Thailand Statistician
October 2024; 22(4): 894-908
http://statassoc.or.th
Contributed paper

Modeling and Forecasting of Russian Federation Cheese Production and Total Cheese Used

Mostafa Abotaleb [a], Ammar Kadi [b], Irina Potoroko [c], Priyanka Lal [d], Soumik Ray [e], Deepa Rawat [f], Tufleuddin Biswas [g], Pankaj Kumar Singh [h], Pradeep Mishra* [i] and Shikha Yadav [j]

[a] Department of System Programming, South Ural State University, Chelyabinsk, Russia.
[b] Research Scholar, Department of Food and Biotechnologies, South Ural State University, Chelyabinsk, Russia.
[c] Department of Food and Biotechnologies, South Ural State University, Chelyabinsk, Russia.
[d] Department of Agricultural Economics and Extension, Lovely Professional University, Punjab, India.
[e] Centurion University of Technology and Management, Paralakhemundi, Odisha, India.
[f] College of Forestry, VCSG Uttarakhand University of Horticulture and forestry, Ranichauri, Tehri Garhwal, Uttarakhand, India.
[g] Department of Agricultural Economics and Statistics, MS Swaminathan School of Agriculture, Centurion University of Technology and Management, Khurda, Odisha, India.
[h] R.D. Engineering College, Ghazibad, Uttar Pradesh, India.
[i] College of Agriculture, Rewa, Jawaharlal Nehru Krishi Vishwavidyalaya, Jabalpur, India.
[j] Department of Geography, Miranda House, University of Delhi, New Delhi, India.
*Corresponding author; e-mail: pradeepjnkvv@gmail.com

Received: 30 January 2022
Revised: 11 July 2022
Accepted: 26 July 2022

Abstract

The primary goal of this research was to evaluate the forecasted behavior of cheese production and total uses in Russia from 1988 to 2020. As a result of a supply-demand imbalance, cheese imports from other nations were necessary to close the gap. Before creating the model, the training and testing sets were split. For both data series, the linear trend model developed by TBATS and Holt was utilized to create the model and estimate the projection. For both sigma and AIC, the best prediction model was found in the TBATS model. Because the TBATS model can decompose data series, we found it to be the best prediction model over Holt's model. As a result of its poorer goodness of fit in both data series, Holt's linear trend model was the best model to use. This study has proven itself to be a valuable resource for policymakers, stakeholders, and researchers alike. Furthermore, we anticipate that the findings of this study will serve as a catalyst for the development of an advanced statistical model or machine learning model for cheese production in the future.

Keywords: Box Cox transformation, time series analysis, Holt's model, TBATS model, prediction.

1. Introduction

Using milk-clotting enzymes and lactic acid bacteria, cheese may be made from raw milk, or it can be made by melting a variety of dairy products and non-dairy raw materials in the presence of melting salts to create cheese. Cassava, goat, sheep, and buffalo milk are used to make cheese, which has a high concentration of protein, calcium, and vitamins. According to the International Dairy Federation’s database, there are over 500 different varieties of cheese produced around the world. The same cheeses are produced in various countries under different names and using different manufacturing procedures (Mishra et al. 2020, Matalas et al. 2001). Russian cheese experts have suggested an upgraded categorization system that includes cheeses from other countries as well. The origin of modern cheese manufacturing in Russia goes back to 1866, although cheese production was a tiny industry before to the Soviet era and it is still so today (Kuzin et al. 2018).

The formulation of predictions contributes to the stability and predictability of the growth of commodities markets in general. Producing companies may benefit from assessing the prospectively projected pricing and demand for certain kinds of goods, which allows them to alter the structure of their production in a manner that is advantageous to them. Federal agencies rely on forecasts for a variety of purposes, including drafting program documents, scheduling economic policy actions, and averting crises (Borodin 2020).

As of now, the production of cheese and cheese products in Russia is on the rise, according to the Institute for Agricultural Market Studies (IAMS). 90% of the market's need for soy will be met by the more than 600,000 tons produced this year. There has also been a tremendous increase in the diversity of Russian cheeses. Private cheese companies produce elite varieties; however, these are produced in very small quantities as compared to the entire output (Kuzina and Ostretsov 2016). In the product market research approach, forecasting models and methodologies are an integral element of the process. The market for agri-food goods is differentiated from other product markets in the broader system of product markets by the degree to which it is important. Because food falls within the purview of the population’s main necessities, there is a need for daily rationed food intake, which is of great relevance. A significant dependency on natural and climatic circumstances is also connected with agricultural output, which is shown in the greater volatility of various markets as a result of this dependence.

It is well known that time series models are utilized for predicting and modeling a variety of instances, such as COVID-19 infections and fatalities, as well as for conducting other case studies based on time series information. Many authors calculated time series modeling and forecasting based on commodity production data series (Abotaleb et al. 2021, Abotaleb 2020, Badr et al. 2021, Mishra et al. 2021b, Lama et al. 2022, and De Livera et al. 2011). Abotaleb (2020) investigated the ARIMA (Autoregressive Integrated Moving Average) and Holts linear trend models for predicting infection, fatalities, and recovery cases in three nations: China, Italy, and the United States. They came to the conclusion that the Holt’s linear trend model performed better than the ARIMA model in all three countries. For online traffic predictions, they employed Holt’s linear trend, Box-Cox transformation, ARMA errors, Trend and Seasonal components (BATS), and Trigonometric seasonality, Box-Cox transformation, ARMA errors, Trend and Seasonal components (TBATS) models, as described in Badr et al. (2021). A number of time series models, including as Holt’s linear trend, the ARIMA and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, were used to study and predict milk pro-duction in South Asian Association for Regional Cooperation (SAARC) nations as well as China (Mishra et al. 2022). According to the ARIMA tech-nique, Ray and Bhattacharyya (2020) seek to assess the trend in total pulse production in India using this approach. For the estimation of the stochastic trend, the years 1961 to 2019 were used. The performance of numerous goodness of model fit criteria is used to determine which ARIMA model is the most effective at capturing the trend of pulse production.

