TOWARD MORE PRECISE SUGAR BEET MANAGEMENT BASED ON GEOSTATISTICAL ANALYSIS OF SPATIAL VARIABILTY WITHIN FIELDS

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ABSTRACT:

Sugar beet yields in England are expected to increase in the future, due to the advances in plant breeding and agronomic progress, but the intra-field variation in yield due to the variability in biotic and abiotic factors should not be ignored. This paper explores the spatial variation in the field in relation to sugar beet growth and yield. It also investigates the possibility of anticipating spatial variation in sugar beet yield based on early assessment of crop biomass. For this study 91 plots were placed in an irregular grid in a 9 ha sugar beet field located in the east of England. The results indicate significant spatial variation in final root yield from 36.5 to 89.5 t/ha across the field. The sampling protocol followed in this field was sufficient to describe the majority of the variation. Some of the observed variation related to the soil moisture and soil organic matter. The spatial variation in root yield at final harvest was correlated with the variation in Leaf Area Index (LAI) measured in July. Therefore variations in LAI observed early in the growing season were a good predictor of the final economic yield of sugar. In addition, preliminary results in two other fields also indicate a significant relationship between the yield map of sugar beet crop and the map of previous crop (winter wheat). These results indicate the feasibility of predicting the variation in sugar beet yield from the yield map of previous crop together with early LAI of the sugar beet crop.

Keywords: sugar beet, within field variability, geostatistics, yield prediction

INTRODUCTION:

Conventionally, agricultural fields are managed with uniform application of tillage and agronomic inputs. In addition to potential adverse effects on the environment, this approach may increase the costs of production and waste the natural resources (Montanari *et al*., 2012), because environmental variables are never uniform even at the field scale, so that crop development and yield vary spatially (Hedge, 2013). This variability could be managed by applying the right amount of inputs in the right place at the right time in order to optimize benefits, increase sustainability and decrease adverse environmental impact (Mondal *et al*., 2011, Najafabadi *et al*., 2011). Factors such as soil fertility, pH, water deficit, weeds, pests and diseases could be managed spatially, while others such as soil texture, topography and climate cannot (Sadler *et al.*, 1998, Frogbrook, 2002).

Sugar beet (*Beta vulgaris* L.), along with sugar cane are the two main global sources of sucrose, for which there is a large global market of high economic importance. Sugar beet currently supplies approximately 40 million tonnes of sucrose annually which represents about 30 % of global demand (Draycottand Christenson, 2003). In 2010-2011 sugar beet occupied approximately 3% of the UK arable land, and this produced around 1.3 million tonnes of sugar with an average root yield of 75 t/ha (Limb, 2012). During the last four decades the sugar beet yield per hectare in the UK has increased significantly as a result of improvements in sugar beet varieties and agronomy (Jaggard *et al.*, 2007) and this is expected to continue in the future (Richter *et al.*, 2006). However, sugar beet growers face various challenges such as the recent changes in weather which are outside the grower's control, while plant nutrients can be added to achieve significant benefits (Draycott and Christenson, 2003). Perhaps the most important factor in northern Europe now and in the future is the soil moisture, since most sugar beet is rain-fed (Freckleton *et al.*, 1999), while in the Mediterranean region the effect of temperature on sugar beet yield could be greater than the effect of drought, due to the increase in the evapotranspiration rate (Abd-El-Motagally, 2004).

The variation within regions and even within fields is, however, expected to be higher than the variation between regions due to the variability in soil properties (Richter *et al.*, 2006). Therefore identifying spatial variation in environmental conditions could provide important information for water and nutrient management and fertilizer application in sugar beet fields (Montanari *et al.,* 2012*,* Sağlam *et al.*, 2011). Some studies have attributed the within-field variation in crop yield to one or few factors such as soil texture and soil organic matter (Shaner *et al.*, 2008) and nutrients (Vanek *et al*., 2008) which have a significant effect on crop yield. Variation in the proportion of sand and stones can cause spatially variable wilting in the sugar beet crop (Zhang *et al*., 2011). Others have referred to some variables such as the diffusion of water and nutrient, which are quite complex and difficult to investigate (Lark, 2012). Since the within-field variation could be due the combined influence of different soil and micro-climate factors, it is quite difficult to isolate the effect of a single environmental factor. In addition, crop stress is usually observed and treated when it becomes visible by which time the damage has already occurred and the crop may not be fully recover (Bouma, 1997). Therefore anticipating the spatial variability in sugar beet yield early in the growing season is also important as it might help the farmers avoid or mitigate the damage before it occurs.

