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Impact of drying temperature and salt pre-treatments on drying behavior and instrumental color and investigations on spectral product monitoring during drying of beef slices

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ABSTRACT

Drying behavior and instrumental color development of beef slices untreated or pretreated with salt or salt and vinegar solutions were monitored by determining the moisture content and the color change by measuring CIELAB values during drying at 50, 60, and 70 °C. Time-series hyperspectral imaging (400–1000 nm) was applied with regard to the development of non-invasive measurement systems based on robust models to predict moisture and color independent of the pre-treatment and drying temperature. Samples pretreated with salt dried the slowest which became more prominent at increasing drying temperatures and the least color change (ΔE = 23) was observed at 60 °C drying temperature. Robust prediction models for moisture content and CIELAB values irrespective of pre-treatment and processing conditions were developed successfully and improved by wavelengths selection with high R^2 (0.94–0.98) and low RMSEP (1.05–5.22) which will support the future development of simple and cost-effective applications regarding non-invasive product monitoring systems for beef drying processes.

1. Introduction

The drying of meat is a well-known processing to preserve this highly perishable food product and enables an extended shelf life without additional cooling. Due to its nutritional value, dried meat is also a popular snack food and appreciated as a good supplementary for the diet of athletes and nutrition-conscious consumers. However, drying processes are usually taken at a sacrifice of very high energy consumption and the food drying sector faces low efficiencies of 35–45% (Mujumdar, 2007).

Besides convection drying, several drying techniques have been investigated to improve the final product quality and process efficiency of meat drying, like superheated steam drying (Adamski, Wróbel, Pakowski, & Szaferski, 2019), which significantly prevents case hardening compared to convection drying (Speckhahn, Srzednicki, & Desai, 2010) and is described as advantageous for not temperature sensitive products (Moreira, 2001). In terms of dehydration by radiation, microwave (Guo, Sun, Cheng, & Han, 2017) or infrared drying of meat (Li, Xie, & Zhang, C. hui, Zhen, S., Jia, W., 2018) have also been observed and showed significant higher energy efficiencies compared to convective drying. However, convection drying by hot air is the most traditional and widest used technique for drying of food products (Mujumdar & Law, 2010). The processing and final quality of dehydrated products is further influenced by raw material quality and pre-treatments applied prior to drying to achieve certain final quality attributes (Deng et al., 2019). With regard to meat dehydration, maturation was determined to decrease the drying rate compared to fresh meat, while freezing increased the drying rate of matured meat, but not for fresh meat (Retz et al., 2017). Salt pre-treatments led to decreasing drying rates compared to untreated samples or samples pre-treated with salt and vinegar (von Gersdorff et al., 2018).

To understand the dynamic development of changes inside a product during dehydration, which is mandatory to develop improved drying strategies, modeling of drying (Onwude, Hashim, Janius, Nawi, & Abdan, 2016) and quality kinetics, like for example product color (Liu et al., 2020; Xiao, Law, Sun, & Gao, 2014), is a common approach. Moreover, product monitoring during processing helps to gain a deeper understanding of processes occurring inside a product. In this context, analytical off-line methods can provide a sound basis to develop product related drying strategies. However, conventional measurements are

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often destructive and time-consuming and lead to interruption of the process, and, thus are not useful with regard to on-line measurements (Liu, Pu, & Sun, 2017).

Conversely, non-invasive measurement systems are non-destructive, rapid in practice and/or applicable for real-time monitoring and online-applications. Moreover, the gained information can be utilized to directly feed back into control mechanisms of the system to adjust and finally terminate the process, which leads to individual drying processes dependent on raw material characteristics and the individual changes during drying, respectively. This approach is also known as *smart processing* or *smart drying* and provides a promising approach in view of increased product and process efficiencies (Martynenko & Bück, 2018; Sturm, 2018; Sturm et al., 2018).

Imaging technologies have been implicated to provide a solution for non-invasive product monitoring of quality attributes or moisture content (MC) (Su, Zhang, & Mujumdar, 2015). In this context, hyperspectral imaging (HSI) has gained more and more interest for the food industry like for non-invasive measurements of chemical and physical attributes, food monitoring and safety evaluation (Ma, Sun, Pu, Cheng, & Wei, 2019; Qin, Chao, Kim, Lu, & Burks, 2013). This technology combines spectroscopy with computer vision, which allows the capturing of 3-dimensional images (hypercubes) with one spectral and two spatial dimensions. This enables the measurement of product compounds and their spatial distribution. Based on the spectral range in question, HSI is differentiated into VNIR (visible and near infrared, 450–1000 nm) and NIR (near infrared, 900–1700 nm), which is important in terms of applicability with respect of cost efficiency since the detectors for VNIR-HSI are less expensive than for NIR-HSI (Qin et al., 2013).

HSI has been applied for the measurement of different properties in fresh meat, such as pH, tenderness, water holding capacity, drip loss and color, which plays an important role regarding quality parameters and helps to classify different quality characteristics of muscle sections (Feng, Makino, Oshita, & García Martín, 2018). In general, the selection of specific wavelengths to reduce image acquisition and computation time further enables the transfer to simpler and more cost efficient multispectral real-time applications (Kamruzzaman, Makino, & Oshita, 2016) equipped with CCD sensors and filters or selective lighting (Chi, Yoo, & Ben-Ezra, 2010).

