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Prediction of Sensory Quality by Near Infrared Reflectance Analysis of Frozen and Freeze Dried Green Peas (*Pisum sativum*)

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ABSTRACT

Frozen, green peas (Pisum sativum *L) of different varieties and different levels of maturity were evaluated by sensory analysis using a panel of ten trained judges. Two texture variables (hardness and mealiness) and four flavour variables (pea flavour, sweetness, fruity flavour, off flavour) were considered. Near infrared reflectance (NIR) analysis was performed with the same material, on both the frozen and freeze dried peas. The NIR instrument was calibrated to predict the sensory variables using the multivariate analytical method of principal component regression. Tenderometer readings of the same peas were also calibrated to predict the sensory variables. NIR analysis on the freeze dried peas showed relative ability of prediction (RAP) values for the sensory variables which were higher than those for the tenderometer readings. The sensory attributes pea flavour and hardness were predicted with higher RAP values by tenderometer readings than by NIR analysis on frozen peas.*

For the rest of the attributes, NIR analysis on frozen peas gave higher RAP values than tenderometer readings. NIR generally gave high RAP values, and this tentative study suggests that NIR analysis could be a useful tool in instrumentally assessing the quality of frozen peas.

Key words: Green peas, *Pisum sativum* L, frozen peas, freeze dried peas, near infrared reflectance (NIR), sensory analysis, principal component regression (PCR).

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ABBREVIATIONS

NIR	Near infrared reflectance
PCA	Principal component analysis
PCR	Principal component regression
RMSP	Root mean square error of prediction
RMSCV	Root mean square error of cross-validation
RAP	Relative ability of prediction

INTRODUCTION

In Scandinavia frozen green peas are a common vegetable at the dinner table. In Norway the annual production of frozen peas has been about 5000 tonnes for the last 5 years. That means a production of about 1·2 kg per caput. The use of canned and dried peas is minor compared with that of frozen.

The sensory quality of peas may be assessed by laboratory studies using a panel of trained judges or by a consumer test (Amerine *et al* 1965). The relationship between product quality and the chemical/physical state of green peas has been studied by Blanchard and Maxwell (1941), Ottosson (1958), Atherton and Gaze (1983), Oleata *et al* (1983), Gaze *et al* (1986), Martens (1986) and others.

The yield and quality of green peas for processing primarily depends on their maturity at the time of harvest (Rutledge and Board 1980). Tenderometer readings are related to the maturity of the peas (Ottosson 1958; Rutledge and Board 1980; Rutledge 1981) and thereby are indirectly related to pea quality. Martens (1986) found that tenderometer value was a relevant but inadequate predictor of internal sensory quality. Atherton and Gaze (1983) recommended that product quality standards for frozen peas should not depend entirely on physical/chemical methods (tenderometry included), but that reference should also be made to sensory analysis of colour, flavour and texture.

Sensory analysis and traditional chemical analysis are often rather time consuming. A quick analysis with sufficient accuracy would save much time in assessing the quality of peas. Near infrared reflectance (NIR) has become a widely used method in food analysis because it is rapid and little or no sample preparation is required (Osborne and Fearn 1986). The technique has been used by many to predict the chemical constituents of peas. Williams *et al* (1978) applied NIR analysis to the determination of protein and moisture in a number of species of pulses and attained a squared coefficient of correlation of 0·89 to 0·96 between protein contents determined by Kjeldahl analysis and NIR analysis. Park *et al* (1982) found correlation coefficients between actual and NIR predicted values of 0·97 for crude protein, 0·77 for crude fat, 0·91 for ash and 0·81 for neutral detergent fibre in dehydrated vegetables. Davies and Wright (1984) determined the protein in pea flour with NIR analysis. The accuracy of the predictions was tested against different data sets and found to be better than 1·5% ($P = 0·95$). Davies *et al* (1985) found that the accuracy of predictions of starch in pea flour was better than 2·6% and of lipid 0·3%. Williams *et al* (1985) used NIR to determine methionine and protein in whole field peas and found the accuracy of prediction to be 0·11 and 0·76 %, respectively. Tkachuk *et al* (1987) found that NIR analysis gave better prediction values for protein in ground than in whole field peas.

