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Comparison of SARIMA and BES for Forecasting Red Chili Production

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ABSTRACT

The goal of this study is to compare the performance of Seasonal Autoregressive Integrated Moving Average (SARIMA) and Bagging Exponential Smoothing (BES) models for forecasting red chili production. The secondary data used in this study came from BPS-Statistics Indonesia and the Ministry of Agriculture. The data include monthly national-level red chili production from January 2013 to December 2021. Data is analyzed using time series approaches such as SARIMA and BES. The performance of both models was compared, and production forecasts were created using the best model. According to the research findings, for this dataset, the SARIMA (1,1,1)(0,1,1)^{12} technique outperforms the BES method since it has lower MAPE and RMSE values, 7.06 and 95,473, respectively. The best model was then applied to anticipate red chili production from January to December 2022, resulting in a highly accurate MAPE of 5.39.

Keywords: Bagging Exponential Smoothing, red chili production, SARIMA

INTRODUCTION

Chili is a major agricultural product in Indonesia, a strategic item that requires special government attention due to the widespread public demand for it. The Ministry of Agriculture's Strategic Plan 2020–2024 lists chili as one of seven important food commodities, alongside rice, corn, soybeans, onions, sugarcane, and beef or buffalo meat. The red pepper (*Capsicum annuum* L.) is an annual horticulture plant that is popular among many groups and is used as a cooking seasoning (Henra *et al.* 2023). According to Chakrabarty *et al*. (2017), fresh red chili includes vitamin A, numerous vitamins B and C, as well as minerals including magnesium and riboflavin. In addition, red chili peppers contain flavonoids including carotene and cryptoxanthin. Red chili plants may thrive at a variety of heights, from lowlands to highlands, in rice fields and moorlands, and even up to 1,000 m above sea level (Imtiyaz *et al*. 2017). The optimal temperature for chili growth is 25–27°C during the day and 18–20°C at night. Chili plants require approximately 100–200 mm of rainfall every month for optimal harvests. Red chili plants thrive on soil with a crumbly or loose texture, fertile, rich in organic matter, a pH of 6–7, and adequate water moisture (Aprianto *et al*. 2023), and require roughly 60–80% moisture. However, high humidity might make plants more prone to disease. If the rainfall is heavy, it is vital to have a wider spacing between plants to keep humidity under control (Imtiyaz *et al*. 2017).

Red chili is continually in demand, due to its numerous applications and the growing range of varieties and food menus that incorporate it. However, red chili production is seasonal. The quantity of red chili produced influences the consumption and price. If the supply does not satisfy the community's consumption needs, scarcity may occur, resulting in price rises (Aprinando 2023). Most of the red chilli produced are consumed by local people, with the remainder exported dried to countries with cold temperatures (Asrof *et al*. 2017). According to BPS statistics (2023), national red chili production is expanding from 2018 to 2022 at a rate of 5.21% each year. During the same time, the producer price of red chili climbed by 6.92% annually. A steady supply of red chili can keep prices stable. Season and weather influence chili plant production in the form of fresh fruit. During the rainy season, chili plants are vulnerable to pests and diseases that can cause chili peppers to rot, resulting in crop failure. This has an impact on market pricing because supply is limited. The converse occurs after chili peppers are harvested or at the end of the dry season, when the price begins to fall due to an abundance of supply (Kementan 2023).

Time series data are collections of data that have been grouped according to the time of observation. These data are often retrieved iteratively at regular intervals. Time series analysis is a statistical technique that examines time series data to detect trends and patterns, it can reveal trends and patterns in data, allowing forecasting models to be constructed that use previous observations to predict future values (Maulana 2018). Autoregressive Integrated Moving

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Average (ARIMA) is a regularly used approach for forecasting time series data, is used to process time-series data with a stationary pattern (no change over time) in mean and variance. Time series data with seasonal trends can be utilized as an extension of the ARIMA model known as SARIMA, or Seasonal ARIMA (Montgomery *et al*. 2015).

Model accuracy can be enhanced using sampling strategies, such as the bootstrap aggregating (bagging) method. Breiman (1996) pioneered bagging, a type of ensemble machine learning in which numerous models are used with the same method (Mu'tashim *et al*. 2023). The bagging method involves training each model on a separate subset of samples from the same dataset. Bergmeir *et al.* (2016) developed bagging to forecast time series data by using resampling for exponential smoothing, often known as Bagging Exponential Smoothing (BES). BES is a combination of several different Exponential Smoothing models created with the goal of enhancing forecast accuracy.

