A Review on Modeling the Drying Kinetics of Agricultural Bio Materials and Wastes

Owoh I. P[1,3], Okonkwo W. I[1,2], Anyanwu C. N[1,2], Ojike O[1,2] and Nwagugu N. I[1,4]

[1]Department of Agricultural and Bioresources Engineering

[2]World Bank African Centre of Excellence for Power and Energy Development

[3]National Centre for Energy Research and Development, University of Nigeria, Nsukka, Nigeria

[4]Project Development Institute, Enugu, Nigeria

DOI: https://doi.org/10.51584/IJRIAS.2025.100500085

Received: 25 April 2025; Accepted: 04 May 2025; Published: 16 June 2025

ABSTRACT

Drying kinetics modeling is critical in optimizing drying processes for biomaterials and wastes, ensuring energy efficiency and product quality. This review provides a comprehensive synthesis of the major modeling approaches applied to drying kinetics, encompassing empirical, semi-theoretical, and theoretical models. Influencing factors such as moisture content, air velocity, temperature, and material structure are discussed. The review further examines modeling techniques specific to agricultural residues, food products, and animal wastes, highlighting the integration of traditional models with modern computational approaches, including artificial intelligence and computational fluid dynamics. Model selection criteria and current research gaps are analyzed, emphasizing the development of adaptive, material-specific models and the integration of real-time monitoring tools. The insights presented aim to guide future research and industrial applications in the valorization of organic wastes and sustainable drying system development.

Keywords: Drying kinetics, Biomaterials, Modeling, Waste valorization, Artificial intelligence

INTRODUCTION

Drying is an age-long practice of reducing or removal of moisture from a product in other to stop or retard the microbial reactions that may degrade, or decompose the product (Chauhan *et al.*, 2015; Ahmad *et al*.,2022). Drying of agricultural products elongates their shelf life, enabling its storage and preservation for an extended time without decomposition. Drying is essential for preserving biomaterials and converting waste into value-added products. Effective drying reduces moisture content, and minimizes transportation costs. Modeling the drying kinetics of biomaterials is vital for optimizing drying equipment and enhancing process efficiency. Biomaterials, such as agricultural residues and food waste, display complex moisture diffusion behaviors due to their heterogeneous composition, necessitating robust and accurate models. This review outlines existing drying models, evaluates their applications, and highlights current research directions.

Mathematical modeling of drying Kinetics

Drying kinetic models are commonly used to estimate drying times of agricultural products during drying. Drying models simply mean a predictive mathematical relationship between the moisture content expressed as moisture ratio and time. Drying kinetics are affected by ambient temperature, air velocity, and material properties (Doymaz and Pala, 2003). Predicting the drying time is critical for boosting drier capacity and optimization or control of the operating conditions during drying (Inyang *et al.*, 2018). In mathematical modelling of drying curve characteristics, the thin layer and equilibrium moisture content models are applied. Mathematical modelling of thin layer drying is important for optimization of operating parameters and performance improvements of the drying systems (Cihan *et al.*, 2007). Thin layer drying models used for modelling the drying phenomenon of agricultural materials are classified into three categories, namely: theoretical, semi-theoretical, and empirical (Afzal and Abe, 2000, Panchariya *et al.*, 2002; Akpinar and Bicer, 2005; Akpinar, 2006). The theoretical approach is concerned with diffusion or simultaneous heat and mass transfer equations. The semi-theoretical models approach is concerned with approximated theoretical equations (Afzal and Abe, 2000; Akpinar and Bicer, 2005). Simplifying the general series solution of Fick's second law or the modification of simplified models generally derives semi-theoretical models. But they are only valid within the temperature, relative humidity, airflow velocity and moisture content range for which they were developed. They require small time compared to theoretical thin layer models and do not need assumptions of the geometry of a typical food, its mass diffusivity and conductivity (Parry, 1985). Nevertheless, the semi-theoretical equations have been successfully applied by many researchers to describe drying rates for various agricultural products. In this category, Henderson and Pabis model, Page model, and Lewis model is extensively utilized by researchers. Empirical models establish a direct relationship between average moisture content and drying time without regards to the fundamentals of the drying process and their parameters which have no physical meaning. Though it is easy to apply the empirical models in drying simulations but they cannot give clear accurate view of the important processes that takes place during drying although they may describe the drying curve for the conditions of the experiments (Afzal and Abe, 2000; Akpinar and Bicer, 2005). Thin layer equations describe the drying phenomena in a unified way regardless of the controlling mechanism. They have been used to estimate drying times of biological products and to generalize drying processes. Recent studies incorporate Computational Fluid Dynamics (CFD) for multiphase drying simulations (Norton & Sun, 2006) and Artificial Neural Networks (ANN) for nonlinear drying behavior prediction (Kumar *et al.*, 2020) as advanced and hybrid drying models for the prediction of drying time in drying of both bio materials and non-bio materials as long as there are sufficient data collection for the machine learning algorithm

