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# Studies comparing the effectiveness of models for drying bitter gourd slices

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**Abstract:** Drying is an essential food preservation method, improving product shelf life and quality while reducing transportation and storage costs. This study evaluated the drying kinetics of bitter gourd slices under halogen drying conditions using both traditional empirical models (Page, Midilli, Logarithmic, Peleg, and Two-Term) and the machine learning-based random forest (RF) model. Experiments were conducted at 60 °C, 65 °C, and 70 °C with slice thicknesses of 3, 5, and 7 mm. Model performance was assessed using the coefficient of determination ($R^2$), root mean square error (RMSE) and mean absolute percentage error (MAPE). The results show that the RF model demonstrated the highest accuracy, with an average $R^2$ of 0.9826, the lowest RMSE (0.0655), and MAPE (1.40 %). Its ability to capture non-linear drying behaviour made it the most reliable model. The Midilli model was the best-performing traditional model, with an average $R^2$ of 0.9851, but its accuracy declined for thicker slices and higher temperatures. Logarithmic and Peleg models exhibited significant errors, particularly during the mid-to-late drying phases. The results highlight RF's robustness and adaptability, outperforming traditional models in handling complex drying dynamics.

**Keywords:** random forest model; *Momordica charantial*; traditional drying model; halogen dryer; moisture content

Drying, one of the oldest food preservation methods, is vital in extending shelf life, reducing packaging costs, and minimising transportation weight. It removes moisture from post-harvest products through simultaneous heat and mass transfer, lowering moisture levels to inhibit microbial growth and preserve quality. The drying process is influenced by factors like temperature, humidity, air velocity, and drying time, making accurate modelling challenging due to the complexity of these interactions. Recent advancements in drying technology aim to address these challenges with both natural and artificial methods in (Azadbakht et al. 2018; Bai et al. 2018; Omari et al. 2018). While natural drying systems, such as solar and wind drying, are cost-effective, they face limitations in parameter control, weather dependency, and contamination risks (Kumar et al. 2016). Artificial drying technologies, including convection (Przybył and Koszela 2023), radiation (Sadin et al. 2014; Delfiya et al. 2022), radio wave, microwave drying (Omari et al. 2018), and combination of mid-infrared and freeze-drying (Antal 2023) offer greater precision and efficiency. Among these, halogen drying has gained popularity for its simplicity and ability to maintain precise temperature control, making it increasingly utilised in food preservation (Planinić et al. 2005; Sumnu et al. 2005; Tran et al. 2023).

Bitter gourd, widely grown in tropical and subtropical regions, is highly valued for its nutritional and medicinal properties (Gayathry and John 2022). In Vietnamese cuisine and traditional medicine, it is used for its health benefits, including lowering blood sugar levels, aiding digestion, and reducing the risk of cardiovascular diseases and cancers. The rising demand for dried bitter gourd, particularly for herbal tea production, highlights the importance of efficient drying methods like halogen drying.

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Effective drying relies on understanding the intricate interplay of multiple factors. Traditional drying models, such as Newton, Page, and Henderson-Pabis, are widely used for predicting drying behaviour based on empirical data (Kaur et al. 2020; Antal 2023; Loan et al. 2023). While these models effectively capture general drying trends, they lack the flexibility to address complex, non-linear patterns influenced by factors such as moisture diffusion, temperature variability, and slice thickness. These limitations can lead to inconsistencies in moisture content, texture, and colour retention, particularly for complex food matrices like bitter gourd. Advancements in machine learning, particularly random forest (RF), provide opportunities to overcome these challenges. Studies have shown RF's superior predictive accuracy in food drying processes, outperforming traditional models in predicting moisture content and quality metrics (Santos Pereira et al. 2018; Keramat-Jahromi et al. 2021). However, its application in predicting bitter gourd drying remains largely unexplored. Therefore, this study explores the application of RF models in drying bitter gourd slices using a halogen dryer, addressing a gap in food drying research. The primary goal is to compare the RF model's performance against traditional drying models to assess its accuracy, reliability, and potential advantages. Additionally, the study investigates the RF model's interpretability through feature importance analysis, identifying key factors influencing the drying process. Insights from this analysis aim to optimise drying conditions, enhancing energy efficiency and product quality. The research highlights the potential of machine learning to advance food processing technologies and lays a foundation for future studies integrating data-driven approaches into food preservation.

## MATERIAL AND METHODS

### Material

The experiment was conducted under laboratory conditions at the Industrial University of Ho Chi Minh City, Vietnam. Fresh bitter gourds were sourced from a local market each morning. Before the experiment, the samples were washed and air-dried. To determine the initial moisture content, the bitter gourd samples were oven-dried at 150 °C until their mass stabilised. The results showed that bitter gourd generally has an initial moisture content ranging from 92 to 95% (wet basis), aligning closely with values reported in previous research studies (Biswas et al. 2018).

