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Prediction of soil organic and inorganic carbon contents at a national scale (France) using mid infrared reflectance spectroscopy (MIRS)

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Summary

This work aimed to evaluate the potential of mid-infrared reflectance spectroscopy (MIRS) to predict soil organic and inorganic carbon contents with a 2086-sample set representative of French topsoils (0–30 cm). Ground air-dried samples collected regularly using a 16 × 16-km grid were analysed for total (dry combustion) and inorganic (calcimeter) carbon; organic carbon was calculated by difference. Calibrations of MIR spectra with partial least square regressions were developed with 10–80% of the set and five random selections of samples. Comparisons between samples with contrasting organic or inorganic carbon content and regression coefficients of calibration equations both showed that organic carbon was firstly associated with a wide spectral region around 2500–3500 cm⁻¹ (which was a reflection of its complex nature), and inorganic carbon with narrow spectral bands, especially around 2520 cm⁻¹. Optimal calibrations for both organic and inorganic carbon were achieved by using 20% of the total set: predictions were not improved much by including more of the set and were less stable, probably because of atypical samples. At the 20% rate, organic carbon predictions over the validation set (80% of the total) yielded mean R^2 , standard error of prediction (SEP) and RPD (ratio of standard deviation to SEP) of 0.89, 6.7 g kg⁻¹ and 3.0, respectively; inorganic carbon predictions yielded 0.97, 2.8 g kg⁻¹ and 5.6, respectively. This seemed appropriate for large-scale soil inventories and mapping studies but not for accurate carbon monitoring, possibly because carbonate soils were included. More work is needed on organic carbon calibrations for large-scale soil libraries.

Introduction

All countries are required to provide regular greenhouse gas inventories. Among them, countries with a quantified emission reduction objective (Annex B countries of the Kyoto Protocol to the United Nations Framework Convention on Climate Change) should produce estimates on a regular basis, including agriculture and forestry activities by using the 2006 Intergovernmental Panel on Climate Change guidelines (IPCC, 2006). While gross fluxes of methane (CH₄) and nitrous oxide (N₂O) are directly computed, carbon dioxide (CO₂) fluxes are derived from the mass-balance approach, from differences over time of variations in biomass carbon and soil organic carbon stocks. Annex B countries need, therefore, to implement systems to quantify soil organic carbon and changes in content. Soil carbon estimates over large areas, at national, continental or global scales (Bernoux *et al.*, 2002; Batjes, 1996), have been proposed on the basis of classical digital maps linked with carbon estimates per map unit, using either soil classification (Batjes, 1996), vegetation or biome delineation (Woomer *et al.*, 2004), or a combination of both (Bernoux *et al.*, 2002). Other spatial estimates involve the interpolation of punctual data using either splines or geostatistical approaches (Bernoux *et al.*, 2007). Saby *et al.* (2008) calculated that the number of sites needed to detect a 1% relative change in soil organic carbon stock (in MgC ha⁻¹) could reach 1 000 000 sites at the European scale. These calculations involve the organic fraction of soil carbon; inorganic soil carbon, which consists mainly of carbonates, is little involved with CO₂ exchanges. Soil organic carbon is often calculated by difference between total carbon and inorganic carbon, the latter being analysed separately. Soil inorganic carbon content provides important information on mineralogy and soil chemical functioning involving pH or exchangeable cations. Thus both organic and inorganic soil carbon fractions are worth determining, but conventional procedures are costly and time consuming and not compatible with the implementation of large monitoring networks. Such networks have to be re-analysed regularly. There is thus an urgent need for time- and cost-effective methods that would provide accurate estimates of soil organic and inorganic carbon, in order to enable such networks.

Several methods have recently been proposed for cost-effective estimates of soil carbon. Cremers *et al.* (2001) tested the laser-induced breakdown spectrometry (LIBS), which is based on atomic emission spectroscopy. Other spectroscopic methods for characterizing soil carbon include the analysis of light diffusely reflected by samples in two neighbouring electromagnetic domains, namely the near infrared (0.8–2.5 µm) and mid infrared (2.5–25 µm) ranges. Often this has involved near infrared reflectance (NIR) spectroscopy (NIRS;

Chang *et al.*, 2001; Barthès *et al.*, 2006; Brunet *et al.*, 2007a), and more recently, visible and NIR (VisNIR, 400–2500 nm) spectroscopy (VisNIRS; Shepherd & Walsh, 2002; Brown *et al.*, 2005, 2006; Brunet *et al.*, 2008). A particular interest in VisNIRS, NIRS and MIRS is their capability to do rapid measurements (about one sample per minute or less), with no consumables or hazardous reagents required, and for limited expenses. Recent reviews highlighted the huge potential of diffuse infrared reflectance spectroscopy for agricultural applications regarding soil fertility assessment, and considered it to be an alternative to traditional soil analyses (Du & Zhou, 2009; Reeves, 2010). The potential of infrared spectroscopy has been tested for decades in a wide range of settings, from field to global scales (Brown *et al.*, 2005). It has gained recent interest because of the increasing need for soil data in environmental studies, for digital soil mapping (Grinand *et al.*, 2008), or climate change mitigation (Feller & Bernoux, 2008). For two decades NIRS has mainly been used as a quantitative tool, to relate spectra to carbon concentrations statistically; whereas MIRS has long been used for qualitative studies and spectral interpretation (McCarty *et al.*, 2002; Reeves, 2010). Indeed, the MIR region includes fundamental vibrations of chemical bonds mainly, which allows visual discrimination of spectral features (peaks); by contrast, the NIR region includes overtones and combinations, which results in much overlapping and few features (Shepherd & Walsh, 2002). Recently, MIRS has also been used for quantitative characterization of soil properties (Janik & Skjemstad, 1995; Janik *et al.*, 1998; Zimmermann *et al.*, 2007), which can thus be performed using different spectral domains through field, laboratory, airborne or satellite measurements (Stevens *et al.*, 2008). Quantitative spectroscopy most often requires calibration: this is usually a multivariate regression procedure that expresses a given property, determined by a conventional method, as a function of absorbance at all or selected wavelengths of the spectral region considered. The calibration equation can then be used to predict that property on new samples from their spectra only, provided that the calibration model has sufficient accuracy. Most determinations of organic and inorganic carbon by NIRS (Chang *et al.*, 2001; Shepherd & Walsh, 2002; Barthès *et al.*, 2006) and MIRS (Janik *et al.*, 1998; McCarty *et al.*, 2002) were accurate ($R^2 > 0.9$) and had a standard error close to the usual standard error for laboratory measurements (around 1 g kg⁻¹ for organic carbon). However, prediction accuracy was often less for heterogeneous sample sets, such as those collected from large regions, than for more homogeneous sets, originating from only a few hectares (McCarty *et al.*, 2002; Brunet *et al.*, 2007a).

