Chapter 27
Gamma Ray Sensor for Topsoil Mapping: The Mole

F.M. van Egmond, E.H. Loonstra, and J. Limburg

Abstract In general, farmers base their crop management decisions on a combination of their background knowledge, their experience with a field, and analysis of soil samples. Optimising agricultural production using precision agriculture requires detailed, high-resolution soil information. This level of detail is usually not available in current agricultural practice due to the cost of traditional soil sampling techniques. However, new sensor technology presents an opportunity to produce high-resolution soil maps, which can be used to support agricultural decision making and crop management. This chapter presents a highly sensitive sensor technology, based on the natural emission of gamma radiation from soil, which makes quantitative mapping of physical and chemical soil properties of the tillage layer possible. This method is shown to be capable of producing the high-resolution maps required for precision agriculture, and evidence is presented that in combination with precision agriculture techniques, it has already contributed to yield improvement.

Keywords Gamma ray sensor · Full-spectrum analysis · Precision agriculture · Digital soil mapping · Fluvisols

27.1 Introduction

In the interest of achieving optimum yields, precision agriculture practices deal with very detailed and spatially differentiated combinations of crop requirements and soil properties in a field. Significant variations in soil properties can exist within a field, and addressing these differences requires more detailed information about the cropping system than traditional agricultural practices allow.

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Precision agriculture uses high-resolution maps of physical and chemical soil properties, together with yield and crop biomass maps, to enable operational decision support in crop management and to derive variable rate application (VRA) maps. VRA maps show the localised doses of an application (e.g. fertiliser or lime) or indicate, for example, the amount of seed potatoes to be planted based on information from the site-specific soil conditions. Ideally, this information should be quantitative, accurate, and of high spatial resolution. The University of Groningen (RUG), Medusa Explorations, and The Soil Company (The Netherlands) have developed a sensor system (called the Mole) that is used commercially for the high-resolution mapping of physical and chemical soil properties of the tillage layer. The method is based on (natural) gamma radiation measurements and field or regional calibration with conventional soil sample analyses.

The fact that gamma radiation carries information on the mineral composition of soils and rocks has been known for a long time (Cook et al., 1996). Already in the early 1930s, gamma detectors were built and used for mineral (uranium) prospecting (de Meijer, 1998). With the advent of scintillation crystals, which replaced the early Geiger–Muller counter-based systems, it became possible to deconvolute the measured gamma radiation into a series of constituents, including the naturally occurring radioactive elements potassium (^{40}K), thorium (^{232}Th), and uranium (^{238}U).

However, it took researchers until the early 1990s to move from a qualitative interpretation of this information in terms of nuclide concentrations to a quantitative interpretation in terms of soil or soil mineral properties. A number of coincidental research findings have contributed to the development of this method.

Firstly, proper calibration methods were devised, which meant that absolute concentrations of radionuclides could be measured with field-based systems. At the same time, several studies were carried out to investigate correlations between radionuclide concentrations and the mineral properties of soil and sediment samples taken during vehicle, airborne, and underwater radiometric surveys (de Meijer, 1998; Cook et al., 1996; Pracilio et al., 2006). Strong correlations were found, for example, between the ^{232}Th radionuclide concentration and the clay content of the topsoil. Gamma radiation originating from depths as far down as 50 cm is able to reach the surface, while radiation originating from below that depth is attenuated by the overlying soil dry matter and soil moisture (Cook et al., 1996, Viscarra Rossel et al., 2007). As a general rule, it has been found that different soil and sediment types are characterised by unique fingerprints (van Wijngaarden et al., 2002; Cook et al., 1996; Pracilio et al., 2006) – i.e. each soil carries a unique concentration of the naturally occurring nuclides ^{40}K, ^{238}U, and ^{232}Th (C_K, C_U, and C_{Th}). Some years later it was found that relationships exist not only between radionuclides and physical soil properties (texture, grain size, etc.) but also between radionuclides and chemical soil properties (heavy metal pollution, fertilisers, nutrients, etc.) (van der Graaf et al., 2007; Viscarra Rossel et al., 2007).

