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Predicting Consumer Price Index Movements with SARIMA: A Case from Kediri City

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ABSTRACT

The city of Kediri plays a significant role in driving the regional economy. One factor that plays an important role in regional economic stability is the Consumer Price Index (CPI). This study aims to predict the Consumer Price Index (CPI) of Kediri City using the Seasonal ARIMA (SARIMA) model, taking into account seasonal patterns. The data used consists of monthly CPI secondary data from January 2020 to December 2023 obtained from the Central Statistics Agency (BPS). The analysis was conducted through several stages, including a stationarity test using the Augmented Dickey-Fuller (ADF) method, model identification using ACF and PACF, parameter estimation, model selection based on the Akaike Information Criterion (AIC) value, and forecasting. The results of the study indicate that the SARIMA(2,2,0)(1,0,0)[12] model has the lowest AIC value. With a narrow confidence interval and a stable trend, this model can accurately predict the CPI for 2024. The forecasting results show that the CPI continues to increase each year. It is hoped that these findings will contribute academically to seasonal time series modelling and assist the government and businesses in developing data-driven economic strategies in area.

1. Introduction

In Indonesia, it is crucial for the government, businesses, and society as a whole to understand how economic indicators move during the development and management process (Togatorop et al., 2024). The Consumer Price Index (CPI) is one indicator that plays a crucial role in indicating the economic condition of a region because it serves as primary instrument for measuring inflation rates and public purchasing power by recording changes in prices of various goods and services consumed by the general public. It is crucial for the government to have ability to project CPI movements so they can formulate appropriate policies to control inflation (Ganessa et al., 2021). Economic and business policy planning becomes less targeted and vulnerable to market uncertainty if CPI does not provide accurate predictions. Therefore, businesses rely heavily on CPI predictions to adjust their business strategies, including determining selling prices, inventory, and investment plans (Kristinae, 2018).

As a city in East Java, Kediri plays a significant role in driving the regional economy. Prices are constantly fluctuating due to the region's rapidly growing trade, services, and industrial sectors (Irfansyah, 2024). Seasonal factors such as religious holidays, harvest seasons, and specific cycles in goods distribution are often the main causes of price fluctuations, which are then reflected in changes in the CPI (Noor & Komala, 2019). Without understanding and modeling these seasonal patterns, forecasts can be inaccurate and irrelevant as a reference. As local economic dynamics continue to change and evolve, utilizing accurate CPI forecasts that take seasonal aspects into account becomes relevant and increasingly important (Faradis et al., 2023).

Accurate CPI predictions have strategic benefits for many parties. These predictions can be used by local governments to make decisions about how to control inflation, maintain stable prices of basic goods, and maintain public purchasing power (Rosdianawati & Surjanto, 2023). Businesses such as small and medium business, local entrepreneurs, and investors can use CPI predictions to develop business strategies that are more market-responsive (Yusuf et al., 2020). Business actors can create pricing policies, promotional strategies, and manage production and distribution more efficiently by understanding price movements. Furthermore, CPI predictions that consider seasonal factors will improve the planning capabilities of government and private sector stakeholders to anticipate market changes (Nafisah & Respatiwulan, 2019). Consequently, this research not only provides practical contributions to Kediri City's economic policy but also adds to the academic literature on CPI prediction methods based on seasonal local economic data.

One of the studies conducted was by Afiyah & Wijaya (2018), which aimed to forecast CPI in Indonesia. The method used in the study was Double Exponential Smoothing. The results of CPI forecast in Indonesia obtained in January 2017 were 127.24. Meanwhile, the MAPE value obtained was 1.24. Another study was conducted by Ruhiat & Effendi (2018), which aimed to forecast the Citarum River discharge. In this study, a comparison was made between the non-seasonal ARIMA model and SARIMA. The results obtained were that SARIMA model was more suitable for use than non-seasonal ARIMA model.