The objective of the present paper was to evaluate the accuracy of MIRS predictions of soil organic and inorganic carbon contents at a country scale, using a national library including about 2000 samples representative of top-soils from France. The 0–30 cm soil depth is that most affected by agricultural practices such as tillage, and is thus considered in most models of soil organic matter dynamics from plot to national levels (Milne *et al.*, 2007). In addition, this depth corresponds to the minimum requirement for carbon estimates at national scales according to the IPCC guidelines (IPCC, 2006).

Materials and methods

Soil samples

Soil samples were taken from the French Réseau de Mesures de la Qualité des Sols (RMQS). This is a national soil quality monitoring network, the first sampling campaign of which took place from 2002 to 2009. This network involves observations of soil properties on a 16×16 -km regular grid across the French metropolitan territory (550 000 km²), and was designed to represent climate, soil and land use diversity over the territory. The inventory will eventually consist of observations from 2 200 sites, but samples from 2 086 sites were available at the time of the study. The sites were selected at the centre of each 16×16 -km cell (Jolivet *et al.*, 2006). At each site, 25 individual core samples were taken from the top-soil (0–30 cm) using an unaligned sampling design within a 400-m² square area. A systematic unaligned sample design combines features and advantages of both simple random and systematic sample designs, and a single sample plot is assigned to a randomly selected location within each cell of the systematic grid. This approach avoids the periodicities of systematic approaches, gives good coverage over an area, is efficient, and deals with most distributions (Caeiro *et al.*, 2003). Core samples were bulked to obtain one composite sample for each site, which was then air-dried, gently crushed and sieved to pass a 2-mm mesh.

Conventional determination of soil organic and inorganic carbon contents

Soil organic carbon content was calculated as the difference between total carbon and inorganic carbon contents. Total carbon content was determined by Dumas combustion analysis with an elemental analyser (Thermo Fisher Scientific CHN NA2000, Waltham, MA, USA), on about 25–30-mg aliquots of finely ground (< 0.25 mm) air-dried soil samples, sealed into tin capsules, according to the standard French procedure NF ISO 10694 (AFNOR, 1995a).

Soil inorganic carbon content was calculated as $0.12 \times$ soil carbonate content. Carbonate content was determined on finely ground (< 0.25 mm) air-dried soil samples using a Bernard calcimeter, according to the standard French procedure NF ISO 10693 (AFNOR, 1995b). The carbonate content was calculated after calibration with a pure calcium carbonate standard and was expressed as equivalent calcium carbonate content.

Distributions of both organic and inorganic carbon contents were characterized by their minimum, maximum, mean, median, standard deviation and skewness; the latter is defined as the third standardized moment:

$$\text{skewness} = \frac{n}{(n-1)(n-2)} \sum_{i=1}^n \frac{(x_i - \bar{x})^3}{SD^3}, \quad (1)$$

where n is the set size, \bar{x} the mean and SD the standard deviation.

Spectrum acquisition and pre-processing

Aliquots of about 0.5 g of < 0.2 -mm ground sample were placed in a 17-well plate and scanned from 4000 to 400 cm^{-1} (2500–25 000 nm) at 4 cm^{-1} resolution, using a Nicolet 6700 Diffusive Reflectance Fourier Transform Spectrophotometer (Thermo Fisher Scientific Instruments, Madison, WI, USA). Thirty-two co-added scans per sample were performed then averaged, and spectra were recorded as absorbance, which is the log transform of the inverse of reflectance. Spectrum acquisition lasted about one minute per sample.

Data processing was performed using The Unscrambler 9.7 software (CAMO Technologies, Woodbridge, NJ, USA) for spectrum transformation and the R-Stat software (R Development Core Team, 2005) for partial least square (PLS) regression (PLSR) and validation. Several usual spectrum pre-processing methods such as first and second derivatives, standard normal variate (SNV) transform or multiplicative scatter correction (MSC) were tested but did not usefully improve predictions. The only beneficial spectrum transformations were the removal of 10 wavelengths at both spectrum ends and smoothing over a five-point segment, which helped reduce noise: this process was applied for subsequent analyses, either qualitative or quantitative. Limited benefit of MIR spectrum pre-processing was also reported by Minasny & McBratney (2008).

Principal component analysis was carried out on spectral data and showed that the two first components accounted for 84% of total variance.

Calibration and validation

Outlier identification was carried out on the response variables (organic and inorganic carbon content) to remove extreme values that might over-influence calibration models. An arbitrary threshold defined by the mean plus eight times the standard deviation was used to identify these outliers. This led to the removal of two samples for organic carbon; no samples were removed for inorganic carbon.

Partial least square regression was used to fit sample spectra to conventional measurements of soil organic and inorganic carbon contents. It is a well-suited and widely used multivariate technique in quantitative spectroscopy. It can handle collinearity that affects infrared spectra by transforming absorbance values with respect to the response variable (organic or inorganic carbon content) in order to reduce the information from hundreds of variables to a few orthogonal factors. Ten-fold cross validation was performed to calculate the standard error of cross validation (SECV). This commonly used model setting was needed because of the large number of calibration samples, and enables grouping without altering the predictive ability of the cross-validated models. The minimum SECV was used to select the optimal number of PLS factors to retain for building the prediction model. Then calibration was performed on the whole calibration set, whereas the cross-validation results referred to a pooled combination of the results obtained from the samples left out during the cross validation procedure. Finally the prediction models were tested on the validation set, which included samples not used for model development. The number of samples used for calibration and validation is presented in the following section.

The ability of the MIRS-PLSR method to predict organic and inorganic carbon was evaluated by using parameters commonly used in quantitative infrared spectroscopy. For each data set, coefficient of determination (R^2 ; Equation 1) and standard error between MIRS predictions and conventional measurements were calculated. The former measures the proportion of the total variance accounted for by the model, and was presented for the validation set only. The latter is the standard deviation of the difference between measured and predicted values, expressed in g kg^{-1} , and was presented for calibration (SEC), cross validation (SECV), and validation (standard error of prediction, SEP; Equation 2). Prediction accuracy on the validation set was also evaluated using the ratio of standard deviation to SEP (denoted RPD; Equation 3) and the ratio of SEP to mean reference value over the validation set (relative SEP, denoted %SEP; Equation 4). A good prediction result is assumed to have small standard error and large R^2 and RPD. As regards the predictions of soil properties using infrared spectroscopy, values proposed by Chang *et al.* (2001) have often been considered: models

with RPD below 1.4 have no predictive ability, those with RPD between 1.4 and 2.0 are acceptable and improvable, and those with RPD above 2.0 have excellent predictive ability. The equations are:

$$R^2 = \frac{[\text{cov}(y_i, x_i)]^2}{\text{var}(y_i) \text{var}(x_i)} \quad , \quad (2)$$

$$\text{SEC or SECV or SEP} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - x_i)^2} \quad , \quad (3)$$

$$\text{RPD} = \text{SD} / \text{SEP}, \quad (4)$$

$$\text{and } \% \text{SEP} = \text{SEP} / \text{mean}, \quad (5)$$

where x_i is the conventional measure and y_i the MIRS prediction for the i^{th} sample, n the number of samples and SD the standard deviation.