ARIMA is superior to Holt's linear model when the mean absolute percentage of mistakes disclosed by Holt's approach is considered. The ARIMA model indicates that India would have the largest milk output, followed by Pakistan and China, however the GARCH model is more suited to Bangladesh's milk production requirements. Our research employed two time series models to anticipate and model cheese production in the Russian Federation (1000 MT (Million tonne)) and overall cheese consumption (1000 MT) in this article. With annual data from 1988 to 2020, we were able to predict the total amount of cheese produced and consumed in the Russian Federation from 2021 to 2030 (1000 MT). It is apparent that both Russian Federation Cheese Production and Total Cheese Usage have increased from 1988 to 2021, as shown in the graph (Figures 1 and 2).

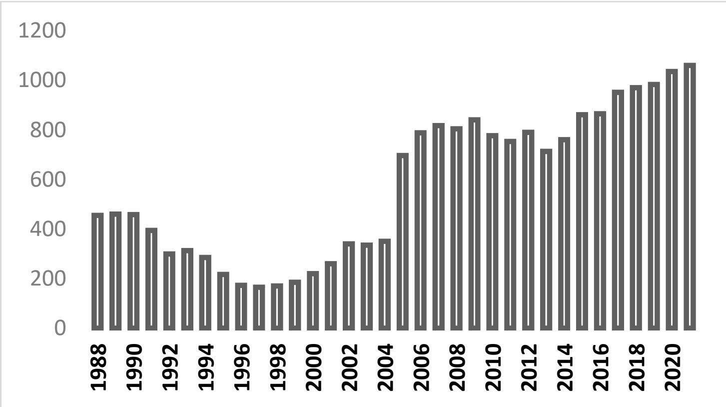

Figure 1 Russian federation cheese production

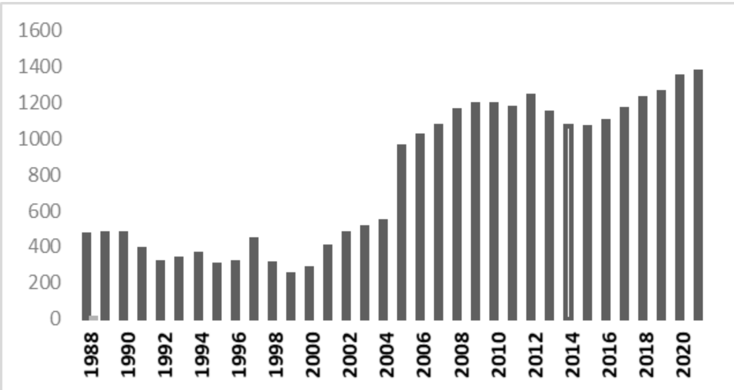

Figure 2 Russian federation total cheese used

2. Materials and Methods

According to the United States Department of Agriculture's website, https://www.usda.gov, information on Russian Federation Dairy, cheese total use by year is being collected for this study. To forecast the behavior, the TBATS model and Holt's linear trend model are employed, respectively.

2.1. Nature of the data

It is possible for time series datasets to incorporate a seasonal component. This is a cycle that repeats over a period of time, such as monthly or yearly, without interruption. When forecasting, this recurring cycle may hide the signal that we desire to model, and in turn, it may deliver a powerful signal to our predictive models.

Seasonal fluctuation may be seen in time series data sets. Seasonal variation, often known as seasonality, is a cycle that repeats itself on a regular basis across time. Our data from 1988 to 2020 is presented on a yearly basis. By examining the time series of each cheese's production and the cheese used This data is characterized by seasonality.

There are many different sorts of seasonality, such as time of day, daily, weekly, monthly, and annual patterns. The determination of whether there is a seasonality component in the time series problem is, as a result, susceptible to interpretation. In order to determine whether or not there is an element of seasonality in the data, the easiest technique is to plot and evaluate the time series data.

Figure 3 represents the actual data graph and the decomposition time series data using the TBATS model for production and use. The extracted components of a TBATS model show the seasonality component in the time series data. Figure 3 depicts the three components (seasonality, slope, and level) in a separate representation. The components of the time series data can be combined to reconstitute the time series data. It is important to note that the seasonal component changes slowly over time, but that season in years that are far apart may have different patterns. The remaining component, depicted in the bottom panel, represents the amount of data that is left over after the seasonal and trend-cycle components have been removed from the data.

