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A prototype sensor for the assessment of soil bulk density

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Abstract

A prototype bulk density sensor (PBDS) to assess soil bulk density (BD) has been developed and tested for top soil (0 - 15 cm). It is a multi-sensor kit, consisting of a penetrometer equipped with a visible and near-infrared (vis-NIR) spectrophotometer. Artificial neural network (ANN) was used to develop a BD prediction model, as a function of penetration resistance (PR), soil moisture content (MC), organic matter content (OMC) and clay content (CLC), using 471 samples collected from various fields across four European countries, namely, Czech Republic, Denmark, the Netherlands and the UK. While penetration resistance (PR) was measured with a standard penetrometer (30 degree cone of 1.26 cm^2 cone-base area), MC, OMC and CLC were predicted with a vis-NIR (1650 – 2500 nm) spectrophotometer (Avantes, Eerbeek, the Netherlands). ANN was also used to model the vis-NIR spectra to predict MC, OMC and CLC. The PBDS was validated by predicting topsoil (0 – 0.15 m) BD of three selected validation fields in Silsoe experimental farm.

The ANN BD model performed very well in training (coefficient of determination (R^2) = 0.92 and root mean square error (RMSE) = 0.05 Mg m^{-3}), validation (R^2 = 0.84 and RMSE = 0.08 Mg m^{-3}) and testing (R^2 = 0.94 and RMSE = 0.04 Mg m^{-3}). The validation of PBDS for BD assessment in the three validation fields provided high prediction accuracy, with the highest accuracy obtained in Downing field (R^2 = 0.95 and RMSE = 0.02 Mg m^{-3}). It can be concluded that the new prototype sensor to predict BD based on, a standard penetrometer

equipped with a vis-NIR spectrophotometer and ANN model can be used for *in situ* assessment of BD. The PBDS can also be recommended to provide information about soil MC, OMC and CLC, as the ANN vis-NIR calibration models of these properties were of excellent performance.

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1 Introduction

Soil strength is a dynamic property that changes with time and space under the influences of climate, soil management practices and plant growth (Koolen and Kuipers, 1983). Soil deformation following a single or multiple passes of heavy agriculture machinery results in soil compaction and structure deterioration, which leads to increase in soil strength, reduction in hydraulic conductivity and infiltration rate, and poor root penetration and plant growth (Franzen et al., 1994; Quraishi and Mouazen, 2013a). Random traffic of heavy machinery during harvest also causes long lasting damage to the soil structure because of deep penetration of downward forces causing deep compaction (Ekwue and Stone, 1995). Deep compaction is difficult to ameliorate, since natural and biological activities are limited at deep soil horizons. Subsoiling is also of limited impact particularly if carried out under heavy and wet soil conditions. Due to the dynamic nature of the soil, soil strength is affected by soil moisture content (MC), organic matter content (OMC), degree of compaction and texture to name a few.

One of the properties to characterise soil compaction is BD (Mouazen and Ramon, 2002), which does not necessarily reflect soil function. Core sampling of a known volume of soil is utilised for the measurement of soil BD (British Standards, 2011), based on drying of the soil cylinder at 105 °C for 24 h. The disadvantageous of this method are that it is very difficult, labour intensive, time costly procedure and prone to measurement error, particularly under dry soil conditions (Mouazen and Ramon, 2006; Quraishi and Mouazen, 2013a). An innovative approach to assess BD based on a complex interrelationship between BD, MC, OMC, clay content (CLC) and penetration resistance (PR) was recently introduced by Quraishi and Mouazen (2013b). They used artificial neural network (ANN) to develop a model to assess BD as a function of PR, MC, OMC and CLC. This model enabled the assessment of BD based on traditional laboratory methods of soil analyses in addition to field measured PR (coefficient of determination (R^2) of 0.81 and root mean square error (RMSE) of 0.11 Mg m^{-3}). However, since soil samples had to be collected in the field where PR is measured, and transferred to the laboratory for the traditional analyses of OMC, MC and CLC, it was concluded that this method did not overcome the disadvantages of the core sampling method of being expensive, slow and labour intensive. Therefore, Quraishi and Mouazen (2013c) has replaced the traditionally measurement methods of MC, OMC and CLC with visible and near infrared (vis-NIR) spectroscopy. By substituting vis-NIR predicted values of MC, OMC and CLC into ANN BD prediction model, authors reported successful prediction of topsoil BD (R^2 of 0.80 and RMSE of 0.08 Mg m^{-3}). They confirmed that the proposed methodology is capable of overcoming the disadvantages of the traditional core sampling method of BD measurement, as vis-NIR spectroscopy enables cost effective and fast prediction of soil properties (Mouazen et al., 2005, 2007, 2009). At this stage, this new methodology requires the development of an instrumentation to enable *in situ* acquisition of multiple georeferenced data, including PR and vis-NIR spectra, to be fed as input data into models to predict BD, as a function of measured PR and vis-NIR predicted MC, OMC and CLC.

