A heterogeneity index to assess machinery to match soil and crop spatial variability

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Abstract

The increase of machinery size to gain work productivity gives concerns that spatial variability can not be addressed sufficiently when using PF methods. Data from soil electric conductivity sensors (EM38) and canopy light reflectance sensors (YARA N-sensor) from fields in Denmark were analysed. The geo-statistical analysis included a determination of semi-variograms and the main parameters from it. In order to directly evaluate the matching of soil or crop variability to VRA machinery size a heterogeneity index was used. The index is called mean correlation distance (MCD). The index values varied highly between fields as well as between data types. Surprising was that the values from the crop data were almost always smaller than those from the soil sensor. The common machinery size of the concerning regions (20 m and more working width) did not fit to the spatial resolution of the crop plant needs. The conclusion is that on some fields an existing potential for optimising inputs can not be reached due to inappropriate machinery size. A decision tree based on variogram parameters is suggested to support farmers in matching machinery size to existing farm and field variability.

Keywords: heterogeneity index, variable rate application, spatial statistics, soil electric conductivity, canopy light reflection

Introduction

Advances in Precision Farming (PF) are not that high and clear as expected some years ago. Although the principles of PF are accepted by farmers and advisors a broad adoption of the technology has not occurred yet. Problematic issues are e.g. particularly decision support systems, recognition of temporal variation and environmental auditing (McBratney et al, 2005). Furthermore, due to the increase of size of machinery in general to gain work productivity a trade-off appears concerning matching the magnitude of the spatial variability when using PF methods. In some regions as in the southern part of the Baltic Sea short range soil variability is very common (Griepentrog & Kyhn, 2000). These soils exist for example in south western regions (northern Germany and Denmark) as well as in south eastern areas (Baltic countries).
The emphasis of technological developments in agriculture has been on mechanization of field operations to increase work rates, productivity and economic efficiency. But large scale machinery seems to have drawbacks to match the general requirements for precision farming. A conflict of aims appears when (i) the application machinery needs to be powerful - means mainly big working width and high operation speeds - and when

(ii) the potential of FP benefits increases with higher soil and crop heterogeneity at short ranges.
Management zones seem to be a compromise often to make fields manageable. A ‘management zone’ defines a sub-region of a field that has a relatively homogeneous combination of yield-limiting factors, for which a single rate of a specific crop input is appropriate. Soil information (topography, soil type, etc.) is valuable for management and can be used to create these more ‘stable’ management zones. However, crops respond to more than soil type, for example to climate, weeds, pests and disease and thus, yield patterns often vary from year to year.
Especially sensor based nitrogen application in North Europe often has the aim to homogenize the crop to ease combine harvesting and to avoid crop logging due to over dosage. This strategy of crop management clearly reduces existing crop spatial variability.
Although today it seems that online sensor systems are more successful than offline mapping systems. But soil describing and mapping should still be regarded as valuable crop management information. Online systems are favourable for highly temporal dynamic nutrients like nitrogen. Offline sampling is common for other properties like nutrient concentrations of P and K but also for soil organic matter (SOM). To discriminate between different plant stresses by using advanced online sensors is still a big challenge and therefore, direct soil nutrient sampling and mapping is necessary to ensure sufficient crop nutrient supply.
Due to high spatial variability of the soils in Denmark and thus, for low geo-statistical ranges detailed mapping of these parameters using a grid sampling method is sometimes economically crucial. Webster and Oliver (2001) recommend spacing between soil samples of about half the effective range which definitely results in not acceptable economic viability.
The approach to describe heterogeneous systems can be conducted on different levels of scale, for regions, fields, patches and even for individual plants of a crop stand ('plant level husbandry'). The absolute scale moves down from about 1 km to sub metre range.
Examples for almost plant scale sampling are described in Solie et al (1999) and LaRuffa et al (2001). They propose that sensing areas of less than 2 m provide the most precise measure for crop nutrition needs, and that real-time, variable-rate sensor applicators should be designed to sense and treat at that scale. In contrast to that other authors like Taylor et al (2003) analysed uniformly treated fields and state that short range variability of less than 20 m is mainly caused by distribution errors of application technology and that current applicators in size are suitable for variable rate dosing.
However, it seems a general trend that if sensing systems are available the sensing resolution goes up and plant scale husbandry seems possible in the near future. Today in PF the mapping approach (soil controlled) or sensor approach (crop controlled) or an overlay of these systems (Ostermeier et al. 2006; Berntsen et al. 2006) are even commercially available.
The 'Integral Scale' and 'Mean Correlation Distance' (MCD) was first defined by Russo & Jury (1987) and Han et al (1994). The purpose was to optimise the size of sampling grids or the number of sampling points per defined area depending on the magnitude of field condition variability. The MCD is especially suitable here in this study because it considers not only nugget, sill and range but, furthermore, the characteristic of the variogram function below range to define a maximum area length which is needed to