Factors Affecting Drying Kinetics

A complex interplay of physical, environmental, and process-related factors influences the drying kinetics of biomaterials. One of the most critical parameters is the initial moisture content, which determines the duration of the constant-rate and falling-rate drying periods, depending on the extent to which water is free or bound within the material's cellular matrix (Mayor & Sereno, 2004; Lewicki, 2006). Drying temperature also plays a pivotal role by enhancing the vapor pressure gradient and reducing water viscosity, thereby accelerating moisture migration; however, excessively high temperatures may lead to shrinkage, degradation, or case hardening (Kumar et al., 2014; Mujumdar, 2014). Environmental conditions such as relative humidity and air velocity directly influence the drying rate. Lower humidity levels improve the vapor pressure differential and increase the drying potential, while higher air velocity helps remove the saturated boundary layer from the material surface, promoting convective mass transfer (Sharma *et al.*, 2009; Henderson *et al.*, 2000). Additionally, the physical characteristics of the material, including thickness, porosity, cellular structure, and surface area-to-volume ratio, significantly impact internal moisture diffusion; denser or thicker materials tend to dry more slowly (Zogzas et al., 1996). Other parameters affecting the drying kinetics are pre-treatment techniques, such as blanching, ultrasonic treatment, and osmotic dehydration, which can modify the structural integrity of biomaterials, enhancing or impeding moisture diffusivity. For instance, ultrasound creates micro channels that facilitate water migration during drying (Nowacka *et al.*, 2012). The drying method and energy source used (convective, solar, infrared, microwave, or freeze-drying etc) also impact the drying behavior by influencing heat transfer mechanisms and moisture removal efficiency (Ratti, 2001; Esper & Mühlbauer, 1998). The drying process is often described using semi-empirical or theoretical models, which rely on parameters such as effective diffusivity, drying rate constants, and activation energy—all of which are sensitive to the aforementioned variables (Midilli *et al.*, 2002). A thorough understanding and integration of these factors are essential for optimizing drying processes and developing accurate predictive models.

Bio Materials and Corresponding Thin Layer Drying Kinetics Models

Many bio materials have been dried, and their thin-layer drying kinetics modeled. Details of the thin layer models and their corresponding equations are presented in Table 1, while Table 2 displays the thin layer models used to predict moisture content and the related agricultural products.

Table .1: Table of thin layer drying models

S/N	Name of Model	Model Equation	Reference
1	Lewis Model	$MR = exp\ (-kt).$	(Kashaninejad *et al.* 2005; Vijayaraj *et al.*, 2007)
2	Logarithmic Model	$MR = a\ exp\ (-kt) + c$	(Erbay and Icier, 2009)
3	Page Model	$MR= exp\ (kt^n).$	(Kahveci and Cihan, 2008; Doymaz and Ismail, 2011)
4	Modified Page Model I	$MR= exp\ [(-k\ t)^n]$	(Al-Mahasneh *et al.*, 2007
5	Modified Page Model II	$MR =exp\ [-(k\ t)^n]$	(Akpinar, 2006a ;Lemus-Mondaca *et al.*, 2009)
6	Modified Page Model III	$MR =exp\ [-(-k\ t)^n]$	(Falade and Solademi, 2010)
7	Modified Page Model IV	$MR = a\ exp[-(kt^n)]$	(Babalis *et al.*, 2006)
8	Modified Page Model V	$MR = exp[-(kt^n)]$	(Jazini and Hatamipour, 2010)
9	Modified Page Model VI	$MR = exp(kt^n)$	(Kurozawa *et al.*, 2012)
10	Modified Page Model VII	$MR = exp[-k(t/L^2)^n]$	(Artnaseaw *et al*., 2010a),
11	Modified Page Model VIII	$MR = exp\ \{-[k(t/L^2)^n]\}$	(Pardeshi and Chattopadhyay, 2010)
12	Modified Page Model IX	$MR = k\ exp\ [(-t/L^2)^n]$	(Kumar *et al.*, 2006)
13	Simplified Fick Model	$MR = k\ exp\ [-c(t/L^2)]$	(Gunhan *et al*., 2005)
14	Henderson Pabis	$MR = 1-exp[-(kt^n)]$	(Shittu and Raji, 2011)
15	Modified Henderson Pabis I	$MR = a\ exp\ (-k_o t) + b\ exp(-k_1 t) + c\ exp(-k_2 t).$	(Erbay and Icier, 2009)
16	Modified Henderson Pabis II	$MR = a\ exp\ (-kt^n) + b\ exp(-gt) + c\ exp(-ht).$	(Corzo *et al*., 2011)
17	Otsura *et al.*, Model	$MR = 1-exp[-(kt^n)]$	(Otsura *et al.*, 1975 from Chen and Wu, 2001)
18	Midilli Kucuk Model	$MR= a\ exp\ (-kt^n)+ bt$	(Ghazanfari *et al*., 2006a; Midilli *et al.*, 2002)
19	Wang and Singh Model	$MR =1 + at+ bt^2$	Kadam and Dhingra, 2011; Akpinar, 2011
20	Thompson Model	$t = a\ ln(MR) + b\ [ln(MR)]^2$	Thompson *et al*.,1968

Table 2. Thin layer models and their corresponding agricultural biomaterials

S/N	MODELS	REFERENCES
1	Lewis model	strawberry (El-Beltagy et al., 2007), red chilli (Hossain et al., 2007), grape seeds (Roberts et al., 2008) and black tea (Panchariya et al., 2002).
2	Page Model	tomato (Doymaz, 2007a), wheat (Rafiee et al., 2008), dates (Hassan and Hobani, 2000) and barberries (Aghbashlo et al., 2007).

