

Mathematical modeling of coffee beans drying: addressing challenges of determining moisture ratio under natural conditions

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ABSTRACT

Coffee bean drying is a critical step in post-harvest processing because it directly affects the quality of the final product. The moisture ratio (MR) during drying is a key parameter that must be carefully controlled to prevent over- or under-drying, both of which can degrade coffee quality. In this study, we investigate fourteen mathematical models existing in the literature that describe the MR during the drying of coffee beans. Each model is evaluated in terms of its formulation, applicability, and relevance to coffee drying. Furthermore, we numerically simulate each model using experimental drying data collected from Génova, Quindío (Colombia), under natural conditions, a region renowned for its high-quality coffee production. The simulations provide a comparison of the accuracy and predictive capability of the models under real-world environmental conditions, highlighting the need for more sophisticated models that integrate humidity, temperature, and real-time weather data to improve the accuracy and efficiency of the drying process.

Key words: Experimental data; natural drying; model evaluation; model validation; weather; integration.

1 INTRODUCTION

Coffee is one of the most widely consumed beverages globally, and its quality is heavily influenced by post-harvest processing, particularly during the drying stage Kleinwächter et al. (2025). Drying is a critical step that reduces the moisture content of coffee beans to a level suitable for storage and milling, typically between 10% and 12% (wet basis) Brando and Brando (2014). Proper drying not only prevents microbial spoilage but also preserves the chemical composition of the beans, including volatile compounds responsible for flavor and aroma Kulapichitr et al. (2019). Conversely, improper drying, whether over-drying or under-drying can lead to defects such as off-flavors, discoloration, and reduced market value Brando and Brando (2014). Therefore, optimizing the drying process is essential to maintain the high standards demanded by the global coffee industry.

Besides, monitoring and collecting real-time data during the coffee bean drying process presents significant challenges due to the dynamic nature of environmental conditions and the need for precise control over parameters, such as moisture content, air temperature, and humidity, in order to fit the data with mathematical models for coffee beans drying process. Traditional methods often rely on time-consuming manual measurements, can be subject to human error, and lack the granularity needed to capture subtle changes in drying conditions. These limitations can lead to inconsistencies in drying quality, ultimately affecting the final product's market value. To address

these challenges in our investigation, the data collection process in Acosta-Minoli et al. (2024) proposes an innovative Internet-of-Things (IoT)-based technology designed for real-time monitoring and analysis of the coffee drying process. This system utilizes portable sensors and advanced data analytics to continuously track critical drying parameters, providing farmers with actionable insights through a user-friendly mobile interface. The study implemented this technology in collaboration with a female smallholder coffee farmer association in Génova, Quindío, Colombia, demonstrating its potential to enhance drying efficiency and coffee quality.

Mathematical modeling has become an indispensable tool for understanding and predicting the drying behavior of agricultural products. These models describe the relationship between moisture content, drying time, and environmental conditions, providing a theoretical framework for optimizing drying parameters Defraeye, T. (2014) For coffee beans, the MR, defined as the ratio of the difference between the initial and equilibrium moisture contents to the difference between the instantaneous and equilibrium moisture contents, is a key parameter that quantifies the drying kinetics Doymaz (2005). Accurate modeling of the MR is crucial for designing efficient drying systems and ensuring consistent product quality.

Several mathematical models have been developed to describe the drying kinetics of agricultural products, including thin-layer drying models, diffusion-based models, and empirical equations. Thin-layer models, such as the Lewis (Newton); Lewis (1921), and Henderson-Pabis models Henderson et al.

(1961), are widely used because of their simplicity and ability to describe the drying process under constant conditions. Diffusion-based models Overhults et al. (1973), on the other hand, account for the internal moisture transfer within the product and are more complex but provide deeper insights into the physical mechanisms of drying. Empirical models derived from experimental data offer a practical approach for predicting drying behavior under specific conditions Franca, Mendonça and Oliveira (2005). The applicability of these models to coffee drying depends on factors such as bean variety, drying method (e.g., sun drying, mechanical drying), and environmental conditions. For instance, sun drying, which is commonly used in small-scale coffee production, is influenced by ambient temperature, humidity, and solar radiation, whereas mechanical drying allows for more controlled conditions but requires precise modeling to optimize energy use. Despite the availability of numerous models, there is no consensus on the most suitable approach for drying. Since solar drying of coffee beans is highly sensitive to environmental conditions, including temperature fluctuations, humidity changes, and inconsistent sunlight exposure. These factors cause uneven drying rates, leading to quality issues like mold growth or over-fermentation. To address this, farmers and researchers Meja, Dubbe and Bekele (2025) test different drying methods, such as hybrid solar dryers S. Deeto, Thepa and Monyakul (2008), to optimize bean quality while adapting to natural weather variations. Performance is typically evaluated through moisture content monitoring and visual inspection of bean defects.

In this study, we investigated and evaluated fourteen mathematical models that describe the drying kinetics of coffee beans. These models are analyzed in terms of their formulation, applicability, and relevance to coffee drying. Génova (Colombia), a region recognized for its exceptional coffee production, presents unique environmental conditions that influence the drying process, making it an ideal case study for assessing model performance. We numerically simulate each model using experimental drying data collected from this region, comparing its predictions with real-world observations. Through this analysis, we seek not only to identify the most accurate and reliable models but also to determine the gaps and limitations in current modeling approaches. Thus, our goal is to pinpoint areas for improvement and innovation in mathematical modeling, paving the way for more precise and adaptive models that better capture the complexities of coffee drying and contribute to the advancement of sustainable and efficient post-harvest processing.

