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Comparison of different illumination systems for moisture prediction in cereal bars using hyperspectral imaging technology

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Moisture content and its distribution is a critical parameter in the production of cereal bars. Inappropriate control of this quality parameter can lead to non-conforming products and excess waste on production lines. In the field of hyperspectral imaging, the search for alternative light sources to stabilised-halogen (cheaper and emitting less heat) is a growing need for the application of this technology in industry. This study compares three different illumination systems for moisture prediction in the visible-near infrared (vis-NIR) range (from 400 nm to 1000 nm). The hyperspectral images were acquired using three illumination systems including two halogen-based systems (stabilised-halogen and conventional-halogen) and an LED-based illumination system. The results showed that halogen-based illumination systems combined with a partial least squares model better predicted moisture in bars. Lower accuracies were obtained when the experiment was performed with an LED-based illumination system, which showed double the error of the halogen-based systems. It was concluded that this is a consequence of the information lost in bands appearing above 850 nm that may be revealing information about the moisture in bars since the second overtone of the water O–H is found at 970 nm. The results demonstrate that conventional halogen-based light systems in the vis-NIR range are a promising method for moisture prediction in cereal bars.

Keywords: hyperspectral, illumination systems, vis-NIR, spectroscopy, classification accuracy, light sources, cereal bars

Introduction

Illumination is one of the critical parameters in hyperspectral imaging (HSI) technology. The illumination system compromises the correct acquisition of the spectral information from the sample. The discrimination power of an HSI system for image segmentation or object detection is determined by the illumination, the spatial–spectral resolution of the camera, the signal-to-noise ratio, and both the preprocessing and analysis methods used for image processing.[1]

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HSI is a real-time, non-destructive method that can be used for food quality analysis and control that combines spectroscopy and imaging techniques.[2] Compared to traditional multispectral imaging technology, HSI can provide a wider spectral resolution.[3] The visible-near infrared (vis-NIR) region of the electromagnetic spectrum is located between 350 nm and 2500 nm. Vis-NIR spectroscopy technology is a molecular/vibrational technique used to study the interactions of electromagnetic waves with a sample. Molecules absorb NIR radiation of defined energy at a specific wavelength, which results in peaks representing the chemical bonds present in the samples. The spectra are products of overtone, vibration and combination bands commonly arising from the C–H, O–H and N–H bonds present in the sample, although these are not the only ones.[4] The large bandwidth in the NIR range and the high degree of collinearity between bands makes their assignment to one chemical compound difficult. One analyte can absorb at multiple wavelengths, which further complicates band assignment.

In the field of hyperspectral imaging, the search for alternative light sources to stabilised-halogen is a growing need for the application of this technology in industry. Stabilised-halogen sources emit too much heat and can compromise the quality of the sample since proper illumination is crucial for attaining the optimal image quality needed for the best performance of image processing algorithms. In contrast, LED-based illumination systems are cheaper and emit less heat. For example, Blanch *et al.*[5] investigated the discrimination power of a halogen-based and a custom LED-based system applied to a specific case. They concluded that when using a customised LED system they could achieve a more balanced energy distribution, showing a considerable gain in discrimination power of up to 10 % in mean classification accuracy. Lawrence *et al.*[6] made a comparison between a traditional halogen and a LED system for faecal contaminant detection. The overall detection rate was 99 % accurate for both systems making the LED light system a feasible alternative to traditional halogen lighting. Carstensen[7] presented a LED imaging system highlighting how advantageous they are to other spectral imaging techniques such as pushbroom imaging. Sawyer[8] and Katrašnik[9] highlighted the importance of having a homogeneous illumination of the sample. Sawyer *et al.*[8] evaluated the illumination system uniformity for wide-field biomedical hyperspectral imaging. The results suggested that conventional illumination sources could be applied in HSI, but in the case of low light levels, custom-made illumination sources might offer improved performance. Katrašnik *et al.*[9] warned of the importance of having a homogeneous illumination of the sample without shadows or specular reflections. They proposed measurements using a ring light and with a diffuse dome illumination system with both systems using halogen light bulbs as the light source.