The sensory quality may be predicted by relating the sensory data to NIR data with the use of multivariate regression. Calibration of NIR reflectance data, by regression, to predict both sensory and chemical/physical properties has been done with frozen peas (Martens and Martens 1986). The measurements with an NIR instrument of 19 standard wavelengths (InfraAlyzer 400, Technicon Industrial Systems, Tarrytown, NY, USA) was then found to be better than tenderometer values at describing the average variation in sensory quality. The technique was also found to predict sensory texture variables better than in the case of the flavour variables. Martens and Martens (1986) concluded that NIR had the potential for predicting the sensory quality of frozen peas.

The 19 standard wavelengths of the InfraAlyzer 400 have been selected for the prediction of chemical constituents, but factors that contribute to the sensory perception of biological material are complex and multivariate. Therefore, by increasing the number of wavelengths, one may increase the information about sensory quality. In the present study the work of Martens and Martens (1986) has been continued with the use of a scanning NIR instrument. It was also of interest to find out if removal of the major part of the water in the peas would reduce the prediction error of the NIR analysis. Some possible reasons for improvement in predictive ability by removal of water are considered.

The flavour and texture quality of the peas was considered in this work since these aspects have been found to be important quality criteria for frozen peas. Schutz *et al* (1984) found that the internal sensory flavour and texture were more important for the purchase and consumption of vegetables than colour and appearanace. Martens (1986) found that the texture variables hardness and mealiness and the fruity and sweet flavour variables were relevant and representative internal sensory quality criteria for normally treated green peas. Sanford *et al* (1988) used principal component regression (PCR) to determine that the dimensions represented by texture and flavour were the most important factors in optimising consumer sensory acceptance of frozen peas. The development of sensory attributes for green peas has been described by Martens (1986). Only the internal sensory quality has been investigated in the present study and some alterations have been made: pea flavour was added to the analysis and the definition of fruity flavour was slightly changed.

EXPERIMENTAL

Materials

The materials used consisted of 60 independent batches of wrinkle-seeded, green peas (*Pisum sativum* L) from the 1987 season. The peas were collected from 27 varieties and at different degrees of maturity. From these batches samples of peas with a diameter of 9 mm or more were used in the study. The peas were blanched within 3 h of harvesting at 90–95°C for 2 min and cooled in tap water ($\sim$6°C). They were then frozen on perforated trays at -40°C (air velocity $\sim 1{\cdot}5$ m s^{-1}) for at least

20 h (batches of 1–5 kg), packed in polyethylene bags and stored at $-20°C$ (air velocity $\sim 0{\cdot}5$ m s^{-1}).

About 70–90 g of whole peas from each batch of the frozen peas were freeze dried in a Hetosicc DC 13 freeze drier (Heto, Birkerød, Denmark).

Physical and chemical measurements

The maturity of the peas was assessed by measuring the hardness with an FMC tenderometer (Canners Machinery Ltd, Simcoe, Canada) immediately after harvesting.

Dry matter was determined by the freeze drying process. It was also determined by drying the frozen peas at 105°C for 16 h.

Sensory analysis

The sensory analysis was performed about 3 months after harvesting. The frozen peas were steam heated at 100°C before evaluation by a trained profile panel of 10 persons. Each of the 10 judges was served each sample twice. Portions of about 20 g were served in a randomised order within replicates and with respect to each judge.

Six sensory attributes were evaluated with the use of an intensity scale of 1 to 9 points. An intensity of 1 point represented no reference to the attribute, and 9 represented a very strong expression of it. The attributes were pea flavour (characteristic/rich), sweetness, fruity flavour (light/aromatic/fresh), off flavour (harsh/bitter/metallic), mealiness and hardness.

The analysis was performed with the use of the Senstec (Tecator, Höganäs, Sweden) registration system. Each judge evaluated a sample by marking an unstructured line of 15 cm for the intensity of each sensory attribute. Numerical values were obtained by automatic registration of the length from the left side of the line to the marking.

NIR analysis

The batches of both frozen and freeze dried peas were homogenised (Moulinette S643, Moulinex, Nieune, France) for about 60 and 30 s respectively prior to NIR analysis. The frozen peas were taken directly from the freezer for homogenisation.

The NIR analysis was performed with an InfraAlyzer 500 (Technicon Industrial Systems) at 2-nm intervals in the range 1100–2500 nm. The effective bandwidth was about 10 nm.

