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The Study of Cereals Price Prediction in Terms of Trade Flows for Anticipate Price Fluctuations in Cambodia by Using ARIMA Model

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Abstract: *The study aims to predict the cereals prices trade flows in Cambodia, considering anticipated price fluctuations by using the ARIMA model. The data on cereals price of Cambodia was deseasonalized by the seasonality index (SI) for seasonality, resulting in monthly prices from 2000 to 2021. The target variable was independently smoothed by single exponential smoothing (SES) and Holt-Winters exponential smoothing (HWES) before transforming to the Box-Cox transformation. The exponential smoothing level (α) of SES was determined at 0.15 based on the seasonal span of data, while αexport and αimport of HWES were optimized at 0.88 and 0.57, respectively. The trend (β) and seasonal (γ) pattern smoothing coefficients were found at the same value of 0.0001 for both export and import after coefficients optimization. The optimized exponential transform parameters λex/SES = 0.017, λex/HWES = 0.22, λim/SES = -0.64, and λex/SES = -0.36 could result to support the seasonality of the data, resulting in uncorrelated residual, zero mean, and constant variance to generate a newly transformed data. By using Akaike Information Criterion (AIC) on univariate data smoothing by SES and HWES, ARIMA(5,1,6)SES and ARIMA(8,1,11)HWES were implemented for the export price, while ARIMA(1,1,0)SES and ARIMA(8,1,6)HWES were also developed for the import price to predict the 20% of the testing set. As a result, the models performed accurate predictions from the starting point in 2018 to November 2019, with a mean absolute percentage error (MAPE) lower than 10% (MAPE < 10%), a good prediction in time series; however, when predicting the prices the end of 2021, the accuracy decreased to 14.07%, 12.87%, 34.63%, and 24.63% for ARIMA(5,1,6)SES, ARIMA(8,1,11)HWES, ARIMA(1,1,0)SES and ARIMA(8,1,6)HWES for long-term prediction, respectively. In summary, these models are suitable for short-term forecasting with an output of MAPE < 10%, a good interpretation score of a model, while it is observed that HWES could perform better than SES in smoothing the cereals price in Cambodia, by reducing MAPE at 30-40% and up to 10-15% lower than SES for short and long-term forecasting, respectively. The accuracy gradually decreased for long-term predictions due to the impact of the Covid-19 crisis since Covid-19 severely affected the actual agricultural products in Cambodia.*

Keywords: Cereals; Deseasonalize; Seasonality index; Single exponential smoothing; Box-Cox transformation

1. INTRODUCTION

The commodities sector is very important for the economy of developing countries. Commodity markets have changed dramatically over the last century, while productivity gains have resulted in a downward trend in commodity prices relative to manufactured goods and services [1]. Commodities, which are essential to modern society, include fundamental material commodities used in production and consumption, such as energy, minerals, and agricultural products [2]. Furthermore, the resource commodity markets play a central role in economic development, international trade, and global economics [3]. In general, the closer integration of resource markets has been accompanied by growing economic and financial instability [2]. The pressures on prices have been exacerbated by the rising use of agricultural commodities, mainly corn and sugar, a recent

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phenomenon with substantial implications for food costs [4]. As regards agricultural products for Cambodia, the agricultural sector in 2018 accounted for up to 23.5% of Cambodia's GDP while milled rice exports totaled 626,225 tons, reported by the United States International Trade Administration (2019). USDA Foreign Agricultural Service (2022) [5] affirmed that Cambodia is a growing market for U.S. agricultural products with exports valued at over $114.57 million in 2021, a 759% increase over the past 10 years.

In Cambodia, the study of commodity price forecasting, especially the cereals price to establish the policy framework or pricing strategy in the long term based on state-of-the-art modeling results still has not been scientifically developed yet, and there is a lack of specific research. Not only the cereals price prediction including rice, cassava, maize, rye, barley, and other cereals but also the trade flows change during the Covid-19 crisis, while Covid-19 had certainly an impact on the global economy and disrupted all business operations worldwide [6]. While machine learning-based and other related deep learning approaches to price prediction models for agricultural commodities are very popular in use by researchers due to the high prediction accuracy, there are still barriers and challenges in adopting new technology in Cambodia [10]. To predict the commodity price, there are many studies with higher accuracy of prediction that have been conducted to solve the problem of time series prediction. Machine learning (ML) techniques and more importantly deep learning algorithms have introduced new approaches where the relationships between variables are modeled in a deep and layered hierarchy [7]. Deep learning models, on the other hand, are more complex and require more data to train, which can lead to overfitting [8], while the ARIMA model is simpler and easier to interpret, and the model also can capture linear and non-linear trends in time series and better suited for short-term forecasting [8-10]. Additionally, the ARIMA model can capture the essential features of a time series, such as trends, seasonality, cycles, and autocorrelation, and provide reliable forecasts with confidence intervals and diagnostic tests. The ARIMA model performs better than the LSTM model in terms of using just one feature – historical price value – and predicting in short-run forecasting [11]. Nevertheless, simple or single exponential smoothing (SES) is the method of time series using single smoothing factor (α) with univariate data with no trend and no seasonal pattern since ARIMA and SES is better than forecasting using the methods individually [12]. Meanwhile, Holt-Winters Exponential Smoothing (HWES) could exhibit both a trend and a seasonal variation to capture complex patterns of time series data by its trend and seasonal smoothing factors, respectively. Therefore, this study is conducted to predict the cereals price for anticipate price fluctuations by using the ARIMA model, while the cereals price of trade flows will be smoothed by SES and HWES to compare the results of the model by using two different smoothing methods. Furthermore, the parameters p, q, and d of the ARIMA model will be optimized by using the Akaike Information Criterion (AIC) test in fitting the models. The study presents the implementation of an ML algorithm using historical series of Cambodia's cereal prices from 2000 to 2021, including the respective indicators of technical analysis in forecasting the cereal's future price.