Calibration set size and selection

The effect of the calibration set size on prediction was tested by increasing the proportion of calibration samples from 10% to 80% of the total set, the remaining fraction being kept for validation. This test was referred to as sampling intensity analysis (Grinand *et al.*, 2008). Regression was performed five times using different random iterations for the selection of calibration samples, in order to assess prediction robustness and reproducibility, which are two important criteria to build up a calibration model. Despite the well-known fact that the calibration set has to be representative of the total set, there are still issues in the way to select it. Random sampling has been reported to produce varying results in heterogeneous sample populations (Islam *et al.*, 2003; Brunet *et al.*, 2007a) but has not been extensively studied yet (Brown *et al.*, 2005). Here the minimum, maximum and mean model parameters (such as SECV, SEC, R^2 , etc.) have been mentioned to provide information on the extent of predictive ability and on significant differences between models.

Results and discussion

Reference carbon data

The soils used in this study were collected from a large geographical area, which covers a wide range of soil units and represents most of the soil types of France. According to the French soil classification, 33 soil reference groups were sampled, with a dominance of Brunisols (Cambisols according to IUSS Working Group WRB, 2006; 27% of the sample set), calcareous soils (Calcosols, 22%) and Luvisols (16%). As a result of the large variety of

soil samples studied, variations in organic and inorganic carbon contents were huge, as measured using conventional procedures (Table 1). Organic carbon ranged from 0.6 to 170 g kg⁻¹ after removal of outliers (up to 250 g kg⁻¹), averaged 25.6 g kg⁻¹ and standard deviation was 78% of the mean. Inorganic carbon ranged from 0 to 104 g kg⁻¹, averaged 6.4 g kg⁻¹ and standard deviation was 250% of the mean. The calcium carbonate content of 1108 samples was below the 1 g kg⁻¹ detection limit, thus the median equalled 0 g kg⁻¹. Distributions of both organic and inorganic carbon were positively skewed (skewness was around 3 for both), with more small than large values, thus medians were smaller than the means, especially for inorganic carbon. Correlation between organic and inorganic carbon contents was not significant ($R = -0.01$, $P = 0.59$).

Semi-qualitative spectrum analysis

Spectral measurements and laboratory results were first used in a qualitative way to identify peaks or absorption regions that characterized carbon fractions. Spectral regions associated with organic carbon variations were identified by testing the significance of difference in mean absorbance at each spectral data point between organic carbon-rich (> 50 g kg⁻¹) and -poor (< 10 g kg⁻¹) samples from Cambisols (the soil class with the largest number of samples), using a Student *t*-test ($P < 0.001$). A similar procedure was carried out for inorganic carbon (> 6.0 and < 1.2 g kg⁻¹, which corresponds to > 50 and < 10 g calcium carbonate kg⁻¹) in the class of Calcosols.

The difference in mean absorbance between organic carbon-rich and -poor top-soils from Cambisols was significant for a wide region between 3550 and 2080 cm⁻¹, and for bands around 1660 and 1150 cm⁻¹ (Figure 1a). Organic matter is a complex mixture of compounds, containing various proportions of chemical groups that are nearly all infrared active (Janik *et al.*, 1998). Thus organic carbon cannot be identified with clearly separated peaks but as a whole spectral region with overlapping bands.

In contrast, numerous small spectral regions differed significantly in mean absorbance between inorganic carbon-rich and -poor top-soils from Calcosols (Figure 1b). Among them, only two could be attributed to stretching or bending vibrations in carbonate molecules, around 2520 and 1800 cm⁻¹, as mentioned by Du & Zhou (2009). Other regions differing significantly in absorbance according to inorganic carbon level could not be attributed to carbonates but more probably to soil properties that correlated negatively with inorganic carbon. This was particularly the case for regions around 1880 and 2000 cm⁻¹, which relate to quartz (Du & Zhou, 2009).

In short, semi-qualitative analysis of spectra showed that absorption of both carbon fractions could be located in the MIR region. Nevertheless, though some carbon compounds have been assigned to specific spectral bands, broad spectral regions corresponding to C-O or C-C vibrations have to be taken into account to fully describe carbon contribution to MIR spectra. Thus a quantitative approach was needed to extract accurate information regarding each carbon fraction. The identification of chemical bonds that affected MIRS prediction of soil organic and inorganic carbon contents was also carried out by studying the coefficients of regression of these contents on absorbance spectra.

Calibration intensity and model robustness

The interest of diffuse reflectance spectroscopy for quantifying soil properties depends on the proportion of samples used for calibration; it also depends on the stability of predictions when different calibration sample selections are carried out. For organic carbon, mean validation RPD and R^2 increased with the proportion of samples used for calibration, markedly when the proportion increased from 10% to 20%, and then only slightly up to 80% (Figure 2a). Moreover, R^2 and RPD were less variable thus more stable when calibration used 20% or 30% samples; below and above these rates, results were more affected by the selection of calibration samples. Reduced stability at large calibration rates could be explained by samples that were atypical for one reason or another. When included in the calibration set, atypical samples would reduce overall calibration quality and thus that of the prediction (validation); and this was more likely to occur when calibration intensity increased. When not included in the calibration set, atypical samples were not predicted well individually (validation), but they did not affect the overall performance of the calibration, and this was more likely to occur when calibration intensity decreased. At a small calibration intensity (10%), it might be assumed that the calibration set was too small to be representative of the total set.

With inorganic carbon, mean and standard deviation of validation R^2 were much less affected by the size of the calibration set (Figure 2b). In contrast, the proportion of calibration samples affected validation RPD more clearly, with a noticeable increase from 10 to 20% then again from 40 to 80%; it also affected the variability of validation RPD, with greater standard deviation when from 40 to 80% samples were used for calibration. Variations in validation RPD and in its variability with the size of the calibration set could be related to the very skewed distribution of conventional data for inorganic carbon, which resulted in large standard deviation (it was three times greater than the mean: Table 1). However, RPD values were always large (> 5) when compared with accuracy thresholds proposed for prediction

models of soil properties using diffuse reflectance (Chang *et al.*, 2001); thus the influence of the size of the calibration set on RPD and its variability was not important. Using 20% of the samples for calibrating both organic and inorganic carbon could thus be considered appropriate for the sample set studied. This indicated that the national soil sample population under study was correctly represented by 20% of the samples. Soil and soil-use diversity is large over all of France but not to the point where a single sample of the total 2086 would represent only itself.