One of the critical parameters in the production of cereal bars in industry is the moisture content after the baking step and moisture distribution. Incorrect moisture control can lead to non-conforming products and excess waste on production lines. The commonly used stabilised-halogen light system is expensive and emits a great deal of heat. Therefore, a cheaper and less heat-emitting alternative is a growing need for the application of HSI in industry.

This study explains the impact of different illumination systems for a specific HSI application. This research aims to determine the impact of the different illumination systems on the prediction of moisture in cereal bars, which could involve considerable savings in the implementation of a hyperspectral imaging control system in industry. The results demonstrated that conventional halogen-based light systems in the vis-NIR range are a promising method for moisture prediction in cereal bars.

Materials and methods

The following section describes the materials and methods used to carry out the study of moisture content determination in bars.

Hyperspectral imaging system

The research was carried out with the Specim FX10 camera. The hyperspectral camera measures reflectance in a specific range of the electromagnetic spectrum. The FX10 camera combines visible and NIR spectroscopy. The NIR spectral region of the camera ranges from the highest wavelengths of the visible range (750 nm) to 1000 nm. Absorptions in this region are caused by overtones of the fundamental vibrations occurring in the infrared (IR) region, by the combination bands of the fundamental vibrations appearing in the IR region and by electronic absorptions.

The Specim FX10 camera works in a line-scan mode in the vis-NIR region. The spatial sampling of the camera is 1024 pixels and it has a high image speed of 327 fps (full range). It includes built-in image correction and free wavelength selection from 224 bands within the camera coverage.

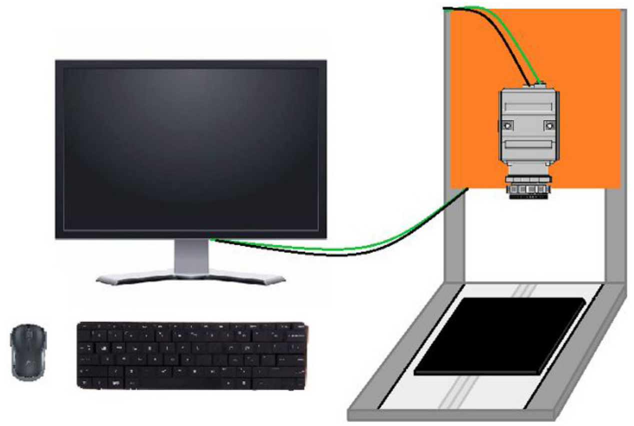

Figure 1. Image acquisition system composed of a Specim FX10 camera mounted above a conveyor belt and a PC to execute the Lumo Scanner image capture software. The illumination system is not included in the figure.

Figure 1 shows the image acquisition system. The system was composed of a Specim FX10 camera and a computer to execute the Lumo Scanner image capture software. Since the camera works in a line-scan mode, the camera was mounted on a fixed structure above a conveyor belt where the sample was placed.

Figure 1 does not include the illumination system installation. Depending on the lighting system, the system was placed in different places. This is explained in more detail in the Hyperspectral imaging collection section below.

Halogen and LED-based illumination systems in HSI

The research that attempted to predict the moisture content in bars using HSI was performed using three different illumination systems. The illumination systems used in this study were stabilised-halogen illumination, conventional-halogen illumination and LED-based illumination (see Figure 2). This article discusses the specification considerations when selecting either halogen or LED illumination systems in this specific HSI application.

Table 1 shows the specifications of the three illumination systems in terms of voltage, power, number of light bulbs and location in the HSI system. Halogen light emits excess heat. This can damage the samples undergoing inspection. In contrast, LEDs generate lower levels of heat in the emission, reducing sample heating.[10] The lifetime of the light source is also an issue to be considered in the selection of the illumination system. In fact, LEDs have ten times the life span of halogens.

