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Determination of hydration kinetic of pinto beans: A hyperspectral images application

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ABSTRACT

Hydration is a typical operation applied to legumes before cooking, reducing time and the associated energy cost. To monitor the process, mass balance method is the most used methodology, despite this method is destructive, repetitive, and time-consuming. For that reason. hyperspectral techniques are presented as an alternative for assessing the hydration process since it is a noninvasive method. Therefore, the objective of this work was to evaluate the technique of hyperspectral imaging for studying the hydration kinetics of pinto beans. For this purpose, a sample of pinto beans was hydrated in distilled water, determining moisture content during the process and taking hyperspectral images by reflectance mode, in the range 400 to 800 nm until constant mass. The moisture content was modelled using Peleg and a sigmoidal model. Next, the images were pre-treated and the median spectral profile for each bean was obtained. Then, a regression model was fitted, using the wavelength that maximized the coefficient of determination (R^2) and minimized the root mean square error (*RMSE*). The results show that Peleg model fit experimental data with R^2 in the range of 0.974 to 0.989 while sigmoidal model of 0.997 to 0.999. On other hand, mean spectral profiles at 632 nm and sigmoidal model give the higher metrics 0.997 and 38.3 for R^2 and *RMSE* respectively. The results showed that hyperspectral imaging in reflectance mode is a tool capable of measuring the hydration level of beans with higher performance at 632 nm, with a determination coefficient R^2 higher than 0.98.

Introduction

Legume grains are a rich source of protein, fiber, and iron, whose consumption has increased in the last decades, mainly due to their health benefits, long shelf life, and easy transport [1]. Although, before its consumption, it is necessary to increase their moisture by hydration before cooking, malting, and germination for tendering tissues, activating enzymes, and/or eliminating antinutritional components [2,3]. Consequently, it is important to perform the hydration process and its kinetics.

The hydration kinetics of legume grains is characterized by the determination of water absorption, equilibrium moisture, and the time required for grain softening [4]. In this sense, knowing the kinetics parameters of hydration allows evaluating the use of new approaches to improve the process optimizing factors such as cooking time, starch gelatinization, protein denaturation, and release of other compounds [5].

The modeling of hydration kinetics of legume grains uses phenomenological, semi-empiric, and empiric equations such as Peleg and Kaptso's models, the most common equations for moisture modeling [6]. These models require performing a controlled-hydration process where the mass of the grains should be recorded during the soaking time, for the next calculus. Indeed, this procedure must continue until equilibrium between moisture inside grains and the media [7,8]. However, this method can be disadvantageous in industry, where quick results are desirable. Therefore, other methods, fast and nondestructive,

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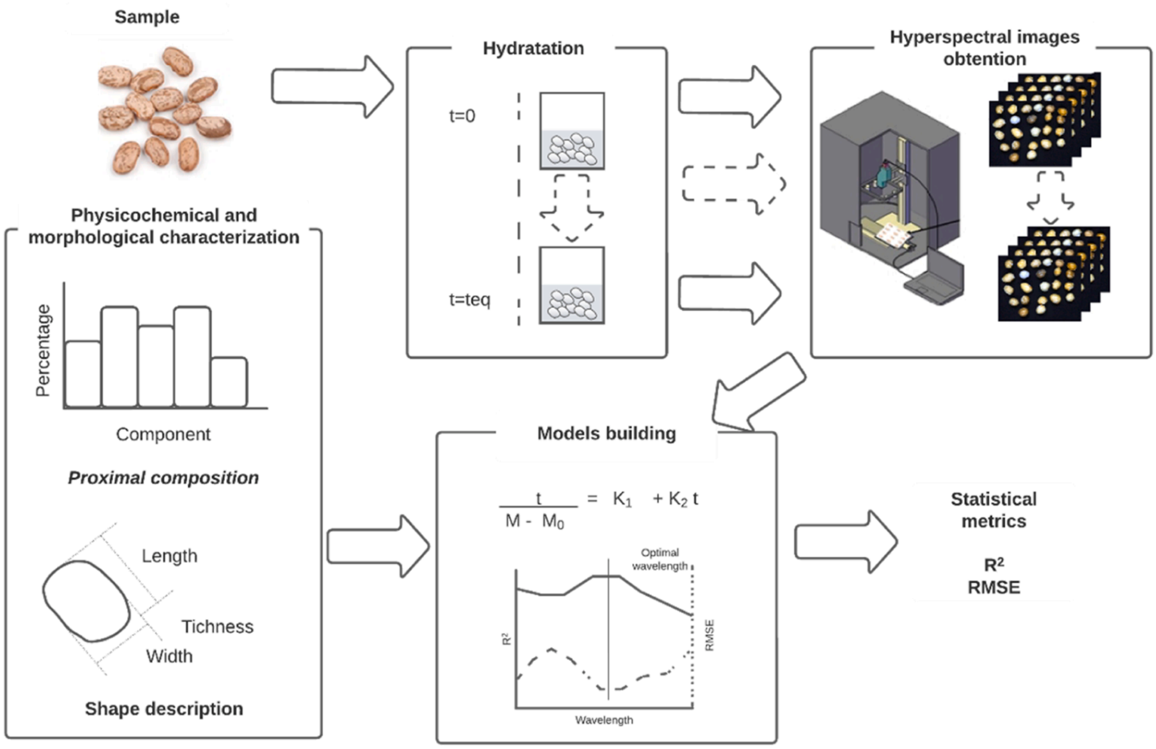

