A Review of Factors Affecting Palm Oil Futures Prices and Forecasting Models

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Abstract- Palm oil futures play a crucial role in the global edible oil market, and their price fluctuations significantly impact food security, energy costs, and economic stability in many regions. Accurately forecasting the price of palm oil futures is essential for government policy-making, enterprise risk management, and investor decision-making. This review comprehensively examines the key factors influencing palm oil futures prices, including the daily closing prices of palm oil, soybean, rapeseed, crude oil, and palm kernel, currency exchange rates (Malaysian Ringgit/Chinese Yuan and United States Dollar/Chinese Yuan), export volumes from Malaysia and Indonesia, and regional precipitation data in areas such as Pahang, Johor, Sarawak, and Sabah. Furthermore, this paper reviews various prediction models applied in this field, such as Linear Regression (LR), Neural Networks (NN), Long Short-Term Memory (LSTM), and Deep Belief Networks (DBN). Despite considerable research progress, two major challenges remain. First, the large number of influencing factors increases the complexity of government regulation and policy response. Second, the prediction accuracy of existing models is still relatively low, especially under volatile or extreme market conditions. To address these issues, future research could explore hybrid modeling approaches and incorporate multi-source data. This review aims to collect possible factors affecting palm oil futures prices and provide a reference for researchers to find data sources for palm oil futures price forecasts. Additionally, it provides insights for researchers to select and improve palm oil futures forecast models.

Indexed Terms- Palm Oil Futures, Prediction Models, Key Factors Influencing Palm Oil Futures Prices, Hybrid Modeling Approaches

I. INTRODUCTION

Palm oil is one of the most widely consumed vegetable oils globally and plays a vital role in the food, cosmetic, and biofuel industries. Due to its widespread usage and economic importance, the price of palm oil futures has become a key indicator in global commodity markets. Malaysia and Indonesia account for approximately 85% of the world's total palm oil production, making Southeast Asia a strategic region in the international palm oil trade [1].

The volatility of palm oil futures prices is influenced by a wide array of factors, including supply and demand dynamics, macroeconomic indicators, climatic conditions, exchange rates, and the prices of related commodities such as soybean, rapeseed, and crude oil [2][3]. For instance, significant correlations have been observed between the prices of soybean oil and palm oil due to their substitutability in both food and industrial applications [4]. Moreover, fluctuations in the Malaysian Ringgit (MYR) and the United States Dollar (USD) against the Chinese Yuan (CNY) also impact export competitiveness and international pricing[5].

Climate variables such as regional precipitation, particularly in palm oil-producing regions like Pahang, Johor, Sarawak, and Sabah, affect palm oil yields and, consequently, future supply and pricing[6]. In addition, geopolitical events, government export policies, and global energy prices contribute further uncertainty to the market, posing challenges for forecasting models [7].

To address these complexities, researchers have applied various models to predict palm oil futures prices. Traditional statistical models such as Linear

Regression (LR) and Autoregressive Integrated Moving Average (ARIMA) are appreciated for their simplicity and interpretability [8]. However, these models often fail to capture nonlinear relationships and complex time-dependent patterns. Therefore, machine learning and deep learning approaches such as Neural Networks (NN), Long Short-Term Memory (LSTM), and Deep Belief Networks (DBN) have been increasingly adopted to improve forecasting performance [9][10].

Despite these developments, two major challenges remain. First, the large number of influencing factors introduces substantial uncertainty, complicating government regulation and enterprise decision-making. Second, the existing forecasting models still suffer from limited accuracy, especially under volatile or extreme market conditions. Therefore, future studies should explore hybrid modeling strategies, utilize multi-source data such as weather conditions, market sentiment, and news analytics, and build more interpretable and adaptive forecasting systems [11].

This review aims to provide a comprehensive summary of the major factors affecting palm oil futures prices and critically assess the forecasting models employed in this domain. The goal is to assist researchers in identifying relevant data sources and selecting suitable methods for palm oil price prediction.

II. LITERATURE REVIEW

This section mainly summarizes and comprehensively describes the factors affecting palm oil futures prices and the palm oil price prediction model.

A. Analysis of influencing factors

The factors that affect palm oil futures prices are very complex, involving market prices, exchange rates and macroeconomics, meteorology and natural environment, supply and demand, etc. The following table summarizes these factors and their related literature support.