2. METHODOLOGY

2.1. Dataset and pre-processing

The data from 2010 to 2021 received from UN COMTRADE Database[2] was transformed from a 4-digit to a 2-digit harmonized system (HS) code. The cereals price data was initiated monthly for both exports and imports from 2015 to 2021, while the other annual time series from 2000 to 2014 was seasonalized accordingly by using the seasonality index (SI) of each month. After that, the generated dataset is split into 80%-training and 20%-testing for developing the ARIMA. The Box-Cox transformation method was used to normalize the scale of the cereals price. The Box-Cox formula is defined as (Eq.1) below.

$$y(\lambda)=\begin{cases}\dfrac{y^{\lambda}-1}{\lambda} & \text{if } \lambda \neq 0;\\ \log y, & \text{if } \lambda = 0.\end{cases} \qquad \text{(Eq.1)}$$

where:

y = target variable

λ = the exponent parameter which varies from -5 to 5

2.2 Seasonality index

In this study, seasonality index (SI) of each month was mainly used to deseasonalize the annual price of cereals trade flows in Cambodia to monthly records from 2000 to 2014. The computation of seasonal mean (SM) and overall mean (OM) was also done after identifying the SI for each month. The assumed monthly price (AMP) was calculated by the predicted seasonal price (PSP), percentage seasonal mean (%SM), and total annual price (AP), while the equation of AMP at time t is defined as (Eq.2) below.

$$AMP_t = PSP_t \times \frac{SM_t}{OM} \qquad \text{(Eq.2)}$$

where:

PSP_t = annual price × %SM

t = point time of each month a year

[2] https://comtradeplus.un.org/TradeFlow

2.3 Single exponential smoothing

Simple or single exponential smoothing (SES) is a technique for smoothing time series with univariate data using the exponential window function. SES was used for smoothing the target variable value of the dataset before inputting to the transformation processing. The basic equation of SES is given in Eq.3 below.

$$S_t = \alpha Y_{t-1} + (1-\alpha)S_{t-1} \qquad \text{(Eq.3)}$$

where: ($0 < \alpha \le 1$; $t \ge 3$)
S_t = the smoothed observation
Y_{t-1} = the original observation
α = the smoothing factor
S_{t-1} = the previous smoothing observation

2.4 Holt-Winters exponential smoothing

Holt-Winters exponential smoothing (HWES) is another method used for smoothing the price of cereals trade flows in the dataset based on the coefficients of three aspects: levels (α), trends (β), and seasons (γ). The equations of HWES are defined as (Eq. 4), (Eq. 5), and (Eq. 6).

Exponential smoothing of original data (at the time t)

$$L_t = \alpha \frac{Y_t}{S_{t-s}} + (1-\alpha)(L_{t-1} + T_{t-1}) \qquad \text{(Eq.4)}$$

Trend pattern smoothing (at the time t)

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \qquad \text{(Eq.5)}$$

Seasonal pattern smoothing (at the time)

$$S_t = \gamma \frac{Y_t}{L_t} + (1-\gamma)S_{t-s} \qquad \text{(Eq.6)}$$

Where ($0 < \alpha, \beta, \gamma < 1$)
Y_t = the target value
L_t = the level value at time t
L_{t-1} = the previous level value
T_t = the trend value at time t
T_{t-1} = the previous trend value
S_t = the seasonal value at time t
S_{t-s} = the previous seasonal value

2.5 Auto regressive integrated moving average

The ARIMA model, a basic model in the time series analysis, is a combination of two processes – autoregressive (AR) and moving average (MA), which is weighted by delayed random components. The universal notation ARIMA(p,d,q) is used to describe the form of the ARIMA model. The letter p is the order of regression, d is the order of differentiation and q is the order of MA. The equations of autoregression and moving average are given as (Eq.7) and (Eq. 8), respectively.

$$Y_t = \omega + \phi Y_{t-1} + \varepsilon_t \qquad \text{(Eq.7)}$$

$$Y_t = \omega + \phi \varepsilon_{t-1} + \varepsilon_t \qquad \text{(Eq.8)}$$

Where
Yt = the target value
ω = the interception
ϕ = coefficient
Yt-1 = the lagged of target
εt = the error
εt-1 = the previous error