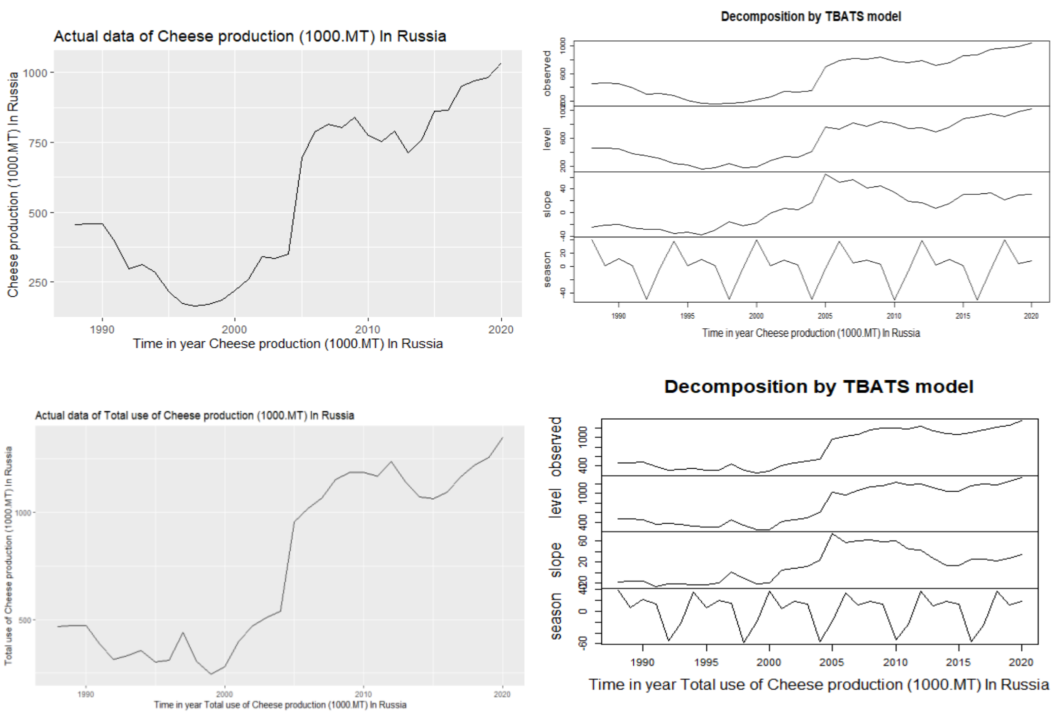

Figure 3 Actual data graph and decomposition using TBATS model

Figure 4 is an illustration of the trend is responsible for the steady decline in the autocorrelation function (ACF) as the delays rise, whereas seasonality is responsible for the “scalloped” form.

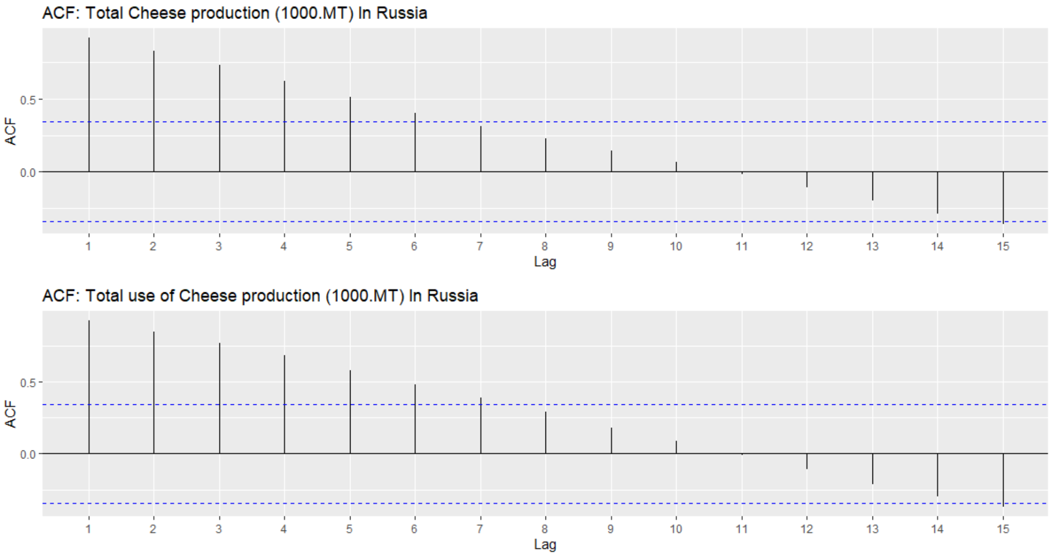

Figure 4 Autocorrelation function plot of cheese production and total uses

2.2. TBATS models (BATS+trigonometric seasonal)

TBATS is an improvement modification of BATS (Exponential Smoothing Method+Box-Cox Transformation+ARMA model for residuals) that allows multiple seasonal incorrect cycles. The TBATS model may deal with data that has nonlinearity and then make the variance of the data more or less constant. Also, TBATS model may be used to solve the autocorrelation problem using the ARMA (Autoregressive moving average) model on residuals. TBATS has the following equation (De Livera et al. 2011, 2010). Equation (1) is a Box-Cox transformation,

$$y_t^{(\omega)} = \begin{cases} \dfrac{y_t^{(\omega)} - 1}{\omega} & \omega \neq 0. \\ \log y_t & \omega = 0 \end{cases} \tag{1}$$

Equation (2) represents the seasonal M pattern

$$y_t^{(\omega)} = l_{t-1} + \phi b_{t-1} + \sum_{i=1}^{T} s_{t-m_{t-1}}^{(i)} + d_t. \tag{2}$$

Equations (3), (4) and (5) are global trends and local trends

$$l_t = l_{t-1} + \phi b_{t-1} + \alpha d_t, \tag{3}$$

$$b_t = \phi b_{t-1} + \beta d_t, \tag{4}$$

$$s_t^{(i)} = s_{t-m_i}^{(i)} + \gamma_i d_t. \tag{5}$$

Equation (6) is the error modeled by ARMA

$$d_t = \sum_{i=1}^{p} \varphi_i d_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t, \tag{6}$$

where $m_1, ..., m_2$ denote that seasonal period, l_t and b_t denote that the level and trend of components of the time series at time t, $s_t^{(i)}$ denote that seasonal component at time t, d_t represents to ARMA(p, q) component and ε_t is white noise process.