Table 1. Analysis of influencing factors

Factor category	Specific factors	Related literature
Market price	Daily closing price of palm oil	The price of palm oil itself will greatly affect the next change in palm oil futures prices.
	Soybean price	Li and Zhao analyzed the relationship between soybean prices and palm oil prices and proposed that soybean oil, as the main competitor of vegetable oil, its price fluctuations directly affect the market demand and price of palm oil[12].
	Rapeseed price	Liew et al. further explored the impact of rapeseed oil prices on the palm oil market. The study showed that rapeseed oil and palm oil are highly substitutable in the international market, so changes in rapeseed oil prices have a significant impact on palm oil prices[13].
	Crude oil price	Hadi et al. studied how fluctuations in crude oil prices affect the palm oil futures market. Since palm oil is often used as a biofuel, fluctuations in crude oil prices can indirectly affect palm oil prices by affecting the biofuel market[14].
	Palm kernel price	Fadhil explored the impact of palm kernel prices on palm oil prices. The authors believe that palm kernel is a by-product of palm oil production, and its price fluctuations directly affect the production cost of palm oil, thereby affecting the price of palm oil[15].
Exchang	MYR/	Liew and Lee proposed the

e Rate and Macroeconomics	CNY	impact of exchange rate fluctuations between the Malaysian Ringgit (MYR) and the Chinese Yuan (CNY) on palm oil exports. Their study showed that when the Malaysian Ringgit depreciated, the price competitiveness of palm oil in the Chinese market increased, driving an increase in export volume and further leading to price increases[16].
	USD/CNY	Goh and Wei studied the impact of the exchange rate between the U.S. dollar (USD) and the Chinese yuan (CNY) on palm oil prices. They found that an appreciation of the U.S. dollar usually increases the cost of palm oil in the international market, leading to price increases; while a depreciation of the Chinese yuan may make the export price of palm oil more favorable, driving exports to increase, and thus affecting palm oil futures prices[17].
Meteorology and natural environment	Precipitation in Pahang, Johor, Sarawak, Sabah	Teoh et al. further analyzed the long-term impact of climate change on palm oil production, pointing out that extreme changes in meteorological conditions, such as extended dry seasons or increased heavy rains, could lead to drastic fluctuations in production, thereby affecting market prices[18].
Supply and demand	Export volume in Malaysia and Indonesia	Afiq and Yasir proposed how the palm oil export volume of Malaysia and Indonesia affects the market price of palm oil. The authors analyzed the relationship between changes in export volume and palm oil futures prices and found that when major producing

		countries (such as Malaysia and Indonesia) increase their exports, supply pressure increases, pushing up palm oil prices. Conversely, a decrease in export volume will cause oversupply in the market and lower prices[19]

Market price factors directly affect palm oil futures prices. Palm oil prices are highly correlated with other vegetable oils (such as soybean oil and rapeseed oil) because these oil crops have a certain degree of substitutability in the international market. In addition, crude oil price fluctuations are also closely related to palm oil price fluctuations, especially when energy prices fluctuate greatly. As a substitute for biofuels, changes in demand will directly affect its price. Palm kernel prices also have a significant impact on palm oil production costs. Exchange rate fluctuations have an important impact on palm oil prices, especially the exchange rate fluctuations between the Malaysian ringgit and the Chinese yuan (MYR/CNY) and the US dollar and the Chinese yuan (USD/CNY). When the Malaysian ringgit depreciates, palm oil becomes more competitive in the international market, leading to price increases; conversely, an appreciation of the US dollar may increase the price of palm oil and reduce demand. Meteorological factors have a direct impact on palm oil production. Studies have shown that changes in precipitation in palm oil producing areas such as Pahang, Johor, Sarawak and Sabah significantly affect production. Extreme weather events or abnormal precipitation can affect the growth and oil production of palm trees, thereby affecting market prices. Supply and demand play a central role in the price fluctuations of palm oil futures. The export volume of palm oil from Malaysia and Indonesia directly affects the supply in the market. Increased export volume usually leads to tight supply, which drives up prices, while reduced export volume may lead to oversupply, which drives down prices.

