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Towards development of on-line soil moisture content sensor using a fibre-type NIR spectrophotometer

Abdul Mounem Mouazen[a,b,*], Josse De Baerdemaeker[b], Herman Ramon[b]

[a] Department of Rural Engineering, Faculty of Agriculture, University of Aleppo, P.O. Box 12214, Aleppo, Syria
[b] Department of Agro-Engineering and -Economics, Faculty of Agricultural and Applied Biological Sciences, Catholic University of Leuven, Kasteelpark Arenberg 30, B-3001 Heverlee, Belgium

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Abstract

As the soil moisture content (w) is a deterministic factor for site-specific irrigation, seeding, transplanting and compaction detection, an on-line measurement system will bring these applications into practice. A fibre-type visible (VIS) and near-infrared (NIR) spectrophotometer, with a light reflectance measurement range of 306.5–1710.9 nm was used to measure w during field operation. The spectrophotometer optical unit was attached to the subsoiler chisel backside to perform the light reflectance measurement from the soil surface on the bottom of the trench opened by the proceeded chisel. The spectrophotometer–optical unit system was calibrated for w under stationary laboratory conditions on samples collected from an Arenic Cambisol field with different soil textures. A partial least square analysis was carried out in order to establish a statistical model relating soil light spectra with the gravimetric w of the 0.005–0.26 kg kg^{-1} range. This model was validated with the full cross validation method resulting in a small root mean square error of cross validation (RMSECV) of 0.0175 kg kg^{-1} and a high validation correlation of 0.978. Further validation of the model developed in the laboratory under stationary state showed also a small root mean square error of prediction (RMSEP) of 0.0165 kg kg^{-1} and a prediction correlation of 0.982. When the NIR sensor-model system was used to determine w, based on on-line field measurement, a relatively larger RMSEP of 0.025 kg kg^{-1} and lower prediction correlation of 0.75 were found. However, a reasonably similar spatial distribution of w was found between the on-line NIR measurement and oven drying methods. Therefore, the on-line NIR w sensor developed is recommended to provide valuable information towards the site-specific applications in soils.

Keywords: Moisture content; On-line measurement; Sensor; Spectrophotometer

1. Introduction

Soil moisture content (w) is one of the most critical soil components for successful plant growth and land management, particularly in drylands. It is determined by a conventional method based on oven drying of samples collected from fields. In spite of the fact that the oven drying method is a difficult, costly and time consuming procedure, it provides discontinuous information about w. An alternative on-line measurement system of w is still an attractive and difficult challenge for researches and engineers involved in the development of precision farming research, particularly

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* Corresponding author. Tel.: +00 32 16 32 8592; fax: +00 32 16 32 8590.
E-mail address: abdul.mouazen@agr.kuleuven.ac.be (A.M. Mouazen).

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in large-scale fields under arid and semiarid zones. Site-specific irrigation, transplanting, seed drilling and compaction detection in such fields might be brought into practice if a successful on-line measurement system of w is incorporated into farm machines.

Stafford (1988) divided the sensors to monitor w from mobile machinery into two categories of contact and non-contact non-destructive sensing systems. While the former systems include the electrical conductivity (Bowers and Bowen, 1975), microwave (Whalley, 1991), capacitance (Bobert et al., 2001) and nuclear magnetic resonance (Paetzold et al., 1987) techniques, the latter include microwave reflectance (Whalley and Bull, 1991) and ground-penetrating radar (Shih et al., 1986) techniques. The near-infrared reflectance (NIR) spectroscopy is a promising non-contact measurement method available to provide rapid information about some soil physical and chemical properties, namely organic matter content, nitrogen, potassium, phosphorous, pH, w, particle size and mineral composition of the soil. It is based on the understanding of the interaction between the incident light and properties of soil surface such that the reflected light characteristics vary due to the surface physical and chemical properties. When light is illuminated towards the soil surface, the radiant energy is distributed through three different processes: reflection, absorbance and transmission. As transmission in soil equals zero, the balance between reflection and absorbance is governed by the influence of the soil physical and chemical properties. These properties determine the colour and roughness of the soil surface, influencing the amount of light reflection and/or absorbance. Bowers and Hanks (1964) found that the intensity of reflected light from the soil surface decreased with increasing w, particle size and organic matter. The w was measured with stationary-state NIR spectroscopy by several researchers (Bowers and Hanks, 1964; Kano et al., 1985; Dalal and Henry, 1986; Slaughter et al., 2001). In comparison with several studies reported about the stationary-state NIR spectroscopy measurement of soil properties, only very few researchers were able to report the development of real-time NIR spectrophotometer measurement systems. This is attributed to the difficulties of building up a real-time spectroscopic measurement system. Moreover, inserting the spectrophotometer illuminating and reflecting units within the soil leads to delicate and breakable instrumentation, particularly when working in fields with gravels and stones. A portable infrared reflectance method based on light emitting diodes was used by Stafford et al. (1989) to measure w. However, the instrument showed limited use because the emitting diodes at 1950 nm were not available commercially. Shonk et al. (1991) introduced a real-time fibre-type NIR spectroscopy measurement system, which utilised a single wavelength light reflectance to measure the percentage of soil organic matter. They declared that the sensor is promising to be useful for prescription applications of soil applied chemicals. Sudduth and Hummel (1993) developed a portable-type NIR spectrophotometer to measure soil organic matter, cation exchange capacity and w to depths from 0.35 to 0.50 m. They found good correlation between soil measured properties and light reflectance under stationary laboratory conditions. However, when measurement was done on-line in the field, they reported inaccurate estimation of soil properties, which was attributed to the variations in soil-to-sensor height during wavelength scanning.

The only research involving the development of a real-time NIR spectroscopy measurement system of w among other soil properties is reported in Shibusawa et al. (1999). The light illumination and reflection fibres are attached to a spectrophotometer of 300–1700 nm VISNIR light source. The optical unit stands above the soil surface at a distance of 0.075 m (Shibusawa et al., 2003). This gap between the soil and optical-sensing unit could lead to a possible soil-to-sensor height variation due to changes in both the soil topography and/or vertical forces acting on the chisel. Furthermore, the several sensing units in the housing make the system complicated and rather expensive. A useful spectrophotometer sensor to measure soil properties should be simple, cheap and properly designed to have continuous touch with soil to avoid the distance variation problem of the soil-to-sensor optical unit that limited the few real-time spectroscopy measurement systems so far.