2 MATERIAL AND METHODS

2.1 Mathematical models for the MR

Throughout this study, the selection of the 14 mathematical models for analyzing the coffee drying process

was guided by a comprehensive literature review, which identified models widely recognized for their accuracy and applicability in describing the drying kinetics of the coffee beans drying process. These models were chosen based on their proven ability to capture the relationship between moisture content, drying time, and environmental conditions, which are critical for optimizing the coffee drying process. The decision to limit the selection to 14 models was driven by the need to focus on the most relevant and widely used frameworks, ensuring a balance between computational efficiency and theoretical robustness, and also to focus on the models that are investigating the moisture ratio in a coffee bean during the drying process.

The Lewis model Lewis (1921), also known as the Newton model, is one of the simplest models for describing the MR. It assumes that the rate of moisture loss is proportional to the current moisture content, which is often used in the initial stages of coffee bean drying, where surface moisture evaporates rapidly. It provides a good approximation for thin-layer drying of coffee beans under constant environmental conditions. In addition, the Page model Corrêa, Resende and Ribeiro (2006) introduces an additional parameter to account for the nonlinearity in the drying process by adding a Page exponent, to describe the drying of coffee beans when the process deviates from simple exponential decay. It is widely used in studies of coffee drying kinetics, especially when the drying rate changes over time due to variations in bean structure or environmental conditions. In addition, the Modified Page model White, Ross and Poneleit (1981) further refines it by adjusting the placement of the exponent, which is particularly useful for predicting moisture content in the later stages of drying. To extend the Lewis model, the Henderson and Pabis model introduces a coefficient to account for the initial moisture content, which is often used to model the drying of coffee beans with high initial moisture levels. However, the drying process reaches a non-zero equilibrium moisture content, which is common in coffee drying. This property can be described by extending the Henderson and Pabis model to the Logarithmic model by adding a constant. Additionally, when the drying process involves two distinct phases, such as surface moisture removal followed by internal moisture diffusion. The two-term model is often used to describe the drying of coffee beans with complex internal structures. When the coffee drying involves multiple mechanisms, such as simultaneous surface evaporation and internal moisture diffusion. The modified Henderson and Pabis model Henderson et al. (1961) is particularly useful for high-precision drying studies because it adds a third term to a two-term model Henderson (1974). On the other hand, if the two drying mechanisms are interdependent, such as when the surface and internal drying rates are influenced by the same environmental factors, the two-term exponential model provides a better description of a complex drying process.

When the drying process is influenced by diffusion mechanisms, which are common in coffee beans due to their porous structure. The Approximation of the diffusion model is particularly useful for predicting moisture gradients within beans by adjusting the Two-term Exponential model Sharaf-Eldeen, Blaisdell and Hamdy (1980) using a new coefficient. In addition, we captured both exponential and linear characteristics of the coffee drying processes. The Midili model is widely used in studies of coffee drying under varying environmental conditions. Hence, by adding a constant term to the Midili model, we can describe the drying process that reaches a constant moisture content. This adjustment is called the modified Midili model Phitakwinai, Blaisdell and Hamdy (2019), Ghazanfari et al. (2006). However, the MR changes quadratically with time, such as in certain types of mechanical drying systems used for coffee beans. A polynomial approach becomes useful when using the Wang & Singh model. In addition, the MR can decrease sigmoidally over time, such as in controlled drying environments with gradual moisture removal, which can be modeled using a sigmoidal function with the logistic model. The Verma model is suitable for coffee drying processes involving two distinct drying rates, that is, when surface and internal drying occur

at different speeds. Finally, the Successive Residues model is used for complex drying processes where multiple mechanisms (e.g., surface evaporation, internal moisture diffusion, and temperature effects) influence the moisture removal rate, which is based on the idea that the drying process can be broken down into successive stages, each governed by different physical mechanisms. Hence, the set of models mentioned for coffee drying is presented in Table 1.

2.2 Experimental data

Experimental data were collected from the drying process of Pergamino coffee beans in Génova (Quindío, Colombia) using a solar-bed thin-layer drying method. Throughout a study by Acosta-Minoli et al. (2024), which proposes an Internet-of-Things (IoT)-based technology for real-time monitoring and analysis of the coffee drying process. This technology utilizes a portable set of sensors and data analytics to collect real-time data on critical parameters such as grain moisture, air temperature, and humidity and can be more reliable than a manual record of the data. Our motivation is to make use of the collected data to fit them into the mathematical models for coffee beans natural drying process.

Table 1: Mathematical models for drying process of coffee beans: the mathematical models selected for analyzing the coffee drying process, chosen through a comprehensive literature review based on their widespread use, accuracy, and applicability in describing the moisture ratio during the drying kinetics, where, the moisture ratio (MR) is a key parameter in the drying of coffee beans, representing the normalized moisture content of the beans during the drying process. It is calculated as the ratio of the difference between the current moisture content (MR_t) and the equilibrium moisture content (MR_e) to the difference between the initial moisture content (MR_0) and (MR_e). Mathematically, $MR = (M_t - M_e) / (M_0 - M_e)$. This ratio starts at 1 when drying begins and decreases toward 0 as the beans approach equilibrium moisture content.