B. review of palm oil price forecasting models

In today's big data era, researchers have already used various models to predict palm oil futures prices. In the study of palm oil price prediction, traditional statistical methods, machine learning methods, and deep learning methods have different advantages and disadvantages. The following table summarizes the input characteristics, prediction performance, advantages and disadvantages of these methods.

Table 2. Traditional Statistical Methods

Models	Input Features	Predicti-on Perform-ance	Advant-ages	Disadvant-ages
Linear Regress-ion (LR)	Historical palm oil prices, market prices of other vegetable oils, weather data (e.g., precipitation)	Moderate, tends to over-simplify relationships	Simple to implement, interpretable	Assumes linear relationships, limited by feature complexity
ARIMA	Historical time series data (price data, economic indicators)	Performs well in stable, non-volatile markets	Good for time-series forecasting, easy to implement	Struggles with volatility, does not handle non-linear patterns well

Table 3. Machine Learning Methods

	Input Features	Prediction Performance	Advantages	Disadvantages
Random Forest	Historical price data, market and economic features, weather data	Good performance in capturing complex interactions	Can handle non-linearities, robust to overfitting	Requires large datasets, less interpretable than LR
Support Vector Machine (SVM)	Historical price data, supply-demand factors, weather data	Performs well with smaller datasets	Effective for high-dimensional data, works well with non-linear data	Difficult to tune parameters, sensitive to noise
XGBoost	Price data, market features, economic factors, export volume data	High performance, handles missing data well	Fast and efficient, good accuracy in predictions	Requires careful tuning, may overfit with small datasets

Table 4. Deep Learning Methods

Models	Input Features	Predictio-n Performa-nce	Advanta-ges	Disadvanta-ges
Long Short-Term Memory (LSTM)	Time series data, weather patterns, historical prices	Excellen-t for sequential data, especially in volatile conditions	Good at capturing long-term dependencies and trends	Computatio-nally intensive, requires large datasets
Gated Recurrent Unit	Time series data, price	Similar to LSTM, often	More efficient than LSTM,	Similar to LSTM, may struggle

(GRU)	and supply data, weather information	faster to train	handles sequential data well	with very long sequences
Deep Belief Network (DBN)	Price data, economic indicators, external market factors	Good for complex, high-dimensional data	Can learn from unstructured data, captures complex patterns	Requires extensive training, difficult to interpret
CNN-LSTM Hybrid Model	Image data (e.g., satellite imagery), time series price data	High prediction accuracy with multi-source data	Combines the strengths of CNN (feature extraction) and LSTM (sequence modeling)	High computational cost, complex architecture

The palm oil price prediction models span from traditional statistical methods to advanced machine learning and deep learning approaches. Linear Regression (LR) and ARIMA are simpler to implement but are limited in handling complex relationships and volatile market conditions. In contrast, machine learning methods like Random Forest, SVM, and XGBoost offer better performance by capturing non-linear interactions, though they require large datasets and can be less interpretable. Deep learning models, particularly LSTM and GRU, excel in capturing long-term dependencies in sequential data but are computationally intensive and need extensive training data. DBN and CNN-LSTM hybrid models perform well on complex data, with the hybrid model providing high accuracy by combining CNN's feature extraction and LSTM's sequence modeling, but at the cost of increased computational demands. Overall, while advanced models offer higher prediction accuracy, they require more resources and careful tuning compared to traditional methods.

III. CHALLENGES AND LIMITATIONS

Despite the substantial progress in forecasting palm oil futures prices using various prediction models, several challenges and limitations still need to be addressed.

A. Complexity of influencing factors

Palm oil prices are affected by a large number of factors, ranging from market prices and macroeconomic indicators to weather conditions and regional agricultural production. The complexity and interdependence of these factors make it difficult to accurately simulate price dynamics. Policymakers and market regulators must consider multiple variables, which makes it challenging to formulate effective policies. The intricate relationships between these variables can lead to unexpected price changes, especially in volatile markets. Model training requires a large amount of data input, but if the input data is not screened, the quality of the input data will be very low, wasting a lot of resources for model training while failing to improve the accuracy of the model. Therefore, there are many factors affecting palm oil futures prices, and it still takes a long time to determine which factors are the main factors.

B. Low Forecast Accuracy

Despite significant improvements in machine learning and deep learning models, forecast accuracy remains relatively low, especially under volatile or extreme market conditions. For example, models such as LSTM and XGBoost may perform well in stable markets but perform poorly during rapid price fluctuations or unexpected economic events. In addition, deep learning models typically require large datasets and extensive computing resources, which may limit practical applications where data availability may be limited.