2.6 Parameters optimization and assessment metrics

In tuning parameters for ARIMA model, Akaike Information Criterion (AIC), an estimate of a constant plus the relative distance between the unknown true likelihood function of the data and the fitted likelihood function of the model, was used to optimize the parameters p, d, and q for the models in this study. After differencing and data stationary testing by using the Augmented Dickey-Fuller Test (ADF Test), the optimal value of d was determined by the number of differencing when the data is stationary. Moreover, p and q were selected with the minimum value of AIC. The equation of AIC is given as (Eq. 9).

$$AIC = 2k - 2\ln(\hat{L}) \qquad \text{(Eq.9)}$$

where:

k = is the number of free parameters to be estimated
$\hat{L}$ = the actual value

After the ARIMA models have been fitted for this study, the next step is to evaluate the accuracy of the models with 20% of validating data. The accuracy of the implemented models was evaluated based on the value of mean absolute percentage error (MAPE) and root-mean-square error (RMSE). The equations of the assessment metrics are shown (Eq. 10) and (Eq. 11) below.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \times 100 \qquad \text{(Eq.10)}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Y_i - \bar{Y}_i)^2}{n}} \qquad \text{(Eq.10)}$$

where:
n = the number of observations
A_t = the actual value
F_t = the forecasted value
Y_i = the actual value
$\bar{Y}_i$ = the predicted value

3. RESULTS AND DISCUSSION

3.1. Seasonality of the cereals price data

The deseasonalization of the annual export and import prices from 2000 to 2014 was conducted to extend the monthly records based on the SI of each month. According to the General Department of Customs and Excise of Cambodia (GDCE), Cambodia initiated the monthly record process of the commodities trade flows from 2015, hence the monthly records from 2015 to 2018 were basically applied to compute SM and OM, while the monthly records from 2019 to 2021 were excluded from SI computation to avoid error rate of conversion since Covid-19 pandemic adversely impacts to global trade flows including Cambodia [13]. Seasonally, the trend of the cereals export prices found an increase in November, December, January, and March (see Fig.1), while the import trend started rising in May and August based on the last decade of cereals trade flows of Cambodia as shown in Fig.2.

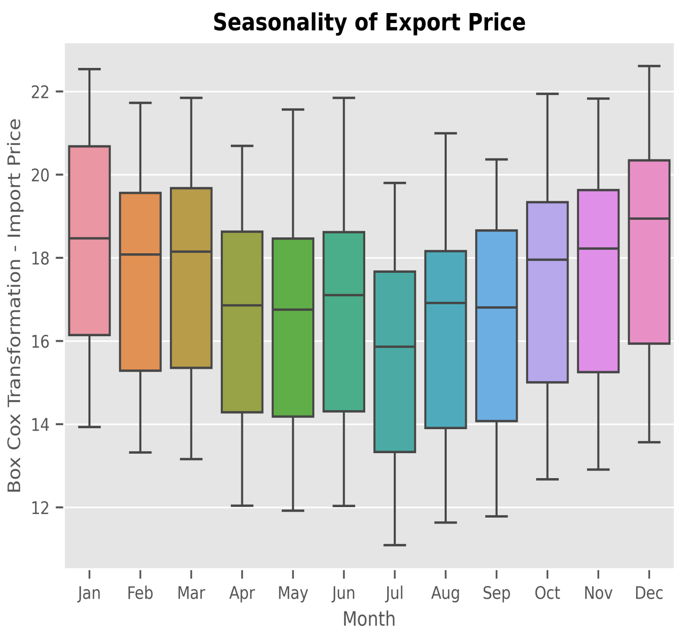

Fig. 1. The seasonality of export price.

As regards the crop harvest season in Cambodia, the Ministry of Agriculture, Forestry and Fisheries of Cambodia (MAFF) also affirmed in USDA Report (2022) [14]: Grain and Feed Annual - 2021, Cambodia's primary crop period, sowing starts in May-June, with the crop harvested in August-September for short- and medium-term varieties and October-January for longer term varieties. The secondary crop period is during the dry season, sowing starts in November-December, with the crop including rice and cashew nuts harvested from February to April. Likewise, according to Britannica (2022) [15] on agriculture, forestry, and fishing in Cambodia, planting typically begins in July or August, with harvesting lasting from November to January under traditional agricultural patterns.

Fig.3 and Fig.4 represent the scatter joint plots of the cereals price export and import of Cambodia in monthly records after the Box-Cox transformation. The monthly export price shows a better distribution in time series than that of the import after transforming, while most observations indicate the transformed value at a range of 12 to 22. On the other hand, in the monthly import price, some observations were investigated at a lower value compared to the other observations in the same month after the Box-Cox transformation was applied to the target variable.

