Statistics and Applications {ISSN 2454-7395 (online)}
Volume 19, No. 2, 2021 (New Series), pp 89–100

Modelling Pepper Export Income in Sri Lanka Using Deterministic Decomposition and Seasonal ARIMA Models

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Received: 27 June 2020; Revised: 16 August 2020; Accepted: 08 October 2020

Abstract

Pepper is the most used spice and flavoring agent in the food industry. Sri Lanka is the fifth largest exporter of pepper in the world. Variations in export income of pepper is a huge matter for farmers, consumers, investors and policy makers in the country. Hence an accurate forecast of export income is extremely important. This study presents a time series modelling approach for forecasting the income of pepper exports in Sri Lanka. Two different models are adopted: deterministic decomposition model which is built decomposing the trend, seasonality and the random variations and Seasonal Auto Regressive Integrated Moving Average (SARIMA) which belongs to the stochastic class of models. The data used in this study are monthly export income of pepper in Sri Lanka from January 2000 to December 2018. Among the two types of models, deterministic decomposition model with Mean Absolute Error (MAE) of 4.36 has a strong potential in forecasting the income of pepper exports in Sri Lanka. As the forecasts from the model shows an increasing pepper export market which will need a higher production of pepper, the government can improve the awareness of farmers about the requirements of pepper in export market by providing infra-structure facilities.

Key words: Deterministic decomposition; Forecasting; MAE; Seasonality; Trend.

1. Introduction

International trade and finance are important economic concepts in a country where international trade in goods and services allows nation to raise their standards of living by exporting and importing goods. Exporting and importing helps in growing national economies and expanding the global market. The more a country exports, the more domestic economic activity is occuring. So, export sector plays a vital role in every country’s economy influencing the level of economic growth, employment opportunities, balance of payments and international relations.

According to the Economic Complexity Index (ECI), Sri Lanka is the 79th largest export economy in the world and the 101st most complex economy. In 2017, Sri Lanka exported \$12B and imported \$21.1B, resulting in a negative trade balance of \$9.1B in net imports (“Sri Lanka (LKA) Exports, Imports, and Trade Partners | OEC - The Observatory of Economic Complexity” , 2020.). Sri Lanka is an island and borders India and Maldives by sea that creates a large possibility in export market. The top export destinations of Sri Lanka

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are the United States, United Kingdom, Germany, India and Italy. Sri Lanka exports 204 products with revealed comparative advantage which includes Ceylon tea, apparel, spice and allied products, aquarium fish, seafood, rubber and rubber-based products, wooden products. Sri Lanka was historically known as the Spice Island and further attracted by the Western nations for its spices. Sri Lankan Spices and Allied products Suppliers export the most sought-after cinnamon, pepper, cloves, cardamoms, nutmeg, mace and vanilla. 56% of Sri Lankan Agricultural exports consists of spices, allied products and essential oils. These varieties are used to season, flavour and aromatise various forms of cuisines across the world.

Pepper is the most significant and widely used spice in the world. There are but a few countries in Asia including Sri Lanka and the Pacific, Brazil and Madagascar that produce pepper. Currently, Sri Lanka ranks at fifth place in terms of area under pepper cultivation and seventh place in terms of production with a world share of 5.7% in production. Pepper is mainly used as a spice and flavoring agent in the food industry. It also has industrial uses in perfumery and pharmaceutical industries. Sri Lanka exports pepper as: black pepper, white pepper, black pepper oil, pepper ground pepper crushed, light berries, organic pepper (Institute of Policy Studies in Sri Lanka and Department of National Planning, 2017). However, majority of the exports are black pepper – neither crushed/ grounded (53% of total export earnings of pepper products in 2012), followed by light berries.

In Sri Lanka, pepper is mainly cultivated in Low and mid country wet and Intermediate agro-climatic zones. The total extent of pepper in Sri Lanka is about 29,378 ha and Matale, Kandy, Kegalle, Badulla, Ratnapura, Monaragala, and Kurunegala are the major districts. Unlike other pepper growing countries, Sri Lanka pepper flowers twice a year during the Maha and Yala rains. Currently about 60% of pepper production of the country is exported, while the remainder is consumed domestically according to government sources (Institute of Policy Studies in Sri Lanka and Department of National Planning, 2017). Sri Lanka is the fifth largest exporter of pepper in the world. India buys 62% of pepper exports from Sri Lanka followed by European, American and other Asian and African countries (Institute of Policy Studies in Sri Lanka and Department of National Planning, 2017). Given that majority of black pepper from Sri Lanka is exported to the low end of the market (India), Sri Lanka should explore high end markets elsewhere. Its widely known that the demand for Sri Lankan pepper is increasing rapidly due to its richer in piperine content, which lends it a superior quality and greater pungency (Ministry of Development Strategies and International Trade and Sri Lanka Export Development Board, 2018). Thus, Sri Lanka has the potential to become a key player in the global pepper market by raising the country’s pepper production penetrating through high value export markets.