### Drying equipment

Figure 1 depicts the halogen dryer setup for the experiments. The dryer measures 550 × 550 × 850 mm, featuring two plates with four stainless steel trays. Each plate includes three 100 W halogen lamps, providing a total power of 600 W. The chamber reaches a maximum temperature of 90 °C. A rotating shaft, controlled by an inverter, positions the trays, while a solid-state relay (SSR) regulates lamp intensity to maintain stable drying temperatures. The SSR reduces intensity once the set temperature is reached. The system has four temperature sensors: one for ambient temperature, two for internal drying temperature, and one for outlet temperature. Two fans at the top expel moisture during drying. Figure 1B shows the DDC-C46 device (PNTECH CONTROLS, Vietnam), which collects data via an RS32 connection. The DDC software records data every 2 min after reaching a steady state. Before each experiment, the dryer was preheated for 30 min to achieve the required conditions. Once stabilised, bitter gourd samples were placed on trays, and the drying process began. The DDC-C46 ensured precise temperature monitoring, contributing to reliable experimental results.

### Determination of moisture content

During the drying process, the sample weight loss of the drying material is determined periodically every 30 min and calculated according to the following formula in published articles (Yasmin et al. 2022):

$$MC = \frac{m_c - m_k}{m_k} \times 100 \tag{1}$$

where: $MC$ – moisture content wet basis of drying material at the time of determination (%); $m_c$ – mass of drying material at time $t$ (g); $m_k$ – mass of drying material at the time of determination $t$ + 1 (g).

### Drying model

***Traditional drying models.*** For mathematical modelling of the drying process, the following equation was used to calculate the moisture ratio ($MR$) of bitter gourd slices before fitting a model:

$$MR = \frac{M_t - M_e}{M_o - M_e} \tag{2}$$

where: $MR$ – moisture ratio (dimensionless); $M_t$ – mean moisture content of the bitter gourd slices at any given time (kg water·kg dry matter$^{-1}$); $M_o$ – initial moisture content (kg water·kg dry matter$^{-1}$); $M_e$ – equilibrium moisture content (kg water·kg dry matter$^{-1}$).

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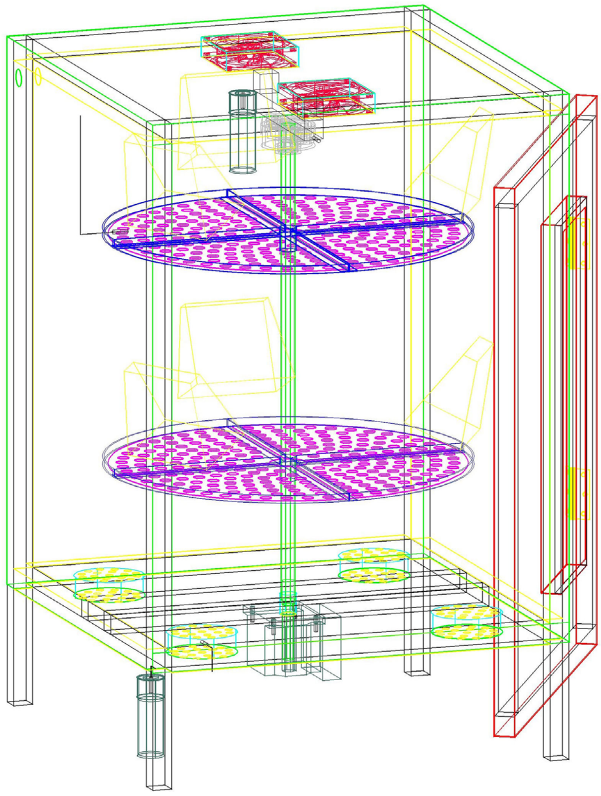
(A)



(B)

Figure 1. Halogen dryer: (A) the dryer; (B) DDC-C46 controller

In long drying processes, the equilibrium moisture content $M_e$ is generally negligible compared to the initial moisture content $M_o$. Therefore, Equation (2) can be simplified to Equation (3) (Movagharnejad and Nikzad 2007).

$$MR = \frac{M_t}{M_o} \tag{3}$$

As a result, measuring the equilibrium moisture content is unnecessary for this Equation. Traditional drying models are often empirical or semi-empirical and are widely used in food drying applications. These models are based on kinetic equations that describe the drying rate over time, typically assuming a particular drying mechanism. Table 1 lists some of the most frequently applied models for drying agricultural products. Each constant in these drying models ($k$, $a$, $b$, $c$, $k_o$, $n$) are determined by regression analysis.

***Random forest model.*** The RF model is a robust machine learning algorithm designed to handle complex, non-linear relationships (Breiman 2001).

