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On-the-go gamma spectrometry and its evaluation via support vector machines: really a valuable tool for site-independent soil texture prediction?

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Abstract.

Soil texture is of particular interest for decision making in agricultural practice. Due to proliferation of precision agriculture and enhanced by climate change, the need for high-resolution soil information is growing. So far, proximal gamma spectrometry has emerged to be an appropriate tool for topsoil texture prediction when applied to a limited number of sites and in homogenous landscapes. However, texture predictions based on on-the-go measurements and at the required spatial resolution need to be universally applicable to widely differing soil properties. Here, prediction models merit further improvement. Support vector machines (SVM) have been shown to allow calibration of site-independent stationary texture prediction models and, in principle, to be able to overcome interference due to different parent materials. In this study, surveying a total of 16 agricultural fields in Germany, it was found that gamma data calibrated via SVM make a valuable contribution to address the increasing demand for high-resolution soil texture information. It is helpful that in agricultural practice soil texture is considered in classes, allowing for certain error tolerance. A spiking approach significantly lowered the overall prediction error. At heterogeneous sites, the spiking samples should be thoroughly selected. Nevertheless, the objective must still be to predict soil information as precise as possible.

Keywords. gamma spectrometry, site-independent, calibration, soil texture prediction, support vector machine

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Introduction

With proceeding implementation of precision farming techniques in current agricultural practice, demand for high-resolution information on soil properties increases. Climate change and its consequences with particular emphasis to drought periods enhances this demand. In terms of water scarcity, soil texture is one of the most crucial soil properties because of its impact on the soil water holding capacity. Soil texture is, moreover, an important information for decision making with respect to e.g. planting or seeding density and spatial fertilizer distribution. Precise information on soil texture could therefore help to increase farmer's income and synchronously reduce ecological impacts of agriculture.

Radionuclides emitting gamma-rays naturally occur in all soils. The overlap of certain radionuclides with current soil properties forms the basis for using gamma spectrometry in soil science. Approximately 90% of the above ground gamma radiation originates from the uppermost 0.3 m of a soil, which is equivalent to the main rooting zone for agricultural crops (Cook et al., 1996; IAEA, 2003). In the past decades, an increasing number of scientists dealt with gamma spectrometry as soil sensing tool aiming to predict a variety of properties (e.g., soil organic matter, available nutrients, peat thickness) of which soil texture turned out to be of special interest (Megumi and Mamuro, 1977; Priori et al., 2014; Heggemann et al., 2017). There is proven causality between a soils' gamma radiation and its sand, silt, and clay content involving pedogenic and mineralogical aspects. Proximal gamma spectrometry has emerged to be an appropriate tool for topsoil texture prediction when applied to individual fields (Reinhardt and Herrmann, 2019), at a limited number of sites (Petersen et al., 2012), and in landscapes with low heterogeneity with respect to pedogenetic and mineralogical conditions (van der Klooster et al., 2011; van Egmond et al., 2010).

However, for a broader use of gamma spectrometry, calibration models need to be transferable to widely differing soil properties and should therefore be able to deal with different soil parent materials. With linear prediction models, this transferability has not yet been sufficiently achieved (Pätzold et al., 2020). In this regard, machine-learning approaches may be superior to linear regression. Support vector machines (SVM) allow calibration of site-independent texture prediction models and are generally able to overcome interference from different parent materials (Priori et al., 2014; Heggemann et al., 2017). For use in agricultural practice, it is essential that gamma measurements can be carried out on-the-go to achieve the required spatial information density.

Materials and Methods

Study Sites

The sample set comprised 16 agricultural fields in different regions of Germany of which twelve were also surveyed in precedent studies (Heggemann et al., 2017; Pätzold et al., 2020). Four sites were added to the aforementioned sample set to in-depth survey factors that might drive the transferability of the models. A particular focus was on sites in regions that are likely to be uniform or at least similar in terms of geological, mineralogical and pedological features and processes. Please note that in the course of this study, the complex of mentioned factors is called "geopedological conditions".