Model	Equation	Reference
$MR = e^{-kt}$	Lewis (Newton)	Lewis (1921)
$MR = e^{-kt^n}$	Page	Page (1949)
$MR = e^{(-kt)^n}$	Modified Page	White, Ross and Poneleit (1981)
$MR = a e^{(-kt)}$	Henderson and Pabis	Henderson et al. (1961)
$MR = a e^{(-kt)} + c$	Logarithmic	Yaldiz, Ertekin and Uzun (2001)
$MR = a e^{(-kt)} + b e^{(-gt)}$	Two-term	Chen and Clayton (1971)
$MR = a e^{(-kt)} + b e^{(-gt)} + n e^{(-ct)}$	Modified Henderson and Pabis	Henderson et al. (1961)
$MR = a e^{(-kt)} + (1 - a)e^{(-kat)}$	Two-term exponential	Sharaf-Eldeen, Blaisdell and Hamdy (1980)
$MR = a e^{(-kt)} + (1 - a)e^{(-kbt)}$	Approximation of diffusion	Overhults et al. (1973)
$MR = a e^{(-kt^n)} + b$	Modified Midilli	Phitakwinai, Blaisdell and Hamdy (2019); Ghazanfari et al. (2006)
$MR = 1 + at + bt^2$	Wang & Singh	Wang and Singh (1978)
$MR = \frac{a_0}{(1 + a e^{kt})}$	Logistic	Chen and Clayton (1971)
$MR = -a e^{(-kt)} + (1 - a)e^{(-k_1t)}$	Verma	Verma et al. (1985)
$MR = a e^{-be^{\frac{-c}{T}} \cdot t} + d e^{-ge^{\frac{-f}{T}} \cdot t}$	Successive Residues	Zhang and Litchfield (1991)

This typical set of data provides a valuable understanding of the moisture reduction dynamics under natural conditions. The study was conducted over 21 days, from October 26, 2023, to November 15, 2023, during which environmental parameters such as temperature and humidity ratio were monitored alongside the moisture content of the beans. The thin-layer drying method, which involves spreading the beans in a single layer to maximize exposure to solar energy, demonstrated a gradual and consistent decrease in moisture content, aligned with the expected drying kinetics for coffee beans. The data revealed that the initial moisture content of approximately 32% (wet basis) was reduced to the target range of 10–12% by the end of the drying period. Variations in drying rates were observed, influenced by fluctuations in ambient conditions, particularly during overcast days, which temporarily slowed the drying process. This dataset not only highlights the effectiveness of solar bed thin-layer drying for Pergamino coffee beans but also underscores the importance of climatic factors in optimizing post-harvest processing for coffee quality preservation.

2.3 Accuracy analysis

The Mean Squared Error (MSE) Cameron and Windmeijer, (1997) is a widely used statistical metric for evaluating the accuracy of mathematical models by quantifying the difference between predicted and observed values. In the context of coffee bean drying, MSE plays a crucial role in assessing the performance of drying models by measuring the average squared deviation between the predicted MR and the experimentally obtained MR values. The MSE is calculated as Equation 1:

$$MSE = \frac{1}{N} \sum_{i=1}^n (MR_{predicted_i} - MR_{experimental_i})^2 \quad (1)$$

where N is the number of observations, $MR_{predicted_i}$ is the predicted MR at the i -th observation, and $MR_{experimental_i}$ is the corresponding experimental value. A lower MSE indicates a closer fit between the model predictions and the actual data, reflecting higher accuracy and reliability. By comparing the MSE values of different drying models, researchers can objectively identify the most suitable model to describe the drying kinetics of coffee beans under specific conditions. For instance, studies have shown that models such as the Page model and the Midilli-Kucuk model often yield lower MSE values for coffee drying, making them more reliable for practical applications, which we are going to investigate in our study. This metric not only enhances the utility of the models, but also aids in optimizing the drying processes, ensuring consistent coffee quality, and improving energy efficiency in post-harvest operations.

In addition, we use R-squared (R^2) Ghazanfari et al. (2006), also known as the coefficient of determination, which is a statistical measure that evaluates how well a model explains the variability of the target variable. It represents the proportion of the total variation in the dependent variable that can be predicted by the independent variables. R^2 ranges from 0 to 1, where a value closer to 1 indicates that the model explains most of the variance, whereas a value close to 0 suggests that the model has little explanatory power. However, a high R^2 does not necessarily imply a good model, as it can be inflated by overfitting, particularly when dealing with multiple predictors.

Mathematically, R^2 is defined as Equation 2:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (2)$$

where:

y_i represents the actual values of the target variable,
 $\hat{y}_i$ represents the predicted values from the regression model,
 $\bar{y}$ is the mean of the actual values, and
 n is the number of observations.

By comparing the residual error with the total variation, R^2 provides insight into how much of the variability in the target variable is captured by the model.

2.4 Correlation analysis

This study aimed to understand the correlation and impact of humidity and temperature on the moisture content of solar-dried coffee beans. To achieve this, we employed Spearman's correlation Wallach and Goffinet (1987), a non-parametric measure of rank correlation that assesses the strength and direction of the monotonic relationship between two variables. Unlike the Pearson correlation, which measures linear relationships, the Spearman correlation is based on the ranked values of the data rather than the raw data itself, making it suitable for nonlinear but consistently increasing or decreasing relationships. Mathematically, the Spearman correlation coefficient (ρ) is calculated as Equation 3:

$$\rho = 1 - \frac{6 \sum_{i=1}^n d_i^2}{n(n^2 - 1)} \quad (3)$$

Here d_i is the difference between the ranks of corresponding values of the two variables, and n is the number of observations. The coefficient ranges from -1 to 1 , where -1 indicates a perfect negative monotonic relationship, 1 indicates a perfect positive monotonic relationship, and 0 indicates no monotonic relationship. By applying this method, we were able to quantify the influence of humidity and temperature on the moisture content of coffee beans during the solar drying process.