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Table 1. Thin-layer drying models developed by researchers for agricultural products (Movagharnejad and Nikzad 2007)

| Model No. | Name | Formula |
|---|---|---|
| 1 | Page model | $MR = \exp(-kt^n)$ |
| 2 | Midilli model | $MR = a\exp(-kt) + bt$ |
| 3 | Logarithmic model | $MR = a\exp(-kt) + c$ |
| 4 | Peleg model | $MR = 1 - \frac{t}{a + bt}$ |
| 5 | Two term model | $MR = a\exp(-k_o t) + b\exp(-k_1 t)$ |

$t$ – time (min); $a$, $b$, $c$, $n$ – coefficients, dimensionless; $k$, $k_o$, $k_1$ – constant drying ratio coefficient (L·min$^{-1}$); $MR$ – moisture ratio

As an ensemble method, RF constructs multiple decision trees from random subsets of data and aggregates their outputs for accurate predictions while minimising overfitting (Svetnik et al. 2003). In food drying, RF surpasses traditional models by learning directly from data, effectively capturing interactions among factors like temperature, humidity, and slice thickness. For bitter gourd drying, RF predicts key outcomes such as moisture content, drying time, and quality metrics without relying on predefined equations (Azmi et al. 2021). As is known, RF is a type of supervised learning algorithm that can be used for both classification and regression tasks. In regression tasks, it predicts continuous values by averaging the results of multiple decision trees. Hence, this study selected the RF regression technique for predicting numerical values for drying. Three input variables consisted of drying time, slice thickness, and temperature – were used as predictors, while the moisture ratio ($MR$) served as the target output. The model was trained on a randomly selected subset of the experimental dataset, and internal validation was carried out using the out-of-bag (OOB) error estimation inherent to random forests. The RF model was implemented with the number of trees set to 500 and the number of predictors sampled at each node set to 3, following standard practice for regression tasks. Important RF parameters, such as sampling with replacement (bootstrap was selected True) and feature importance evaluation, were also enabled to enhance model interpretability. This configuration allowed the RF model to efficiently capture complex, non-linear drying dynamics without reliance on predefined kinetic equations. The detailed statistical evaluation of RF model performance, including $R^2$, RMSE, and MAPE metrics, is presented separately below.

***Evaluation performance of drying models.*** The performance of drying models, such as random forest and traditional methods, can be evaluated using several key metrics. Root mean squared error (RMSE) assess the magnitude of prediction errors, with RMSE being more sensitive to large deviations, while the coefficient of determination ($R^2$) score measures how well the model explains the variance in drying data. Mean absolute percentage error (MAPE) provides a percentage-based error for easier interpretation across different experiments. Additionally, computational efficiency, model robustness, and generalisation capacity are essential, as random forest and traditional models differ in their training time and ability to handle diverse drying conditions. These metrics are calculated as follows:

$$R^2 = 1 - \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 / \sum_{i=1}^{n}(y_i - \overline{y}_i)^2 \tag{4}$$

$$\text{RSME} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \tag{5}$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{6}$$

where: $y_i$ – measured value of observed target in experiment and $\hat{y}_i$ – predicted value from drying models; $n$ – number of validation points; the accuracy assessment of a model is a compromise between these measured values.

### Experimental setup

Several studies (Biswas et al. 2018; Yan et al. 2019), indicate that the drying temperature for bitter gourd typically ranges between 40 °C and 80 °C, depending on the slice thickness and drying method used. Therefore, this study examines drying temperature and slice thickness as key factors impacting the drying process. Temperature settings of 60, 65, and 70 °C were selected, along with bitter gourd slices of 3, 5, and 7 mm thickness. The drying duration was standardised at 9 h across all experimental conditions. Each experiment was conducted in triplicate, and the average result was calculated for each condition.

## RESULTS AND DISSCUSSION

### Results of experiment

This study collected 270 data points across nine experimental conditions, each repeated three times,

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to train and test the RF model for predicting *MR* during bitter gourd drying. The dataset, split into training and testing groups, included drying time, slice thickness, and temperature as independent variables, with *MR* as the dependent variable. The same data were used to evaluate traditional drying models. The Table 2 presents the training performance results across the nine conditions.

Table 2 provides a detailed comparison of the model parameters and statistical metrics used to evaluate the drying behaviour of bitter gourd slices under varying thicknesses and temperatures. The analysed models include Page, Midilli, Logarithmic, Peleg, Two-term, and RF. Key parameters (e.g. $k$, $k_o$, $k_1$, $a$, $b$, $c$, $n$) and statistical metrics $R^2$, RMSE, and MAPE are presented for each model.

The RF model consistently outperforms traditional models across all conditions, with $R^2$ values nearing 1.0 (e.g. 0.9999), RMSE as low as 0.0030, and MAPE as low as 0.05% (e.g. at 65 °C and 5 mm thickness). This highlights its superior predictive accuracy. Traditional models like Midilli and Logarithmic also show strong performance under specific conditions (e.g. $R^2$ of 0.9975 for Midilli at 60 °C and 3 mm thickness) but generally exhibit higher RMSE and MAPE values. The Peleg and Two-term models demonstrate