Seasonal Autoregressive Integrated Moving Average (SARIMA) model is a time series analysis method specifically designed to handle data with seasonal characteristics, in addition to long-term trends and fluctuations (Wahyuningtyas et al., 2021). SARIMA was born as an evolution of the ARIMA method, with the addition of a seasonal component that can manage periodic changes, for example, annual, monthly, or weekly patterns that often appear in economic data, including CPI (Dimashanti & Sugiman, 2021). SARIMA's main strength lies in its ability to structurally sort seasonal and non-seasonal components, allowing seasonal characteristics that recur each period to be modeled precisely without neglecting the long-term trends contained in the data (Rizki & Taqiyyuddin, 2021). This makes SARIMA ideal for application to CPI data, which generally exhibits recurring patterns of price increases or decreases, for example, leading up to major holidays or during the harvest season (Yahya, 2022).

Although SARIMA method has been widely used in forecasting economic data such as inflation and consumer price index, most previous research has focused on national or provincial scale. Few studies have applied the SARIMA model specifically to a regional microeconomic context, such as city level, even though seasonal characteristics and local consumption patterns can vary significantly. Previous research has been conducted primarily at the national or provincial scale, while studies at the city level are rare, even though local characteristics significantly influence price prediction. Considering this, this research aims to examine how Consumer Price Index (CPI) changes in Kediri City, identify seasonal factors that contribute to price fluctuations, and develop a more accurate forecasting model for predicting future CPI values. This study will also assess the accuracy of the model, ensuring its usefulness to local governments, entrepreneurs, and academics interested in regional economic studies. This research is limited to the analysis of monthly CPI data for Kediri City within a specific timeframe, subject to data availability. The focus is limited to statistics and seasonal patterns in CPI movements, without further discussion of other external factors such as government policies or global economic conditions that may impact local prices.

2. Literature Review

2.1 CPI Prediction

The Consumer Price Index (CPI) is a key economic indicator used to measure inflation and price stability in a region. CPI forecasting plays a crucial role in economic policy planning, business strategy, and consumer purchasing power analysis (Kristinae, 2018). Several previous studies have examined CPI forecasting using various statistical and econometric methods. Afiyah and Wijaya (2018) used the Double Exponential Smoothing method to forecast the CPI in Indonesia and obtained a Mean Absolute Percentage Error (MAPE) of 1.24%, indicating that even a simple method can provide fairly good forecasting results. Meanwhile, Ganessa et al (2021) found that seasonal factors, such as harvest time, religious holidays, and the new school year, significantly influence price fluctuations, which are then reflected in the CPI.

Conversely, Noor and Komala (2019) examined the CPI by expenditure group and found that food and transportation prices were most sensitive to seasonal changes. These results emphasize the importance of considering seasonal factors in CPI forecasting to make the predictions more accurate and relevant for policy needs.

2.2 SARIMA model applications

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model is a development of the ARIMA model specifically designed to handle time series data containing trend and seasonal components (Wahyuningtyas et al., 2021). By incorporating seasonal parameters, SARIMA is able to model recurring patterns that frequently appear in monthly or quarterly economic data, such as commodity prices, inflation, and financial market indices (Dimashanti & Sugiman, 2021).

In the context of inflation and CPI forecasting, several studies have demonstrated the superiority of SARIMA over non-seasonal models. Rizki and Taqiyyuddin (2021) applied SARIMA to predict inflation rates in Indonesia and found that models with seasonal parameters provided better accuracy based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values. Yahya (2022) research on national CPI forecasting also concluded that the SARIMA model with specific parameters was able to provide narrow confidence intervals, thereby increasing forecast accuracy.

In addition to economics, Lin and Chen (2021) used SARIMA to predict monthly temperatures in Nanjing, China, and demonstrated that this model is effective in capturing both seasonal patterns and long-term trends. In Indonesia, Lukmaini et al (2023) applied SARIMA to inflation data from East Kalimantan Province and obtained the best model SARIMA(0,1,1)(1s,0,0)[12] which fits the annual seasonal pattern. These findings confirm the flexibility of SARIMA in various forecasting fields.

2.3 Related Studies

Although numerous studies have used SARIMA for inflation and CPI forecasting, most have focused on national or provincial-scale data (Ganessa et al., 2021; Nafisah & Respatiwulan, 2019). However, economic conditions at the city level often have unique characteristics, such as consumer consumption patterns, local trade cycles, and the influence of seasonal factors such as religious holidays and the new school year (Irfansyah, 2024; Noor & Komala, 2019).