The smoothing parameters are given by α, β, Y_i for $i = 1, 2, ...T$ and ϕ is the dampening parameter, which gives more control over trendextrapolation when the trend component is damped (Taylor 2003). For seasonal data the following equations representing trigonometric exponential smoothing models,

$$s_t^{(i)} = \sum_{j=1}^{k_i} \alpha_{j,t}^{(i)} \cos\left(\lambda_j^{(i)} t\right), \tag{7}$$

$$\alpha_{j,t}^{(i)} = \alpha_{j,t-1}^{(i)} + k_1^{(i)} d_t, \tag{8}$$

$$\beta_{j,t}^{(i)} = \beta_{j,t-1}^{(i)} + k_2^{(i)} d_t. \tag{9}$$

where $k_1^{(i)}$ and $k_2^{(i)}$ are the smoothing parameters, $\lambda_j^{(i)} = 2\pi_j / m_i$. This is an extended, modified single source of error version of single seasonal multiple sources of error representation suggested by Hannan et al. (1970) and is equivalent to index seasonal approaches when $k_i = m_i / 2$ for evenvalues of m_i and when $k_i = (m_i - 1)/2$ for odd values of m_i. But most seasonal terms will require much smaller values of k_i, thus reducing the number of parameters to be estimated.

In the single seasonal multiple sources of error setting an alternative (Harvey 1990), but equivalent formulation of representation (2) is preferred by Durbin and Koopman (2012) which can be obtained hyper-parameterizing the single seasonal multiple sources of error version of (2) using

$$\alpha_{j,t}^{(i)} = s_{j,t}^{(i)} \cos\left(\lambda_j^{(i)} t\right) - s_{jt}^{*(i)} \sin\left(\lambda_j^{(i)} t\right), \tag{10}$$

$$\beta_{j,t}^{(i)} = s_{j,t}^{(i)} \sin\left(\lambda_j^{(i)} t\right) - s_{jt}^{*(i)} \cos\left(\lambda_j^{(i)} t\right), \tag{11}$$

$$s_t^{(i)} = \sum_{j=1}^{k_i} s_{j,t}^{(i)}, \tag{12}$$

where

$$s_{j,t}^{(i)} = s_{j,t-1}^{(i)} \cos\lambda_j^{(i)} + s_{j,t-1}^{*(i)} \sin\lambda_j^{(i)} + \left[k_1^{(i)} \cos\left(\lambda_j^{(i)} t\right) + k_2^{(i)} \sin\left(\lambda_j^{(i)} t\right)\right] d_t, \tag{13}$$

$$s_{j,t}^{*(i)} = -s_{j,t-1} \sin\lambda_j^{(i)} + s_{j,t-1}^{*(i)} \cos\lambda_j^{(i)} + \left[k_2^{(i)} \cos\left(\lambda_j t\right) - k_1^{(i)} \sin\left(\lambda_j t\right)\right] d_t, \tag{14}$$

$$s_t^{(i)} = \sum_{j=1}^{k_i} s_{j,t}^{(i)}. \tag{15}$$

Equations (16) and (17) are seasonal patterns modeled by the Fourier model,

$$s_{j,t}^{(i)} = s_{j,t-1}^{(i)} \cos\lambda_j^{(i)} + s_{j,t-1}^{*(i)} \sin\lambda_j^{(i)} + \gamma_1^{(i)} d_t, \tag{16}$$

$$s_{j,t}^{*(i)} = -s_{j,t-1} \sin\lambda_j^{(i)} + s_{j,t-1}^{*(i)} \cos\lambda_j^{(i)} + \gamma_2^{(i)} d_t, \tag{17}$$

the notation $TBATS\left(p, q, m_1, k_1, m_2, k_2, \ldots, m_T, k_T\right)$ is used for these trigonometric models.

2.3. Holt's linear trend method

The exponentially weighted moving average is a smoothing random variability average (Holt 2004) provided an equation.

Forecast Equation:

$$\hat{y}_t(h) = m_t + h z_t. \tag{18}$$

Level Equation:

$$m_t = \alpha y_t + (1-\alpha)(m_{t-1} + z_{t-1}). \tag{19}$$

Trend Equation:

$$z_t = \beta^*(m_t - m_{t-1}) + (1-\beta^*) z_{t-1}, \tag{20}$$

where $\hat{y}_t(h)$ is denoted as h-time-step forecast; m_t represent an estimate of the level of series at time t, z_t denotes an estimate of the trend (slope) of the series at time t, α is the smoothing parameter for level, $0 \le \alpha \le 1$ and β^* is the smoothing parameter for the trend $0 \le \beta^* \le 1$ that's with simple exponential smoothing.

2.4. Techniques for measuring the accuracy of forecasts

Following the selection of a model, the accuracy of the forecasted value based on the selected model must be determined in order to determine the dependability of the forecasted value. Among the approaches available in the literature are the root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), mean error (ME), and mean percentage error (MPE), among others (MPE). Table 1 contains further computations and information on the accuracy-measuring instruments mentioned previously.

Table 1 Forecasts accuracy measuring tools

Accuracy measuring tool	Shortcut	Formulation
Mean absolute error (Average sum of all absolute errors)	MAE	$MAE = \frac{\sum_{t=1}^{n} \lvert e_t \rvert}{n}$
Mean error	ME	$ME = \frac{\sum_{t=1}^{n} e_t}{n}$
Mean squared error	MSE	$MSE = \frac{1}{n}\sum_{t=1}^{n} e_t^2$
Mean percentage error	MPE	$MPE = \frac{1}{n}\sum_{t=1}^{n} pE_t$
Mean absolute percentage error, also known as mean absolute percentage deviation (MAPD)	MAPE	$MAPE = \frac{1}{n}\sum_{t=1}^{n} \lvert pE_t \rvert$
Mean Absolute Scaled error (MASE)	MASE	$MASE = \frac{e_t}{\frac{1}{n-2}\sum_{i=2}^{n} \lvert y_i - y_{i-1} \rvert}$

Table 1 (Continued)

Accuracy measuring tool	Shortcut	Formulation
Autocorrelation of errors at lag 1 (ACF1)	ACF1	$ACF1 = 1 - B - \frac{B(2-B)(1-w)}{w+2B(1-w)}B$ B is the learning rate and w is the proportionof covariance matrix.

2.5. Technique for improving the forecast

TBATS and Holt's linear trend model were used to improve the forecasting accuracy. The average of the forecasts from both models was used. Table 2 shows the average Forecasting cheese production and the average Forecasting total usage of cheese production.