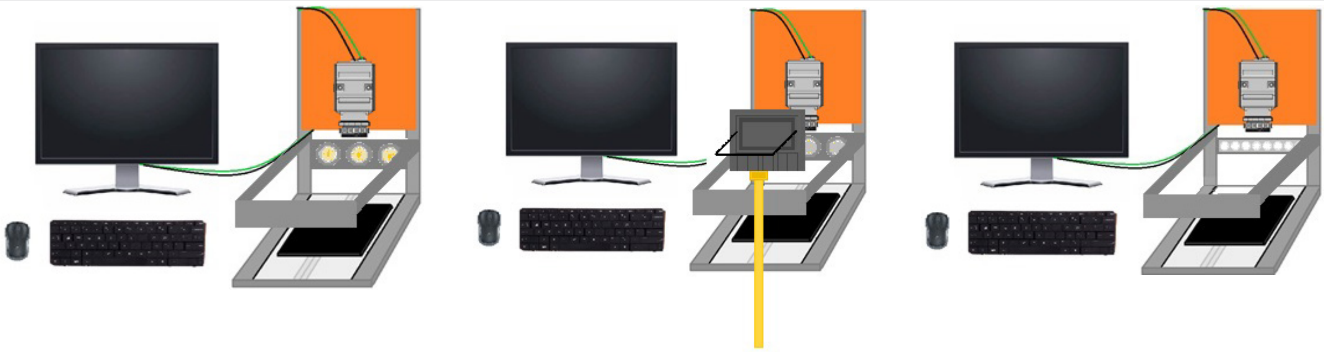

Figure 2. The three illumination systems mounted on the HSI equipment. From left to right: stabilised-halogen, conventional-halogen and LED-based illumination systems.

Table 1. Specifications of the three illumination systems.

	Voltage (V)	Power (W)	No. of light bulbs	Location
Stabilised-halogen	12	20	6	Perpendicular to the movement of the conveyor belt, both sides.
Conventional-halogen	220–240	400	1	Perpendicular to the movement of the conveyor belt, one side.
LED	24	20	15	Perpendicular to the movement of the conveyor belt, one side.

Hyperspectral imaging collection, image calibration and identification of the region-of-interest (ROI)

Forty-three cereal bars were used to evaluate how the different illumination systems affected the prediction of moisture in bars in hyperspectral imaging systems. First, the images were taken with the FX10 hyperspectral camera from Specim, using the three different illumination systems described above, two halogen-based systems (stabilised-halogen and conventional-halogen) and one LED-based illumination system. A total of 129 images were obtained, 43 images per illumination system.

To reduce the effect of changes in illumination that could disrupt the acquisition of the reflectance spectrum of the sample, the raw images were calibrated with white (maximum reflectance: 100 %) and black (minimum reflectance: 0 %) references. The camera acquired the dark reference spectrum automatically by closing the lens. The white reference was collected from a Teflon white standardised reference. Hence, the normalisation of the spectrum was calculated according to Formula (1), where R is the normalised spectrum, R_0 the original raw spectrum and R_w and R_d the white and dark references, respectively.

$$R = \frac{R_0 - R_d}{R_w - R_d} \tag{1}$$

Once the image was obtained, segmentation was carried out to take only the values of the spectrum that belonged to the product and avoid capturing information from the background. This was achieved by establishing a threshold that allowed the ROI from the background or other objects that were not of interest to be distinguished. One spectrum was acquired from each pixel that was part of the ROI. The mean reflectance spectrum was acquired from every pixel belonging to each bar.

Determination of moisture content in bars

After the HSI collection, the cereal bars were ground up and the reference moisture content was analysed using a HR83 Halogen (Mettler Toledo) thermobalance. The bars moisture content was measured at 140 °C. The range of moisture content in the bar samples was 2.76–7.57 %.

Data preprocessing and analysis

From the spectra obtained by HSI and the different illumination systems, and the moisture content values obtained from the thermobalance, a partial least squares (PLS) model was performed to determine if there was a correlation between both measures. The *RMSE* (root mean squared error) and the R^2 coefficient were calculated to evaluate the predictive ability and to determine how well the models were adjusted. The R^2 values vary from 0 to 1, where 1 represents a perfect adjustment of the model and 0 represents the maximum error. The *RMSE* indicated the difference between the values predicted by the model and the measured values, whereby higher values indicate greater prediction deviation. As the number of samples was not very high, cross-validation (venetian blinds with 10 data splits) was used to validate the performance of the models.