Research at the city level is still limited, even though local forecasting models can provide more relevant information for regional policymakers. Ruhiat & Effendi (2018) compared ARIMA and SARIMA models for Citarum River discharge data and showed that SARIMA outperformed when seasonal patterns were strong. This indicates that models with a seasonal component are essential for regional contexts where price fluctuations are influenced by the annual cycle. Therefore, this study aims to fill this gap by applying the SARIMA model to Kediri City CPI data. The forecasting results are expected to support local governments and business actors in formulating inflation control strategies and economic planning based on local data.

3. Methodology

Data used in this research is secondary data obtained from Badan Pusat Statistik (BPS). Variable used is Consumer Price Index of Kediri City for four years, from January 2020 to December 2023. CPI is calculated using base year of 2018 based on consumption patterns resulting from Survey Biaya Hidup (SBH).

This research is quantitative with a predictive approach. Data analysis method used for time series analysis is Seasonal ARIMA (SARIMA). The software used is R 4.3.1. The following are steps for implementing the SARIMA model:

3.1 Stationary test

This test is conducted to determine whether the data used for analysis is stationary in terms of mean and variance, as this test is one of the requirements for the SARIMA method. If the data is not stationary, differencing the data is necessary (Lukmaini et al., 2023).

Time series data is said to be stationary if the mean and variance remain constant over time. The procedure for testing stationarity in the mean uses the Augmented Dickey-Fuller (ADF) test. The ADF test can address residual autocorrelation by adding lags of differences in variable values as explanatory variables (augmentation), thus making the test results more stable and valid, especially for data with a strong temporal relationship. The following is the hypothesis for the ADF stationarity test (Aktivani, 2020):

$H_0: \rho = 0$ (there are unit roots, variable Z is not stationary)

$H_1: \rho \neq 0$ (there are not unit roots, variable Z is stationary)

Where the test statistics used are as follows:

$$\tau = \frac{\hat{\rho}}{std(\hat{\rho})} \tag{1}$$

Then the statistical results of the calculations are compared with the table τ_α

3.2 Identify model

The next step is to identify a model by referring to ACF and PACF plots, as well as the unit root test. The appropriate model combination can be determined by examining several criteria from these plots. The general equation for ARIMA model is as follows:

$$\Phi_p(B)(1-B)^d Z_t = \Theta_0 + \Theta_q(B)\alpha_t \tag{2}$$

where:

$\Phi_p(B) = (1 - \Phi_1 B - .. - \Phi_p B^p)$: operator AR (p)

$\Phi_q(B) = (1 - \Phi_1 B - .. - \Phi_q B^q)$: operator MA (q)

$(1-B)^d$: differencing orde d

α_t : residual value at t

By involving seasonal factors, the SARIMA model has following general equation:

$$\Phi_p(B^S)\Phi_p(B)(1-B)^d(1-B^S)^d Z_t = \Theta_0 + \Theta_q(B)\Theta_q(B^S)\alpha_t \tag{3}$$

where:

$\Phi_p(B)$: AR non seasonal

$\Phi_p(B^S)$: AR seasonal
$(1-B)^d$: *differencing* non seasonal
$(1-B^S)^d$: *differencing* seasonal
$\Theta_q(B)$: MA non seasonal
$\Theta_q(B^S)$: MA seasonal
α_t : residual value at t

After selecting several models, the next step is to estimate the parameters to get the best coefficient value from the model. This step is carried out by verifying several predetermined models to find the most appropriate and best model. The best model is determined by looking at Akaike Information Criterion (AIC) value (Fathurahman, 2017). This is final stage of SARIMA analysis forecasting. Prediction values are obtained through a mathematical process based on the selected model structure and built from historical data. After the prediction values are obtained from calculations, next step is to find residual value of model by calculating difference between predicted value and actual data.

