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Near infrared spectroscopy for within-field soil characterisation – Small local calibrations compared with national libraries spiked with local samples

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Summary

The advantage of using near infrared spectroscopy to increase sample point density in farm soil mapping relies on the number of conventional laboratory analyses for the calibrations being kept to a minimum. The objectives with the present study was to compare the performance of small farm scale calibrations (25 samples) to a larger national soil library (396 samples) and to test if a site specific sample set selected from the national library, consisting of the 50 samples spectrally most similar to those of the local sites could increase performance. In addition the national library and the selected subsets were augmented with up to the 25 local calibration samples to test whether that would have any additional effect on prediction errors and bias. Calibrations were made for predicting within-field variation in clay, silt, sand, soil organic carbon, pH and phosphorus. Selecting a subset of samples from the national library did not improve the results compared to using the entire national library. However, spiking both libraries with local samples reduced the RMSEP considerably, mainly due to a decrease in bias and often resulted in comparable results to the local calibrations. There was a tendency for better clay and SOC predictions when spiking a reduced national library compared to spiking the entire national library, sometimes even resulting in better predictions than using the local calibrations. However, using local calibrations seems to be the best alternative for predictions of soil parameters at the farm or field scale, even with as few samples as 25.

Introduction

Use of diffuse near infrared (NIR) spectroscopy has attracted interest among soil scientists, and has been proposed as a possible method for soil characterisation at an increased spatial resolution compared with that possible with conventional laboratory analysis. Apart from taking conventional soil samples, the technique also allows for development of in-field measurements (Christy, 2008; Maleki *et al.*, 2008). In precision agriculture, e.g. for variable rate fertiliser application or liming, cost-effective strategies for reliable soil information at a high spatial resolution are highly desirable. Several studies have shown the possibility to predict a number of soil properties important for decision support in crop production, e.g. soil texture, soil organic C (SOC), pH and phosphorus (e.g. Chang *et al.*, 2001; McCarty & Reeves, 2006; Viscarra Rossel *et al.*,

2006). To take full advantage of the technique, the number of calibrations or reference samples needs to be kept to a minimum. Large national, regional or global calibrations would be favourable in that respect, but the overall variation or the geographical scale for which calibrations are representative clearly influences their absolute precision (Sudduth & Hummel, 1996). This will be especially evident when predicting the variation at a smaller scale (Brown, 2007). For assessing within field variation, calibrations based on smaller or more similar areas have resulted in better predictions for a number of soil properties (Sankey *et al.*, 2008). In particular, soil properties indirectly estimated due to correlations to other more spectrally active properties could be difficult to predict with large calibration models, because of the likely site-specific nature of those correlations (Reeves *et al.*, 1999). Important soil properties for farmers such as plant-available nutrients and pH are some examples and published prediction results for these properties are typically very variable. In the visible region soil organic matter has broad absorption bands due to its darkness, resulting in a steeper slope in the transition over to the NIR region in highly organic soils (Baumgardner *et al.*, 1985). However, mineralogy and texture may also have a similar influence on colour (Hummel *et al.*, 2001) while iron rich minerals show more specific features (Clark, 1999). In the NIR region several bands are assigned to organic matter absorption. Bands near 1730, 1760, 2050 and 2300-2350 nm are among the more prominent (Stenberg, 2010). The strongest features in the NIR region can be assigned to clay minerals mostly due to OH, metal-OH, H₂O and CO₃ overtones and combinations. For example kaolinite absorbs characteristically at doublets near 2200 and 1400 nm. Illite and montmorillonite has single bands near 1400 and 2200 nm, and in addition near 1900 nm. Illite has weaker bands also near 2300 and 2400 nm (Clark, 1999). Mineral salts and proton activity (pH) on the other hand are not expected to absorb in the visNIR. It must be assumed that these parameters are estimated through co-variations of visNIR to organics and minerals, which is reasonable for example by regulating the pH buffer capacity or the fertility influencing the removal of nutrients with the harvest. It is obvious that co-variations like these are easily disturbed by farmers practice like liming and fertilization, but perhaps less so at the field scale with uniform management (Stenberg *et al.*, 2010).

In the majority of the field-scale NIR calibrations presented in earlier studies, substantial numbers of samples, often amounting to hundreds, were included in the calibrations and could correspond to more than five samples per ha (e.g. McCarty & Reeves, 2006; Viscarra Rossel *et al.*, 2006; He *et al.*, 2007). Compared with the conventional sample point density in farm soil mapping in Sweden of between 0.3 and 1 samples per ha, the advantage of using NIR spectroscopy is lost when that many reference samples are used. However, reducing the number of calibration samples could result in less reliable calibrations. Shepherd & Walsh (2002) found a rapid decrease in predictability with less than 100-200 calibration samples from a soil sample library containing soils from several countries in eastern and southern Africa. However, a farm-scale calibration in Sweden with as few as 25 calibration samples resulted in satisfactory predictions comparable to other studies for clay and soil organic matter content, to some extent for sand, but not so good for pH and available P (Wetterlind *et al.*, 2008; Wetterlind *et al.*, 2010). Especially pH and P gained from using 80-90 samples in the calibrations instead of only 25, which was explained by less robust calibrations due to their indirect nature.

Combining global and local samples by adding a few local ones to a more general soil library and recalibrating (here referred to as spiking) was proposed by Brown (2007) as another way to reduce the number of local samples while obtaining reliable predictions. In a study on a second-order Uganda watershed (~600 ha in size), he found that spiking a global library consisting of over 4000 soil samples from Africa, Asia, Europe, and America (with the vast majority from USA) by adding 10 to 206 or 418 local samples reduced prediction errors and often resulted in better predictions than using only local calibrations (about 206 or 418 samples). Sankey *et al.* (2008) also reported improved prediction results for clay content, organic and inorganic C using the same global calibration set spiked with local samples (52-234 samples) from three highly variable landscape study sites (~10-30 000 ha) in Montana, USA, compared with using the global or local calibrations alone.

Larger bias often arises when applying calibrations to soils with a different soil type than those in the calibration (e.g. Reeves *et al.*, 1999). One possible way of reducing this effect when using a large soil library could be to exclude soils with a different soil type from the soil of interest in the calibrations. For example, a so-called LOCAL algorithm first presented by Shenk *et al.* (1997) for predictions of haylage and maize grain selected the spectrally most similar samples for each unknown sample and computed sample-specific calibrations. Chang *et al.* (2001) used a similar approach for predictions of several soil properties in over 700 USA soils. However, to our knowledge there are no previous studies combining samples of local calibration sets (“spiking”) with a selection of spectrally similar samples of a national calibration set, nor spiking wider spectral libraries with local samples at the farm scale.

In the present study we focus on the farm scale, which is small (~100 ha) compared to those mentioned above and presumably much more homogenous. At least they are limited to agricultural soils. The objectives was to test i) if as few as 25 calibration samples at the farm scale (Wetterlind *et al.*, 2010) perform better than calibrations based on a larger national calibration set that we know produce stable calibrations for Clay and SOC (Stenberg, 2010), ii) if a site specific set selected from the national library, consisting of the 50 samples spectrally most similar to those of the local sites increase performance or reduce bias, and iii) if spiking the national library and the reduced national sets with up to the 25 local calibration samples would have any additional effect on prediction errors and bias. The calibrations were made for predicting within-field variation in clay, silt, sand, SOC, pH and ammonium acetate lactate-extractable phosphorus (P-AL).

Materials and methods

National library

The national soil library consisted of 396 samples representative of Swedish agricultural land collected between 1988 and 1995 (Fig. 1). Six to 20 subsamples from the topsoil (0-20 cm) representing an area of 10-20 m² were bulked to form a composite sample. Before further analyses, all samples were dried at 25-30 °C, crushed and passed through a 2 mm sieve (Eriksson *et al.*, 1997). Soil organic carbon (SOC) was analysed on finely ground

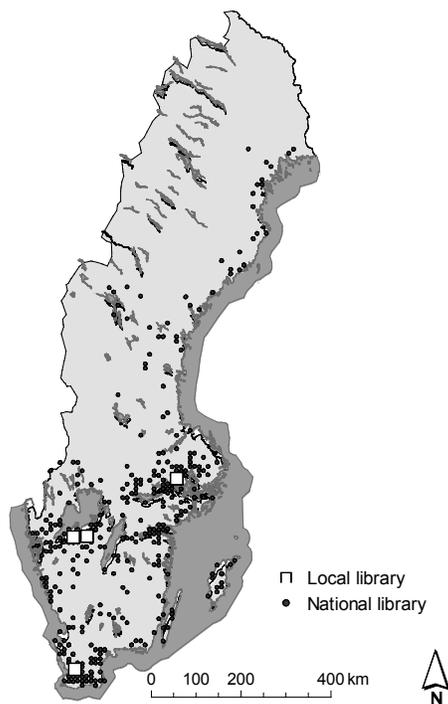


Fig. 1. The location of the local and national sample sets.

soil using a LECO CNS 700 elemental analyser. Soil texture was analysed by the sedimentation/pipette method according to Gee & Bauder (1986) and divided into clay < 0.002 mm, silt 0.002-0.06 mm and sand 0.06-2 mm. The pH was measured in deionised water at a soil:water volume ratio of 1:5 (SS-ISO 10 390) and ammonium acetate lactate-extractable phosphorus (P-AL) was analysed according to Egnér *et al.* (1960) (SS-02 83 10).

Local library

Four farms in the south of Sweden, representing three of the main agricultural areas, were used to create local farm-scale soil libraries (Fig. 1). The studied areas were on adjacent fields with a total area of 97 hectares at the farm Hacksta (59°33'N, 17°02'E), 78 hectares at the farm Sjöstorp (55°41'N, 13°19'E), 69 hectares at the farm Bränneberg (58°20'N, 13°4'E) and 62 hectares at the farm Kärtrorp (58°21'N, 13°36'E).

The soil sampling took place in autumn between the years 2005 and 2007. To guide sampling to cover as much of the general soil variation as possible soil electrical conductivity (EC_a) was recorded prior to sampling (Wetterlin *et al.*, 2010) with an EM38 (Geonics Ltd., Mississauga, Ontario, Canada). The conductivity measurements were carried out along transects parallel to the tramlines 10 m apart at Hacksta and Kärtrorp and 24 m apart at Bränneberg and Sjöstorp at a speed of about 15 km/h. Twenty-five soil samples at each farm were targeted according to the EC_a results. The targeting strategy involved selecting sampling sites based on the degree of variation in interpolated EC_a maps and is described in more detail in Wetterlin *et al.* (2010). Ten or 20 subsamples from the 0-20 cm soil layer within a radius of about 6 m were bulked to form a composite sample. Before all analyses the soil was air-dried and crushed to pass a 2 mm sieve. The chemical analyses for pH and P-AL were the same as for the national soil samples. The same particle size classes as for the national samples were used for defining the clay, silt and sand fractions, but the analytical methods differed to some extent. The clay content was analysed using a sedimentation method modified from Gee & Bauder (1986), the sand fraction was determined by sieving and the silt fraction was determined by difference. Soil organic carbon content was analysed through dry combustion at 900 °C with a Vario MAX analyzer (Elementar, Analysensysteme GmbH, Hanau, Germany).

Besides the 25 calibration samples, between 81 and 112 additional soil samples per farm, analysed as described above, were used as validation samples.