In conjunction with the development of better spectrum analysis and fingerprinting methods, smaller and better gamma data acquisition systems were developed. Previous systems for measuring radioactivity have been converted into sensors for measuring radioactivity-related soil properties. This chapter describes a method by which relatively low-cost, high-resolution soil maps can be produced by using these sensors and how farmers can use these maps in precision agriculture for yield improvement.

27.2 Equipment and Data Analysis Methods

In the past, most field gamma ray-logging systems were built from NaI scintillation crystals and used a 'windows' spectrum analysis to determine the concentration of the radionuclides. Our innovations, related to both the type of detector material used and the method of data analysis, have significantly improved the quality of gamma measurements (Koomans et al., 2007) and the level of detail and accuracy of the maps.

27.2.1 Hardware

Traditional gamma radiometers use crystals like sodium iodide (NaI), which are not the most efficient capturers of gamma radiation. They are also brittle and therefore accident-prone. Commercially available alternatives are bismuth germanate ($Bi_4Ge_3O_{12}$ or BGO) and caesium iodide (CsI). BGO has a low peak resolution, which rules out its use in cases where nuclear fallout radionuclides (such as ^{137}Cs) are the subject of interest. Furthermore, this material is rather expensive and prone to temperature instability. CsI is a very robust alternative to NaI and BGO. The higher density of CsI compared to NaI yields better efficiency, especially for smaller crystal sizes. The Soil Company's sensor utilises a 70-mm $\times$ 150-mm CsI crystal coupled to a photomultiplier unit and a 512-channel MCA system (Plate 27.1a). The system stores the full spectral information, which enables post-processing of the spectral data at a later stage.

27.2.2 Spectral Data Analysis

In order to convert the measured spectral information into concentrations of radionuclides, the 'windows' analysis method is frequently applied (Grasty et al., 1985). Here, the activities of the nuclides are found by summing the intensities of the spectrum found in a certain interval surrounding a peak. In the classic 'windows' approach, three peaks are used to establish the content of ^{232}Th, ^{238}U, and ^{40}K. A major flaw of the method is the limited amount of spectral information that is incorporated into the analysis. Another weakness is the inherent use of 'stripping factors' to account for contributions of radiation from nuclide A into the peak of nuclide B (Plate 27.1b).