The overall objectives are to assess the spatial correlation of sugar beet yield with measured variables and also with the yield map of the immediately preceding winter wheat crop.

RESEARCH METHODOLOGY:

Research site and measurements:

The study was conducted in three sugar beet fields located in the east of England, but only the results of one field are presented in this paper. The field called White Patch with area of 9 ha is located in Broom's Barn Research Station and it was selected on basis of known intra-field variability in soil type, aspect and the perception that there is likely to be significant spatial variation in factors deemed likely to be important as driving variables. According to a previous soil analysis at Broom's Barn using a regular 40x40 m soil sampling grid (5 per ha), the White Patch field has three different soil types; loam, sandy clay loam and, sandy loam (Draycott and Evans, 2012). This information provided an initial picture of spatial variation to identify the number and the allocation of samples needed in the present study (Webster and Lark, 2012). All field operations were uniform across the field and with farmer responsibility for all operations. The field was drilled in 23March2012 and the variety of sugar beet planted was Valeska. Parts of the field were excluded from the study due to the presence of other experiments, but a suitable number of plots were identified to represent the different soil types. The sampling scheme was an irregular grid in two dimensions and the sampling intervals for main plots ranged between 24 to 40m. To reveal the variation over shorter distances and the nugget effect, some nested samples with 10 m intervals were identified purposively within each soil type (Fig.1) (Webster and Oliver, 2007, Webster and Lark, 2012). The area of each plot was 2x2 m, and a differential Global Positioning System (dGPS) was used for georeferencing the plots. All the soil and plant samples, microclimate and other measurements were taken from these plots. The plots were harvested by hand on 25 September 2012 and the samples sent to the British Sugar factory in Wissington for analysis in exactly the same way as for commercial farmers.