The aim of this paper was to design and validate a prototype BD sensor (PBDS), as a new tool for rapid, cost effective and *in situ* assessment of BD, as a function of measured PR, and vis-NIR predicted MC, OMC and CLC.

2 Materials and methods

2.1 Field measurement and soil sampling

Field measurement of topsoil (0-15 cm depth) PR and BD was carried out in summer of 2010, 2011 and 2012, in 19 fields across different Europe countries as shown in Table 1 (Quraishi and Mouazen, 2013a, 2013b & 2013c). Avenue, Orchard, Ivy ground, Beechwood, Clover hill, Upbury, Chipping and Downing fields are situated at Silsoe experimental farm, Cranfield University, the UK. Two fields were part of a Research Station for arable farming and field production of vegetables in Lelystad, the Netherlands. Two other fields were located at Wageningen University, Wageningen, the Netherlands. One field in Czech Republic and two fields in Denmark were measured in 2010 as part of FutureFarm FP7 project (http://www.futurefarm.eu/). Measurement at Odstone field in Leicestershire, the UK was carried out in a grassland field. Three fields were measured at Duckend Farm near Bedford in Bedfordshire, the UK. Figure 1 and Table 1 show the texture classes of all fields used in this study.

Soil BD was measured using Kopecki ring core sampling kit, whereas PR measurement was carried out with Eijkelkamp penetrologger with a 30 degree cone of 1.26 cm^2 cone-base area (Eijkelkamp, 2009) in 2010 and 2011. In 2012, PR was measured using a new prototype penetrometer designed in this study, which is explained below. The number of samples collected from each field varied, depending on the size of the field, but ranged from 4 to 48

(Table 1). At each sampling point, three PR measurements, one bulk soil sample and one BD core sample were collected. The PR measurement was carried out within half a meter distance from the BD core sample location, ensuring that both measurements were taken either in or outside a wheel rut. The PR readings were averaged in one reading (Quraishi and Mouazen, 2013b). A total of 408 bulk soil samples and BD core samples were collected in 2010 and 2011. These samples were used to develop a general calibration model to predict BD. Three additional field measurements were carried out in 2012 to validate the measurement accuracy of PBDS using the general calibration model. These fields were Ivy Ground, Chipping and Downing (Table 1), all in Silsoe experimental farm. In total, 87 samples were collected from these three fields using the PBDS. Out of the 87 locations, BD was measured at 63 sampling points only using a Kopecki ring kit.