The impact of different preprocessing methods on the spectra was also analysed. The collected spectra were influenced by the physical properties of the samples. Data pretreatment was used to minimise the contributions of physical variables that incorporate irrelevant information into the spectra.[11]

The normalised spectra obtained from the Specim FX10 camera were pretreated using different methods. The data were preprocessed with the standard normal variate (SNV) method, the Savitzky–Golay 1st derivate and the Savitzky–Golay 2nd derivate, all followed by mean centring (MC).

Mean centring consisted of changing the origin of the new variable scale to the mean of the variable before centring. The fundamental property of centred data is that the mean value of each of the variables is equal to zero. This pretreatment does not modify the variance of the data.[12] The SNV method was used to eliminate the multiplicative interferences produced by the diffraction and difference in the particle size. Each of the spectrum's mean values treated with SNV is 0 and variance is 1. Therefore, it is independent of the original absorption values.[13] 1st and 2nd derivatives are techniques used to remove a baseline shift from the signal. This method is called smoothing. This treatment is based on adjusting a polynomial of the appropriate degree for a small wavelength interval. The new values work better than the original values because some of the noise affecting them is removed.[12] The second derivative removes linear and constant background noises. The main differentiating algorithm is the Savitzky–Golay algorithm. This algorithm calculates first or higher order derivatives including a smoothing factor. The user determines the number of adjacent variables to be used in the estimation of the polynomial approximation used in the derivative. One disadvantage of the use of smoothing derivatives is that they decrease the value of the signal-to-noise ratio.[14] The reference moisture values were autoscaled. Autoscaling consists of centring the data followed by normalisation.[12]

Thus, the mean of the new autoscaled variables is 0 and the variance is 1.

Data analysis and models were performed with SOLO Software Release 8.6.2 (Eigenvector Research Inc.).

Results and discussion

Most commercial hyperspectral systems use stabilised-halogen lighting systems. This type of illumination system is costly and the heat emitted by the halogens can affect the samples. The study was conducted using 43 bar samples provided by the food industry. The moisture content range was 2.76–7.57 %, with the average being 4.55 % and the standard deviation 1.77 %.

Different prediction models were used to determine if there was a correlation between the spectra obtained by HSI and the reference moisture results obtained by the thermobalance. In these first analyses, linear regression models based on the PLS technique were constructed. The *RMSE* statistic and the correlation coefficient R^2 were calculated to evaluate the predictive ability of the models as described above.

Moisture content prediction with stabilised-halogen illumination system

The first model was built using the stabilised-halogen illumination system; the most commonly used lighting system in HSI. Figure 3 shows the raw spectra in reflectance before any preprocessing.

Based on the results shown in Table 2, the best PLS models for moisture content prediction in bars were based on the 2nd Savitzky–Golay derivative followed by MC with five latent variables (LV) (*RMSE* = 0.254 and R^2 = 0.979 in cross-validation). However, all the models investigated were usable, showing low *RMSE* and a high R^2 in cross-validation.

Moisture content prediction with a conventional-halogen illumination system

The next model was built using conventional-halogen illumination. Figure 4 shows the raw spectra in reflectance before any preprocessing.

Based on the results shown in Table 2, the best PLS models for moisture content prediction in bars were based on the SNV-normalised spectra followed by MC with five LVs (*RMSE* = 0.228 and R^2 = 0.979 in cross-validation). However, all the models investigated were usable, showing low *RMSE* and a high R^2 in cross-validation.

Moisture content prediction with an LED-based illumination system

The last model was built using LED-based illumination. Figure 5 shows the raw spectra in reflectance before any preprocessing.

Based on the results shown in Table 2, the best PLS models for moisture content prediction in bars were based on SNV-normalised spectra followed by MC with seven LVs (*RMSE* = 0.516 and R^2 = 0.914 in cross-validation). However, all the models investigated were usable, showing low *RMSE* and a high R^2 in cross-validation.