In three geological regions, pairs of sites were selected to test universal model validity when only one of the sites was in the calibration set. The Münster-2 site is located next to Münster-1. Its soils have developed from Cretaceous marls that were partially covered with aeolian sands. The sites Meckenheim-1 and Meckenheim-2 (linear distance = 2 km) were suggested to replace each other in the calibration. The soils have each developed predominately from loess but at the Meckenheim-1 site, sediments from the nearby stream turned out to have an impact. The parent material in Goerzig was also loess and it was assumed that other loess derived sites would calibrate appropriate prediction models.

Soil sampling

The number of sampling points of each site and their distribution were based on either systematic or stratified sampling to best reflect the given soil heterogeneity. If available, preliminary conducted geophysical sensor surveys (gamma spectrometry and electromagnetic induction) were considered. Soil samples were taken from the uppermost 0 – 0.3 m. Laboratory texture analyses were conducted via the combined sieve and pipette method (ISO 11277, 2002). Grain sizes were classified into sand (2000–63 µm), silt (63–2 µm), and clay (<2µm) in accordance with the World Reference Base for Soil Resources (IUSS Working Group WRB, 2015). The texture classes were adapted to the scheme of the German Soil Survey Handbook (AG Boden, 2005). For the soil map of the study site Uckermark-2, texture classes were further grouped according to Association of German Agricultural Inspection and Research Institutes (VDLUFA; for details see VDLUFA, 2000).

Table 1. Descriptions of the investigated fields regarding soil texture, gamma measurements and parent materials. Note that information is given only for those sites that were not present in preceding studies of Heggemann et al., 2017 and Pätzold et al., 2020.

Site		Sand [%]	Silt [%]	Clay [%]	TC [cps]	K [cps]	Th [cps]
Münster-2	mean	70	13	16	601	78	14
n = 35	min	55	11	9	539	70	10
	max	77	18	26	657	88	19
	cv [%]	6	11	20	5	6	14
	parent material:	Cretaceous marls, partially aeolian sands					
Goerzig	mean	18	61	19	1245	171	35
n = 77	min	13	37	5	997	141	26
	max	49	66	23	1302	186	42
	cv [%]	33	6	12	4	5	7
	parent material:	Loess					
Meckenheim-2	mean	10	56	31	1230	152	37
n = 15	min	9	51	26	1193	141	35
	max	12	64	38	1300	166	41
	cv [%]	10	7	12	3	5	5
	parent material:	Loess					
Meckenheim-1	mean	12	68	19	1313	159	37
n = 15	min	10	64	15	1263	150	35
	max	13	72	23	1352	171	42
	cv [%]	9	3	13	2	4	5
	parent material:	Loess					

Gamma measurements

Principles

Gamma quants have discrete energy levels characteristic of the radionuclide source. The used mobile gamma spectrometer can detect 40-Potassium (K-40), 238-Uranium (U-238) and 232-Thorium (Th-232) directly in the field with sufficient precision due to their natural abundance and energy level (Pickup and Marks, 2000). In addition, total gamma counts (TC) are measured. Monitoring the radionuclides by so called Regions of Interest (ROIs; also known as "windows method") is a common approach. The ROIs ranged from 1.37–1.57 MeV for K-40, 1.66–1.86 MeV for U-238, and 2.41–2.81 MeV for Th-232 and 0.4–2.81 MeV for TC (Reinhardt and Herrmann, 2019). ROIs for U-238 were not included in this study because its measurements may be erroneous due to several reasons (Dickson and Scott, 1997; Schnug and Lottermoser, 2013; Söderström et al.; 2016). In contrast, K-40 and Th-232 can be reliably detected (Rawlins et al., 2007; Schuler et al., 2011).

Due to attenuation, gamma quants mainly originate from topsoil, i.e. the uppermost 0.3 m (Cook et al., 1996; IAEA, 2003). There are two main reasons for the more or less pronounced relationships between radionuclides and soil texture that have to be considered (Megumi and Mamuro, 1977; Priori et al., 2014; Heggemann et al., 2017). First, sorption capacity for radionuclides is tied to the specific surface area of the grain size fractions (sand, silt, clay). Second, K-40, U-238, and Th-232 are incorporated in the lattice structure of certain minerals in varying amounts (Reinhardt and Herrmann, 2019). In general, the quality and quantity of radionuclides in soils are controlled by the mineralogy and geochemistry of the parent material, but also by geological and pedogenic processes (Reinhardt and Herrmann, 2019; Dickson and Scott, 1997; Wilford et al., 1997). Due to multiple interactions between these controlling factors and the resulting gamma signature, the interpretation of gamma spectra remains complex. Further, the statistical distribution of radioactive decay is only constant over a long period of time (Gilmore, 2011) and on-the-go gamma spectrometry captures not only small-scale soil heterogeneity, but also decay-rate based variability. In consequence and considering the linear spectra alignment along the measurement/tractor lanes, a moving window approach was applied for smoothing. From five subsequent spectra, the mean values for each ROI were calculated, i.e., each spectrum was considered in five mean values. The total number of measuring points (i.e., spatial data density) was not reduced. More details of the smoothing approach are described in Pätzold et al., 2020.