Only few studies focused on application of time series HSI and multispectral systems for meat drying processes, i.e. prediction of MC and water distribution during dehydration at 40 °C (Wu et al., 2013) or the prediction of MC, moisture distribution and CIELAB L*, a* and b* values related to each beef treatment for different maturation stages (Retz et al., 2017) and seasonings (von Gersdorff et al., 2018) at 70 °C drying air temperature. However, for industrial monitoring applications it is necessary to develop models and select parameter-specific wavelengths to increase the robustness against influencing factors related to raw material quality and process settings, which requires the inclusion of several process settings and raw material qualities into the model development. The aim of an increased model robustness is often mentioned in research studies (Feng et al., 2018; Su, Bakalis, & Sun, 2020), but rarely implemented.

The MC is the main attribute in view of dried food products, but appearance that is highly influenced by the product color is important as well, for example with regard to satisfaction of consumers' quality requirements for final products. In order to gain a deeper understanding of changes in MC and color of beef during drying, and thus to develop improved drying strategies and on-line monitoring approaches concerning increased efficiencies for beef drying processes, the objective of the present study was to 1) investigate the drying behavior and development of instrumental color of beef slices pretreated with different solutions and dried by convection at three temperatures. 2) To develop one robust prediction model per parameter (MC, CIELAB L*, a* and b*) independent of the drying temperature or the pre-treatment and 3) to select specific wavelengths to develop simpler models with regard to multispectral monitoring applications.

2. Materials and methods

2.1. Sample preparation

For the experiment 3 kg (± 0.35 kg) roast beef (*longissimus dorsi*) from four 26 month old heifers of the Uckermarker breed was used. They were raised on grassland and slaughtered according to the German law and the codes of good practices in a slaughter house in Northern Germany. Two days after slaughter, 1 kg portions were vacuumed, and shock frosted at −55 to −60 °C for 120 min. The beef was stored at −18 °C (Liebherr GP 1486 Premium, Germany) and thawed for 18 h at 2 °C in a fridge (FKUv 1613 Premium, Liebherr, Germany) before slicing. For each drying experiment the beef was sliced in the direction of the fiber to 5 mm thickness with an electrical slicer (Graef, Allesschneider Vivo V 20, Germany) equipped with a smooth knife. Afterwards, 24 pieces (50 × 50 mm^2) were cut out of the slices with a sharp knife.

Two solutions with a salt content (NaCl) of 10% (m/v) were prepared, one water based (S), the other one with apple vinegar as the solvent (S+V). For each treatment 8 pieces were dipped in the solution, the remaining 8 pieces stayed untreated as blind samples (b). The samples were then stored at 2 °C overnight and dabbed with a tissue before further measurements.

2.2. Drying and measurements

The samples were dried in a convective drier (HT mini, Innotech Ingenieursgesellschaft mbH, Germany) at 50, 60 or 70 °C, respectively, with a constant air velocity of 0.6 m/s. 4 repetitions were conducted for each pre-treatment and the respective drying temperature.

Weighing (lab scales, E2000D, Sartorius, Germany) and instrumental color measurement (CIELAB L*, a* and b* values (CIE, 2018)), with a Chroma Meter (CR-400, Minolta, Japan) by averaging the CIELAB values of three spots of each sample, were conducted before and during the trials. The instrumental color measurements was carried out with a D65 illuminant and the Chroma Meter was calibrated with a standard ceramic white plate (Konica Minolta) before each experiment. The measurements were done directly after slicing, after seasoning/storage and throughout the dehydration process applying intervals of every 20 min during the first hour, in two 30 min intervals during the second hour and hourly thereafter until the final MC of 14–20% was reached. After drying, half of the samples were used to determine the final moisture content by oven drying (SLE 500, Memmert GmbH, Germany) at 105 °C for 24 h (AOAC, 2016) until a constant weight was achieved. For the remaining samples the water activity ($a_{w)}$ (LabSwift, Novasina, Switzerland) was analyzed at a constant temperature of 23 °C.

The MC at each measurement point was used to calculate the moisture ratio (MR) during drying, according to Rayaguru and Routray, 2012 with the simplified equation:

$$\mathrm{MR} = \frac{\mathrm{M}}{\mathrm{M_i}} \tag{1}$$

with M as moisture content at a given time, and M_i as the initial moisture content. The drying rate (DR) was expressed as

$$\mathrm{DR} = \frac{\mathrm{M_t} - \mathrm{M_{t+\Delta t}}}{\Delta \mathrm{t}} \tag{2}$$

where M_t and $M_{t+\Delta t}$ express the MC of the samples at time t and t + Δt.

The averaged instrumental color measurements of CIELAB L* (lightness), a* (redness) and b* (yellowness) values were used to calculate the color change during drying with the following equation:

$$\Delta E = \sqrt{(L^*_i - L^*_t)^2 + (a^*_i - a^*_t)^2 + (b^*_i - b^*_t)^2} \tag{3}$$

with *i* expressing the initial L*, a* and b* values before drying and *t* expressing the values at every measuring point.

2.3. Hyperspectral imaging

VNIR-HSI measurements were taken in the spectral range of 400–1000 nm with an ImSpector V10E PFD camera combined with a linear translation stage (SPECIM Spectral Imaging Ltd., Finland). A 35 mm lens (Xenoplan 1.9/35, Schneider Optische Werke GmbH, Germany) was positioned with a distance of 27 cm to the conveyor tray. The detailed procedure and the image processing techniques to achieve the average reflectance of each beef slice (dark noise removal, segmentation etc.) performed with MATLAB 2013b software (TheMathwork, Nattick, USA) is described by Crichton et al. (2017), Retz et al. (2017) and von Gersdorff et al. (2018). Fig. 1 shows an example of image segmentation with the RGB image, the NIR thresholded image and the final segmented image.