The results showed that both halogen-based illumination systems combined with a PLS model offered better prediction of moisture in bars. Lower accuracies were

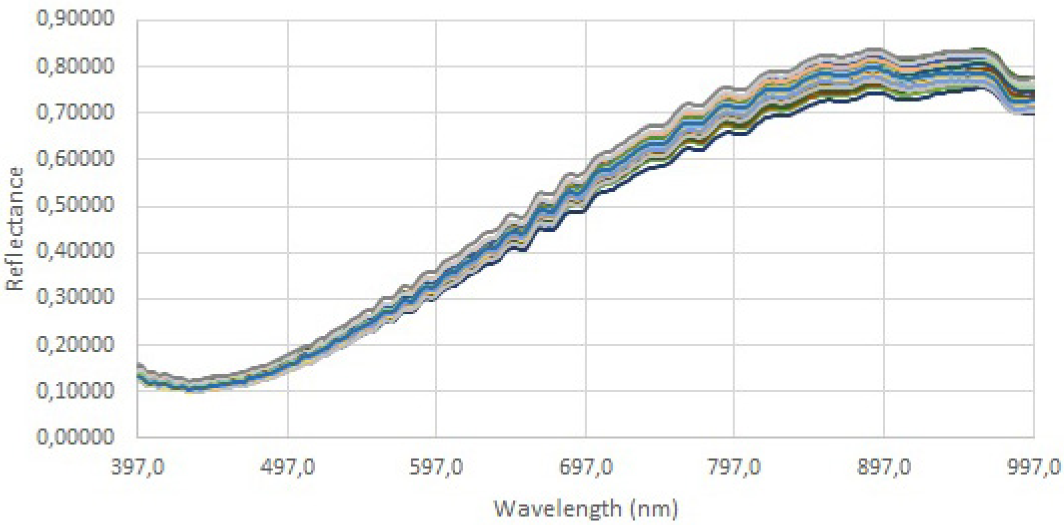

Figure 3. Cereal bar samples reflectance spectra based on stabilised-halogen illumination.

Table 2. Overview of R^2 and *RMSE* values for the PLS linear regression models for moisture prediction in bars using each illumination system.

	LV	Preprocessing method	R^2 cal	R^2 cv	*RMSEC*	*RMSECV*
Stabilised-halogen	4	SNV + MC	0.987	0.978	0.204	0.262
	4	1DV + MC	0.983	0.970	0.230	0.308
	5	2DV + MC	0.988	0.979	0.192	0.254
Conventional-halogen	5	SNV + MC	0.990	0.979	0.155	0.228
	5	1DV + MC	0.983	0.960	0.206	0.314
	4	2DV + MC	0.986	0.976	0.186	0.244
LED-based system	7	SNV + MC	0.972	0.914	0.294	0.516
	4	1DV + MC	0.888	0.855	0.585	0.668
	6	2DV + MC	0.894	0.814	0.568	0.754

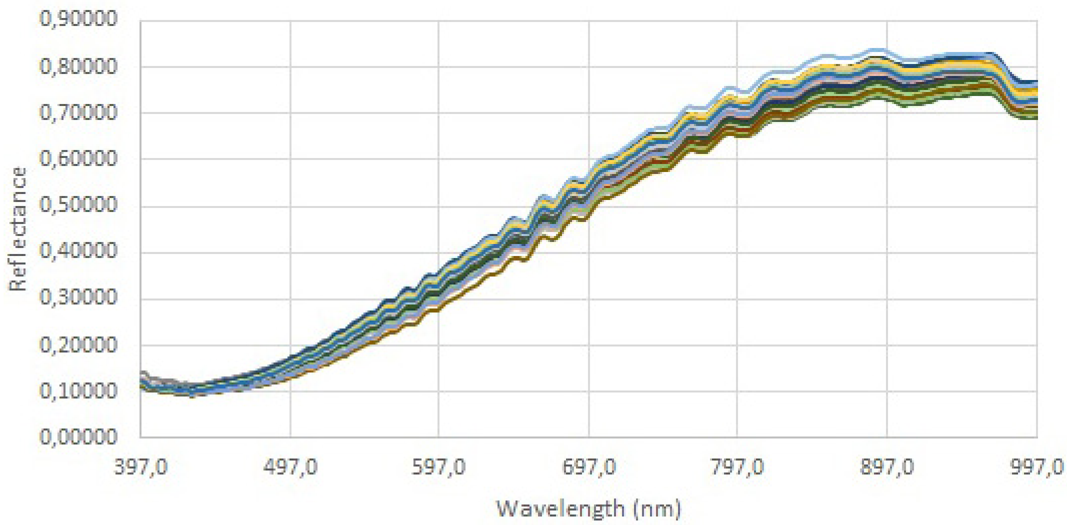

Figure 4. Cereal bar samples reflectance spectra based on conventional-halogen illumination.