2.2 Prototype bulk density sensor (PBDS)

The PBDS was designed and developed to predict multiple soil properties in addition to BD. It consists of a rod and cone assembly connected to a load cell, which has a maximum load of 1000 N. A 50 channel global positioning system (GPS) was used to record the sampling location. The 30 degree, 1.26 cm^2 base-area cone connected to the rod were assembled with a fibre type standalone vis-NIR spectrophotometer (1650 – 2500 nm) (Avantes, Eerbeek, The Netherlands), as shown in Fig. 2. Light illumination fibre was connected to a 10 watt halogen lamp, whereas detection fibres were connected to 256 pixel Indium Gallium Arsenide (InGaAs) detector. The resultant spectra were of 7 nm resolution, and consisted of 256 wavelengths. The selection of 1650 – 2500 nm wave range spectrophotometer was based on previous studies confirming this range to be the most significant for MC, OMC and CLC prediction with vis-NIR spectroscopy (Stenberg et al., 2010; Kuang et al., 2012). This multi-sensor instrumentation was connected to a laptop for data logging using AvaSoft 7.7 software

(Avantes, Eerbeek, the Netherlands) (Fig. 2). The optical assembly of the PBDS was first tested in the laboratory under controlled conditions by inserting the cone in the soil placed in black containers to avoid the effect of ambient light. After successful laboratory testing, the sensor was tested and validated in the three validation fields in Silsoe experimental farm in 2012 (Table 1). The PBDS was inserted in the soil at a constant speed to a depth of 20 cm, along which the vis-NIR soil spectra and PR were recorded at a sampling resolution of 10 Hz.

2.3 Laboratory analyses

Soil samples collected from all fields (Table 1) were analysed for MC, OMC and average field CLC using oven drying (British Standards, 2007), loss of ignition (British Standards, 2000), and particle size distribution (British Standards, 1998) methods, respectively. Soil BD were measured by the oven drying method (British Standards, 2007), by drying the samples at 105 °C for 24 h to obtain MC and calculate dry BD (British Standards, 2011).

2.4 Establishment of visible and near infrared (vis-NIR) calibration models

Two separate sample sets collected from the UK were used for vis-NIR spectra modelling. The first set was used to develop calibration models of MC and OMC, whereas the second set was used to develop CLC model. Samples for the first set were collected from Beechwood, Clover Hill, Upbury, Ivy Ground, Chipping and Downing fields in Cranfield experimental farm in Silsoe (Table 2). In total, 111 samples were collected from these six fields to form a farm-scale (Silsoe farm) calibration models for MC and OMC. The second set consisting of 63 samples (Aldhumayri, 2012; Alhwaimel, 2013) were collected from Silsoe farm (e.g. Avenue, Orchard, Ivy ground, Chipping and Downing fields), a farm in Lincolnshire

(Vicarage, Marshalls, and Thetford fields), a farm in Cambridgeshire (Ely and Wypemere fields), a field in Norfolk (Elveden field) and a field in Shropshire (Shropshire). Therefore, samples used to develop the CLC model can be classified as multi-county-scale model.

All samples listed in Table 2 were scanned in the laboratory with the same fibre type vis-NIR spectrophotometer of PBDS (Avantes, Eerbeek, The Netherlands), linked with the penetrometer cone (Fig. 2). Before scanning, stones and plant residues were removed from the soil samples and placed in a glass container after mixing. This was done to exclude interference of stone and plant debris in soil spectra. Each sample was scanned 10 times in diffuse reflectance mode. White reference was used before scanning and at 30 min interval to re-calibrate the spectrophotometer.

2.4.1 Spectra pre-processing and development of visible and near infrared (vis-NIR) calibration models

After averaging the 10 spectra of each soil sample in one spectrum, the resultant spectra were smoothed by averaging 5 successive wavelengths. The spectra were then exported to Microsoft Excel 2010, where the noise from either end of the spectra was removed and remaining range of 1653-2498 nm was withheld. STATISTICA 11 ANN toolbox (StatSoft, Inc., Tulsa, USA) was used to establish calibration models for MC, OMC and CLC, using spectra of the samples listed in Table 2. The networks were multilayer perceptron (MLP) ANN and used Broyden-Fletcher-Goldfarb-Shanno (BFGS) training algorithm with very fast convergence (StatSoft, 2011). The hidden and output layers consisted of hyperbolic tangent (Tanh) transfer function, since it produced the best results, compared to other transfer functions.