Table 2. Model parameters and statistical metrics for fitting drying models

| Thickness (mm) | Temperature (°C) | Model | Model parameters | | | | | | | $R^2$ | RMSE | MAPE (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | $k$ | $k_o$ | $k_1$ | $a$ | $b$ | $c$ | $n$ | | | |
| 3 | 60 | Page | 0.0018 | – | – | – | – | – | 1.3049 | 0.9975 | 0.0154 | 0.63 |
| | | Midilli | 0.0080 | – | – | 1.0420 | 0.0001 | – | – | 0.9908 | 0.0294 | 2.31 |
| | | Logarithmic | 0.0075 | – | – | 1.0877 | – | 0.0500 | – | 0.9922 | 0.0271 | 2.35 |
| | | Peleg | – | – | – | 108.3927 | 0.7356 | – | – | 0.9767 | 0.0468 | 4.42 |
| | | Two term | – | 0.0087 | 0.0086 | 0.5423 | 0.5181 | – | – | 0.8825 | 0.1051 | 2.44 |
| | | RF | – | – | – | – | – | – | – | 0.9975 | 0.0309 | 0.35 |
| | 65 | Page | 0.0009 | – | – | – | – | – | 1.3861 | 0.9985 | 0.0125 | 0.23 |
| | | Midilli | 0.0064 | – | – | 1.0566 | 0.0001 | – | – | 0.9900 | 0.0319 | 1.54 |
| | | Logarithmic | 0.0058 | – | – | 1.1372 | – | 0.0850 | – | 0.9914 | 0.0295 | 1.50 |
| | | Peleg | – | – | – | 148.7522 | 0.6598 | – | – | 0.9793 | 0.0459 | 2.61 |
| | | Two term | – | 0.0072 | 0.0072 | 0.4309 | 0.6519 | – | – | 0.9815 | 0.0435 | 1.57 |
| | | RF | none | – | – | – | – | – | – | 0.9999 | 0.0030 | 0.10 |
| | 70 | Page | 0.0021 | – | – | – | – | – | 1.4246 | 0.9966 | 0.0163 | 0.72 |
| | | Midilli | 0.0148 | – | – | 1.0471 | 0.0000 | – | – | 0.9829 | 0.0366 | 2.54 |
| | | Logarithmic | 0.0143 | – | – | 1.0599 | – | –0.0151 | – | 0.9840 | 0.0354 | 2.97 |
| | | Peleg | – | – | – | 48.5400 | 0.8560 | – | – | 0.9468 | 0.0645 | 7.23 |
| | | Two term | – | 0.0149 | 0.0150 | 0.5173 | 0.5345 | – | – | 0.9824 | 0.0371 | 1.83 |
| | | RF | – | – | – | – | – | – | – | 0.9918 | 0.0302 | 0.32 |
| 5 | 60 | Page | 0.0007 | – | – | – | – | – | 1.4523 | 0.9948 | 0.0232 | 0.59 |
| | | Midilli | 0.0069 | – | – | 1.0579 | –0.0001 | – | – | 0.9825 | 0.0424 | 2.75 |
| | | Logarithmic | 0.0063 | – | – | 1.1352 | – | –0.0819 | – | 0.9847 | 0.0397 | 2.77 |
| | | Peleg | – | – | – | 135.0474 | 0.6761 | – | – | 0.9692 | 0.0563 | 4.37 |
| | | Two term | – | 0.0078 | 0.0078 | 0.5499 | 0.5396 | – | – | 0.9732 | 0.0526 | 2.82 |
| | | RF | – | – | – | – | – | – | – | 0.9964 | 0.0193 | 0.08 |
| | 65 | Page | 0.0006 | – | – | – | – | – | 1.4532 | 0.9938 | 0.0253 | 0.34 |
| | | Midilli | 0.0063 | – | – | 1.0516 | –0.0002 | – | – | 0.9824 | 0.0427 | 2.11 |
| | | Logarithmic | 0.0057 | – | – | 1.1456 | – | –0.0985 | – | 0.9845 | 0.0401 | 2.08 |
| | | Peleg | – | – | – | 149.7336 | 0.6504 | – | – | 0.9718 | 0.0541 | 3.21 |
| | | Two term | – | 0.0073 | 0.0073 | 0.5115 | 0.5723 | – | – | 0.9713 | 0.0546 | 2.06 |
| | | RF | – | – | – | – | – | – | – | 0.9988 | 0.0112 | 0.05 |

