

# Near-Infrared Spectroscopy (NIRS) applied to legume analysis: A Review

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**Abstract**— *Legumes are very important basic foods on the daily diet for humans being, due to the input of proteins, starch, fiber, fat, vitamins and minerals. The conventional methods to determine their chemical composition are time consuming, expensive, produce a lot of chemicals, and are destructive analysis. The need of non-invasive alternative methodologies has pointed out the Near Infrared Spectroscopy (NIRS) as a promising analytical tool for the main components in food, this in combination with chemometrics techniques for the construction of models for the prediction of analytical factors for routine use.*

*The purpose of this paper is to present a review of the usefulness of NIRS for analysis of various components in legumes of different origin such as beans, soybeans, peas, chickpeas and beans and the its usefulness for analysis of legumes and its reliability for its establishment as a routine analysis, thus avoiding the consumption of time in traditional techniques, generation of chemical residues and destruction of the sample.*

*It was found that NIRS is a technique capable to predict the content of protein, starch, dietary fiber, etc. in a fast and reliable way, in legumes. Being able to replace conventional techniques for the determination of these components.*

**Index Terms**— Legumes, non-destructive analysis, Near-infrared Spectroscopy, chemometrics, starch, protein, fiber.

## I. INTRODUCTION

Around 20 legumes types are used as dry grains for human nutrition. Among these, common bean (*Phaseolus vulgaris* L.) is highly consumed in Latin America and Africa, pea (*Pisum sativum* L.) in Asia, chickpea (*Cicer arietinum* L.) in India and lentil (*Len culinaris* Med.) in countries of the Middle East [1]. Consumption of legumes increases each year, in general, legumes are sources of complex carbohydrates, protein and dietary fiber, having significant amounts of vitamins and minerals, and high energetic value [2].

In the food industry, the safety and quality of food is still considered as an important issue around the world, which are directly related to the health and social progress of people. Consumers are gradually looking for quality labels and trust marks in food products, and expect manufacturers and retailers to provide high quality products. All these factors

have highlighted the need for reliable techniques to evaluate the quality of food [3].

Laboratory methods have been developed and refined to provide nutrient information to the industry, farmers and researchers. However, typical evaluation techniques are expensive and time-consuming [4]. The Green Analytical Chemistry (GAC) started as a search for practical alternatives to replace contaminant methodologies for the non-toxic ones with the aim to reduce the energy consumption, reagents and solvents as well as the toxicity of wastes in the laboratory [5].

In recent years, considerable research has been developed using spectroscopic techniques, such as the medium infrared (MIR), near infrared (NIR) and Raman, which are considered attractive and promising analytical tools in research, control and industrial laboratories. Compared to conventional methods of analysis based on ultraviolet-visible or electrochemical spectroscopy, vibrational spectroscopy techniques are often non-destructive and could provide very rapid analysis without pretreatment of the sample. In addition, IR spectroscopy can be used to analyze samples in the solid, liquid or gas state, at macro or microscopic level, potentially dangerous reagents are avoided which benefits the environment, the health of the operator and reduces the costs of external treatment of industrial chemical waste [6]. This seems to present them as the most promising options, however, all these benefits cannot be fully exploited without the interdisciplinary area of chemometrics, which allows to design or select the optimal measurement procedures and experiments, which provides the maximum chemical information from the spectral data [7].

The availability of non-destructive instruments that allow to evaluate the changes during the shelf life or to estimate quality parameters can have a wide number of practical applications in the product chain: during maturation, in the production process, during storage and during the distribution [8].

This document addresses a review of the research carried out in the analysis of various components in legumes of different origin such as beans, soybeans, peas, chickpeas and beans. This in order to offer a general overview of the usefulness of NIR in this type of products and its reliability for its establishment as a routine analysis, thus avoiding the

consumption of time in traditional techniques, generation of chemical residues and destruction of the sample.

From this review, the data can be taken as a basis by other researchers to establish more specific applications and with greater reliability.