2.4. Prediction models

After the average relative reflectance spectrum of each slice was calculated, the spectral information and the data of the invasive measurements (weight, instrumental color) were used to develop PLSR prediction models with Rstudio software V.3.5.1, 2018, pls Package (Rstudio PBC, Boston, USA). The objective of the development of PLSR models was to find linear relationships between individual wavelengths in reflectance spectra and specific measured values (Westad & Marten, 2000). The data of all slices independent of the pre-treatment or drying temperature was combined to assess the likelihood to build one robust model per quality parameter based on measured and spectral data. The data set was split randomly to 70% to build the PLSR model meanwhile to validate the model with the remaining 30% of the data. In a first step, the model was built including 10 principal components. Afterwards the model was further developed into such a manner that 90% of the variance could be explained with only 3 components for all parameters (MC, L*, a* and b* values). The coefficient of determination R^2 and the RMSEP (root mean square error of prediction) were thereafter used to evaluate the developed model. The selection of characterized wavelengths was carried out with the determination of the standardized regression coefficient at each wavelength, which was previously applied successfully in terms of non-invasive measurements in meat (ElMasry, Sun, & Allen, 2012; Liu, Qu, Sun, Pu, & Zeng, 2013). The higher the regression coefficient, regardless of the sign, the more variations were explained by the wavelength for the related parameter.

2.5. Statistical analysis

To determine the effect of drying temperature and pre-treatment on final CIELAB color pattern and water activity a two-factorial Analysis of Variance (ANOVA) was calculated Rstudio software V.3.5.1, 2018 (Rstudio PBC, Boston, USA). The four animals were used as replicates for each drying temperature and pre-treatment including the values of each eight (instrumental color) and four slices (aw), respectively. The evaluation of the differences between the means were done using the Tukey post-hoc test and significance was considered as $P < 0.05$.

3. Results and discussion

3.1. Drying behavior

Fig. 2a-c show the drying curves for beef slices with different pre-treatments at 50 °C, 60 °C and 70 °C and Fig. 2d-f the respective drying rates (DR), which clearly show the influence of temperature and pre-treatment on the drying behavior of beef. According to different studies the water holding capacity (WHC) (Bess et al., 2013; Chabbouh et al., 2011; Teixeira, Pereira, & Rodrigues, 2011; von Gersdorff et al., 2018) is increasing after salt treatments during cooking or drying. Therefore, the samples pre-treated with the salt solution dried the slowest due to the ability of the myofibrils to swell and bind salt solutions which induced the solubilization of myofibrillar proteins by the Na^+- and Cl^--ions (Desmond, 2006). In the present study there is a slight indication that this effect becomes more prominent with increasing drying temperatures. However, the influence of salt on the WHC is impacted by many pre- and postmortem factors (Cheng & Sun, 2008). Sodium chloride is further known to release iron from sarcoplasmic proteins and, thus, is responsible for the denaturation of myoglobin (Kristensen & Purslow, 2001) and therefore acts as a prooxidant for lipids which must be taken into account regarding the drying behavior and the shelf life of dried meat.

In the present study, for all drying temperatures, the blind samples showed the highest drying rates (DR) in the beginning of the drying process. However, for drying at 50 °C, the drying rate across the different pre-treatments developed similarly at a MR of 0.5, while drying at 60 and 70 °C resulted in similar DR only at a MR of 0.38. Drying processes are characterized by a complex interaction of heat and mass transfers (Mühlbauer & Müller, 2020). At higher temperatures the vapor pressure inside the product increases compared to the surrounding environment which leads to increased vapor flows to the surface (Mujumdar & Devahastin, 2000), which explains the differences in the present DRs. The illustrated DRs and the development of MR of salted samples (S) showed the lowest DR, caused by an increased water holding induced by salt (Goli, Ricci, Bohuon, Marchesseau, & Collignan, 2014), which is in accordance with a previous study (von Gersdorff et al., 2018). However, the results of samples treated with S+V are not in accordance with the former study (von Gersdorff et al., 2018) in that samples seasoned with S+V showed increased drying rates compared to untreated samples. Those different results might be a result of the salt/acid concentration related to the beef, which is documented to influence the water holding capacity in different ways (Medyński, Pospiech, &

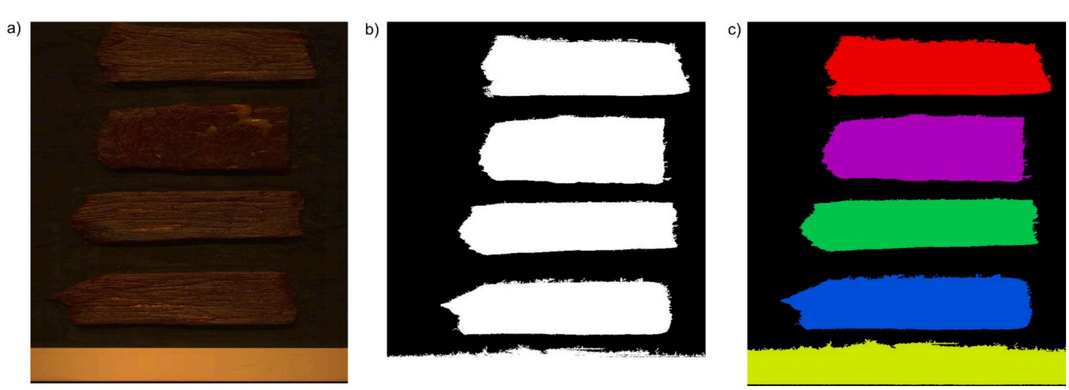

Fig. 1. Beef slice segmentation of a complete raw image: a) RGB image, b) NIR threshold image, c) final segmented image with pseudo-colored shapes corresponding to beef slices and white reference.

