Soil Studies 11(1), 27-34
http://doi.org/10.21657/soilst.1143238

RESEARCH PAPER

Field scale variability in soil properties and silage corn yield

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How to cite

Birol, M., & Günal, H. (2022). Field scale variability in soil properties and silage corn yield. *Soil Studies 11*(1), 27-34. http://doi.org/10.21657/soilst.1143238

Article History
Received 18 April 2022
Accepted 8 June 2022
First Online 1 July 2022

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Keywords
Field variability
Geostatistics
Modeling
Corn quality
Spatial structure

Abstract

Field scale spatial variability of soil properties, crop quality parameters and yield are needed to evaluate the efficiency of management practices in crop production. The purpose of this study was to determine the magnitude of field variability in soil properties, silage yield of corn (*Zea mays* L.) varieties, and to characterize their spatial structures, and map the stated attributes. The experiment was conducted in an alluvial flood plain of lower Kazova watershed in Tokat province of Turkey. Several physical and chemical soil properties and silage corn yield were determined. Coefficient of variation (CV%) varied from 1.0% (pH) to 38.1% (P_2O_5) in herbicide not applied plots and from 0.9% (pH) to exchangeable Na (55.1%) in herbicide applied plots. Calcium carbonate, organic matter and clay displayed well defined spatial structure. Sand, pH and electrical conductivity (EC) showed moderate spatial dependency. However, silt, moisture content, bulk density, plant available phosphorus and potassium had weak spatial structure. Silage corn yield distribution map successfully distinguished the three corn hybrids planted. The difference in vegetation period among three corn hybrids was effective in distinguishing the location of hybrids within the field. However, the variability in each of the hybrids blocks was assumed to occur due to the difference in short range soil properties. The longest range values were obtained for silage corn yield at both herbicide applied and herbicide unapplied plots.

Introduction

Spatial variability in soil properties, agricultural practices (tillage, irrigation, fertilizer application etc.) and pest and pathogen damage cause significant spatial and temporal changes in crop yield within a field (Al-Gaadi et al., 2018). However, small-scale variability in soil properties or even in yield is not often taken into account by farmers (Hausherr-Lüder et al., 2019). However, monitoring soil and yield variability within a field can help farmers to make right decisions to improve crop yield and to prevent environmental pollution (Kayad et al., 2019). Variable-rate application of fertilizers within a field improves nutrient use efficiency and also decreases water pollution (Tagarakis & Ketterings, 2018).

Precision agriculture can be defined as site-specific management of inputs within a field to obtain the desired crop yield. Adoption of precision farming is needed to optimize crop production and to reduce environmental pollution risks caused by over application of agrochemicals (Roy & George, 2020). Plant nutrients in soils are usually provided by application of either a mineral fertilizer or animal manure. When nutrients are applied at rates higher than the crop removal, concentration of particular nutrient is elevated to levels that sometimes may hinder the availability of other nutrients. Some of nutrients such as nitrate and phosphorus may leach to ground/surface water, and create serious problems for ecosystem or human health (Al Tawaha et al., 2022). The budget of farmers will also be negatively affected by the application of excess amount of fertilizers. Therefore, the requirement and the amount of inputs should preciously be determined to sustain the productivity and profitability of agricultural production.

Published by Soil, Fertilizer and Water Resources Central Research Institute, Ankara, Turkey

In order to apply appropriate amounts of agrochemicals, it is important therefore, to determine and map the spatial pattern of soil properties. Spatial variability of soil properties within a single field is needed to design a site-specific crop management and to delineate management zones (Bogunovic et al., 2017; Hausherr-Lüder et al., 2018). In this context, Piotrowska-Długosz et al. (2016) considered spatial variability of phosphorus (P) to improve the management decision. Considering the within field spatial variability of P helps to develop a more productive and efficient crop management system. Goulding (2016) used the variability of soil pH within a field to organize the variable-rate lime application for reclamation of an acidic soil. In a recent study, Günal (2021) used the information on spatial variability of salinity and sodicity in a field to determine the amount of chemicals and water needed to reclaim saline-sodic soils in Turkmenistan.

Internal (soil forming factors such as parent material, topography etc.) and external factors (management related such as fertilization, soil tillage etc.) contribute to the spatial distribution of the soil properties (Barton et al., 2004; Atreya et al., 2008). (Cambardella et al., 1994) attributed strong spatial dependence of a soil property to the internal factors and weak spatial dependence to management related external factors. The interaction between soil characteristics, position of the landscape and climate should be taken into account when yield has significant changes from year to year. Therefore, soil properties and position of a landscape have been reported as the main cause of spatial variability of yield within a field (Maestrini & Basso, (2018). In addition, tillage practices and the management of crop residues significantly affect the small-scale variability in plant growth, crop yield, soil properties, distribution of weeds, pests and diseases (Qiu et al., 2016).