## II. NEAR INFRARED SPECTROSCOPY

Spectroscopy analysis exploits the interaction of electromagnetic radiation with atoms and molecules to provide the physical (structural), chemical, qualitative and quantitative information that is contained within the wavelength or frequency of the energy spectrum that is absorbed or emitted [9].

Near-infrared (NIR) spectroscopy is a technique that collects the reflected light of a sampled material in the near-infrared region of the electromagnetic spectrum that extends from about 780 to 2500 nm (i.e., 12800 to 4000  $\text{cm}^{-1}$ ), is an alternative method that can give information on the biological composition and surface characteristics of foods. NIR absorption signals of chemical compounds can be observed as a consequence of vibrational energy transitions of molecular bonds in chemical compounds, each type of molecule vibrates in its own unique way; and molecular vibrations interact with light to create a unique spectral. When the radiation interacts with the sample, the incident radiation can be reflected, absorbed or transmitted, and the relative contribution of each phenomenon depends on the chemical composition, the physical parameters of the sample (the main sources of spectral variance include size, shape and curvature), the position and orientation during scanning, as well as its light scattering properties that are related to the microstructure [10]–[13]. In the NIR region, energy transitions occur over more than one energy level and thus overtone vibration is one of the main forms. In addition to overtones, a combination of different vibrational transitions decreases significantly with their order, the absorption bands corresponding to overtone and combined vibration have low intensity. Compared to other molecular bonds (C=O, S-H, etc), hydrogen bonds (C-H, O-H, N-H) have a higher absorption intensity in the NIR region and thus dominate the NIR spectrum. Each compound has special characteristics in these hydrogen bonds and other molecular bonds and hence owns a unique NIR spectrum that behaves as a fingerprint [14].

The usefulness of this technique is mainly attributed to: 1) Its capacity for non-destructive analysis, since no sample preparation or reagent consumption is needed; 2) it is fast, economical and 3) it is accurate and precise, among others [15].

One of the most important characteristics of the vibrational spectroscopy is the possibility to carry out the simultaneous analysis of different components in the same sample from a single instrumental measurement. However, the near infrared spectrum is composed by a great set of

overtones and combined bands. This, in combination with the complex chemical composition of the sample, makes the quantitative analysis extremely difficult. The spectrum can be further complicated by dispersion effects dependent on wavelength, instrumental noise, environmental effects and other sources of variability. Consequently, it is difficult to assign specific absorption bands to specific functional groups and much less to the chemical components. For this, the application of multivariate statistical techniques (chemometrics) is required to extract information about the quality attributes that are "hidden" in the NIR spectrum (calibration model). This involves regression techniques coupled with spectral preprocessing [6], [10], [16].

## III. CHEMOMETRICS

According to the International Society of Chemometrics (ICS), chemometrics is the science of relating the measurements made to a chemical process or system with the state of the system through the application of mathematical or statistical methods. Chemometrics uses mathematics, statistics and formal logic to a) design or select optimal experimental procedures; b) provide the maximum possible chemical information from the analysis of the chemical data; and c) obtain knowledge about chemical systems. Chemometrics has become an essential tool in modern analytical instrumentation in general, and in particular, in instruments based on vibrational spectroscopy, which allow the treatment of large amounts of information on the concentration of the components of the samples and the properties of a large number of these, which can be analyzed relatively quickly [6], [17].

Near infrared spectrum is analyzed to obtain information about the structure of a chemical compound present in a sample. In order to get efficient qualitative and quantitative information from data coming from NIR spectroscopy, chemometrics tools are necessary [18].

The chemometrics in the analysis of NIRS for the construction of a predictive model starts with spectral pre-processing treatment to remove high-or low frequency interferences. Different types of pre-treatment are polynomial baseline correction, Savitzky-Golay derivative, Standard Normal Variate (SNV), mean-centering and unit variance normalization. After the spectral pre-processing treatment, the calibration algorithms can be applied for classification and quantification. In order to do the above, many multivariate analytical tools are used, such a Principal Component Analysis (PCA), Principle component Regression (PCR), Multi-linear regression (MLR), Partial least squares regression (PLS), modified partial least squares regression (MPLS), Partial least squares discriminant analysis (PLS-DA), Linear discriminant analysis (LDA) [19]. Fig 1 presents a summary description about each of the points to follow for the construction of a NIR model.