ANN models for MC, OMC and CLC were developed using 60, 20 and 20% of the first (e.g. 111 samples for MC and OMC) and second (e.g. 63 samples for CLC) sample sets (Table 2) in training, validation and testing, respectively. The validation of ANN models consisted of re-aligning the weights and biases of the training model, whereas the testing phase was to simply test the network with the test dataset. A total of 100 ANN networks were trained, out of which 5 networks were selected for further analysis. The prediction performances of these models were evaluated by means of R^2 and RMSE. Residual prediction deviation (RPD), which is the ratio of standard deviation of reference measured values (for training, validation or test sets) divided by the RMSE was used to compare between different calibration models developed (Williams, 1987, Stenberg et al., 2004, Viscarra Rossel et al., 2006). Table 3 shows the classification adopted for this study based on RPD values as stated by Viscarra Rossel et al. (2006).

2.5 Development of bulk density model

A model to predict BD (dependent variable), as a function of PR, MC, OMC and CLC (independent variables) was developed with ANN, using STATISTICA 11 ANN toolbox (StatSoft, Inc., Tulsa, USA). The network was a MLP ANN using the BFGS training algorithm. A hyperbolic tangent (Tanh) was utilised as the hidden and output activation function, since it produced the best results compared to other activation functions, such as exponential and logarithmic functions (Quraishi and Mouazen, 2013b).

The values of MC, OMC and CLC used as input for ANN were obtained from laboratory reference measurement for all fields measured in 2010 and 2011 (Table 1), apart from Duckend 1-3 (Gonzales et al., 2013), Clover Hill, Beechwood, Upbury, Ivy Ground (2011), whose MC, OMC and CLC were predicted using vis-NIR calibration models. These models were also used for data from Chipping, Ivy Ground and Downing fields collected in 2012. In total, 471 samples (408 samples from 2010 and 2011, and 63 samples from 2012) were used to develop and validate the BD model. These samples were randomly divided into training

(60%), validation (20%) and test (20%) sets. The prediction performance of the BD model was evaluated by means of R^2 and RMSE.

2.6 Field mapping

Maps of BD, MC and OMC were developed for Downing field only, as an example. In this field 48 points were measured with the PBDS, out of which 24 points were selected to collect core samples with the Kopecki ring kit. Two types of maps were developed for each property, namely, full-point maps and comparison maps. The former maps were based on 48 points of BD, MC and OMC measured with the PBDS (Fig. 3), whereas the latter maps were based on 24 points collected either with Kopecki ring or PBDS (Fig. 3).

Semi-variograms analysis was carried out for the comparison and full-point maps using Vesper 1.63 software developed by the Australian Centre for Precision Agriculture (Minasny et al., 2005). Spherical model (Eqn. 1) was adopted to calculate semi-variance, since it resulted in the lowest root mean square error of prediction (RMSEP).

$$\gamma = C_0 + \left(C_1 \times \left(\frac{3h}{2A} - \frac{h^3}{2A^3}\right)\right) \qquad 0 < h < A \tag{1}$$

Where, γ is semi-variance, C_0 is the nugget value, C_1 is sill, h is the lag distance, and A is range.

Based on the variogram data, maps of BD, MC and OMC were developed with ArcGIS ArcMap (ESRI ArcGIS™ version 10, CA, USA). Ordinary kriging with the semi-variogram data (Table 4) was performed to map the spatial variation. Minimum and maximum neighbours during the analyses were set to two and five, respectively. For the comparison maps, variogram model of the reference measured BD, MC and OMC was used to perform ordinary kriging. Predicted BD, MC and OMC maps were later developed using the same models. Error map of BD was also developed by subtracting measured and predicted values of the 24 validation points. For the full-point maps, predicted values of BD, MC and OMC were used for ordinary kriging based on semi-variogram data listed in Table 4. On the basis of average nearest distance, a lag size of 4.92 m was selected for all three properties. The range was adjusted to reduce the RMSEP for the spatial prediction with a grid size of 1 m.