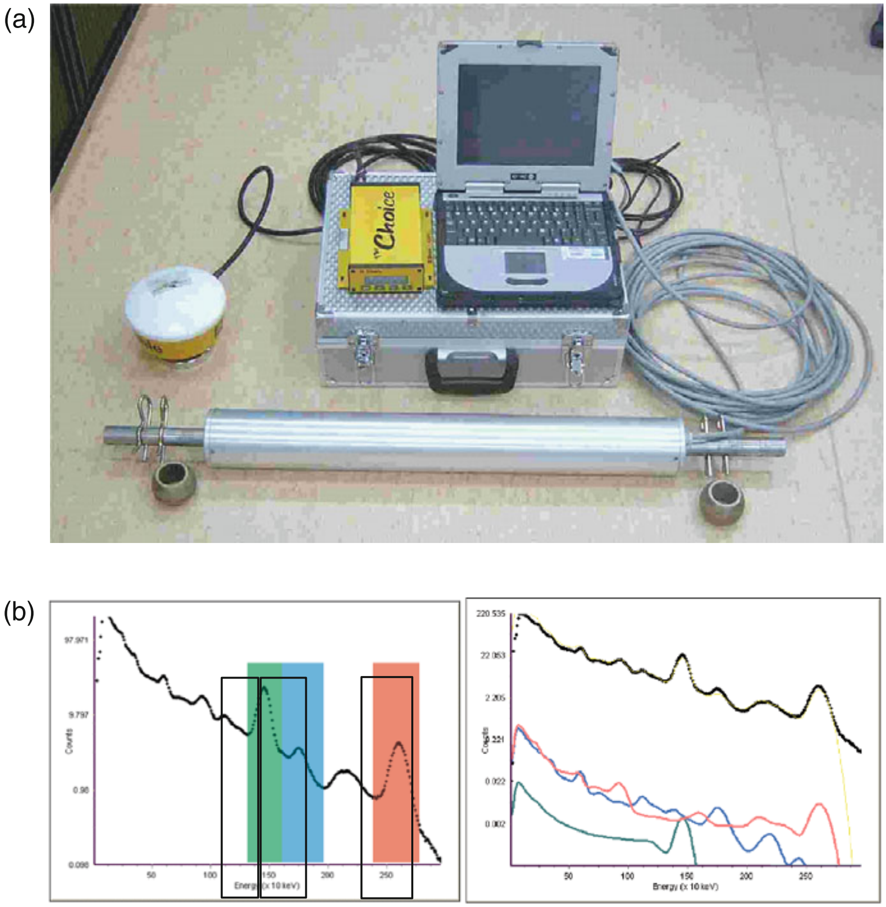

Plate 27.1 (**a**) The Mole system (The Soil Company, Groningen) consisting of a detector, a GPS, and a laptop. (**b**) *Left*: 'Windows' surrounding the ^{40}K, ^{238}U, and ^{232}Th peaks (*left to right*). *Right*: FSA analysis of a natural gamma spectrum. The measured spectrum (*black dots*) is fitted with a curve (*yellow*); green, blue, and red curves are standard spectra for ^{40}K, ^{238}U, and ^{232}Th, respectively

The Soil Company's Mole sensor system incorporates a different method to analyse gamma spectra. In contrast to the 'windows' method, our full-spectrum analysis (FSA) method incorporates virtually all of the data present in the measured gamma spectrum. With FSA, a chi-squared algorithm is used to fit a set of 'standard spectra' to the measured spectrum (see Plate 27.1b). (A standard spectrum is the pure response of the detector system used on a 1 Bq/kg source of a given radionuclide in a given geometrical setting.) The fitting procedure yields the multiplication factors needed to reconstruct the measured spectrum from the standard spectra of the individual nuclides. The multipliers are equal to the actual concentrations of the radionuclides in becquerel per kilogram that led to the measured spectrum. This method is described in detail by Hendriks et al. (2001). Hendriks showed that the associated uncertainty in the FSA method is at least a factor of 1.7 less than that in the ‘windows’ method.

27.2.3 Fingerprinting and Soil Sampling

During field measurements, the Mole is placed on a tractor and driven across the field. A reading of the gamma spectrum and the GPS position is stored on a computer every second (Plate 27.1a). A constantly updated map, created on the go, shows the variation of the total count (spectrum) of gamma radiation ‘live’ in the field.

To translate the gamma data into soil maps, calibration with soil parameters is required. With this aim, soil samples are taken down to a depth of 25–30 cm (tillage depth), within a 2 m radius of the sensor. The locations of the soil samples are chosen based on the gamma variation in the data identified from the maps. The locations selected for soil sampling should reflect the overall soil variation in the field. At these sample sites, a gamma spectrum is measured for 5 min. The soil samples are analysed in the laboratory and the soil parameters are related to the corresponding gamma readings by regression analysis. The resulting regression equations allow the interpolated gamma readings to be translated into soil property maps. Soil sampling is conducted on the same day as the gamma survey of the field. The gamma spectrum analysis, regression, interpolation, map calculation, and quality control processes are conducted in the office.

The fingerprints of soil types and their properties depend on parent material, soil-forming processes, and age, among other things. In agriculture, soil nutrient levels are influenced by management practices and vary between different farming systems. Therefore calibrating the gamma data for soil nutrient maps has to be based on soil samples from that specific field or farm. However, physical soil properties and their natural gamma readings can be compared within a geological unit. To illustrate this, a dataset of soil samples and their gamma readings from an 800 ha farm on marine clays in Zeeland, The Netherlands, has been collected. The dataset consisted of 89 samples and was divided into a calibration dataset containing 46 samples and a validation dataset containing 43 samples. (Multiple) linear regression was performed using the calibration dataset and the best fits for each soil property are listed in Table 27.1. Soil texture (clay, silt, and loam) shows a good correlation when compared across the farm. However, soil nutrients like organic matter and magnesium show poor correlations on a farm scale, but these improve significantly when considered at field scale.

The Soil Company has gradually built a large database of soil samples and their gamma readings. This database is used to generate general spatial patterns of different soil properties and provides ‘extra’ regional sample data for the correlation of nuclides with physical soil properties (and sometimes organic matter and magnesium). For a graphical illustration of the data in Table 27.1, two of the correlations are plotted in Fig. 27.1. Similar plots can be made for other physical and chemical soil properties.