These chemometrics techniques have been widely and successfully applied for the quantitative analysis of spectroscopic data due to their great ability to overcome common problems such as collinearity, overlap band and interactions, and the ease of implementation due to the availability of software. Multiple linear regression (MLR) is the oldest and the least used method, it allows establishing a link between a reduced number of wavelengths and a property of the sample [24].

The principal components analysis (PCA) is a mathematical procedure that allows to extract useful information from data, the relations between objects, the relations between objects and variables and the global correlation of variables. It identifies orthogonal directions of maximum variance in the original data and projects the data in a space of smaller dimensionality formed from a subset of the components of greater variance. Orthogonal directions are linear combinations (principal components) of the original variables, and each component explains a part of the total variance of the data. More clearly, the goal of PCA is to express the main information that is contained in the initial variables, in a smaller number of variables or factors, which are the so-called main components that describe the main variations in the data. The principal component regression (PCR) is obtained by the regression of the relevant property in the main components, it is widely used for data that have a high degree of covariance in the independent variables or when bad conditioning matrices are presented [24]–[26].

oriented along the maximum covariance directions between the spectral matrix X and the response vector Y. This method ensures that the latent variables are ordered according to their relevance to predict the variable Y. The interpretation of the relationship between the data X and the data Y (the regression model) is simplified, since this relationship is concentrated in the lowest possible number of latent variables. The PLSR method works particularly well when the various X variables express common information, that is, when there is a large amount of correlation, or even collinearity, which is the case of the spectral data [27].

Once the model has been developed, its accuracy must be evaluated, for which the following statistical parameters are usually determined: the coefficient of determination ( $R^2$ ) which indicates the percentage of variance present in the chemical values reproduced in the calibration or prediction, the root mean squared error of calibration (RMSEC), the root mean square error of prediction (RMSEP), the root mean square error of cross validation (RMSECV) that gives an average of the uncertainty that can be expected for the predicted values. The predictive capacity of a model can be evaluated with the residual prediction deviation (RPD), which is defined as the relationship between the standard deviation of the response variable and RMSEP. A RPD < 1.5 means that calibration is not feasible; between 1.5 and 2.0 that allows distinguishing high and low values; Between 2.0 and 2.5, approximate quantitative predictions are possible; and finally, RPD values > 2.5 identify models with good prediction accuracy and RPD > 3.0 with excellent accuracy. A reliable PLS model must have a high value of  $r^2$ ,  $R^2$  and RPD and a low value of RMSECV [27]–[29].

#### IV. APPLICATIONS OF NEAR INFRARED SPECTROSCOPY IN THE FOOD INDUSTRY

Near infrared spectroscopy (NIRS) has analytical potential as a non-destructive, quick and easy to use technique that has gained popularity in recent years as a tool for the analysis of moisture, protein, fat, starch, fiber, etc., in the food industry that includes cereals, fruits, vegetables, etc.

It was evaluated the viability of using NIR spectroscopy to monitor individual units and to predict operational parameters in corn processing products. Dry solids, ethanol, starch, sugars and dextrans can be analyzed. The PLS models developed showed sufficient accuracy as indicated by  $r^2$ , RMSE and RPD. The validation results indicated that near infrared models can be developed and that can predict various parameters accurately (RMSEP: 0.16–1.14%, RPD: 3.0–6.3) [30].