VisNIR measurements

Spectra were determined using a FieldSpec Pro FR scanning instrument (Analytical Spectral Devices Inc., Boulder, CO, USA, www.asdi.com). The instrument was equipped with a bare optic fibre connected to a probe with a 20W Al-coated halogen tungsten light source placed 7 cm over the sample, resulting in a field of view of ~ 7.5 cm². Reflectance spectra were recorded in relation to an external white reference (Spectralon) and each soil sample spectrum comprised 100 averaged spectra collected from a rotating sample. The resulting total area analysed was about 50 cm². The spectral range covered both the visible and the near infrared regions (VisNIR), 350-2500 nm, sampled at 1.4-2 nm intervals with a spectral resolution of 3-10 nm. A wavelength interval of 1 nm was interpolated to the instrument output file, resulting in spectra consisting of 1 data point every nm.

Reduced national library

In order to take advantage of the large national library but at the same time use the samples that resembled the different farms most closely, one subset consisting of the 50 samples spectrally most similar to each farm was selected from the national library. The assumption was that similar VisNIR spectra indicate similar soil properties. In practice the similarity was estimated from PCA scores. The selection was initialised by a principal component analysis (PCA) on the national library with Unscrambler 9.7 (CAMO PROCESS AS, Oslo, Norway). Using this PCA model, scores for the four farms (both calibration and validation samples) were calculated with the passive projection function in Unscrambler 9.8. That is, the local samples did not influence the national library PCA, but their scores were predicted by the national PCA model from the local samples visNIR spectra. The similarity between scores from the first six principal components (PCs) for all samples in the national library and the predicted scores for each of the four farms were estimated in Scilab 5.0.3 (www.scilab.org). The algorithm calculated the mean and standard deviation in multivariate space for each farm and the 50 national samples closest to the means were selected. This was done for the highest number of PCs where at least 30 of the 50 samples were within a distance of two standard deviations from the mean, never using less than two PCs.

Calibrations

All VisNIR data and statistics analyses were carried out using the Unscrambler 9.7. The recorded VisNIR spectra were transformed to apparent absorbance by $\log(1/\text{reflectance})$ and each spectrum was transformed by first-order derivative and smoothed by a second order polynomial in segments of 21-points (Savitzky & Golay, 1964). The shortest wavelengths were excluded due to excessive noise and the calibrations were made on the 460-2490 nm wavelengths. Removing the 1900 nm water peak (1840-1941 nm) improved the calibration results and was therefore applied for all calibrations.

Calibration models were established for clay, silt, sand and SOC content, pH and P-AL using partial least squares (PLS) regression (Martens & Naes, 1989). Calibrations were made for the four local libraries, the national library and the four reduced national libraries. In addition, the national and the reduced national libraries were spiked by augmenting 5, 10, 15, 20 and all 25 samples from the local library and recalibrated. The

samples were included in the same order as they were selected according to their EC_a value (see Local library), which, because of the selection method used, meant that most of the range in EC_a values was already included in the first samples. Cross-validation with 25 randomly selected segments was used to determine the optimum number of PLS factors included in the calibrations by minimization of the RMSECV.

The calibration models were validated at each farm using 81 (Sjöstorp), 94 (Bränneberg), 103 (Kärrtorp) and 112 (Hacksta) independent validation samples. The validations were evaluated by the R^2 value of the relationship between the VisNIR estimate of the soil property and the reference measurement, the root mean squared error of prediction (RMSEP) and bias-corrected SEP. The relationships between RMSEP, SEP and bias are presented in equations 1-3:

$$RMSEP = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{n}} \quad (1)$$

$$Bias = \frac{\sum_{i=1}^n (\hat{y}_i - y_i)}{n} \quad (2)$$

$$SEP = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_i - y_i - Bias)^2}{n-1}} \quad (3)$$

where \hat{y} is the predicted value and y is the measured value for sample i , with n number of samples.

The ratio of performance to deviation (RPD) was calculated mainly for comparison of calibration performance between parameters. It was calculated as the standard deviation (s.d.) of the validation set divided by the RMSEP (Williams, 1987). The RPD is commonly used for relating the prediction error to the variation in the data and a handful of attempts have been made to define a good prediction of soil parameters. For example Chang *et al.* (2001) divides prediction results into three classes with i) good predictions as RPD>2.0 and R^2 >0.8; ii) predictions with potential as RPD ~1.4-2.0 and R^2 of 0.50-0.80; and iii) unreliable predictions as RPD<1.4 and R^2 <0.5. This may serve as a guideline, but it is always important not to look too exclusively at a single measurement. Whether the prediction errors are sufficiently low for practical use has to be determined in each situation.

Results

Descriptive statistics on the soil properties for the different calibration and validation sets of the samples conventionally analysed in the laboratory are shown in Table 1. Bränneberg and Hacksta have soils that are rather typical for the agricultural plains of Sweden, with higher clay content than the sandy soils of Kärrtorp and Sjöstorp. A boundary between two different types of glacial till soil divided Sjöstorp into one 60 ha part with clay till and one 18 ha part with sandy till. The lowest variation in soil texture and SOC were found at Bränneberg, whereas Kärrtorp for example varied greatly in

Table 1. Results from conventional laboratory analysis of soil properties for the different calibration and validation sets

	National	Bränneberg			Hacksta			Kärrtorp			Sjöstorp		
		Local	RN ^a	Val ^b	Local	RN	Val	Local	RN	Val	Local	RN	Val
Clay/%													
n ^c	396	25	50	61	25	50	112	24	50	65	25	50	81
min.	0	41	4	37	22	16	25	20	0	11	12	4	12
max.	75	59	71	58	62	71	66	34	24	34	48	64	52
mean	26	46	32	45	49	44	46	28	7	28	27	27	24
s.d. ^d	20	4	17	5	8	13	8	4	5	5	11	13	9
Silt/%													
n	396	25	50	61	25	50	112	24	50	65	25	50	81
min.	2	36	19	36	28	17	25	26	8	17	19	14	13
max.	79	51	72	56	49	58	58	48	68	43	38	65	38
mean	36	46	42	48	38	39	39	35	29	33	27	35	29
s.d.	16	5	13	5	6	9	6	6	14	4	4	10	4
Sand/%													
n	396	25	50	61	25	50	112	24	50	65	25	50	81
min.	1	4	3	4	2	1	2	22	24	27	14	3	12
max.	98	17	70	16	47	54	43	54	91	72	65	82	73
mean	38	7	26	7	13	17	15	37	65	40	46	38	47
s.d.	26	3	17	2	10	12	9	8	16	7	14	18	12
SOC/%													
n	396	25	50	58	25	50	112	24	50	65	25	50	81
min.	0.4	1.7	0.8	1.8	1.4	0.9	1.3	3.4	0.7	3.1	1.3	0.9	1.2
max.	6.9	2.8	6.2	2.8	4.1	5.5	4.5	9.3	6.9	8.2	3.3	6.2	3.4
mean	3.0	2.4	2.9	2.3	2.4	2.3	2.3	4.9	3.7	4.2	1.9	2.2	1.8
s.d.	1.6	0.3	1.3	0.2	0.6	1.1	0.6	1.7	1.6	0.8	0.5	1.1	0.4
pH													
n	396	25	50	94	25	50	112	24	50	103	25	50	81
min.	4.7	6.5	5.3	6.4	6.4	5.5	5.9	5.6	4.9	5.5	6.3	5.4	6.1
max.	8.7	7.0	8.1	7.1	6.8	7.9	7.6	6.8	7.7	7.1	7.8	8.1	7.8
mean	6.4	6.8	6.3	6.9	6.6	6.5	6.6	6.2	6.2	6.5	6.9	6.6	6.9
s.d.	0.7	0.1	0.6	0.1	0.1	0.6	0.2	0.3	0.7	0.3	0.4	0.6	0.4
P-AL/mg 100g⁻¹													
n	389	25	50	94	25	49	112	24	50	103	25	50	81
min.	1.8	1.1	1.8	1.3	2.3	2.2	2.1	1.8	2.4	1.2	5.3	1.9	3.5
max.	29	19	25	6.8	21	29	43	10	26	26	24	25	30
mean	9.8	3.8	8.0	3.3	7.5	9.5	8.8	4.0	11	4.4	12	9.5	10
s.d.	6.0	3.3	5.2	1.1	4.5	6.7	6.6	1.9	5.6	3.6	5.3	6.3	5.6

^a Reduced national calibration set

^b Validation set

^c Number of samples

^d Standard deviation

SOC. The highest SOC content was found at Kärrtorp, with higher SOC content in some of the validation samples than could be found in the national library. One of the 25 local calibration samples at Kärrtorp was identified as an outlier and excluded from further

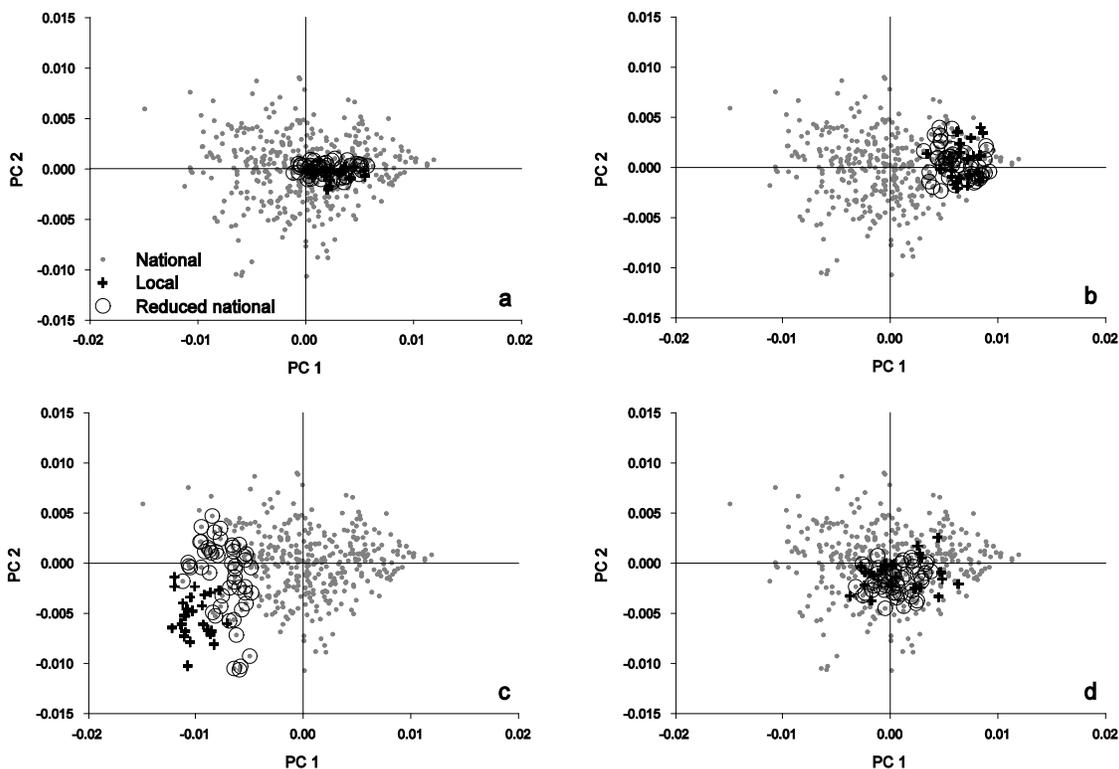


Fig. 2. Score plots for the two first principal components in a principal component analysis (PCA) for the national data set, reduced national data set and 25 projected local samples at a) Bränneberg, b) Hacksta, c) Kärtrorp and d) Sjöstorp.

analyses due to its very high SOC content. For phosphorus, only seven of the 396 national samples had P-AL content over $30 \text{ mg } 100\text{g}^{-1}$ and these were not included in the P-AL calibrations. At Hacksta, the 50 reduced national calibration samples included one sample with a P-AL content over $30 \text{ mg } 100\text{g}^{-1}$ which was excluded from the P-AL calibrations. Notably, some of the validation samples at Hacksta had P-AL of over $30 \text{ mg } 100 \text{ g}^{-1}$ but were kept in the validation. The local libraries covered the range of the validation samples for most of the soil properties at the four farms. Exceptions were pH, the highest P-AL values at Hacksta and the lowest clay and silt and highest sand and P-AL values at Kärtrorp.