Data acquisition and analysis

Gamma measurements were recorded with the RSX-1 spectrometer (Radiation Solutions Inc., Canada) with two 4.2 L thallium activated sodium iodide crystals mounted on a steel frame designed for coupling to tractor's three-point linkage. Measurement height above soil surface was 0.3 m at a frequency of 1 Hz. GPS data were provided by an external antenna coupled to the internal GPS module. Field gamma spectra were recorded on-the-go, i.e. while driving over the fields at velocities of 0.7 to 1.5 m s^{-1}. For calibration purposes, reference soil samples were taken from 0 - 0.3 m depth and were conventionally analysed. To account for the instrument's footprint, the entire gamma measurements within a radius of five meter around each sampling point were averaged (van der Veeke et al., 2021). Gamma spectra were processed with the commercial RadAssist software (Radiation Solutions Inc., Mississauga, ON, Canada), which uses the so so-called windows approach, i.e., besides the total counts (TC), the Regions of Interest (ROI) for K-40, U-238, and Th-232 were also analysed. We used R 3.2.2 (R Core Team, 2015) for calculating the statistics as well as the prediction models. For evaluating and displaying spatial data, ArcGIS software package (v. 10.1, ESRI Inc., Redlands, CA, USA) and QGIS (v. 3.12.1-București, Free Software Foundation Inc., Floor, Boston, MA, USA) were used.

Calibration and Validation

Site-independent prediction models for soil texture were successfully calibrated using support vector machines (SVM) in previous studies including various sites with largely different geopedological conditions and based on stationary measurements (Heggemann et al., 2017). The purpose of these preceding studies was to test the general transferability of prediction models and the usefulness for different practical applications. The present study is now concerned with figuring out the performance of SVM calibrated prediction models when applied to completely unknown sites while driving over the field. Training on the calibration dataset was generally performed with 100 times 10-fold cross-validation to find the best prediction models based on the lowest prediction error for sand, silt, and clay. To test the performance of the SVM calibrated models for unknown sites, each site was excluded from the calibration set and the model was then recalibrated. Subsequently, for validation, the recalibrated models were applied to the respective excluded site (validation of the test set). In the course of this work these sites are going to be denoted as hold-out sites. Finally, a spiking approach to improve prediction quality with few reference samples per site was tested. To this end, each site was excluded from the calibration set one by one with the exception of each five spiking samples of the respective site remaining in the calibration set and the model was then recalibrated. Again, for validation, the recalibrated models were applied to the respective site.

Results and Discussion

Throughout the project years, numerous sites were surveyed. Some were chosen because of their geopedological settings, some because of their geographical distribution across Germany. In this section, we focus on those sites that promise the greatest gain in knowledge. The performance of the site-independent prediction models applied to the hold-out sites is shown in Table 2. For evaluation of prediction quality, the mean absolute error (MAE), and root mean square error (RMSE) are presented.

Table 2. Mean absolute errors and root mean square errors for the predictions of the respective hold-out sites (test-set validation).