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Table 2. To be continued

| Thickness (mm) | Temperature (°C) | Model | Model parameters $k$ | $k_0$ | $k_1$ | $a$ | $b$ | $c$ | $n$ | $R^2$ | RMSE | MAPE (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 5 | 70 | Page | 0.0012 | – | – | – | – | – | 1.4558 | 0.9968 | 0.0172 | 0.61 |
| | | Midilli | 0.0106 | – | – | 1.0616 | −0.0001 | – | – | 0.9810 | 0.0417 | 2.74 |
| | | Logarithmic | 0.0101 | – | – | 1.0889 | – | −0.0310 | – | 0.9827 | 0.0397 | 2.97 |
| | | Peleg | – | – | – | 78.1136 | 0.7900 | – | – | 0.9533 | 0.0653 | 5.87 |
| | | Two term | – | 0.0109 | 0.0110 | 0.5265 | 0.5403 | – | – | 0.9787 | 0.0441 | 2.02 |
| | | RF | – | – | – | – | – | – | – | 0.9990 | 0.0105 | 0.12 |
| 7 | 60 | Page | 0.0003 | – | – | – | – | – | 1.5343 | 0.9922 | 0.0294 | 8.02 |
| | | Midilli | 0.0041 | – | – | 1.0448 | −0.0003 | – | – | 0.9881 | 0.0363 | 23.62 |
| | | Logarithmic | 0.0034 | – | – | 1.3150 | – | −0.2735 | – | 0.9897 | 0.0339 | 22.50 |
| | | Peleg | – | – | – | 236.3799 | 0.4846 | – | – | 0.9846 | 0.0414 | 29.59 |
| | | Two term | – | 0.0030 | 0.0029 | 21.1317 | −20.0788 | – | – | 0.9835 | 0.0428 | 5.02 |
| | | RF | – | – | – | – | – | – | – | 0.9696 | 0.0488 | 1.01 |
| | 65 | Page | 0.0003 | – | – | – | – | – | 1.5248 | 0.9929 | 0.0280 | 2.34 |
| | | Midilli | 0.0047 | – | – | 1.0486 | −0.0003 | – | – | 0.9853 | 0.0402 | 10.82 |
| | | Logarithmic | 0.0040 | – | – | 1.2499 | – | −0.2051 | – | 0.9872 | 0.0375 | 10.34 |
| | | Peleg | – | – | – | 208.2510 | 0.5358 | – | – | 0.9801 | 0.0468 | 14.22 |
| | | Two term | – | 0.0056 | 0.0056 | -6.7904 | 7.8043 | – | – | 0.9558 | 0.0697 | 11.43 |
| | | RF | – | – | – | – | – | – | – | 0.9984 | 0.0853 | 0.28 |
| | 70 | Page | 0.0008 | – | – | – | – | – | 1.4496 | 0.9962 | 0.0123 | 0.89 |
| | | Midilli | 0.0075 | – | – | 1.0611 | −0.0001 | – | – | 0.9834 | 0.0411 | 5.34 |
| | | Logarithmic | 0.0069 | – | – | 1.1257 | – | −0.0694 | – | 0.9855 | 0.0384 | 5.40 |
| | | Peleg | – | – | – | 122.2889 | 0.6993 | – | – | 0.9676 | 0.0574 | 9.13 |
| | | Two term | – | 0.0083 | 0.0083 | 0.5491 | 0.5388 | – | – | 0.9755 | 0.0499 | 4.95 |
| | | RF | – | – | – | – | – | – | – | 0.9997 | 0.0097 | 0.69 |

RF – random forest; RMSE – root mean square error; MAPE – mean absolute percentage error

more variability, with lower $R^2$ values and less reliable predictions. For instance, at 60 °C and 3 mm thickness, the Page model achieves an $R^2$ of 0.9975 but shows higher RMSE (0.0154) and MAPE (0.63%) compared to RF. In contrast, the Two-term model underperforms, with $R^2$ of 0.8825 and MAPE of 2.44%.

As slice thickness increases, the performance of traditional models declines significantly. For example, the Midilli and Logarithmic models maintain high $R^2$ values at 3 mm but degrade as thickness rises to 7 mm. At 7 mm thickness, Peleg shows an $R^2$ of 0.9533 and a MAPE of 29.59% (e.g. at 60 °C), highlighting its diminished reliability. Meanwhile, the RF model remains robust, with $R^2$ values near 1.0, low RMSE (e.g. 0.0105), and minimal MAPE (e.g. 0.12% at 7 mm thickness and 70 °C), demonstrating its consistency and adaptability.

In summary, while traditional models like Page, Midilli, and Logarithmic offer reasonable fits under specific conditions, their predictive accuracy decreases with increasing thickness. The RF model, however, consistently delivers superior performance across all conditions, making it the most accurate and reliable choice for modelling the drying kinetics of bitter gourd slices.

**Performance evaluation of drying models**

***Performance of drying models in drying conditions.*** Figure 2 compares actual and predicted *MR* values for various drying models at 60 °C across three slice thicknesses. For 3 mm slices, the RF and Midilli models demonstrate superior accuracy, closely matching the observed data throughout the drying process, while minor deviations are observed in the Peleg and Two-term