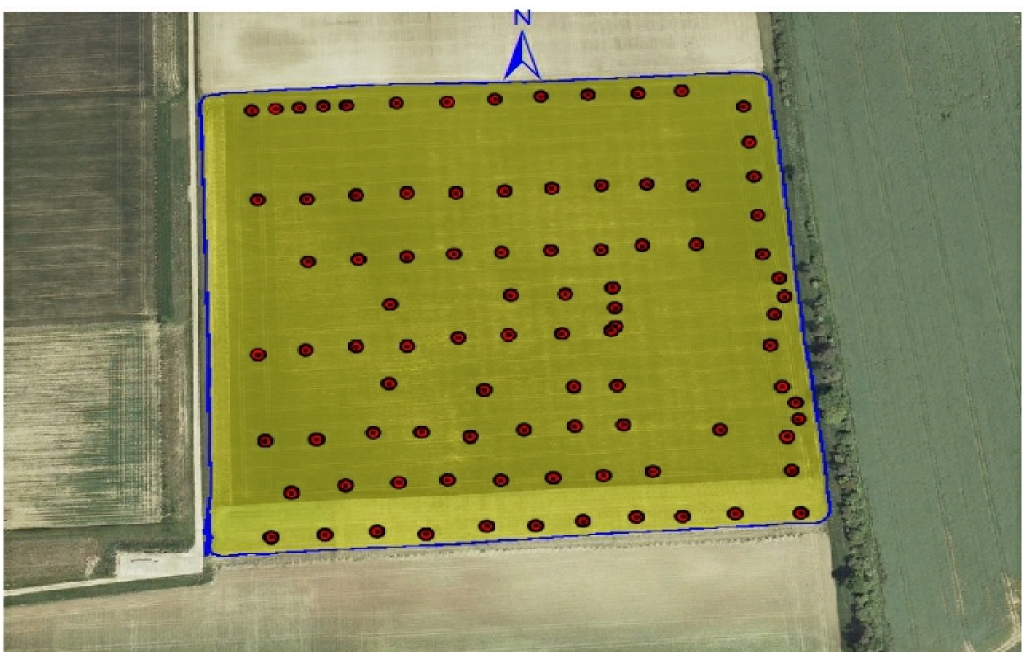

Figure. 1.The field map and the position of samples in White Patch field, near Bury St Edmunds, England shown on a Google Earth satellite image. Field size is 300×300 m.

Geostatistical analysis:

The data for each variable were examined by histogram and skewness coefficient to detect any departure from normality, because the variogram is sensitive to asymmetry (Kerry and Oliver 2007). The experimental variograms which can explain the spatial variation were calculated for each variable by Matheron's Methods of Moment (MoM) and fitted by a suitable model using GenStat software (Webster and Oliver 2007).

For Kriging interpolation, the model parameters with the original set of data were then passed to ArcGIS software to create a predicted map using the geostatistical analyst tool available in ArcGIS software to show the scales of within-field variation.

RESULTS:

The summary statistics of the studied parameters (Table1) showed a low coefficient of skewness. These variables were therefore normally distributed which is desirable for geostatistical analysis (Montanari *et al.*, 2012). The coefficients of variation (%CV) which indicates how the spatial variation differed from one variable to another and ranged between 32% for LAI and 15% for organic matter (Table1). The preliminary results of geostatistical analysis showed that all the variables, for which results are presented here, varied spatially (Table2). The variogram shapes and the fitted model differed considerably from one variable to another (Fig 2, A-D). A spherical model gave the best fit to LAI and root yield, an exponential one to soil organic matter, and circular model to soil moisture. However, most of these variograms reached their upper limit (sill) which means the variation in these properties is patchy producing areas with high value and others with low values (Frogbrook *et al.*, 2002). Since the variograms eventually stabilized with lag distance (Fig 2), the sampling protocol accounted for the majority of spatial variation in the field. As the variograms indicate the patchy variation, the average extent of these patches which is determined by the range of the variogram also differed between the studied variables. It was as long as 132.9 m for soil moisture and as short as 22.9 m for soil organic matter, and it ranged between these values for other variables. The degree of spatial dependency which can be computed as a proportional ratio of nugget to sill semi-variances was very strong for all the studied variables (Table 2).

Variation in organic matter and soil moisture:

The maps created based on ordinary kriging interpolation show considerable spatial variation in soil organic matter and soil moisture. The areas of low and high values of these variables were distributed as patches with some differences in average extent of the patches (Fig 3, A and B). The percentage of organic matter significantly varied throughout the field from 1.9 to 3.6% and soil moisture from 0.14 to 0.39 (Table 1). Most of the area of high organic matter and soil moisture was from the west toward the middle of the field which is almost the same area of loamy soil in the previous soil map of this field. Some areas of low organic matter were also associated with low soil moisture content with a correlation coefficient of 0.37 (Table 3). The area of low soil moisture appeared as a continuous patch from the southeast corner toward the north and this patch was discontinuous for organic matter (Figure 4 A and B).

Sugar yield t/ha and yield value £/ha

Associated with the spatial variation in soil organic matter and soil moisture, significant variation was also observed in LAI during July and consequently the root varied at final harvest from 36.5 to 89.5 t/ha (Table 1).

Table1. Summary statistics for some studied variables.

Variable	Mean	Minimum	Maximum	C.V%	Skewness
Organic matter, %	3.4	1.9	3.6	15	0.47
Soil moisture	0.46	0.14	0.39	21	0.60
Leaf area index	1.9	0.77	3.45	32	0.42
Root yield, t/ha	58.8	36.5	89.5	21	0.43

Table2. The fitted model and their main parameters for studied variables.