Site	Sand		Silt		Clay	
	MAE	**RMSE**	**MAE**	**RMSE**	**MAE**	**RMSE**
	------------------------- [%]-------------------------					
Münster-1	7.6	11.0	5.1	9.0	9.8	13.8
Münster-2	4.5	5.7	2.2	2.7	3.1	3.6
Ahrweiler	3.2	4.1	7.4	9.0	6.8	8.9
Meckenheim-1	5.6	6.1	5.8	6.7	7.7	9.7
Meckenheim-2	1.3	1.7	8.2	9.0	6.6	7.8
Cologne	12.4	13.3	17.1	18.2	1.0	1.5
Goerzig	12.7	14.3	14.3	16.3	3.0	3.9
Rheinbach-1	7.1	8.3	16.1	17.0	29.0	30.4
Uckermark-1	3.8	5.3	3.3	4.4	2.5	2.9
Uckermark-2	5.1	7.1	4.4	6.7	2.7	3.4
Rengen	3.6	4.0	9.1	10.1	3.4	4.3
Scheyern	14.3	15.0	22.1	24.5	5.1	6.9
Schleidweiler	13.9	15.4	15.5	16.3	6.4	7.4
Siebeldingen	10.4	13.1	8.0	10.2	5.3	6.1
Vinxel	6.2	8.1	19.4	22.4	8.6	10.6
Wesseling	5.8	7.3	12.0	12.7	8.2	8.7

Overall, the results vary greatly depending on the study site and the grain size fraction. Of 16 sites, seven are predicted with MAE < 10% for all texture fractions. Across the entire sample set, one third of the MAE’s is greater than 10% and for some sites, it is even greater than 20%. MAE < 5% is considered excellent for texture predictions (Hobley and Prater, 2018, Vos et al. 2016) and suitable for Precision Farming applications whilst MAE > 10% is not sufficient (Heggemann et al., 2017). Both, the negative and the positive results are worth a detailed consideration. For Uckermark-1, Uckermark-2, and Münster-2 MAE is each below or equal to 5% for all three texture fractions and, thus, suitable for precision farming. Moreover, single fractions are predicted precisely (MAE < 5%) at various sites.

The study site Münster-2 is directly neighbouring Münster-1. It is thus not surprising, that the calibration dataset including Münster-1 would yield sufficient prediction accuracy when applied to Münster-2 as hold-out site. Surprisingly, this does not hold true for the vice-versa way because sand, silt, and clay content of Münster-1 are predicted significantly worse. Considering the great impact of geology and mineralogy on gamma spectra, this result pointed to differing parent material at least for subareas of Münster-1. This was underlined by means of the differing range of clay contents. Clay content in Münster-1 ranged from 9 to 55% with a mean of 26%. For Münster-2, clay contents were remarkably lower with a maximum of 26%. The differences were caused by the occurrence of Pleistocene glacial till in subareas of Münster-1. Beyond that, the parent materials of both sites were equal and consisted of Cretaceous marls that were partially covered by aeolian sand in varying thickness.

However, for Uckermark-1 and Uckermark-2 all texture fractions were precisely predicted without site-specific reference samples of each site. Obviously, the prediction model comprising the Uckermark-1 sample set is appropriate for Uckermark-2 and vice versa. This result was even more interesting because these sites are located eight kilometres linear distance apart from each other. The parent material at both sites is Pleistocene glacial till and obviously rather homogeneous over the distance between the fields. Moreover, it covers vast areas of north-eastern German younger moraine landscapes and the model might be valid for large areas.

Concerning the sites in Münster and Uckermark, site-specific gamma calibration might not be mandatory. In these cases, the parent materials mineralogy is obviously more important than the occurring range of sand, silt, and clay content. It is supposed that the mineralogical variability of the parent material is a crucial aspect for model transferability.

However, in Germany, a variety of soil maps and geological maps gives information or at least hints on a sites' mineralogy and parent material and these maps were, of course, considered when characterising the sites in the course of this study. Moreover, maps could potentially be used for distinct a priori reference sampling and e.g. designing nationwide sampling campaigns. Nevertheless, constituting appropriate databases for calibration still means tremendous effort and is in particular challenging with respect to geological and mineralogical differences within landscapes that are not depicted on the available maps. The neighbouring sites Rheinbach-3 and Rheinbach-4 (n = 15 (each), aerial distance = 2 kilometres) serve as example for this difficulty. These two fields were assumed to act as 'paired sites' based on the information from both the available geological and soil maps. The assumption was that these predominantly loess derived sites could replace each other in the calibration. However, this did not hold true and is most probably due to the fact that the Rheinbach-4 was partially influenced by fluvial sediments of the nearby stream. These fluvial sediments were similar to loess in terms of sand, silt and clay contents. Nevertheless, these sites differed in their gamma signatures and were obviously not compatible with respect to the parent materials. It should be mentioned, that neither the soil map nor the geological map pointed to any difference in parent materials. Yet, the deficiency in the degree of information details is probably a map scale problem. For the Rheinbach sites, the available maps were at a scale of 1:100,000 and 1:50,000 for geology and soil, respectively.