Quantifying spatial variability is fundamental for understanding the underlying the factors affecting variation in productivity throughout a field (Leroux & Tisseyre, 2019). Classical statistics, geostatistics and fractal theory are the most common methods to define spatial variability. Geostatistics in soil science has been used to determine the spatial variability of soil properties (Surucu et al., 2013; Günal et al., 2012). The purpose of this study was to determine spatial variability of soil characteristics silage yield in a field where three corn hybrids grown under five different soil tillage systems.

Material and Methods

Study area

The experiment was conducted in Kazova Plain located at Tokat province of Turkey. Soils in study area were formed over alluvium and the slope was nearly level. Long term (1929-2021) annual average total precipitation of study area is 446 mm and the temperature is 12.4 °C (Anonymous, 2022). Based on meteorological data, soil moisture regime is Ustic and soil temperature regime is Mesic (Soil Survey Staff, 1999).

Methods

The experiment was conducted in a complete randomized block design with three replicates and continued three years. The experiment consisted of three block for each corn hybrid and a total of 45 plots. The size of individual plots was 6.5 m x 20 m (130 m^2). Corn seeds were sown at 70 cm interrow and 20 cm intra-row spacings. Three corn hybrids (Girona, Borja and Mataro) have been grown under 2 conventional, 2 reduced and a no-till tillage systems (Figure 1). Tillage practices used in the experiment were; 1.) Irrigation + moldboard plow + Disc harrow, 2.) moldboard plow + rotovator, 3.) Rotovator, 4.) Chisel + disc harrow, and 5.) No-till (direct sowing). The vegetation period of corn hybrids used in the experiment were different.

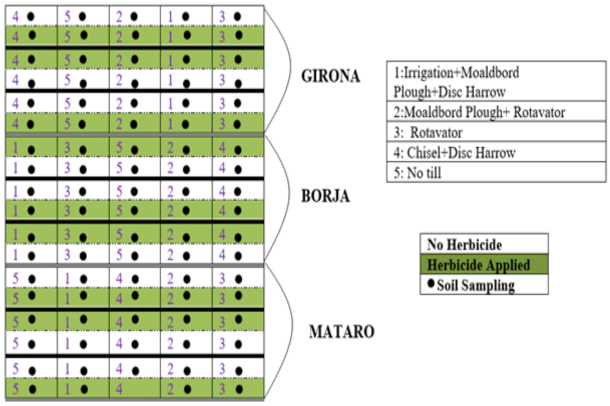

Figure 1. Experimental design and the treatments

Hybrid 1 (Girona, FAO 450): This is a single hybrid variety and an average of 100-105 days needed for the harvest maturity. The Girona is known with a high harvest index. Hybrid 2 (Borja, FAO 500): This is a single hybrid variety that reaches grain harvest maturity in average of 105-110 days and is recommended for silage production. The Borja is known with a high harvest index. Hybrid 3 (Mataro, FAO 550): This is known as a single hybrid variety with a high harvest index, and reaches the harvest maturity in average of 110-115 days (Anonymous, 2006).

Soil samples from 0-10 cm, 10-20 cm and 20-30 cm depths were sampled both from herbicide applied and non-herbicide plots. Total of 45 soil samples from each of soil layers for herbicide and non-herbicide plots were collected. All soil samples have been analyzed for some of physical and chemical characteristics. The data obtained for each layer at a particular sampling point have been averaged for 0-30 cm depth.

Soil Analyses

Particle size distribution was determined using the hydrometer method in a sedimentation cylinder; with sodium hexametaphosphate as the dispersing agent Gee & Bouder (1986). Bulk density and water content were determined using a soil core method (Blake & Hartge, 1986). Soil reaction (pH) and electrical conductivity (EC) were measured in 1:2 soil–water suspensions (Rhoades, 1982). Part of each sample was analyzed for organic matter by using the Walkley–Black dichromate oxidation procedure (Nelson & Sommer, 1982). Available phosphorus was extracted with 0.5M sodium bicarbonate ($NaHCO_3$) (Olsen et al., 1954) and determined by spectrophotometry. Total nitrogen was determined with (Bremner, 1965), available potassium with (Thomas, 1982) and calcium carbonate with (Allison & Moodie (1965) methods. Exchangeable Na and Ca was extracted with ammonium acetate determined by flame spectrometry (Soil Survey Laboratory, 1992).