Table 27.1 Results of the separate calibration and validation of soil properties and gamma measurements for an 800-ha farm in Zeeland, The Netherlands

	Calibration				Validation	
Soil properties	Nuclide	N^a	R^2	RMSE[b]	N^c	RMSE[b]
Clay (<2 μm)	^{232}Th	46	0.85	3.7	43	3.1
Fine silt (<16 μm)	^{232}Th	46	0.80	6.8	43	5.4
Loam (<50 μm)	^{232}Th	46	0.82	8.1	43	8.7
M0 (median grain size)	^{40}K	46	0.84	9.5	43	13.3
Organic matter	^{40}K, ^{137}Cs	46	0.51	0.41		
Organic matter	^{40}K, ^{137}Cs	15	0.88	0.24		
Magnesium	^{238}U, ^{137}Cs, ^{40}K	46	0.65	15.2		
Magnesium	^{232}Th, ^{137}Cs	15	0.90	4.5		

[a]Number of samples used for calibration
[b]RMSE for clay, silt, loam, and organic matter is depicted in %; for M0 in μm; and for Mg in mg kg^{-1} dry matter
[c]Number of samples used for validation

In general, correlation plots had an R^2 ranging from 0.6 to 0.95. If the analysis explained less variance, the regression results were not used in the prediction of a soil property.

The gamma data from the field were interpolated using inverse distance weighting. Applying the regression equation from Fig. 27.1 to some of the gamma maps of this farm yielded the map of clay content shown in Fig. 27.2.

The intervals shown in the legend are comparable to the statistical error, and variation in the maps can therefore be considered as a significant variation. To check the reliability of a derived soil map, the map values on the sample locations were compared with the actual (measured) soil property values. The R^2 values between the predicted values and the sampled soil properties varied between 0.7 and 0.98. The image was compared to existing soil maps where available. In these cases, validation was performed by applying regression equations of the calibration dataset (Table 27.1, Fig. 27.1) to the gamma data of the separate validation dataset. For clay, this yielded an R^2 of 0.86 with an RMSE of 3.1% (Table 27.1). Results for validation of other soil properties in this dataset have an R^2 between 0.72 and 0.84, with RMSE between 5.4 and 13.3 (Table 27.1). The patterns in the soil maps corresponded well with the farmers' qualitative knowledge of the fields and confirmed their perception during tillage.

Maps of bulk density, water retention, etc. can be calculated using pedotransfer functions and the physical soil and organic matter maps. Maps of compaction risk, nematode risk, etc. can also be calculated based on information from agricultural research on the subjects (RBB, 1970).