The differences in overall soil variation at the four farms according to their VisNIR spectra can be seen in Fig. 2, which shows the score plots for the first two principal components (PC) for the 25 local samples together with the national library and the reduced national data set for the different farms. While three of the farms were projected well within the sample space of the national samples, only a few samples from Kärtrorp overlapped the national samples in the first two PCs. It is also noticeable that the relatively small farm sites are distributed over a large proportion of the scores of the national library, especially for the diverse Sjöstorp site, but also for the homogenous Bränneberg site. Due to the relatively small number of national samples, only two or three PCs were used in the selection of the four reduced national libraries (two at Kärtrorp and Bränneberg and three at Hacksta and Sjöstorp). The variation in the national

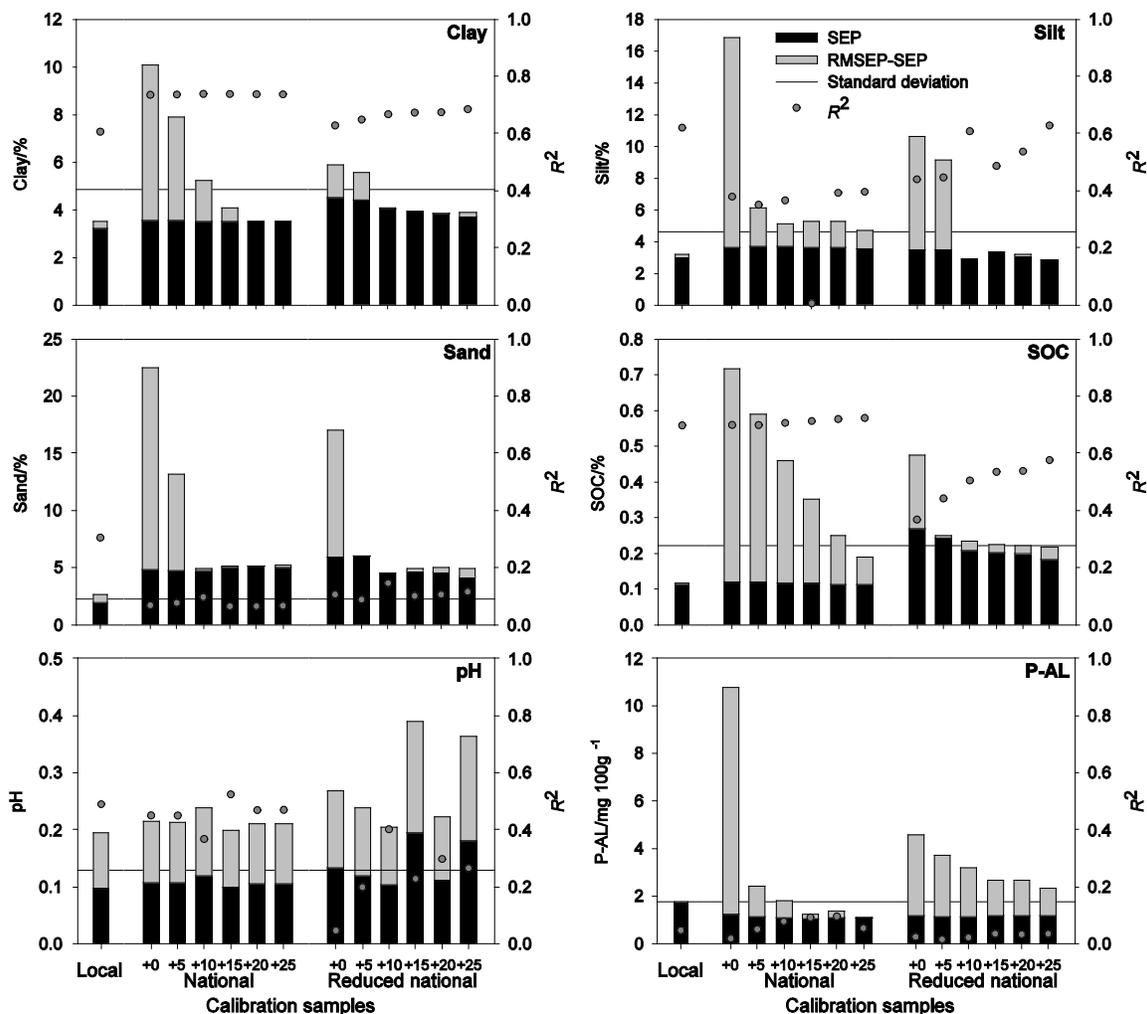


Fig. 3. Bränneberg: Prediction results for the local, national, spiked national, reduced national and spiked reduced national calibrations.

library was explained to 77% by two PCs and to 87% by three. Two PCs explained 80% of the variation at Kärtrorp, but only 52% of the variation at Bränneberg. At Hacksta and Sjöstorp, three PCs explained 85% and 90% of the variation, respectively. The distribution in the different soil parameters in the reduced national libraries resembled best to the corresponding local sample set at Hacksta and second best at Sjöstorp (Table 1).

Local calibrations

Prediction results for all four farms are shown in Figs. 3-10 and Tables 2-5. As could be expected, clay and SOC content were generally best predicted. At Hacksta and Sjöstorp, sand was also predicted with high R^2 values and low RMSEP values (Figs. 4 and 6). P-AL was best predicted at Sjöstorp, with R^2 values of about 0.6. However, RMSEP values were high compared with the standard deviation (RPD = 1.2). The best predictions of pH were also found for Sjöstorp, with R^2 values of 0.7 and RPD values of 1.6 at best.

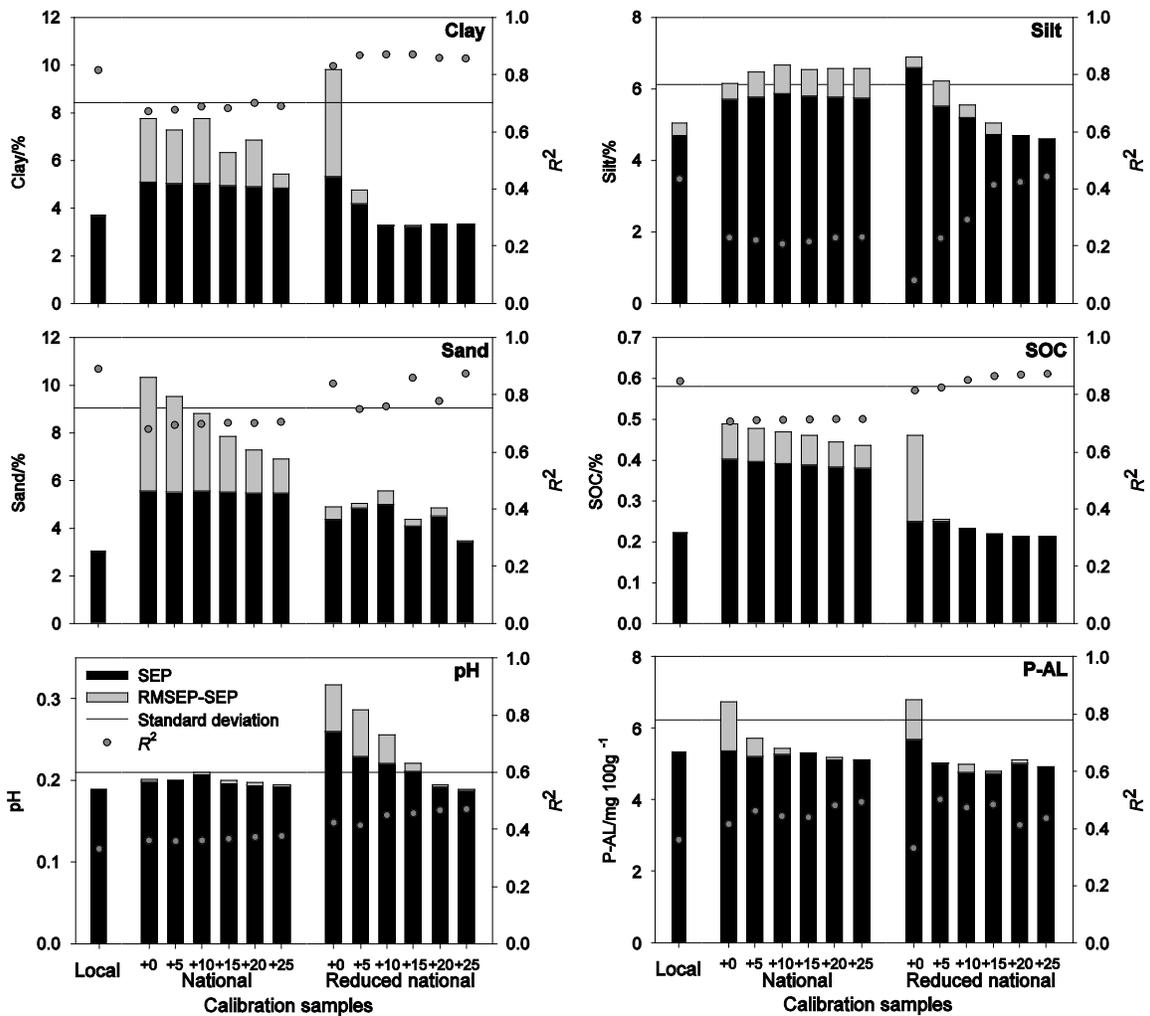


Fig. 4. Hacksta: Prediction results for the local, national, spiked national, reduced national and spiked reduced national calibrations

The predictions for silt at Bränneberg were almost as good as for clay, at least for the local calibration and for the spiked reduced national calibrations. The VisNIR calibrations failed to predict silt at the other farms.

Local versus national calibrations

In general, the lowest RMSEP values were obtained using the local calibrations. The national or reduced national calibrations without local samples did not manage to predict the within-field variation with lower RMSEP values than the local calibrations at any farm. However, calibrations on national or reduced national libraries spiked with local samples often reduced the RMSEP values to the same level as the local calibrations or, mainly in the case of clay and SOC, to an even lower level. The lower RMSEP values obtained when local samples were included in the national and reduced national calibrations were mainly due to a reduction in bias, as can be seen in Figs. 3-6 and 7-10 respectively.