The unforeseen variations in export value (export income) can complicate budgetary planning in a country. Hence an accurate forecasting method of export income is extremely important for efficient monitoring and planning of export commodities. Many attempts have been made in the past to develop forecasting models for export quantity and price of various commodities around the world. Most of the past research have focused on forecasting the export quantity or export volume of a commodity. Autoregressive Integrated Moving Average (ARIMA) and Bayesian Artificial Neural Network (BANN) were used in forecasting the imports and exports of the Philippines and the two models were compared using comparison methods (Urrutia *et al.*, 2019). Seasonal autoregressive integrated moving average (SARIMA) methodology has been applied for modelling and forecasting of monthly export of meat and meat products from India (Paul *et al.*, 2013). ARIMA model by using Box-Jenkins methodology was used to forecast the export/import of wood based panel in

India (Plywood, 2015). A forecasting model was built for Exports of Dates in Pakistan for the next 15 years using ARIMA technique (Naz, 2012). An analysis has been done in India about the production and export performance of black pepper (Mokshapathy, 2017).

There are some research papers related to pepper in Sri Lanka in current literature. Analysis and a comparison were done among the small and large scale pepper farmers considering production levels and costs, income and profitability of pepper cultivation. The study has concluded that there is a significant difference between small and large scale pepper farmers in the extent cultivated, incomes received, cost of production and profits earned (Sivarajah, 2018). No studies have been conducted on modelling and forecasting the export income of pepper in any country so far. In this context, it is necessary to know to what extent the export income is being fluctuated and to draw meaningful policy conclusion. Hence, this study focuses on the objective of modelling and forecasting the pepper income in Sri Lanka by using time-series models.

2. Materials and Methodology

Two main approaches to the research problem with their methodologies are discussed in here: deterministic decomposition method and is built decomposing the trend, seasonality and the random variations and second method is based on SARIMA, and it belongs to the stochastic class of models.

2.1. Data collection

In the context of export sector, export volume and export value are important terms. Export volume refers to the quantity of goods exported. It is usually in kilograms, Metric tons. Generally, Tons is used for calculating export volume in worldwide. Export value is the value of export goods in currency and it may be measured in any currency such as USD, EURO, and RUPEES. Export value represents the total worth of a commodity hence this is the total export income of that commodity to the country. This study is based on the export income of pepper in Sri Lanka. Based on the varieties of pepper, they are compiled according to the trade classification harmonized system with coding as HS 090411, HS 090420, HS 090412 which represents dried pepper (crushed or ground), fruits of genus capsicum or pimento (dried, crushed or ground) and pepper (crushed or ground) respectively. Monthly data on total pepper export value (US Dollar Millions) in Sri Lanka were collected from Sri Lanka Exports Development Board for the period of January 2000 to December 2018 (228 observations). The data set was divided into two parts as 80% and 20% for the model building and model validation respectively. Historical data in the period from January 2000 to March 2015 was used in the model identification and the data from April 2015 to December 2018 was used for the model validation. R statistical package was used in analysis and modelling of pepper export income.

2.2. Preliminary analysis

One of the most common data pre-processing technique is data cleaning. It includes fill in missing values, smooth noisy data, identify or remove outliers and resolve inconsistencies. In this study, the data set is first explored to identify the outliers and the missing values. There were no any missing values or outliers detected in the data set. Therefore, the original series was taken for model fitting. A stationary time series is defined as a time series whose mean and variance are constant over time. In order to identify the stationary of a time series, statistical tests are used. The three tests Kwiatkowski-Phillips-Schmidt-Shin (KPSS), Augmented Dickey Fuller (ADF) and Phillips Perron (PP) were used in this study to check the stationary of the time series.

2.3. Time series forecasting methods

Time series is a set of time-ordered observations of a process where the intervals between observations remain constant such as hours, weeks, quarters, months, years. Time series analysis can be applied to any variable that changes over time. The main objective of time series analysis is to develop models that best capture an observed time series in order to understand the underlying causes. Time series models used for forecasting include decomposition models, exponential smoothing models, ARIMA models and SARIMA models.