Fig. 1. Summary graph of bean hydration kinetics by HSI.

should be studied to obtain the moisture content of grains during the hydration process for performing kinetics studies.

An interesting approach is hyperspectral system imaging (HSI) to monitor the hydration process. HSI is a nondestructive technique that has multiple applications, for instance, the assessment and prediction of moisture content in foods, which was recently studied. Yang, He, Lu, Ren and Wang [9] applied HSI to predict moisture content in cooked beef, and Ma, Sun and Pu [10] applied this technique for predicting moisture content in pork at diverse methods of drying. On the other hand, Caponigro, Marini and Gowen [11] combined NIR-HSI for assessing moisture content on hydrogels composed of agar, starch, gelatin, and blended.

In fact, HSI is a tool with high potential for use in agriculture and quality control of agri-food products; with a wide range of applications from satellite images to macroscopic and cellular levels [12,13]. Its application has been tested in obtaining crop field information, even considering environmental variables for decision making up to the detection of ingredients used in processed food formulations [14,15]. More recent work explores applications combined with other tools such as visible/near-infrared spectrum imaging [16–18] and artificial intelligence [19]. Taghinezehad et al. (2023) mention that HSI can be a powerful technique for controlling food drying processes.

Consequently, the main objective of this study was to evaluate the use of HSI for moisture modeling in legumes grain, which could allow us to predict the degree of hydration of pinto beans (Fig. 1).

Materials and methods

The experimental procedure is shown in Fig. 2. Likewise, each step of the flowchart is explained in the following paragraphs.

Sample beans

For the present study, 3 kg of common beans (*Phaseolus vulgaris*) of the "*Pinto*" variety were purchased from the local market in Chachapoyas, Peru. First, the beans were selected according to their homogeneity in size, color, and weight, discarding beans that presented mechanical and biological damage. Next, the samples were stored in a clean and dry plastic container at 15 °C for two weeks to get homogeneous moisture in the beans until processing.

Sample characterization

Samples (250 grains) of "Pinto" beans (*Phaseolus vulgaris*) were characterized by obtaining mean values for width (W), length (L), and thickness (T) using a vernier caliper (Stanley co, standard). Using these values surface (S), volume (V), and specific surface (Sps) were calculated using the Eqs. (1) to (3) [4].

$$S \approx \pi * a\sqrt{\frac{(L*W)^a + (L*T)^a + (T*W)^a}{3}} \wedge a = 1.6075 \quad (1)$$

$$V = \frac{\pi * L * W * T}{6} \quad (2)$$

$$S_{sp} = \frac{S}{V} \quad (3)$$

In addition, moisture, protein, fat, and ash were determined according to AOAC (2010) in a similar way to the works of Miano and Augusto [4], and Kaptso, Njintang, Komnek, Hounhouigan, Scher and Mbofung [20].

Hydration process

For the hydration process, 15 g (19 to 20 grains approximately per each repetition) of the sample were placed in an Erlenmeyer glass of 500 mL which contained double-distilled water at 20 °C, controlled by constant temperature water bath (Heating Bath B-305, Buchi). The mass of each sample was controlled every 15 min during the first two hours and every 30 min until it reached equilibrium. Each sampling time, the beans were drained, dried superficially, and weighed immediately, as