describe the concerning variability. This ensures reliable index values for a variety of functions as for example spherical, exponential and gaussian.
The authors of this paper hypothesise that today for many variable rate applications the machinery size (working width) is not appropriate and hence not able to address the existing spatial variability of plant needs across a field. This means that an existing potential for optimisation of inputs can not be utilised, although this potential can be measured by sensors and described after the data analysis.

Materials and Methods

Fields and fertilisation strategy

Geo-referenced soil electric conductivity (SEC) data as well and canopy light reflection (CLR) data for 8 Danish agricultural fields were provided by the Danish Agricultural Advisory Service (DAAS). Although the number of fields is relatively small they are located within different regions in Denmark. Adapted to field sizes and mechanisation the working width of the tramline systems varied from 12 to 34 m. That gave a lateral resolution of the same for the CLR data and of half that value for the SEC data, because the EM38 sensor was pulled across the field within and between the tramlines. The SEC measurements took place at maximum water holding capacity (field capacity) during winter time. The CLR data were collected by a YARA N-sensor in early spring during 2nd application of nitrogen which was varied in dose rate. The 1st nitrogen application after winter time was applied with a uniform dose rate which is common in Denmark even within PF farming strategies.

Table1. Basic field data and sampling patterns for all fields for soil electric conductivity (SEC) and canopy light reflection (CLR) measurements

Field / Parameter		Area (ha)	n	Track spacing (m)	Point spacing (m)
Egeskov /	SEC	24.3493	3902	11.4	5.8
	CLR	"	5363	24.1	2.0
Nibe /	SEC	34.9229	2967	20.2	6.1
	CLR	"	6928	20.5	2.9
Odder /	SEC	10.0685	711	17.3	5.9
	CLR	"	1373	34.7	2.1
Spørring /	SEC	1.1198	220	6.4	7.5
	CLR	"	424	12.7	2.1
Tappernøje /	SEC	3.1668	360	15.5	5.9
	CLR	"	651	27.6	1.7
Tommerup /	SEC	4.6846	774	12.3	5.4
	CLR	"	1898	12.0	1.9
Viborg /	SEC	1.0932	168	14.9	5.3
	CLR	"	623	13.7	1.5
Aarhus /	SEC	1.8216	283	15.8	4.7
	CLR	"	760	16.3	1.6

Data acquisition

Soil sensing: The em38-sensor provides fast and non-destructive measurements of the apparent soil electric conductivity (SEC). The SEC is strongly correlated with soil mineral particle sizes (clay content) if measured at field capacity. The standard GEONICS EM38 is operated in either the vertical or horizontal mode (GEONICS, Mississauga, Canada). SEC was measured to a depth of approximately 1.50 m (vertical mode) with a GEONICS EM38DD sensor mounted on a sledge and pulled by a light vehicle. The sledge was equipped with a Global Positioning System (GPS) and a data logger on the motorbike. The spatial track data patterns across the fields were different (Tab. 1) and varied according to the tramline width. The size of the sampling area is relatively small and around 1 to 2 m^2. The sampling rate was at 1 Hz.

Crop sensing: The YARA N-sensor is a commercially available system (YARA International ASA, Norway) that measures canopy light reflection (Reusch 2003). Selected bandwidth are used to compute a parameter which correlates with the crop biomass or crop chlorophyll density of the scanned spot. The system assumes that estimated biomass correlates with the crop's nitrogen demand and applies nitrogen fertiliser in real-time on-the-go. The N-sensor measurements were logged in early May, just before the second N-application similar as described in Berntsen et al. (2006).

The spatial track data patterns across the fields are the same as the tramlines used for all application passes (Tab. 1). The size of the sampling area of the N-Sensor is relatively big and depends also on mounting height above ground of the sensor on top of the tractor cabin. The area was 20 m^2 as a sum of 4 simultaneously scanned and averaged spots pointing around the vehicle.