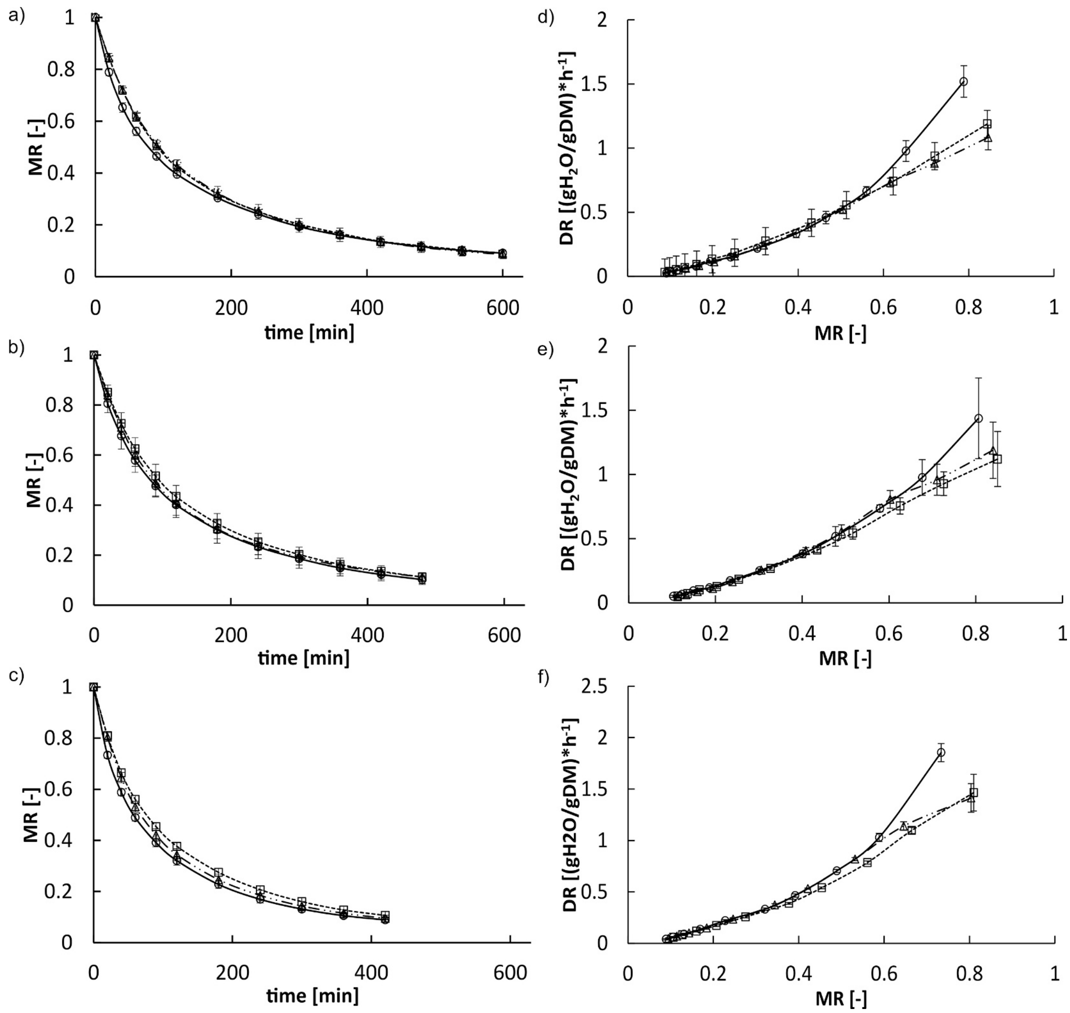

Fig. 2. Moisture ratio (MR) as a function of time for blind beef samples (b —○—), samples pre-treated with salt (S --□--) and with salt and vinegar (S+V —△—) dried at a) 50 °C, b) 60 °C and c) 70 °C and respective drying rates (DR) as a function of MR d)-f) ± standard deviations at each measurement point ($n = 4$).

Kniat, 2000). Medyński et al. (2000) showed that the drip loss is reduced for meat samples after acid treatment and above a certain salt concentration the drip increased for raw and cooked meat. In the present study, the applied salt concentration in the S+V treatment might have been too low and the effect of acid induced swelling of the muscle fibers might have led to an increased water binding during drying (Desmond, 2006; Teixeira et al., 2011). In addition, other factors such as the seasoning step influences the quality of the product as documented by Han et al. (2011). By comparing immersing and tumbling they found that curing time increases the transfer of the marinade into the meat. The dipping in the present study probably led to a reduced diffusion of the S+V solution into the beef samples compared to tumbling or immersing. Goli et al. (2014) described an approximation of the pH of the meat to the pH of the seasoning solution at longer immersion times. Further the degree of maturation (Cheng & Sun, 2008; Huff-Lonergan & Lonergan, 2005) and the freezing treatment (Leygonie, Britz, & Hoffman, 2012), as well as cumulative effects (Aroeira et al., 2016; Kim, Liesse, Kemp, & Balan, 2015) might have impacted the drying kinetics. Additionally, different cattle breeds, sex and cut were used in the different trials, which could influence both the seasoning and the drying behavior, due to different characteristics and composition of the cut in question (Cafferky et al., 2019; Nassu et al., 2017).