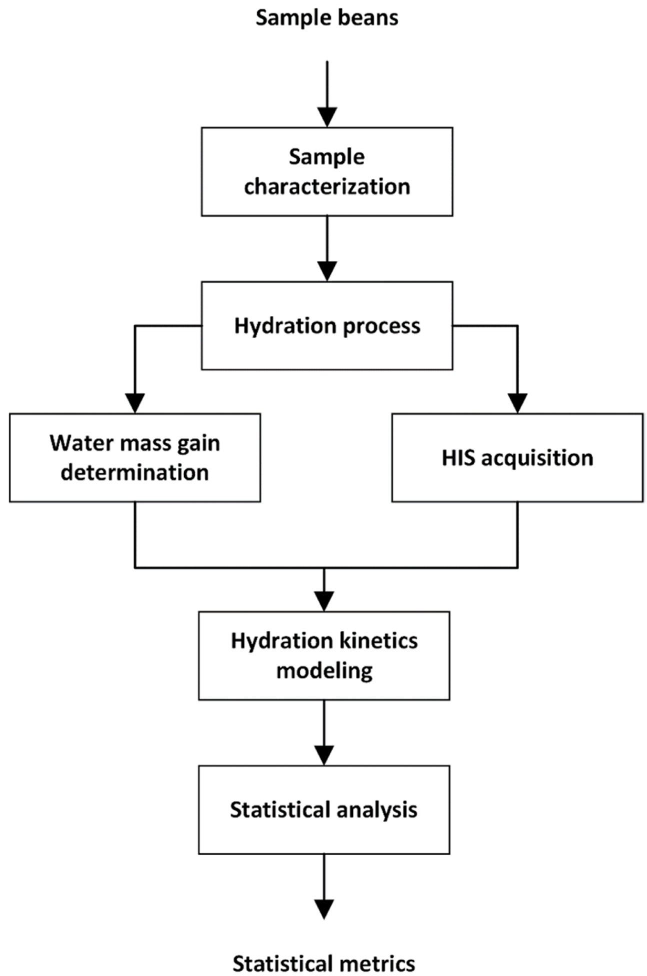

Fig. 2. Experimental procedure in hydration process of beans.

described by Oroian [21], and Ulloa, Rosas-Ulloa, Ramírez-Ramírez and Ulloa-Rangel [22].

The moisture content at each time step (M_t) was calculated by mass balance, considering the initial sample mass (m_0), the moisture (M_0), and the obtained mass at each time step. Likewise, researchers like Miano et al. [6], Ulloa, Enríquez López, Contreras Morales, Rosas Ulloa, Ramírez and Ulloa Rangel [23] and Oliveira, Colnaghi, da Silva, Gouvêa, Vieira and Augusto [24] despise the transfer of soluble solids between beans grain and water for considered not significant in the mass balance. This process was realized in triplicate.

Hyperspectral images acquisition

Previous to obtaining hyperspectral image of the grains, the parameters of functioning of the camera were programmed (Pika XC; Resonon Inc. Montana, USA), as follow: speed of sample platform = 0.5 cm/s, diaphragm aperture = 6.4 mm and distance to surface = 28.3 cm [25]. After that, calibration procedure was conducted using white and black references as described in the investigation performed by Castro, Prieto, Guerra, Chuquizuta, Medina, Acevedo-Juárez and Avila-George [26] and Vásquez et al. [25]. Subsequently, hyperspectral images of the grains of beans were acquired, being able to obtain fifty-seven images of fifty-nine grains in each hydration time by SpectrononPro 2.62 software (Resonon Inc. Montana, USA) [26]. The system was operated in reflectance mode with line-by-line scanning in the 400–800 nm range (see Fig. 3).

For the extraction of the average spectral information (reflectance) of each bean's hyperspectral image throughout the hydration process, a guide created in Matlab by Castro et al. [26] was used, obtaining a total of 1121 spectra. Finally, the mean spectra were pre-treated using a second-order Savitsky-Golay filter with 11 frames to eliminate any noise generated when images were obtained.

Modeling hydration kinetic and HIS

Modelling hydration kinetic

The *Peleg* model [27] and a *sigmoidal* model [20] were used for modeling the hydration kinetics of the pinto bean. For this, the moisture contents (% dry basis) were tabulated against the hydration time (min). The Peleg model describes hydration behavior with downward concave shape through its parameters with physical explanation (Eq. (4)) and the sigmoidal model (semi-empiric) describes hydration kinetics behavior with a sigmoid shape, characterized by beans with low-permeability-to-water seed coat (Eq. (5)).

$$M_t = M_0 + \frac{t}{k_1 + (k_2 * t)} \tag{4}$$

$$M_t = \frac{M_{eq}}{1 + \exp[-k_k * (t * \tau)]} \tag{5}$$

Where, M_0 is the initial moisture content in the dried base (% d.b.), k_1 is the hydration rate (min• (% d.b.$^{-1}$)) and k_2 is the parameter related to the equilibrium moisture content (% d.b.$^{-1}$), k_k related to hydration rate (min^{-1}), τ time to achieve the inflection point of the hydration curve (min) and M_{eq} which is the equilibrium moisture content (% d.b.).