Data analysis

We used the software SURFER (Golden Software) for the interpolation, mapping and variogram computation. The model fitting was conducted using SURFER's autofit-function corrected by manual parameter changes. The lag direction for determining the variogram parameters was chosen to be in the direction of driving (not omni-directional). The reason was that most of the field data were retrieved from so called strip trials with long tracks instead of quadratic plots. Only the fields Egeskov and Nibe were relatively big (more than 20 ha) and of almost quadratic shape. EXCEL (Microsoft) integrated the model functions and calculated the Mean Correlation Distance (MCD).

The MCD is defined by Han et al (1992) as follows:

$$MCD = \int_0^{h_{\max}} \frac{S - \gamma(h)}{S} dh \qquad (1)$$

Where

$h_{\max}$: range (m)

S : sill

h : lag distance

$\gamma(h)$: variogram function or model

Results and Discussion

The results from the geo-statistical analysis for all 8 fields are presented in Table 2 and 3. For both the soil as well as the crop data the nugget values were small or even 0. Only for field Nibe the nugget-sill ratio was high for the CLR data due to a high nugget value. A low nugget-sill ratio indicates a large degree of spatial correlation.
The variogram ranges also showed a clear characteristic because the values from the SEC were always higher than those calculated from the CLR data. Spørring was the only field where soil and crop properties gave almost the same range value.
Other geo-statistical soil property investigations showed similar results for Danish fields (Albrechtsen et al, 2000, Greve et al, 2003).
The MCD determination from SEC and CLR data resulted also in different values mainly because the range values already showed big differences. The MCD values for the SEC data varied from 16 to 96 m and for the CLR data from 15 to 80 m. Only one field (Spørring) had a MCD value less than 20 m in soil sensing but there were 5 fields (Spørring, Tappernøje, Tommerup, Viborg and Aarhus) which showed a MDC less than 20 m for the measured crop properties.

Table 2. Geo-statistical analysis of Soil Electric Conductivity (SEC) including the Mean Correlation Distance (MCD) for 8 Danish agricultural fields

	Nugget $(mS/m)^2$	Sill $(mS/m)^2$	Nugget/ Sill Ratio (%)	Range (m)	Model	MCD (m)
Egeskov	4.0	32.0	12.5	210	Spher.	96
Nibe	2.0	35.0	5.7	189	Spher.	78
Odder	1.0	18.5	18.5	140	Spher.	58
Spørring	0.1	3.5	2.9	39	Spher.	16
Tappernøje	2.0	-	-	-	Linear	-
Tommerup	1.0	27.0	3.7	90	Expo.	59
Viborg	0.7	6.4	10.9	64	Spher.	29
Aarhus	0.0	270.0	0.0	135	Expo.	86

Table 3. Geo-statistical analysis of Canopy Light Reflection (CLR) including the Mean Correlation Distance (MCD) for 8 Danish agricultural fields

	Nugget (-)	Sill (-)	Nugget/ Sill Ratio (%)	Range (m)	Model	MCD (m)
Egeskov	0.00	0.315	0.0	56	Spher.	22
Nibe	0.38	0.780	48.7	75	Spher.	52
Odder	0.00	0.260	0.0	124	Spher.	80
Spørring	0.00	0.199	0.0	41	Spher.	16
Tappernøje	0.00	0.001	0.0	44	Spher.	17
Tommerup	0.00	0.360	0.0	38	Spher.	15
Viborg	0.00	0.600	0.0	36	Spher.	14
Aarhus	0.00	0.158	0.0	40	Spher.	16

Surprising is the low range variability for the CLR systems compared with the SEC systems although the soil sensor had a much higher resolution and the crop sensor even operated in a moving average mode because sampling overlaps occur due to relatively high sampling size and sampling frequency. But obviously the variability of the crop biomass is much higher than for the soil clay content as measured by the soil sensor.

There are no publications about spatial analysis of CLR data except from Thiessen (2002). The measuring and parameter methodology is almost the same as described in this study. The main difference is the location (Northern Germany) and the sensor sampling resolution of about 1 m^2. The value range for the MCD was similar although the sampling spot size was much smaller. Furthermore Thiessen (2002) found out that the crop spatial variability is not constant during the vegetation period. He showed that the variability decreased in range and MCD as vegetation period progressed. It can be concluded from those results that the crop stand properties became more uniform.