The homogenised samples were packed in standard black cups. An open cup (189-0822-01) was used for the frozen peas and a closed cup (189-B090-02) for the freeze dried material. The samples were measured at a temperature of about 22°C.

The detected diffuse reflectances (R) were transformed to apparent absorbances ($\log 1/R$). The mean spectrum of three repacks of each sample was used for calibration.

Data analysis

The number of datapoints in the spectra was decreased in order to reduce computing time by averaging every three adjacent datapoints starting with the first three points and continuing with the next three etc. A selection of alternate averages, making a total of 116 variables, was entered into the data analysis.

The spectral data for each batch were then subjected to multiplicative scatter correction (Martens *et al* 1983) to reduce nonlinear scatter effects. Previous works with wheat (Martens *et al* 1983) and meat (Geladi *et al* 1985; Isaksson and Næs 1988) have demonstrated that simpler calibration models can be obtained with the use of multiplicative scatter correction.

The multivariate data analytical method PCR (Gunst and Mason 1979; Cowe and McNicol 1985) was used for calibration. With this method the variables are transformed to eigenvectors called principal components using a principal component analysis (PCA) algorithm (Wold *et al* 1984). The regressions are performed with these principal components as independent variables and the sensory attributes as dependent variables. The principal components were incorporated into a regression model in decreasing order of their eigenvalue (Næs and Martens 1988). Spectral data from frozen and freeze dried peas and tenderometer readings from fresh peas were subjected to calibration.

To validate the calibration model the PCR was performed with the use of cross-validation (Stone 1974). The cross-validation was performed with four segments (calibration repeated four times), each time treating a quarter of the entire calibration sample set as a test set (prediction samples) while the rest of the samples were used for calibration. As a result all the calibration samples were treated as prediction samples once.

The predictive accuracy of a calibration model is described by the root mean square error of prediction (RMSP) (Martens and Martens 1986) which is defined for the sensory variable y_j by:

$$\mathrm{RMSP}=\sqrt{\frac{1}{I}\sum_{i=1}^{I}(\hat{y}_i-y_i)^2}$$

where y_i is the sensory data from analysis of sample number i, $\hat{y}_i$ is the predicted value, and I is the number of objects used in the prediction.

An average of RMSP^2 for all cross-validation segments was computed for each principal component model. The square root of this average is called the root mean square error of cross-validation (RMSCV) (Martens and Naes 1987).

In order to compare the predictive ability of the calibration models for the different sensory variables, the relative ability of prediction (RAP) was used (Martens and Martens 1986). This term takes into account the level of experimental error in the reference data. RAP is defined for sensory variable y_j by:

$$\mathrm{RAP}=\frac{S_{\mathrm{tot}}^{2}-\mathrm{RMSCV}^2}{S_{\mathrm{tot}}^{2}-S_{\mathrm{ref}}^{2}}$$

where S_{tot} is the standard deviation of the reference data y_j in all the samples. S_{ref} is a standard error that indicates the uncertainty of the analysis due to the judges, and is defined for sensory variable y_j by:

$$S_{\mathrm{ref}}=\sqrt{\frac{1}{IN}\sum_{i=1}^{I}S_i^2}$$

where S_i is the standard deviation of the points (each point is the mean of two replicates) from the judges at sample number i, I is the number of samples, and N is the number of replicates for each judge. By removal of S_{ref}, the RAP equation will express the squared multivariate correlation coefficient (Martens and Næs 1987).

The predictive ability explained by RAP will have a value between 0 and 1. A RAP value of 0 means that the prediction error, RMSCV, is equal to S_{tot}, while 1 means that the prediction is perfect and the RMSCV is equal to S_{ref}. An increase in S_{ref} increases the RAP, but the S_{ref} will never exceed the error of prediction expressed as RMSCV.

The transformations and regressions were executed with the software Unscrambler version 2.0 (CAMO A/S, Trondheim).

RESULTS AND DISCUSSION

Results from the sensory analysis, tenderometer measurements and analysis of dry matter are given in Table 1. The mean value ($\bar{y}$), range, standard deviation (S_{tot}) and standard error due to experimental noise (S_{ref}) are shown. The peas were chosen to span a wide range of variation with respect to maturation which also gave a large quality variation. S_{tot} and S_{ref} were used in the calculations of RAP.

The correlation coefficients between the different sensory attributes are given in Table 2. There is a high intercorrelation between the variables.