Modelling hydration by reflectance

Modeling of hydration by reflectance was done using HSI technology. Previously, the reflectance and moisture content values of the beans "Pinto" were ordered and saved in *.xlsx format during each time of hydration. A sequence was implemented in MatLab 2021b to select an optimal wavelength from the maximization of determination coefficient (R^2) and minimization of mean square root deviation (RMSE) by linear regression between moisture content and reflectance [28]. Finally, the hydration kinetics was modeled using the Peleg and Sigmoidal models using the moisture content and reflectance value at optimized wavelength instead of moisture content as the dependent variable, both in relation to hydration time (min). The functions carried out in Matlab was uploaded to Matlab files interchange web in the following link "https://es.mathworks.com/matlabcentral/fileexchange/158, 986-algorithm-for-modelling-pinto-bean-hydration-kinetics".

Fitting and statistical analysis

The Levenberg–Marquardt algorithm implemented in MatLab 2021b - MathWorks software was used to fit data in the Peleg and Sigmoidal models (see Fig. 4). For statistical analysis, the regression value R^2, the values of the root mean square error (*RMSE*), with a confidence level of 95 % were evaluated using the Eqs. (6) and (7) [4,6,8].

$$R^2 = \frac{\sum_{i=1}^{n} (\widehat{y}_i - y_i)^2}{\sum_{i=1}^{n} (\widehat{y}_i - y_t)^2} \tag{6}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \widehat{y}_i)^2} \tag{7}$$

Where, $\widehat{y}_i$ is the experimental value, y_i is the predicted value and n is the number of observations.

Results and discussion

Physicochemical analysis during fermentation

Table 1 shows the characteristic dimensions of beans and their

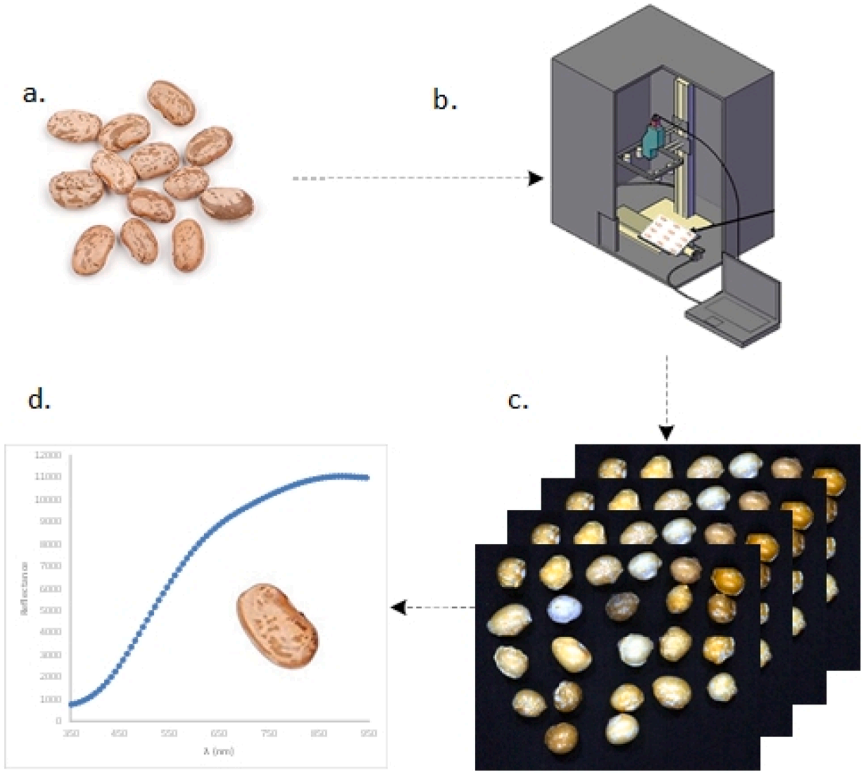

Fig. 3. Hyperspectral imaging system: (a) samples, (b) camera HSI, (c) imagen spectral and (d) spectral mean.

chemical composition. The results of the dimensions are slightly different to other varieties such as Azufrado, Peruano bola, Mayacoba, and Canario, as reported by Ulloa et al. [23] even for the same variety presented slight differences as reported by Ulloa et al. [22]. While chemical composition in moisture, protein, lipid, and ash are similar to those reported by Ovando-Martínez, Osorio-Díaz, Whitney, Bello-Pérez and Simsek [29], Anino, Onyango, Imathiu, Maina and Onyangore [30], and SánchezArteaga et al. (2015).