3.2. *Evolution of CIE color pattern*

Although the seasoning influenced the instrumental color before drying, L*, a* and b* values were almost identical after drying for all pre-treatments with the samples appearing dark brown with almost identical ΔE with very low and nearly invisible temperature induced differences (Fig. 3). ΔE was higher for samples dried at 50 °C and 70 °C than for samples dried at 60 °C. One reason might be that both, long drying times at low temperature as well as high temperatures negatively affected the quality, and, therefore, the instrumental color of the final product.

The means and standard deviations of final CIELAB values are shown in Table 1. a* and b* values show a clear tendency that drying at 50 °C maintained redness and yellowness better than 60 and 70 °C. The development of the instrumental color in the present study might have been influenced by several factors: (i) A heat induced denaturation of myoglobin has been observed to be most dominant between 65 and 80 °C (Martens, Stabursvik, & Martens, 1982) which is in accordance with the highest final a* values achieved at 50 °C drying temperature compared to 60 °C or 70 °C. (ii) Heat treatments are known to increase the oxidization from oxi- and myoglobin to metmyoglobin (Bernofsky, Fox Jr, & Schweigert, 1959; Yin & Faustman, 1993) resulting in decreased a* values. The metmyoglobin formation decreases with the intensity of heat treatments, due to a shorter exposure time to oxygen

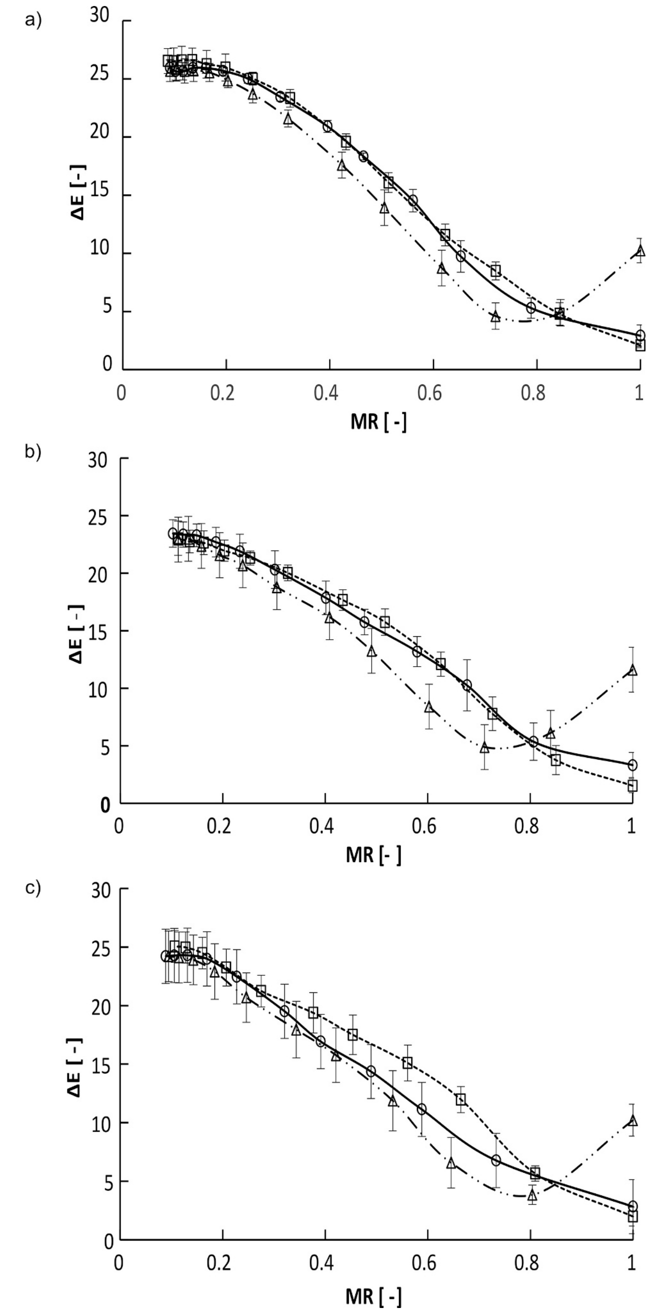

Fig. 3. Development of the total color change ΔE as a function of moisture ratio (MR) for blind beef samples (b —○—), samples pre-treated with salt (S --□--) or salt and vinegar (S+V —△—) dried at a) 50 °C, b) 60 °C and c) 70 °C ± standard deviations at each measurement point (n = 4).

which oxidizes the oxy- or deoxymyoglobin to metmyoglobin (Liu, Sun, Cheng, & Han, 2018). Dehydration, therefore, results in a high level of formation of metmyoglobin due to relatively long processing times. (iii) It has been reported that impaired lightness was more likely occurring in such a case that the dehydration process greatly increased the concentration of pigments (i.e. myoglobin, oxymyoglobin, and metmyoglobin) (Ferrini, Comaposada, Arnau, & Gou, 2012). (iv) Lipid oxidation is caused by several factors during processing. Heat treatments have been shown to increase lipid oxidations in meat but have also been determined to be dependent on the duration of the heat treatment (Domínguez, Gómez, Fonseca, & Lorenzo, 2014). Lipid oxidation and has been shown to be positively correlated to L* values (Luciano et al., 2009), which might explain the significantly higher L* values for samples dried

Table 1
CIELAB L*, a* and b* means and standard deviations of blind beef slices (b), slices pre-treated with salt (S) and salt and vinegar (S+V) after drying at 50 °C, 60 °C and 70 °C.