Martens (1986) found quality criteria covering the variation caused by maturation and growing season that seemed to be valid independent of variety. Ottosson (1958) found only small differences between varieties measured with chemical methods. Variation due to different varieties was therefore not considered in this study.

TABLE 1

Results from the sensory analysis, tenderometer readings and analysis of dry matter. Mean of 60 pea batches ($\bar{y}$), range total standard deviation (S_{tot}) and the experimental noise standard error (S_{ref})

	$\bar{y}$	*Range*	S_{tot}	S_{ref}
Pea flavour	5·4	2·3–7·3	1·1	0·29
Sweetness	5·5	2·2–7·2	1·2	0·25
Fruity flavour	3·6	1·2–5·2	1·0	0·31
Off flavour	2·9	1·8–6·6	1·0	0·29
Mealiness	4·4	2·2–6·8	1·3	0·33
Hardness	4·8	2·6–8·0	1·4	0·27
Tenderometer	135·2	88–200	31	—
Dry matter[a] (g kg^{-1})	223	179–288	25	—
Dry matter[b] (g kg^{-1})	195	138–281	31	—

[a] Dried at 105°C for 16 h.
[b] Freeze dried.

TABLE 2
Correlation coefficients between the different sensory attributes

	Sweetness	*Fruity flavour*	*Off flavour*	*Mealiness*	*Hardness*
Pea flavour	0·94	0·97	−0·94	−0·93	−0·92
Sweetness	—	0·94	−0·89	−0·90	−0·94
Fruity flavour	—	—	−0·90	−0·96	−0·93
Off flavour	—	—	—	0·83	0·85
Mealiness	—	—	—	—	0·92

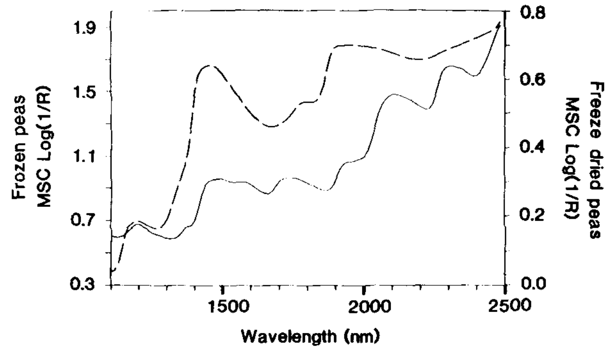

Fig 1. An example of NIR spectra of sample with a tenderometer value of 110. Spectra of both the freeze dried (——) and frozen (– –) samples are illustrated. The absorbance scale (log $1/R$) for frozen peas is to the left of the diagram while that to the right is for freeze dried peas.

Examples of NIR spectra for a pea sample are shown in Fig 1. Spectra from both the frozen and freeze dried samples are illustrated. The freeze dried peas had lower log ($1/R$) values and more distinct peak widths.

By removal of water, the level of absorbance will decrease. This is partly due to less absorption of energy by water. The peaks become more distinct when there is less overlapping by water absorbance. Also, there is more difference between the refractive indices of the particles and air than between the particles and water. The reflection will increase when the difference in the refractive indices increases.

Homogenisation produced smaller particles of the freeze dried material than homogenisation of the frozen, which gave more reflection surfaces. Increased reflection leads to smaller 'diffuse thickness' (Birth 1978) of the material. The path of radiation before the light is reflected back to the detector becomes shorter, and consequently there will be less absorption of radiant energy.

Both spectra had peaks at absorption bands for water (1450 nm and 1940 nm). Other peaks of interest in the spectra may be the 1520–1570 and 2100–2120 nm areas, in which there are absorption bands for carbohydrates (Osborne and Fearn 1986). The amount of carbohydrates in peas is quite high. Martens (1986) found levels of starch of about 5·0 % and of sugar of about 7·5 % in 96 different pea samples from three different seasons.

The RAP made it possible to compare the ability of NIR to predict the different sensory variables. To be able to see the development with different calibration models, the RAP values are presented in Fig 2 as functions of the number of principal components. RAP values with NIR analysis (frozen and freeze dried samples) and tenderometry as predictors are illustrated.