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue V May 2025

3	Modified Page I	sesame hull (Al-Mahasneh et al., 2007)
4	Modified Page II	mint and basil leaves (Akpinar, 2006a), aloe vera (Vega et al., 2007), papaya (Lemus-Mondaca et al., 2009)
5	Modified Page III	sweet potato slices (Falade and Solademi, 2010)
6	Modified Page IV	figs (Babalis et al., 2006)
7	Modified Page V	Plums (Jazini and Hatamipour, 2010)
8	Modified Page VI	mushrooms (Kurozawa et al., 2012)
9	Modified Page VII	red beet (Kaleta and Gornicki, 2010), jujube (Fang et al., 2009) and black grape (Togrul, 2010)
10	Modified Page VIII	soy-fortified wheat based ready to eat snacks (Pardeshi and Chattopadhyay, 2010)
11	Modified Page IX	onion slices (Kumar et al., 2006)
12	Otsura et al Model	rough rice (Otsura et al., 1975 from Chen and Wu, 2001);
13	Simplified Ficks Model	bay leaves (Gunhan et al., 2005), apricot (Togrul and Pehlivan, 2003), and apple (Togrul, 2005).
14	Henderson and Pabis	African breadfruit seed (Shittu and Raji, 2011), banana, mango, and cassava (Koua et al., 2009), and onion (Sawhney et al., 1999).
15	Henderson and Pabis I	pistachio (Aktas and Polat, 2007), kiwifruit (Doymaz, 2009a), and coconut (Madhiyanon et al., 2009)
16	Logarithmic Model	green bell pepper (Doymaz and Ismail, 2010), pineapple (Kingsly et al., 2009), peach (Kingsly et al., 2007), bar bunya bean (Kayisoglu and Ertekin, 2011), and white mulberry (Doymaz, 2004a).
17	Midilli *et al*., Model	savory leaves (Arslan and Ozcan, 2012), purslane (Demirhan and Ozbek, 2010a), and eggplant (Ertekin and Yaldiz, 2004).

Advances in Drying Kinetics Modeling

AI and Machine Learning

Artificial Intelligence (AI) and Machine Learning (ML) have increasingly been applied to drying kinetics modeling to overcome the limitations of traditional physics-based methods, offering accurate predictions of moisture content, drying rates, and process optimization without explicitly solving complex differential equations (Shan *et al*., 2020; Tosun *et al*., 2022). Techniques such as artificial neural networks (ANN), support vector machines (SVM), and genetic algorithms (GA) have been widely used to model non-linear relationships in drying data, showing high predictive performance across various biomaterials (Erbay & Icier, 2010; Golpour *et al*., 2015). Furthermore, hybrid models that integrate ML with first-principles approaches are emerging, enhancing model generalization and interpretability (Chen *et al*., 2021). The use of deep learning and real-time sensor data also enables adaptive control and intelligent optimization of drying systems, paving the way for smart, automated drying technologies (Tosun *et al*., 2022). A compilation of the applications of AI and machine learning in modeling drying kinetics of agricultural products is shown in Table 3.

Table:3 Applications of AI and Machine Learning in Modeling Drying Kinetics of Agricultural Products

S/N	**Agricultural Product**	**AI/ML Method**	**Key Findings**	**Reference**
1	Carrot Slices	Artificial Neural Networks (ANN)	ANN provided higher prediction accuracy of the moisture ratio compared to traditional thin-layer models.	Kaya et al., 2008
2	Tomato Slices	Support Vector Machines (SVM), ANN	SVM and ANN accurately predicted moisture content during drying; SVM showed superior generalization.	Kalantari & Azizi, 2017
3	Banana	Adaptive Neuro-Fuzzy Inference System (ANFIS)	ANFIS accurately predicted moisture content and drying rate; it outperformed RSM models.	Jangam & Thorat, 2010
4	Apple Slices	Random Forest Regression	RF model combined with image processing accurately predicted moisture content non-destructively.	Pan *et al.*, 2015
5	Sweet Potatoes	Deep Learning (CNN)	CNN-based image analysis enabled real-time drying stage classification and moisture prediction.	Zhang *et al.*, 2021

Computational Fluid Dynamics (CFD)

CFD simulation models are based on heat and mass transfer for optimization of dryer geometry and the drying processes using the Navier–Stokes equations as the governing equations, Energy, continuity, and momentum equations (Ahmad *et al*., 2023; Mellalou *et al*.,2021; Rouissi *et al.*, 2021)

Computational Fluid Dynamics (CFD) has become a vital tool in drying kinetics modeling, enabling detailed simulation of heat and mass transfer, airflow distribution, and moisture evolution in drying systems with spatial and temporal resolution that traditional models often lack (Younis *et al.,* 2017; Ratti, 2001). By solving the Navier–Stokes, energy, and species transport equations, CFD helps in analyzing complex geometries, optimizing dryer design, and improving energy efficiency and product quality (Nathakaranakule *et al.*, 2007; Karim & Hawlader, 2005). CFD also facilitates the study of coupled phenomena such as shrinkage, phase change, and turbulence effects during drying, especially in porous media (Kumar & Prasad, 2007). Integrating CFD with experimental data and advanced modeling approaches like multiphysics and AI further enhances its predictive power and practical applicability (Tosun *et al*., 2022).

Multiscale and Multi-Physics Modeling

Multiscale and multi-physics modeling provides a comprehensive framework for understanding drying kinetics by integrating phenomena from cellular-scale moisture transport to bulk-level heat and mass transfer (Waananen & Okos, 1996; Zhang et al., 2014). These models couple thermal, mass, and structural dynamics to simulate the complex interactions that occur during drying, especially in porous biomaterials (Cai & Chen, 2008; Shan et al., 2020). Numerical techniques such as finite element analysis and computational fluid dynamics, often implemented in platforms like COMSOL and ANSYS, enable flexible, multi-physics simulation environments (Younis et al., 2017). Despite their promise, challenges remain regarding computational load, multiscale parameter estimation, and experimental validation, though recent advances in image-based modeling and machine learning are helping to address these issues (Tosun et al., 2022). Table 4 compiles some examples of multiscale and multi-physics modeling approaches used to analyze the drying kinetics of agricultural products.