3 RESULTS

3.1 Numerical Simulations

We conducted data fitting using the fourteen mathematical models, as detailed in Table 1, to determine the MR of coffee beans. Among these models, the Successive Residues model was particularly noteworthy, as it incorporated temperature data from Génova (Colombia). The fitting process was executed using the `scipy` package, and the evaluation metrics were computed using the `sklearn` package.

Therefore, for the optimization framework, various empirical and semi-theoretical drying models were fitted to experimental moisture ratio (MR) data using non-linear least squares optimization via the “`curve_fit`” function from the SciPy library. To ensure robust fitting, each model was defined with an associated set of initial parameter guesses (p_0) and corresponding parameter bounds. These initial values were chosen based on physical reasoning, prior literature, and the behavior of the moisture loss curve, ensuring a feasible starting point for the optimization process. For example, in the Page model, the parameters k and n were initialized to 0.1 and 1.0, respectively, with lower bounds set to zero to maintain physical plausibility. Also, models with more complex behavior, such as the two-term or modified Henderson and Pabis models, required more parameters and thus broader bounds to accommodate additional exponential terms. By constraining the parameters within realistic intervals, the optimization procedure avoided overfitting and non-physical solutions, ultimately enabling

reliable parameter estimation and model comparison based on statistical metrics such as RMSE and R^2 .

Initial observations indicated significant data volatility, primarily due to substantial fluctuations in relative humidity and temperature. As illustrated in Figure 1, the models generally struggled to accurately describe the MR. However, the Successive Residues model emerged as the most accurate, exhibiting the lowest MSE and the highest R^2 value. The reliability of this model in predicting coffee bean drying under natural conditions can be attributed to the inclusion of temperature, a critical factor in natural drying processes. Despite this, the final MR predicted by the Successive Residues model was 0.6885, which deviated considerably from the desired real value.

In terms of the final MR, the Modified Page model provided a closer fit with a value of 0.2402, followed by the Logistic model ($MR_f=0.2660$) and the Wang & Singh model ($MR_f=0.2805$). These models demonstrated a better alignment with the expected MRs, suggesting their potential utility in specific drying scenarios.

To assess the practical utility of these models, we extended the fitting process to 330.5 hours from the start of the drying process and attempted to predict the MR for the subsequent 147 hours. Figure 2 shows that the discrepancy between the real and predicted final MR widened for the Successive Residues model ($MR_f=0.8199$). Similar trends were observed for other models, including the Modified Page model ($MR_f=0.6623$), Logistic model ($MR_f=0.6641$), and Wang & Singh model ($MR_f=0.6798$). This indicates that although these models perform well within the initial fitting period, their predictive accuracy diminishes over extended durations.

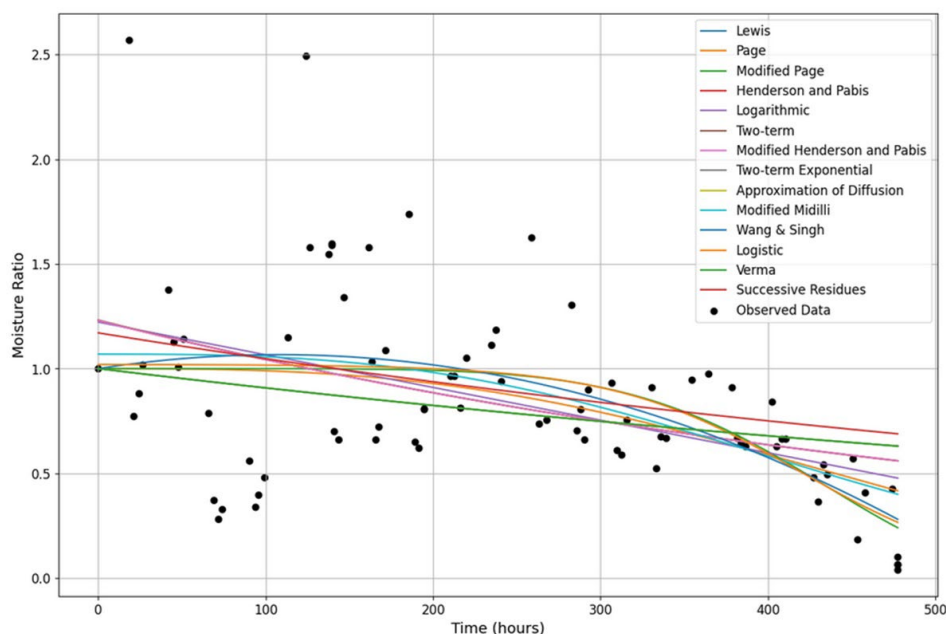


Figure 1: Model performance in describing moisture ratio (MR) under fluctuating environmental conditions. While most models struggled, the Successive Residues model showed the best accuracy, likely due to its incorporation of temperature, although its final MR prediction (0.6885) remained notably different from the real value.