This study describes the development of a simple and reliable, fibre-type NIR spectrophotometer sensor for the on-line measurement of w. A comparison between maps of the on-line NIR spectrophotometer and oven drying methods is presented.

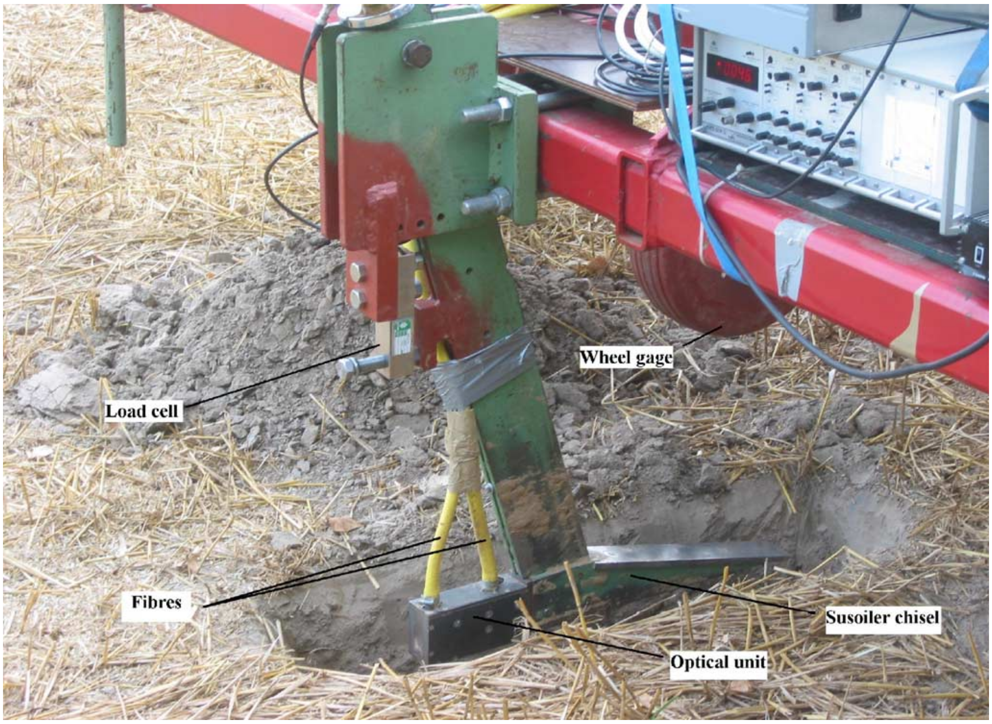


Fig. 1. Subsoiler–optical unit set up ready for on-line field measurement.

2. Materials and methods

2.1. Sensor design

A sensor for the real-time measurement of soil compaction indicated as dry bulk density was developed by Mouazen et al. (2003a). The system consists of a medium-deep subsoiler fixed to a frame, which is mounted on the three-point hitch of the tractor (Fig. 1). The on-line determination of dry bulk density required the parallel on-line measurement of subsoiler draught, cutting depth and w values to be substituted into the following numerical–statistical hybrid model (Mouazen and Ramon, 2002):

$$\rho_d = \sqrt[3]{\frac{D + 0.2136w - 73.9313d^2}{1.6734}} \quad (1)$$

where D is the draught [kN], w is the gravimetric moisture content [kg kg^{-1}], d is the cutting depth [m] and ρ_d is the dry bulk density [Mg m^{-3}].

Draught was measured by a commercially available shear beam load cell shown in Fig. 1, whereas depth was measured by a wheel gauge developed by Mouazen et al. (2003b).

In order to measure w, a Corona fibre VISNIR spectrophotometer developed by Zeiss Company was used. It is fast, precise and robust, without moving parts, which makes it suitable to be permanently aligned on mobile machines. In addition to the InGaAs diode-array for measurement in the NIR region (944.5–1710.9 nm), a Si array is available for the measurement in the visible (VIS) and short infrared wavelength region (306.5–1135.5 nm). The light source is a 20 W tungsten halogen lamp illuminating the targeted soil surface. The light illumination and reflectance fibres were collected together at a 45° angle position in the lens holder, as shown in Fig. 2. The lens holder was fitted within a protecting iron case forming the optical unit. The latter was attached to the backside of the subsoiler chisel (Fig. 1), which ensures the continuous penetration of the optical unit throughout the trench opened by the preceding chisel.