Table 4. Table of multiscale and multi-physics modeling approaches used to analyze the drying kinetics of agricultural products,

S/N	Agricultural Product	Method of study	Key Features	References
1	Apple	FEM, multiscale	Cell deformation + tissue drying	Wang et al. (2019)
2	Grape	COMSOL Multi physics	Coupled heat/mass, shrinkage	Lahsasni & Kouhila (2016)
3	Tomato	Pore-network, multiscale	Microscale diffusion & shrinkage	Li et al. (2020)
4	Maize	CFD-DEM	Granular dynamics + heat transfer	Saberi & Ghasemi (2021)

Model Selection and Evaluation Criteria

Graphical and statistical analyses are always used to validate and select the best-fitted models in kinetics modeling. The key performance metrics for determining the model of best fit (goodness of fit) are;

Mean Relative Error. (MRE)

The models with Mean relative error (MRE) values below or equal to 10% are usually considered as a good fit (Simal *et al.*, 2005). It is given as equation (1)

$$MRE(\%) = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{X_{exp,i}-X_{pred,i}}{X_{exp,i}}\right| \quad (1)$$

Coefficient of Determination (R^2)

The coefficient of determination (R^2) is the square of the correlation coefficient, quantifying the proportion of variance in the dependent variable that can be explained by the independent variable. R^2 values range from 0 to 1; a value of 0 indicates no explained variance, while a value of 1 signifies that the model accounts for all variance in the dependent variable. Typically, the model with the highest coefficient of determination (R^2) and a low root mean square error (RMSE) (Demir et al., 2004) is selected as the best-fitting model.

It is given as R^2 and expressed as equation (2)

$$R^2 = 1 - \frac{\sum(X_{exp}-X_{pred})^2}{\sum(X_{exp}-X_{avg\ exp})^2} \quad (2)$$

where

$Y_{obv.}$ is the experimental value

Y_{pred} is the predicted value

Y_{avg} is the average of the observed values

Average Absolute Difference (AAD),

The Average Absolute Difference (AAD), also known as Mean Absolute Error (MAE), provides a measure of how far off the predictions were from the actual values, on average. This metric quantifies and compares the average magnitude of errors between the values predicted by the models and the actual values. It is given as equation (3)

$$AAD = \frac{1}{N}\sum_{i=1}^{N}\left|X_{exp,i} - X_{pred,i}\right| \quad (3)$$

Root Mean Square Error

Root mean square error (RMSE) or sometimes referred to as root mean square deviation (RMSD) is derived by squaring the differences between the sum of the experimental value of the moisture ratio and the predicted value, dividing that by the number of test points, and then taking the square root of that result.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Xexp,i - Xpred_i)^2}{N}} \quad (4)$$

RMSE = root mean square error

I = variables

N = Number of data points

$X\ exp,i$ = mean experimental moisture ratio

$X\ pred,i$ = mean predicted moisture ratio

Mean Absolute Error (MAE)

The mean absolute error is defined as the ratio of the absolute error of the predicted to the actual value. Using this method, one can determine the magnitude of the absolute error in terms of the actual size of the observations. Mean absolute error, MAE, is a quantity used to measure how close forecasts or predictions are to the eventual outcomes. The mean absolute error is given by (Tripathy and Kumar, 2008; Mota *et al.*, 2010)

The mean absolute error (MAE) is given as equation (5)

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}[exp_i - pred] \quad (5)$$

Where:

n is the number of data points or observations.

Σ denotes the summation symbol.

exp,*i* is the actual experimental value

pred,*i* is the predicted value

|Actual - Predicted| represents the absolute difference between the actual value and the predicted value for each data point.

Chi-Square (χ^2) test

The Chi-Square (χ^2) test measures how close your model's predictions are to the experimental (actual) data points**.** It does this by squaring the difference between predicted and actual values and summing them up. The smaller the result, the better your model is at matching the real data. It is given as equation (6) by Ertekin, C., & Yaldiz, O. (2004).

$$\chi^2 = \sum_{i=1}^{N}\frac{\left(X_{exp.i} - X_{pred.i}\right)^2}{X_{pred.i}} \quad (6)$$

It can be normalized depending on the parameters being evaluated (goodness of fit or relative error per degree of freedom) and the type of data being analyzed. The normalized chi-square is given as equation (7)

$$\chi^2 = \frac{1}{N-n}\sum_{i=1}^{N}(Xexp,i - Xpred,i)^2 \quad (7)$$

Despite the evaluations of all the model testing criteria, model robustness should be evaluated under varying conditions such as temperature, humidity, and material thickness to ensure generalizability. A sensitivity analysis of model parameters further aids in understanding the influence of each variable on drying behavior (Henderson *et al.,* 1997).

Research Gaps and Future Directions

Need for Material-Specific Models

Generic models often fail to capture the unique drying behaviors of specific biomaterials. There is a need for customized models that integrate moisture-binding mechanisms and internal structure changes during drying.

Integration with Real-Time Monitoring Systems

The use of sensors and data acquisition systems allows for real-time monitoring of drying parameters. Future models should incorporate feedback loops and predictive control systems for dynamic adaptation (Ratti, 2001).

Climate-Resilient and Energy-Efficient Drying

Future drying models must support energy-efficient systems that adapt to fluctuating climatic conditions, particularly in solar and hybrid drying.

Open Access Databases and Modeling Platforms

Collaborative platforms that house experimental data and model parameters are necessary for cross-laboratory comparison and development.

Coupled Modeling Approaches

Integrating mechanical, thermal, chemical, and biological phenomena into a unified modeling framework—e.g., drying and microbial inactivation—offers a complete process understanding (Chen *et al.*, 2020).