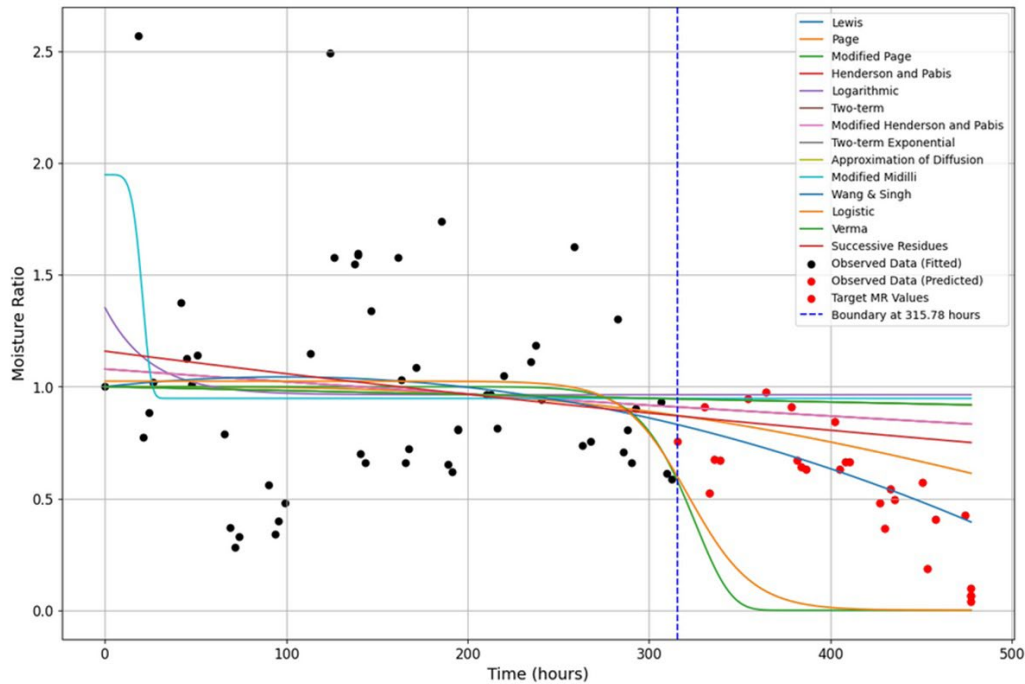


Figure 2: Predicted vs. real moisture ratio (MR) over an extended drying period. While the Modified Page, Logistic, and Wang & Singh models initially provided a close fit, their predictive accuracy declined over longer durations, with increasing discrepancies in MR values.

3.2 Models prediction performance

Table 2 summarizes the performance metrics for all the models, including the initial and final MRs, MSE, and R^2 values. The Lewis model, with an MSE of 0.1876 and R^2 of 0.0273, showed limited predictive capability, as evidenced by its high final MR of 0.8472. Similarly, despite their lower MSE values (0.1833 and 0.1829, respectively), the Page and Modified Page models still resulted in final MRs that were higher than desired.

The Henderson and Pabis model, along with its modified version, exhibited moderate performance, with MSE values of approximately 0.1847 and R^2 values of 0.0420. However, their final MRs of 0.7952 suggest that these models may not be sufficiently accurate for precise drying predictions. The Logarithmic model, with an initial MR of 1.3730 and a final MR of 0.9198, further underscores the challenges in achieving accurate MR predictions.

The Two-term and Modified Henderson and Pabis models showed similar performance metrics, with MSE values of 0.1847 and R^2 values of 0.0420. While consistent, these models did not significantly improve the predictive accuracy of the baseline models.

The Modified Midilli model, with an initial MR of 1.9126 and a final MR of 0.9126, demonstrated a higher initial MR, but failed to converge to a lower final MR, indicating potential limitations in its applicability for long-term drying predictions.

Table 2: Error estimation for fitted and predicted data for drying mathematical models.

Model	MR ₀	MR _f	R ²	MSE
Lewis (Newton)	1	0.9459	0.0042	0.2208
Page	1	0.8753	0.0135	0.2188
Modified Page	1	0.6332	0.0311	0.2149
Henderson and Pabis	1.0787	0.9107	0.0105	0.2194
Logarithmic	1.3525	0.9637	0.0196	0.2174
Two-term	1.0788	0.9107	0.0105	0.2194
Modified Henderson and Pabis	1.0787	0.9107	0.0105	0.2194
Two-term exponential	1	0.9459	0.0042	0.2208
Approximation of diffusion	1	0.9459	0.0042	0.2208
Modified Midilli	1.9478	0.9478	0.0286	0.2154
Wang & Singh	1	0.8370	0.0516	0.2181
Logistic	1.0247	0.6422	0.0331	0.2144
Verma	1	0.9459	0.0042	0.2208
Successive Residues	1.1587	0.8719	0.1439	0.1899

The Wang & Singh and Logistic models, with final MR of 0.6798 and 0.6641, respectively, showed promise but still fell short of the desired accuracy. The Verma model,

similar to the Lewis model, exhibited high final MRs, further highlighting the need for more refined modeling approaches.

The Successive Residues model, despite its higher R^2 value and lower MSE, still resulted in a final MR that was significantly higher than the target value. This suggests that while incorporating temperature data improves model performance, additional factors such as airflow, bean variety, and drying method may need to be considered to enhance the predictive accuracy.

In more extended simulations for less than 330.5 hours, the models exhibited increasing discrepancies between the predicted and observed moisture ratio (MR) values. These deviations are likely due to environmental variations, such as fluctuations in temperature, relative humidity, cloud cover, and rainfall, that are not adequately captured by the current solar drying model. Practically, this highlights the challenge of relying on deterministic models for long-duration predictions, especially in regions with variable weather. Thus, accurate prediction of the coffee beans drying process requires not only modeling the drying kinetics but also reliable forecasting of regional weather conditions, including ambient temperature, humidity levels, cloud coverage, and precipitation.

3.3 Analysis of coffee bean drying process through correlation and regression

We performed a Spearman correlation, as illustrated in Figure 3, a heatmap provides the relationships between key variables involved in the coffee bean drying process, including moisture content, relative humidity, grain temperature, and overall temperature. The correlation matrix highlights the significant

associations between these variables. Notably, the moisture content exhibited a positive correlation with relative humidity ($\rho=0.65$) and a negative correlation with both grain temperature ($\rho=-0.51$) and overall temperature ($\rho=-0.65$). The strong inverse relationship between relative humidity and temperature ($\rho=-0.93$) suggests that higher ambient temperatures contribute to reduced humidity levels, which, in turn, facilitates moisture reduction in coffee beans. These findings are consistent with the expected physical interactions governing the drying process, where increased temperatures enhance moisture evaporation, whereas higher humidity levels slow down the drying efficiency.