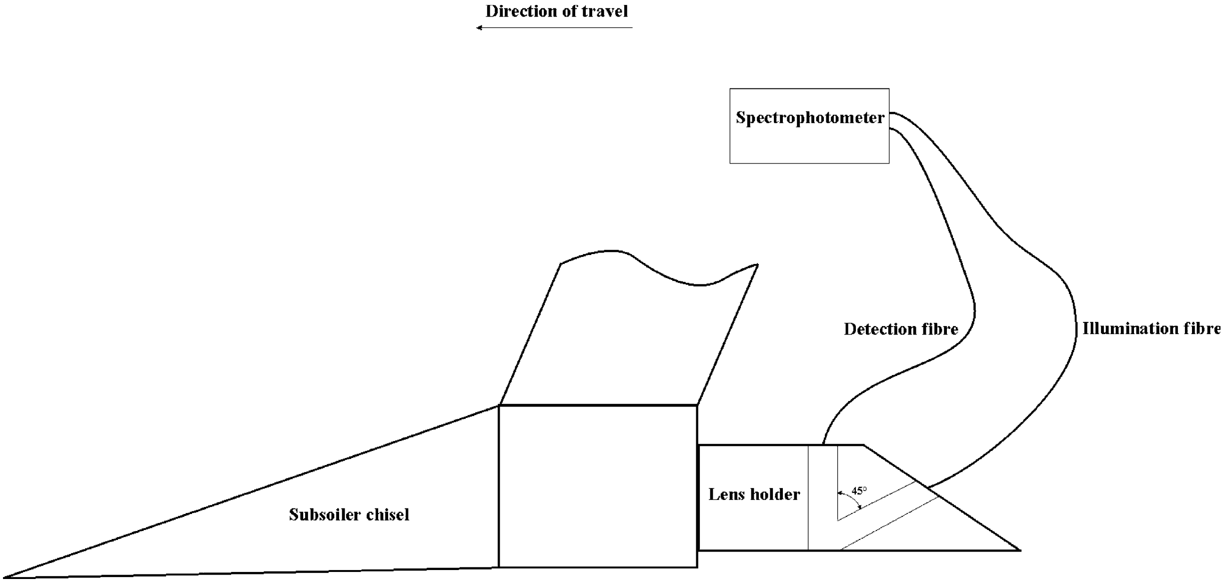


Fig. 2. Schematic illustration of lens holder as attached to the subsoiler chisel backside.

This design provides a continuous cover of the optical unit by the soil flowing back into the opened trench, ensuring that the targeted soil spot on the bottom of the trench receives the light of the spectrophotometer halogen lamp only. This eliminates the need of a special cover for the optical unit to protect from the surrounding light. In order to minimise the negative effect of soil-to-sensor distance variation, a continuous sliding of the lens holder bottom side along the trench bottom surface is preserved. To obtain a smooth soil surface, the lens holder bottom side was carefully smoothened.

2.2. Field description and sampling procedure

The 70,000 m^2 experimental field was located in the Zoutleeuw region, southeast of Brussels, Belgium. The soil type is an Arenic Cambisol, according to the FAO classification. The soil texture fractions were determined by a combination of wet sieve and hydrometer tests, using the USDA Soil Classification, as shown in Table 1. The soil texture over the field down to 0.15 m is non-homogeneous, including three textures of sandy loam, loam and silt loam, as listed in Table 1. A total of 46 soil samples were collected from the upper 0.2 m layer during the growing season of wheat based on 50 m × 50 m grid, and they subjected for the texture analysis and NIR spectrophotometer sensor calibration.

2.3. Sensor laboratory calibration

The calibration portion of this study aimed to establish a statistical model, which relates the light reflectance characteristics with the corresponding w determined by the oven drying method.

2.3.1. Preparation of soil samples

The 46 soil specimens collected from the Zoutleeuw field based on 50 m × 50 m grid were used to perform the laboratory sensor calibration. Soil samples were subjected to oven drying at 60 °C for 24 h, after which they were ground and sieved with a 0.002 m sieve. From each sample, 35 g of sieved soil was placed in a 0.060 m × 0.015 m plastic dish. Soil in the dish was first shaken and compacted before

Table 1
Soil texture defined according to the USDA Soil Classification

Property	Sandy loam ($g\,kg^{-1}$)	Loam ($g\,kg^{-1}$)	Silty loam ($g\,kg^{-1}$)
Sand (>50 μm)	562.77	464.24	335.12
Silt (2–50 μm)	362.41	443.74	540.49
Clay (<2 μm)	74.82	92.02	124.39

Table 2
Comparison of sample statistics between model and full cross validation and laboratory validation groups

Sample group	Number of samples	Minimum ($\mathrm{kg\,kg^{-1}}$)	Maximum ($\mathrm{kg\,kg^{-1}}$)	Mean ($\mathrm{kg\,kg^{-1}}$)	Standard deviation ($\mathrm{kg\,kg^{-1}}$)
Model and full cross validation	744	0.0046	0.2596	0.1264	0.0844
Laboratory validation	84	0.0046	0.2529	0.1263	0.0848

the surface was carefully leveled in order to obtain a maximum amount of reflected light. In fact, the preparation of a compacted and smooth sample surface in the dish aimed first of all to have a similar soil surface to the surface created beneath the subsoiler chisel during the on-line field measurement stage. The overall subsoiler vertical forces act downwards as found by Mouazen and Neményi (1999), which creates a compacted trench bottom in a similar way to the creation of a hard pan by different ploughs. Moreover, it is expected that during the on-line field measurement, the compacted trench bottom side is leveled by the smooth surfaces of the chisel and lens holder coming behind, sliding over the compacted soil surface. In order to develop a proper model for the determination of w using the developed sensor design, the same lens holder to be used in the field was used during the laboratory calibration. Three reflectance readings were taken from each soil specimen by rotating the plastic dishes a 120° angle. After the measurement of all samples was completed for the dry state, water was added uniformly over the sample. Six w levels of 0.005, 0.05, 0.10, 0.15, 0.20 and 0.26 $\mathrm{kg\,kg^{-1}}$ were selected during the calibration. The field capacity of all three soil textures was expected to be around 0.26 $\mathrm{kg\,kg^{-1}}$; therefore, no further w beyond this level was considered. The selected w range of 0.005–0.26 $\mathrm{kg\,kg^{-1}}$ (Table 2) covers the most acquired plant and organic activities during the cropping season. By the end of the laboratory measurement stage, a total of 828 spectral measurements were obtained.

2.3.2. Processing of spectra

The spectra were first reduced from 306.5–1710.9 nm to 401.4–1699 nm to eliminate the noise at edges of each spectrum, which might reduce the predictability of the model. These spectra were then normalised by the maximum normalisation technique. Normalisation is typically used to get all data to approximately the same scale or to get a more even distribution of the variances and the average values. The maximum normalisation process is performed on a sample spectrum by dividing each reflection value by the sample maximum absolute reflection as follows:

$$X'(i,k) = \frac{X(i,k)}{\mathrm{Max}(\mathrm{Abs}(X(i,*)))} \tag{2}$$

where $X'(i,k)$ is the maximum normalised spectrum, $X(i,k)$ is the sample reflection [%] and $X(i,*)$ is sample maximum absolute reflection [%].