Table 2 Average of forecasting by using TBATS and Holt's linear trend model for Cheese production, and total used (1000.MT) In Russian federation

Year	PF TBATS	PE Holt's linear trend	Average	PF TBATS	PE Holt's linear trend	Average
	Forecasting cheese production			Forecasting total use of cheese production		
2021	1059.279	1066.456	1062.868	1386.151	1374.3	1380.226
2022	1039.284	1097.907	1068.596	1350.512	1400.6	1375.556
2023	1115.720	1129.350	1122.535	1416.706	1426.8	1421.753
2024	1192.616	1160.787	1176.702	1515.407	1452.9	1484.154
2025	1186.474	1192.216	1189.345	1523.367	1479.0	1501.184
2026	1222.287	1223.639	1222.963	1565.053	1505.1	1535.077
2027	1244.705	1255.055	1249.880	1595.647	1531.1	1563.374
2028	1224.710	1286.464	1255.587	1560.009	1557.1	1558.555
2029	1301.147	1317.867	1309.507	1626.202	1583.0	1604.601
2030	1378.042	1349.264	1363.653	1724.903	1608.9	1666.902

Note: PF: Point Forecast

The total framework of the methodology for using TBATS and Holts linear trend for forecasting is depicted in Figure 5.

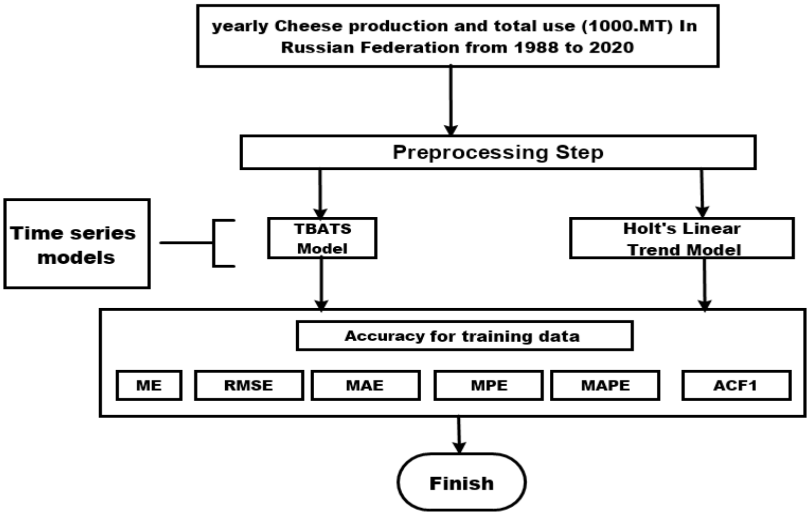

Figure 5 Framework of the methodology

3. Results

Overall, the cheese production and total utilization of the product performed admirably. Table 3's first row contains an example of this. According to the table, cheese output increased from 165 to 1035 (1000.MT) for the year, with an average and standard deviation of 560 and 291.144, respectively. The total number of cheese applications, on the other hand, spans from 246 to 1348 (1000.MT), with an average and standard deviation of 756 and 395.922, respectively. We also discovered a demand-supply imbalance in the Russian cheese market, which we corrected by importing cheese (Murtuzalieva et al. 2017). Both data series exhibit positive skewness, followed by a range of –0.5 to 0.5, confirming that they have a broadly symmetrical distribution. Both cheese production and total cheese consumption have kurtosis values of 1.453 and 1.214, respectively, and are based on a platykurtic distribution, indicating that the number of outliers is unlikely to be significant.

Table 3 Descriptive statistics of the yearly cheese production and total use (1000.MT) in Russian federation from 1988 to 2020

Cheese (1000.MT) in Russian federation	Minimum	Maximum	Mean	Standard deviation	Skewness	Kurtosis
Production	165	1035	560	291.144	0.058	1.453
Total use	246	1348	756	395.922	0.071	1.214

In order to estimate the behavior of time series data, it is necessary to first divide the data into its constituent components (i.e. irregular, trend, and seasonal) before creating the model (Ray et al 2021). The TBATS model has a unique feature that allows it to extract distinct components from a data series (see Figure 3). It is possible to estimate the smoothing and damping parameters using the TBATS model since it divides the data series into three components: level, slope, and seasonal. After extracting the series, it is observed that, the trending component have some stochastic nature, confirmed Holt's model can be used to develop time series model.

It has been determined that the TBATS model (1, {0,0}, 1, {<6,2>}) is the most appropriate for both the production and total uses of cheese data series. It is indicated that the Box-Cox transformation is 1, (doing nothing), the order of ARMA error is (0, 0), and the damping parameter is 1 (basically doing nothing) (see Table 4). 1.242, 0.182, 0.006, and 0.008 were the smoothing parameters measured for the production series, corresponding to α, β, γ_1, and γ_2 for the test series. The smoothing parameters, namely α, β, γ_1, and γ_2 for the total usage data series were 1.242, 0.182, 0.006, and 0.008 for the α, β, and gamma-2 smoothing parameters, respectively. The smoothing parameter alpha has a value larger than one, which confirms the first learning ability for both the series and the first learning ability for the first series.