4. Findings and Analysis

The data used is CPI for Kediri City obtained from Badan Pusat Statistik (BPS). The predicted CPI refers to data from January 2021 to December 2024. CPI is a crucial indicator for measuring inflation and regional economic conditions, particularly in Kediri City. The following is a visualization of CPI for past year (in 2024):

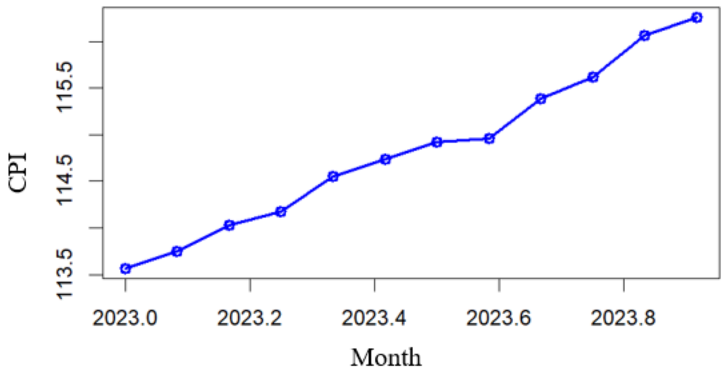

Figure 1: Visualization of Kediri City CPI for the Past Year

Based on Figure 1 above, there is a consistent and gradual increase from January 2023 with a CPI of 113.2 to December 2023 with a CPI of 116.2. There was no decrease in CPI during 2023, meaning that inflation in Kediri City was considered stable and moderate during that year without any major price fluctuations. From July to September, there was a sharper increase than in the previous and subsequent months, this is due to price increases during the Eid al-Adha celebrations and new school year. To provide a broader picture of CPI, Figure 2 shows the overall CPI data from 2020 to 2023.

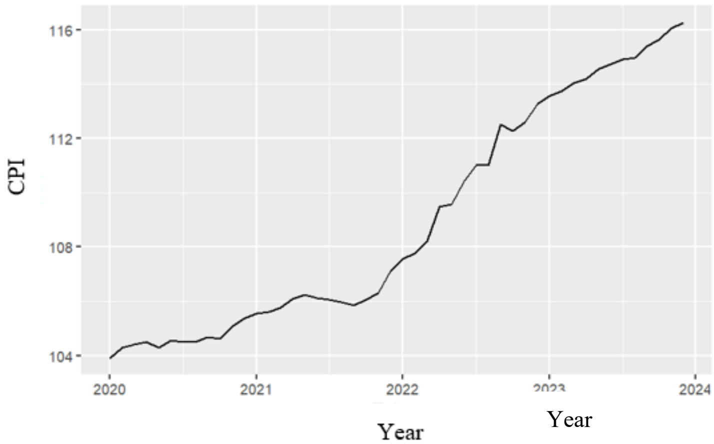

Figure 2: Visualization of Kediri City CPI from 2020-2023

Based on Figure 2, there was a consistent increase from 2020 to 2023. CPI value rose from around 104 in early 2020 to over 116 at the end of 2023. This indicates a cumulative increase of approximately 12 index points in the prices of goods and services in general over the past four years. A sharper increase occurred from mid-2022 to early 2023. This reflects higher inflation, likely partly due to the recovery from the Covid-19 pandemic. To further clarify seasonal and non-seasonal patterns, the following graph shows the seasonal and non-seasonal components over the four years.

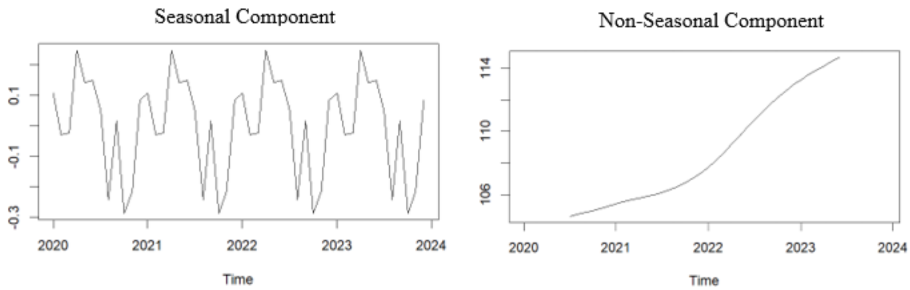

Figure 3: Seasonal and Non-Seasonal Component Data

Figure 3 shows a plot of the seasonal and non-seasonal components of the CPI data over four years. The seasonal component data visualization shows a similar pattern of fluctuations each year, indicating that prices experience consistent seasonal fluctuations. Several specific seasons influence this, including Ramadan and Eid al-Fitr, the harvest season, and the new school year. The non-seasonal component data visualization shows a sustained upward trend in the CPI, reflecting structural inflation, indicating no downward trend from 2020 to 2024.