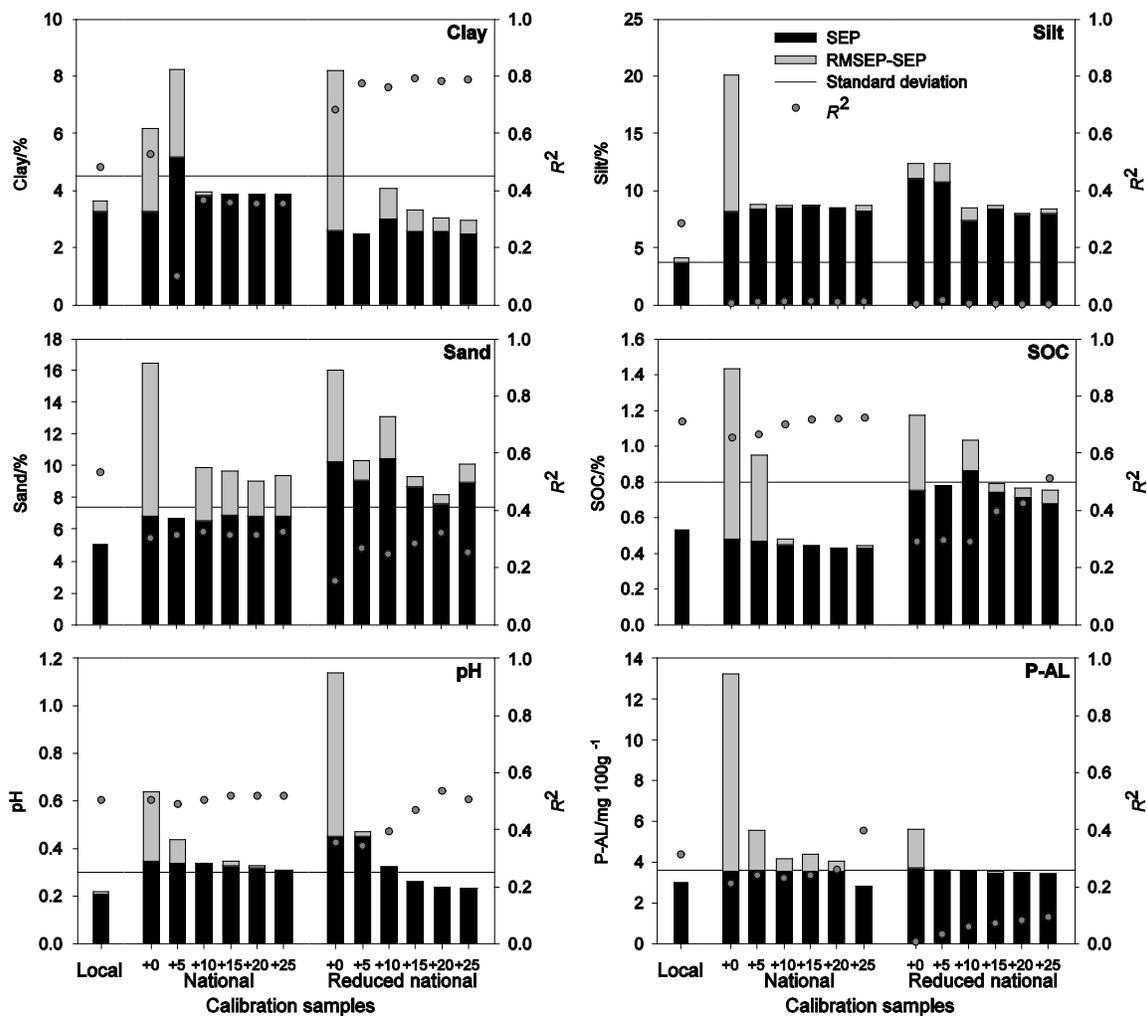


Fig. 5. Kärtrorp: Prediction results for the local, national, spiked national, reduced national and spiked reduced national calibrations

National versus reduced national calibrations

At Hacksta, using the spiked reduced national library resulted in better predictions than the spiked national library for clay, silt, sand and SOC content (Fig. 4), with higher R^2 values and lower RMSEP values. The predictions for clay content were also improved at Kärtrorp and to some extent at Sjöstorp when using the spiked reduced national calibrations (Figs. 5 and 6, Tables 4 and 5). At Sjöstorp there was also some improvement in prediction results for SOC content. At Kärtrorp, the corresponding predictions for pH resulted in lower RMSEP values compared with using the entire spiked national library. However, in this case the R^2 values were not improved. At Bränneberg the predictions for silt were the only values that improved when the spiked national library was used (Fig. 3).

Discussion

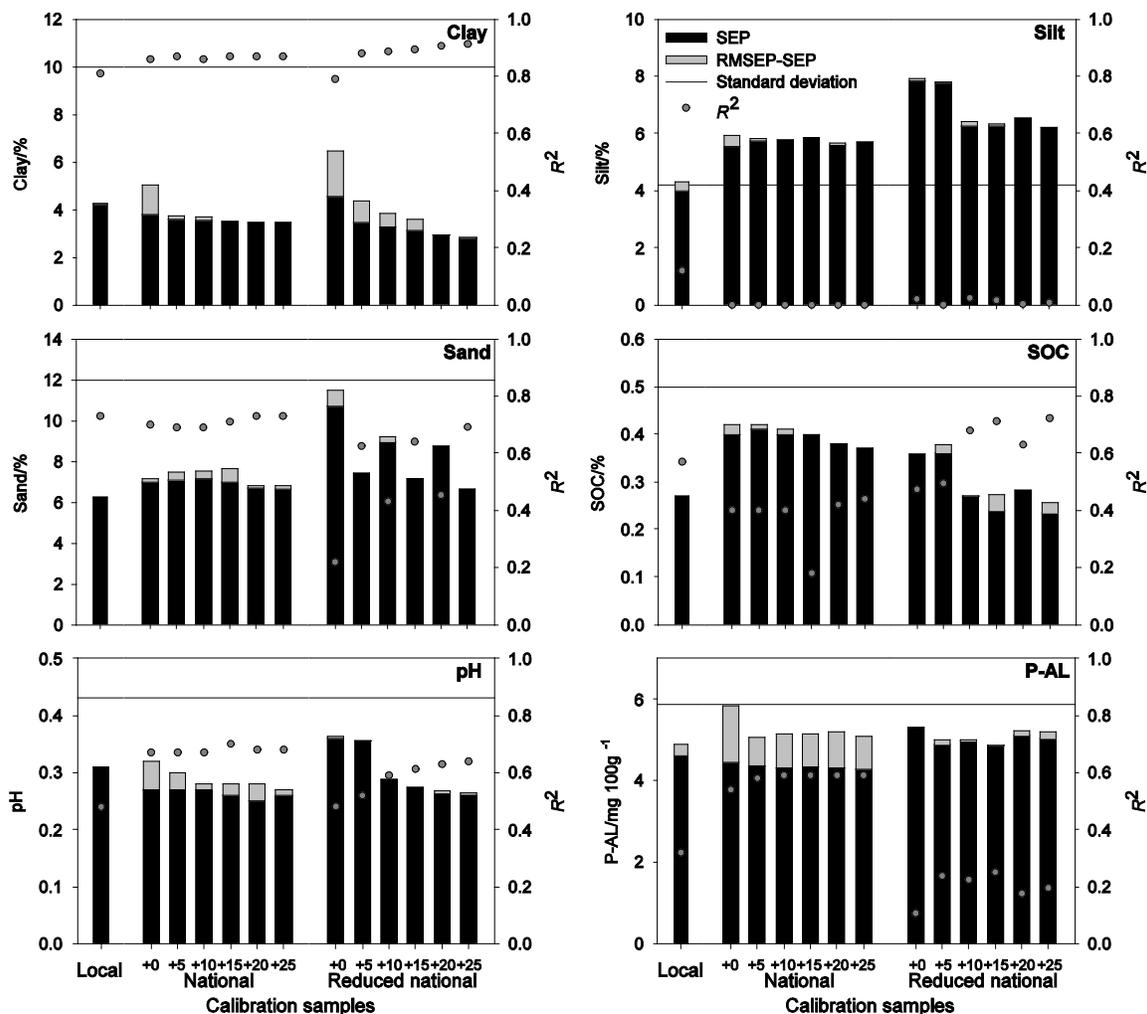


Fig. 6. Sjöstop: Prediction results for the local, national, spiked national, reduced national and spiked reduced national calibrations.

The best predictions were generally achieved for clay and SOC, which are also soil properties that are commonly well predicted with NIR spectroscopy (Chang *et al.*, 2001; Shepherd & Walsh, 2002; Sørensen & Dalsgaard, 2005; Viscarra Rossel *et al.*, 2006). Of the three textural classes, clay was best predicted, followed by varying results for sand and no good predictions for silt. This order of accuracy of prediction is common in studies including all three textural classes, although better predictions are sometimes obtained for sand and silt than those presented in this study (Malley *et al.*, 2000; Islam *et al.*, 2003; Moron & Cozzolino, 2003; McCarty & Reeves, 2006). As expected clay is better predicted due to the spectral signatures of the clay minerals typically dominating the NIR-spectra (Stenberg *et al.*, 2010). The sand fractions mainly consist of quartz and feldspars which are relatively featureless and have a high reflectance in the visNIR (Hunt & Salisbury, 1970). Sand can therefore be assumed to be predicted mainly as a mirror image of clay. The silt fraction can be assumed to be a mixture of sand and clay minerals and is therefore difficult to distinguish in the visNIR.

Table 2. Bränneberg: Prediction results for the independent validation samples using local, national, spiked national, reduced national and spiked reduced national calibrations

