix according to Equation 9 with the FIML method, variables that significantly affect endogenous variables at each location in DKI Jakarta, are presented in Table 6.

Table 6. SpVAR (1.3) Significant Parameter with Uniform Weight

Equation Model	Significant Variable
Rainfall in South Jakarta (y_{11t})	y_{13t-1}, y_{11t-3}, y^*_{11t-3}
Air Temperature in South Jakarta (y_{12t})	y^*_{12t-1}, y_{13t-1}, y^*_{12t-2}
Humdity in South Jakarta (y_{13t})	y_{13t-1}, y_{13t-2}, y_{12t-2}, y^*_{12t-2}
Rainfall in East Jakarta (y_{21t})	y^*_{23t-1}, y_{22t-3}, y^*_{22t-3}
Air Temperature in East Jakarta (y_{22t})	y_{22t-1}, y^*_{22t-1}, y_{23t-1}, y^*_{23t-1}, y_{21t-2}, y^*_{21t-2}, y_{23t-3}, y^*_{23t-3}
Humdity in East Jakarta (y_{23t})	No variable significant
Rainfall in Central Jakarta (y_{31t})	y_{31t-1}, y^*_{31t-1}, y^*_{32t-3}
Air Temperature in Central Jakarta (y_{32t})	y^*_{33t-1}, y^*_{32t-3}, y_{33t-3}, y^*_{33t-3}
Humdity in Central Jakarta (y_{33t})	y^*_{33t-1}, y^*_{32t-1}, y^*_{32t-3}
Rainfall in West Jakarta (y_{41t})	y_{41t-1}, y^*_{42t-1}, y^*_{43t-1}
Air Temperature in West Jakarta (y_{42t})	y^*_{42t-1}, y_{41t-1}, y^*_{41t-1}, y^*_{43t-1}, y_{41t-2}
Humdity in West Jakarta (y_{43t})	y_{43t-1}, y^*_{42t-1}, y_{42t-2}, y^*_{42t-2}
Rainfall in North Jakarta (y_{51t})	No variable significant
Air Temperature North Jakarta (y_{52t})	y_{52t-1}, y^*_{51t-1}, y_{53t-1}, y^*_{53t-1}, y^*_{51t-3}, y_{53t-3}
Humdity North Jakarta (y_{53t})	y_{53t-1}

Based on Table 6, the estimation results from the SpVAR (1.3) model with uniform weighting on various climate variables in the DKI Jakarta area. In this analysis, the significant variables in each model equation play a key role in providing insight into the factors that influence climate conditions in each region. In this model, each weather variable is considered as a function of its previous values and interactions with weather variables in other areas. For example, in South Jakarta, rainfall predictions are influenced by air humidity in the area in the previous month, rainfall in the previous three months, and rainfall in other areas that occurred in the previous three months. The air temperature in South Jakarta is influenced by the air temperature in other areas in the previous month, the air humidity in that area in the previous month, and the air temperature in other areas in the previous two months. Air humidity in the South Jakarta area is influenced by air humidity in the previous month, the previous two months, the air temperature in the previous two months, and the air temperature in other areas in the previous two months.

A similar interpretation can be applied to other areas such as East Jakarta, Central Jakarta, West Jakarta and North Jakarta.

Conclusion

Utilizing the SpVAR (1,3) model with uniform weights for rainfall data analysis in DKI Jakarta Province reveals a comprehensive consideration of spatial influences within the model. The interconnectedness of rainfall, air temperature, and air humidity is notably significant not only within the prediction area but also extends to other regions. However, it is essential to highlight specific equations where significant variables play a crucial role in model predictions, namely air humidity in East Jakarta and rainfall in North Jakarta. The significance of air humidity in East Jakarta can be attributed to the unique characteristics of this area as an industrial zone. Industrial activities often contribute distinct environmental factors, impacting humidity levels and, consequently, influencing the overall weather patterns in the region. On the other hand, the significance of rainfall in North Jakarta is likely associated with its coastal proximity. Coastal regions tend to experience different weather patterns due to the influence of marine factors, which could explain the specific importance of rainfall in the predictive model for this particular area. In summary, the SpVAR (1.3) model with uniform weights takes into account spatial influences, revealing the interconnected dynamics of rainfall, air temperature, and air humidity across various regions in DKI Jakarta Province. The identification of specific significant variables in certain equations, such as air humidity in East Jakarta and rainfall in North Jakarta, underscores the nuanced and area-specific factors that contribute to the overall predictive capacity of the model.

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Author Contributions

Rinda Lolita Melanwati: Created initial drafts, gathered and analyzed data, and composed research findings. Eni Sumarminingsih and Henny Pramoedyo: Involved in reviewing outcomes and assessments and providing writing recommendations. Software used: R and Minitab.

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Conflicts of Interest

The authors declare no conflict of interest.

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