CIELAB	Drying temperature / Pre-treatment*	50 °C	60 °C	70 °C
L*	b	18.87^{c} (± 2.07)	19.56^{bc} (± 2.00)	21.06^{a} (± 1.23)
	S	19.16^{bc} (± 2.43)	20.17^{abc} (± 1.38)	21.04^{a} (± 0.92)
	S+V	20.26^{ab} (± 1.68)	20.20^{abc} (± 1.78)	21.12^{a} (± 1.37)
a*	b	3.96^{a} (± 1.55)	3.01^{bc} (± 0.32)	2.64^{c} (± 0.37)
	S	4.10^{a} (± 0.97)	2.91^{bc} (± 0.73)	2.67^{c} (± 0.31)
	S+V	4.07^{a} (± 1.10)	3.08^{bc} (± 0.61)	3.51^{ab} (± 0.59)
b*	b	2.43^{a} (± 0.96)	1.66^{c} (± 0.33)	1.86^{bc} (± 0.38)
	S	2.53^{a} (± 0.57)	1.61^{c} (± 0.50)	2.09^{abc} (± 0.38)
	S+V	2.54^{a} (± 0.80)	1.72^{c} (± 0.56)	2.34^{ab} (± 0.66)

a-c Means with different superscripts are significantly different ($P < 0.05$ according to Tukey post-hoc test).
Standard deviations in brackets.
* b, blind; S, salt pre-treatment; S+V, salt and vinegar pre-treatment.

at 70 °C in the present study. The salt induced oxidation of lipids and thus increased L* values did not show a significant influence regarding lightness in the present. (v) Acid treatments are known to induce myoglobin denaturation and thus to different relations of myoglobin forms inside the meat (Fernández-López, Sayas-Barberá, Pérez-Alvarez, & Aranda-Catalá, 2004). This effect is obviously in the present study regarding the high ΔE due to high L* and low a* values after seasoning with S+V, but low pH treatments did not significantly influence the final color. (vi) Shrinkage might have led to measuring mistakes of instrumental color due to resulting uneven surfaces, which could, at least partially, explain higher L* values for samples dried at 70 °C. Tornberg (2005) reviewed the influence of heat during cooking on sarcomeric, myofibrillar and connective tissue proteins of meat and summarized that increasing temperature increases the degree of shrinkage. In the present study, shrinkage was not taken into consideration and, therefore, the theory of a measuring errors is speculative.

The changes of physicochemical parameters like protein denaturation or oxidation processes that influence the instrumental color of beef during drying have not been investigated in the present study. However, it is well known from other studies (Song et al., 2020; Yang et al., 2018) that increasing color changes are correlated to increasing losses of valuable compounds. Other quality parameters than color should be investigated for beef drying in future research. This will improve the understanding of changes of quality parameters and will support the development of monitoring systems in view of development of improved drying strategies and process control techniques.

3.3. *Water activity*

The results of the water activity a_w and the related standard deviations are shown in Table 2. According to Fontana (2007) definition, all experiments led to stable products regarding bacterial growth ($a_w < 0.84$). The pre-treatment did not significantly ($p < 0.05$) influence the aw, but the results indicate that drying at 60 °C might lead to higher aw values compared to samples dried at 50 or 70 °C. However, due to a low number of samples analyzed in this study and different results regarding pH and a_w of a final meat product documented by Petit, Caro, Petit, Santchurn, & Collignan (2014), it is unfeasible to deduce a clear

Table 2
Water activity ($a_{w)}$ means and standard deviations of blind beef slices (b), slices pre-treated with salt (S) and salt and vinegar (S+V) after drying at 50 °C, 60 °C and 70 °C.

Drying temperature / Pre-treatment*	50 °C	60 °C	70 °C
b	0.76^{ab} (± 0.04)	0.79^{a} (± 0.06)	0.76^{ab} (± 0.04)
S	0.73^{b} (± 0.06)	0.79^{a} (± 0.04)	0.76^{ab} (± 0.03)
S+V	0.74^{ab} (± 0.05)	0.77^{ab} (± 0.06)	0.73^{b} (± 0.03)

a-b Means with different superscripts are significantly different ($P < 0.05$ according to Tukey post-hoc test).
Standard deviations in brackets.
* b, blind; S, salt pre-treatment; S+V, salt and vinegar pre-treatment.

connection, but might show that a_w is a function of several characteristics of the final product (chemical components, physicochemical state, porosity, temperature, and surface tension) (Rahman & Labuza, 2007).

3.4. Spectral analysis

Applications of HSI regarding prediction of meat quality parameters already exist. However, investigations on time-series applications for beef drying are rare and limited to only a single drying condition (Retz et al., 2017; von Gersdorff et al., 2018; Wu et al., 2013). As seen in Figs. 2 and 3, different pre-treatments and drying conditions have an impact on the development of product MC and ΔE during drying of beef slices. Fig. 4a shows the averaged relative reflectance of beef slices prior to the pre-treatments and storage over night, after the pre-treatments with S or S+V or kept untreated as b and after drying at 50 °C, 60 °C and 70 °C (Fig. 4b).