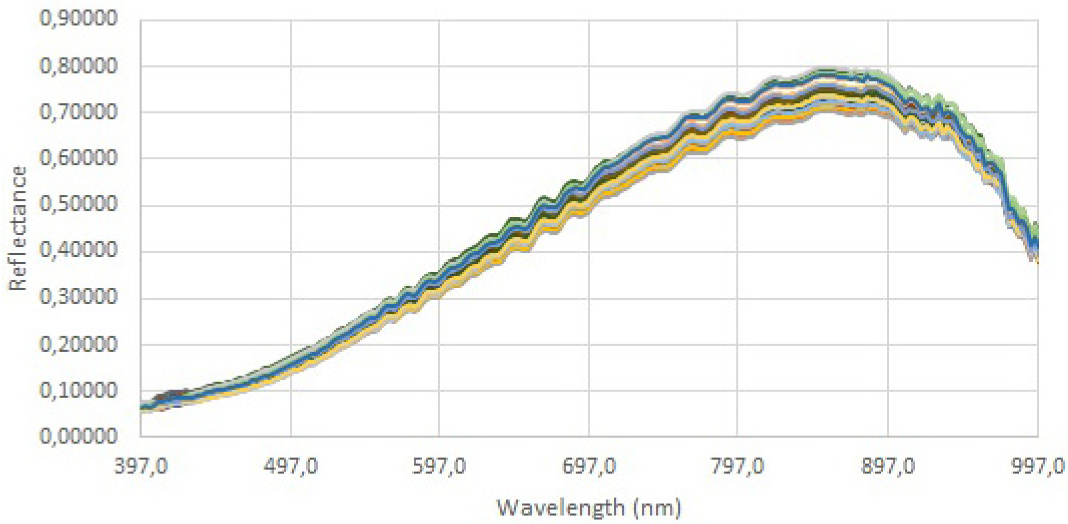

Figure 5. Cereal bar samples reflectance spectra based on LED-based illumination.

obtained when performing the experiment with the LED-based illumination system, showing double the error of halogen-based systems. Figure 6 shows the reflectance spectra comparison between both halogen-based systems (stabilised- and conventional-halogens) and the LED-based lighting system.

The figure above shows that in the spectra obtained by the LED-based system, data information is lost in bands appearing after 850 nm that may reveal information about the moisture in bars since the second overtone of water O–H is found at 970 nm.

The results show that, in this particular study case, it is important to have a wider range of measurement only covered by halogen systems in comparison to LED.

Conclusions

The results showed that PLS models based on conventional halogen-based illuminated hyperspectral images provided the best prediction of moisture in cereal bar samples, showing an R^2 of 0.979 in cross-validation and an *RMSECV* of 0.228.

Lower accuracies were obtained when the experiment was performed with the LED-based illumination system, which showed double the error of the halogen-based systems with an R^2 of 0.914 and an *RMSECV* of 0.516.

The stabilised-halogen based illumination system also showed very good results in the prediction of moisture content in bars, with an R^2 of 0.979 and an *RMSECV* of 0.254 in cross-validation. The best preprocessing for all the models trained was SNV followed by MC except for the stabilised-halogen system that required 2nd Savitzky–Golay derivative as preprocessing.

As can be seen in the comparison of the spectra in the three illuminations, the LED-based illumination loses information in bands appearing after 850 nm. In contrast, both halogen-based illumination systems maintain those data and give information on those bands that may be revealing information about the moisture in bands since the second overtone of water O–H is found at 970 nm.