The maximum normalisation is a normalisation that “polarizes” the spectra. The peaks of all spectra with positive values touch $+1$, while spectra with values of both signs touch -1. Since all the soil spectra in this study have positive values, the peaks of these spectra touched $+1$.

The first derivatives of the normalised spectra were computed using the Savitzky–Golay method. This method enables to compute the first or higher order derivatives, including a smoothing factor, which determines how many adjacent variables will be used to estimate the polynomial approximation used for derivation. A second order polynomial approximation was selected.

2.3.3. Model establishment

The objective of this task is to build a statistical model between the processed spectra and soil surface w. Several statistical modelling techniques can be adopted for the proper calibration performance, such as the linear and non-linear multiple regression analyses, the principal component analysis and the partial least square analysis (PLS). The PLS was used in this study for relating the variations in one-response variables (w) to the variations of several predictors (wavelengths). The NIR spectroscopy measurements of w depended on the fact that water absorption bands occur at 1450, 1950 and 2950 nm (Plamer and Williams, 1974), which resulted from resonance in the molecular vibration of the illuminated water molecule (Whalley and Stafford, 1992). Therefore, the predictors for the PLS were defined around the available sensitive wavelength of 1450 nm, only that the wavelength band of 1366–1670 nm was related with the oven dried w using the PLS. The 828 spectral measurements were divided into two groups of 744 and 84 spectra (Table 4). The former group was used for the establishment of the PLS statistical model, whereas the latter group was used for the laboratory validation of the established model. As the successful establishment of the PLS model consists of modelling and validation procedures, the full cross validation method was used according to the PLS modelling procedure. The first group of 744 spectra was used for the combined PLS and full cross validation procedure. The established PLS model was further tested to predict w using the remaining 84 spectra.

2.4. Field measurement

The subsoiler with the optical unit linked was attached to a frame, which was mounted onto the three-point hitch of the tractor. The electrical system, besides the spectrophotometer, consisted of several modules: a basic power supply, travel speed sensor, global positioning system, signal conditioning system, amplifier and data acquisition system. The travel speed was measured using a Doppler radar that was mounted pointing backwards to avoid the effects of stubble or grass movement after the measurement frame passed. The accuracy of the sensor was tested in previous experiments and all errors were smaller than 2.5%. Position, latitude and longitude were determined with a Trimble AgGPS132 differential global positioning system (DGPS). The antenna was mounted just above the sensor to obtain a submeter accuracy. The speed sensor signal was acquired at a frequency of 200 Hz, while the DGPS information was stored at 1 Hz. The spectral signal however was acquired and stored at 0.225 Hz. Each spectrum was an average of five successive spectra.

The on-line field measurement was carried out in a Zoutleeuw field, the same field where soil samples were collected for spectrophotometer laboratory calibration. A part of the 70,000 m^2 total field area, an area of 2300 m^2 was used for the experiment. The experiment was carried out after harvesting wheat. The optical sensor attached to the backside of the subsoiler chisel was pulled throughout parallel lines of 10 m apart, as shown in Fig. 3. These lines were perpendicular in direction to the tramlines, so that 12 and 15 lines were measured in parts A and B, respectively. The subsoiler was driven at a travel speed of 1200 m h^{-1} setting the chisel tip at a 0.15 m depth. After measurement of each line, soil samples were immediately collected from the trench bottom, at 10 m distance for verification. They were dried in an oven at 105° for 24 h to determine w.

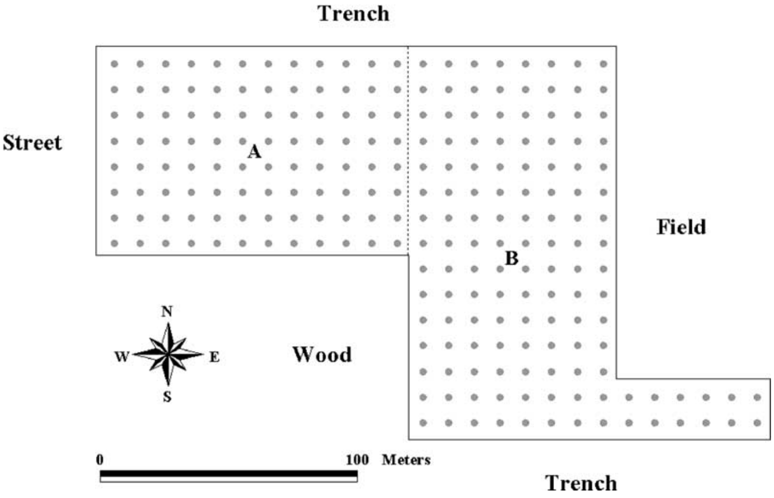


Fig. 3. Sampling and mapping design based on the 10 m × 10 m grid.

2.5. Development of different maps

The ARCVIEW GIS 3.1 software was used to draw the maps of w, measured with the NIR spectrophotometer sensor, and the oven drying method together with the error map between the two methods. All three maps were developed from a 10 m × 10 m grid data in order to harmonise the resolution of all maps. The grid was interpolated using the inverse distance weighing (IDW) method. The interpolation grid size of all maps had a radius of 25 m and a power of 2. The map cell size was 1 m^2 with 154 rows and 264 columns.

3. Results and discussions

3.1. Laboratory investigation

The laboratory investigation of spectral characteristics of soil samples with different w shows considerable variations in the shape of the spectra. The darker soil surface that resulted from higher w decreases the light reflectance due to more surface absorbance. It is shown clearly in Fig. 4 that the highest light reflectance occurred at the driest soil surface. At a wavelength of 1450 nm, one of the water light absorbance wavelengths, a trough in the spectrum starts to appear at a w of 0.05 $\mathrm{kg\,kg^{-1}}$. The depth and size of this trench increases with increasing w. However, a smaller difference in the shape of the absorbance trough is found between w values of 0.2 and 0.25 $\mathrm{kg\,kg^{-1}}$, which can be attributed to the sample w approaching the field capacity. This means that all the sample pores are filled with water and the 1450 nm wavelength becomes less sensitive to the light absorbance beyond the limit of the field capacity. It should be noted that during this study, the widest possible range of 0.005–0.26 $\mathrm{kg\,kg^{-1}}$ of w is involved, covering the usable w range by plant. Table 2 provides a review of the samples statistics based on artificially created variation in w by adding an equal amount of water in equal increment of 0.05 $\mathrm{kg\,kg^{-1}}$. However, any w exceeding the field capacity has minor importance for the site-specific irrigation, transplanting, seeding and compaction detection, which is the intention to be reached in this study.