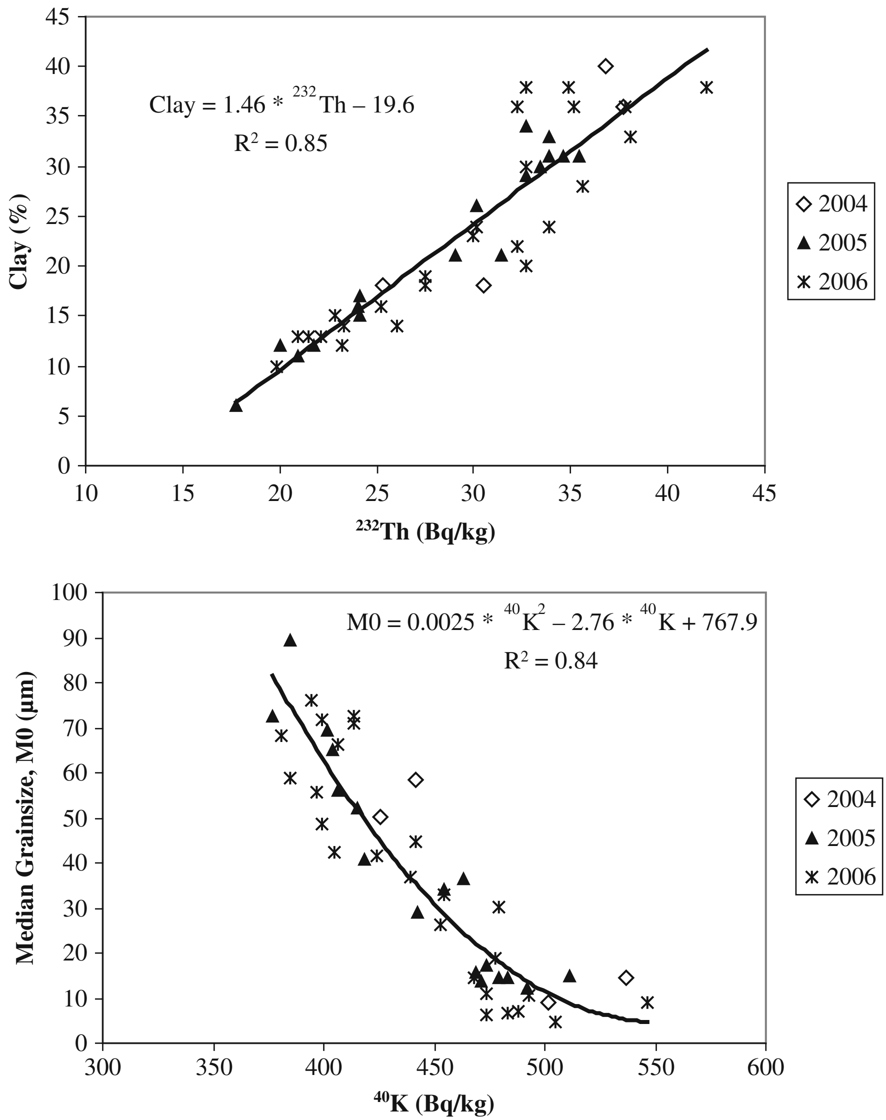

Fig. 27.1 Soil samples of clay content (%, *top*) and median grain size (M0, *bottom*) versus ^{232}Th and ^{40}K readings. Data from an 800-ha farm (Zeeland, The Netherlands) taken in three successive years

The standard set of reported maps from a field measurement consists of four types: regionally calibrated maps of physical soil properties, field or farm calibrated maps of chemical soil properties, maps calculated based on pedotransfer functions, and calculated risk maps.

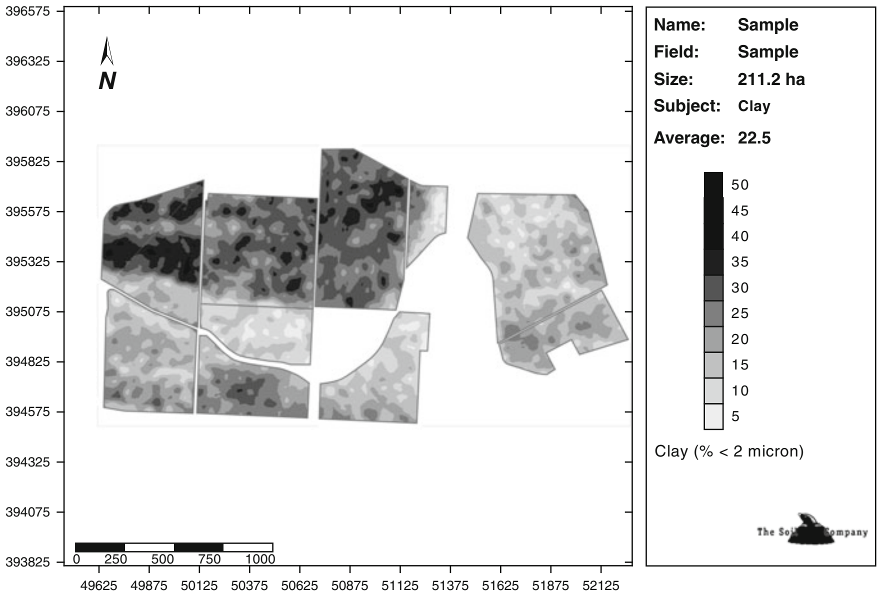

Fig. 27.2 Gamma-based map of the clay content of 10 fields (211 ha in total, Zeeland, The Netherlands) derived from the equation in Fig. 27.1

27.3 Applications

In The Netherlands, experience has been gained from several precision agriculture applications derived from or based on the gamma ray-based soil maps. Table 27.2 gives an overview of some of these applications and their general benefits.