As shown in Fig. 4a, the absorption peaks can be divided into two categories. Those wavelengths beyond 700 nm correspond to water absorption while in the visible area (lower than 700 nm) pigments are mostly dominant. The spectra of the untreated samples showed two absorption peaks at 760 and 970 nm which are related to the third and second overtones of O—H stretching vibrational modes, respectively (Qian Yang, Sun, & Cheng, 2017). After storage overnight and different pre-treatments, the weak absorption peak at 760 nm disappeared probably due to the water insulation by the salt. Different muscle pigments lead to absorption maxima and dips in the reflectance spectra. Those appear at around 430 nm and 560 nm for deoxymyoglobin, for oxymyoglobin at 540 nm and 580 nm and for metmyoglobin around 410, 500 and 630 nm which was investigated and compared by Millar, Moss, & Stevensen (1996). While the dips for deoxymyoglobin and oxymyoglobin became visible, the dips related to metmyoglobin were not that prominent in the present study. The absorption at 630 nm might indicate the oxidation from oxymyoglobin and deoxymyoglobin to metmyoglobin, since it only occurred after storage overnight for all treatments. Similarly, Liu et al. (2018) observed absorption at 620 nm after 45 s of microwave heating, which showed in consistency with our claim the oxidation from deoxymyoglobin or oxymyoglobin to metmyoglobin during processing. Furthermore, it can be seen from Fig. 4a that the samples pretreated with salt and vinegar showed the highest reflectance because decreasing pH values led to the increase of light reflectance (Serdaroğlu, Abdraimov, & Önenç, 2007). It is worthwhile to note that a significant level of noise (visible in Fig. 4a and b) was related to the range of 400-500 nm, probably owing to the poor illumination provided by the halogen bulbs used. As a result, only the spectral range of 500–1000 nm was included into further analysis.

After the drying process, the reflectance spectra were almost identical independent of the pre-treatment (Fig. 4b). This probably resulted from an increasing concentration of pigments accompanied by the decreased lightness values caused by the loss of moisture. Additionally, the chemical changes of myoglobin to met-,oxy- and deoxymyoglobin might also partially explain such effect (Liu et al., 2018).

The selection of wavelengths can improve the performance of a prediction model and further simplifies a model since it avoids the repetition of spectral information due to multi-collinearity of hyperspectral data (ElMasry et al., 2012) and thus reduces the high dimensionality of the hyperspectral data and the time for the acquisition of spectral and spatial data (Xing, Ngadi, Wang, & De Baerdemaeker, 2006). Therefore, it saves computation time (Kamruzzaman et al., 2016), which makes it more applicable for real-time monitoring. For MC, five wavelengths were selected (512, 645, 745, 780 and 975), for lightness seven wavelengths (502, 544, 564, 580, 634, 699 and 929), for redness (a*) five wavelengths (532, 566, 590, 649, and 702) and for yellowness (b*) 4 wavelengths (546, 580, 642 and 709). The selected wavelengths were used to build predictive models, their computed results are shown in Fig. 5 with key parameters describing a good model performance (R^2 and RMSEP) illustrated in the right hand side of Table 3.

The results show that the visible and the NIR range implies specific wavelengths for MC and CIELAB L* prediction, while for CIELAB a* and b* prediction they have been found only in the visible range.

The developed models for the different parameters show a good performance regarding high R^2s and low RMSEPs. Table 3 shows the slight improvement of the prediction models between the usage of the full spectral range and the reduced sets of wavelengths. Regardless of drying temperature or pre-treatment, the models can predict the quality parameters with a high accuracy. Thus, unlike using selected sets of wavelengths depending on the pre-treatment before beef drying (Retz et al., 2017; von Gersdorff et al., 2018), the results of the present study enable the usage of spectral imaging to monitor MC and instrumental

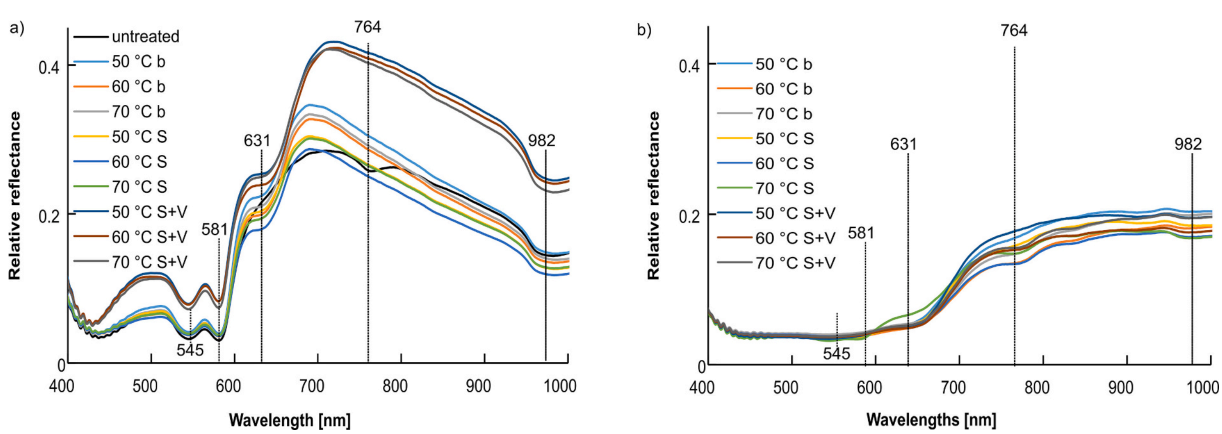

Fig. 4. Averaged reflectance spectra of untreated beef slices and beef slices with different pre-treatments before drying at a) three different temperatures and b) after drying. The meat specific reflectance wavelengths are highlighted.