The wavelength band of 1366–1670 nm of the first derivative of the normalised spectra was related with the oven-dried w using the PLS. The established PLS model is based on providing a linear correlation between the measured and predicted w values, as shown in Fig. 5. The response between the measured

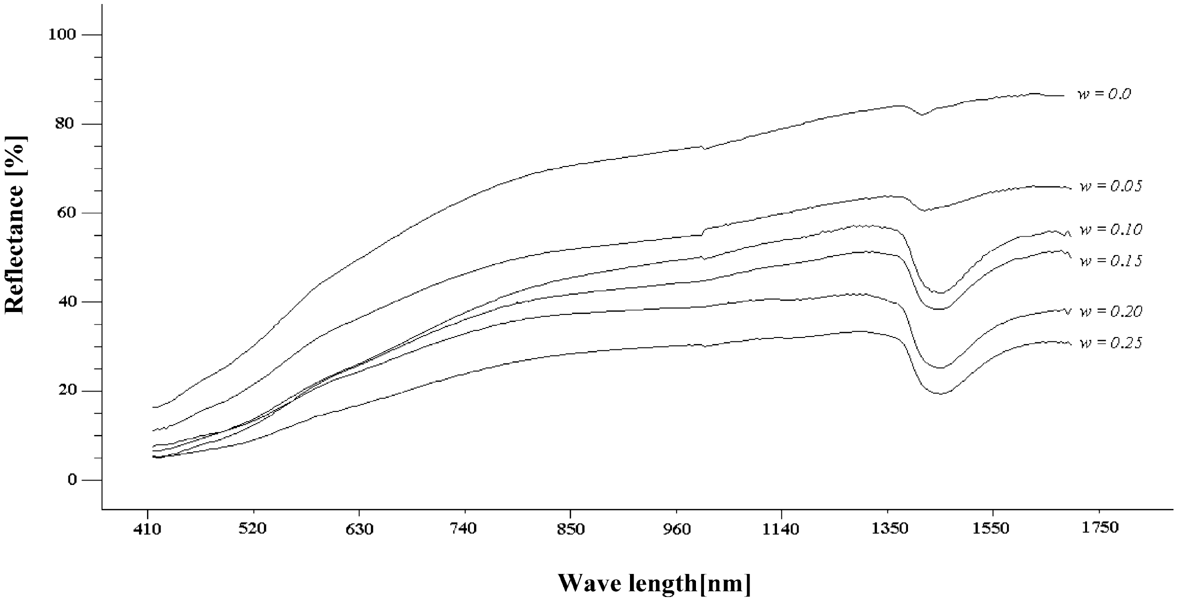


Fig. 4. Laboratory spectrum shape change due to variation in soil moisture content (w).

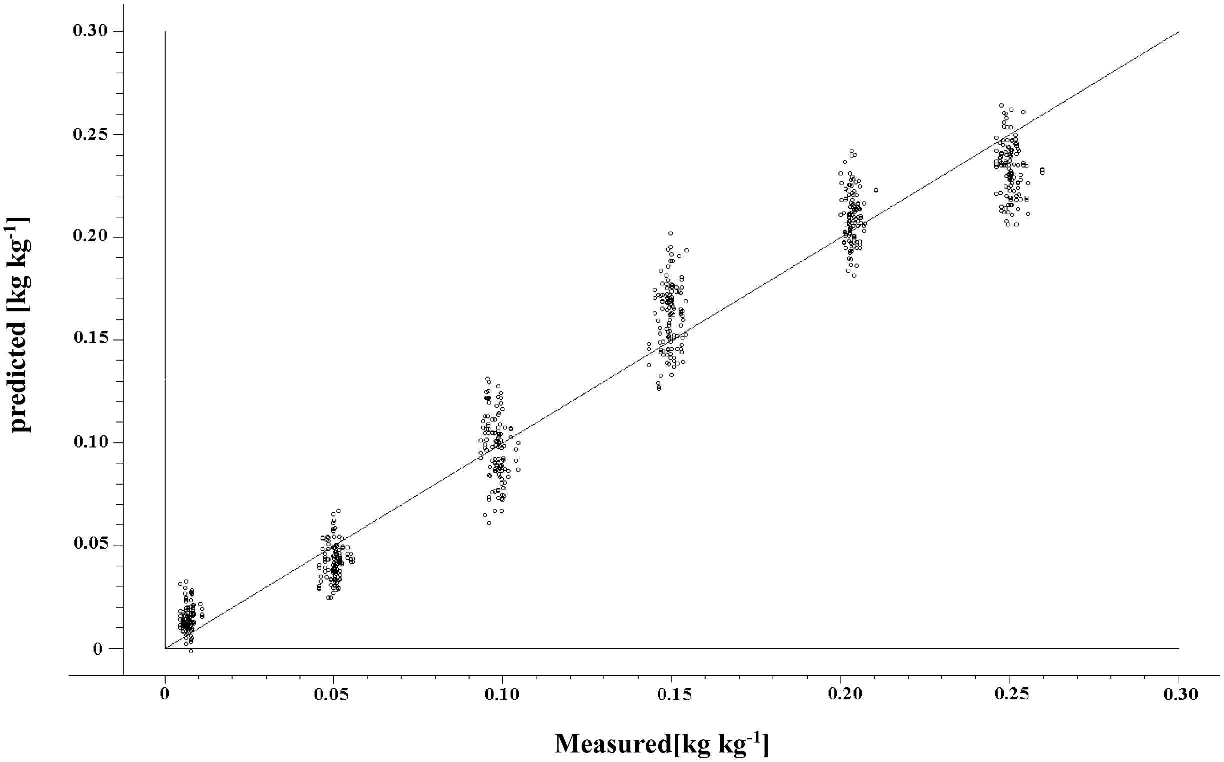


Fig. 5. Plot of the linear correlation between the measured and predicted soil moisture content (w) based on partial least square (PLS) model and full cross validation method.