Spectral profiles

Fig. 5 shows the spectral profile of the pinto beans for different times of hydration from 0 to 1200 min, evidencing a sigmoidal shape with a higher slope in the range of 400 to 800 nm. Likewise, an upward shift of the spectrum is shown when hydration time increases. Despite being a different food matrix in beef cuts, when it was dehydrated, the spectrum has a downward shift by increasing the dehydration time Ren and Sun [31], which shows that when a sample has higher water content, the spectrum in terms of reflectance presents higher values, evidencing a causal relationship between these two variables.

Hydration kinetics modeling

The hydration kinetics of Pinto beans were suitably fitted to both Peleg and Sigmoidal Model. Table 2, shows that both models present high values of R^2, being higher when sigmoidal model was used. This evidences that the pinto bean has a sigmoidal behavior of hydration kinetics, which is commonly in legume grains. In fact, legume grains such as pinto beans mostly present sigmoidal behavior due to the seed coat's impermeability to water [4]. This causes water to get into through the micropyle and hilum [32], and slowly hydrating the grains from inside. As the seed coat gets hydrated from the inside, its permeability to water increases, letting water enter through the seed coat and accelerating hydration [6]. From this point, hydration continues until it reaches equilibrium.

There are three published works where the pinto bean was used. One of them, used the Peleg model to fit hydration kinetics, reporting values of 1.56 for k_1 and 0.0071 for k_2 [33]. These parameters are different from the used pinto beans in the present work, especially for k_1, which is related to the reciprocal of hydration rate. Besides that, thew work of Carvalho et al. [34] also reported pinto beans hydration kinetics with downward concave shape behavior, using Peleg model to fit the data. Nevertheless, they reported the data at 30, 40 and 50 °C, which can also affect to the hydration kinetics behavior since higher soaking temperatures can reduce lag phase of sigmoidal shape behavior [20].

In other work, pinto bean presented sigmoidal behavior with a long lag phase [35]; however, without fitting data to a model. All these works and the current work show different hydration kinetics for pinto beans. This corroborates the fact that despite the same variety of beans, hydration kinetics can be very different. This is due to the intrinsic properties of the grains as initial moisture content and/or composition differences [6] caused by different growth conditions and storage conditions [35]. This result suggests that hyperspectral imaging for moisture monitoring should be evaluated for beans with different storage and growth conditions.

Hyperspectral analysis for hydration kinetics evaluation

First, the optimum wavelength which better detects moisture of pinto beans was searched. In Fig. 6, the relationship between the R^2 and the RMSE of the correlation between moisture content and reflectance is presented. The optimum wavelength was 632 nm, which obtained a maximum determination coefficient (R^2), and minimum root means square error (RMSE). This indicates that 632 nm is the most suitable wavelength to predict the moisture content of pinto beans. In other words, by taking images using 632 nm of wavelength, moisture content can be predicted without using a destructive method. Caponigro et al. [11] reported that samples with very high moisture content absorb a large quantity of NIR light resulting in signal saturation above 1384 nm, while samples with very low moisture content absorb only a small