Meanwhile, we perform a regression analysis (see Figure 4) to determine the relationship between coffee bean moisture content and three environmental variables: relative humidity, grain temperature, and overall temperature. The negative trends observed in the scatter plots indicate that as the temperature increases both at the grain level and in the surrounding environment, the moisture content in the coffee beans decreases. The observed negative correlation aligns with the theoretical drying models, where heat promotes the evaporation of water from the beans, thereby accelerating the drying process. Similarly, the negative relationship between moisture content and relative humidity suggests that when the surrounding air is more saturated with moisture, the drying efficiency is reduced due to lower evaporation rates. These findings are crucial for optimizing coffee bean drying conditions, as they indicate that controlling temperature and humidity is essential for efficiently achieving the desired moisture levels.

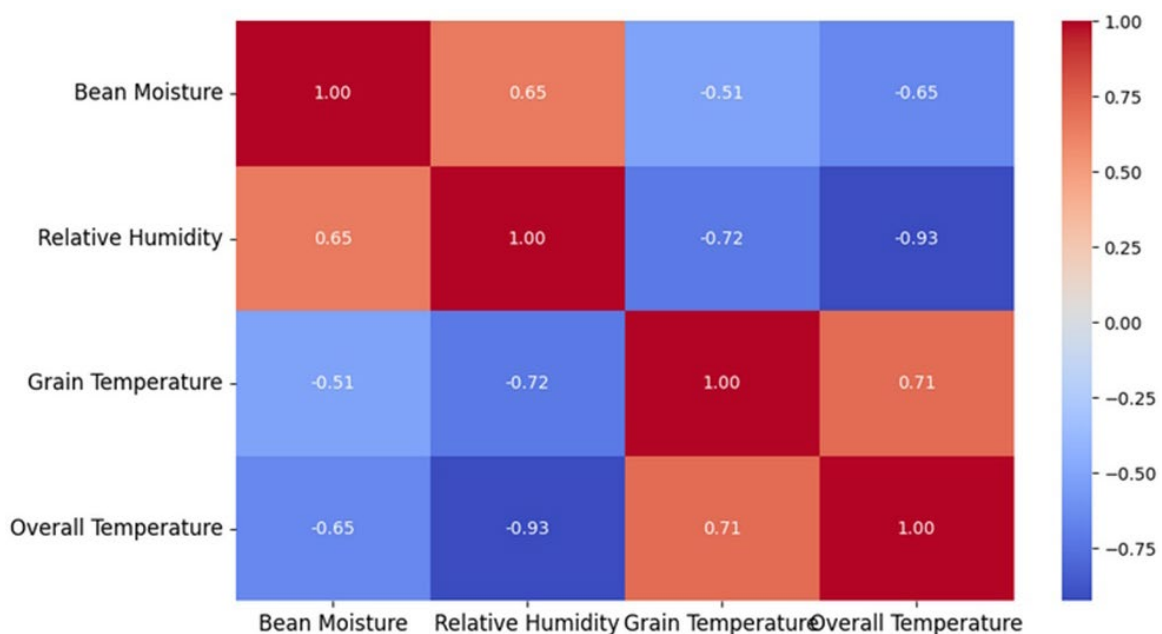


Figure 3: Spearman correlation heatmap of key variables in the coffee bean drying process. Moisture content shows a positive correlation with relative humidity and a negative correlation with temperature, whereas the strong inverse relationship between temperature and humidity highlights their impact on drying efficiency.

The results presented in Figures 3 and 4, and Table 3 underscore the importance of carefully managing the temperature and humidity during the drying process to ensure optimal moisture reduction in coffee beans.

The strong negative correlation between temperature and moisture content suggests that higher temperatures are beneficial for drying; however, this must be balanced to prevent overheating, which could degrade bean quality. Therefore, managing the relative humidity is critical, as excessive humidity may slow drying rates and increase the risk of fungal contamination. These analyses can be integrated into mathematical drying models to enhance the efficiency of MR prediction.

The 3rd-degree polynomial regression Ostertagová (2012). was selected as the optimal trade-off between complexity and generalizability for coffee drying prediction. For Relative Humidity (RH), the model ($MR = -0.0033 \cdot RH^3 + 0.7880 \cdot RH^2 - 61.2610 \cdot RH + 1586.2151$) achieved the strongest fit ($R^2=0.370$, $RMSE=8.133$), where the negative cubic term (-0.0033) moderates the positive quadratic effect (0.7880) at high RH levels, physically representing moisture sorption saturation. Grain Temperature's polynomial ($MR = -0.0352 \cdot T^3 + 2.3717 \cdot T^2 - 54.8712 \cdot T + 462.4931$) showed reduced but significant predictive power ($R^2=0.267$), with the dominant quadratic term (2.3717) capturing the non-

monotonic relationship between temperature and drying rate. For Overall Temperature, the model ($MR = 0.0344 \cdot T^3 - 2.4591 \cdot T^2 + 55.9356 \cdot T - 372.6359$) demonstrated comparable performance to RH ($R^2=0.373$), where the positive cubic term (0.0344) counteracts the strong negative quadratic coefficient (-2.4591), reflecting the competing effects of thermal acceleration versus case hardening at different temperature ranges. The consistent magnitude of RMSE values (8.116-8.778 across predictors) and stable cross-validation metrics ($\pm 10\%$ variation) confirm the 3rd-degree's robustness against overfitting, avoiding the erratic oscillations of higher-order polynomials while capturing essential nonlinearities in coffee's hygrothermal behavior.