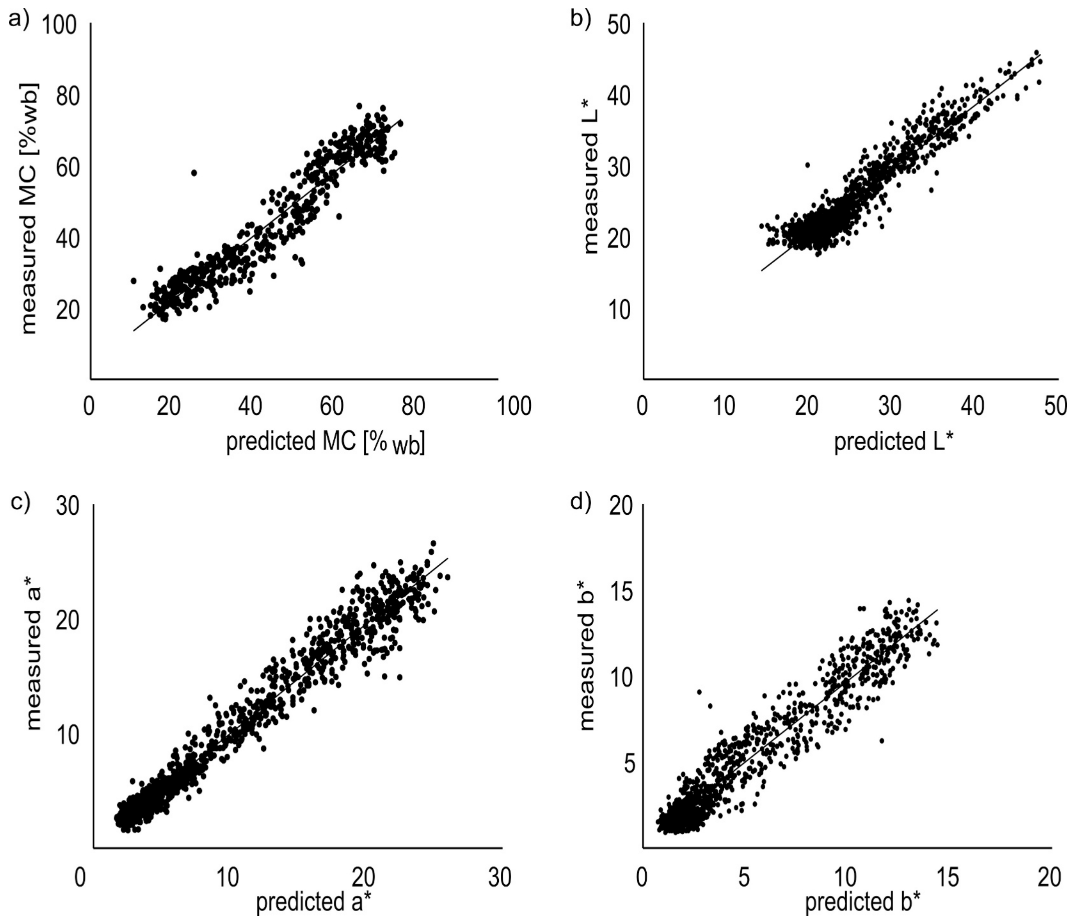

Fig. 5. Scatter plots of measured vs. predicted a) MC, b) L*, c) a* and d) b* values for beef slices during drying. PLSR models are based on reduced sets of wavelengths. Model performance parameters are shown in Table 3.

Table 3
Comparison of performance indicators of PLSR models developed from full and reduced sets of wavelengths and independent of pre-treatment and drying temperature for prediction of moisture content (MC), CIELAB L*, a* and b* values of beef slices during drying.

Parameter	Full set of wavelengths		Reduced set of wavelengths	
	R^2	RMSEP	R^2	RMSEP
MC	0.944	5.758	0.953	5.263
L*	0.947	1.998	0.948	1.975
a*	0.978	1.605	0.982	1.475
b*	0.959	1.1	0.963	1.05

R^2 = coefficient of determination, RMSEP = root mean square error of prediction.

color in real-time during drying process. The results will support the development of monitoring systems and to use the data gained from non-invasive MC and color measurements to link them to physiochemical changes to be investigated in future work to improve drying strategies for high quality dried beef. The results further offer the potential to be used regarding the development of a multispectral imaging system. Regarding cost-effective monitoring solutions the outcome of the present study can be transferred to a simpler application, consisting of selective lighting combined with CCD cameras and thus enable also small scale processors to use non-invasive measurement systems in processing.

4. Conclusions

In this study, pre-treatment and drying temperature showed a joint influence on the drying behavior and instrumental color changes during the dehydration of beef. The samples pre-treated with salt solution dried the slowest, followed by salt and vinegar treatment, while blind samples dried the fastest. This effect increased slightly with increasing drying temperature. ΔE was the lowest for samples dried at 60 °C and did not visible differ across the pre-treatments. Although the drying behavior and the instrumental color difference varied between the experiments, the hyperspectral data acquired during drying allowed the development of robust PLSR prediction models for MC, CIELAB L*, a* and b* values independent of drying temperature or pre-treatment. An exclusion of uninformative wavelengths by selection of parameter specific wavelengths led to simpler models and, therefore, the ability to acquire smaller amounts of data while maintaining the accuracy of prediction. Further, an inclusion of other beef cuts and, in general, meat varieties as well as other quality parameters could be of future interest to predict product parameters during drying by varying prediction models in an industrial significance and in regard to product controlled drying for beef.

Author contributions

Conceptualization, G.vG., B·S., S.K.; methodology, G.vG., B.S.; software, B.S., S.K., G.vG.; validation, B.S., G.vG., S.K.; formal analysis, all; investigation, G.vG, B.S.; resources, G.vG.; B.S.; data curation, G.vG, S.K.; writing—original draft preparation, G.vG., S.K.; writing—review and editing, all; visualization, G.vG., S.K.; supervision, B.S, S.K.; project administration, B.S., G.vG.; funding acquisition, B.S., O.H.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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