3 Results and discussion

3.1 Performance of visible and near infrared (vis-NIR) general calibration models

Table 5 shows the prediction accuracy of MC, OMC and CLC general calibration models for the training, validation and test sets. Figure 4 shows scatter plot of measured against predicted values of MC, OMC and CLC for the test set. The results reveal that the performance of all vis-NIR general calibration models of the three soil properties is classified as excellent (RPD > 2.5), except for MC in the test set, where the performance is found to be very good (RPD = 2.46).

3.1.1 Moisture content model

Values of RMSE, RPD and R^2 for the prediction of MC in the test set are 2.60%, 4.03 and 0.94, respectively, which are of similar magnitude to those obtained by Mouazen et al. (2006) for multiple-field scale calibration (RMSE = 2.10%, RPD = 3.22 and R^2 = 0.91). Although a smaller wavelength range was used in the current study (1650 – 2500 nm), as compared to that used by Mouazen et al. (2006) (350 – 2500 nm), the ANN adopted in the current study improves the prediction accuracy of vis-NIR spectroscopy, as compared to partial least squares (PLS) regression analysis adopted by Mouazen et al. (2006), which was also confirmed by Mouazen et al. (2010). Upadhyaya et al. (1994), Slaughter et al. (2001) and Ben-Dor et al. (2008) also reported similar PLS model accuracy for MC prediction with R^2 values of 0.99, 0.97 and 0.98, respectively, for independent validation sets.

3.1.2 Organic matter content model

The OMC is predicted with a lower accuracy (RMSE = 0.82%) in comparison to MC (Table 5), which may be attributed to the low standard deviation (SD) of 2.15%. The average OMC in clay fields is considerably higher (8.03%) than that in sandy loam fields (3.26%), which results in empty gap in OMC range (Fig. 4). Although a high R^2 value of 0.96 is calculated, a large slop and intercept can be observed. However, the small RMSE value of 0.82% confirms the model applicability to predict OMC, especially with RPD value of 2.46, which is classified as a very good quantitative model for prediction (Table 3). Ben-Dor et al. (2008) reported a R^2 of 0.94 and a RMSE of 8.7% for independent validation, which is less accurate than the results achieved in current study (R^2 = 0.96 and RMSE = 0.82%).

3.1.3 Clay content model

The performance of the clay model for the prediction of CLC for the test set is encouraging (R^2 = 0.92; RMSE = 4.53% and RPD = 3.68). Waiser and Morgan (2007) reported *in situ* prediction of CLC for field moist soils with smaller accuracy (R^2 = 0.83, RMSE = 6.1% and RPD = 2.36). Bricklemyer and Brown (2010) also predicted clay using lab measured spectra but also with reduced accuracy (R^2 = 0.75, RMSE = 5.16%, and RPD = 1.8), as compared to those obtained in the current study (Table 5). Both authors used PLS regression, whereas

ANN was adopted in the current study, which proves that ANN is a more robust and provide more accurate estimations when compared to PLS regression (Mouazen et al., 2010).

3.2 Performance of general bulk density (BD) model

The general ANN BD model performs notably well in training, validation and testing (Fig. 5 & Table 6), with excellent performance in testing (R^2 = 0.94, RMSE = 0.04 Mg m^{-3}). The high vis-NIR prediction accuracies of MC, OMC and CLC reported in this study reinforces the high accuracy achieved for the prediction of BD. Quraishi and Mouazen (2013b) stated that the sum of error attributed to the laboratory reference analyses of MC, OMC and CLC accounted for 9% of the total error. It is suggested that by combining the vis-NIR spectroscopy coupled with ANN to predict MC, OMC and CLC, the error associated with laboratory analysis is avoided. This might explain the decrease in RMSE of BD prediction from 0.11 Mg m^{-3} (Quraishi and Mouazen, 2013b) to 0.04 Mg m^{-3} (Table 6), for input data about soil properties obtained from laboratory analysis and vis-NIR spectroscopy, respectively.