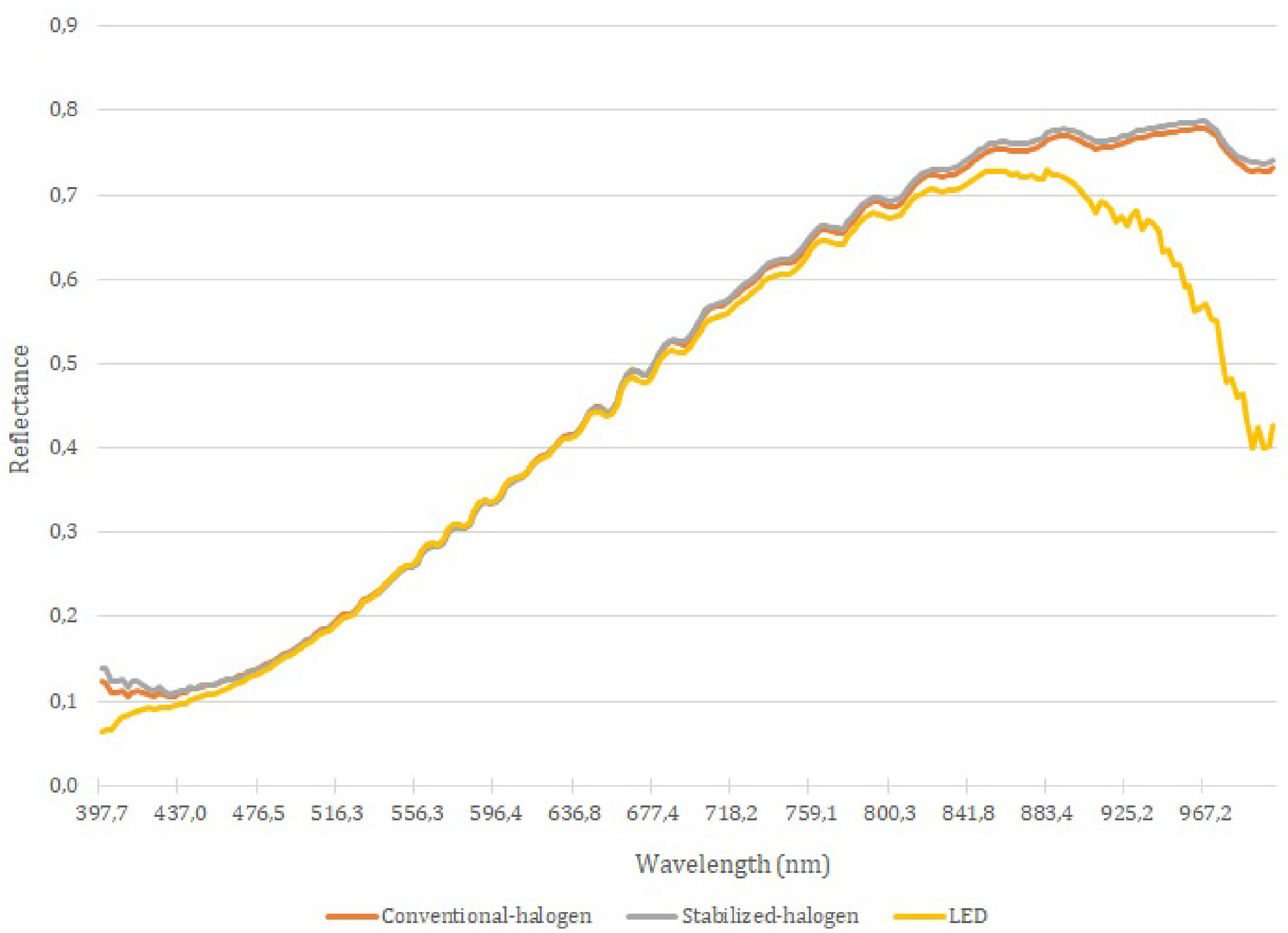

Figure 6. Reflectance spectra comparison between halogen-based and LED-based systems.

In conclusion, very good results in moisture content prediction in bars were achieved with the spectra obtained with conventional-halogen illumination systems, which would be cheaper than using stabilised systems.

For the LED light system, the results obtained were not so good in this case, showing double the error obtained in both halogen-based systems. This was because the LED-based system does not cover the second overtone of water O–H which is at 970 nm and which would give relevant information about the moisture content in bar samples in this study. The results demonstrate that conventional halogen-based light systems in the vis-NIR range are a promising method for moisture prediction in bars. The present research lays the ground for future studies to investigate different illumination techniques such as LED-based systems, where the second overtone of water O–H is not a key factor in the prediction of the result.

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