Very few studies have addressed such questions. Shepherd & Walsh (2002) reported similar result for a very diverse set including about 1100 samples from seven countries and 10 soil orders in eastern and southern Africa. They observed that stable validation results for top-soil organic carbon could be achieved with 20% of the samples for calibration. They also noted that a global model might be more robust than local models in their ability to predict values for new samples even though geographically distinct samples were used in the calibration. Similarly, when discussing calibration sample size for a more homogeneous set including 283 samples from six sites with similar soils in north central Montana (USA), Brown *et al.* (2005) observed an optimum when using 35% randomly selected samples for calibration. Increasing the calibration sample size did not result in meaningful increase in prediction accuracy and thus was not worthwhile. The results of the present study also suggested that optimal calibration set size for heterogeneous soil sample populations could be estimated at 20 to 35% of the samples for organic carbon and inorganic carbon predictions. However, such calibration intensity cannot be considered appropriate for all soil sample sets: Brunet *et al.* (2007b) observed that optimal calibration sample size ranged between 50% and 75% for organic carbon for an extremely diverse set of 436 soil samples originating from about 300 locations in 40 countries and representing 13 soil orders,. This strongly suggests that more work is needed to estimate optimal calibration sample size depending on the set diversity and the soil property considered.

Quantifying soil inorganic carbon content at a national scale

Calibration was built using 20% of the total number of samples (418 out of 2086), with five different random selections of calibration samples. For validation, R^2 was 0.97 and RPD averaged 5.6 and was greater than 5.3 whatever the replicate (Table 2). Thus MIRS prediction of inorganic carbon was excellent for the sample set considered, as also shown by the comparison between MIRS predictions and reference measurements presented in Figure 3b and in Figures 4c and 4d. Depending on the selection of calibration samples, variation in R^2

was less than 0.01 and RPD ranged from 5.3 to 6.0, thus both were stable. Relative SEP nevertheless represented a large proportion of mean reference value for inorganic carbon (43 to 48%), mainly because of the very skewed distribution of inorganic carbon reference data. . The mean reference value was small (6.4 g kg^{-1}) because many samples included no carbonates; relative prediction error could not be considered as an appropriate indicator of prediction accuracy for variables for which the average value is much smaller than the maximum. Not surprisingly, the map of MIRS predictions of inorganic carbon (Figure 4c), as did that of conventional measurements (Figure 4d), showed that the soils richest in inorganic carbon were located on calcareous substrates, especially in the chalk Champagne (north-east), in the calcareous Prealps (south-east), in areas of Jurassic limestone along the Aquitaine Basin (south-west) and along the Pyrenees (south). Soils developed from calcareous materials were completely decalcified under wet climates (Jura and northern Prealps, centre-east).

Literature has also reported excellent predictions for inorganic carbon with diffuse reflectance spectroscopy. McCarty *et al.* (2002) achieved MIRS prediction of inorganic carbon with $R^2 = 0.98$, RPD = 9.0 and %SEP = 19% with a more intensive calibration (75%) over a diverse set of 237 soil profile samples originating from nine states from central US and having a fairly wide range in inorganic carbon ($0\text{--}65 \text{ g kg}^{-1}$). Brown *et al.* (2005), studying a more homogeneous set with narrow range in inorganic carbon ($0\text{--}26 \text{ g kg}^{-1}$) and intensive calibration (70%), achieved VisNIRS prediction of inorganic carbon with $R^2 = 0.94\text{--}0.96$, RPD = 4.0–4.9 and %SEP = 19–24% depending on the selection of the calibration set (five replicates). Brown *et al.* (2006) also reported cross-validation $R^2 = 0.83$ (RPD and relative error could not be calculated) for a very large, diverse set originating from four continents and having a wide range in inorganic carbon ($0\text{--}129 \text{ g kg}^{-1}$). In contrast, somewhat disappointing VisNIRS cross validation of inorganic carbon was reported by Summers *et al.* (2011) for a fairly diverse but small top-soil sample set from South Australia with narrow range in inorganic carbon ($0\text{--}51 \text{ g kg}^{-1}$; 75 samples, $R^2 = 0.69$, RPD = 2.1, %SECV > 100%). In the latter case the use of reflectance instead of absorbance could be a possible reason for less accurate predictions than in other studies. Considering only those studies that used absorbance, relative prediction error tended to increase and R^2 and RPD to decrease when the range in inorganic carbon increased.

Quantifying soil organic carbon content at a national scale

Calibration for this used 20% of the total set size, with five replicates. For validation, R^2 and RPD averaged 0.89 and 3.0 and were greater than 0.88 and 2.7, respectively, whatever the replicate (Table 2). The SEP ranged from 6.3 to 7.2 g kg⁻¹, representing 25 to 28% of the mean reference value. This indicated very good MIRS prediction of organic carbon for the sample set considered; however predictions were less accurate than for inorganic carbon. Examples of comparisons between measured and MIRS predicted organic carbon values are presented in Figure 3a and Figures 4a and 4b. The maps of MIRS predictions (Figure 4a) and conventional measurements (Figure 4b) of organic carbon were very similar, and strongly driven by climate and land use. The soils richest in organic matter were located in the mountains (Alps in the south-east, Pyrenees in the extreme south-west, Massif Central in the south-centre, Jura in the centre-east), in other cool regions extensively covered by forests and pastures such as Burgundy and Lorraine (centre-east), and in intensive livestock production areas such as Brittany and Normandy (north-west). In contrast, soils poor in organic matter were located in areas of large-scale crop cultivation such as the Parisian Basin (north-centre) and Aquitaine Basin (south-west), and in vineyard areas such as along the Mediterranean coast (south-east).

Others authors have reported MIRS prediction of organic carbon with PLSR. McCarty *et al.* (2002) found similar results for organic carbon prediction over a fairly heterogeneous sample set from central US ($R^2 = 0.94$, RPD = 4.1, %SEP = 26%) but used more samples for calibration (75%). Viscarra Rossel *et al.* (2006) using a leave-one-out cross validation achieved worse results for organic carbon for a very homogeneous set of 118 top-soil samples collected in an Australian field, with much smaller R^2 (0.73) and RPD (1.7) though relative standard error of cross validation was low too (11%). In contrast, Zimmermann *et al.* (2007), also using high calibration intensity (85%), found better results for organic carbon ($R^2 = 0.94$, RPD=4.1, %SEP=10%) for a diverse set of 111 top-soil samples representative of Switzerland. Comparable results have been achieved by using VisNIRS with PLSR. For instance, for a large and very diverse top-soil sample set with a large calibration intensity (67%), Shepherd & Walsh (2002) reported validation $R^2 = 0.91$ and %SEP = 19%. Brown *et al.* (2005) achieved validation $R^2 = 0.81$ and RPD = 2.2 when averaging five replicates over a smaller and more homogeneous set and with a large calibration intensity (70%). For a very large and very diverse set (3794 samples from four continents) and using boosted regression trees, Brown *et al.* (2006) obtained cross-validation R^2 values of 0.82. Thus comparison with published results suggests that the results of the present study were very satisfactory: the

accuracy of organic carbon prediction model was comparable to others for similarly heterogeneous soil sample sets but using much fewer samples for calibration.