The maximum RAP value with NIR analysis of freeze dried peas was higher than with tenderometer readings. Compared with the predictive ability of NIR on frozen peas, the tenderometer gave a higher maximum RAP value for pea flavour and slightly higher for hardness. NIR analysis on frozen peas showed higher RAP values for the remaining attributes. A tenderometer reflects variations due to resistance to compression and extrusion (Rutledge 1981), but on the whole it did not reflect the variation in internal sensory quality as well as the NIR.

Tenderometer readings had the lowest prediction errors when predicting hardness with a RAP value of 0·91 and fruity flavour with 0·86. The tenderometer value was correlated to hardness ($r = 0{\cdot}94$) and fruity flavour ($r = -0{\cdot}89$). A relatively high ability of prediction expressed as RAP was therefore not unexpected. With an increasing tenderometer value, the hardness will increase and the fruity flavour will weaken mainly because of the decreasing amount of sugar, increasing amount of starch and less water.

The maximum predictive ability, expressed as RAP, for freeze dried peas was higher than for frozen peas except when predicting off flavour. The RAP values of off flavour were about equal in the two different NIR analyses. The high RAP values for the freeze dried peas demonstrate that information about the sensory quality was improved by the removal of water. The absorbance level decreased and the chemical constituents contributed relatively more to the spectra. There is a possibility of structural damage during freeze drying if a critical temperature is exceeded (Bellows and King 1972). Possibly structures and/or chemical bondings are changed in such a way that the specific absorbances explained more about the attributes when built into a calibration model. Some of the components or structures that either contribute to off flavour or are correlated to it may have been destroyed during the freeze drying process.

Sweetness, fruity flavour, hardness and mealiness were the best predicted sensory attributes for both NIR analyses. The freeze dried material showed maximum RAP values between 0·93 and 0·98, while the values of the frozen material ranged from 0·88 to 0·91. Pea flavour was also among the best in NIR analysis of the freeze dried material (0·93). Off flavour had the lowest RAP values with both the freeze dried and frozen material with maximum values of 0·84 and 0·83, respectively. This accuracy in predicting sensory attributes suggests that NIR could be a useful tool in assessing the quality of peas. Even NIR analysis of frozen peas gave information about the quality with relatively high accuracy.

Martens and Martens (1986) related sensory data for frozen peas to NIR data (19 standard wavelengths) by partial least squares regression. They found a predictive ability, expressed as RAP, for texture variables (0·79) higher than for flavour variables (0·67). In the present work there was no tendency for prediction ability of the flavour variables (pea flavour, fruity flavour, sweetness, off flavour) to be lower than that of the texture variables (hardness, mealiness).