The time series data includes national red chili production data. Time-series analysis can assist anticipating future national red chili production. When evaluating time series data, the choice of a forecasting model influences the accuracy and validity of the prediction results, as well as the decisions made based on the results. Based on this description, the goal of this research was to assess the performance of the SARIMA and BES models using national red chili production data and to forecast red chili production using the most effective way.

METHODS

The data used in this study were secondary, specifically red chili production figures received from the Central Statistics Agency and the Ministry of Agriculture. The data is monthly national data from January 2013 to December 2022. This time series data was used to identify long-term trends in red chili output. The data was divided into two parts: training and testing. Training data covered the period January 2013 to December 2019, whereas testing data cover the period of January 2020 to December 2021. Forecasting was accomplished by discovering patterns in training data, which were then verified against the testing data. Additional data from January to December 2022 were utilized to compare real and forecast data and assess forecast accuracy. The SARIMA and BES methodologies, combined with R Studio software, were utilized to analyze the data for this study's goal. This study's data analysis was divided into the following 6 steps: (1) exploring data; (2) creating a SARIMA model; (3) constructing a BES model; (4) comparison of the performances of SARIMA and BES models based on RMSE and MAPE; (5) forecasting red pepper production for the next 12 months using the best models; and (6) measuring the accuracy between forecast data and real data using MAPE.

Stationarity

The time series data pattern exhibits stationarity. Montgomery *et al*. (2015) define stationary time series data as those that are unaffected by changes throughout time. If the time-series plot shows no notable upward or downward trend and no seasonal pattern, the data is stagnant. Data stationarity can also be explored using ACF plots. If the ACF plot does not show a gradual decrease in value, the data is stationary.

Data stationarity is classified into two types: stationary in mean and stationary in variance. The Augmented Dickey-Fuller (ADF) test is a formal method for determining stationarity in mean. A *p*-value of less than 0.05 indicates that the data is steady on mean. Data is considered stationary if variance in the time series are constant. Calculating the value of λ can help determine this. If λ is not equal to 1, it indicates that the time series data is not stationary in variance. To stabilize the data, we used the Box-Cox transform. This transformation is mathematically characterized as follows (Wei 2006):

$$T(y_t) = \begin{cases} ln\, y_t & \lambda = 0 \\ (y_t^{\lambda} - 1)/\lambda, & \lambda \neq 0 \end{cases} \quad (1)$$

where
y_t = *t*th *time series*
λ = Transformation parameters

SARIMA

The SARIMA (Seasonal Autoregressive Integrated Moving Average) approach was used to evaluate data with seasonal patterns, which are patterns that repeat over a given time frame. SARIMA(p,d,q)(P,D,Q)^s models were created by determining the right order for each model (Montgomery *et al*. 2015) as follows:

$$\Phi_P(B^S)\phi_p(B)(1-B)^d(1-B^S)^D Y_t = \delta + \theta_q(B)\Theta_Q(B^S)\varepsilon_t \quad (2)$$

where

p, *d*, and *q*	= AR non-seasonal order, differential order, and MA order
P, *D*, and *Q*	= AR seasonal order, differential order, and MA order
Y_t	= Time series data in the *t*th period
δ	= Constant
ε_t	= Residual in the *t*th period
B	= Backshift operator
S	= Seasonal period
Φ_P	= Seasonal AR components

Θ_Q = Seasonal MA component

BES

Bergmeir *et al*. (2016) created the Bagging Exponential Smoothing (BES) technique to improve prediction accuracy in monthly data forecasting by breaking down time series data into trend, seasonal, and remainder or residual components using the Seasonal-Trend Loess (STL) decomposition method. STL was used for data with seasonal indications, whereas Loess was used to evaluate seasonal components and trends (Hyndman and Athanasopoulos 2018). The nomenclature for the STL decomposition method (Cleveland *et al*. 1990) is as follows:

$$Y_v = T_v + S_v + R_v, \quad v = 1, \dots, n \tag{3}$$

where
Y_v = Time series data
T_v = Trending components
S_v = Seasonal components
R_v = Residual components
n = Number of data

Moving Block Bootstrap (MBB) was then used on the remainder components. The three previously separated components were re-combined, and each bootstrap result is smoothed exponentially. Then, each AIC value was chosen as the best model for predicting by adding the prediction values from all models and calculating the average (Figure 1).