C. Model Interpretability

Deep learning and complex machine learning models often suffer from a lack of interpretability, which poses a significant challenge for decision-makers. Models like Long Short-Term Memory (LSTM) networks, Random Forest, and Deep Belief Networks provide high accuracy but operate as black-box models, meaning that it is difficult to understand the rationale behind their predictions. This lack of transparency makes it challenging for policymakers and industry leaders to trust the predictions and act upon them confidently. In contrast, simpler models like Linear Regression (LR) or ARIMA are more interpretable, offering clear insights into the factors influencing predictions, but they often fall short in terms of predictive power, especially when handling complex, non-linear relationships. The trade-off between accuracy and interpretability remains a key limitation in palm oil price forecasting.

D. Data Quality and Availability

The accuracy and robustness of forecasting models depend heavily on the quality of the input data. Many models perform poorly when data is incomplete, inaccurate, or inconsistent. For example, data related to regional precipitation, export volumes, or currency exchange rates may be sparse or difficult to obtain, resulting in gaps in the model's ability to learn from historical trends. In addition, economic data such as GDP growth rates or trade volumes may not be updated in real time, limiting the model's ability to respond quickly to new developments. Missing or noisy data can lead to biased forecasts, while the lack of high-frequency data can hinder the model's ability to respond to sudden changes in market conditions. In particular, the numerous factors that affect palm oil futures prices pose a great challenge to researchers in terms of data collection.

E. Lack of real-time adaptability

Existing models often rely on static datasets for training, which makes them difficult to adapt to rapidly changing conditions. The palm oil market is subject to many destabilizing factors, such as changes in the global supply chain, political instability, and extreme weather events. Current models often have difficulty updating their forecasts in real time as new data becomes available. This limitation is particularly critical in financial markets, where rapid adaptation is essential for success. Real-time learning techniques have been proposed, in which models are continuously updated as new information becomes available, but they are still in the experimental stage and face challenges related to data synchronization and model stability.

The complexity of the factors influencing palm oil prices presents a significant challenge for forecasting models. The price dynamics are influenced by a range of variables, including market prices of related commodities, macroeconomic indicators, weather conditions, and regional agricultural production. The interdependence of these factors makes it difficult to accurately simulate price movements. Policymakers and market regulators face the difficulty of considering multiple variables when designing policies, as the intricate relationships between these factors often lead to unexpected price fluctuations, particularly in volatile markets. Additionally, the training of forecasting models requires substantial data input, but if this data is not properly screened or lacks quality, it diminishes the accuracy of predictions. The challenge remains in identifying which factors are the most influential in determining palm oil futures prices. This complexity, combined with the need for extensive data collection, makes it difficult to formulate precise and effective forecasting models, and considerable resources are often spent without substantial improvements in accuracy.

IV. FUTURE DIRECTIONS

While current models have made significant contributions to the prediction of palm oil futures prices, there is room for improvement and further research. Below are several potential future directions to address the challenges and limitations identified in this review:

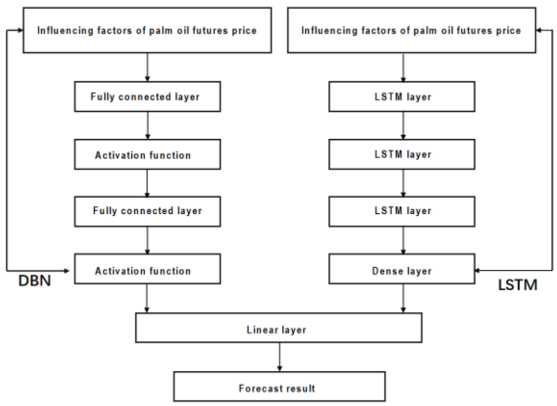
A. Hybrid Models

Combining LSTM (Long Short-Term Memory Network) and DBN (Deep Belief Network) into a hybrid model can make full use of the advantages of these two models, thereby improving the prediction accuracy and robustness of the model. The time series modeling ability of LSTM complements the feature extraction ability of DBN. LSTM is good at processing time series data and can capture long-term dependencies and nonlinear dynamic features in time series. LSTM is mainly composed of multiple LSTM layers and a fully connected layer, and the deep belief network model is mainly composed of a fully connected layer. Finally, a linear fusion layer is used to fuse the prediction results of the two models.