In the present study, large organic carbon values were noticeably under-predicted by MIRS. Studying a large and very diverse sample set with VisNIRS, Shepherd & Walsh (2002) attributed such poor predictions to possible errors in the laboratory analytical methods rather than to genuine lack of VisNIRS predictive power. Moreover, it is worth noting that in the present study organic carbon reference data were not measured but calculated by difference between total carbon and inorganic carbon, which caused error accumulation. As a consequence, the less than perfect MIRS predictions of organic carbon ($R^2 = 0.89$) might result from imperfect reference data. In contrast, inorganic carbon, for which reference data was by direct measurement, was much more accurately predicted, especially at large values. Other studies involving MIRS or VisNIRS predictions of organic and inorganic carbon similarly reported more accurate results for inorganic than for organic carbon. McCarty *et al.* (2002) measured organic carbon after soil acidification, which they acknowledged might remove some organic carbon. Brown *et al.* (2005) calculated organic carbon reference data by difference between total and inorganic carbon. Both procedures might result in some imprecision. In addition, McCarty *et al.* (2002) reported that carbonate absorption bands in the MIR domain could mask spectral features important for organic carbon calibration. As far as sample sets which include carbonated soils are considered, calibration models for organic carbon will not be completely satisfying because of either spectral perturbations by carbonates or imperfect reference data for organic carbon.

Spectral regions of greatest relevance

The chemical compounds that affected MIRS predictions strongly were identified by studying the coefficients of PLS regression of organic and inorganic carbon contents on absorbance at every wave-number (Figure 5). Regressions built using 20% or 100% samples yielded similar coefficients, which confirmed that 20% samples represented the total set properly.

Some spectral regions contributed heavily to MIRS prediction of soil organic carbon content. Positively contributing regions were from 2700 to 3600 cm^{-1} and especially around 2920 cm^{-1} , which has been assigned to aliphatic C-H stretch of carboxylic acids, humic acids and humin especially, and around 1230 cm^{-1} , which has been ascribed to C-O stretch and O-H bending in humic acids and aromatic amines (Silverstein & Webster, 1998; Tan, 2003). These regions were comparable to those where absorbance was significantly greater for Cambisols rich in organic carbon than for those with small contents (Figure 1a). The region around 1880 cm^{-1} ,

attributed to quartz (Du & Zhou, 2009), had a heavy negative contribution to organic carbon prediction, which is consistent with the fact that sandy soils are poor in organic matter in general (Barthès *et al.*, 2008). This region is one of the very few where absorbance was less for organic-rich Cambisols than for those organic-poor.

Spectral regions that had major positive contribution to MIRS prediction of soil inorganic carbon content were (i) around 2520 and 1800 cm^{-1} , which have been ascribed to carbonate (Du & Zhou, 2009; D'Acqui *et al.*, 2010); (ii) around 1660 cm^{-1} , assigned to asymmetric stretching of O-C-O in carbonate (Su & Suarez, 1997) but also to 2:1 clays such as montmorillonite (Du & Zhou, 2009); (iii) around 1080 cm^{-1} , assigned to symmetric stretching of O-C-O in carbonate (Su & Suarez, 1997) but also to 1:1 clays such as kaolinite (Du & Zhou, 2009); and (iv) around 490 cm^{-1} , ascribed to Fe-O bending vibrations (Russell, 1979), which might be related to iron oxide-rich residual clays that result from weathering of calcareous materials. The region around 1340 cm^{-1} , which has been attributed to quartz (D'Acqui *et al.*, 2010), had a substantial negative contribution to carbonate prediction, which is consistent with the fact that carbonated soils include little quartz. On the whole, regions that had large positive (or negative, respectively) contributions to carbonate prediction were those where absorbance was significantly larger (or smaller, respectively) for Calcosols rich in, than for Calcosols poor in, inorganic carbon (Figure 1b).

Conclusion

The present work demonstrated that MIRS yielded accurate predictions of top-soil organic and inorganic carbon contents at the scale of a medium-sized country (France), which has not been demonstrated so far. Analysis of variance between spectra of soils rich and poor in organic or inorganic carbon, as well as regression coefficients of calibration equations, showed that the MIRS signature of organic carbon involved a wide spectral band around 2500–3500 cm^{-1} while that of inorganic carbon was related to some narrow bands, especially around 2520 cm^{-1} .

Varying the proportion of samples used for calibration showed that 20% could be considered an optimal level for MIRS prediction of both organic and inorganic carbon contents, for a sample set representing the top-soil diversity of France. This calibration rate resulted in accurate and stable predictions: ranges of SEP, validation R^2 and RPD were 6.3–7.2 g kg^{-1} , 0.88–0.90 and 2.7–3.1 for organic carbon, and 2.6–2.9 g kg^{-1} , 0.97 and 5.3–6.0 for inorganic carbon, respectively. The similarity between regression coefficients of calibration equations which used 20% and 100% of the total set confirmed that 20% was the optimal calibration

intensity for the studied set. This was an important result, which has not been established clearly so far.

An important interest of MIRS (and other infrared spectroscopies) is that numerous soil properties such as nitrogen and clay contents, pH, cation exchange capacity, can be inferred from the same spectrum, as long as corresponding reference data are available for calibration. Moreover, once determined, calibrations can be used to make predictions with samples from new sampling campaigns (with a possible need for calibration strengthening through spiking; Guerrero *et al.*, 2010), which makes diachronic studies easier. However, though MIRS is appropriate for large-scale soil inventories and for many environmental and mapping studies, the accuracy of MIRS predictions presented here did not seem to be good enough for monitoring soil organic carbon precisely. This might be attributed to the noticeable proportion of carbonated samples included in the sample set, as carbonates complicate spectral and conventional characterizations of organic carbon thus its calibration. More work is needed to improve organic carbon calibration in large-scale soil libraries including carbonated soils, for instance through sample set stratification or spectrally local calibrations.

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Table 1. Descriptive statistics of the reference dataset (min is the minimum, max the maximum, and SD the standard deviation).