The effect of types of rice flours (white and brown rice flours), levels of fat replacement and levels of wheat gluten on the NIR spectra of rice cookies was investigated by Wionsiri *et al.* [31] and they evaluated the potential of near infrared (NIR) spectroscopy to predict moisture, fat, protein and gluten content of rice cookies in different forms (intact

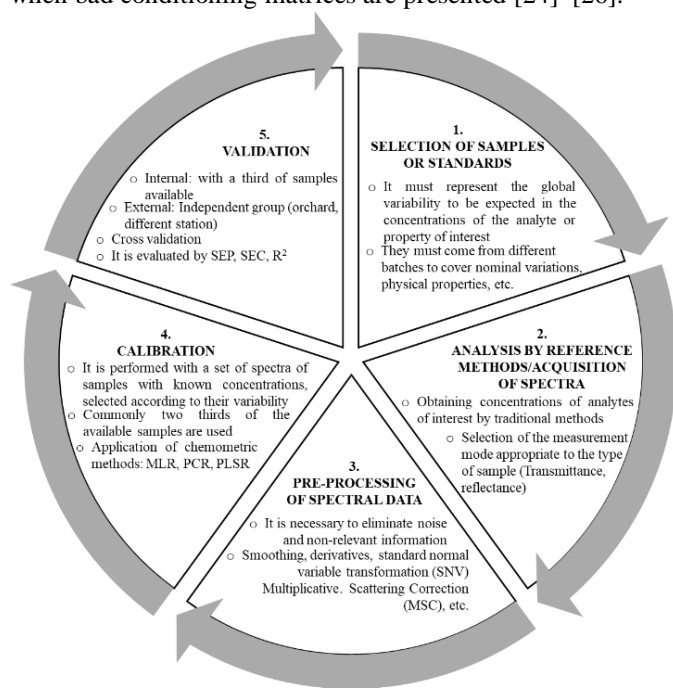


Fig 1. Process for the construction of a NIR prediction model [6], [10], [20]–[23]

Partial least squares regression analysis (PLSR) is widely used to obtain a quantitative prediction of the parameters of interest. In the PLS regression, an orthogonal base of latent variables is constructed one by one in such a way that they are

and milled). Partial least squares regression produced models with coefficient of determination ( $R^2$ ) values greater than 0.88 from NIR spectra for intact samples and greater than 0.92 for milled samples. These models were able to predict the four components with a ratio of prediction to deviation greater than 2.7 and 3.8 in intact and milled samples, respectively. The results suggest that the models obtained from the intact samples can be successfully applied for determining the chemical composition of rice cookies and showed the potential use of NIR spectroscopy to analyze rice cookies.

Liu, Zhou, & Ren, [32] developed calibration models from Fourier transform near infrared (FT-NIR) spectra of whole and milled grain samples of naked oats, for the estimation of protein, lipid, starch,  $\beta$ -glucan and avenanthramides content. The optimized models for all parameters, in whole grain/milled samples showed that FT-NIR could be used as a rapid and accurate method for selecting higher-quality naked oats in a breeding program as well as for quality control by the food industry.

Magwaza, Messo, Laurie, Laing, & Shimelis [33] developed NIRS-based models for quantifying protein content of sweet potato, 104 varieties were sampled and analyzed using NIR spectrometer. Calibration models were developed by subjecting spectral and reference datasets to partial least squares regression. Models that yielded the highest coefficient of determination ( $R^2$ ), residual predictive deviation (RPD) and lowest root mean square error of calibration (RMSEC) and prediction (RMSEP) were selected. The results demonstrated that NIRS can predict protein content on sweet potatoes, rapidly and accurately.

This review demonstrates the wide range of use that NIR technology can have and its application in a variety of food products.

#### ***Near-infrared Spectroscopy applied in legumes***

Garden peas are an important culture for the canning industry. They should be processed when immature. Because of its very fast ripening this kind of vegetable has been subjected to detailed investigation. In the early 1990s, British companies created a Research Club and assigned to CCFRA (Campden & Chorleywood Food Research Association) the job to examine possibility of ripeness determination of peas by NIRS [34]. Martens & Martens [35] demonstrated that reflectance spectroscopy can be applied to predict sensory properties in frozen peas. Isaksson & Kjolstad [36] applied reflectance and transmittance to determinate sensory parameters, DM, protein, ash, sucrose and starch in frozen peas.