CONCLUSION

Modeling drying kinetics is key for process optimization in bio-material drying. While empirical and semi-theoretical models are widely used because of their ease of application, advanced computational tools offer improved accuracy and adaptability. Emphasis should be placed on creating smart, adaptive systems informed by real-time data and tailored to specific biomaterial properties. Further research should be focused on advanced computational tools for improved accuracy and adaptability

REFERENCES

1. Akpinar, E. K., Bicer, Y., & Yildiz, C. (2003). Thin layer drying of red pepper. Journal of Food Engineering, 59(1), 99–104. https://doi.org/10.1016/S0260-8774(02)00425-9
2. Kucuk, H., Midilli, A., Kilic, A., & Dincer, I. (2014). A review on thin-layer drying-curve equations. Drying Technology, 32(7), 757–773. https://doi.org/10.1080/07373937.2013.873047
3. Kumar, N., Sarkar, B. C., & Sharma, H. K. (2011). Effect of air velocity on kinetics of thin layer carrot pomace drying. Food Science and Technology International, 17(2), 143–153. https://doi.org/10.1177/1082013211398832

4. Aghbashlo, M., Kianmehr, M. H., & Samimi-Akhijahani, H. (2009). Evaluation of thin-layer drying models for describing drying kinetics of barberries (Berberis vulgaris). Journal of Food Process Engineering, 32(2), 278–293. https://doi.org/10.1111/j.1745-4530.2007.00216.x
5. Aghbashlo, M., Kianmehr, M.H., and Samimi-Akhijahani H. (2007). Evaluation of thin-layer drying models for describing drying kinetics of barberries (Barberries Vulgaris). Journal of Food Process Engineering 32: 278-293.
6. Ahmad, A.; Prakash, O.; Sarangi, S.K.; Singh Chauhan, P.; Chatterjee, R.; Sharma, S.; Kumar, R.; Tag, S.M.; Kumar, A.; Salah, B.; et al. (2023)Thermal and CFD Analyses of Sustainable Heat Storage-Based Passive Greenhouse Dryer Operating in No-Load Condition. Sustainability 2023, 15, 12067. https://doi.org/ 10.3390/su151512067
7. Ahmad,A.; Prakash,O.; Kumar,A.;Chatterjee,R.; Sharma,S.; Kumar,V.; Kulshreshtha,K.;Li,C.;Eldin,E.M.T.(2022). A Comprehensive State-of-the-Art- Art Review on the Recent Developments in Greenhouse Drying. Energies 2022,15,9493.
8. Akpinar, E. K. (2006). Mathematical modelling of thin layer drying process under open sun of some aromatic plants. Journal of Food Engineering, 77(4), 864–870. https://doi.org/10.1016/j.jfoodeng.2005.08.014
9. Akpinar, E.K. (2006). Determination of suitable thin layer drying curve model for some vegetables and fruits. Journal of Food Engineering, 73: 75-84.
10. Aktas, T., and Polat, R. (2007). Changes in the drying characteristics and water activity values of selected pistachio cultivars during hot air drying. Journal of Food Process Engineering 30 : 607-624.
11. Al-Mahasneh, M.A., Rababah, T.M., and Al-Shbool M.A. (2007). Thin-layer drying kinetics of sesame hulls under forced convection and open-air sun drying. Journal of Food Process Engineering 30: 324-337.
12. Arslan, D., and Ozcan, M.M. (2012). Evaluation of drying methods with respect to drying kinetics, mineral content, and color characteristics of savory leaves. Food Bioprocess Technol. 5: 983-991.
13. Artnaseaw, A., Theerakulpisut, S., and Benjapiyaporn, C. (2010a). Drying characteristics of Shiitake mushroom and Jinda chili during vacuum heat pump drying. Food and Bioproducts Processing 88: 105-114.
14. Babalis, S.J., Papanicolaou, E., and Kyriakis, N. (2006). Evaluation of thin-layer drying models for describing drying kinetics of figs (Ficus carica). Journal of Food Engineering 75: 205- 214.
15. Babalis, S.J., Papanicolaou, E., and Kyriakis, N. (2006). Evaluation of thin-layer drying models for describing drying kinetics of figs (Ficus carica). Journal of Food Engineering 75: 205- 214.
16. Cai, J., & Chen, L. (2008). Multiphysics modeling of heat and mass transfer in porous media drying. Drying Technology, 26(12), 1373–1383. https://doi.org/10.1080/07373930802464022
17. Chauhan,P.S.;Kumar,A.;Tekasakul,P.(2015)Applications of software in solar drying systems: A review. Renew. Sustain. Energy Rev. 2015,51,1326–1337.
18. Chen C.H.and Wu P.C. (2001). Thin-layer drying model for rough rice with high moisture content. Journal of Agricultural Engineering Research 80: 45-52.
19. Chen, H. et al. (2020). Mathematical modeling of drying processes. Bioresour. Technol., 299, 123213. https://doi.org/10.1016/j.biortech.2020.123213
20. Chen, L., Xu, Q., & Zhang, M. (2021). Hybrid modeling approaches in food process engineering: A review. Trends in Food Science & Technology, 112, 642–653. https://doi.org/10.1016/j.tifs.2021.04.020
21. Demirhan, E., and Ozbek, B. (2010a). Drying kinetics and effective moisture diffusivity of purslane undergoing microwave heat treatment. Korean J. Chem. Eng. 27: 1377-1383.
22. Doymaz, I. (2004a). Drying kinetics of white mulberry. Journal of Food Engineering 61: 341 346.
23. Doymaz, I. (2007). The kinetics of forced convective air-drying of pumpkin slices. Journal of Food Engineering 79: 243-248.
24. Doymaz, İ. (2009a). "Kinetic modeling of drying of kiwifruit slices." Journal of Food Engineering, 90(2), 200-207. DOI: 10.1016/j.jfoodeng.2008.06.034
25. Doymaz, I., and Ismail, O. (2010). Drying and rehydration behaviors of green bell peppers. Food Science and Biotechnology 19: 1449-1455.
26. Doymaz, I., and Ismail, O. (2011). Drying characteristics of sweet cherry. Food and Bioproducts Processing 89: 31–38.