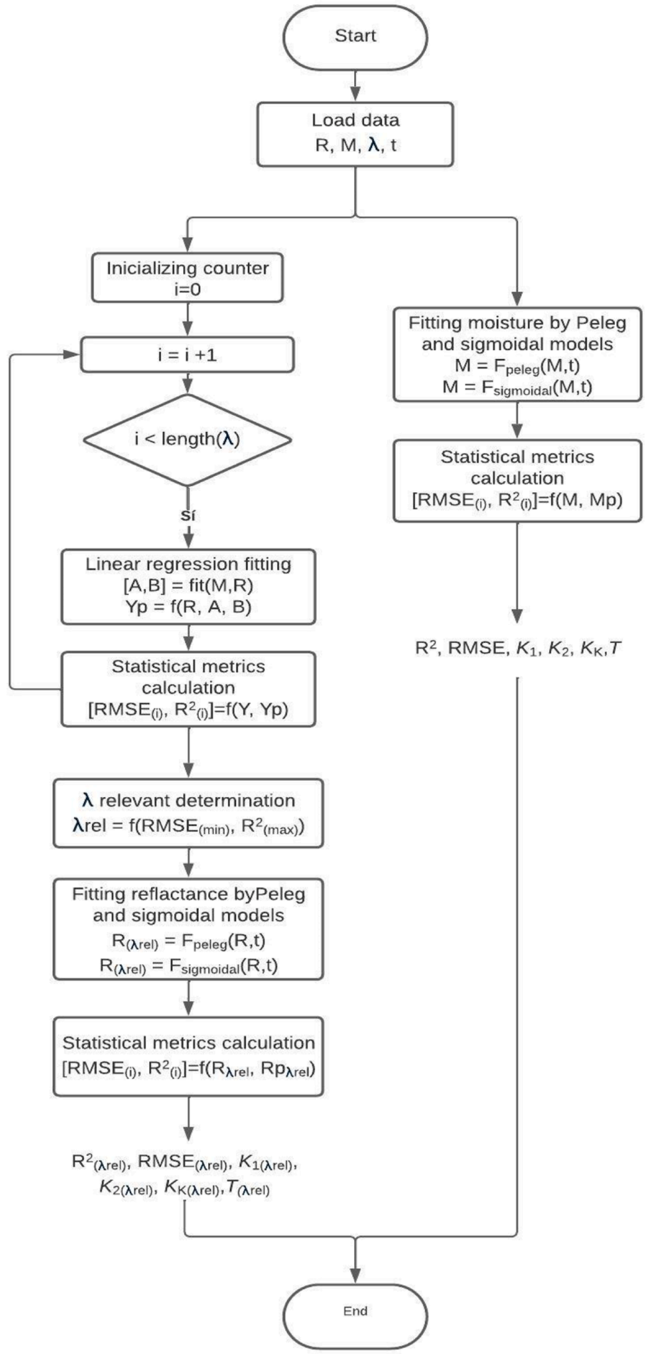

Fig. 4. Flowchart for wavelength selection algorithm.

Table 1
Values physicochemical of the bean sample.

Physical properties		Chemical composition	
Thickness-T (*mm*)	8.49 ± 0.93	Moisture (% d. b)	13.42 ± 0.02
Width-W (*mm*)	9.64 ± 0.85	Protein (%)	22.25 ± 0.03
Length-L (*mm*)	12.40 ± 1.09	Fat (%)	1.47 ± 0.05
Surface-S (mm^3)	580.10 ± 91.19	Ash (%)	5.85 ± 0.07
Volume-V (mm^3)	540.02 ± 128.50		
Specific surface-Sps (mm^{-1})	1.10 ± 0.11		

quantity of light, resulting in a low signal.

The relationship between the reflectance and the moisture content of the bean grains during hydration was $R^2 = 0.9966$, evidencing the existence of a similarity between both physical parameters. This value is higher than the one reported by Mendoza et al. [28] who obtained 0.789 as the determination coefficient for the prediction of water uptake and reflectance of other common beans. This low prediction value is due to using a linear fit model such as PLSR. In contrast, Ren and Sun [31], who determined a high relationship between water and reflectance values of a $R^2 = 0.92$ in the range of 1000 to 1500 nm in rehydrated samples of meat slices, due to the excitation of $O - H$ bonds that particularly the water molecule counts.

Using reflectance and the optimum wavelength, hydration kinetics can be plotted and described. Fig. 7 shows the hydration kinetics

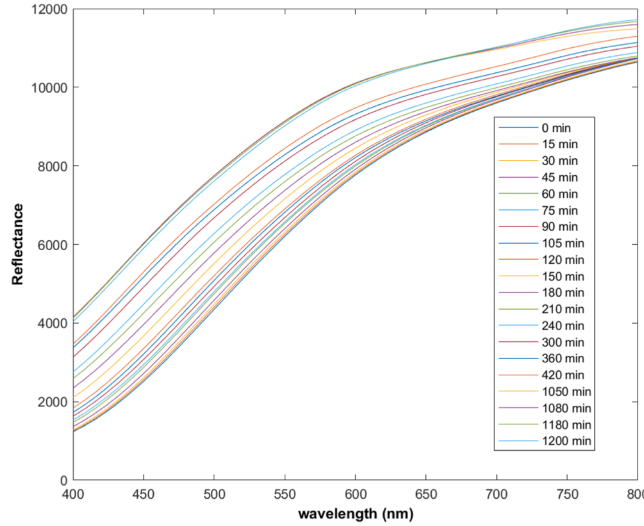

Fig. 5. Mean spectral profile at different soaking times.

Table 2
Fitting parameters from Peleg model and Sigmoidal model for moisture content and reflectance.