	Local	National						Reduced national					
		+0	+5	+10	+15	+20	+25	+0	+5	+10	+15	+20	+25
Clay/%													
PC ^a	3	7	7	7	7	7	7	6	6	6	6	6	6
R ²	0.61	0.74	0.74	0.74	0.74	0.74	0.74	0.63	0.65	0.67	0.67	0.67	0.68
RMSEP ^b	3.5	10.1	7.9	5.2	4.1	3.1	3.5	5.9	5.5	4.1	3.9	3.9	3.9
SEP ^c	3.2	3.5	3.6	3.5	3.5	3.5	3.5	4.5	4.4	4.0	3.9	3.8	3.7
Bias	1.5	-9.4	-7.1	-3.9	-2.1	-0.6	0.1	-3.8	-3.4	-0.9	0.0	0.7	1.2
RPD ^d	1.3	0.5	0.6	0.9	1.2	1.5	1.4	1.0	1.1	1.5	1.5	1.6	1.5
Silt/%													
PC	3	10	10	10	10	10	10	2	2	9	7	9	9
R ²	0.62	0.38	0.35	0.37	0.00	0.39	0.40	0.44	0.45	0.61	0.49	0.54	0.63
RMSEP	3.2	17	6.1	5.1	5.2	5.3	4.7	11	9.1	2.9	3.3	3.1	2.8
SEP	3.0	3.6	3.7	3.6	3.6	3.6	3.6	3.5	3.5	2.9	3.3	3.1	2.8
Bias	-1.1	-17	-4.9	-3.6	-3.8	-3.9	-3.1	-10	-8.4	-0.2	0.1	-0.5	-0.3
RPD	1.4	0.3	0.7	0.9	0.9	0.9	1.0	0.4	0.5	1.6	1.4	1.5	1.6
Sand/%													
PC	10	8	8	10	9	9	9	10	9	11	9	9	9
R ²	0.30	0.07	0.08	0.10	0.06	0.06	0.07	0.11	0.09	0.15	0.10	0.10	0.11
RMSEP	2.6	22.5	13.1	4.9	5.1	5.1	5.2	17.0	6.0	4.5	4.9	5.0	4.9
SEP	1.9	4.8	4.7	4.7	5.0	5.1	5.0	5.9	6.0	4.5	4.7	4.6	4.2
Bias	-1.8	22.0	12.2	1.6	1.0	0.8	1.3	15.9	1.2	-0.4	-1.4	-2.0	-2.6
RPD	0.8	0.1	0.2	0.4	0.4	0.4	0.4	0.1	0.4	0.5	0.5	0.4	0.4
SOC/%													
PC	3	8	8	8	8	8	8	10	10	11	11	11	11
R ²	0.70	0.70	0.70	0.71	0.71	0.72	0.72	0.37	0.44	0.50	0.53	0.54	0.58
RMSEP	0.12	0.72	0.59	0.46	0.35	0.25	0.19	0.48	0.25	0.23	0.22	0.22	0.22
SEP	0.11	0.12	0.12	0.12	0.12	0.11	0.11	0.27	0.24	0.21	0.20	0.20	0.18
Bias	0.03	-0.71	-0.58	0.12	-0.33	-0.22	-0.15	-0.39	0.07	0.11	0.10	0.10	0.12
RPD	1.9	0.3	0.4	0.5	0.6	0.9	1.1	0.5	0.9	0.9	1.0	1.0	1.0
pH													
PC	3	15	15	16	14	15	15	1	1	2	16	2	18
R ²	0.49	0.45	0.45	0.37	0.52	0.47	0.47	0.05	0.20	0.40	0.23	0.30	0.27
RMSEP	0.10	0.25	0.14	0.16	0.11	0.15	0.12	0.46	0.37	0.15	0.20	0.12	0.22
SEP	0.10	0.11	0.11	0.12	0.10	0.11	0.11	0.13	0.12	0.10	0.20	0.11	0.18
Bias	-0.03	0.23	0.09	0.10	0.04	0.11	0.06	-0.44	-0.35	-0.11	0.04	-0.04	0.12
RPD	1.33	0.53	0.97	0.86	1.28	0.90	1.13	0.29	0.36	0.89	0.68	1.12	0.62
P-AL/mg 100g⁻¹													
PC	8	10	8	7	7	7	8	1	1	1	1	1	1
R ²	0.05	0.02	0.05	0.08	0.09	0.10	0.06	0.02	0.02	0.02	0.04	0.03	0.04
RMSEP	1.8	11	2.5	1.8	1.2	1.4	1.1	4.6	3.7	3.2	2.7	2.7	2.4
SEP	1.7	1.2	1.1	1.1	1.1	1.1	1.1	1.2	1.2	1.2	1.2	1.2	1.2
Bias	0.4	11	2.2	1.5	0.6	0.9	0.2	4.4	3.5	3.0	2.4	2.4	2.0
RPD	1.0	0.2	0.7	1.0	1.4	1.3	1.6	0.4	0.5	0.6	0.7	0.7	0.8

^a Number of PLS components used.

^b Root-mean-squared error of prediction.

^c Bias-corrected squared error of prediction.

^d Ratio of performance to deviation (standard deviation divided by RMSEP).

Table 3. Hacksta: Prediction results for the independent validation samples using local, national, spiked national, reduced national and spiked reduced national calibrations

	Local	National						Reduced national					
		+0	+5	+10	+15	+20	+25	+0	+5	+10	+15	+20	+25
Clay/%													
PC ^a	8	7	7	6	7	6	7	10	10	10	10	10	10
R ²	0.82	0.67	0.68	0.69	0.68	0.70	0.69	0.83	0.87	0.87	0.87	0.86	0.86
RMSEP ^b	3.7	7.7	7.3	7.7	6.3	6.9	5.4	9.8	4.8	3.3	3.3	3.3	3.3
SEP ^c	3.7	5.1	5.0	5.0	5.0	4.9	4.9	5.3	4.2	3.3	3.2	3.3	3.3
Bias	0.7	-5.9	-5.3	-5.9	-3.9	-4.9	-2.4	-8.3	-2.3	0.5	0.6	0.0	-0.1
RPD ^d	2.3	1.1	1.2	1.1	1.3	1.2	1.6	0.9	1.8	2.6	2.6	2.6	2.5
Silt/%													
PC	3	10	10	10	10	10	10	2	2	2	2	4	4
R ²	0.43	0.23	0.22	0.21	0.22	0.23	0.23	0.08	0.23	0.29	0.41	0.42	0.44
RMSEP	5.0	6.2	6.5	6.6	6.5	6.6	6.6	6.9	6.2	5.5	5.0	4.7	4.6
SEP	4.7	5.7	5.8	5.9	5.8	5.8	5.8	6.6	5.5	5.2	4.7	4.7	4.6
Bias	-1.9	-2.4	-3.0	-3.2	-3.1	-3.2	-3.2	2.1	2.9	1.9	1.8	-0.4	-0.4
RPD	1.2	1.0	0.9	0.9	0.9	0.9	0.9	0.9	1.0	1.1	1.2	1.3	1.3
Sand/%													
PC	9	11	11	11	11	11	11	7	3	3	9	3	10
R ²	0.89	0.68	0.69	0.70	0.70	0.70	0.70	0.84	0.75	0.76	0.86	0.78	0.87
RMSEP	3.0	10.3	9.5	8.8	7.8	7.3	6.9	4.9	5.1	5.5	4.4	4.8	3.5
SEP	3.0	5.6	5.5	5.6	5.5	5.5	5.4	4.4	4.8	5.0	4.1	4.5	3.4
Bias	0.6	8.7	7.8	5.6	5.6	4.9	4.3	2.2	1.6	2.5	1.6	1.8	0.5
RPD	3.0	0.9	0.9	1.0	1.2	1.2	1.3	1.9	1.8	1.6	2.1	1.9	2.6
SOC/%													
PC	6	8	8	8	8	8	8	9	10	10	10	10	10
R ²	0.85	0.71	0.71	0.71	0.71	0.71	0.71	0.81	0.82	0.85	0.86	0.87	0.87
RMSEP	0.22	0.49	0.48	0.47	0.46	0.44	0.44	0.46	0.26	0.23	0.22	0.21	0.21
SEP	0.22	0.40	0.40	0.39	0.39	0.38	0.38	0.25	0.25	0.23	0.22	0.21	0.21
Bias	0.03	-0.28	-0.27	-0.26	-0.25	-0.23	-0.21	-0.39	-0.06	0.01	0.01	0.02	0.02
RPD	2.6	1.2	1.2	1.2	1.3	1.3	1.3	1.2	2.3	2.5	2.7	2.7	2.7
pH													
PC	8	14	14	15	14	14	14	8	8	8	8	8	8
R ²	0.33	0.36	0.36	0.36	0.37	0.37	0.38	0.42	0.41	0.45	0.46	0.47	0.47
RMSEP	0.19	0.20	0.20	0.21	0.20	0.20	0.20	0.32	0.29	0.26	0.22	0.19	0.19
SEP	0.19	0.20	0.20	0.21	0.20	0.20	0.19	0.26	0.23	0.22	0.21	0.19	0.19
Bias	-0.01	0.04	-0.01	0.03	-0.04	-0.03	-0.03	0.18	0.17	0.13	0.07	0.04	0.03
RPD	1.1	1.1	1.1	1.0	1.1	1.1	1.1	0.7	0.7	0.8	1.0	1.1	1.1
P-AL/mg 100g⁻¹													
PC	2	13	13	13	13	13	13	2	6	3	3	2	5
R ²	0.36	0.42	0.46	0.44	0.44	0.48	0.49	0.33	0.50	0.47	0.48	0.41	0.44
RMSEP	5.4	6.8	5.7	5.4	5.3	5.2	5.1	6.8	5.0	5.0	4.8	5.1	4.9
SEP	5.3	5.4	5.2	5.3	5.3	5.2	5.1	5.7	5.0	4.8	4.7	5.0	4.9
Bias	-0.8	4.1	2.4	1.5	0.5	0.5	0.4	3.8	0.5	1.5	0.9	1.1	0.2
RPD	1.2	0.9	1.1	1.1	1.2	1.2	1.2	0.9	1.2	1.2	1.3	1.2	1.3

^a Number of PLS components used

^b Root-mean-squared error of prediction.

^c Bias-corrected squared error of prediction.

^d Ratio of performance to deviation (standard deviation divided by RMSEP).

Table 4. Kärntorp: Prediction results for the independent validation samples using local, national, spiked national, reduced national and spiked reduced national calibrations

	Local	National						Reduced national					
		+0	+5	+10	+15	+20	+25	+0	+5	+10	+15	+20	+25
Clay/%													
PC ^a	2	6	8	7	7	7	7	5	4	4	5	4	4
R ²	0.5	0.5	0.1	0.4	0.4	0.4	0.4	0.7	0.8	0.8	0.8	0.8	0.8
RMSEP	3.6	6.2	8.2	4.0	3.9	3.9	3.9	8.2	2.5	4.0	3.3	3.0	3.0
SEP	3.3	3.3	5.2	3.8	3.9	3.9	3.9	2.6	2.5	3.0	2.6	2.6	2.5
Bias	1.6	-5.2	-6.4	-1.1	0.3	0.5	0.4	-7.8	-0.2	2.7	2.1	1.6	1.6
RPD	1.2	0.7	0.5	1.1	1.2	1.2	1.2	0.5	1.8	1.1	1.4	1.5	1.5
Silt/%													
PC	9	14	14	14	14	14	14	10	9	6	9	9	9
R ²	0.3	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.02	0.00	0.00	0.00	0.00
RMSEP	4.2	20	8.7	8.7	8.7	8.5	8.7	12	12	8.5	8.7	8.0	8.4
SEP	3.8	8.2	8.4	8.5	8.7	8.5	8.3	11.1	10.7	7.4	8.4	7.9	8.0
Bias	-1.9	-18.4	-2.6	2.1	1.3	0.7	2.8	-5.7	6.3	5.3	2.6	1.9	2.7
RPD	0.9	0.2	0.4	0.4	0.4	0.4	0.4	0.3	0.3	0.4	0.4	0.5	0.4
Sand/%													
PC	9	11	11	11	10	10	10	8	8	9	8	7	9
R ²	0.53	0.30	0.31	0.32	0.31	0.31	0.32	0.15	0.27	0.25	0.28	0.32	0.25
RMSEP	5.0	16.4	6.7	9.9	9.7	9.1	9.4	16.0	10.3	13.1	9.3	8.2	10.1
SEP	5.1	6.8	6.7	6.5	6.9	6.8	6.8	10.3	9.1	10.5	8.7	7.6	9.0
Bias	0.1	15.0	0.8	-7.5	-6.9	-6.0	-6.6	12.4	-5.0	-7.9	-3.6	-3.2	-4.8
RPD	1.5	0.4	1.1	0.7	0.8	0.8	0.8	0.5	0.7	0.6	0.8	0.9	0.7
SOC/%													
PC	9	8	8	8	8	8	8	8	8	8	7	8	9
R ²	0.71	0.65	0.67	0.70	0.72	0.72	0.72	0.29	0.30	0.29	0.40	0.42	0.51
RMSEP	0.53	1.43	0.95	0.48	0.44	0.43	0.44	1.17	0.77	1.03	0.79	0.76	0.75
SEP	0.53	0.48	0.47	0.45	0.44	0.43	0.43	0.75	0.78	0.87	0.75	0.72	0.68
Bias	0.07	-1.35	-0.83	-0.18	-0.06	-0.04	0.11	-0.90	0.05	0.57	0.27	0.26	0.33
RPD	1.5	0.6	0.9	1.7	1.9	1.9	1.9	0.7	1.1	0.8	1.0	1.1	1.1
pH													
PC	7	16	14	16	16	16	16	17	13	18	12	14	14
r ²	0.50	0.50	0.49	0.50	0.52	0.52	0.52	0.35	0.34	0.39	0.47	0.54	0.51
RMSEP	0.22	0.64	0.44	0.34	0.35	0.33	0.31	1.14	0.47	0.32	0.26	0.24	0.23
SEP	0.21	0.35	0.34	0.34	0.33	0.32	0.31	0.45	0.45	0.32	0.26	0.24	0.23
Bias	-0.06	0.54	0.27	0.06	0.12	0.09	0.03	1.05	0.14	0.02	-0.03	0.01	-0.03
RPD	1.4	0.5	0.7	0.9	0.9	0.9	1.0	0.3	0.6	0.9	1.1	1.3	1.3
P-AL/mg 100g⁻¹													
PC	7	13	14	13	14	15	8	1	2	1	1	1	1
R ²	0.31	0.21	0.24	0.23	0.24	0.26	0.40	0.01	0.03	0.06	0.07	0.08	0.09
RMSEP	3.0	13.2	5.6	4.2	4.4	4.1	2.9	5.6	3.6	3.5	3.5	3.5	3.4
SEP	3.0	3.6	3.6	3.6	3.6	3.6	2.9	3.7	3.6	3.6	3.5	3.5	3.5
Bias	0.3	12.7	4.3	2.2	2.5	1.9	0.3	4.3	-0.6	0.2	0.5	0.3	0.1
RPD	1.2	0.3	0.6	0.9	0.8	0.9	1.3	0.6	1.0	1.0	1.0	1.0	1.1