27. El-Beltagy, A., Gamea, G.R., and Essa, A.H.A. (2007). Solar drying characteristics of strawberry. Journal of Food Engineering 78: 456-464.
28. Erbay, Z., & Icier, F. (2010). A review of thin layer drying of foods: Theory, modeling, and experimental results. Critical Reviews in Food Science and Nutrition, 50(5), 441–464. https://doi.org/10.1080/10408390802437063
29. Erbay, Z., and Icier, F. (2009). A review of thin layer drying of foods: theory, modeling, and experimental results. Critical Reviews in Food Science and Nutrition 50: 441–464.
30. Ertekin, C and O. Yaldiz. (2004). Drying of eggplant and selection of a suitable thin layer drying model. Journal of Food Engineering, 63: 349- 359.
31. Ertekin, C., & Firat, M. Z. (2017). A comprehensive review of thin-layer drying models used in agricultural products. Critical Reviews in Food Science and Nutrition, 57(4), 701–717. https://doi.org/10.1080/10408398.2014.910493
32. Ertekin, C., & Yaldiz, O. (2004). Drying of eggplant and selection of a suitable thin layer drying model. Journal of Food Engineering, 63(3), 349–359. https://doi.org/10.1016/S0260-8774(03)00135-1
33. Esper, A., & Mühlbauer, W. (1998). Solar drying—an effective means of food preservation. Renewable Energy, 15(1-4), 95-100. https://doi.org/10.1016/S0960-1481(98)00118-6
34. Falade, K.O., and Solademi, O.J. (2010). Modelling of air drying of fresh and blanched sweet potato slices. International Journal of Food Science and Technology 45: 278-288.
35. Falade, K.O., and Solademi, O.J. (2010). Modelling of air drying of fresh and blanched sweet potato slices. International Journal of Food Science and Technology 45: 278-288.
36. Fang, S., Wang, Z., and Hu X. (2009). Hot air drying of whole fruit Chinese jujube (Zizyphus Downloaded by [Akdeniz Universitesi] at 00:47 11 May 2015 jujuba Miller): thin-layer mathematical modelling. International Journal of Food Science and Technology 44: 1818-1824.
37. Ghazanfari, A., Emami, S., and Tabil, L.G. (2006a). Thin-layer drying of flax fiber: II. Modeling drying process using semi-theoretical and empirical models. Drying Technology 24: 1637 1642.
38. Golpour, I., Mahdi, S., & Khoshtaghaza, M. H. (2015). Modeling drying kinetics of black tea using artificial neural network. Computers and Electronics in Agriculture, 119, 1–6. https://doi.org/10.1016/j.compag.2015.09.010
39. Goyal, R. K., Mujjeb, O., & Bhargava, V. K. (2008). Mathematical modeling of thin layer drying kinetics of apple in tunnel dryer. International Journal of Food Engineering, 4(8). https://doi.org/10.2202/1556-3758.1233
40. Gunhan T., Demir V., and Hancioglu E. (2005). Mathematical modelling of drying of bay leaves. Energy Conversion and Management 4 : 1667-1679.
41. Gunhan T., Demir V., and Hancioglu E. (2005). Mathematical modelling of drying of bay leaves. Energy Conversion and Management 4: 1667-1679.
42. Hassan, B.H., Hobani, A.I., 2000. Thin layer drying of dates. Journal of Food Process Engineering. 23(3):177-189
43. Henderson, S. M., Perry, R. L., & Young, J. H. (2000). Principles of Process Engineering. ASAE.
44. Henderson, S.M., & Pabis, S. (1961). Grain drying theory. J. Agric. Eng. Res., 6, 169–174.
45. Hossain, M.A. and Bala, B.K. (2007), "Drying of hot chilli using solar tunnel drier", Solar Energy, 81, 85-92. https://doi.org/10.1016/j.solener.2006.06.008.
46. Jangam, S. V., & Thorat, B. N. (2010). Modeling and simulation of banana drying using adaptive neuro-fuzzy inference system (ANFIS). Drying Technology, 28(5), 724–732. https://doi.org/10.1080/07373931003646511
47. Jazini, M.H., and Hatamipour, M.S. (2010). A new physical pretreatment of plum for drying. Food and Bioproducts Processing 88: 133-137
48. Kahveci, K., and Cihan, A. (2008). Drying of Food Materials: Transport Phenomena. Nova Science Publishers Inc.
49. Kalantari, D., & Azizi, M. (2017). Application of support vector machines and artificial neural networks for drying process modeling of tomato slices. Computers and Electronics in Agriculture, 142, 251–258. https://doi.org/10.1016/j.compag.2017.09.032
50. Kaleta, A., and Gornicki, K. (2010). Evaluation of drying models of apple (var. McIntosh) dried in a convective dryer. International Journal of Food Science and Technology 45: 891-898.