4 DISCUSSION

In this study, we evaluated the performance of fourteen mathematical models to describe the drying kinetics of coffee beans in Génova (Quindío, Colombia). The drying process under study involves the complex structure of *Pergamino* coffee beans. Despite the application of a wide range of models, including widely used drying models such as Logistic, Modified Page, and Wang & Singh models, the results indicated that none of the models performed exceptionally well in capturing the drying behavior of coffee beans under the

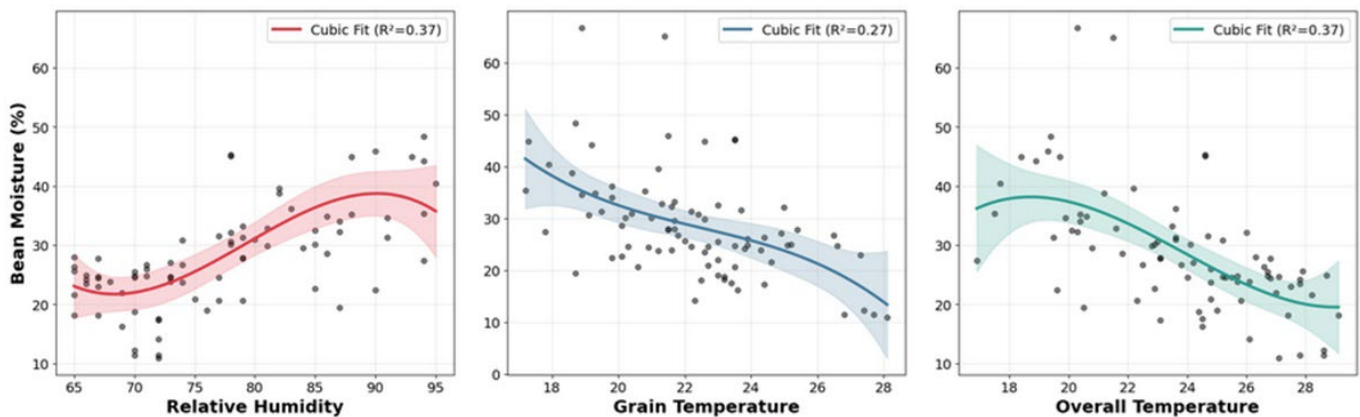


Figure 4: 3rd degree polynomial non-linear regression analysis of coffee bean moisture content against relative humidity, grain temperature, and overall temperature. The negative trends indicate that higher temperatures accelerate drying by promoting moisture evaporation, which is aligned with the theoretical drying models.

Table 3: Key Spearman Correlations in Coffee Drying data using the data collected from the Quindío region to highlight the strong relations between the moisture and the environmental properties.

Relationship	Correlation value	Interpretation
Relative Humidity vs Bean Moisture	0.65	Strong positive
Overall Temp vs Bean Moisture	-0.65	Strong negative
Grain Temp vs Bean Moisture	-0.51	Moderate negative
Relative Humidity vs Overall Temp	-0.93	Very strong negative

given conditions. However, the Logistic, Modified Page, and Wang & Singh models emerged as the closest approximations, suggesting that these models partially capture the underlying dynamics of the drying process.

The relatively poor performance of the models highlights the complexity of the drying process, which is influenced by multiple factors, including the unique structure of coffee beans, environmental conditions, and the interaction between moisture, temperature, and humidity. This underscores the need for more sophisticated modeling approaches that can better account for these complexities. Specifically, the integration of humidity and temperature effects into the drying models is critical because these factors play a significant role in the solar bed layer drying process.

Besides, deterministic models used for predicting moisture ratio often fail to accurately describe solar drying processes because they rely on fixed equations and inputs that ignore real-world complexities. These models cannot account for dynamic environmental fluctuations such as sudden cloud cover, wind gusts, temperature, or humidity changes that nonlinearly affect drying rates. Additionally, deterministic approaches treat environmental properties like humidity and temperature as constants, while in reality, these parameters fluctuate continuously during drying. This rigidity prevents the models from adapting to stochastic disturbances, including rainfall or nighttime moisture reabsorption, resulting in systematic prediction errors and significant moisture ratio fluctuations under field conditions.

As a future direction, we propose the development of a new set of models that incorporate the effects of humidity and temperature, leveraging weather prediction data to simulate real-world drying conditions more accurately. Hence, time series models, Long Short-Term Memory (LSTM) networks, artificial neural networks (ANNs), and stochastic differential equations (SDEs) can significantly enhance solar drying predictions by addressing the limitations of deterministic approaches. Time series analysis captures temporal dependencies in environmental data (e.g., humidity, temperature), enabling short-term forecasting of drying rates. LSTMs extend this capability by learning long-term patterns in sequential data, making them ideal for handling intermittent solar exposure or diurnal fluctuations. ANNs approximate complex nonlinear relationships between input variables (e.g., irradiance, airflow) and moisture content, adapting to diverse crop-specific drying behaviors. Meanwhile, SDEs incorporate randomness into differential equations, explicitly modeling environmental uncertainties like sudden cloud cover or wind gusts. Such models could provide a more robust framework for optimizing the drying process, improving the energy efficiency, and ensuring the quality of the final product. This approach would not only address the limitations observed in this study but also contribute to the advancement of drying

technologies for coffee and other agricultural products in similar climates.