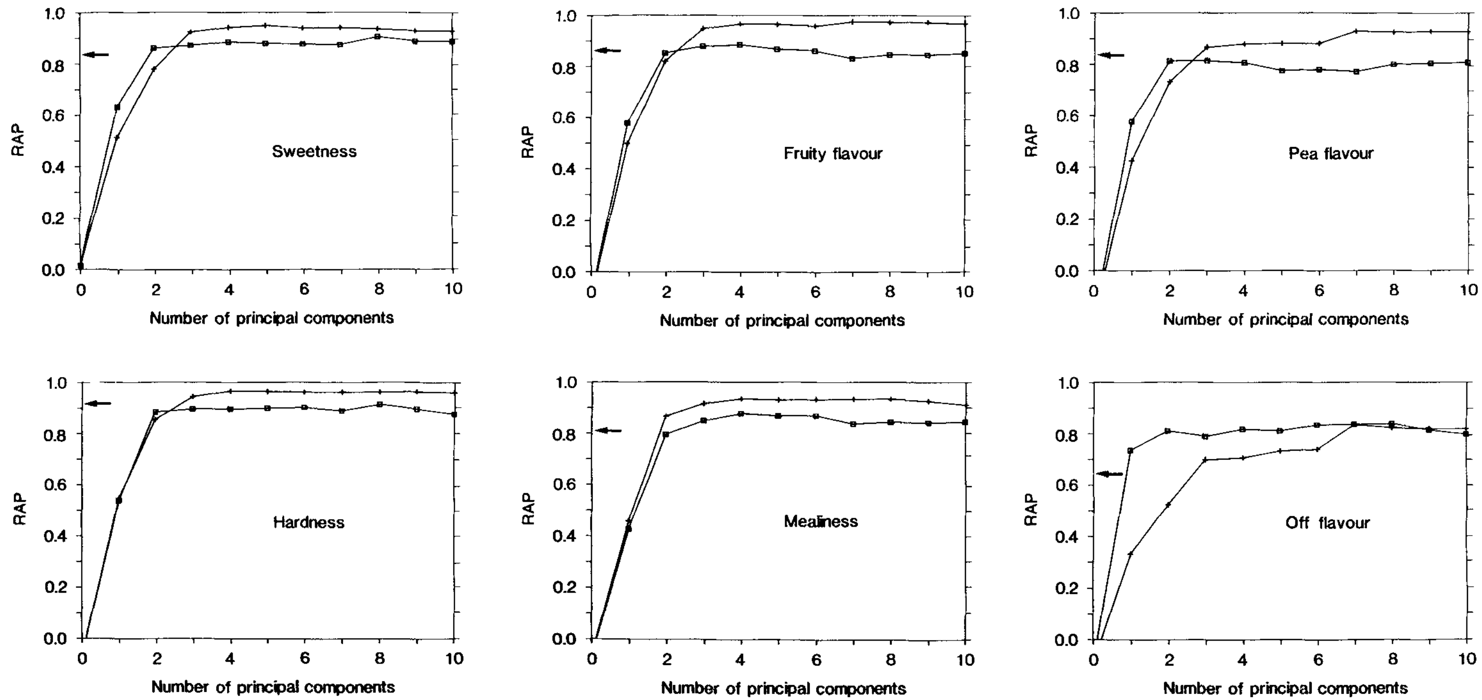

Fig 2. The relative ability of prediction (RAP; see text) illustrated as a function of the number of principal components in the regression models. Six different internal sensory attributes are predicted by both NIR analysis and tenderometer readings. RAP for NIR analysis of both freeze dried and frozen peas are illustrated (+ freeze dried peas, □ frozen peas). RAP values for tenderometer reading are indicated with arrows.

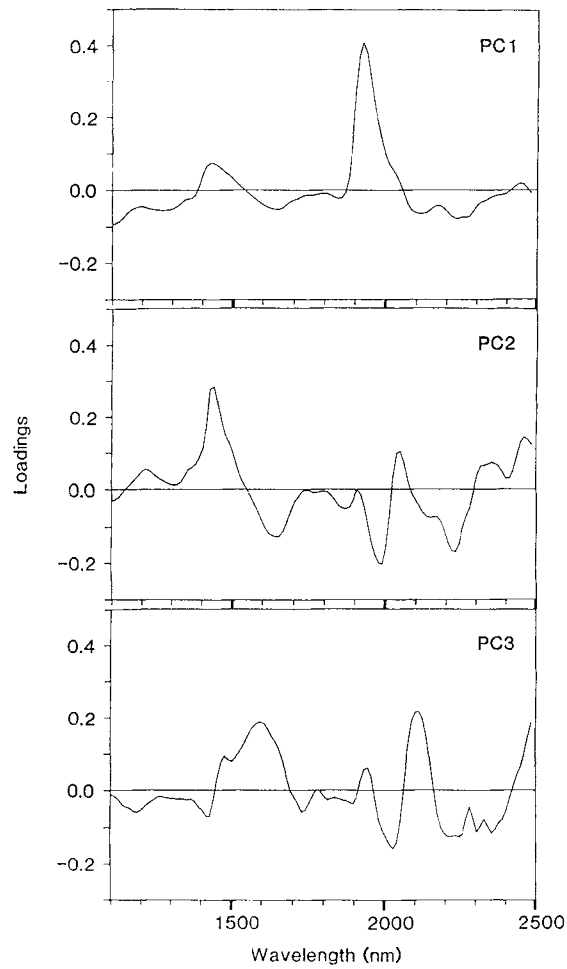

Fig 3. Principal component loadings at each datapoint of the NIR spectrum of freeze dried peas. The principal components PC1, PC2 and PC3 are numbered according to decreasing eigenvalues.

An increased number of wavelengths possibly increased the ability to predict flavour variables compared with the texture variables. This improvement has to be verified by a comparative study of the two NIR instruments using the same regression technique and the same material for analysis.

Loading plots of the three first principal components of freeze dried peas and the two first principal components of frozen peas are illustrated in Figs 3 and 4. For freeze dried peas, the three first principal components contributed to the major predictive ability with all the sensory attributes. The first principal component generally contributed more than the second, which contributed more than the third.