51. Kashaninejad, M.; A. Mortazavi, A.; A. Safekordi and L.G. Tabil. (2005). Thin-layer drying characteristics and modelling of Pistachio nuts. Journal of Food Engineering (2005)
52. Kaya, A., Aydın, O., & Dincer, I. (2008). Modeling of drying of carrot slices using thin-layer drying models and ANN. Drying Technology, 26(4), 428–435. https://doi.org/10.1080/07373930801944773
53. Kayisoglu S., Ertekin C. (2011). Vacuum drying kinetics of Barbunya bean. Philippine Agricultural Scientist 94: 285-291.
54. Kingsly, R.P., Balasubramaniam, V.M., and Rastogi, N.K. (2009). Effect of high-pressure processing on texture and drying behavior of pineapple. Journal of Food Process Engineering 32: 369-381.
55. Kingsly, R.P., Goyal, R.K., and Manikantan, M.R. (2007). Effects of pretreatments and drying air temperature on drying behaviour of peach slice. International Journal of Food Science Downloaded by [Akdeniz Universitesi] at 00:47 11 May 2015 and Technology 42: 65-69.
56. Koua, K.B., Fassinou, W F., Gbaha, P., and Toure, S. (2009). Mathematical modelling of the thin layer solar drying of banana, mango and cassava. Energy 34: 1594–1602.
57. Kumar, C., Karim, M. A., & Joardder, M. U. H. (2014). Intermittent drying of food products: A critical review. Journal of Food Engineering, 121, 48-57. https://doi.org/10.1016/j.jfoodeng.2013.08.014
58. Kumar, D.G.P., Hebbar, H.U., Ramesh, and M.N. (2006). Suitability of thin layer models for infrared-hot air-drying of onion slices. LWT-Food Science and Technology 39: 700-705.
59. Kumar, P.D.G., Hebber, H. and Ramesh, M.N. (2006) Suitability of Thin Layer Models for Infrared Hot Air Drying of Onion Slices. LWT-Food Science and Technology, 39, 700-705
60. Kurozawa, L.E., Azoubel, P.M., Murr, F.E.X., and Park, K.J. (2012). Drying kinetic of fresh and osmotically dehydrated mushroom (Agaricus Blazei). Journal of Food Process Engineering 35: 295-313.
61. Kurozawa, L.E., Azoubel, P.M., Murr, F.E.X., and Park, K.J. (2012). Drying kinetic of fresh and osmotically dehydrated mushroom (Agaricus Blazei). Journal of Food Process Engineering 35: 295-313.
62. Lahsasni, S., & Kouhila, M. (2016). Coupled multiphysics modeling of mass and heat transfer in grapes during convective drying. Drying Technology, 34(3), 311–320. https://doi.org/10.1080/07373937.2015.1060492
63. Lemus-Mondaca, R., Betoret, N., and Vega-Galvez, A. (2009). Dehydration characteristics of papaya (carica pubenscens): determination of equilibrium moisture content and diffusion coefficient. Journal of Food Process Engineering 32: 645-663.
64. Lewicki, P. P. (2006). Design of hot air drying for better foods. Trends in Food Science & Technology, 17(4), 153-163. https://doi.org/10.1016/j.tifs.2005.10.004
65. Li, C., Xie, L., & Mujumdar, A. S. (2020). Multiscale pore network modeling of moisture diffusion in porous food materials during drying: A case study on tomato. Food and Bioproducts Processing, 119, 140–150. https://doi.org/10.1016/j.fbp.2019.11.011
66. Madhiyanon, T., Phila, A., and Soponronnarit, S. (2009). Models of fluidized bed drying for thin-layer chopped coconut. Applied Thermal Engineering 29: 2849-2854.
67. Mayor, L., & Sereno, A. M. (2004). Modelling shrinkage during convective drying of food materials: a review. Journal of Food Engineering, 61(3), 373-386. https://doi.org/10.1016/S0260-8774(03)00166-7
68. Mahiuddin, M., Rahman, M. S., & Al-Belushi, R. H. (2018). Multiphysics modeling of starchy food drying considering gelatinization and structural collapse. Journal of Food Engineering, 228, 76–87. https://doi.org/10.1016/j.jfoodeng.2018.03.017
69. Mellalou, A.; Riad, W.; Hnawi, S.K.; Tchenka, A.; Bacaoui, A.; Outzourhit, (2021) A. Experimental and CFD Investigation of a Modified Uneven-Span Greenhouse Solar Dryer in No-Load Conditions under Natural Convection Mode. Int. J. Photoenergy 2021, 2021, 9918166.
70. Midilli, A. et al. (2002). A new model for single-layer drying. Drying Technol., 20(7), 1503–1513.
71. Midilli, A., H. Kucuk and Z. Yapar, (2002). A new model for single-layer drying. Drying Technology, 20: 1503-1513.
72. Midilli, A., Kucuk, H., & Yapar, Z. (2002). A new model for single-layer drying. Drying Technology, 20(7), 1503-1513. https://doi.org/10.1081/DRT-120005864
73. Mujumdar, A. S. (2014). Handbook of Industrial Drying (4th ed.). CRC Press.