5 CONCLUSIONS

While the current models provide a foundational understanding of drying kinetics, the challenges encountered in this study emphasize the need for innovative modeling strategies that integrate environmental variables and real-time weather data. This will enable more precise control and optimization of the drying process, ultimately enhancing the sustainability and quality of coffee production in the region.

6 AUTHOR CONTRIBUTION

Conceptual Idea: Romero, J.; Sekkak, I.; Cabrera, T.; Methodology design: Romero, J.; Cabrera, T.; Sekkak, I.; Mesa, M.; Lagos, C.; Eraso, F.; Data processing and analysis: Romero, J.; Sekkak, I. Mesa, M.; Writing and editing: Romero, J.; Sekkak, I.; Mesa, M.; Cabrera, T.; Lagos, C.; Eraso, F.; Supervision of the project: Romero, J.; Eraso, F.

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8 REFERENCES

- ACOSTA-MINOLI, C. et al. IoT-based technology for the coffee drying process data analysis of small farmers. **Revista Facultad de Ingeniería**, 33(69):17404, 2024.
- BRANDO, C. H. J.; BRANDO, M. F. P. Method of coffee fermentation and drying. **Em Cocoa and Coffee Fermentations**, 2014.
- CAMERON, A. C.; WINDMEIJER, F. A. G. An R-squared measure of goodness of fit for some common nonlinear regression models. **Journal of Econometrics**, 77(2):329-342, 1997.
- CHEN C. S.; CLAYTON, J. T. The effect of temperature on sorption isotherms of biological materials. **Transactions of the ASAE**, 14(5):0927-0929, 1971.
- CORRÊA, P. C.; RESENDE, O.; RIBEIRO, D. M. Drying characteristics and kinetics of coffee berry. **Revista Brasileira de Produtos Agroindustriais**, 8(1):1-10, 2006.

- DEETO, S.; THEPA, S.; MONYAKUL, V. The experimental new hybrid solar dryer and hot water storage system of thin layer coffee bean dehumidification. **Renewable Energy**, 115:954-968, 2018.
- DOYMAZ, I. Drying characteristics and kinetics of okra. **Journal of Food Engineering**, 69(3):275-279, 2005.
- FRANCA, A. S.; MENDONÇA, J. C. F.; OLIVEIRA, S. D. Composition of green and roasted coffees of different cup qualities. **LWT - Food Science and Technology**, 38(7):709-715, 2005.
- GHAZANFARI, A. et al. Thin-layer drying of flax fiber: II. Modeling drying process using semi-theoretical and empirical models. **Drying Technology**, 24(12):1637-1642, 2006.
- HENDERSON, S. M. Progress in developing the thin layer drying equation. **Transactions of the American Society of Agricultural Engineers**, 17(6):1167-1168, 1974.
- HENDERSON, S. M.; P. S. **Grain drying theory**. 1. Grain drying theory. 1. Temperature effect on drying coefficient. *Journal of Agricultural Engineering Research*. 1961.
- KLEINWÄCHTER, M.; BYTOF, G.; SELMAR, D. Chapter 11 - Coffee beans and processing. In: PREEDY VICTOR, R.; VINOOD B. **Coffee in health and disease prevention**. Academic Press, p. 105-114, 2025.
- KULAPICHITR, F. et al. Impact of drying process on chemical composition and key aroma components of Arabica coffee. **Food Chemistry**, 291:49-58, 2019.
- LEWIS, W. K. The rate of drying of solid materials. **Industrial and Engineering Chemistry**, 13(5):427-432, 1921.
- MEJA, E. M.; DUBBE, S. K.; BEKELE, A. Investigating the performance and optimization of solar coffee drying technologies-a systematic review. **Journal of Food Processing and Preservation**, p. 7907660, 2025.
- OVERHULTS, D. G. et al. Drying soybeans with heated air. **Transactions of the American Society of Agricultural Engineers**, 16(1):0112-0113, 1973.
- OSTERTAGOVA, E. Modelling using polynomial regression. **Procedia Engineering**, 48:500-506, 2012.
- PHITAKWINAI, S.; THEPA, S.; NILNONT, W. Thin-layer drying of parchment Arabica coffee by controlling temperature and relative humidity. **Food Science and Nutrition**, 7(9):2921-2931, 2019.
- SHARAF-ELDEEN, Y. I.; BLAISDELL, J. L.; HAMDY, M. Y. Model for ear corn drying. **Transactions of the American Society of Agricultural Engineers**, 23(5):1261-1265, 1980.
- VERMA, L. R. et al. Effects of drying air parameters on rice drying models. **Transactions of the American Society of Agricultural Engineers**, 28(1):296-0301, 1985.
- WALLACH, D.; GOFFINET, B. Mean squared error of prediction in models for studying ecological and agronomic systems. **Biometrics**, 43(3):561-573, 1987.
- WANG, G. Y.; SINGH, R. P. Single layer drying equation for rough rice. **Paper - American Society of Agricultural Engineers**, 19:78, 1978.
- WHITE, G. M.; ROSS, I. J.; PONELEIT, C. G. Fully-exposed drying of popcorn. **Transactions of the American Society of Agricultural Engineers**, 24(2):0466-0468, 1981.
- YALDIZ, O.; ERTEKIN, C.; UZUN, H. I. Mathematical modeling of thin layer solar drying of sultana grapes. **Energy**, 26(5):457-465 2001.
- ZHANG, Q.; LITCHFIELD, J. B. An optimization of intermittent corn drying in a laboratory scale thin layer dryer. **Drying Technology**, 9(2):383-395, 1991.