The first and second principal components after analysis of freeze dried peas showed positive correlation to hardness and negative correlation to sweetness. The loading plots of the first and second principal components are similar to the water

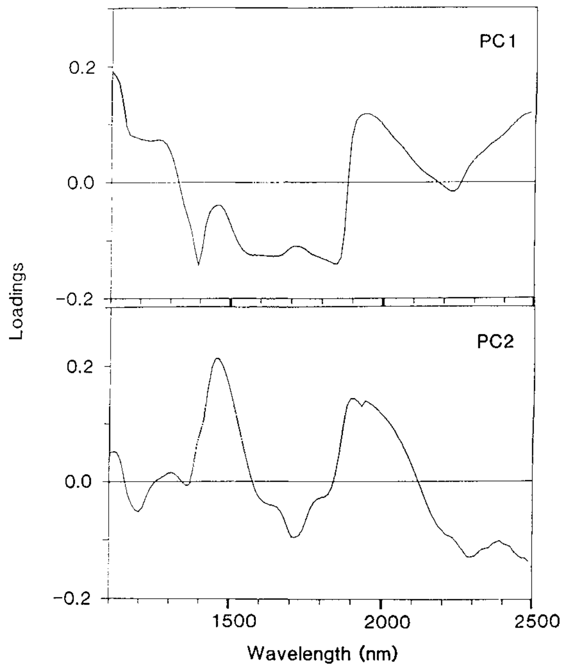

Fig 4. Principal component loadings at each datapoint of the NIR spectrum of frozen peas. The principal components PC1 and PC2 are numbered according to decreasing eigenvalues.

and carbohydrate spectra (Williams and Norris 1987), respectively. The third principal component was positively correlated to sweetness and negatively correlated to hardness, and the loading plot had a structure which resembled that of a carbohydrate spectrum, possibly amorphous sucrose (Davies and Miller 1988).

For frozen peas, only the two first principal components contributed to the major predictive ability. Both of the loading plots resemble the NIR water spectrum and have only slight structures of carbohydrate spectra. The first and second principal components were then likely to span most of the water variation.

The spectra from freeze dried peas contained relatively more information about sensory attributes than did the spectra from frozen peas. The information seems to have been collected from more fine structured principal components related to carbohydrates.

The content of starch increases and that of sugar decreases during maturation of the peas (Ottosson 1958) and indicates that the amount of carbohydrates is important for the quality. A tentative interpretation would also be that the water binding ability, here represented with the remaining water after freeze drying, is important for the sensory quality.

The minimum values of the prediction errors expressed as RMSCV, with NIR and tenderometer readings as predictors, are given in Table 3. The freeze dried peas gave lower prediction errors than frozen peas for all sensory variables except for off flavour which had an RMSCV value only slightly higher than that of the frozen

TABLE 3
Minimum of root mean square error of cross-validation (RMSCV; see text) with NIR analysis and tenderometer readings as predictors for sensory quality attributes

	NIR		*Tenderometer readings*
	Freeze dried	*Frozen*	*Fresh*
Pea flavour	0·40 (7)	0·54 (3)	0·52
Sweetness	0·36 (5)	0·44 (8)	0·54
Fruity flavour	0·34 (7)	0·45 (4)	0·47
Off flavour	0·49 (7)	0·48 (8)	0·64
Mealiness	0·46 (4)	0·55 (4)	0·64
Hardness	0·37 (4)	0·49 (8)	0·48

( ) Number of principal components which gave the lowest prediction errors.

peas. The tenderometer readings gave higher prediction errors expressed as RMSCV than those of the freeze dried peas.

Lower RMSCV values for freeze dried as opposed to frozen peas mean greater accuracy and suggest that more information about the material was retrieved when the major part of the water was removed. The prediction then comes closer to the 'true' value measured by sensory analysis.

Further studies are needed to make calibration models for use by producers and the processing industry. Pea samples must be chosen to represent the normal range of variation with respect to varieties and maturities. Also seasonal effects need to be included by calibration with peas from more than one year. Instruments suitable for field and industrial use have to be selected, or constructed if not available.

CONCLUSIONS

NIR analysis gave higher predictive ability than tenderometer readings for most of the internal sensory texture and flavour variables of frozen peas. NIR analysis of freeze dried peas gave better predictive ability of texture and flavour for frozen peas than NIR analysis on frozen peas.

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