Soy is recognized for its protein, fat and dietary fiber content. Its fiber has good nutritional and functional properties, neutral and colorless flavor, which makes it interesting for its incorporation into food without changes in quality, unlike wheat fiber [37]. Several authors have focused on the potential of NIR spectroscopy for the determination of

dietary fiber in different foods such as soybean [38] and wheat, oats, ready-to-eat cereals, barley, among others [39]–[45]. Soy proteins and fats produce considerable interest in relation to the possible health effects of the human diet. In the process of cultivation, the content of raw protein and fat are key factors to ensure the quality of the soy [46], [47].

Common Bean (*Phaseolus vulgaris* L.) are considered a good source of protein, starch, fiber and mineral nutrients for a large part of the world and have been associated with health benefits due to their antioxidant capacity [48], [49].

Traditional methods of analysis, such as Kjeldahl and Soxhlet, which are often used to measure the content of crude protein and fat, require excessive time, generate waste and destroy the sample. The official methods for determining dietary fiber are expensive in terms of time consumption, chemical solvents and high cost enzymes [37].

The near infrared spectroscopy (NIRS) has been used for the analysis of many components in various types of legumes. Table I – IV shows a resume of some investigations of Near-infrared spectroscopy applied in Faba bean (*Vicia faba* L.), Soy bean (*Glycine max* L.), Chickpea (*Cicer arietinum* L.), Pea (*Pisum sativum* L.) and common bean (*Phaseolus vulgaris* L.).

Several studies showed that the physical characteristics of the seeds, such as the size of the particles, water content and the interaction between the constituents, significantly influenced the absorption of the near infrared and led to the variation of the NIR results [50], [51]. Plans, Simó, Casañas, Sabaté, & Rodríguez-Saona [52] reported the spectrum did not present any clustering in PCA, they did not find discrimination by color of the bean seed could be associated with the elimination of the seed coat and the grinding of the sample, since the bean seed coat can provide unique chemical information to separate the samples based on their color. Hacisalihoglu, Larbi, & Settles, [53] on the contrary, found differences between white and colored beans when analyzing whole seeds by means of NIR. Some studies indicate that the physical characteristics of seed samples, such as particle size, water content and interactions between constituents significantly influence near infrared absorption and lead to variations in NIR results [50], [51].

**Table I. Near-Infrared spectroscopy applied in Faba bean (*Vicia faba* L.)**

Sample	Parameter	Accuracy		Conclusion
		R <sup>2</sup>	RPD	
244 samples milled and intact seed	Protein <sup>(M)</sup>	0.97	> 4	The models developed for milled samples was superior to the one for intact seed, possibly due to the large differences in the size of the particles.
[54]	<sup>(W)</sup>		2 - 2.5	The models for oil content prediction cannot be used for practical analysis of germplasm
	Starch <sup>(M)</sup>	0.93	≈ 3	Values of RPD > 4, indicate an extremely good prediction of protein. The model for starch from ground samples presented RPD close to 3, demonstrating a good predictive capacity
	<sup>(W)</sup> Polyphenols <sup>(M)</sup>		2 - 2.5	
	Oil	0.89	2 - 2.5	

(Milled<sup>(M)</sup>, Whole<sup>(W)</sup> seeds)