2.4. Components of a time series

The components of a time series are trend, seasonal variation, cyclic changes, and irregular factors. Trend is the long-term change in the mean level and often thought of as the underlying growth or decline component in the series. Cyclic changes within a time series are similar to the seasonal component in that it is revealed by a wavelike pattern. Once the trend and cyclic variations have been accounted for, the remaining movement is attributed to irregular fluctuations.

2.5. Seasonality in a time series

Seasonal variation, or seasonality, are changes that repeat themselves within a fixed period such as weekly, monthly, quarterly. Seasonality may be caused by various factors, such as weather, vacation, and holidays and consists of periodic, repetitive, and generally regular and predictable patterns in the levels of a time series. Seasonality of a time series can be detected in many ways including graphical methods and statistical tests. The run sequence plot is considered as a first step in analyzing any time series plot. Seasonal subseries plot, box plot, Auto Correlation Function (ACF) plot do an excellent job in showing seasonal variations. In this study, ACF plot is used to identify seasonality among graphical methods. If there is a significant seasonality, ACF plot shows spikes at lags equal to the seasonal period. Student *t*-test and Wilcoxon Signed-Ranks test are some popular statistical tests for detecting seasonality in a time series (Nwogu *et al.*, 2016).

In R software, Webel-Ollech overall seasonality test combines results from different seasonality tests. It combines the results of the QS-test and the Kruskal-Wallis (KW) test. If the p-value of the QS-test is below 0.01 or the p-value of the KW test is below 0.002, the WO-test will classify the corresponding time series as seasonal. This test is used in this study to identify seasonality in theoretically (Ollech, 2019).

2.6. SARIMA model

SARIMA models are used in cases where the time series exhibits a seasonal variation. It is formed by including additional seasonal terms in the ARIMA model. A seasonal autoregressive notation (P) and a seasonal moving average notation (Q) will form the multiplicative process of SARIMA as ARIMA $(p, d, q)(P, D, Q)s$ where subscripted letter ‘s’ shows the length of seasonal period. The multiplicative SARIMA model has the form in (1).

$$\Phi_P(B^s)\varphi_p(B)\nabla_s^D\nabla_{z_t}^d = \Theta_q(B)\Theta_Q(B^s)\varepsilon_t \quad (1)$$

where $\Phi_P(B^s)$ is the seasonal AR operator of order P, φ_p is the regular AR operator of order p, ∇_s^D represents the seasonal differences, ∇^d represents the regular differences, $\Theta_Q(B^s)$ the seasonal moving average of order Q, $\Theta_q(B)$ is the regular MA order of order q and ε_t is a white noise process.

The Box-Jenkins (BJ) methodology of estimating a time series model consists of four iterative steps: Model identification, Estimation of model parameters, Diagnostic checking and forecasting. First tentative model parameters are identified through ACF (Auto Correlation Function) and PACF (Partial Auto Correlation Function), then coefficients of the most likely model are determined, next steps involves is to forecast, validate and check the model performance by observing the residuals through Ljung Box test and ACF plot of residuals.

2.7. Decomposition method

Time series can be decomposed into various sub-components and their effects can be checked in the data in series. Mainly, time series data composed of seasonal pattern and trend pattern. There are two different decomposition models possible.

Additive Decomposition: Here, the total data are taken as the sum of the decomposed components.

$$X_t = seasonal(S_t) + trend(T_t) + random$$

Multiplicative Decomposition: Here, the given time series data are treated as the product of the decomposed components.

$$X_t = seasonal(S_t) \times trend(T_t) \times random$$

An additive model is appropriate if the magnitude of the seasonal fluctuations does not vary with the level of time series. The multiplicative model is appropriate if the seasonal fluctuations increase or decrease proportionally with increases and decreases in the level of the series. Multiplicative decomposition is more prevalent with economic series because most seasonal economic series do have seasonal variations which increase with the level of the series. Often the transformed series can be modeled additively when the original data is not additive. In particular, logarithm turn a multiplicative relationship into an additive relationship. So, a multiplicative relationship can be fitted by fitting a more convenient additive relationship to the logarithms of the data and then to move back to the original series by exponentiating.

The steps involved in developing the multiplicative decomposition model in this study are listed below.

- *Estimating the trend and the seasonal factors*

  Here, both trend and the seasonal effects were estimated specifying a regression equation. To decide upon the mathematical form of a trend, one must first draw the plot of the time series. The number of seasonal factors is equal to the frequency of the series (e.g. monthly data = 12 seasonal factors, quarterly data = 4, etc.)