RESULTS AND DISCUSSION

Data Exploration

The first stage of data analysis was conducted by investigating national red chili production statistics from January 2013 to December 2021. The modeling used 108 data points to represent total national red chili production across 8 years, with the *X*-axis representing observation time and the *Y*-axis representing red chili production in quintal units (Figure 2). Data on national red chili output from January 2013 to December 2021 reveals that November 2021 had the highest production. In contrast, the lowest national red chili production was recorded in November 2013. This decline in production might be attributed to meteorological conditions such as the wet season and the presence of natural disaster such as the eruption of Mount Sinabung in North Sumatra Province, one of Indonesia's primary provinces for red chili. According to BMKG's (Indonesian Agency for Meteorological, Climatological and Geophysics) predictions, October and November 2013 marked the start of the rainy season in several Indonesian regions. This is consistent with Naura and Riana's (2018) conclusion that climate change, such as rainfall, can reduce red chili production. The average monthly national red chili production over the last 9 years, from 2013 to 2021, was 965,781 quintals.

SARIMA Modeling

The construction of the SARIMA model must be tested on the entire dataset. The resulting time series data plot (Figure 2) indicates that the data are not likely to be stationary in terms of mean or variance. The ADF test was used to determine the stationarity of the mean data set. The data is considered steady on mean if the ADF test has a *P*-value < 0.05 (Table 1).

The Box-Cox transformation was then used to evaluate the stationery in the variance. The λ value of 0.9999, which is close to 1, indicates that the data are steady in variance. The whole data was then separated into training and testing sets. Model identification was carried out on the training data using ACF and PACF plots. Figure 3 indicates that, with a difference of 1, the

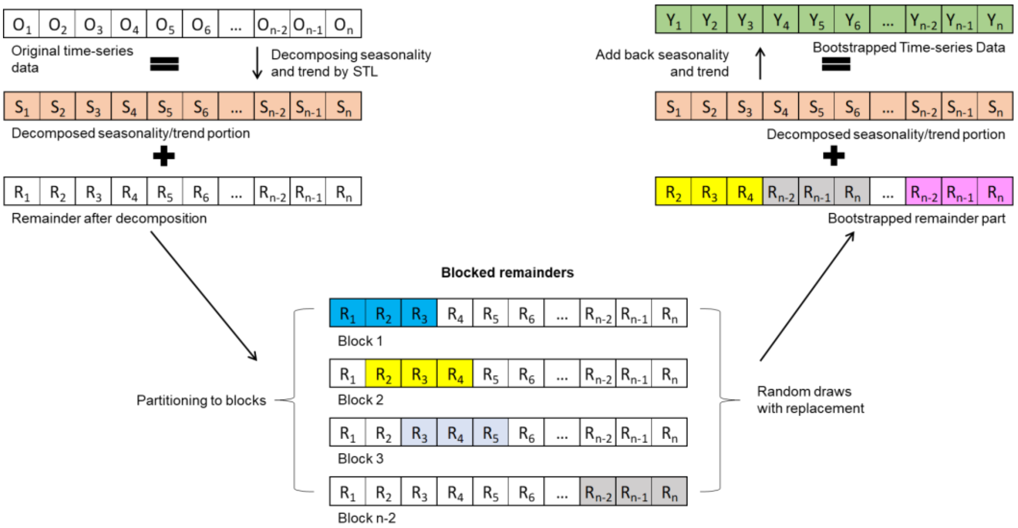

Figure 1 Illustration *of* Moving Block Bootstrap (MBB).

ACF value is interrupted at lag 2, indicating that the Moving Average (MA(q)) model of order 2. The PACF value is likewise interrupted at lag 2, indicating that the autoregressive (AR(*p*)) model has an order of 2. The possible models or preliminary models are $(2,1,0)(0,1,2)^{12}$ and $(0,1,2)(2,1,0)^{12}$.