**Table II. Near-Infrared spectroscopy applied in Soy bean (*Glycine max* L.)**

Sample	Parameter	Accuracy			Conclusion
		R <sup>2</sup>	RMSEC	RMSEP	
153 whole grains	Crude Protein	0.97	0.61	0.76	The results showed that the NIR spectra has a significant potential as a rapid and non-destructive method for protein and fat contents
[55]	Fat	0.97	0.36	0.41	
100 powder samples	Moisture	0.8	0.28	1.55	It is possible to predict moisture, ashes, proteins, lipids and carbohydrates in soybeans using NIRS. the best calibration models were those developed for protein and moisture content, however the technique can predict all parameters.
[56]	Protein	0.81	0.58	1.61	The results demonstrated the feasibility of using NIR in the control of soybeans and replacement the laborious methods.
	Lipids	0.71	1.13	1.2	
	Ash	0.63	0.07	0.38	
	Carbohydrates	0.5	1.11	3.71	
80 samples	Dietary Total Fiber	0.8	1.7*	0.86	The prediction models satisfactorily allowed the determination of the content of dietary fiber with acceptable coefficient of determination and low RMSEP, confirmed that the NIRS is a technique that may be useful to replace the traditional methods for routine analysis, rapidly and accurately
[37]					
40 samples [57]	Crude fiber	0.44-0.55	0.17-0.19**	1.3-1.5***	Bulk models should perform well for soybean protein and oil, but not well for fiber; These results confirm that NIR technology is a method that can be useful, fast and accurate to replace the routine analysis methods for total dietary fiber in soy samples.
	Protein	0.79-0.90	1.02-1.99**	2.2-3.3***	
	Oil	0.77-0.87	0.96-1.9**	2.1-2.8***	

(\*RMSECV, \*\*SECV, \*\*\*RPD)

Table III. Near-Infrared spectroscopy applied in Chickpea and Pea (*Cicer arietinum* L., *Pisum sativum* L.)

<sup>(M)</sup>Milled samples, <sup>(W)</sup> Whole samples, <sup>(FS)</sup> Fresh samples,

<sup>(Fz)</sup> Frozen sample

Sample	Parameter	Accuracy			Conclusion
		R <sup>2</sup>	SECV	RPD	
156 samples of pea	Crude Protein <sup>(M)/(W)</sup>	0.99/0.94	0.27/0.57	8.33/3.85	For both species, NIR calibration accuracy was in general better on ground that whole samples for chemical composition, but better on whole than grounds samples for physical or functional properties.
	Moisture <sup>(M)/(W)</sup>	0.90/0.51	0.19/0.39	3.23/1.43	
151 samples of Chickpeas	Fat <sup>(M)/(W)</sup>	0.77/0.84	0.36/0.31	2.04/2.50	
	Ash <sup>(M)/(W)</sup> Total Dietary Fiber <sup>(M)/(W)</sup>	0.77/0.72	0.18/0.19	2.00/1.85	
[58]	Seed Weight <sup>(M)/(W)</sup>	0.89/0.88	1.50/1.50	2.94/2.94	
	Hydration capacity <sup>(M)/(W)</sup>	0.82/0.90	3.33/2.65	2.33/3.03	
	Percentage of husk <sup>(M)/(W)</sup>	0.64/0.74	5.46/5.05	1.64/1.96	
	Peeling efficiency <sup>(M)/(W)</sup>	0.59/0.80	1.23/0.85	1.56/2.22	
	Cooking quality <sup>(M)/(W)</sup>	0.53/0.71	2.93/2.40	1.41/1.89	
		0.64/0.70	0.70/0.66	1.64/1.82	
114 samples (Fresh and frozen) green pea [34]	Firmness <sup>(Fs)/(Fz)</sup> Alcohol Insoluble solids <sup>(Fs)/(Fz)</sup>	0.96/0.84			It was found that nondestructive measurement of chemical and physical indices of maturity by NIR is a method with a good accuracy for assessment of the raw material quality
	Dry matter <sup>(Fs)/(Fz)</sup>	0.97/0.96			
	Sensory attributes	0.97/0.97			The correlation between the NIR and sensory attributes texture and flavor can be accepted as good results for a nondestructive method.
	Firmness of skin				
	Firmness of flesh	0.83			

	Sweet flavor	0.82			
	Strength of pea flavors	0.76			
	Brightness of color	0.89			
		0.73			
123 dry pea samples (Flour)	Amylose	0.95			The authors successfully developed MLR models to predict amylose, resistant, digestible and total starch in dry pea flours. The MLR models had coefficients of determination $R^2$ from 0.76 to 0.95 and showed good correlations between the model predicted and laboratory measured values.
[59]	Resistant starch	0.76			The study demonstrates that the vis-NIR reflectance spectroscopy can be used to estimate simultaneously amylose, RS, DS and total starch in dry pea.
	Digestible starch	0.8			
	Total starch	0.88			

Table IV. Near-Infrared spectroscopy applied in common bean (*Phaseolus vulgaris* L.)