- *Calculating the irregular component; for an additive model* $\varepsilon_t = Y_t - T_t - S_t$
- *Analyzing the residual component.*
- *Whichever method was used to decompose the series, the aim is to produce stationary residuals.*
- *Choosing a model to fit the stationary residuals.*
- *Forecasting can be achieved by forecasting the residuals and combining with the forecasts of the trend and seasonal components.*

2.8. Forecasting accuracy

The forecast errors are the difference between the actual values in the test set and the forecasts produced using only the data in the training set. The two most commonly used scale-dependent measures are based on the absolute errors or squared errors: The smaller the difference, the better the model is. Several criteria such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Weighted MAPE can be used to compare different forecasting models. In this study, two different error metrics are considered for the evaluation of the forecasting models: MAE and MAPE. MAPE usually expresses the prediction accuracy of a forecasting model as a percentage and it is defined in (2) and MAE is given in (3).

$$\text{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\frac{|y_i-\hat{y_i}|}{y_i} \tag{2}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i-\hat{y_i}|}{y_i} \tag{3}$$

where $\hat{y_i}$ = estimated value of y_i, y_i = actual value, n = number of observations.

3. Results and Discussion

Results under the two approaches; deterministic decomposition and Seasonal ARIMA model are clearly explained in here.

3.1. Year wise evaluation of pepper export value

According to Figure 1, a clear seasonal pattern in export income in Sri Lanka can be observed in each year. The export value of pepper decreases in April in each year while it increases to a maximum value in June – July period. Another significant feature is that export value has gradually increased in each year. This proves that there is a significant pattern of export income of pepper in Sri Lanka in each year.

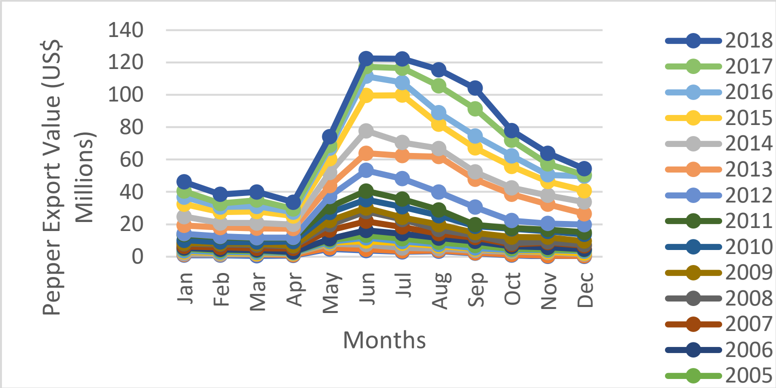
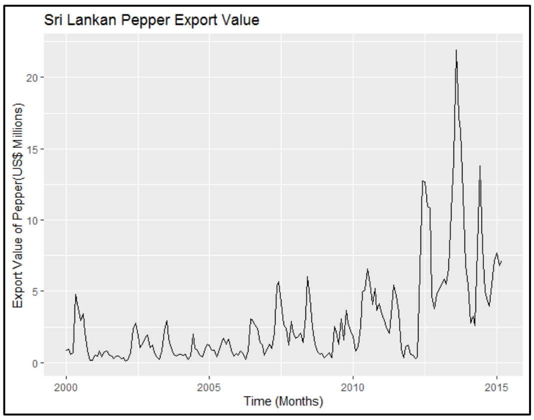


Figure 1: Pepper export income evaluation in Sri Lanka – Year-wise

3.2. SARIMA model

As the series does not contain missing values, the original series was used in model fitting. On plotting the export income data of pepper as shown in Figure 2, a slight trend with a seasonality can be observed. It is confirmed with the slow declines and oscillations given in the ACF plot of the series in Figure 3. Further seasonality WO test in R software which is a combined tests of QS-test, the QS-R test and the KW-R-test was also performed and all *p* values of the tests were less than 0.05 indicating the series exhibits seasonality.