However, there can be further blurring on the content level of soil maps and especially of geological maps, as the following example shows. Loess, the prevailing parent material at Rheinbach-1, Rheinbach-2, Siebeldingen and Goerzig, covers great areas of German agricultural landscapes. The respective soils have in common that they are very important sites for crop production because of their pronounced soil quality. In view of its geology, Loess has to be concerned more in detail. It might be formally denoted to be geologically uniform but Loess differs significantly with respect to its mineralogy and, thus, also in terms of its gamma signature. This is because the term "Loess" only describes the transport mechanism of the sediment but the material itself can vary greatly depending on its area of origin. These differences are also reflected in the mineralogical composition and grain size distribution. It is, thus, comprehensible that the predictions for the Goerzig site are not sufficient despite there are three other Loess dominated sites in the calibration. The Goerzig site is located approximately 400 kilometres apart from all other Loess sites. It is assumed that soil maps and geological maps, which in principle could provide valuable a priori information regarding the need for site-specific reference samples, cannot depict the required detail level.

Use of soil texture information in practice

However, in practical soil survey, mapping, and precision farming, texture prediction is usually not requested on the exact scale but in distinct, more or less wide spanning classes allowing for a certain error tolerance. Therefore, a prediction that matches the correct class would be sufficient.

Figure 1 shows observed and predicted clay contents for the study sites Uckermark-1 and Uckermark-2 based on the entire on-the-go measurements. For the presented grid (24*24 m) at Uckermark-1, a mean clay content was calculated from all on-the-go based clay predictions located within each grid cell. In other words, each grid cell represents the averaged predicted clay content based on all on-the-go measurements recorded in its area. Besides, no further geostatistical data treatment was done. Classification of values is oriented towards AG Boden (2005). The predictions are marked by pronounced small-scale variation, which is quite typical for the respective soils in younger moraine landscapes. To us, the most important result is the good match between observed and predicted clay contents. A rather small deviation between observation and prediction occurs at a quarter of the reference sample points whilst most of the predictions do nearly perfectly match the observed clay content class. This is a tremendous success in view of the given small-scale heterogeneity of the site.