A *P*-value of less than 0.05 indicates that the model parameter is significant. The Ljung-Box and Jarque Bera tests employed the autocorrelation in the remainder and normality test, with a *P*-value higher than 0.05 indicating that the model had white noise. Model overfitting was carried out by adding an order from an existing preliminary model. The SARIMA $(1,1,1)(0,1,1)^{12}$ model was chosen as the best model since it satisfies the white noise assumption, all parameters are meaningful, and the AIC is low (Table 2).

The best SARIMA model was used to forecast production for the next 12 periods. Figure 4 shows that the predicted plot follows a similar pattern to the actual data. The projection indicates the maximum estimate in March 2021 of 1,216,0006 quintals (121.6 thousand tons) and the lowest prediction in October 2020 of 928,435.5 quintals (92.84 thousand tons). The graph further indicates that the forecast pattern closely matches the actual production pattern.

BES Modeling

The process of doing BES on time-series data involves multiple stages. The first step was to modify Box-Cox to stabilize the variance. Furthermore, data

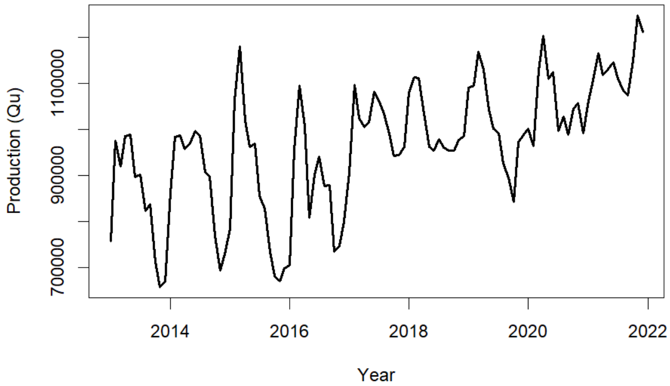

Figure 2 National red pepper production data plot 2013–2021.

Table 1 ADF test results of National Red Chili Production

Region	Component	*P*-value	Remark
National	Non-Seasonal	0.01**	Stationary
	Seasonal	0.6962	Not stationary

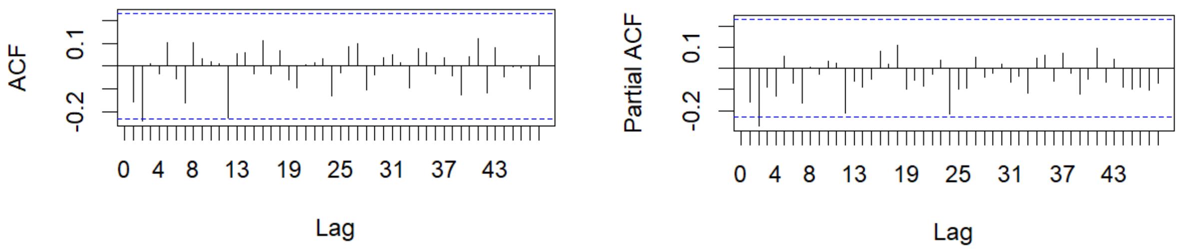

Figure 3 Plots of ACF and PACF training data that have been stationary.

Table 2 Test Results of Tentative Model and *Overfitting Model*

SARIMA model	Ljung-Box	Jarque Bera	AIC
Tentative			
$(2,1,0)(0,1,2)^{12}$	+	0.32	1792.89
$(0,1,2)(2,1,0)^{12**}$	+	0.18	1792.04
Overfitting			
$(0,1,2)(0,1,2)^{12}$	+	0.29	1790.89
$(2,1,2)(0,1,2)^{12}$	+	0.44	1792.24
$(1,1,1)(0,1,2)^{12}$	+	0.54	1789.03
$(1,1,1)(0,1,1)^{12}$	**+**	**0.17**	**1790.49**

Remarks: + Significant at lag 5, 10, 15, 20, 25, 30.

was decomposed using the STL approach since time series data had seasonal characteristics. This stage divided the data into trend, seasonal, and reminder components, as shown in Figure 5.

Following decomposition, the remainder components were used in the bootstrapping procedure. To create 100 new data series, up to 99 data points were created from the original data using a block size of 24. If the reminder components have a limited diversity, this procedure produces a sequence of synthetics that are identical to one another. Figure 6 depicts the results of the bootstrapping approach with MBB, with the original series indicated in black and the synthetic series identified in various colors.