Table 4 TBATS model fitted the yearly cheese production and total use (1000.MT) In Russian federation from 1988 to 2020

Cheese (1000.MT) in Russian federation	Model	*Box-Cox transformation (Lambda)	Smoothing parameter				Damping parameter for trend	Prediction	
			α	β	γ_1	γ_2		σ	AIC
production	*TBATS	1	1.242	0.182	–0.006	0.008	1	74.173	419.607
Total use		1	1.17	0.144	–0.009	0.008	1	99.01	438.67

Note: *TBATS(1, {0,0}, 1, {<6,2>})

Table 5 Holt's linear trend model fitted the yearly cheese production and total use (1000.MT) in Russian federation from 1988 to 2020

Cheese (1000.MT) in Russian federation	Box-Cox transformation (Lambda)	Smoothing parameters		Initial states		Sigma	AIC
		α	β	L	B		
production	1.008	1	0.138	548.547	2.652	86.455	415.456
Total use	1.102	1	0	760.289	54.989	191.629	467.988

Holt's linear trend model was employed for both of the data in Table 5. There are 1.008 and 1.102 Box-Cox transformations for the production and total use data series in the table (Svetunkov et al., 2022). A single alpha value in both series indicates that the initial learning capacity has been demonstrated. It's possible that because of its lower sigma and AIC, the TBATS model is a more accurate predictor of future events than Holt's linear model (Tables 4 and 5). When considering the lower values of the following parameters: ME (mean absolute error), RMSE (relative mean square error), MAE in Table 6.

Table 6 TBATS, and Holt's linear trend model fitted the yearly cheese production, and total used (1000.MT) in Russian federation from 1988 to 2020

Model	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Cheese production (1000.MT) in Russian federation							
TBATS	15.19832	74.17318	50.94314	4.645088	11.78647	1.043649	–0.0171244
Holt's Linear	6.465795	76.99454	50.39175	1.97011	11.14052	1.032353	0.1303266
Total use (1000.MT) in Russian federation							
TBATS	18.98847	99.01034	64.00107	3.439924	10.97888	0.9822706	–0.0203028
Holt's Linear	–1.20598	92.52411	58.66463	–3.402072	10.90201	0.9003684	0.1672764

We forecasted the behavior of each data series using these two models, which we found to be accurate (see Tables 7 and 8). The TBATS and Holt's linear models were used to anticipate cheese output and total uses from 2021 to 2030, which were depicted in the tables. At alpha 0.2 and 0.05 levels of significance, all of the predicted values are inside the confidence interval, which confirms the accuracy of the prediction. From 2021 to 2030, the TBATS model predicted cheese production to range from 1059.279 to 1378.042 (1000.MT) while the Holt's linear model predicted cheese production to range from 1066.456 to 1349.264 (1000.MT).

Table 7 Forecasting cheese production, and total used (1000.MT) in Russian federation by using TBATS model

	Forecasting cheese production (1000.MT) in Russia by using TBATS model					Forecasting total use of cheese production (1000.MT) in Russia by using TBATS model				
Year	PF	Lo 80	Hi 80	Lo 95	Hi 95	PF	Lo 80	Hi 80	Lo 95	Hi 95
2021	1059.279	964.2221	1154.336	913.9021	1204.656	1386.151	1259.264	1513.038	1192.0941	1580.207
2022	1039.284	888.0307	1190.537	807.9622	1270.606	1350.512	1156.131	1544.894	1053.2316	1647.793
2023	1115.720	924.5853	1306.855	823.4045	1408.036	1416.706	1173.604	1659.807	1044.9140	1788.497
2024	1192.616	968.5900	1416.642	849.9978	1535.234	1515.407	1231.836	1798.977	1081.7223	1949.091
2025	1186.474	933.7161	1439.233	799.9139	1573.035	1523.367	1204.374	1842.360	1035.5099	2011.225
2026	1222.287	944.8878	1499.686	798.0417	1646.532	1565.053	1215.957	1914.148	1031.1574	2098.948
2027	1244.705	945.1436	1544.267	786.5653	1702.845	1595.647	1219.713	1971.582	1020.7048	2170.590
2028	1224.710	904.1887	1545.232	734.5149	1714.906	1560.009	1158.747	1961.271	946.3315	2173.686
2029	1301.147	961.2201	1641.073	781.2738	1821.020	1626.202	1201.533	2050.871	976.7273	2275.677
2030	1378.042	1019.7602	1736.325	830.0971	1925.988	1724.903	1278.052	2171.754	1041.5035	2408.303

Note: (PF: Point Forecast); An error term alpha of 0.2 has the lower and higher bounds of predictive interval Lo 80 and Hi80, respectively, while an error term alpha of 0.05 has the lower and higher bounds of predictive interval Hi95.)

Table 8 Forecasting Cheese production, and total used (1000.MT) in Russian federation by using Holt's linear trend model

	Forecasting cheese production (1000.MT) in Russia by using Holt's linear trend model					Forecasting total use of cheese production (1000.MT) in Russia by using Holt's linear trend model				
Year	PF	Lo 80	Hi 80	Lo 95	Hi 95	PF	Lo 80	Hi 80	Lo 95	Hi 95
2021	1066.456	961.7646	1171.063	906.3071	1226.408	1374.3	1256.393	1491.181	1193.523	1552.673
2022	1097.907	939.3438	1256.282	855.3187	1340.053	1400.6	1233.829	1565.274	1144.646	1651.746
2023	1129.350	922.0793	1336.309	812.2065	1445.757	1426.8	1222.669	1627.901	1113.236	1733.338
2024	1160.787	906.1661	1414.947	771.1489	1549.335	1452.9	1217.424	1684.554	1090.902	1805.839
2025	1192.216	890.2760	1493.524	730.1123	1652.818	1479.0	1215.965	1737.362	1074.387	1872.504
2026	1223.639	873.8037	1572.645	688.1682	1757.13	1505.1	1217.193	1787.422	1062.017	1935.006
2027	1255.055	856.4361	1652.621	644.8345	1862.748	1531.1	1220.459	1835.385	1052.794	1994.340
2028	1286.464	838.0002	1733.624	599.8432	1969.935	1557.1	1225.335	1881.678	1046.068	2051.156
2029	1317.867	818.3981	1815.752	553.0400	2078.839	1583.0	1231.526	1926.599	1041.386	2105.907
2030	1349.264	797.5744	1899.058	504.3349	2189.544	1608.9	1238.814	1970.362	1038.416	2158.922

Note: (PF: Point Forecast); Lo 80 and Hi80 are (respectively) the lower and higher bounds of predictive interval for an error term alpha = 0.2; Lo 95 and Hi95 are (respectively) the lower and higher bounds of predictive interval for an error term alpha = 0.05.)