Soil property	Sample No	Min	Max	Mean	Median	SD	Skewness
Organic carbon / g kg ⁻¹	2084	0.6	170.0	25.6	19.4	19.9	3.2
Inorganic carbon / g kg ⁻¹	2086	0.0	103.9	6.4	0.0	16.0	3.1

Table 2. Calibration and validation statistics for MIRS predictions of soil organic and inorganic carbon contents; min, max and mean refer to minimum, maximum and mean values measured for five random partitionings of calibration and validation sets; standard errors of calibration (SEC), of cross validation (SECV) and of prediction (SEP) are in g kg⁻¹.

Soil property		Factors No	Calibration			Validation				
			Sample No	SEC ^a	SECV ^a	Sample No	SEP ^a	R ^{2b}	RPD ^c	%SEP ^d
Organic carbon	Min	20	418	4.4	6.1	1666	6.3	0.88	2.7	0.25
	Max	24	418	6.3	8.0	1666	7.2	0.90	3.1	0.28
	Mean	23	418	5.1	6.9	1666	6.7	0.89	3.0	0.26
Inorganic carbon	Min	16	418	1.3	1.8	1668	2.6	0.97	5.3	0.43
	Max	24	418	3.1	4.1	1668	2.9	0.97	6.0	0.48
	Mean	20	418	2.1	2.9	1668	2.8	0.97	5.6	0.45

^aSEC, SECV and SEP are standard errors of calibration, cross validation, and prediction, respectively.

^bR² is the coefficient of determination over the validation set.

^cRPD is the ratio of SEP to standard deviation of the reference value over the validation set.

^d%SEP is the ratio of SEP to the mean reference value over the validation set.

Figure 1. Comparison of mean spectra (a) between Cambisols rich and poor in organic carbon (> 50 or < 10 g kg⁻¹), and (b) between Calcosols rich and poor in inorganic carbon (> 6 or < 1.2 g kg⁻¹; corresponding to > 50 and < 10 g calcium carbonate kg⁻¹, respectively); grey regions indicate significant difference at $P < 0.001$ (Student t -test).

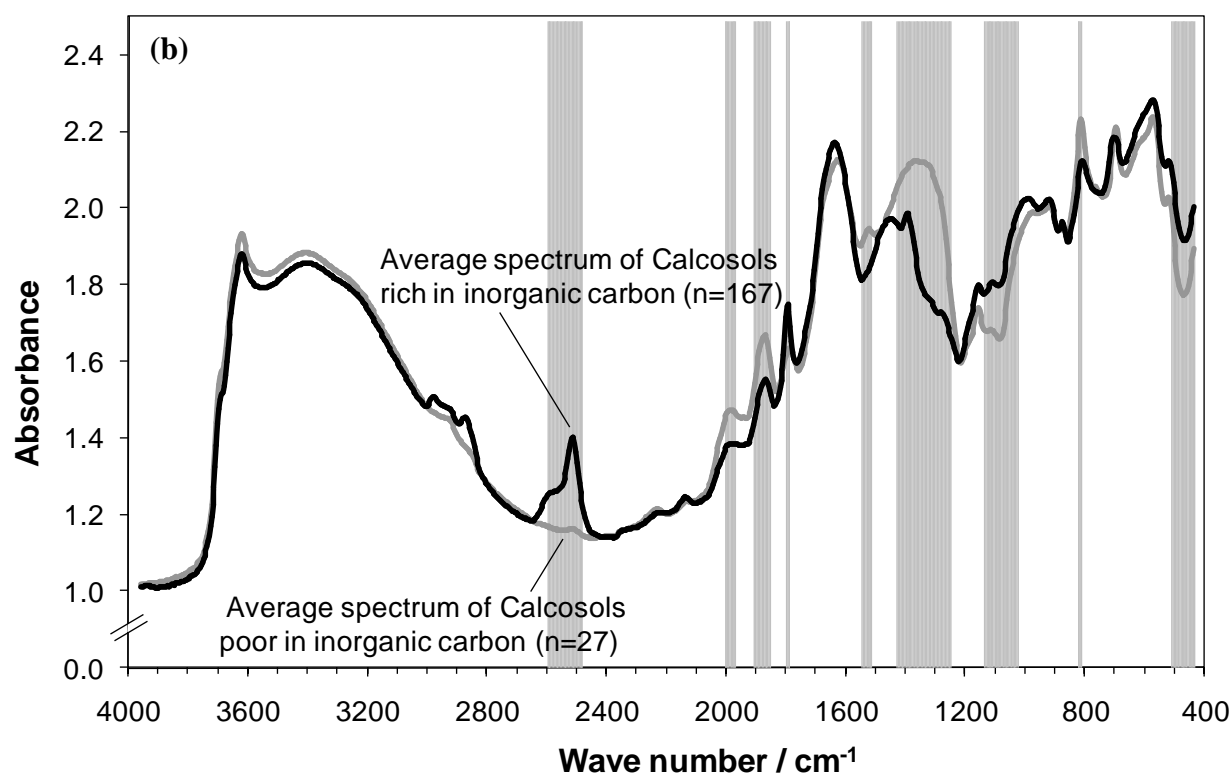
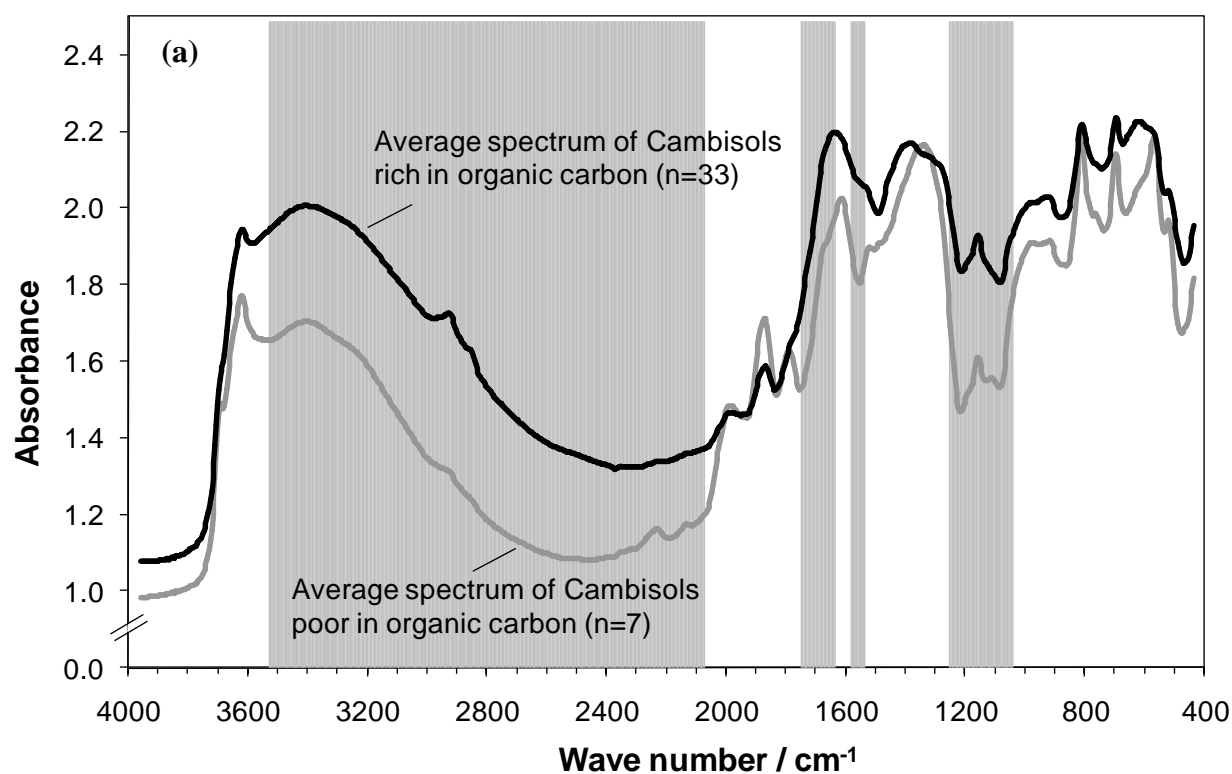