Variables	Model	Sill	Range, m	Nugget	Spatial dependency
Organic matter, %	exponential	0.18	22.9	0.078	0.33
Soil moisture	circular	0.0025	13.9	0.00012	4.6
Leaf area index	spherical	0.27	77.4	0.081	23
Root yield, t/ha	spherical	135.5	105.5	9.9	0.08

Table3. The correlation coefficients between studied variables.

	Organic matter, %	Soil moisture	Leaf area index
Organic matter, %	-		
Soil moisture	0.37	-	
Leaf area index	0.28	0.45	-
Root yield, t/ha	0.48	0.36	0.43

The variation in root yield only reached its maximum variance (135.5) over long range (105.5 m, Table 2). The areas of low LAI were generally in areas of low soil moisture and organic matter (Figure 3, B-C) with correlation coefficients of 0.45 and 0.28 respectively (Table 3). These areas were also associated with low root yield (Figure 3, D) with correlation coefficients of 0.36 and 0.48 respectively with soil moisture and organic matter (Table 3).

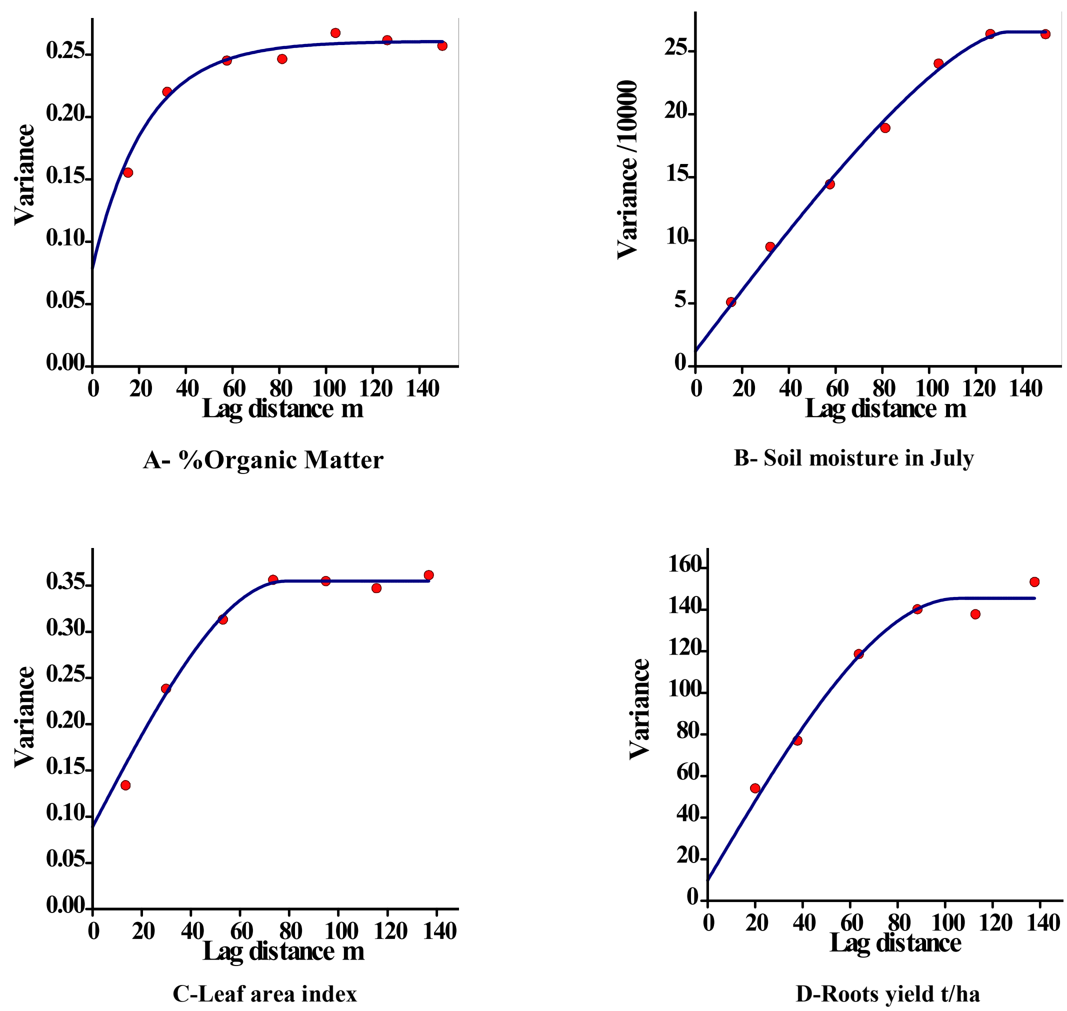

Figure 2. Experimental variograms for (A) organic matter, %, (B) soil moisture in July 2012, (C) leaf area index in July 2012 and (D) sugar beet root yield, t/ha, at harvest in September 2012.