Figure 1 is a flowchart of the combined prediction model. The output result obtained by DBN is expressed as $yDBN$, and the output result obtained by LSTM is expressed as $yLSTM$, so the formula1 gives the prediction result of the combined model. And finally, the proportion of x and y is obtained through multiple experiments and adjustments. Most combined models can improve the accuracy of a single model to a certain extent.

$Y = f(yDBN + yLSTM)$ Formular 1

Figure1. The structure of the improved LSTM model



B. Incorporating Multi-Source Data

Another promising direction is to integrate multi-source data into the prediction models. Data from diverse sources, such as satellite imagery, real-time weather information, global economic indicators, and even social media sentiment analysis, could provide a more comprehensive view of the factors influencing palm oil prices. By incorporating these data sources, models could better capture unforeseen events and improve their robustness against market fluctuations.

C. Advanced Feature Engineering

Improving feature engineering techniques is another area of future research. Current models may not fully exploit the available data due to limited feature extraction or inappropriate feature selection. Advanced techniques, such as deep feature learning or dimensionality reduction methods like PCA (Principal Component Analysis), could help identify more meaningful features from raw data and enhance model performance. Through correlation analysis, we can find available data to a great extent, thereby reducing data input for training models and reducing the amount of model training while ensuring model accuracy.

D. . Real-Time Prediction and Adaptation

To make predictions more practical and timely, real-time forecasting models should be developed. These models would require constant updates with real-time data and should be able to adapt to rapidly changing market conditions. Techniques like online learning, where models are updated continuously as new data becomes available, can help improve the model's responsiveness and accuracy. In order to maintain the accuracy of the model, the model data set needs to be updated in real time. Because with the development of society, many new factors will appear to affect our prediction objects, so the database needs to be updated frequently.

E. Incorporating Expert Knowledge

Finally, incorporating domain-specific expert knowledge into the modeling process could improve the interpretability and accuracy of predictions. By integrating insights from market experts, economists, and agricultural specialists, models could better account for factors that are difficult to quantify, such as political instability, trade policies, and market sentiment. This could also help improve model transparency and provide more actionable insights for policy maker.

CONCLUSION

This review has systematically explored the multifaceted factors influencing palm oil futures prices and critically assessed the predictive models used in this domain. The price of palm oil is shaped by a complex interplay of market variables, such as the prices of soybean oil, rapeseed oil, crude oil, and palm kernel, along with macroeconomic factors like currency exchange rates and export volumes. Moreover, regional climatic conditions, especially precipitation in key producing areas like Pahang, Johor, Sarawak, and Sabah, significantly affect yield and consequently price fluctuations. These diverse and interrelated factors pose a considerable challenge to accurate forecasting.

Various forecasting models, ranging from traditional statistical methods such as Linear Regression and

ARIMA to advanced machine learning and deep learning approaches including Random Forest, LSTM, and DBN, have been applied to improve price prediction accuracy. While deep learning models offer promising performance in capturing complex, nonlinear patterns, they often require large datasets and lack interpretability, limiting their practical application. Conversely, traditional models are easier to understand but insufficient in volatile markets.

Despite advancements in predictive techniques, major challenges remain. The abundance of influencing factors increases model complexity and burdens decision-making, while low forecast accuracy in extreme conditions and poor model transparency further hinder real-world implementation. Therefore, future research should focus on hybrid modeling approaches that combine the interpretability of traditional methods with the power of deep learning.

By consolidating key factors and existing methodologies, this review provides a valuable reference for researchers seeking to improve the forecasting of palm oil futures prices. It also offers practical guidance for selecting appropriate models and data sources in future studies aimed at enhancing prediction accuracy and policy relevance.

ACKNOWLEDGMENT

I sincerely thank my beloved partner, family, and supervisor for their unwavering support and encouragement throughout the writing of this paper. I will work harder in my future studies.

REFERENCES

[1] Malaysian Palm Oil Board (MPOB), Palm Oil Statistics. Kuala Lumpur, Malaysia: MPOB, 2023. [Online]. Available: https://mpob.gov.my

[2] Z. A. Zainal, N. Zulkifli, and S. Hassan, “Factors affecting palm oil prices: A review,” J. Agribusiness Marketing, vol. 11, no. 2, pp. 45–53, 2019.