Figure 2. Validation R^2 and RPD (ratio of standard deviation to standard error of prediction) for (a) organic carbon and (b) inorganic carbon depending on the proportion of calibration samples (mean and standard deviation over five replicates).

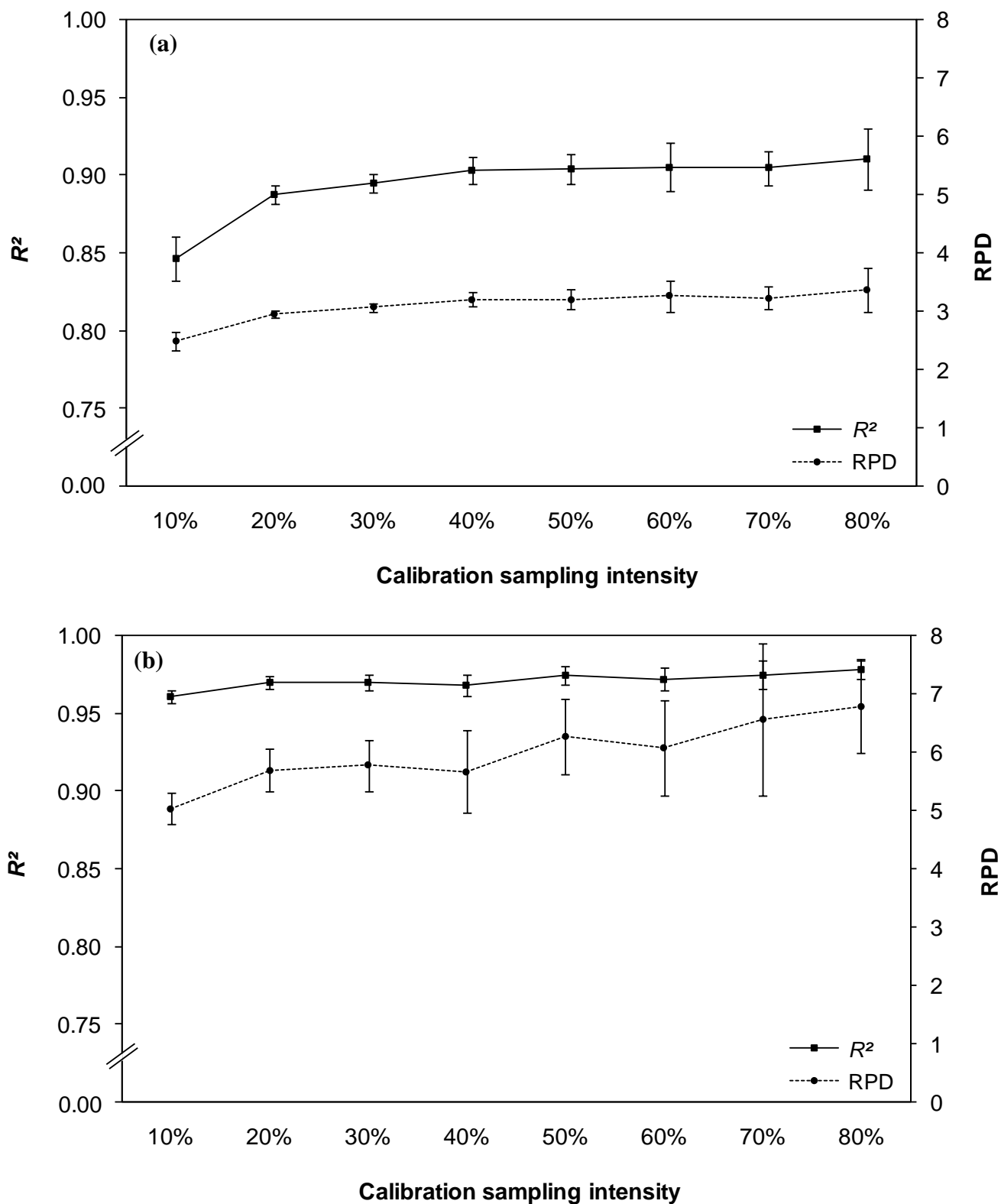


Figure 3. Comparisons between reference measurements and MIRS predictions of (a) organic carbon and (b) inorganic carbon over the validation set (1666 samples for organic carbon and 1668 for inorganic carbon, after random selection of 418 calibration samples; SEP is the standard error of prediction and RPD the ratio of standard deviation to SEP).