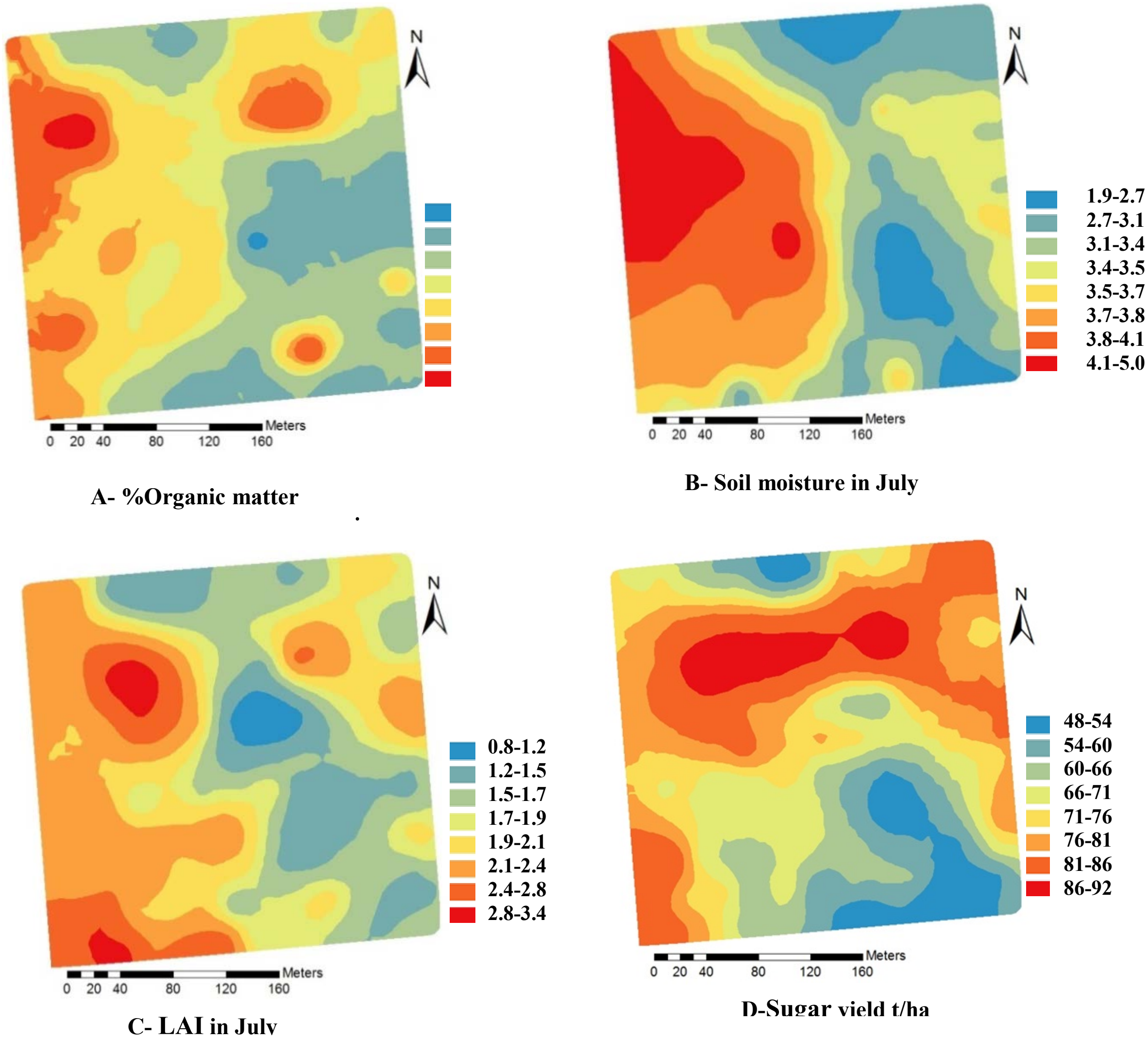

Figure 3.Kriged maps for (A) soil organic matter, %, (B) soil moisture in July 2012, (C) leaf area index in July 2012 and (D) sugar beet root yield, t/ha, at harvest in September 2012

The areas of high root yield were associated with some areas of high organic matter and were located in the western part of the field toward northeast. The variations in sugar beet root approximately followed the same patterns of spatial variation as LAI measured in July (Fig. 3 C , D) with a correlation coefficient of 0.43 (Table 3).

Results in two other fields of sugar beet showed significant relationship between the yield map of sugar beet and the yield map of previous crop (data not shown).

DISCUSSION:

The variation in crop yield and some associated variables to some extent followed the same patterns and distributed as a patches of low and high values. However the average extents of these patches differed from one variable to another. The areas of high soil moisture and soil organic matter corresponded to the area of loamy soil in the map produced by Draycott and Evans, (2012), which is located in the western part of the field. As a result some areas of high root yield were also found in this part and especially associated with areas of high organic matter. Therefore mapping soil texture is important for site-specific water and nutrient management, because it is strongly related to these variables (Safari *et al.*, 2013). The areas of low soil moisture and organic matter were mostly located in the southeast corner of the field toward the north and appeared as patches with different sizes. These areas were also associated with low LAI and were mostly located in the same area of the field where there a slope. Consequently some of these areas were also associated with low root yield at final harvest. This indicates that field topography could be one of the main driving variables which was causing spatial variation in soil forming factors and erosion and this might reflect on crop yield (Kumhálová *et al*., 2008). It can also cause significant variation in solar radiation received which in turn leads to spatial variation in microenvironment such as soil and air temperature, soil moisture, evapotransperation and photosynthesis (Fu and Rich, 1999). Although, it is not possible to change the field topography and soil texture by agronomic practice, but it can still be used to understand the causes of variation (Godwin and Miller, 2003, Draycott and Christenson, 2003). The variation in root yield generally followed the same patterns of the spatial variation in LAI measured in July. The areas of high root yield were slightly different, but some of the areas of low values were located in the same parts. This indicates the possibility of using the spatial variation in LAI observed early in the growing season as a good predictor of the final economic yield of sugar. Thus agricultural inputs should spatially vary according to these patches and the areas of low LAI should perhaps receive more inputs than areas with high values, which may increase the uniformity of final economic yield in the field. Moreover a preliminary analysis of the relationship between the yield map of sugar beet crop in 2012 and the yield map of previous crop (winter wheat) showed a good correlation. This indicates to the feasibility of predicting the spatial variation in sugar beet yield from the yield map of previous crop.

CONCLUSION:

All the variables studied varied spatially and the sampling protocol followed in this field was sufficient to describe the majority of the variation. Some of the observed variation in crop growth could be attributed to the variation in soil moisture and soil organic matter which in turn were affected by soil texture and field topography. The spatial variation in final yield was almost the same as the variation in LAI measured in July. Therefore variation in LAI observed early in the growing season was good predictor of the final yield of roots.

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