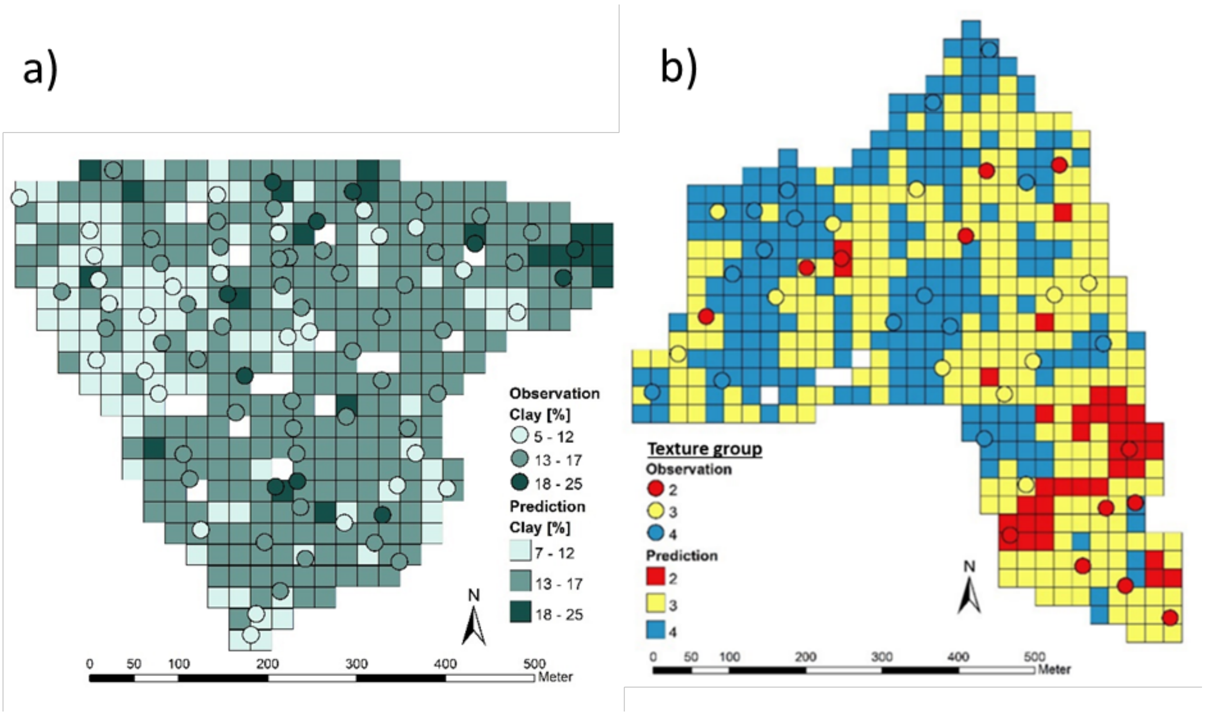

Fig 1. Observed and predicted (a) clay content at Uckermark-1 (35 ha) classified according to the common German scheme of AG Boden (2005) and (b) texture groups at Uckermark-2 (25 ha) according to the scheme of the Association of German Agricultural Analytical and Research Institutes (VDLUFA). The sites can be denoted as hold-out sites as they were each excluded from the respective calibration data set.

Soil texture and agriculture

As far as agricultural practice in Germany is concerned, information on sand, silt or clay content is valuable and comes with certain empirically based recommendations when translated into the corresponding texture classes using the scheme of the Association of German Agricultural Inspection and Research Institutes (VDLUFA). This procedure was exemplary done for the study site Uckermark-2 (Fig. 1(b)). The observed sand, silt, and clay contents and the respective predictions (for each grid cell) were translated into the scheme of VDLUFA comprising five relatively wide spanning texture classes from ‘sandy’ (1) to ‘clayey’ (5). This scheme is the basis for so-called target classes for e.g. lime dosage, pH, potassium, magnesium and phosphate and gives dedicated management recommendations. Most predictions are in line with the respective reference samples. Deviations occur at some points where the observed texture is sandy while predictions tend to underestimate the sand content. There is no obvious reason for this underestimation. The corresponding site Uckermark-1 contributes to the underlying prediction model and reveals similar range of sand contents; further, the geopedological setting is at least similar and likely uniform. However, with regard to the occurrence of a total of three (out of five) texture classes according to the VDLUFA scheme and in view of the pronounced small-scale heterogeneity, the prediction for this hold-out site was satisfactory.

Spiking to improve prediction accuracy

However, since prediction accuracy is low at a couple of sites at least for certain grain size fractions there is potential to improvements. In proximal soil sensing, spiking training data with few samples is widely used to improve prediction quality at little effort (Seidel et al., 2019; Breure et al., 2022). The training data of each site was therefore excluded from model calibration one by one. Subsequently, five randomly selected samples of the respective fields were re-inserted to spike the calibration models. The general idea behind using a) only five and b) randomly selected samples for spiking was based on certain considerations. First, it was assumed that for a broader use of gamma spectrometry in agricultural practice, reference sampling must not be costly and extensive. Second, it became evident in the course of this and previous studies that there are not always appropriate a priori information on soils or parent materials respectively of which, e.g., stratified reference sampling could be orientated towards (see above). Third, approaches involving the gamma measurements themselves for stratified sampling were tested but finally rejected because they did not significantly improve prediction quality at all (results not shown).

Tab. 2: Mean absolute errors and root mean square errors with the spiked calibration data set. Note that predictions for Uckermark-1 and Uckermark-2 were done with a model that comprised only 5 samples of each of the two sites in total. This was done because the sites can replace each other (see above and Tab. 1). Full consideration of one of the sites would have impeded evaluation oft he spiking approach. For the other sites, the entire sample sets of Uckermark-1 and Uckermark-2 were included. Changes in MAE and RMSE as compared to prediction with the non-spiked model are given in brackets.