and predicted values slopes down when w exceeds 0.2 kg kg^{-1}, which can be attributed to the less sensitivity of water light absorbance of the 1450 nm wavelength, as w approaches the field capacity. Generally, the model shows encouraging validation results when the full cross validation method is used (Table 3). No differences are found between the validation done with full cross validation and the Leverage correction methods. The root mean square error of cross validation (RMSECV) is 0.0175 kg kg^{-1}. This relatively small value of the RMSECV demonstrates the model predictability, since the RMSECV is usually considered as the simplest and most efficient measure of the uncertainty on future PLS model predictions. It can be calculated by the following equation:

$$\text{RMSECV} = \sqrt{\frac{\sum_{i=1}^{m}(\hat{y}_i - y_i)^2}{m}} \tag{3}$$

Table 3

Comparison of PLS1 results considering all samples without removing outliers and with removing outliers

Term	Without removing outliers	With removing outliers
RMSECV[a] (kg kg^{-1})	0.0175	0.0163
Bias of cross validation (kg kg^{-1})	1.19E−06	1.02E−06
Cross validation correlation	0.9780	0.9810
S.D./RMSECV[b]	4.8228	5.1779
PC1[c]	0.0394	0.0355
PC2	0.0309	0.0268
PC3	0.0293	0.0253
PC4	0.0275	0.0239
PC5	0.0266	0.0233

[a] RMSECV is the root mean square error of cross validation.

[b] S.D./RMSCV is the ratio of the standard deviation to the root mean square error of cross validation.

[c] PC is a principal component.

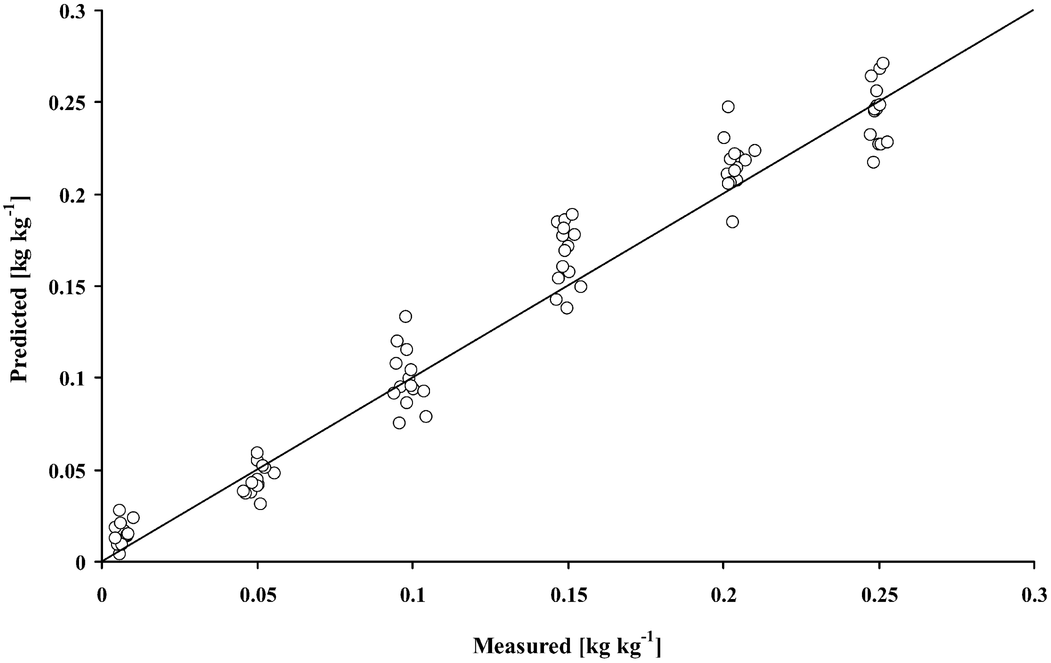


Fig. 6. Plot of the linear correlation between the measured and predicted soil moisture content (w) of the 84 validation set.

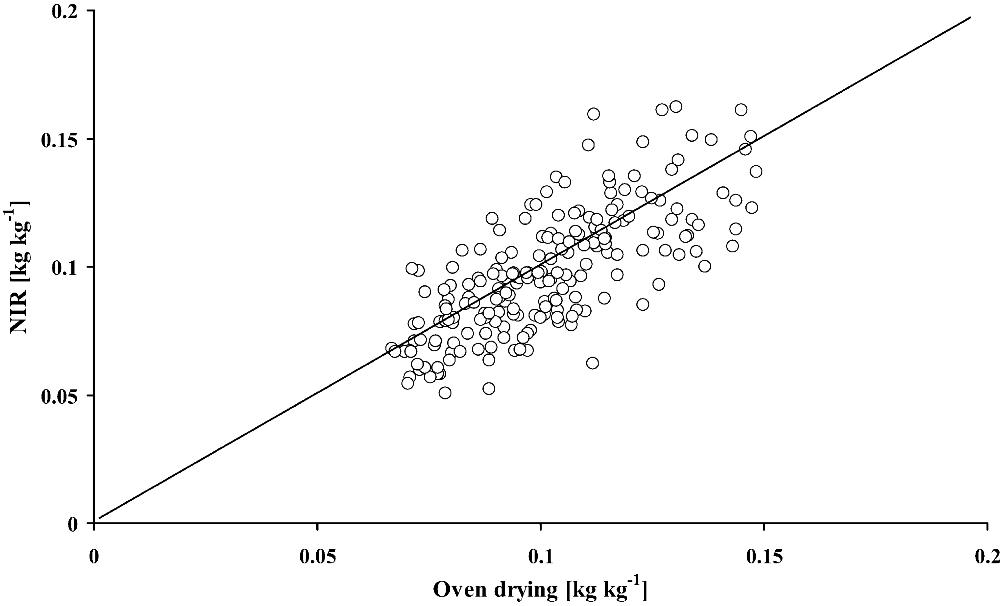


Fig. 7. Plot of on-line field measurement of soil moisture content (w) with near-infrared (NIR) spectrophotometer vs. oven drying technique.

where m is the number of validated objects, and $\hat{y}_i$ and y_i are the predicted and measured value of ith observation in the test.