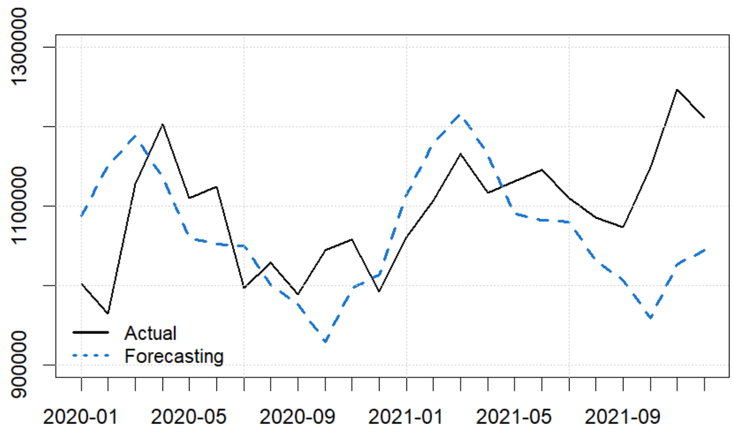

Figure 4 Actual data plot and forecast for 2020–2021.

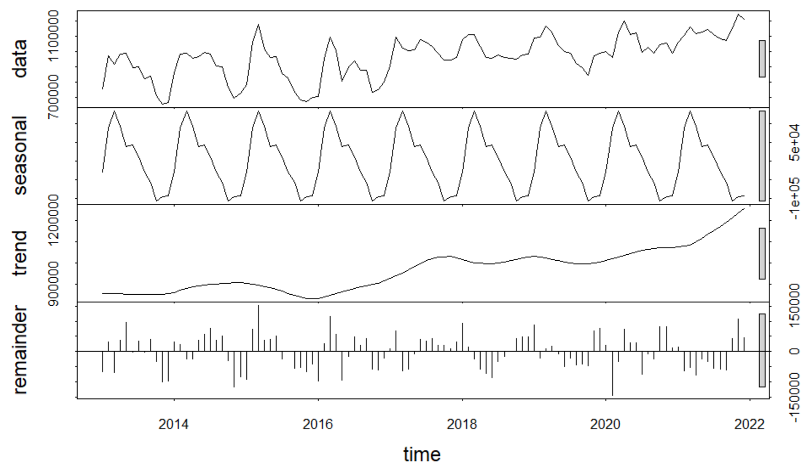

Figure 5 Production data deconstruction plot. \

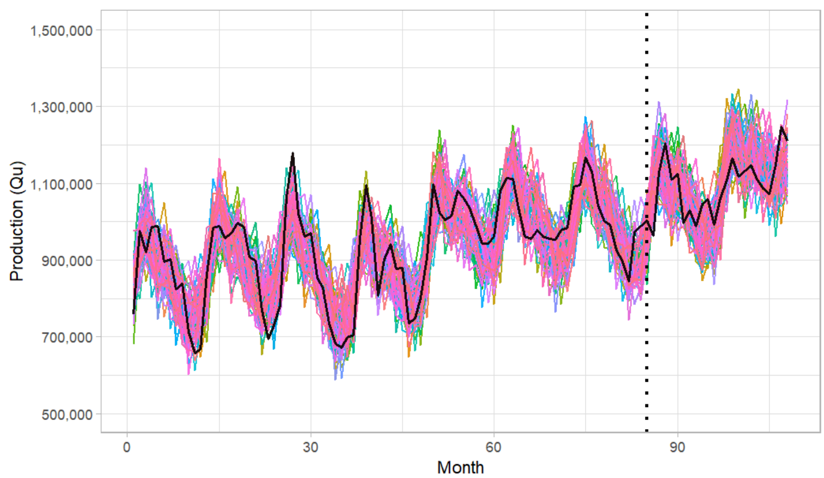

Figure 6 Bootstrapped series production data.

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The Triple Exponential Smoothing or Holt's Winter method was used to forecast each bootstrapped series training dat a, and the average value was calculated for each month. Figure 7 depicts the visualization of the forecast and test data, with the test data represented by a black line, the forecast data represented by a dotted red line, and the bootstrapped result represented by a gray line.