Site	Sand				Silt				Clay			
	MAE		RMSE		MAE		RMSE		MAE		RMSE	
	--[%]--											
Münster-1	6.2	(-1.4)	8.6	(-2.4)	2.8	(-2.3)	3.7	(3.3)	5.4	(-4.4)	7.6	(-6.2)
Münster-2	3.3	(-1.2)	4.2	(-1.5)	2.6	(0.4)	3.7	(3.7)	3.0	(-0.1)	3.6	(0)
Ahrweiler	3.3	(0.1)	4.4	(0.3)	6.6	(-0.8)	8.1	(7.9)	6.7	(-0.1)	8.8	(-0.1)
Meckenheim-1	4.1	(-1.5)	4.7	(-1.4)	6.0	(0.2)	6.9	(6.4)	6.4	(-1.3)	9.2	(-0.6)
Meckenheim-2	1.3	(0)	1.6	(0)	6.7	(-1.5)	8.0	(7.9)	4.9	(-1.7)	6.0	(-1.8)
Cologne	12.6	(0.2)	13.9	(0.5)	10.6	(-6.5)	12.8	(12.3)	1.2	(0.2)	1.5	(0)
Goerzig	9.3	(-3.4)	11.1	(-3.2)	13.0	(-1.3)	15.9	(15.5)	4.3	(1.3)	5.3	(1.4)
Rheinbach-1	3.5	(-3.6)	4.5	(-3.8)	5.4	(-10.7)	6.4	(6)	3.2	(-25.8)	3.8	(-26.6)
Uckermark-1	4.6	(0.8)	6.9	(1.5)	4.4	(1.1)	5.4	(5.1)	2.2	(-0.3)	2.7	(-0.2)
Uckermark-2	6.5	(1.4)	9.2	(2.1)	5.6	(1.2)	8.4	(8.2)	3.4	(0.7)	4.4	(1)
Rengen	1.9	(-1.7)	2.2	(-1.8)	3.0	(-6.1)	4.0	(3.9)	3.1	(-0.3)	4.0	(-0.3)
Scheyern	6.9	(-7.4)	8.2	(-6.8)	14.7	(-7.4)	17.1	(16.4)	5.5	(0.4)	7.3	(0.3)
Schleidweiler	7.0	(-6.9)	8.1	(-7.3)	4.9	(-10.6)	5.6	(5.6)	4.6	(-1.8)	5.6	(-1.8)
Siebeldingen	7.5	(-2.9)	9.8	(-3.3)	8.5	(0.5)	10.4	(10)	5.2	(-0.1)	6.1	(0)
Vinxel	6.8	(0.6)	8.6	(0.5)	9.2	(-10.2)	10.9	(10.6)	5.7	(-2.9)	6.9	(-3.8)
Wesseling	4.3	(-1.5)	6.7	(-0.6)	5.7	(-6.3)	7.5	(6.8)	4.4	(-3.8)	6.4	(-2.3)

The performance of the resulting prediction models when spiked with five randomly selected samples of each site is shown in Table 2. In general, the spiking procedure improved the prediction quality for all texture fractions at all study sites (differences in brackets). It yielded 22 out of 48 predictions for sand, silt, and, clay being marked by MAE < 5%. There were 5 of 48 predictions with MAE > 10%.