Sample	Parameter	Accuracy			Conclusion
		$R^2$	SEP	RPD	
54 genotypes (White and colored)	Protein	0.96-0.97		> 3	FT-NIR gave better predictive performance that dispersive systems for determination of components
[52]	Starch	0.95-0.96		> 3	
	Amylose	0.94-0.95		> 2.50	
121 samples [60]	Moisture	0.94	0.39		With RPD values from the validation set is concluded that NIRS is an adequate technique for the analysis of protein and starch in beans
	Starch	0.88	0.9	> 2	
	Protein	0.94	0.56	> 4	
	Fat	0.74	0.13		
55 samples [61]	Aroma <sup>(1/2/3)</sup>	0.34/0.30/0.31	0.75/0.78/0.67	1.07/1.03/1.19	The cooked and dried <sup>(3)</sup> samples presented the best predictions.
	Flavor <sup>(1/2/3)</sup>	0.55/0.04/0.70	0.78/1.13/0.71	1.48/1.03/1.62	
	Mealiness <sup>(1/2/3)</sup>	0.43/0.57/0.81	1.24/1.08/0.83	1.28/1.46/1.90	$R^2$ and RPD showed that NIR was not able to evaluate the perception of the husk; however, it was able to predict flavor, mealiness, roughness and brightness of the shell.
	Peel:				
	Perception <sup>(1/2/3)</sup>	0.03/0.04/0.26	1.70/1.51/1.28	0.87/0.98/1.16	

	Brightness <sup>(1/2/3)</sup>	0.59/0.52/0.55	0.89/1.16/0.97	1.61/1.23/1.47	
	Roughness <sup>(1/2/3)</sup>	0.40/0.39/0.59	1.24/1.25/1.05	1.32/1.30/1.55	
90 seed coats [62]	Dietary fiber <sup>(W/M)</sup>			1.23/2.60	For ash and calcium were obtained sufficiently good results for a robust screening. For prediction of ash, calcium, fiber and magnesium were obtained acceptable values for ground husk. The prediction of uronic acids obtained a poor correlation.
	Uronic acids <sup>(W/M)</sup>			1.40/1.49	
	Ashes <sup>(W/M)</sup>			2.03/3.49	
	Calcium <sup>(W/M)</sup>			2.40/3.57	
	Magnesium <sup>(W/M)</sup>			1.33/1.50	
267 samples [53]	Starch	0.56		1.5	The prediction models for the protein content showed the best correlations, for starch and seed weight the models were considered acceptable.
	Protein	0.82		2.4	
	Weight	0.74		1.9	

<sup>1)</sup> Raw, dried, ground; <sup>2)</sup> cooked with high proportion of water, not dried; <sup>3)</sup> cooked, dried, ground; <sup>(W)</sup> Whole and <sup>(M)</sup> milled samples

## V. CONCLUSION

In this review the great potential of NIR spectroscopy analyses for food, mainly legumes have been assessed. The existing studies conclude and agree that the NIR methodology is capable of predicting contents of starch, proteins, dietary fiber, among others, in different types of legumes in a fast, reliable, accurate manner, with minimal or no sample preparation and without destroying it. In addition, it may be able to replace conventional methods for the determination of major components, which are time-consuming, use reagents and generate a large amount of chemical residues. The main disadvantage of the application of NIR technology is the need to develop calibration models, in which a large amount of analysis is required by traditional reference methods and in this way correlating their chemical data with their spectra, reflected in a lot of work related to the chemometric analysis.

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