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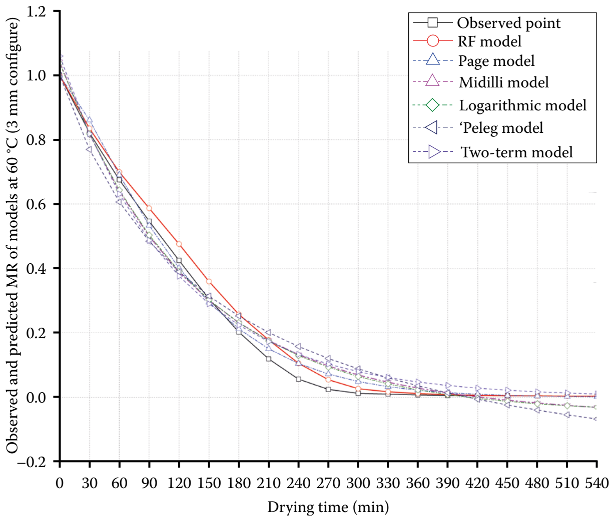
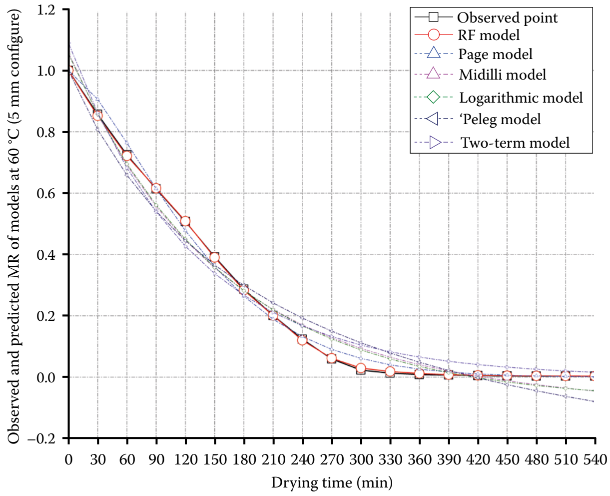
models during later stages. For 5 mm slices, the RF and Midilli models maintain their strong performance, with the Page and Logarithmic models showing slight deviations, particularly in the mid-drying stages, and the Peleg model exhibiting increasing discrepancies in the later stages. For 7 mm slices, the RF model outperforms all other models, particularly during intermediate drying stages, while the Midilli model remains competitive but underpredicts *MR* at higher drying times. The Peleg and Two-term models fail to capture non-linear drying behaviour effectively, showing the largest deviations. Overall, the RF model consistently delivers the most accurate predictions across all thicknesses, with the Midilli model performing well for thinner slices. Traditional models like Peleg and Two-term struggle with thicker slices, highlighting the RF model's robustness in managing complex, non-linear drying dynamics. Performance at 65 °C across 3, 5, and 7 mm thicknesses.

Figure 3 presents the performance of various drying models at 65 °C across three slice thicknesses. For 3 mm slices, the RF model delivers exceptional accuracy, followed closely by the Midilli model with minimal deviations. The Page and Logarithmic models are reasonably accurate but show slight underpredictions during later stages, while the Peleg and Two-term models exhibit significant inaccuracies in the final phases. For 5 mm slices, the RF model continues to dominate, with Midilli and Page models maintaining strong performance but showing minor underestimations during later drying stages. In contrast, the Logarithmic and

(A)




(B)




(C)

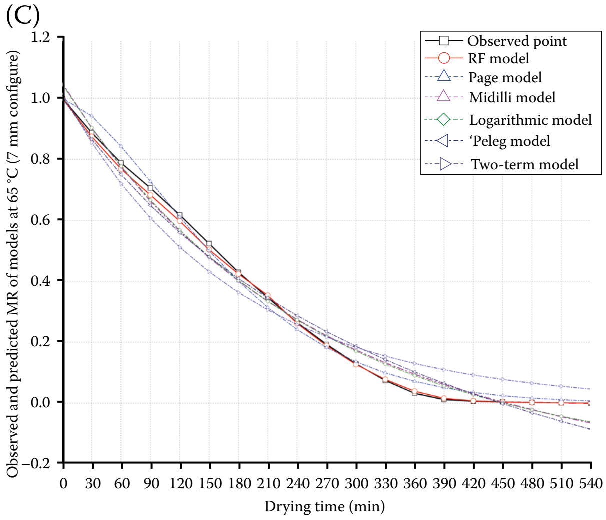



Figure 2. Comparison of observed and predicted moisture ratios (*MR*) for various drying configurations: (A) 60 °C, 3 mm; (B) 60 °C, 5 mm; (C) 60 °C, 7 mm