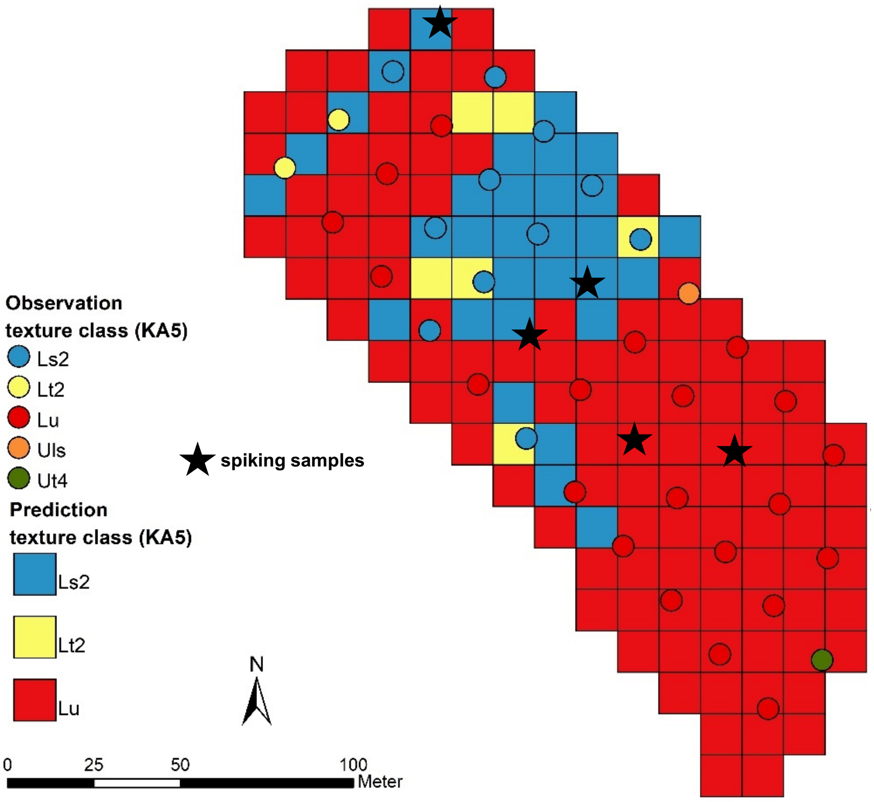

Fig 2. Observed and predicted texture classes according to the common German scheme of AG Boden (2005) at Rheinbach-1 using the spiked calibration data set.

Rheinbach-1 is the site with the most significant improvement from the spiking procedure. After spiking the calibration set, the MAE for sand, silt and, clay decreased by 3.6, 10.7 and 25.8% respectively. The single texture fractions were then translated to the texture classes according to the German Soil Survey (AG Boden, 2005). The resulting map is shown in Figure 2. In case of deviations, the clay content was underestimated but, in general, the major zones with respect to the area share were correctly predicted. With the aid of common pedotransfer functions, such texture classes could be used to derive information on related soil properties, e.g. water holding capacity, of which are important for decision making in practical agriculture (see also Pätzold et al., 2020). The example Rheinbach-1 shows that few spiking samples can allow for much more precise predictions. Nevertheless, it should be noted that this site is small (2.1 ha). The composition of the parent material and soil texture are related to the surface relief at this sloped field, which is typical for this landscape (Sauer and Felix-Henningsen. 2006). It is assumed that spiking samples will have the greatest effect when they capture the overall variability of the relevant parameters of a site. Here, the spiking samples were well distributed across the slope, making the large effect of spiking therefore comprehensible.

In contrast to Rheinbach-1, predictions for Siebeldingen were improved to a minor degree only (Tab. 2). The Siebeldingen site comprised 25 ha and three different parent materials plus their respective mixing forms. In total, this variability was not adequately reflected by five spiking samples. The small MAE improvement was therefore not surprising. Likewise, at some other sites the improvement after spiking is not always satisfactory either, but without obvious reason. This applies particularly to the Scheyern, Cologne, and Goerzig sites. However, the overall improvement of the prediction models resulting from each five randomly spiked samples was judged to be a good success. Across all study sites, spiking lowered MAE to <5 % in 46 % of all texture class predictions (Tab. 2). This MAE level is considered suitable for precision farming applications (Heggemann et al., 2017).

Conclusion

Gamma data calibrated with support vector machines can make a valuable contribution to address the increasing demand for high-resolution information on soil texture. Accurate and site-independent predictions are generally possible. However, sensor-based information on soil texture are even more relevant for regions that are not covered by soils maps. Soil sensing services are widely available but are particularly reliable in regions where the geopedological variability on the landscape scale is small. In contrast, there are still deficits in landscapes with large geopedological variability, e.g. in mid-mountain ranges in Germany and other parts of Europe. Such regions are on one hand most challenging to soil sensing. On the other hand, for agricultural practice the soil texture determination in more or less wide spanning classes allows for certain tolerance for minor prediction errors. Nevertheless, the objective should still be to predict soil information as precise as possible and to further improve soil sensing methods. In this respect, a large database for gamma spectra is still desirable, because it would allow for improved prediction models even after adding limited data that my serve for spiking and enlarging existing models.

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