Model Evaluation

The prediction accuracy results from the test data were used to evaluate the model's performance. To identify which approach produces the best prediction results among the methodologies, the Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) figures were compared. Lower MAPE and RMSE values imply that the model utilized is more effective and reliable (Table 3). Based on the constructed model, it can be inferred that the SARIMA $(1,1,1)(0,1,1)^{12}$ model outperforms the national red chili production statistics. This is because the model has lower MAPE and RMSE values than the others (Figure 8).

Comparison between Forecast Results and Actual Data

The best-performing model was then used to forecast data from January to December 2022. The predicted results were then compared to actual data (Table 4), yielding an average MAPE of 5.39.

CONCLUSION

The findings of the comparison of the SARIMA model with BES demonstrate that SARIMA outperforms the other models in terms of national red chili production statistics. The SARIMA $(1,1,1)(0,1,1)^{12}$ model was used to anticipate the period January–December 2022. A comparison of projected findings to actual data yielded a MAPE of 5.39.

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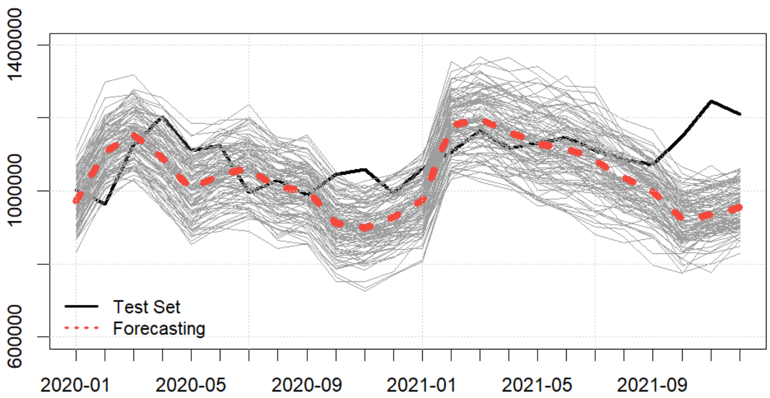

Figure 7 Actual data plot and forecast with BES

Table 3 Model Accuracy

Model	MAPE	RMSE
SARIMA $(1,1,1)(0,1,1)^{12}$	7.06	95,473.93
BES	8.09	119,673.93

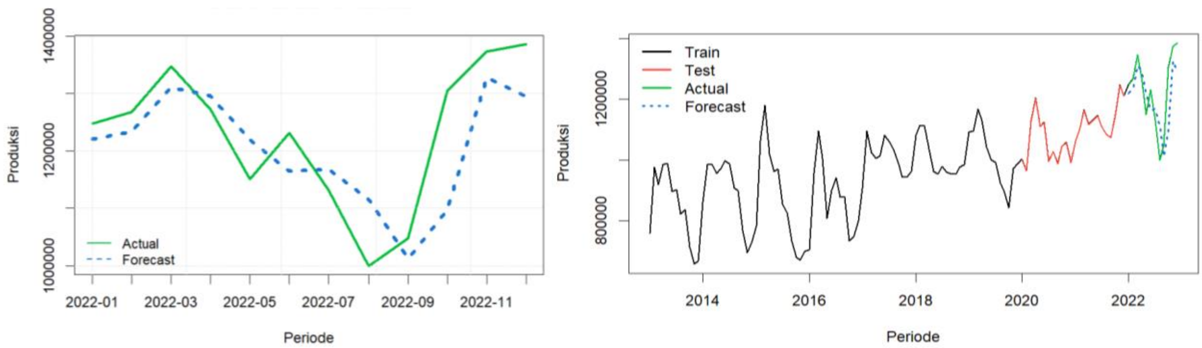

Figure 8 Visualization of actual data and forecast by SARIMA $(1,1,1)(0,1,1)^{12}$ Method.

Table 4 MAPE forecast data with actual

Period	MAPE
Jan 22	2.17
Feb 22	2.74
Mar 22	2.72
Apr 22	1.82
May 22	6.03
Jun 22	5.36
Jul 22	3.25
Aug 22	11.56
Sep 22	3.36
Oct 22	15.84
Nov 22	3.33
Des 22	6.56

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