^a Number of PLS components used

^b Root-mean-squared error of prediction.

^c Bias-corrected squared error of prediction.

^d Ratio of performance to deviation (standard deviation divided by RMSEP).

Table 5. Sjöstopr: Prediction results for the independent validation samples using local, national, spiked national, reduced national and spiked reduced national calibrations

	Local	National						Reduced national					
		+0	+5	+10	+15	+20	+25	+0	+5	+10	+15	+20	+25
Clay/%													
PC ^a	3	7	7	7	7	7	7	12	11	11	11	11	11
R ²	0.81	0.86	0.87	0.86	0.87	0.87	0.87	0.79	0.88	0.89	0.89	0.91	0.91
RMSEP ^b	4.3	5.0	3.8	3.7	3.5	3.5	3.4	6.4	4.4	3.9	3.6	3.0	2.8
SEP ^c	4.2	3.8	3.6	3.6	3.5	3.5	3.5	4.6	3.5	3.3	3.1	2.9	2.8
Bias	0.8	3.3	1.2	1.1	0.4	0.3	0.1	-4.6	-2.6	-2.1	-1.9	-0.4	-0.5
RPD ^d	2.4	2.0	2.7	2.7	2.9	2.9	2.9	1.6	2.3	2.6	2.8	3.4	3.6
Silt/%													
PC	1	10	10	12	12	10	12	10	12	9	11	13	13
R ²	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.02	0.02	0.00	0.01
RMSEP	4.3	5.9	5.8	5.8	5.8	5.6	5.7	7.9	7.8	6.4	6.3	6.5	6.2
SEP	4.0	5.6	5.7	5.8	5.8	5.6	5.7	7.8	7.8	6.3	6.2	6.5	6.2
Bias	-1.7	2.2	1.0	0.6	-0.2	0.9	-0.5	1.5	1.2	1.6	1.2	0.4	-0.2
RPD	1.0	0.7	0.7	0.7	0.7	0.7	0.7	0.5	0.5	0.7	0.7	0.6	0.7
Sand/%													
PC	4	11	11	11	11	10	10	10	13	13	12	12	13
R ²	0.73	0.70	0.69	0.69	0.71	0.73	0.73	0.22	0.63	0.43	0.64	0.45	0.69
RMSEP	6.2	7.2	7.5	7.5	7.7	6.8	6.8	11.5	7.4	9.2	7.1	8.7	6.6
SEP	6.2	7.0	7.1	7.1	7.0	6.7	6.7	10.7	7.4	9.0	7.1	8.8	6.7
Bias	0.0	1.7	2.6	2.5	3.2	1.4	1.7	4.4	-0.2	2.3	0.2	0.7	0.4
RPD	2.0	1.7	1.7	1.7	1.6	1.8	1.8	1.1	1.7	1.3	1.8	1.4	1.9
SOC/%													
PC	4	8	8	8	8	8	8	12	12	10	12	13	12
R ²	0.57	0.40	0.40	0.40	0.18	0.42	0.44	0.47	0.49	0.68	0.71	0.63	0.72
RMSEP	0.27	0.42	0.42	0.41	0.40	0.38	0.37	0.36	0.38	0.27	0.27	0.28	0.26
SEP	0.27	0.40	0.41	0.40	0.40	0.38	0.37	0.36	0.36	0.27	0.24	0.28	0.24
Bias	0.01	0.12	0.11	0.09	0.03	0.01	0.01	0.01	-0.12	-0.04	-0.13	-0.13	-0.10
RPD	1.9	1.2	1.2	1.2	1.3	1.3	1.4	1.4	1.3	1.8	1.8	1.8	1.9
pH													
PC	2	14	13	13	13	13	13	6	3	7	7	7	7
R ²	0.48	0.67	0.67	0.67	0.70	0.68	0.68	0.48	0.52	0.59	0.61	0.63	0.64
RMSEP	0.31	0.32	0.30	0.28	0.28	0.28	0.27	0.36	0.36	0.29	0.27	0.27	0.26
SEP	0.31	0.27	0.27	0.27	0.26	0.25	0.26	0.36	0.35	0.29	0.27	0.26	0.26
Bias	0.04	0.18	0.13	0.09	0.10	0.11	0.10	0.08	-0.05	0.02	0.04	0.05	0.05
RPD	1.4	1.3	1.4	1.5	1.5	1.5	1.6	1.2	1.2	1.5	1.6	1.6	1.6
P-AL/mg 100g⁻¹													
PC	2	9	9	9	9	9	9	2	4	6	6	6	6
R ²	0.32	0.54	0.58	0.59	0.59	0.59	0.59	0.11	0.24	0.22	0.25	0.18	0.20
RMSEP	4.9	5.8	5.1	5.1	5.1	5.2	5.1	5.3	5.0	5.0	4.9	5.2	5.2
SEP	4.6	4.5	4.4	4.3	4.3	4.3	4.3	5.3	4.9	5.0	4.9	5.1	5.0
Bias	1.7	3.8	2.6	2.8	2.8	2.9	2.8	0.3	-1.2	0.7	0.6	1.3	1.3
RPD	1.2	1.0	1.2	1.1	1.1	1.1	1.2	1.1	1.2	1.2	1.2	1.1	1.1

^a Number of PLS components used

^b Root-mean-squared error of prediction.

^c Bias-corrected squared error of prediction.

^d Ratio of performance to deviation (standard deviation divided by RMSEP).

The predictions for pH presented here are about what could be expected according to the literature, with RMSEP values well in line with earlier findings but with R^2 values amongst the lowest presented (Reeves *et al.*, 1999; He *et al.*, 2005; McCarty & Reeves, 2006; Viscarra Rossel *et al.*, 2006). This somewhat contradictory relationship is due to the very narrow distribution of pH at the four sites (Table 1) resulting in very low RPD-values. This is especially the case at Bränneberg and Hacksta. At Kärtrorp and Sjöstorp the variation is slightly higher, while the RPD-values and R^2 's are also slightly higher despite RMSEP-values being higher. The difficulties in predicting pH is in line with pH being predicted through secondary relationships to the visNIR (Stenberg *et al.*, 2010).

Predictions for P-AL suffer from the same problem as pH, not having direct features in the visNIR and having a modest variation in the present sites apart from a few very high values, and were not satisfactory in this study. Good prediction results have been presented in earlier reports though (Malley *et al.*, 1999; Daniel *et al.*, 2003; Maleki *et al.*, 2006). Unfortunately, a large variety of laboratory reference methods are used, making comparisons difficult.

Local versus national calibrations

The main difference between using the local calibrations and the unspiked larger national library for calibrations was a larger bias in the latter case, but for many soil properties R^2 values were also reduced (Figs. 3-6). However, these reductions in R^2 values were not consistent and in some cases, e.g. clay content at Bränneberg and Sjöstorp, using the national calibration models led to increased R^2 values. At Sjöstorp, one explanation for this could be that the two differing parts of the farm may have led to unreliable interpolations with as few as 25 samples, so a calibration including more samples could improve calibration results by better filling gaps.

Including local samples in the national libraries almost always improved the prediction results compared with using the unspiked libraries, confirming results presented by Brown (2007) and Sankey *et al.* (2008), also at the smaller more homogenous scale in the present study. The improvement was mainly expressed as a reduction in RMSEP values and only moderately in terms of enhanced R^2 values, which can mainly be attributed to the reduction in bias (Tables 2-5) as indicated by the difference between RMSEP and SEP in Figs. 3-6. The simple shift in intercept as a result of spiking samples to the larger national models is very clear in Figs. 7-10. The great reduction in root mean squared deviation (RMSD) for predictions of SOC in upland soil samples from a catchment in Uganda observed by Brown (2007) on adding local samples to a global library was also mainly attributed to a decrease in bias. A suggested explanation for this large improvement was a relative lack of highly weathered soils in the global library. However, there were only moderate reductions in RMSD for predictions of shallow wetland, "dambo", soils from the same area.

In the present study, spiked and recalibrated national models never resulted in substantially lower RMSEP values than using local calibrations alone. With a few examples of slight improvements and a few more with more or less equal results this