The ratio of the standard deviation (S.D.) of the calibration set to the RMSECV is also a very important parameter for assessing how large the error (RMSECV) is with respect to the range of w encountered during calibration or measurement. This ratio is desired to be larger than 2 for a good calibration (Sinnaeve et al., 2001). The S.D. to RMSECV ratio has larger values than 2 as shown in Table 3. Another indication of the model future prediction is the bias, which is the difference between the average predicted value and average measured value, written as:

$$\text{Bias} = \frac{1}{m}\sum_{i=1}^{m}\hat{y}_i - y_i \tag{4}$$

When all the 744 samples were considered, the bias was small. The RMSECV, bias and cross validation correlation were improved (Table 3) when the 31 selected outliers were excluded from the PLS analysis, which also supported the model performance. This was confirmed by the smaller values of the principal components of the removed outlier analysis.

When the developed PLS model was further validated by predicting w of the remaining 84 samples, the root mean square error of prediction (RMSEP) and prediction correlation were even better (Table 4). In contrast with the cross validation method, removing the outliers has led to unexpected but minor degradation in the RMSEP and prediction correlation values. The linear correlation, shown in Fig. 6, provides further illustration of the 1450 nm wavelength sensitivity declination to water absorbance between 0.2 and 0.25 kg kg^{-1} w.

Table 4
Comparison of laboratory and on-line field prediction statistics

Term	Laboratory	Field
RMSEP[a] (kg kg^{-1})	0.0165	0.0250
Bias of prediction (kg kg^{-1})	0.0129	0.0313
Prediction correlation	0.9820	0.7450
S.D./RMSEP[b]	5.1151	3.3760

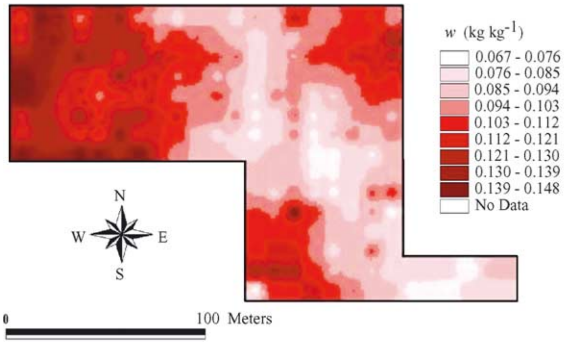
[a] RMSEP is the root mean square error of prediction.

[b] S.D./RMSEP is the ratio of standard deviation to the root mean square error of prediction.

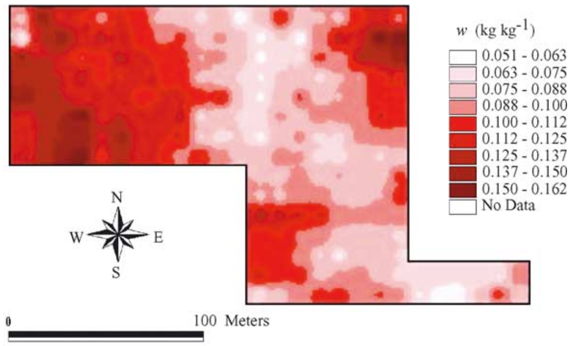
3.2. On-line field validation of PLS

In order to fully evaluate the PLS model developed to predict w using soil spectra taken during on-line field measurement, the spectra should be subjected to the same processing procedure as that followed during the PLS model establishment. Thus, these spectra are first reduced from 306.5–1710.9 to 401.4–1699 nm, and then normalised using maximum normalisation expressed by Eq. (2) and finally subjected to the Savitzky–Golay method. Before all these processing steps, the spectra are selected for the right position according to the selected 10 m × 10 m grid to match the same grid of w sampling for oven drying. Fig. 7 shows a proper linear fitting between the NIR and oven dried w, with rather larger RMSEP and larger bias (Table 4). The larger error and smaller correlation are attributed to the fact that the on-line measurement is usually accompanied with noise and notching vibrations. Furthermore, driving the tractor in a perpendicular direction to the tramlines can enlarge the probability of soil-to-sensor distance variation. This can result in increased tractor pitching during passing the tramlines. When this occurs, the intensity of the light reflected from the soil surface changes dramatically, leading to sometimes a complete deformation of the spectra. However, the spectral processing before prediction minimises the influence of light intensity changes as long as light reflection is detected by the spectrophotometer. When the soil-to-sensor distance variation is greatest at the crossing of the tramlines, no spectrum is recorded and the reading is lost at the corresponding soil point. This leads to the recommendation to drive parallel to the tramlines.

Reasonably similar spatial patterns of w measured with the NIR spectrophotometer and oven drying methods are observed in Fig. 8, with nearly equal ranges of 0.051–0.162 and 0.067–0.148 kg kg^{-1}, respectively. The wider w range of the former can be attributed to few points with bad spectra, which has only a minor effect on the spatial variation of w. On the other hand, zones of dry and wet soil can be distinguished easily in both maps. The error map (Fig. 9) of the two measured w illustrates the position of the few points with bad spectra that increased the w range of the NIR spectrophotometer measurement technique over the oven drying method. The error ranges from 0 to 0.049 kg kg^{-1}, but it is normally distributed about



Oven drying w



NIR spectrophotometer w

Fig. 8. Comparison of near-infrared (NIR) spectrophotometer and oven drying moisture content (w) maps based on $10\,\mathrm{m} \times 10\,\mathrm{m}$ grid.