3.3 Validation of prototype bulk density sensor (PBDS)

The BD values of 63 samples collected from Ivy ground (2012), Chipping, and Downing fields were predicted using the BD model developed with ANN, based on the input data of PR measured with the PBDS, and vis-NIR predicted values of MC OMC and CLC. The vis-NIR spectroscopy shows high prediction accuracy for MC, OMC and CLC for all three validation fields, when compared with the standard laboratory measurement methods using samples collected from the same sampling positions (Table 7). For the CLC model, the error calculated for all three fields is less than 8% of the average field CLC value. Since the soil sample used for CLC model was an average of the whole field, it was not possible to compare point-by-point predicted with measured CLC. The scatter plots in Fig. 6 shows a good fit between the measured and predicted values of MC and OMC for each validation field. Best results are obtained for Chipping field with the lowest RMSE for both MC (0.32%) and OMC (0.09%). The measurement accuracy of the clayey soil Ivy field is similar to the other two fields (RMSE = 0.51% and 0.11%, respectively). In Downing field, the prediction accuracy for both MC (RMSE = 0.60%; RPD = 3.68) and OMC (RMSE = 0.12%; RPD = 2.74) is excellent, but less accurate than the other two fields (Table 7).

In addition to the possibility of measuring MC, OMC and CLC with the PBDS, BD can also be assessed. The predicted and measured BD in Downing field are in a good agreement (R^2 = 0.95 and RMSE = 0.02 Mg m^{-3}). Less satisfactorily prediction performances are observed in Ivy and Chipping fields with RMSE of 0.04 and 0.03 Mg m^{-3}, respectively (Table 6 and Fig. 7). Literature shows no similar studies about the assessment of BD, as a function of PR, MC, OMC and CLC measured with a PBDS. Therefore, the PBDS system introduced in the current study proves to be unique in the assessment of BD as well as the prediction of other properties that are relevant for land management.

3.4 Field mapping

3.4.1 Comparison maps

Comparison maps of measured and predicted BD, MC and OMC were developed for Downing field only, as an example. The semivariograms parameters for studied soil properties are shown in Fig. 8 and Table 4. The kriging method used was similar to that of Quraishi and Mouazen (2013a), but spherical semivariance model was used in the current work instead of exponential semivariance model. Mouazen and Ramon (2006) also carried out similar investigation to compare measured and predicted maps of soil properties for sandy loam soil. An equal maximum lag distance of 41 m is calculated for BD and MC, whereas a maximum lag distance of 65 m is calculated for OMC, which is attributed to low variation of OMC throughout the field.

Figure 9 compares between the spatial distributions of measured and predicted BD. It can be observed that BD varies throughout the field, with high BD values encountered in the top left, top and bottom right corner of the field. The predicted BD map shows similar spatial patterns to the corresponding measured map, with a similar range of 1.40 to 1.67 Mg m^{-3}. The error map shown in Fig. 9c illustrates that the maximum error is encountered in the top left, top and bottom right hand side of the field. The error ranges from -0.054 to -0.001 Mg m^{-3}.

The measured and predicted MC maps (Figs. 10a and 10b, respectively) show very similar spatial patterns, which can be attributed to the high match between vis-NIR predicted and measured MC (Fig. 6 & Table 7). It can be observed that MC gradually decreases from the top right corner to the bottom left corner. The error map in Fig. 10c illustrates that the error ranges between -0.86 to 1.76%, with the largest negative and positive errors encountered towards the central area, and left and right hand side areas of the field, respectively.