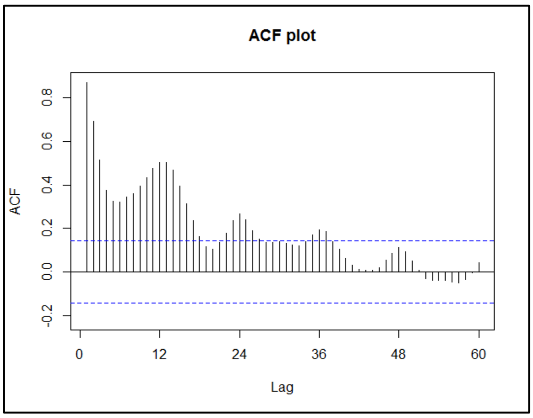


Figure 2: Time series plot of export income

Figure 3. ACF plot of the series of pepper in Sri Lanka

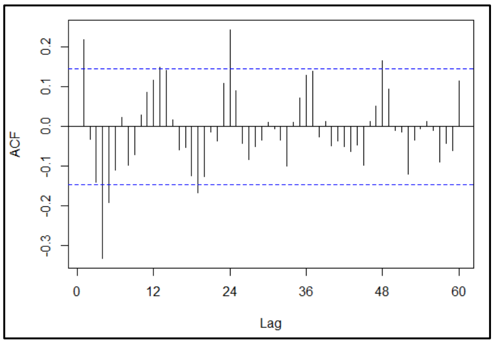


Figure 4: ACF of the first differenced series

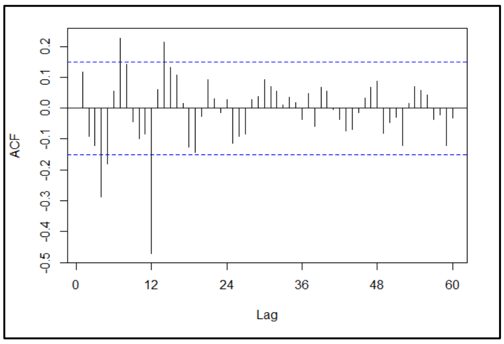


Figure 5: ACF of the first and Seasonal differenced series

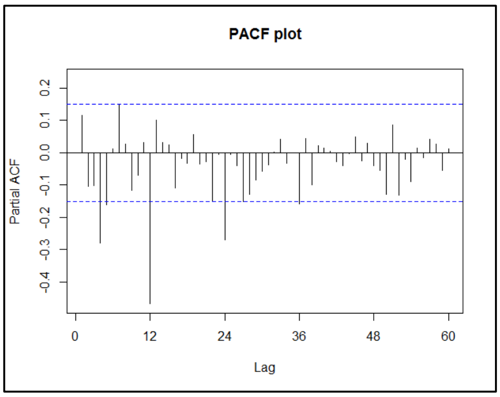


Figure 6: PACF of the first differenced and seasonal differenced series

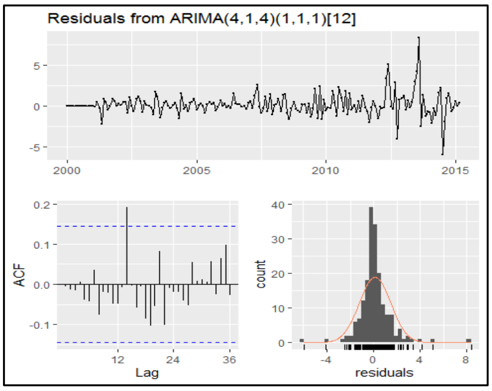


Figure 7: Model adequacy of ARIMA (4,1,4) (1,1,1) [12] model

Since KPSS (*p* value=0.1) test suggest that the series is not stationary at 5% level of significance, first difference of the series was taken. The ACF plot of the first differenced series is shown in Figure 4 which shows significant spikes at lags 12, 24 which identifies the seasonality period as 12.

A seasonal difference at lag 12 was taken then for better identification of the model parameters. Through the investigation of the ACF and PACF of the first and seasonal differenced series shown in Figure 5 and Figure 6, the seasonal and non-seasonal lags were identified as; Seasonal AR lags: 12, 24, 36, Seasonal MA lags: 12, Non – seasonal AR lags: 4, 5 and Non – seasonal MA lags: 4, 5. Then, several SARIMA models were tested and ARIMA (4, 1, 4) (1, 1, 1) [12] was identified as the best model with lowest AIC value (637.01) for modelling the income of pepper exports in Sri Lanka.

The ARIMA (4, 1, 4) (1, 1, 1) [12] model is represented as in (4).

$$\phi(B^{12})\varphi(B)\left(x_t - \mu\right) = \theta(B^{12})\theta(B)w_t \tag{4}$$

where,

Non- seasonal component:

$AR: \varphi(B) = 1 - 0.3229B - 0.0529B^2 + 0.2058B^2 - 0.1188B^3$

$MA: \theta(B) = 1 + 0.2922B + 0.1463B^2 + 0.1228B^2 + 0.5227B^3$

Seasonal component:

$Seasonl\ AR: \phi(B^{12}) = 1 + 0.3291B^{12}$

$Seasonl\ MA: \theta(B^{12}) = 1 + 0.7016B^{12}$

Residuals of the fitted model was evaluated as in Figure 7. Ljung Box test returns a large *p* value (0.1612) indicating that the residuals are random and independent variance at 5% level of significance. Further ARCH test gives large *p* value (0.9336) indicating the residuals have a constant variance at 5% level of significance.