The data analysis begins with a visual exploration of the data and diagnostic tests to identify basic characteristics of the time series data, such as trends, seasonality, and other fluctuations. The model used is SARIMA, a statistical data analysis that forecasts time series data by considering long-term trend patterns, seasonality patterns (seasonality), correlations with past data (autoregressive), and the average of previous errors (Dabral & Murry, 2017).

The first step in forecasting data with SARIMA is to test for stationarity. Stationarity testing is a prerequisite for producing valid parameter estimates in SARIMA model (Lin & Chen, 2021). The following are results of data stationarity test:

Table 1. Results of Stationarity and Differentiation Test

	Stationarity test	Differentiation-1	Differentiation-2
ADF	-2.5539	-2.0203	-4.9169
Lag order	3	3	3
P-value	0.3529	0.5699	0.01

The test used to test stationarity in this study is Augmented Dickey-Fuller (ADF) test. Based on Table 1, the ADF test shows a p-value of 0.3529, which is >0.05, making it non-stationary. Therefore, data differentiation is necessary. In the first data differentiation, the p-value is 0.5699, but since this value is >0.05, the data is still not stationary (Sharma et al., 2024). Since it is still non-stationary, further differentiation is necessary. In the second differentiation, the p-value is 0.01. Since the p-value is <0.05, it can be concluded that the data is stationary. The following plots of ACF and PACF data after second differentiation are shown:

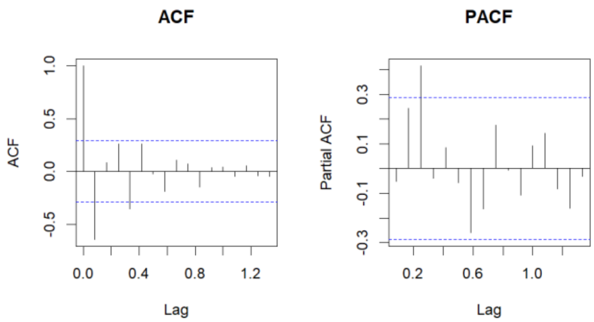

Figure 4. Plot of ACF and PACF after *differencing*

Autocorrelation and partial autocorrelation patterns are found when the data becomes stationary due to non-stationary initial data. This is indicated by ACF and PACF plots, as well as formal tests such as the ADF test in Figure 4. Two-fold differentiation was performed to eliminate strong trends (d = 2). While the ACF lacks a clear pattern, the PACF plot shows a significant increase up to the second lag. This suggests the possibility of an autoregressive (AR) component up to the second order and an absent moving average (MA) component. Therefore, several non-seasonal candidate models were tested, including:

Table 2. Parameter of SARIMA Model

SARIMA model	Parameter	p-value	Description
SARIMA $(0,2,2)(1,0,0)^{12}$	ma1	0.0000	Significant
	ma2	0.0003	Significant
	sar1	0.6035	Non-Significant
SARIMA $(0,2,3)(1,0,0)^{12}$	ma1	0.0000	Significant
	ma2	0.0148	Significant
	ma3	0.9696	Non-Significant
	sar1	0.6029	Non-Significant
SARIMA $(1,2,1)(1,0,0)^{12}$	ar1	0.0135	Significant
	ma1	0.0000	Significant
	sar1	0.7926	Non-Significant

SARIMA $(2,2,0)(1,0,0)^{12}$	ar1	0.0000	Significant
	ar2	0.0000	Significant
	sar1	0.4817	Non-Significant
SARIMA $(2,2,1)(1,0,0)^{12}$	ar1	0.0015	Significant
	ar2	0.0257	Significant
	ma1	0.5658	Non-Significant
	sar1	0.5964	Non-Significant
SARIMA $(3,2,0)(1,0,0)^{12}$	ar1	0.0000	Significant
	ar2	0.0021	Significant
	ar3	0.7196	Non-Significant
	sar1	0.5340	Non-Significant
SARIMA $(4,2,0)(1,0,0)^{12}$	ar1	0.0000	Significant
	ar2	0.0012	Significant
	ar3	0.3136	Non-Significant
	ar4	0.3020	Non-Significant
	sar1	0.6607	Non-Significant