The comparison maps between the measured and predicted OMC (Fig. 11a and 11b, respectively) also illustrate similar spatial variation pattern, which is also similar to MC distribution pattern. A large area of high OMC can be observed at the right hand side of the field. The low band of OMC towards the left hand side of the field is identical to that of MC. Indeed, OMC diminishes from top right corner to bottom left corner of the field, which is in-line with that of the MC variation. The error map in Fig. 11c also shows negative error at the central area (-0.18 to -0.05%), whereas positive error can be observed at the right and left hand side (0.05 to 0.19%) of the field. The spatial pattern of OMC map is similar to that of

MC, which can be explained by the positive correlation between the two properties (Quraishi and Mouazen, 2013b).

3.4.2 Full-point maps

The full-point maps for BD, MC and OMC were generated using 48 points predicted with the new BDPS. The spherical semivariograms used for kriging are shown in Fig 12, whose properties are listed in Table 4. Full-point maps (Fig. 13) show more detailed information in comparison to the corresponding comparison maps (Figs. 9, 10 and 11) due to the higher resolution of sampling points of the former maps (Mouazen and Ramon, 2009; Quraishi and Mouazen, 2013a). It can be observed that the majority of the field BD lies between 1.36 to 1.60 Mg m^{-3} (about 80% of the field area). This part of the field requires minimal tillage operations according to the packing density criteria, which states that soils with a packing density of 1.40 Mg m^{-3} (equivalent to a BD of 1.36 Mg m^{-3} for 10% CLC) to 1.75 Mg m^{-3} (equivalent to a BD of 1.60 Mg m^{-3} for 10% CLC) is neither strong nor loose soil (Hodgson, 1974). A small part of the field with a larger BD than 1.60 Mg m^{-3} (about 20% of the field area) will require more aggressive tillage intervention. Both BD and MC maps illustrates high values in the upper side of the field, where heavy traffic and surface water flow from the adjacent road take place. Avoiding or reducing damage to the soil at this part will preserve good soil structure for plant growth and water infiltration. The OMC map provides less obvious spatial similarity to MC map than corresponding comparison maps produced with a smaller number of points of 24. This necessitates the need to increase the sampling resolutions to allow for a better understanding of the spatial variation in soil properties. The sampling resolution will depend on the size of the field, cost involved for sample analysis, and other requirements associated with the land management practices. With the PBDS proposed in this study, the collection of a large number of sampling points for the analysis of multi-soil properties, quickly and in a cost-effective manner becomes possible.

4 Conclusions

A new prototype bulk density sensor (PBDS) to predict bulk density (BD), as a function of *in situ* measured PR and visible and near infrared (vis-NIR) predicted moisture content (MC), organic matter content (OMC) and clay content (CLC) was developed and tested in three fields in the UK. Artificial neural network (ANN) was implemented to establish BD model, as a function of vis-NIR predicted MC, OMC and CLC. Results allowed the following conclusions to be drawn:

1. The vis-NIR general calibration models of MC, OMC and CLC provided excellent quantitative prediction accuracies with ratio of prediction deviation (RPD) of 5.86, 7.84 and 4.94, respectively.
2. The independent testing of MC and OMC models performance in the validation fields demonstrated high accuracy for MC (R^2 = 0.94 and RMSE = 0.32%) and OMC (R^2 = 0.90 and RMSE = 0.09%).
3. The performance of the BD general calibration model was found to be promising, with R^2 of 0.94 and RMSE of 0.04 Mg m^{-3} in the test set.
4. Predicted BD with the new PBDS showed very good correlation with measured values (R^2 = 0.95 and RMSE = 0.02 Mg m^{-3}).
5. Comparison maps between measured and PBDS predicted soil properties showed high spatial similarities. The full-point maps based on double number of points of 48 provided more detailed information than the comparison maps (24 points). The fast

and cost effective sampling provided by the PBDS introduced in this study will support a high resolution mapping of the spatial variation in soil properties.

The new PBDS requires further validation in new fields. Furthermore, the BD model will be updated for new soil texture classes such as silt, silty clay and sandy clay to broaden the applicability of the approach. This system can be then further developed for evaluations throughout the soil profile.

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