Peleg Model					
Parameters	k_1	k_2	–	R^2	*RMSE*
Moisture	4.2856 ± 0.0925	0.0058 ± 0.0003	–	0.974 ± 0.0078	5.94 ± 1.0191
Reflectance	0.2101 ± 0.0145	$3.0\times10^{-4} \pm 1.0\times10^{-4}$	–	0.988 ± 0.008	76.0 ± 15.6930
Sigmoidal Model					
Parameters	τ	k_k	M_{eq}	R^2	*RSME*
Moisture	241.5861 ± 41.0452	0.0081± *	117.5608± 7.6253	0.999± 0.1727	1.18±*
Reflectance	−46.818±39.9971	0.003±0.0005	1.0555×10^4±158.1031	0.997±0.0025	40.2 ± 7.3078

Note: * zero.

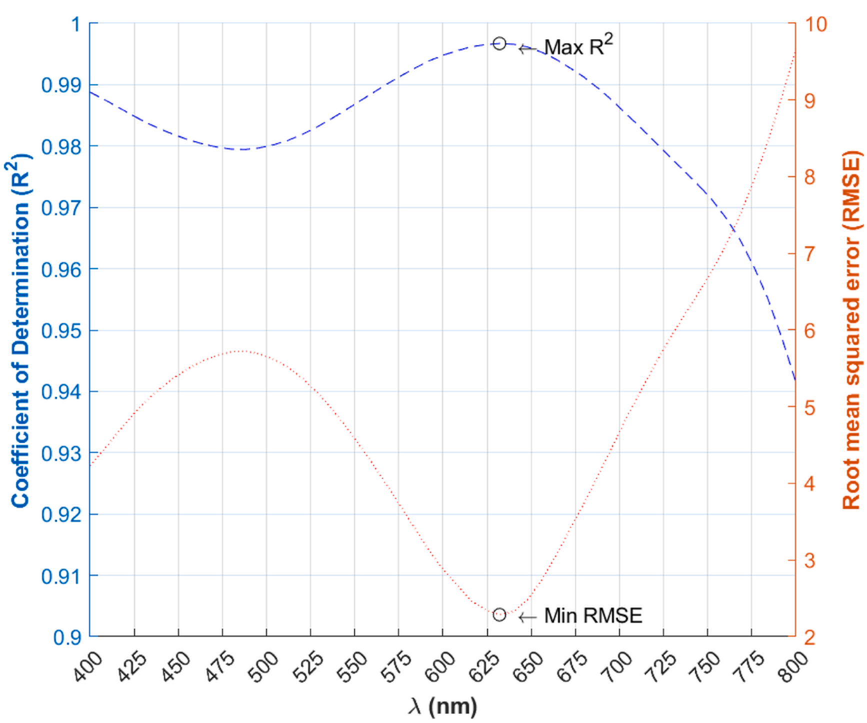

Fig. 6. Relevant wavelength selection by mean of *RMSE* and R^2.