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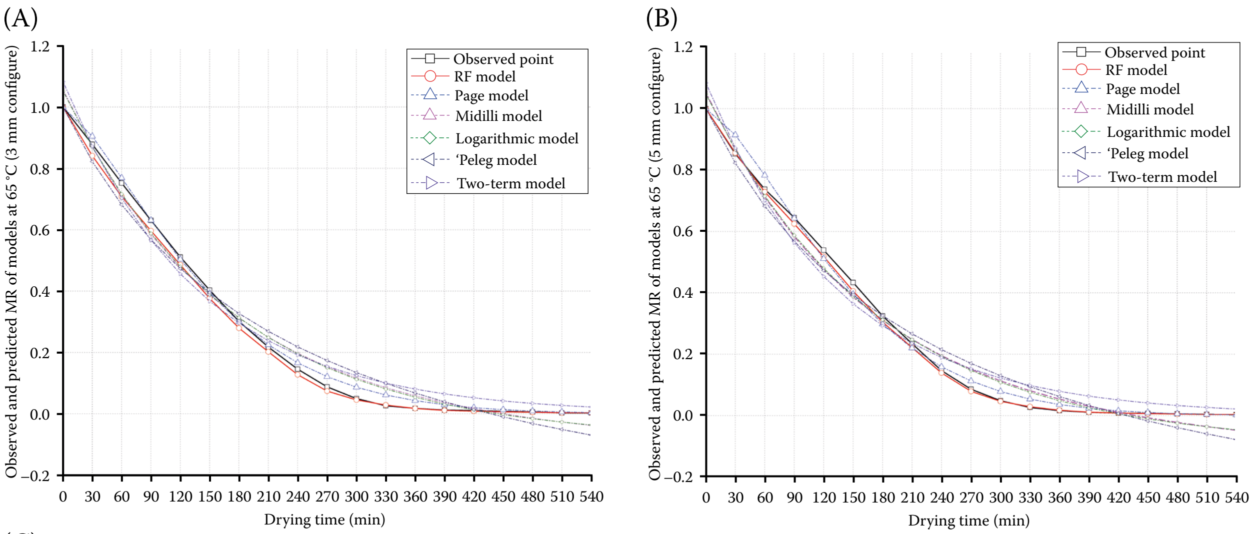
Peleg models exhibit increasing deviations, particularly at reduced drying rates in the final stages. For 7 mm slices, the RF model remains the most accurate, effectively capturing mid-drying trends, while the Midilli model demonstrates slight deviations in the later stages. Traditional models such as Page, Logarithmic, and Two-term underpredict moisture beyond 270 minutes, and the Peleg model displays significant errors, failing to account for non-linear moisture diffusion. Overall, the RF model achieves the highest predictive accuracy across all slice thicknesses, particularly for thicker slices. While the Midilli model remains competitive, its accuracy diminishes as slice thickness increases. Traditional models, especially Peleg and Two-term, struggle to adapt to the complexities of non-linear drying conditions, underscoring RF's robustness. Performance at 70 °C Across 3 mm, 5 mm, and 7 mm thicknesses.

Figure 4 compares observed and predicted MR values for various drying models at 70 °C across different slice thicknesses. For 3 mm slices, the RF model demonstrates exceptional accuracy throughout the drying process, with the Midilli model performing well and showing minimal deviations. The Page and Two-term models provide moderate accuracy, while the Logarithmic and Peleg models underestimate moisture removal during the later stages. For 5 mm slices, the RF model continues to excel, maintaining its strong predictive performance. The Midilli model remains effective but exhibits slight deviations in the later stages, whereas the Page and Two-term models show growing inaccuracies. The Logarithmic and Peleg models struggle significantly, failing to capture mid-drying dynamics and non-linear trends. For 7 mm slices, the RF model remains the most accurate, though minor deviations occur in the later stages due to increased drying complexity. The Midilli model shows greater deviations compared to thinner slices, and traditional models such as Page, Logarithmic, Peleg, and Two-term exhib-



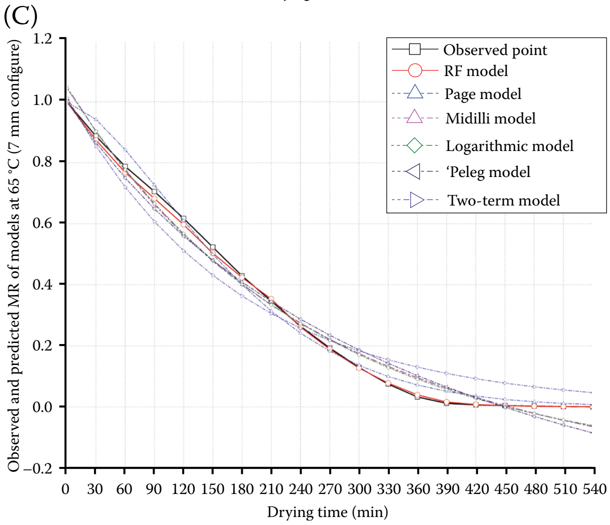




Figure 3. Comparison of observed and predicted moisture ratios (*MR*) for various drying configurations: (A) 65 °C, 3 mm; (B) 65 °C, 5 mm; (C) 65 °C, 7 mm

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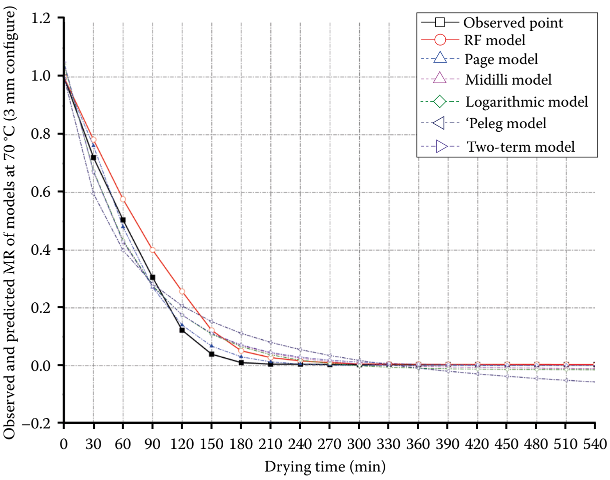
it substantial errors, particularly in the mid-to-late drying stages. Overall, the RF model consistently delivers superior accuracy across all slice thicknesses, reinforcing its effectiveness in managing complex, non-linear drying dynamics at higher temperatures. Overall, the RF model proves highly reliable under high-temperature and non-linear conditions, particularly for thicker slices. While the Midilli model performs well, it shows diminishing accuracy for 7 mm slices. Traditional models, especially Peleg and Logarithmic, are least effective for advanced drying stages.