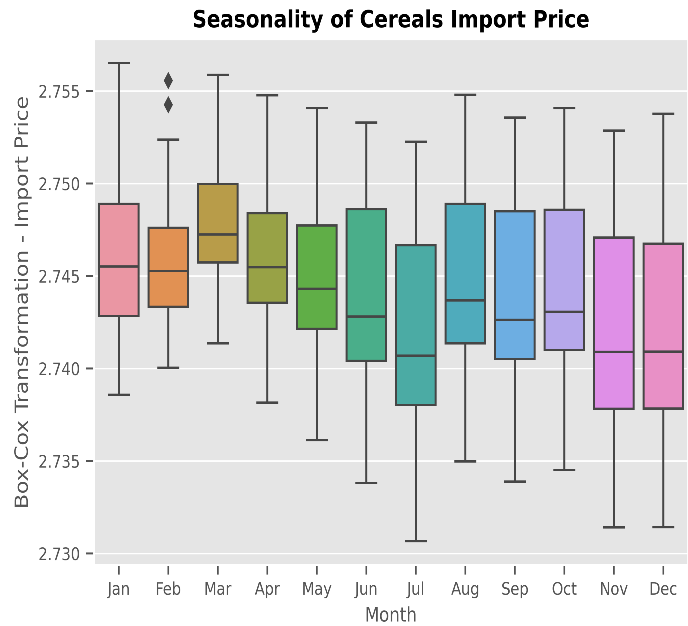

Fig. 2. The seasonality of import price.

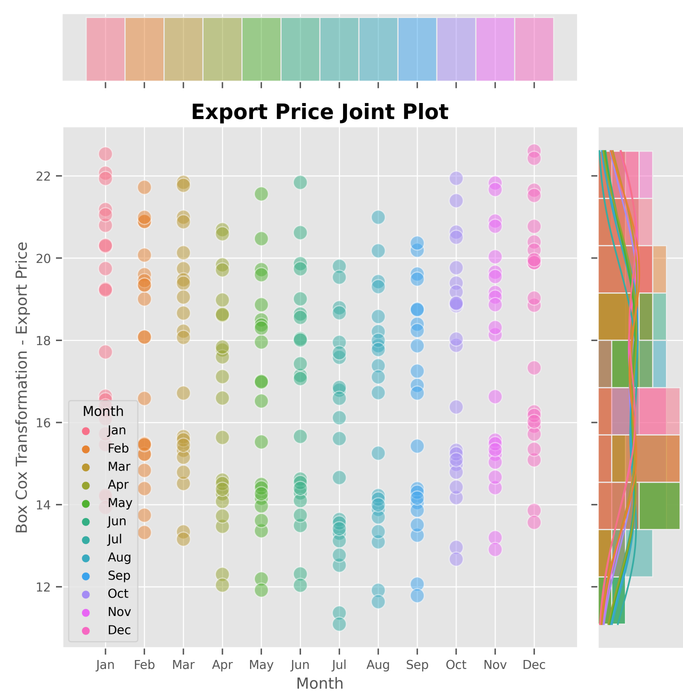

Fig. 3. The export price scatter joint plot.

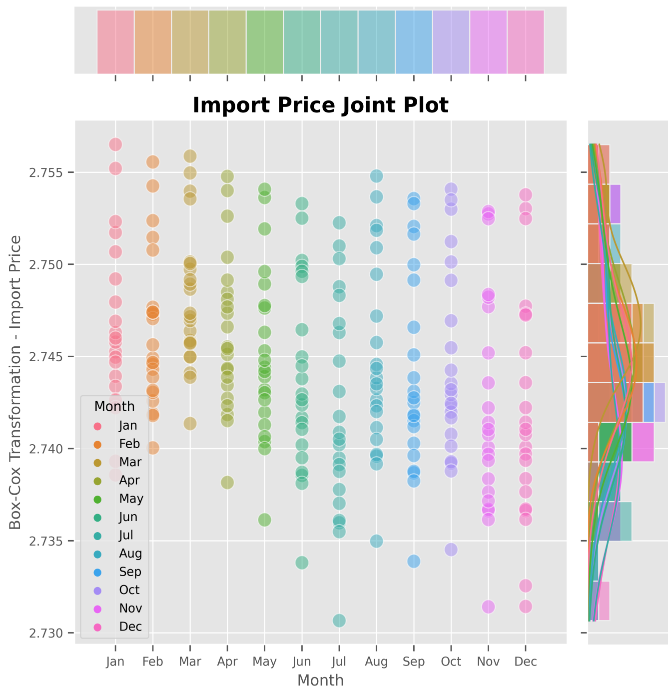

Fig. 4. The import price scatter joint plot.

3.2 The data smoothing and transformation

The data smoothing by using SES and HWES in the cereals price in terms of export and import are shown in Fig.5 and Fig.6, respectively. The results of HWES could generate a better fit to the actual price since the three aspects of HWES: the exponential smoothing level (α), trend (β), and seasonality (γ) components are more effective to fit with a typical value (average), a slope (trend) over time, and a cyclical repeating pattern (seasonality) of the actual cereal price trade flow patterns in Cambodia. In the meantime, SES independently has only one exponential smoothing level (α) which could not be well-suited to the time series data of the agricultural products trade flows in Cambodia.