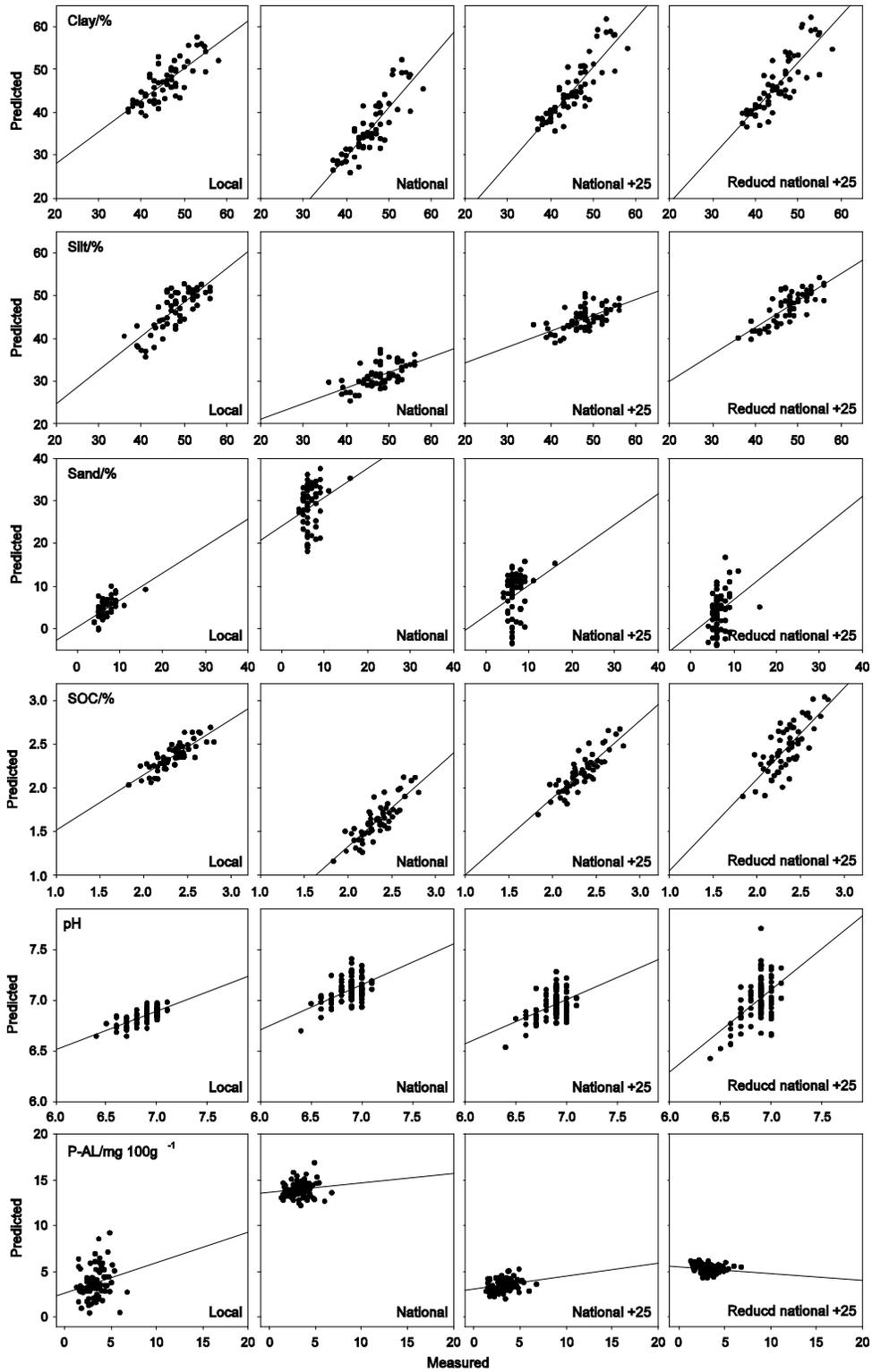


Fig. 7. Bränneberg: NIR-predicted versus laboratory-analysed clay, silt, sand and SOC content, pH and P-AL content using the local calibration, national calibration, national calibration spiked with 25 local samples or spiked reduced national calibration.

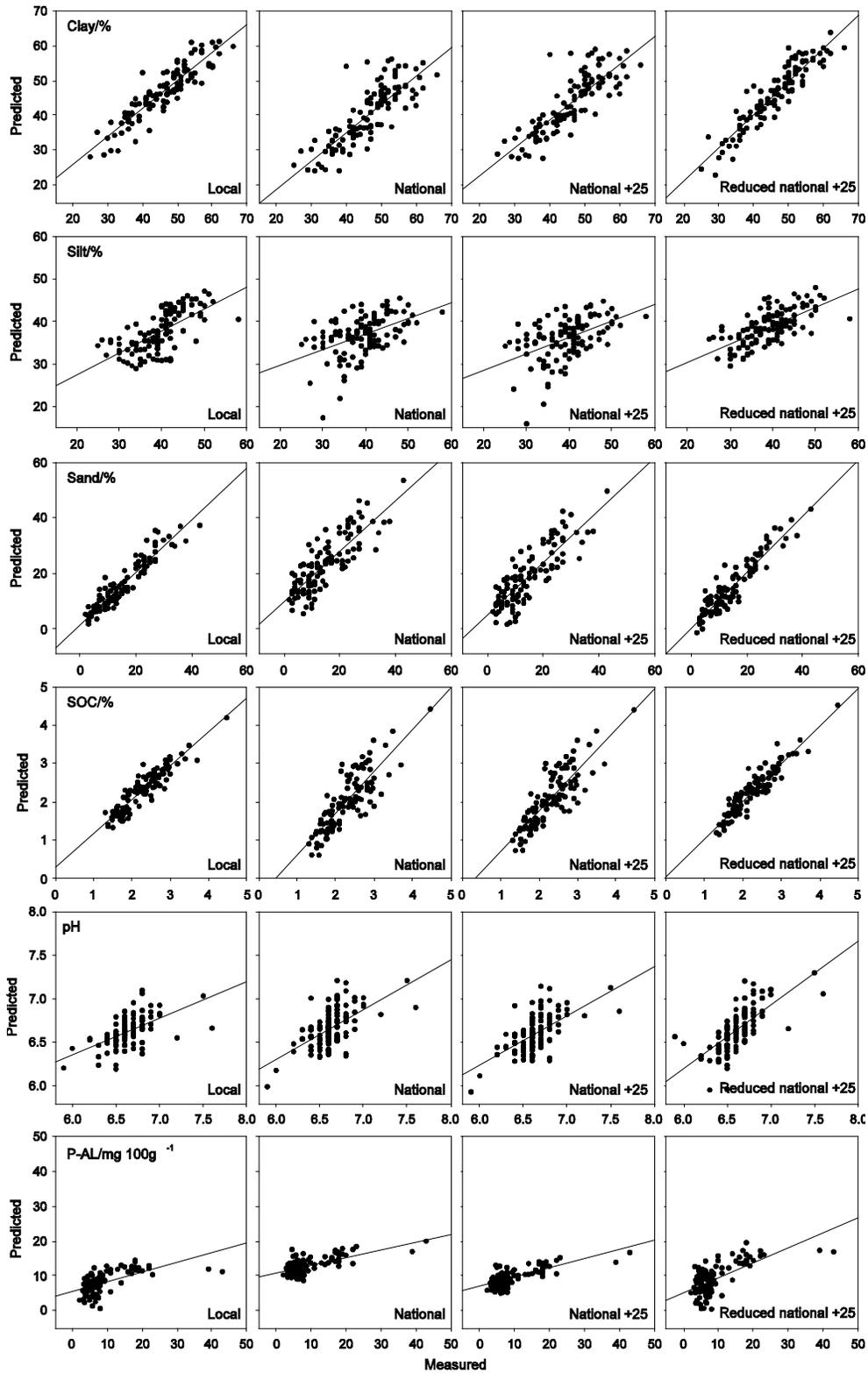


Fig. 8. Hacksta: NIR-predicted versus laboratory-analysed clay, silt, sand and SOC content, pH and P-AL content using the local calibration, national calibration, national calibration spiked with 25 local samples or spiked reduced national calibration.

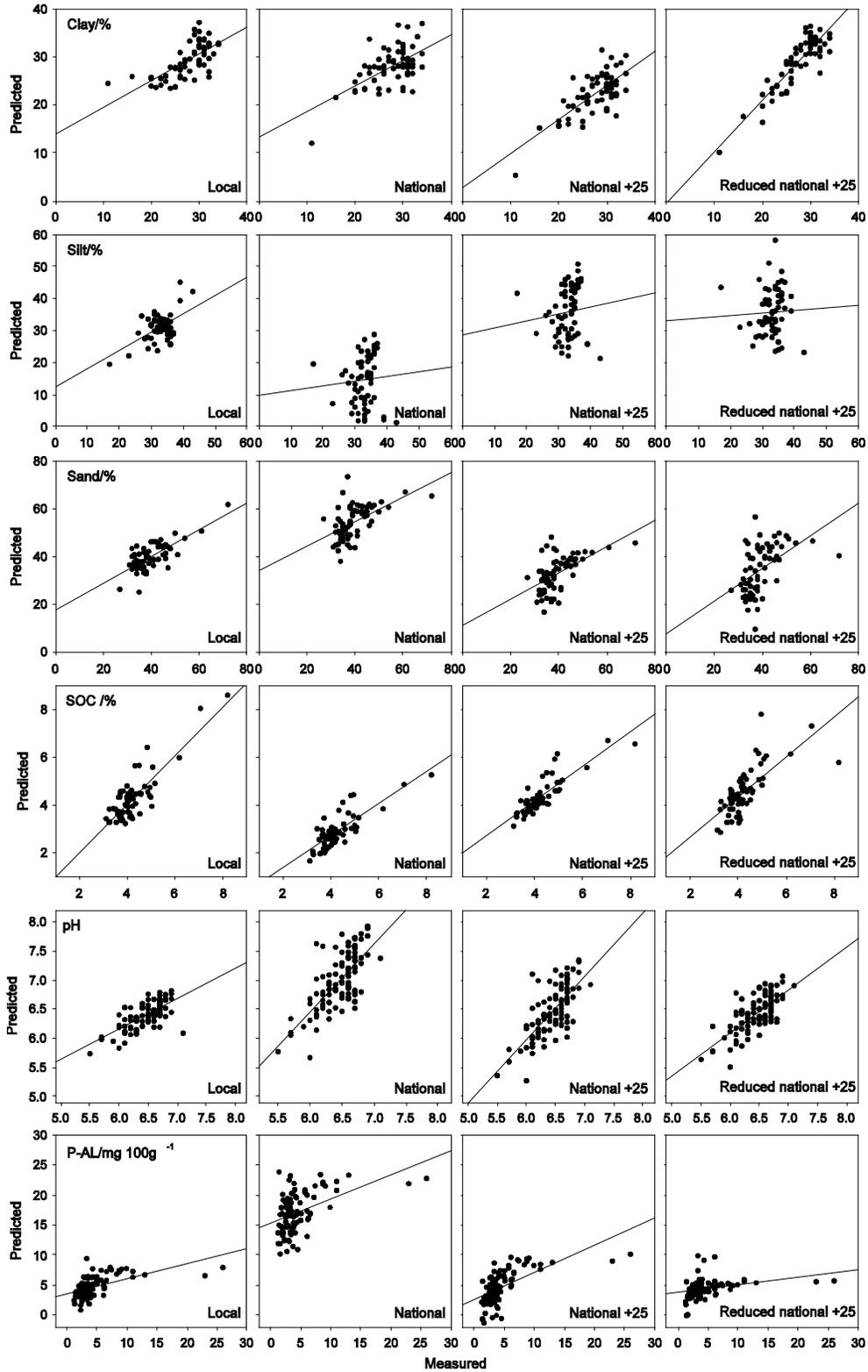


Fig. 9. Kärtrorp: NIR-predicted versus laboratory-analysed clay, silt, sand and SOC content, pH and P-AL content using the local calibration, national calibration, national calibration spiked with 25 local samples or spiked reduced national calibration.