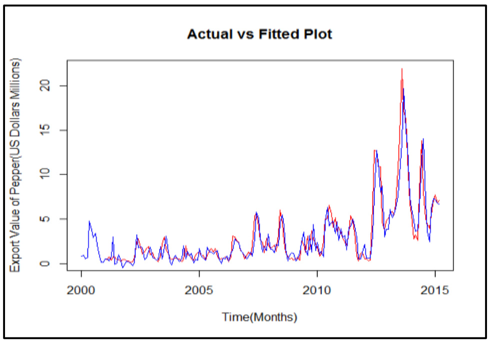


Figure 8: Actual and Fitted values

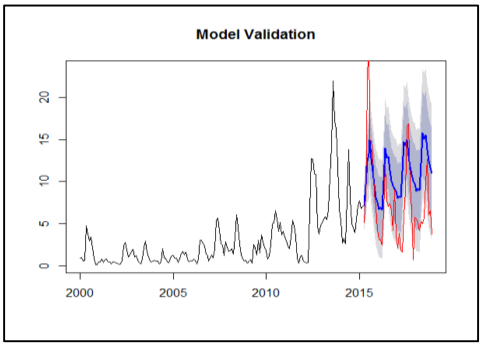


Figure 9: Model validation

In Figure 8, red lines shows the actual data and the blue line shows the fitted data points from (4) where it suggests that the identified model is suitable in forecasting the pepper export income beyond the year 2015 hence the gap between two lines is minimum. 20% of the data was used in model validation and it is shown in Figure 9.

It gives a considerable low MAE (4.76) and MAPE (43.81) which outlines ARIMA (4, 1, 4) (1, 1, 1) [12] is quite good in forecasting the income of pepper exports in Sri Lanka.

3.3. Deterministic decomposition method

As the series of pepper export income have seasonal variations which increase or decrease with the level of the series, multiplicative decomposition is used as shown in Figure 10. It shows the observed series, trend line, seasonal pattern and random part of the series. Hence the decomposition model looks as shown in (5). As the logarithms turn a multiplicative relationship into an additive relationship, taking the logarithms of both sides gives the additive model as shown in (6). Hence the logarithm of the series was taken as shown in Figure 11.

$$Y_t = T_t.S_t.\varepsilon_t \tag{5}$$

$$log(Y_t) = log(T_t) + log(S_t) + log(\varepsilon_t) \tag{6}$$

Both trend and the seasonal effects were estimated specifying a regression equation. The number of seasonal factors is equal to the frequency of the series: there are 12 seasonal factors as monthly data is used in here.

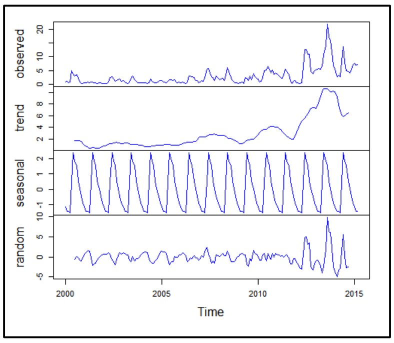


Figure 10: Decomposition of the time series plot of pepper export income of Sri Lanka

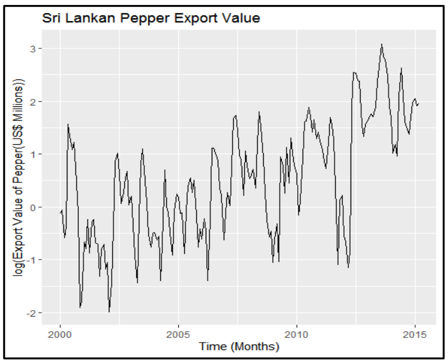


Figure 11: Log transformed series

The regression equation results are shown in Figure 12, where t = 1,2,3…, is for trend, dm1 is the dummy variable for the 1st month, dm2 for the second month etc. In order to avoid the dummy variable trap, one dummy variable is excluded from the regression model.

```
Call:
lm(formula = log(exp_val) ~ t + ., data = AP)

Coefficients:
(Intercept)          t        dm1        dm2        dm3        dm4        dm5        dm6
 -321.65810    0.16034   -0.01112   -0.18049   -0.25171   -0.40714    0.69329    1.13516
        dm7        dm8        dm9       dm10       dm11
    0.95050    0.77802    0.42310    0.12388    0.05692
```

Figure 12: Estimated trend and seasonal effects from regression equation

The error component can be obtained by subtracting trend and seasonal components as $\varepsilon_t = Y_t - T_t - S_t$ and the plot of that error component is shown in Figure 13.