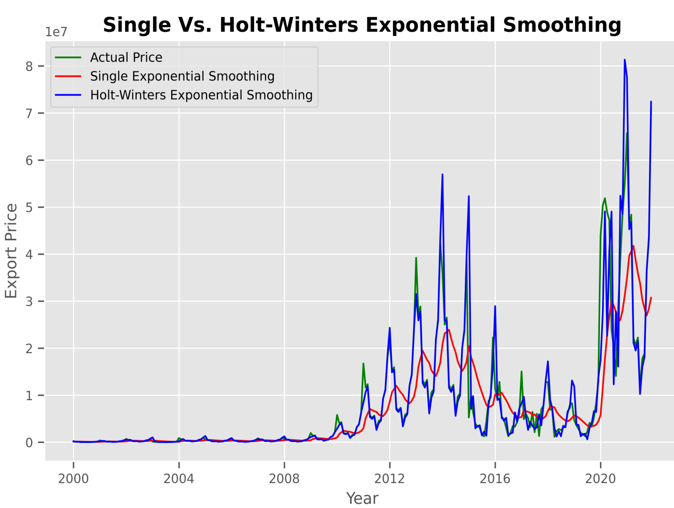

Fig. 5. The export price smoothing by SES and HWES.

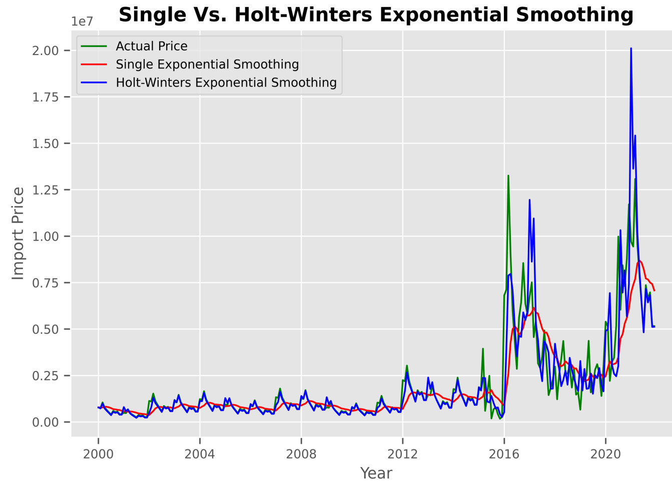

Fig. 6. The import price smoothing by SES and HWES.

The smoothing and transformation of the cereals price data in terms of export and import are illustrated in Table 1. The exponential smoothing level (α = 2/span+1) was determined at 0.15 for both trade flows based on the actual span of seasonality. Furthermore, the additive for the trend pattern and multiplicative for the seasonal pattern were identified into HWES since the trend is considered to be additive with roughly constant in the series and the seasonal variations are changing proportional to the level of the time series. Furthermore, the values of exponential smoothing level by using HWES were optimized at 0.88 and 0.57 which are in a range of 0 to 1 ($0 < \alpha < 1$) for α_{export} and α_{import}, respectively. The trend (β) and (γ) seasonal pattern smoothing factors were observed at the same value of 0.0001 for both cereals trade flows in Cambodia. It is understandable that the actual price of cereals indicating the previous values in the target variable is weighted more heavily according to the optimization of the values of β and γ in smoothing data before transforming into Box-Cox transformations.

Table 1 Summary of smoothing and transformation

Method	Smoothing Level (Export)			Box-Cox Transform (λ_{export})
	α_{export}	β_{export}	γ_{export}	
SES	0.17	-	-	0.017
HWES	0.88	0.0001	0.0001	0.022
Method	Smoothing Level (Import)			Box-Cox Transform (λ_{import})
	α_{import}	β_{import}	γ_{import}	
SES	0.15	-	-	-0.64
HWES	0.57	0.0001	0.0001	-0.36

The Box-Cox was accordingly used to transform the target variable which is the cereals price to fit the ARIMA model. The auto-scale of Box-Cox could transform the cereals price to obtain a good time-series decomposition with the exponential transform parameter – lambda (λ_{export}), resulting in the different values of $\lambda_{ex/SES}$ and $\lambda_{ex/HWES}$ at 0.017 and 0.022, respectively. Furthermore, the exponential transform parameter of the import price (λ_{import})

smoothing by SES ($\lambda_{im/SES}$) indicated a negative value of -0.64, while the import price which was smoothed by using HWES ($\lambda_{im/HWES}$) was found at -0.36. As a result, the optimized values of λ_{export} and λ_{import} could output the uncorrelated residual, zero mean, and constant variance to generate newly transformed data for the next predictive study. The optimized values are in the range of -5 to 5 (-5 > λ_{export}, λ_{import} > 5), hence the values of λ_{export} and λ_{import} smoothing by SES and HWES are the optimal values for the data transformation.