Based on Table 2, we can conclude the best model by looking at the AIC values of each model. Here are the AIC values of several SARIMA models:

Table 3. AIC Values of SARIMA Models

SARIMA model	AIC
SARIMA $(0,2,2)(1,0,0)^{12}$	33.14527
SARIMA $(0,2,3)(1,0,0)^{12}$	35.66821
SARIMA $(1,2,1)(1,0,0)^{12}$	35.78225
SARIMA $(2,2,0)(1,0,0)^{12}$	32.24632
SARIMA $(2,2,1)(1,0,0)^{12}$	34.50383
SARIMA $(3,2,0)(1,0,0)^{12}$	34.64235
SARIMA $(4,2,0)(1,0,0)^{12}$	36.24778

AIC is a measure of quality in statistical models, specifically for selecting the best model from several candidate models (Dewi & Ahadiyah, 2022). Based on Table 3 above, SARIMA model $(2,2,0)(1,0,0)^{12}$ has the smallest AIC value among the other models, namely 32.24632. Based on the consideration of Tables 2 and 3, it can be concluded that the SARIMA model $(2,2,0)(1,0,0)^{12}$ with autoregressive parameters, meaning ARIMA (2,2,0) model is the best model. Based on the Ljung-Box test value, the p-value is 0.3992, where this value is > 0.05, meaning the model has met the white noise assumption. Therefore, it can be concluded that SARIMA model is good enough and suitable for use for forecasting. The next step is to forecast the best model. The following are forecasting results of ARIMA (2,2,0) model:

Table 4. Best Forecasting Results

Period	Forecast	Low	High
January 2024	116.50	116.25	116.76
February 2024	116.74	116.39	117.11
March 2024	116.99	116.56	117.43
April 2024	117.23	116.73	117.74
May 2024	117.48	116.92	118.05
June 2024	117.72	117.11	118.35
July 2024	117.97	117.30	118.64
August 2024	118.22	117.50	118.93

September 2024	118.46	117.70	119.22
October 2024	118.71	117.91	119.51
November 2024	118.95	118.11	119.79
December 2024	119.19	118.32	120.07

Based on Table 4, the confidence interval is still quite narrow, indicating that SARIMA model has good and stable prediction accuracy. We show Figure 5 below to further clarify whether or not the prediction results have improved.

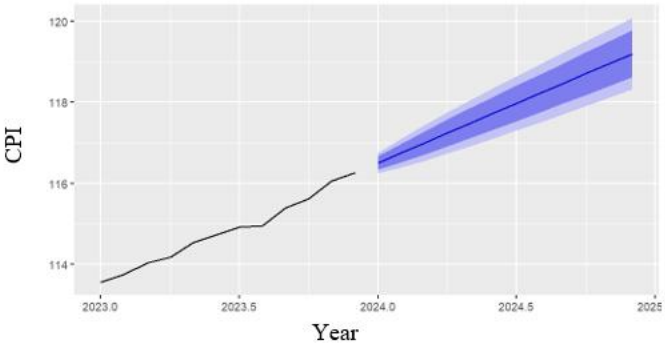

Figure 5. Forcesting result of 2024

Figure 5 above shows a gradual and consistent increase in CPI throughout 2024, with a projection approaching 119-120 by the end of 2024, indicated by the blue line in the middle. The blue area represents a 95% confidence interval, meaning with 95% confidence, CPI value for each month in 2024 will be within this area. The predictions indicate a consistent increase in the CPI in 2024, reflecting seasonal and structural inflationary pressures. This projection is crucial for formulating price control policies and business strategies for local businesses

5. Conclusion

This study produces a forecasting model for Consumer Price Index (CPI) for Kediri City using SARIMA approach. By considering seasonal factors, this model successfully predicts CPI value for one year in 2024. With the smallest AIC value and a narrow confidence interval, the best model produced can project CPI value for 2024 with high accuracy. The prediction results show a slow and consistent increase in CPI trend throughout 2024. These results are very helpful for local governments and business actors in making data-based economic policies, especially in terms of planning pricing strategies and controlling inflation, especially in Kediri City. This study adds to the academic literature on the use of SARIMA method on local economic data influenced by seasonal factors.

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Conflict of interest statement

The author declares no commercial or financial relationships that could be construed as a potential conflict of interest.

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