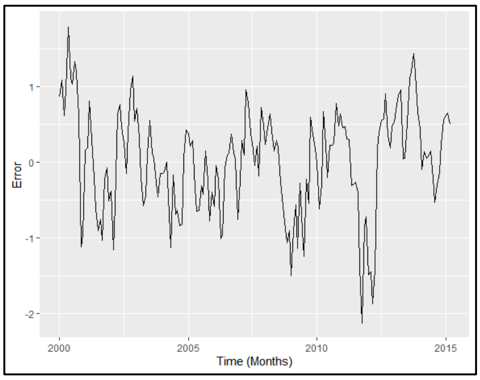


Figure 13: Time series plot of error component

As the series seems to be stationary, for further evidence stationary tests were carried out. Stationary tests confirm that the series of error component is stationary at 5% level of significance. As the residuals are stationary, next step is to fit a model for stationary residuals. ARMA (2, 1) model was selected as the best model with lowest AIC value (227.55) among many tentative models that were tested based on the ACF and PACF of the stationary residuals. The fitted ARMA (2, 1) model for the stationary residuals is given in (7).

$$x_t = 0.0179 + 0.0440x_{t-1} + 0.4757x_{t-2} + \varepsilon_t + 0.8487\varepsilon_{t-1} \quad (7)$$

Model adequacy of the fitted model for residuals was evaluated as in Figure 14. According to Figure 14, ACF plot of the residuals of the ARMA (2, 1) model shows that all autocorrelations are within the threshold limits indicating the residuals are behaving random. Further Ljung Box test on squared residuals gives large p value (0.0909) indicating the residuals have a constant variance at 5% level of significance.

Forecasting of the export income of pepper beyond year 2015 was achieved by forecasting the residuals and combining with the forecasts of the regression model that contains trend and seasonal components. Figure 15 represents the model validation of the time series decomposition model where black color series represents the actual data and the red color represents the forecasted data. Forecasting accuracy of the 20 % of the test data is measured with MAE and MAPE with values 4.3567 and 41.8718 respectively.

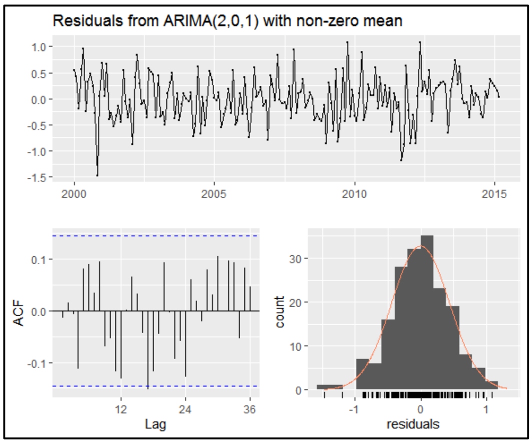


Figure 14: Model adequacy of ARMA (2,1) model

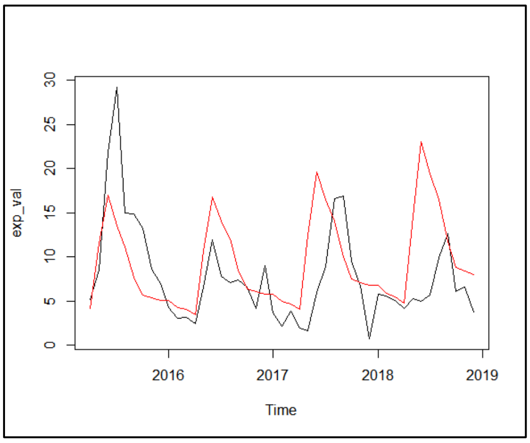


Figure 15: Model validation of the time series decomposition model

3.4. Model comparison

In order to identify the best model from SARIMA and the time series deterministic decomposition models, the forecasting accuracy of both models were compared with error metrics MAE and MAPE. The model comparison results are shown in Table 1.