3.2 The cereals price prediction by using ARIMA model

Fig.7 and Fig.8 demonstrate the results of cereals price prediction in terms of export and import by the ARIMA models, respectively. After the first differencing on price value smoothing by SES and HWES, the data is stationary by Augmented Dickey-Fuller Test (ADF Test), in resulting a p-value lower than 0.05 (p-value < 0.05) to reject the null hypothesis of non-stationary. To optimize the parameters p, d, and q for the ARIMA model in this study, the Akaike Information Criterion (AIC) was implemented to compare the fit of several regression models with the lowest value of AIC for both cereals trade flows. As a result of optimization, ARIMA(5,1,6)$_{SES}$ and ARIMA(8,1,11)$_{HWES}$ were developed for the cereals export price, while ARIMA(1,1,0)$_{SES}$ and ARIMA(8,1,6)$_{HWES}$ were also implemented for the import to forecast the 20% of testing data from 2018 to 2021.

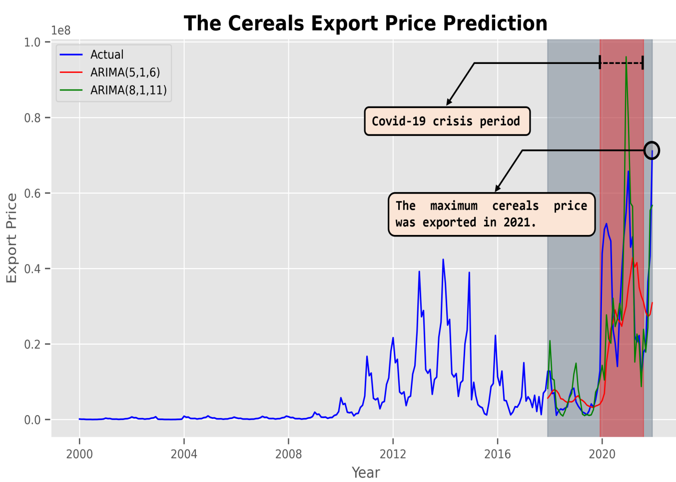

Fig. 7. The ARIMA prediction of the cereals export price smoothing by SES and HWES.

In terms of export trade flow, ARIMA(5,1,6)$_{SES}$ and ARIMA(8,1,11)$_{HWES}$ could perform well in short-term of the cereals price prediction from 2018 to December 2019, resulting in MAPE lower than 10% (MAPE < 10%) in comparing to the actual export price value after inversing from the Box-Cox transformation (see Table 2). It could take a notion that the models smoothing by SES and HWES could result in a good prediction for a short run of the time series, while the smoothing efficiency between SES and HWES has no significant difference in short-term forecasting since the models produced MAPE at lower than 10%, which is good forecasting of a model for time series [16].

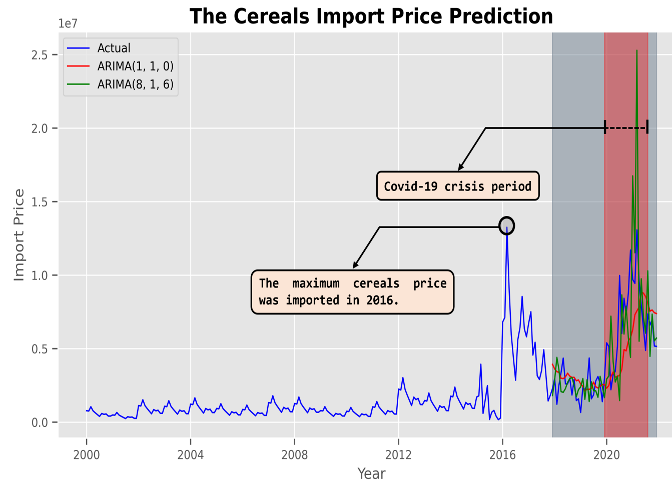

Fig. 8. The ARIMA prediction of the cereals import price smoothing by SES and HWES.

Likewise, ARIMA(1,1,0)$_{SES}$ and ARIMA(8,1,6)$_{HWES}$ of the import price also provided good results in prediction for short-run forecasting, indicating MAPE at 4.64% and 2.61%, respectively. Furthermore, RMSE in short-term prediction of all implementing models performed at lower than 1 before inversing from Box-Cox transformation. In validating metrics, RSME also resulted in a lower value than that of the mean and RMSE values of testing observations after inversing from transformation. For example, the RMSE of the ARIMA(5,1,6)$_{SES}$ was found at 360815.39, which is lower than 5214614.89 and 1279079.97 of the mean and RMSE in the testing set, respectively.