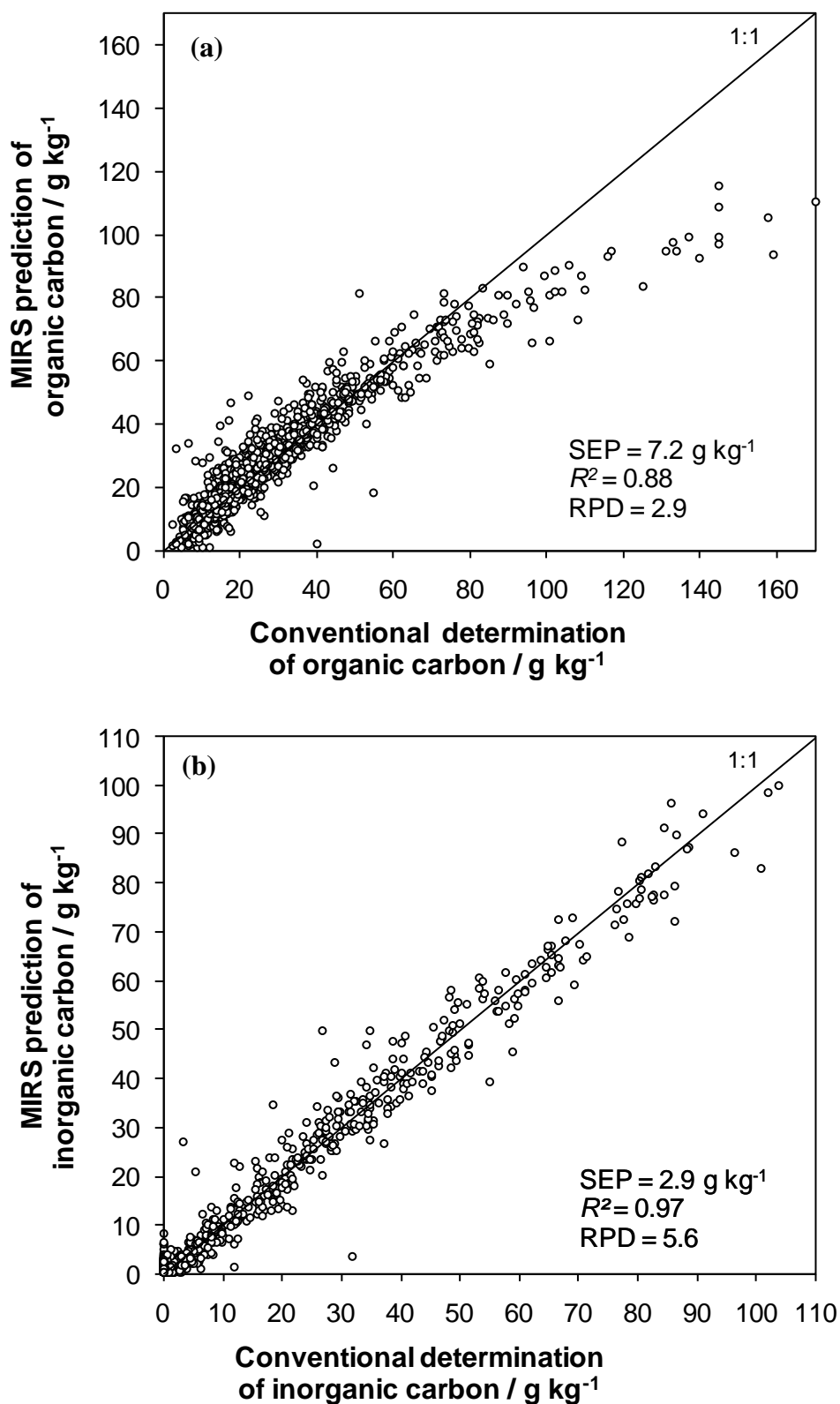


Figure 4. Maps of MIRS predictions (a, c) and reference determinations (b, d) of top-soil organic and inorganic carbon content (0–30 cm) in samples from across France; 20% randomly selected sites, located on the small map, were used for calibration.

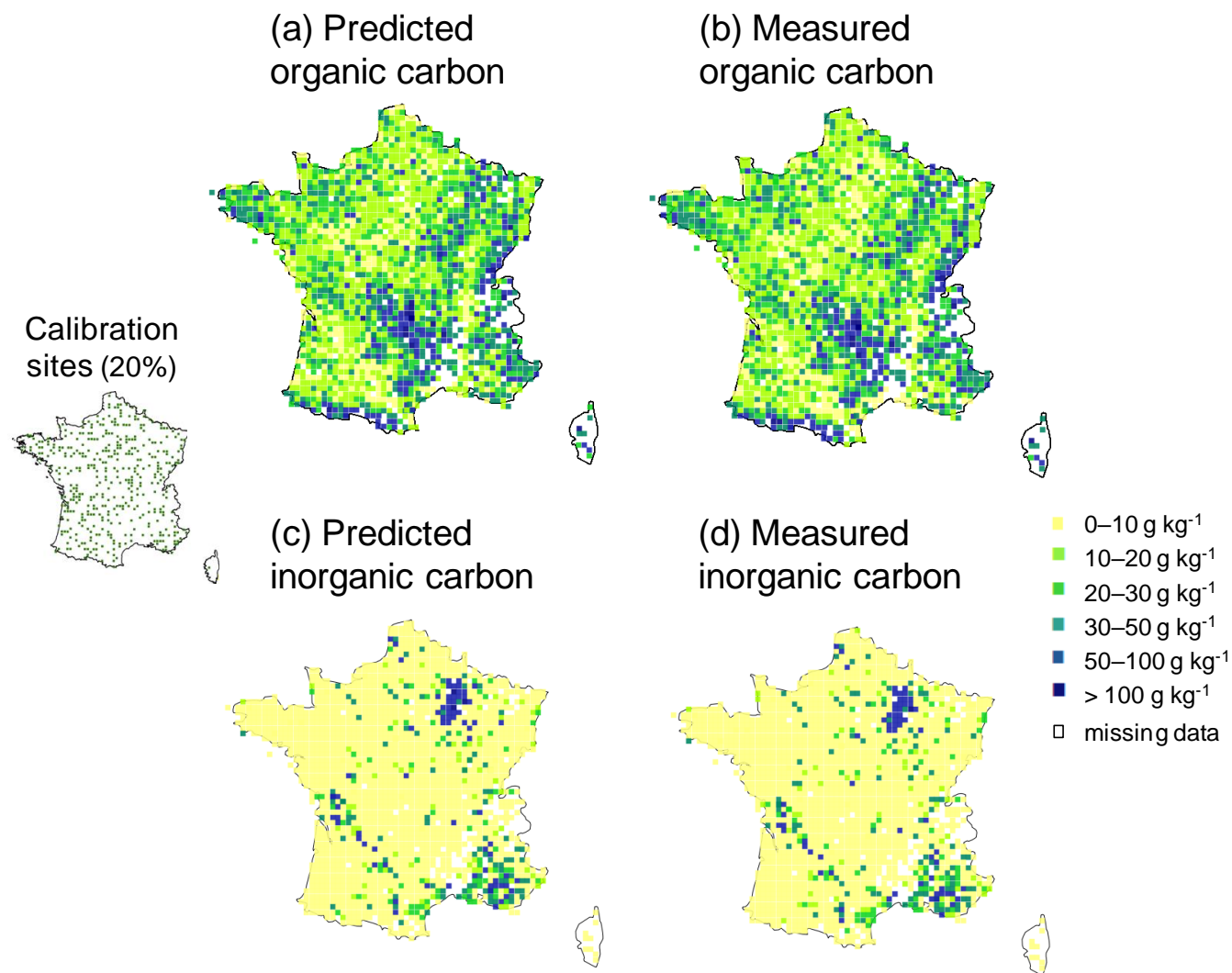


Figure 5. Coefficients of regression of (a) organic and (b) inorganic carbon content on absorbance spectra, models being developed by using 20% or 100% of the samples from across France.