***Influence of temperature on drying models.*** Temperature significantly influences drying kinetics, with distinct trends across conditions. At 60 °C, the slower drying rate supports extended moisture diffusion, with RF showing exceptional accuracy and Midilli performing well during early and late stages, while traditional models like Logarithmic and Peleg exhibit significant deviations, especially for thicker slices. At 65 °C, faster drying promotes uniform moisture removal, with RF delivering near-perfect predictions and Midilli improving during mid-drying stages. Traditional models like Page and Two-term perform better but still struggle with thicker slices, while Logarithmic and Peleg models show notable inaccuracies. At 70 °C, rapid drying enhances efficiency, with RF excelling across all thicknesses. Midilli remains strong but shows reduced accuracy for thicker slices in later stages, while traditional models, particularly Logarithmic and Peleg, display substantial deviations. Overall, RF consistently outperforms traditional models, demonstrating superior flexibility and accuracy, with Midilli being the most competitive traditional model, particularly at moderate drying conditions.

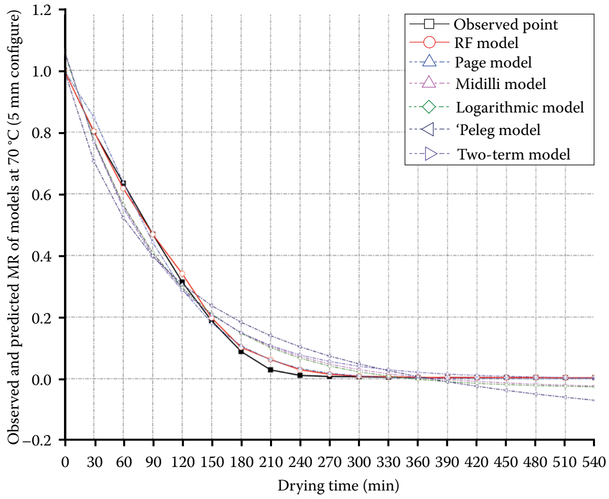
## CONCLUSION

Bitter gourd slices were dried using a halogen drier at 60 °C, 65 °C, and 70 °C, with thicknesses of 3, 5, and

(A)




(C)




(C)

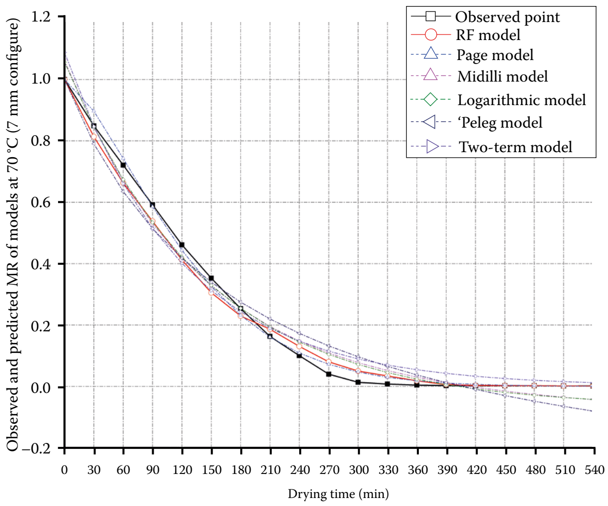



Figure 4. Comparison of observed and predicted moisture ratios (*MR*) for various drying configurations: (A) 70 °C, 3 mm; (B) 70 °C, 5 mm; (C) 70 °C, 7 mm

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7 mm. This study compared traditional empirical drying models (Page, Midilli, Logarithmic, Peleg, and Two-Term) with a machine learning approach, RF, to predict the drying kinetics of bitter gourd slices. The RF model consistently outperformed traditional models, achieving the highest $R^2$ values and lowest error metrics (RMSE and MAPE), thanks to its ability to capture complex, non-linear interactions between drying parameters. Among traditional models, Midilli and Page performed well under moderate conditions but struggled with variability in temperature and slice thickness.

Temperature significantly impacted model accuracy, with higher temperatures improving fits across all models due to accelerated moisture removal. However, traditional models, limited by their simplified equations, often failed to address the multi-dimensional effects of temperature and moisture diffusion. While RF demonstrated superior flexibility and accuracy, its reliance on extensive data and computational resources may pose challenges for industrial use. In contrast, traditional models remain practical for applications requiring moderate accuracy due to their simplicity and ease of implementation.

This study highlights the need to choose drying models based on operational requirements and resources. Hybrid approaches combining RF's accuracy with the interpretability of traditional models could offer a balanced solution, providing high precision, practicality, and adaptability for diverse drying processes.

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