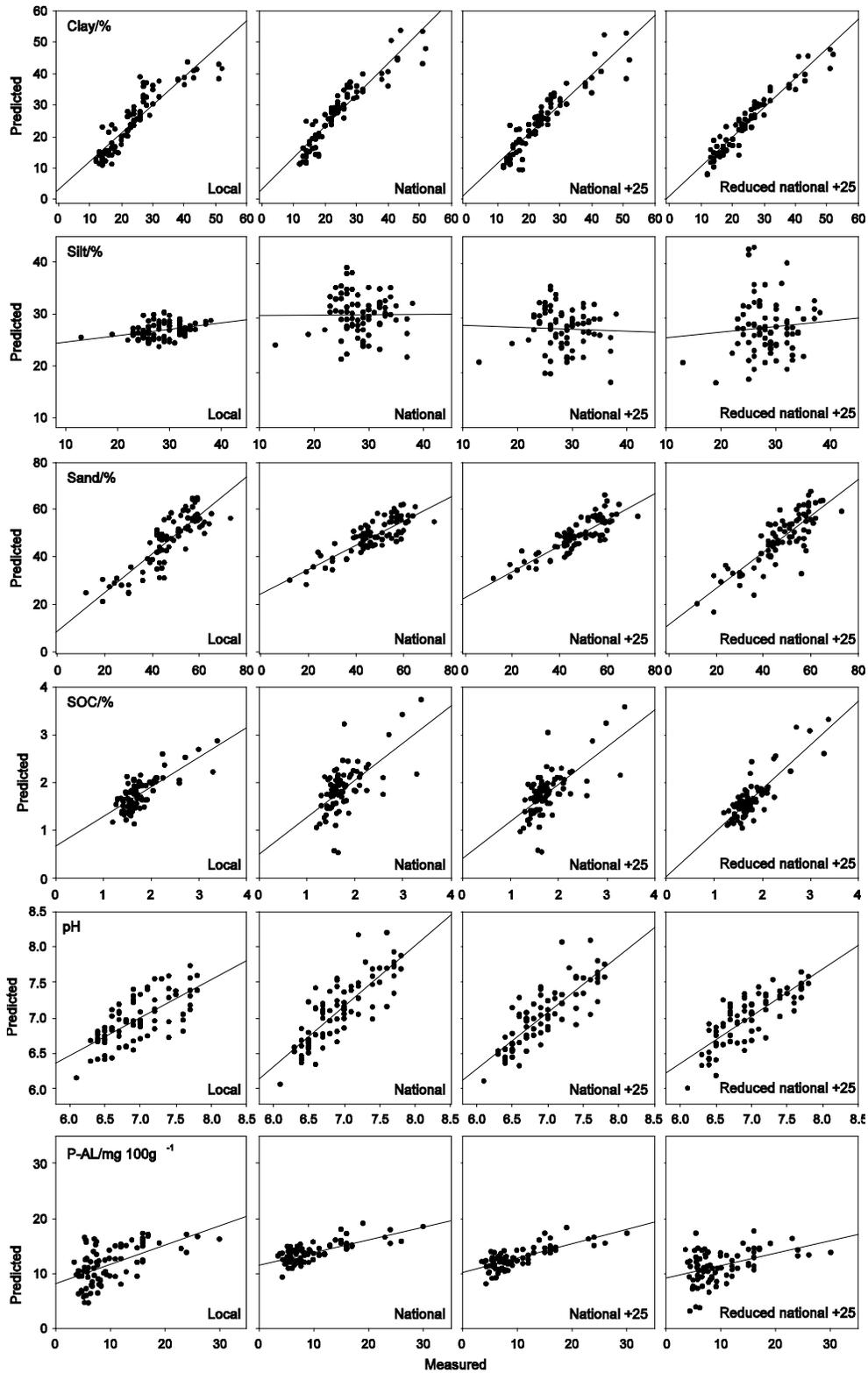


Fig. 10. Sjöstop: NIR-predicted versus laboratory-analysed clay, silt, sand and SOC content, pH and P-AL content using the local calibration, national calibration, national calibration spiked with 25 local samples or spiked reduced national calibration.

corresponds to the small and variable differences for clay and SOC between the calibrations with the spiked global library and the local only samples found by Brown (2007). However, it partly contradicts with the observations for clay and SOC by Sankey *et al.* (2008), who obtained substantially better predictions for some sites using the global library spiked with local samples compared with using only local samples. Regarding the variability in results between sites the present study agrees with both these studies. The studied sites in Sankey *et al.* (2008) were many times larger and more variable compared to the farms in the present study and to some extent also to the sites in Brown (2007). This may be one explanation to the substantial improvements found in their study. In addition, the number of local calibration samples in Sankey *et al.* (2008) was considerably more sparsely distributed with only 1 sample per several hundreds ha. Despite the larger number of samples compared to our study their local samples may have covered the soil variation of their sites to a lesser extent.

National versus reduced national calibrations

There was a tendency for better predictions using the reduced national libraries compared with the national libraries, but only when spiked with local samples and not as a general rule. The calibrations using spiked national libraries did not result in better predictions than calibrations using spiked reduced national libraries in more than a few cases, and this was generally for soil properties that were very poorly predicted in any case. However, there were three clear exceptions where the national calibrations resulted in better predictions than the reduced national calibrations, namely SOC at Kärntorp and clay and SOC at Bränneberg (Figs. 3 and 5).

The clear benefit of using the reduced national calibrations compared with the entire national calibrations at Hacksta could probably be related to the fact that Hacksta has a soil that is very typical of the agricultural region north of Stockholm (Fig. 1), from where a number of the national samples originate. In fact, scrutiny of the geographical origin of the reduced national library at Hacksta revealed that almost all 50 samples came from that region (Fig. 11). The other three sites have been represented by 50 samples distributed over the larger part of agricultural land in Sweden. Apparently the clay content and SOC has had a large influence as the reduced national library for the clayey Bränneberg site is represented predominantly in the agricultural planes dominated by clayey soils relatively low in SOC (Eriksson *et al.*, 1997; Eriksson *et al.*, 1999) while the reduced library for the low clay and high SOC Kärntorp site is hardly represented at all in these areas. This is in accordance with the fact that spectral features of clay minerals and SOC dominate the appearance of the visNIR spectra of dry soil. This means that despite that, at least for Hacksta and Sjöstorp, the parameter distributions of the reduced national library and the local sample sets resemble each other fairly well (Table 1). It is only for Hacksta, with its highly congregated geographical distribution of the reduced national samples (Fig. 11) that similarities can be assumed to have been utilised in the selection at a higher level of detail, like mineralogical composition. Why this has not been possible for the other sites is most probably because there have not been enough samples within the same clay and SOC range. For example the range in clay content are very narrow at Bränneberg and Kärntorp (Table 1). At Kärntorp it can also be assumed that the high SOC has had a large influence on the visNIR spectra and subsequently on the selection of the

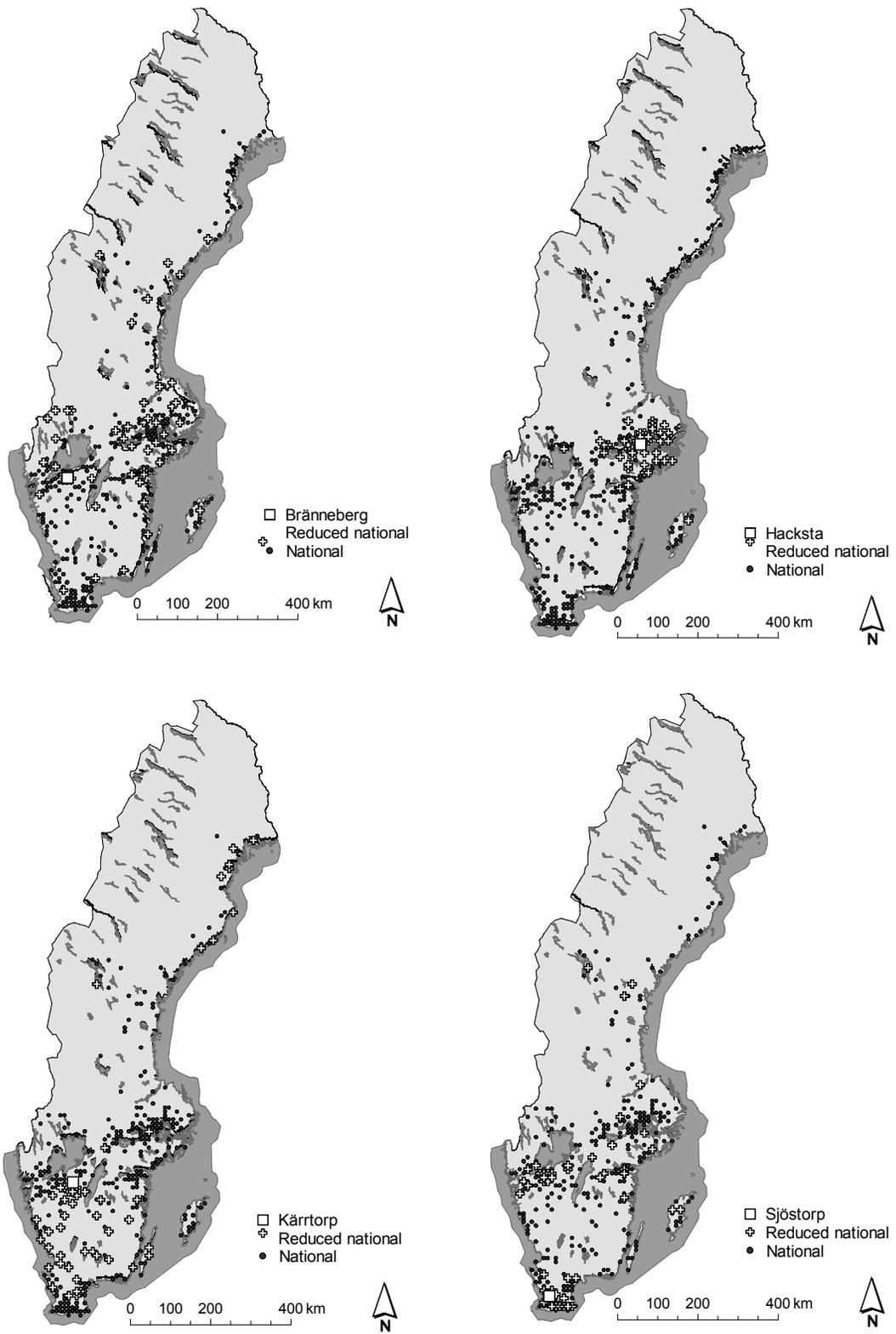


Fig. 11. Geographical distribution of the reduced national sample sets for the four farms.

reduced library. That it is not enough with similarities in the predicted parameter only, but that the soil composition at a higher level of detail may also be influential is supported by the improvements Sankey *et al.* (2008) presented when predicting clay and SOC at one site using a subset of calcareous soil samples compared with using the whole library.

This said, it might be expected that at least at Hacksta the unspiked reduced national calibrations should result in better predictions in terms of RMSEP compared with the national calibrations. This was however not the case (Table 3; Fig 4) as bias was still high, especially for clay and silt where the best effects were expected, but already when spiked with 5 local samples the reduced library performed better than the national library (Fig 4).

Conclusions

At present, using local calibrations seems to be the best alternative for predictions of soil parameters at the farm or field scale, even with as few samples as 25. The local calibrations outperformed both the national library (396 samples) and the reduced national libraries (50 samples) for all soil parameters at all farms.

The potential for good calibration was highest for clay and SOC. For silt, pH and P reliable calibrations can not be expected with 25 calibration samples. The potential for sand was found to be intermediate.

Whereas the selection of a subset of samples from the national library that were spectrally similar to the local samples (reduced national library) did not improve the results compared to using the entire national library, spiking both libraries with local samples reduced the RMSEP considerably, mainly due to a decrease in bias, resulting in RMSEP values comparable to those for the local calibrations.

There was a tendency for better predictions when spiking a reduced national library compared to spiking the entire national library, particularly for clay and SOC, sometimes even resulting in better predictions than using the local calibrations.

An interesting aspect of an increased and continuous use of local calibrations is the new type of national soil library that would arise as a consequence: a library including both the national and the local scales. How that would affect the necessity of new local calibrations is interesting, however difficult to investigate before it becomes a reality.

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