Clay maps from the Zeeland farm were used to reduce the amount of sugar beet seed needed by 13%, while maintaining the same yield. Another precision agriculture application used the clay content map to achieve a more homogeneous size distribution of seed potatoes. This is an attractive perspective for farmers, as seed potatoes in the 28–55 mm size range are worth more. The clay content map has been translated into a variable planting distance map (Fig. 27.3), and this has improved financial yields on average by 6% or 230 € ha^{-1} in a 4-year trial.

27.4 Future Developments

Currently research is being conducted on the integration of gamma ray sensing with other sensor techniques like EM38 (Chapters 29, 33, and 28). This can yield complementary data that can perhaps further enhance data-based decision making by farmers and offer new possibilities for precision agriculture. Improved data interpolation and sample location selection techniques are being automated to improve

Table 27.2 Tested precision agriculture strategies and their measured and perceived benefits in The Netherlands

Application	Base map(s)	Desired effect	Benefits
Variable planting distance	Clay content/water retention	Homogeneous size distribution of potatoes/broccoli	5% negative up to 15% positive financial benefit
		Reducing amount of sugar beet seed	13% reduction in cost while maintaining yield
Variable fertiliser amount	Nutrient or clay content	Saving fertiliser or improving yield	Up to 60% reduction in fertiliser
			10% yield improvement consumer potatoes
Variable application compost	Organic matter	Reducing organic matter variation in field	Improved soil structure, water retention
Variable liming	pH and organic matter	More homogeneous pH	Improved sugar yield sugar beets
Variable nematode control	*Trichodorus* risk	Reduction in granular products	40–60% savings on chemicals
Variable tillage speed	Compaction risk	Less compaction due to tillage	Variable tillage patterns are highly recognisable

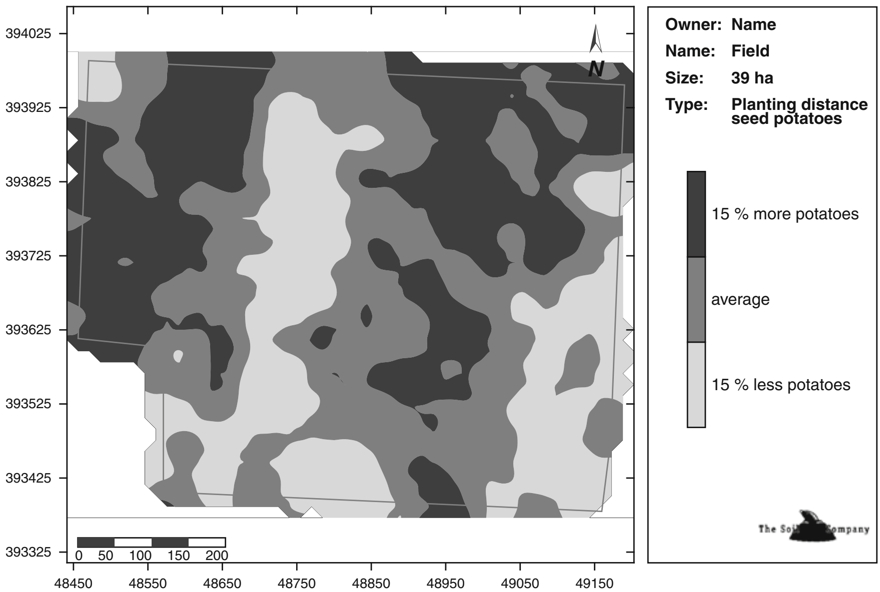

Fig. 27.3 Map of recommended variable planting distance calculated from the gamma-based clay content map of Fig. 27.2

map quality and enable commercial implementation of the process. Additionally, alternative methods of data analysis are being examined for use instead of, or complementary to, the current regression analysis method to determine if or how gamma sensor measurements and their translation into soil data could be improved.

27.5 Conclusions

Sensor technology based on gamma ray sensing can be used for creating quantitative topsoil maps in conventional units that farmers are familiar with. The method is highly sensitive and is used to make high-resolution maps for precision agriculture. The patterns in the soil maps are recognisable to farmers and confirm their perception during tillage. The quantitative aspect of the soil property maps enables operational decision support for crop management. This work has shown that accurate sensor technology and precision agriculture can contribute to yield improvement.

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