Table 1: Model Comparison Results

Model Type	MAE	MAPE
SARIMA (4, 1, 4) (1, 1, 1) [12]	4.76	43.81
Deterministic decomposition model	4.36	41.87

According to Table 1, it is clear that deterministic decomposition model is the best model for forecasting the export income of pepper in Sri Lanka because it has minimum MAE and MAPE.

4. Results and Discussion

Forecasting the export income of pepper in Sri Lanka with time series modelling approach was carried out through this study. Monthly data on total pepper export value (US Dollar Millions) in Sri Lanka were used for the analysis. Two main approaches have been implemented to solve the research problem. First model is implemented as a stochastic class of models; SARIMA model. Second model is a Deterministic Decomposition model which assumes that the export income of pepper in Sri Lanka is a composition of three parts: a trend component, a seasonal component and an irregular component. The chosen decomposition model is multiplicative. After investigating time series approaches, the deterministic decomposition model was evidently selected as the best approach in forecasting the export income of pepper in Sri Lanka. ARIMA (4, 1, 4) (1, 1, 1) [12] which was selected as the best model under stochastic models approach also do a quite good job in forecasting export income of pepper in Sri Lanka but the best results can be achieved by the deterministic decomposition model which demonstrates a good performance in terms of both explained variability and forecasting. Most forecasted values are similar to actual values. Forecasts from the model shows a significant positive trend which can be considered as a growth of pepper export market in Sri Lanka in the future. Therefore, this study helps Sri Lankan pepper exporters to consider about long term investment decisions by identifying trends in the export value. As well as this may be useful for the government policy makers to rethink about the policy agenda of the country. As the forecasts shows an increasing pepper export market which will need a higher production of pepper, the government can improve the awareness of farmers about the requirements of pepper in export market by providing infra-structure facilities such as establishing central collecting, processing, storage centres to improve quality of pepper at the intermediary stages of the value chain, by providing land and loans for the cultivation purposes. Forecasts also depicts an important piece of information for potential investors in the pepper export market. The researchers who are interested in this field also can conduct time series regression approaches by incorporating the factors which are affecting to the pepper export income in Sri Lanka. This forecasting method can be generalized in analysing the export income of other commodities with necessary alterations.

Acknowledgement

Authors wish to thank Department of Statistics and Computer Science, Sri Lanka Exports Development Board and Mr. S.B.M.S.S. Gunarathne for their enormous contribution.

References

Institute of Policy Studies in Sri Lanka and Department of National Planning (2017). *Analysis of Cinnamon Pepper and Cardamom Value Chains in Sri Lanka*. Ministry of National Policies and Economic Affairs, Govt. of Sri Lanka.

Ministry of Development Strategies and International Trade and Sri Lanka Export Development Board. (2018). *National Export Strategy of Sri Lanka*. Govt. of Sri Lanka.

Mokshapathy, S. (2017). Production and export performance of black pepper. *International Journal of Humanities and Social Science,* **2**(**4**), 36-44.

Naz, F. (2012). A univariate times series modelling of dates exports in Pakistan. *Journal of Contemporary Issues in Business Research* ©, **1**(**2**), 57–68.

Nwogu, E. C., Iwueze, I. S. and Nlebedim, V. U. (2016). Some tests for seasonality in time series data. *Journal of Modern Applied Statistical Methods*, **15**(**2**), 382–399. https://doi.org/10.22237/jmasm/1478002920.

Ollech, D. (2019). Package 'seastests'. R package version 0.14.2. https://cran.r-project.org/web/packages/seastests/seastests.pdf

Paul, R. K., Panwar, S., Sarkar, S. K., Kumar, A., Singh, K. N., Farooqi, S. and Choudhary, V. K. (2013). Modelling and forecasting of meat exports from India. *Agricultural Economics Research Review*, **26**(**2**), 249–255.

Plywood, I. (2015). Modelling and forecasting export and import of Indian wood based panel using ARIMA models. *Elixir Statistics,* **63**, 18145-18148.

Sivarajah, P. (2018). Impact of land size on productivity, income and profits from pepper cultivation in Sri Lanka. *AGROFOR International Journal,* **1**(**3**), 127-132. https://doi.org/10.7251/AGRENG1603127S.

Sri Lanka (LKA) Exports, Imports, and Trade Partners | OEC - The Observatory of Economic Complexity. (n.d.). Retrieved on June 11, 2020, from the following link https://oec.world/en/profile/country/lka/.

Urrutia, J. D., Abdul, A. M. and Atienza, J. B. E. (2019). Forecasting Philippines imports and exports using Bayesian artificial neural network and autoregressive integrated moving average. *AIP Conference Proceedings,* **2192**, 090015-1-090015-11.