Table 2 The summary of ARIMA in short-run forecasting

Metric	Export		Import	
	ARIMA$_{SES}$	ARIMA$_{HWES}$	ARIMA$_{SES}$	ARIMA$_{HWES}$
MAPE	4.67%	2.72%	4.64%	2.61%
RMSE	360815.39	2154055.56	146683.19	71915.50

Nevertheless, the accuracy of the implemented models decreased after the model pursued forecasting to the end of 2021 (see Table 3). As a result of model evaluation, ARIMA(5,1,6)$_{SES}$ decreased its accuracy by increasing MAPE from 4.67% to 14.07, and ARIMA(8,1,11)$_{HWES}$ also decreased its accuracy, resulting in MAPE at 12.87%. Similarly, ARIMA(1,1,0)$_{SES}$ and ARIMA(8,1,6)$_{HWES}$ resulted correspondingly in a higher MAPE at 34.63% and 23.63%, respectively. In this regard, it is viewed as relatively good in prediction (20% < MAPE < 50%) according to Moreno et al., (2013) [16]. It is observed that the ARIMA model degrades its accuracy when trying to predict in long-term since ARIMA uses past data and parameters and is typically insufficient for long-term forecasting [17] and some limitations [7]. Despite that, the RMSE score of the models still showed lower than the mean and RMSE values of the testing set. On the other hand, based on the MAPE findings, HWES could perform better than SES in smoothing the cereals price data. The ARIMA models smoothing by HWES could improve the accuracy at approximately 30-40% higher than SES for short-run forecasting and up to 10-15% for long-term forecasting since the trend and seasonal pattern aspects of HWES could fit the models well to the actual context of the cereals trade flows in Cambodia.

Table 3 ARIMA modeling results until 2021

Metric	Export		Import	
	ARIMA_{SES}	ARIMA_{HWES}	ARIMA_{SES}	$\text{ARIMA}_{\text{HWES}}$
MAPE	14.07%	12.87%	34.63%	23.63%
RMSE	1922971.83	1614772.68	351039.04	2847925.82

In addition to accuracy degradation, the results of the model initiated a lower accuracy from early 2020 to 2021 since the Covid-19 pandemic sent shock waves through the world economy and triggered the largest global economic crisis from December 2019 [13]. Likewise, Cambodia was also severed acutely by the Covid-19 crisis which had caused dramatically changed the trade flows in Cambodia, including agricultural products. Additionally, Cambodia started practicing border restrictions and closed the border with Vietnam and Thailand on March 2020 [18] and Covid-19 has severely affected the Cambodian economy in February 2021 [19]. Furthermore, Covid-19 led to a significant economic and social challenge [20] and a negative impact [21] for Cambodia. Therefore, Covid-19 is a main factor that adversely impacts the actual trade flows of cereals since Cambodia mostly exchanges agricultural products with the neighboring countries, while The OEC (2021) [22] also reported that Vietnam is Cambodia's fastest-growing origin for the cereal import in 2019-2020.

4. CONCLUSIONS

This study is conducted to forecast the cereal price by using the ARIMA model as regards the anticipated price fluctuation. After deseasonalizing by using SI of each month, SES and HWES were independently used to smooth the target variable of the cereals trade flows. The Box-Cox transformation was used as a feature engineering to support the seasonality of the data. After smoothing by SES and HWES, the exponential transform parameters were optimized at $\lambda_{ex/SES} = 0.017$, $\lambda_{ex/HWES} = 0.22$, $\lambda_{im/SES} = -0.64$, and $\lambda_{ex/SES} = -0.36$ to obtain a good time-series decomposition. $\text{ARIMA}(5,1,6)_{\text{SES}}$ and $\text{ARIMA}(8,1,11)_{\text{HWES}}$ were implemented for the cereals export price while $\text{ARIMA}(1,1,0)_{\text{SES}}$ and $\text{ARIMA}(8,1,6)_{\text{HWES}}$ were developed to predict 20% of testing set. As a result, the models could perform good predictions with MAPE lower than 10% in short-term forecasting. However, the models degraded their accuracy by increasing MAPE to 14.07%, 12.87%, 34.63%, and 24.63% for $\text{ARIMA}(5,1,6)_{\text{SES}}$, $\text{ARIMA}(8,1,11)_{\text{HWES}}$, $\text{ARIMA}(1,1,0)_{\text{SES}}$ and $\text{ARIMA}(8,1,6)_{\text{HWES}}$ for long-term prediction, respectively. As regards the effectiveness of smoothing methods, HWES could result in the accuracy in predicting the cereals price of Cambodia at approximately 30-40% higher than SES for short-term and up to 10-15% for long-term forecasting. Based on the findings, it could be observed that the pattern of ARIMA forecasting models is directional and it is applicable for short-run forecasting since it can be effectively engaged profitably for either export or import price prediction. However, many factors affect Cambodia's cereals price forecasting such as low quality of dataset, the impacts of the Covid-19 crisis, inadequate information related to the agricultural products trade flows in Cambodia, etc. Additionally, to improve the performance of the model in long-term prediction, some engineering features and deep learning models such as LSTM or Recurrent Neural Networks (RNN) should be taken into consideration for further study.