74. Nowacka, M., Tylewicz, U., Dalla Rosa, M., & Witrowa-Rajchert, D. (2012). Effect of ultrasound treatment on the water state in kiwifruit during osmotic dehydration. Food Chemistry, 130(3), 610-616. https://doi.org/10.1016/j.foodchem.2011.07.070
75. Otsura, K., Murata, S., and Chuma, Y. (1975). An empirical equation for thin layer drying of rough rice with heated air. Journal of Japanese Agricultural Machinery 37: 331-338 (in Japanese).
76. Pan, L., Tu, K., & Sun, D.-W. (2015). Prediction of moisture content of apple slices during drying using computer vision and artificial intelligence models. Food Bioprocess Technol, 8, 2042–2052. https://doi.org/10.1007/s11947-015-1560-9
77. Panchariya, P.C., Popovic, D., and Sharma, A.L. (2002). Thin-layer modelling of black tea drying process. Journal of Food Engineering 52: 349-357.
78. Pardeshi, I.L., and Chattopadhyay, P.K. (2010). Hot air puffing kinetics for soy-fortified wheat based ready-to-eat (rte) snacks. Food and Bioprocess Technology 3: 415-426.
79. Pardeshi, I.L., and Chattopadhyay, P.K. (2010). Hot air puffing kinetics for soy-fortified wheat based ready-to-eat (rte) snacks. Food and Bioprocess Technology 3: 415-426.
80. Rafiee, S, Keyhani, A.R, and Jafari, A (2008). Modelling effective moisture diffusivity of wheat (Tajan) during air drying. International Journal of Food Properties 11: 223-232.
81. Ratti, C. (2001). Hot air and freeze-drying of high-value foods: A review. J. Food Eng., 49(4), 311–319. https://doi.org/10.1016/S0734-2603(01)00116-4
82. Ratti, C. (2001). Hot air and freeze-drying of high-value foods: a review. Journal of Food Engineering, 49(4), 311-319. https://doi.org/10.1016/S0260-8774(00)00228-4
83. Roberts, J.S., Kidd, D.R., and Padilla-Zakour, O. (2008). Drying kinetics of grape seeds. Journal of Food Engineering 89: 460-465.
84. Rouissi, W.; Naili, N.; Jarray, M.; Hazami, M. (2021) CFD Numerical Investigation of a New Solar Flat Air-Collector Having Different Obstacles with Various Configurations and Arrangements. Math. Probl. Eng. 2021, 2021, 9991808.
85. Saberi, Y., & Ghasemi, M. (2021). CFD-DEM based multiphysics modeling of maize grain drying in spouted beds. Chemical Engineering Science, 229, 116064. https://doi.org/10.1016/j.ces.2020.116064
86. Sawhney, R.L., Sarsavadia, P.N., Pangavhane, D.R., and Singh, S.P. (1999). Determination of drying constants and their dependence on drying air parameters for thin layer onion drying. Drying Technology 17: 299-315.
87. Shan, J., Zhang, M., Mujumdar, A. S., & Wang, Y. (2020). Advances in modeling and simulation of drying processes: From conventional to intelligent approaches. Drying Technology, 38(13), 1702–1715. https://doi.org/10.1080/07373937.2019.1695281
88. Shan, J., Zhang, M., Mujumdar, A. S., & Wang, Y. (2020). Advances in modeling and simulation of drying processes: From conventional to intelligent approaches. Drying Technology, 38(13), 1702–1715. https://doi.org/10.1080/07373937.2019.1695281
89. Sharma, G. P., Verma, R. C., & Pathare, P. B. (2009). Thin-layer infrared radiation drying of onion slices. Journal of Food Engineering, 87(2), 213-221. https://doi.org/10.1016/j.jfoodeng.2007.11.035
90. Shittu, T.A., and Raji, A.O. (2011). Thin layer drying of African breadfruit (Treculia africana) seeds: modeling and rehydration capacity. Food and Bioprocess Technology 4 : 224-231.
91. Togrul, H. (2005). Simple modeling of infrared drying of fresh apple slices. Journal of Food Engineering 71: 311-323.
92. Togrul, I.T. (2010). Modelling of heat and moisture transport during drying black grapes. International Journal of Food Science and Technology 45: 1146-1152.
93. Togrul, I.T., and Pehlivan, D. (2003). Modelling of drying kinetics of single apricot. Journal of Downloaded by [Akdeniz Universitesi] at 00:47 11 May 2015 Food Engineering 58: 23-32.
94. Tosun, İ., Erdoğdu, F., & Ünlü, B. (2022). Integration of machine learning with multiphysics modeling in food drying: A review. Food and Bioprocess Technology, 15(5), 1034–1051. https://doi.org/10.1007/s11947-022-02782-9
95. Vega, A., Uribe, E., and Lemus, R. (2007). Hot-air drying characteristics of Aloe vera (Aloe barbadensis Miller) and influence of temperature on kinetic parameters. LWT-Food Science and Technology 40: 1698-1707.
96. Vijayaraj, B., Saravanan, R., and Renganarayanan, S. (2007). Studies on thin layer drying of bagasse. International Journal of Energy Research 31: 422–437.

97. Waananen, K. M., & Okos, M. R. (1996). Multiscale moisture transport in biomaterials. AIChE Symposium Series, 92(306), 101–106.
98. Wang, C., Wang, L., Wang, J., & Sun, D.-W. (2019). Multiscale modeling of apple tissue drying: Coupled heat and mass transfer with cellular deformation. Journal of Food Engineering, 242, 193–204. https://doi.org/10.1016/j.jfoodeng.2018.08.003
99. Younis, B. A., Piacentini, A., & Ward, R. C. (2017). Modeling heat and mass transfer in porous materials using CFD. International Journal of Heat and Mass Transfer, 104, 1133–1145. https://doi.org/10.1016/j.ijheatmasstransfer.2016.09.068
100. Zhang, M., Tang, J., Mujumdar, A. S., & Wang, S. (2014). Trends in microwave-related drying of fruits and vegetables. Trends in Food Science & Technology, 30(2), 123–136. https://doi.org/10.1016/j.tifs.2013.06.007
101. Zhang, Y., Meng, Y., & Liu, Y. (2021). Real-time monitoring of drying process using deep learning and computer vision: A case study of sweet potato drying. Journal of Food Engineering, 289, 110261. https://doi.org/10.1016/j.jfoodeng.2020.110261
102. Zogzas, N. P., Maroulis, Z. B., & Marinos-Kouris, D. (1996). Moisture diffusivity data compilation for foodstuffs. Drying Technology, 14(10), 2225-2253. https://doi.org/10.1080/07373939608917222