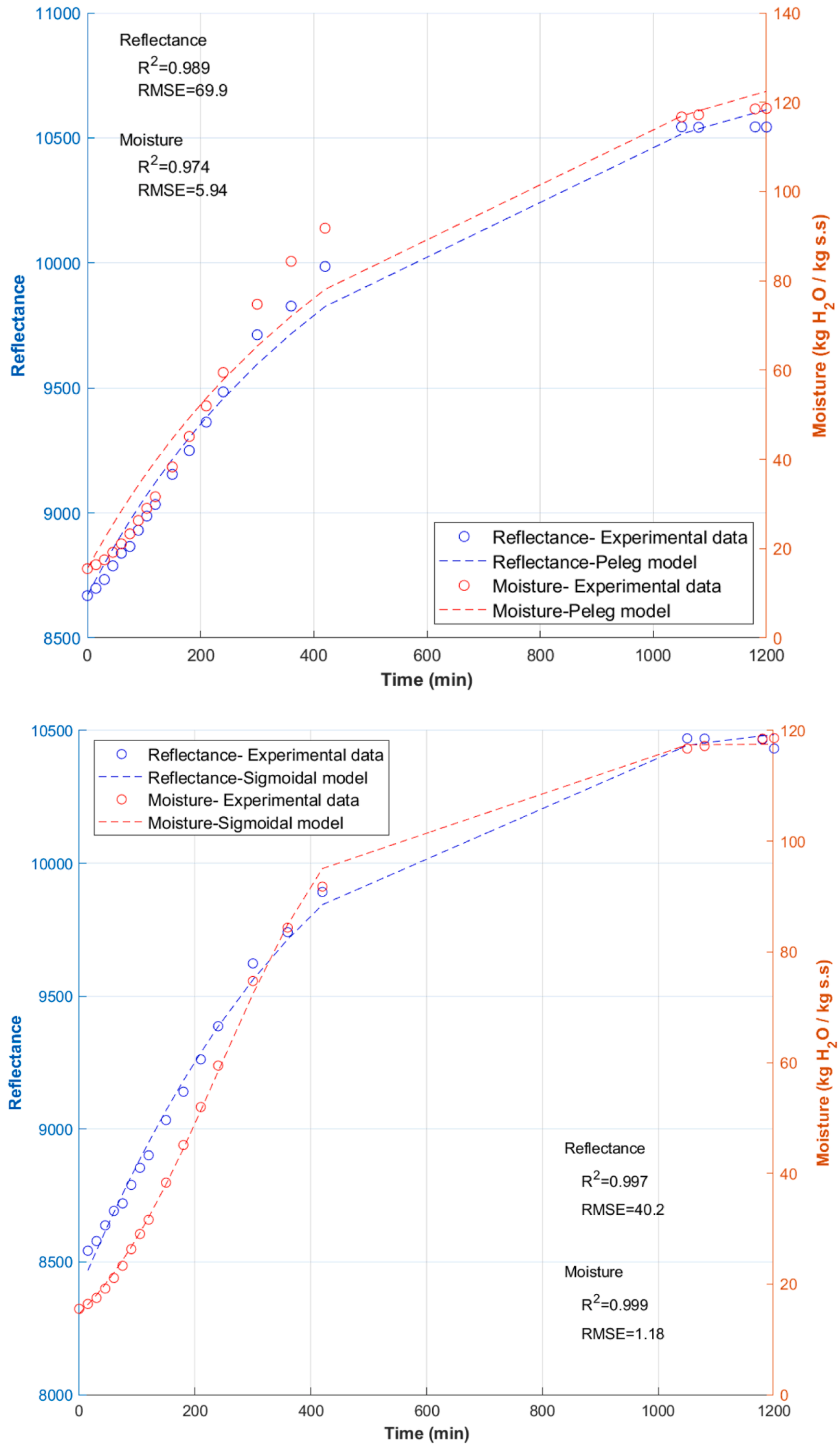

Fig. 7. Hydration kinetics and reflectance models of Pinto beans. The dots represent the mean of data and discontinuous lines represent the model fitting.

evaluated using the moisture content behavior against hydration time and using reflectance of beans against hydration time. Further, Fig. 7 demonstrated the sigmoidal behavior of hydration kinetics, corroborating the best-fitting goodness of the sigmoidal model (Table 1). Regarding the use of reflectance, hydration kinetics was described almost the same as using moisture content no matter which model was considered, evidencing a high correlation between moisture and reflectance.

Conclusions

The hyperspectral imaging technique was used to monitor the hydration of pinto beans. Mean reflectance spectra were obtained in the 400 to 800 nm range. The best relationship between moisture content and reflectance value was identified at 632 nm, with a goodness of fit of $R^2 = 0.9966$ and $RMSE = 2.30$. The hydration kinetics were subsequently modelled using the Peleg and Sigmoidal equations, resulting in high goodness of fit of $R^2 = 0.989$ and $R^2 = 0.996$, respectively.

Hyperspectral imaging is a promising tool for monitoring and modelling the hydration kinetics of pinto beans. This technique is useful for beans with both sigmoidal and concave downward shapes of hydration kinetics. Consequently, future studies using more grains are required to validate the optimal wavelength.

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This work was not finance by some organism.

CRediT authorship contribution statement

Tony Chuquizuta: Conceptualization, Data curation, Funding acquisition, Methodology, Software, Validation, Writing – original draft, Writing – review & editing. **Segundo G. Chavez:** Conceptualization, Formal analysis, Investigation, Methodology, Writing – original draft. **Alberto Claudio Miano:** Conceptualization, Formal analysis, Investigation, Methodology, Writing – review & editing. **Marta Castro-Giraldez:** Conceptualization, Investigation, Methodology, Supervision, Writing – original draft. **Pedro J. Fito:** Conceptualization, Investigation, Methodology, Supervision, Writing – review & editing. **Hubert Arteaga:** Conceptualization, Methodology, Writing – original draft. **Wilson Castro:** Conceptualization, Formal analysis, Methodology, Software, Supervision, Validation, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Tony Steven Chuquizuta Trigoso reports equipment, drugs, or supplies was provided by Universidad Nacional Autónoma de Chota.

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