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REFERENCES

[1] Ventimiglia, L. (2012). Commodity markets. Handbook of Critical Issues in Finance, 49–55. https://doi.org/10.4337/9781849805957.00014

[2] Zhang, Q., Hu, Y., Jiao, J., & Wang, S. (2022). Exploring the Trend of Commodity Prices : A Review and Bibliometric Analysis.

[3] Schaeffer, P. V. (2008). Commodity Modeling and Pricing. In Commodity Modeling and Pricing. https://doi.org/10.1002/9781118267905

[4] Antwi, E., Gyamfi, E. N., Kyei, K. A., Gill, R., & Adam, A. M. (2022). Modeling and Forecasting Commodity Futures Prices: Decomposition Approach. IEEE Access, 10, 27484–27503. https://doi.org/10.1109/ACCESS.2022.3152694

[5] USDA. (2022). Report Name : Cambodia: Grain and Feed Annual USDA Foreign Agricultural Service. Report, CB2022-0001, 1–14. https://www.fas.usda.gov/data/cambodia-grain-and- feed-annual-3

[6] Choi, T. (2020). Innovative " Bring-Service-Near-Your-Home " Operations under Corona-Virus (COVID-19 / SARS-CoV-2) Outbreak : Can Logistics Become the Messiah ? 1. Transportation Research Part E, 101961. https://doi.org/10.1016/j.tre.2020.101961

[7] UNDP. (2020). Adaptation and Adoption of Industry 4.0 in Cambodia. https://www.undp.org/cambodia/

publications/adaptation-and-adoption-industry-40-cambodia

[8] Siami-Namini, S., Tavakoli, N., & Siami Namin, A. (2019). A Comparison of ARIMA and LSTM in Forecasting Time Series. Proceedings - 17th IEEE International Conference on Machine Learning and Applications, ICMLA 2018, 1394–1401. https://doi.org/10.1109/ICMLA.2018.00227

[9] Adebiyi, A. A., Adewumi, A. O., & Ayo, C. K. (2014). Comparison of ARIMA and Artificial Neural Networks Models for Stock Price Prediction. 2014, 9–11.

[10] Meyler, A.; Kenny, G.; Quinn, T. (1998). Forecasting Irish Inflation Using ARIMA Models. Research Department: Dublin, Ireland, 1998

[11] Tabachnick, B.G.; Fidell, L. S. (2001). Review of Using Multivariate Statistics. In Contemporary Psychology: A Journal of Reviews (Vol. 28, Issue 8). https://doi.org/10.1037/022267

[13] Ohyver, M., & Pudjihastuti, H. (2018). Arima Model for Forecasting the Price of Medium Quality Rice to Anticipate Price Fluctuations. Procedia Computer Science, 135, 707–711. https://doi.org/10.1016/j.procs.2018.08.215

[14] World Bank. (2022). World Development Report 2022 : Finance for an Equitable Recovery. https://doi.org/10.1596/978-1-4648-1730-4

[15] USDA. (2022). Report Name : Cambodia: Grain and Feed Annual | USDA Foreign Agricultural Service. Report, CB2022-0001, 1–14. https://www.fas.usda. gov /data/cambodia-grain-and-feed- annual-3

[16] Britannica. (2022). Cambodia - Rice Production, Livestock Farming, Illegal Logging, and Fisheries https://www.britannica.com/place/Cambodia/Agriculture-forestry-and-fishing

[17] Montaño Moreno, J. J., Palmer Pol, A., Sesé Abad, A., & Cajal Blasco, B. (2013). El índice R-MAPE como medida resistente del ajuste en la previsiońn. Psicothema, 25(4), 500–506. https://doi.org/10.7334/psicothema2013.23

[18] Adam Heyes, Chip Stapleton, & Katrina Munichiello. (2022, December 18). Autoregressive Integrated Moving Average (ARIMA) Prediction Model. Investopedia. https://www.investopedia.com/terms/a/autoregressive-integrated-moving-average-arima.asp

[19] Kingdom closes border with Vietnam over outbreak - Khmer Times. Khmer Time. https://www.khmertimeskh.com/703485/kingdom-closes-border-with-vietnam-over-outbreak/

[20] Ngin, C. (2022). COVID - 19 and the Tourism Sector in Cambodia: Impact, Response and the Road to Recovery. http://www.cps.org.kh/wp-content/uploads/2022/02/Cambodia-Report-Final.pdf

[21] UNDP. (2021). 2021 COVID-19 ECONOMIC AND SOCIAL IMPACT ASSESSMENT IN CAMBODIA An Integrated Modelling Approach. https://www. undp.org/cambodia/publications/2021-covid-19-economic-and-social-impact-assessment-cambodia.

[22] Asian Development Bank. (2020). COVID-19 Active Response and Expenditure Support Program: Project Administration Manual. April, 1–11. https://www.adb.org/sites/default/files/linked-documents/54195-001-sd-03.pdf

[23] Ventimiglia, L. (2012). Commodity markets. Handbook of Critical Issues in Finance, 49–55. https://doi.org/10.4337/9781849805957.00014