For the same time period, the TBATS model projected total cheese consumption to be 1386.151 to 1724.903 (1000.MT) while the Holt's linear model estimated total cheese consumption to be 1374.3 to 1608.9 (1000.MT). Because the TBATS model provides excellent forecasting accuracy for both series, it may be considered as the superior accuracy model to Holt's linear model in terms of accuracy (Figure 6). The predictor line for both models, as shown in the figure, indicated that the forecasting accuracy of the TBATS model is very high and outperforms the forecasting accuracy of Holt's linear model (Mishra et al. 2021a; Devi et al. 2021).

4. Discussion

This study's findings revealed that time series analysis with a typical statistical model can be utilized to estimate the forecasting nature of several important commodities based on data availability. The goal was to select the best statistical model among the TBATS and Holt's linear models of Russian cheese production and total uses data series. We infer from the data visualizations in the results section that a demand-supply gap exists in the Russian cheese market, which might be bridged by expanding production. After dissecting the data series using the TBATS model, we discovered that the trending component of both series had a stochastic nature, hence we chose Holt's model in addition. Because of its lower sigma and AIC values, the TBATS model may be regarded the best prediction model for the series among the TBATS and Holt's linear models (error prediction). On the other hand, Holt's linear model performed better on the training database with lower goodness of fit values (Mishra et al. 2021a). The forecast provided by the TBATS model outperformed the Holt's model. The average anticipated value generated from both models can be used to accurately forecast Russian cheese production and consumption (see Table 2).

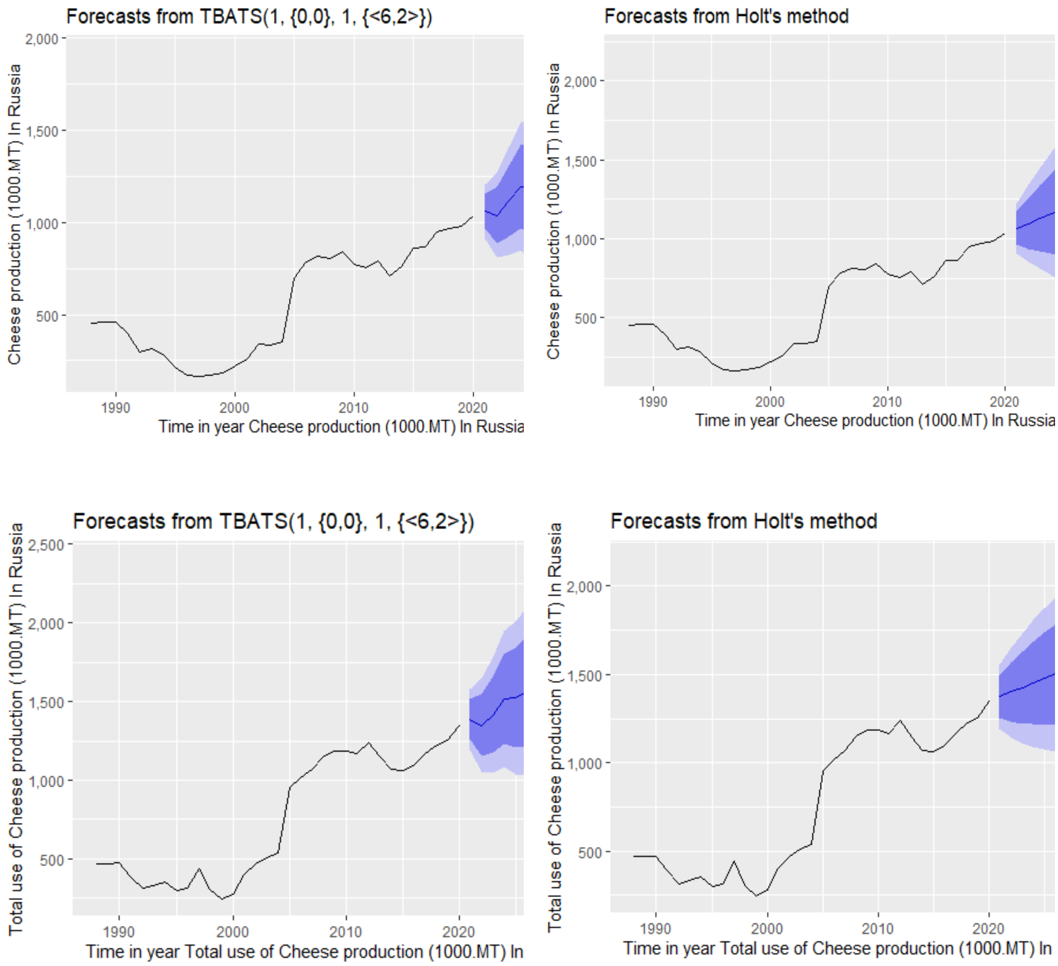

Figure 6 Forecasting graph from TBATS and Holt's linear model of Russian cheese production and total uses

5. Conclusions

Practically, the study is vital due to the rising consumption of dairy products in general, and cheese in particular, as a staple in Russia. Forecasting is the fundamental instrument to anticipate the nation's demands. In this study, we used historical data to anticipate Russia's cheese output from 1988 to 2021. Because Russia was part of the USSR before that, it is impossible to obtain values of cheese production and consumption before that. Based on these data, we created time series models for Russian cheese production. The best model is chosen using TBATS and Holt's linear model. The forecast obtained from the TBATS model performed well for both the series. But in terms of error accuracy, Holt's linear model performed batter than TBATS model (Figure 6). The predictor line in the graphical figure shows that both models outperformed, as the line stays in between the confidence interval; upper and lower limit. This study will help researchers and policy makers as strong evidence of future prediction of cheese production in Russia.