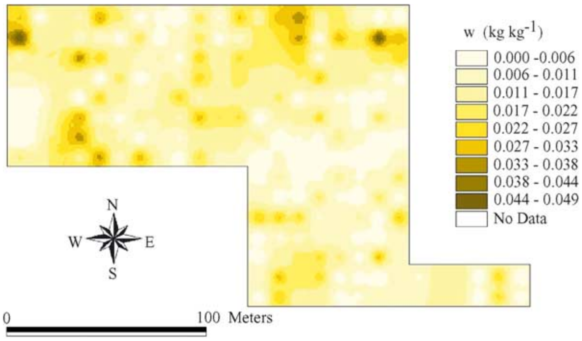


Fig. 9. Map of moisture content (w) error between near-infrared (NIR) spectrophotometer and oven drying methods based on $10\,\mathrm{m} \times 10\,\mathrm{m}$ grid.

the error value of $0\,\mathrm{kg\,kg^{-1}}$, as shown in Fig. 10. It is clear that errors larger than $0.03\,\mathrm{kg\,kg^{-1}}$ are valid for only 13 points out of the total sample set of 204 points. A small standard deviation of the w error of $0.0103\,\mathrm{kg\,kg^{-1}}$ is found. The similar shape of the two maps provides confidence in the developed NIR sensor for the on-line measurement of w, working in fields of sandy loam, loam and silt loam soils. Special attention should be paid to the tractor driving direction to be parallel to the tramlines in order to minimise the soil-to-sensor distance variation, keeping the lens holder unit with smooth and continuous sliding on

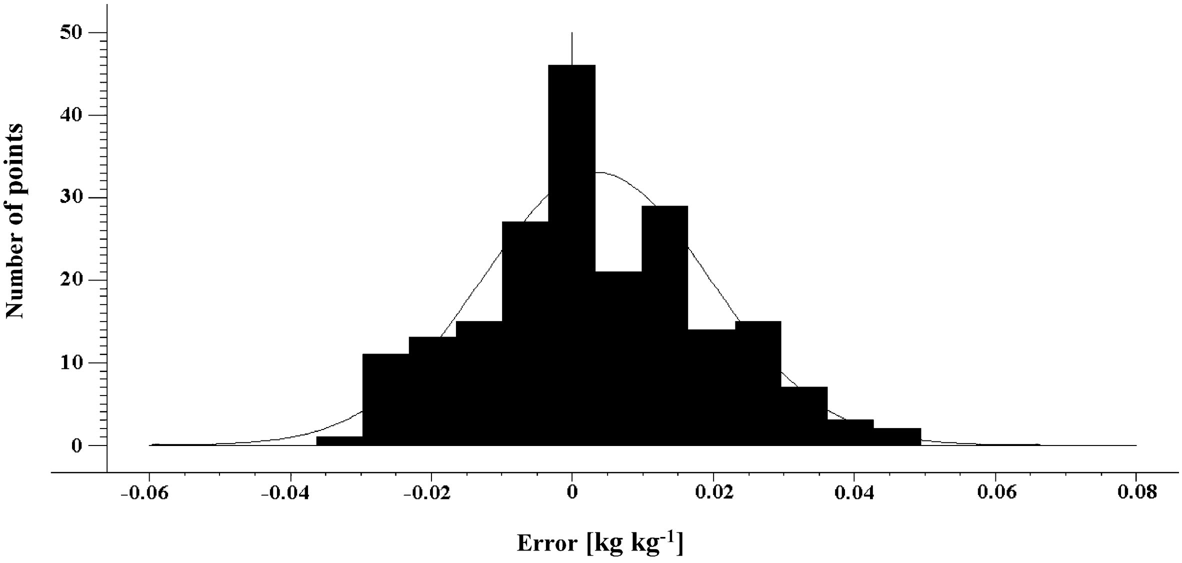


Fig. 10. Normal distribution of the prediction error of moisture content (w).

the trench bottom. Knowledge about the spatial variation of w will allow for site-specific applications related to w, namely site-specific irrigation, seeding and transplanting in addition to on-line measurement of soil compaction.

It can be concluded that w can be measured on-line with a fibre-type NIR spectrophotometer. In order to increase the accuracy of the NIR measurement, other influencing parameters such as organic matter and density should be taken into account. Extending the sensor application for all soil textures requires incorporating extra laboratory measurements of spectra taken from soil samples of another soil texture. However, the developed NIR spectrophotometer sensor–PLS modelling system can be recommended for on-line measurement of w in fields with sandy loam, loam and silt loam soils. The ready-to-use w sensor should be equipped with a general calibration model valid for different soil organic matters, densities and textures.

4. Conclusions

A VISNIR infrared spectrophotometer was used as the basic technique to build a soil sensor for the on-line measurement of w. The sensor was attached to a subsoiler chisel backside to detect the light reflectance from the trench bottom side opened by the chisel. The PLS analysis was used to build the calibration model using 744 spectra by relating the NIR spectrophotometer and oven drying measurement methods of w. The model was validated with the full cross validation method, resulting in a small root mean square error of cross validation of $0.0175\,\mathrm{kg\,kg^{-1}}$ and a high validation correlation of 0.978. An additional validation of the PLS model was performed on the separate 84 spectra, which were not involved in the PLS cross validation stage. This validation indicated good performance. The root mean square error of prediction was $0.0165\,\mathrm{kg\,kg^{-1}}$ and the prediction correlation was 0.982. In spite of the fact that these prediction indicators degraded when the NIR measurement of w was carried out on-line in the field, the spatial variation of w between the NIR spectrophotometer and oven drying methods was quite similar. The error between the two measurement methods showed a normal distribution with a small standard deviation of $0.0103\,\mathrm{kg\,kg^{-1}}$. Therefore, the developed NIR spectrophotometer sensor is recommended for on-line measurement of w in sandy loam, loam and silt loam soils. The sensor performance can be improved during field operation if the tractor is driven in a direction parallel to the tramlines, which minimises the soil-to-sensor distance variation. As future work, the sensor application could be extended to provide on-line measurement of other soil physical and chemical properties, namely micro- and macro elements, pH and texture. Establishment of a proper statistical model for each property is the key for successfully carrying out on-line measurement of soil properties.

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