The authors assume that variable rate application (VRA) technology is appropriate for these fields because both soil as well as crop parameters are spatially not uniform. The sill values are high and nugget-sill ratios are low which shows that there are almost no random errors and effects. In order to address this described variability the distribution - machinery should be able to target fertiliser with varying dose rates to particular field spots. By using currently common VRA machinery in Denmark of working width around 20 m and more seems not to be recommendable for MCDs lower than 20 m. The working width should be adapted to the range of variability means should have the same value as the concerning MCD. The common uniform as well as variable rate applicators of fertiliser are centrifugal disc spreaders (Griepentrog & Persson, 2000).

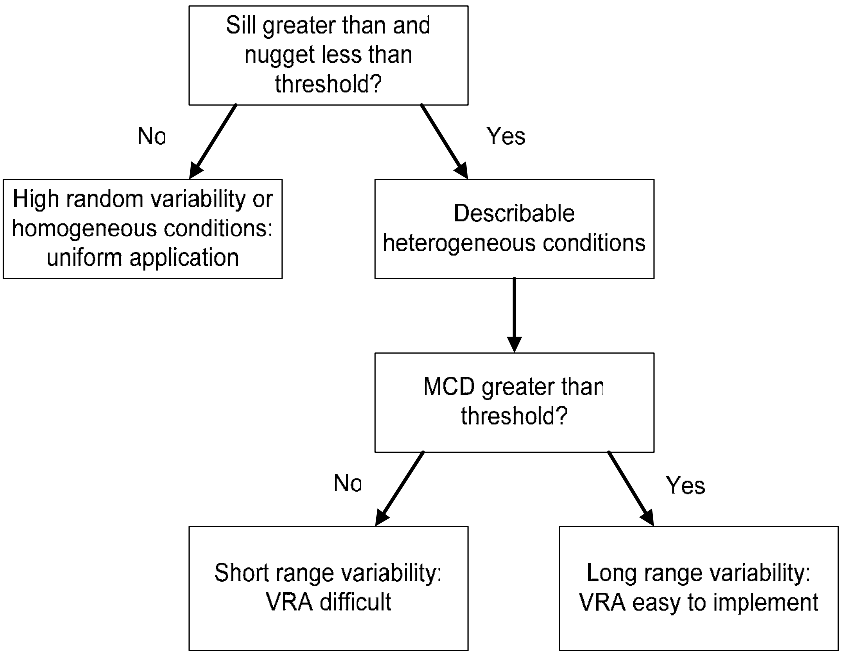

Figure 1. Decision support to assess applicability of VRA machinery based on variogram parameters

High random and short range variability could be addressed by application technology with very high resolution e.g. of sub metre width. This could be achieved using a sprayer with nozzle switching or similar. Some modern pneumatic fertiliser spreaders

have controllable dose rates for each outlet. This allows splitting the boom into sub-sections.
To support farmer's decisions we suggest that before considering to invest in VRA technology or to implement PF methodologies to farms or fields to analyse either soil data or crop data derived form today easy available sensors as EM38 or YARA N-sensor. Information from both systems give a good estimates about the existing farm or field spatial variability by using semi-variogram parameters. In Figure 1 a decision tree is shown to support and simplify this process. A similar but more general scheme was developed by McBratney & Pringle (1999). They suggested to base decisions on average variograms as threshold values. The authors of this paper suggest to use the MCD values directly as an indicator to decide whether technology matches the variability or not.
The MCD can also give useful information when calculated from application maps. An application map is the result of a crop management recommendation based on soil sampling or other information sources. This recommendation could have had the aim to average short range variability e.g. by introducing management zones. However, the application map can be regarded as the interface between crop management recommendations and the technology following to execute this task. An MCD calculated from the application map can have the aim to show that the existing technology fits or to determine what size the technology should have. If existing technology can not be used then a conclusion for the farmer could be not to apply PF methods to his farm or for a particular field.

Conclusions

The statistical analysis of soil and crop data showed that short range variability exists which is smaller than commonly used application machinery with particular working width. The proposed MCD index can support the farmer in helping him to evaluate farm and field heterogeneity in relation to machinery size.

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