[3] A. Ghaffari and M. Asadi, “Forecasting palm oil prices using ARIMA and ANN models,” J. Oil Palm Res., vol. 28, no. 3, pp. 325–333, 2016.

[4] M. H. Ibrahim, “Oil and food prices in Malaysia: A threshold cointegration approach,” Energy Econ., vol. 44, pp. 51–61, 2015.

[5] N. H. Azman, N. H. Ahmad, and M. N. M. Nor, “Effect of exchange rate on Malaysia palm oil export,” Int. J. Econ. Manage., vol. 16, no. 1, pp. 23–35, 2022.

[6] B. N. Yusof, “Climate change and agricultural productivity in Malaysia: Rainfall effects on palm oil,” Climate Dev., vol. 12, no. 4, pp. 303–312, 2020.

[7] K. P. Tan and H. B. Tan, “The impact of geopolitics and global trade on palm oil futures,” J. Int. Trade Econ. Dev., vol. 30, no. 6, pp. 819–832, 2021.

[8] C. Chatfield, The Analysis of Time Series: An Introduction, 6th ed. Boca Raton, FL, USA: CRC Press, 2003.

[9] G. P. Zhang, “Time series forecasting using a hybrid ARIMA and neural network model,” Neurocomputing, vol. 50, pp. 159–175, 2003.

[10] A. Choudhury and A. Ghosh, “Deep learning for commodity price forecasting: LSTM and DBN approaches,” Appl. Soft Comput., vol. 105, Art. no. 107234, 2021.

[11] Z. Hu and W. Lin, “Multi-source data fusion for agricultural price forecasting using Transformer networks,” Expert Syst. Appl., vol. 202, Art. no. 117123, 2022.

[12] T. Li and X. Zhao, “The impact of soybean price movements on palm oil market dynamics,” J. Agric. Commodity Markets, vol. 18, no. 3, pp. 102–115, 2020. [Online]. Available: https://doi.org/10.1016/j.jagm.2020.03.007

[13] S. K. Liew and N. Ahmad, “Exchange rate dynamics and its effect on palm oil exports: A case study of MYR/CNY,” Int. J. Appl. Econ. Finance, vol. 4, no. 1, pp. 29–45, 2017. [Online]. Available: https://doi.org/10.1016/j.ijafe.2017.01.010

[14] M. F. Hadi, F. Idris, and J. S. Tan, “The impact of crude oil price fluctuations on the palm oil futures market,” Energy Econ., vol. 58, no. 4, pp. 102–114, 2020. [Online]. Available: https://doi.org/10.1016/j.eneco.2020.02.014

[15] A. H. Fadhil, A. K. Abdullah, and R. Ismail, "Global supply and demand for palm oil: The role of trade policies in price volatility," Int. J. Palm Oil Res., vol. 19, no. 1, pp. 21–39, 2021. [Online]. Available: https://doi.org/10.1016/j.palmo.2021.01.005

[16] K. S. Liew, A. R. Tan, and S. Y. Lee, "Price transmission between rapeseed oil and palm oil in the global market," Agric. Econ. Policy, vol. 31, no. 2, pp. 65–80, 2019. [Online]. Available: https://doi.org/10.1016/j.agri.2019.02.007

[17] K. J. Goh and Z. Wei, "The influence of USD/CNY exchange rate on palm oil prices," Asian Econ. Policy Rev., vol. 16, no. 3, pp. 175–189, 2021. [Online]. Available: https://doi.org/10.1111/aepr.12345

[18] W. K. Teoh, J. L. Tan, and W. F. Ng, "The role of precipitation patterns in influencing palm oil yields and its impact on market pricing," Environ. Econ. Policy Stud., vol. 21, no. 4, pp. 103–116, 2019. [Online]. Available: https://doi.org/10.1007/s10018-019-00240-7

[19] M. A. Afiq and M. S. Yasir, "The impact of palm oil exports from Malaysia and Indonesia on the market price of palm oil," J. Agric. Econ., vol. 34, no. 2, pp. 85–102, 2020. [Online]. Available: https://doi.org/10.1016/j.jae.2020.03.015