Author Contributions

Conceptualization, M.A.,A.K. and I.P..; methodology, P.L., S.R.,.D.R., M.A., and T.B.; software, P.K.S., P.M., M.A, and S.Y..; validation, all the authors; formal analysis, M.A., A.K. and I.P..; investigation, P.L., S.R.,.D.R., M.A, and T.B.; resources, all the authors; data curation, P.M., M.A, and K.A.; writing—original draft preparation, P.M. and S.Y., writing—review and editing, all the authors; visualization, P.M.; supervision, M.A., A.K., and P.M., All authors have read and agreed to the published version of the manuscript.

Acknowledgements

The work was supported by Act 211 Government of the Russian Federation (contract no. 02.A03.21.0011). The work was supported by the Ministry of Science and Higher Education of the Russian Federation (government order FENU-2020-0022). The research was supported by RSF grant 22-26-00079.

References

Abotaleb MSA. Predicting COVID-19 cases using some statistical models: An application to the cases reported in China Italy and USA. Acad J Appl Math Sci. 2020; 6(4): 32-40.

Abotaleb M, Ray S, Mishra P, Karakaya K, Shoko C, Al Khatib AMG, Ray M, Fernando WHH, Lounis M, Balloo R. Modelling and forecasting of rice production in south Asian countries. AMA Agric Mech Asia Afr Lat Am. 2021; 51(3): 1611-1627.

Badr A, Makarovskikh T, Mishra P, Abotaleb M, Al Khatib AMG, Karakaya K, Redjala S, Dubey A, Attal E. Modelling and forecasting of web traffic using Holt's linear, bats and TBATS models. J Math Comput Sci. 2021; 11(4): 3887-3915.

Borodin K. The model of differentiated products market for its development forecasting (on the example of the cheese market). Econ Math Methods. 2020; 56(3): 68-78.

De Livera AM, Hyndman RJ, Snyder RD. Forecasting time series with complex seasonal patterns using exponential smoothing. J Am Stat Assoc. 2011; 106(496): 1513-1527.

De Livera AM. Automatic forecasting with a modified exponential smoothing state space framework. Monash Econometrics and Business Statistics Working Papers. 2010; 10(10): 1-29.

Devi M, Kumar J, Malik DP, Mishra P. Forecasting of wheat production in Haryana using hybrid time series model. J Agric Food Res. 2021; 5:100175.

Durbin J, Koopman SJ. Time series analysis by state space methods. 2nd ed. New York: Oxford University Press; 2012.

Hannan EJ, Terrell RD, Tuckwell NE. The seasonal adjustment of economic time series. Int Econ Rev. 1970; 11(1): 24-52.

Harvey AC. Forecasting, structural time series models and the Kalman filter. New York: Cambridge University Press; 1990.

Holt CC. Forecasting seasonals and trends by exponentially weighted moving averages. Int J Forecasting. 2004; 20(1): 5-10.

Kuzin AA, Medvedeva NYA, Zadumkin KA, Vakhrusheva VV. Development scenarios for Russia's dairy industry. Econ Agro-Ind Complex. 2018; 11(6): 73-88.

Kuzina E Yu, Ostretsov, VN. The state and prospects of cheese production in Russia. Dairy Bull. 2016; 1: 21.

Lama A, Singh KN, Singh H, Shekhawat R, Mishra P, Gurung B. Forecasting monthly rainfall of Sub-Himalayan region of India using parametric and non-parametric modelling approaches. Model Earth Syst Environ. 2022; 8:837-845.

Matalas A, Zampelas A, Stavrinos V. The Mediterranean diet: Constituents and health promotion. Boca Raton: CRC Press; 2001.

Mishra P, Fatih C, Niranjan HK, Tiwari S, Devi M, Dubey A. Modelling and forecasting of milk production in Chhattisgarh and India. Indian J Anim Res. 2020; 54(7): 912-917.

Mishra P, Ray S, Al Khatib AMG, Abotaleb M, Tiwari S, Badr A, Balloo R. Estimation of fish production in India using ARIMA, Holt's linear, BATS and TBATS models. Indian J Ecol. 2021a; 48(5): 1254-1261.

Mishra P, Al Khatib AMG, Sardar I, Mohammed J, Karakaya K, Dash A, Ray M, Narsimhaiah L, Dubey A. Modeling and forecasting of sugarcane production in India. Sugar Tech. 2021b; 23, 1317-1324.

Mishra P, Matuka A, Abotaleb MSA, Weerasinghe WPMCN, Karakaya K, Das SS. Modeling and forecasting of milk production in the SAARC countries and China. Mod Earth Syst Environ. 2022; 8: 947-959.

Murtuzalieva TV, Panasenko SV, Slepenkova EV, Tultaev TA, Pogorilyak BI. Import substitution strategy and ways of marketing, its implementation using the dairy industry of the Russian Federation as an example. Acad Strateg Manag J. 2017; 16(2): 1-14.

Ray S, Bhattacharyya B. Time series modeling and forecasting on pulses production behavior of India. Indian J Ecol. 2020;47 (4): 1140-1149.

Ray S, Das SS, Mishra P, Al Khatib AMG. Time series SARIMA modelling and forecasting of monthly rainfall and temperature in the south Asian countries. Earth Syst Environ. 2021; 5(3): 531-546.

Svetunkov I, Kourentzes N, Ord JK. Complex exponential smoothing. Nav Res Logist. 2022; 69(8): 1108-1123.

Taylor JW. Exponential smoothing with a damped multiplicative trend. Int J Forecast. 2003; 19(4): 715-725.