Silage Yield

Plants on randomly selected six strips with 6 m length were harvested 5 cm above the soil surface and weighed. Based on the results obtained from harvested corn plants, the silage yield for herbicide applied and not applied blocks have been calculated as kg ha^{-1}. In this study, silage yield determined at the end of third year have been presented.

Statistical and Spatial Analyses

Descriptive statistics of the analyzed data viz., minimum, maximum, mean, standard deviation, coefficient of variation, and skewness were computed using SPSS 21.0 statistical software. The spatial structural analysis of soil properties and silage corn yield and mapping were carried out using GS$^+$ (version 7.0) software. Spherical, exponential or linear models were fitted to the semivariograms and the model used was selected based on visual best fit and the corresponding coefficient of determination (R^2) for the regression. In addition, residual sum of squares (RSS) was used to choose the best variogram model. Cross-validation was used to validate the accuracy of model by eliminating one observation at a time, and estimating the value at that location with the remaining data. Then the difference between the actual and estimated value for each data location was calculated (Li et al., 2011).

The semivariogram for each variable was calculated using a measure of variability between pairs of points at various distances. The distance between pairs at which the variogram was calculated is called lag distance. Model parameters (nugget variance (Co), range (A) and sill (Co+C) were calculated for each of the variable. Nugget semivariance shows the variance at zero distance, and represents variability that is not detectable at the sampling scale of the study or variability caused due to or sampling and analytical error. Lag distance between measurements at which one value for a variable does not influence neighboring values is described as sill. The range is the distance at which the points have no longer spatially independent (Trangmar et al., 1986). The nugget to sill ratio is defined as spatial dependency. The spatial dependence of variables was classified into three classes based on the nugget to sill ratio value (Cambardella et al., 1994). The variable is considered to have strong spatial dependence if the ratio is <0.25, the variable is considered to have moderate spatial dependence if the ratio is between 0.25 and 0.75, and the variable is considered to have weak spatial dependence, if the ratio is >0.75.

Results and Discussion

Clay content ranges from 34.4 to 56.7% with an average of 44.0%. Silt content ranges from 32.8 to 46.7% with an average of 41.2 (Table 1). High silt content of experimental site caused a formation of hard and impermeable surface crust in some places (Figure 2). Yang et al. (2020) indicated that rain drop impact breaks down the weak aggregates and clogs soil pores, which further leads to firm packing of particles particularly in soils with high silt content. Surface crust prevents the infiltration of water as well as emergence of plants. The nonhomogeneous distribution of moisture and crop yield within the field can be associated with the non-permeable layer observed on soil surface especially during germination stage of the plant growth. Aubert et al. (2011) also stated that silty soil disperses especially in the depressed parts of the field, and resulting in the formation of surface crust up to 7 cm thick following dry conditions.

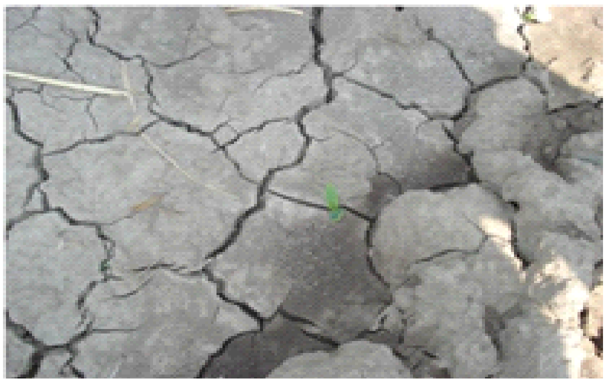

Figure 2. Surface crust in high silty locations of the experimental site

Organic matter (OM) content within non-herbicide plots ranged from 1.24 to 2.12% and the average OM was 1.71% (Table 1). The OM content in herbicide applied plots was between 1.40 and 2.27% with a mean value of 1.66% (Table2). Weeds almost completely covered the soil surface in non-herbicide plots, and competed with corn plants for nutrients, water and sunlight (Figure 3). Therefore, average silage yield in herbicide applied plots (36987.0 kg ha^{-1}) was 8.5% lower compared to the silage yield (40152.4 kg ha^{-1}) recorded in non-herbicide plots (Table 1 and 2). The nutrients and water have been highly used by weeds in almost everywhere of the plots. Kaur et al. (2018) indicated that weeds are more aggressive, easily adapt to new environment, and persist longer than the main crops in the field. Low silage yield in weedy plots is related to the ability of weeds to extract more water and nutrients from the soil compared to the corn. Higher concentrations of P and K in herbicide applied plots, where weeds have been controlled both mechanically and chemically can be attributed to the consumption of nutrient. The variability of data among the sampling locations was evaluated with the coefficient of variation (CV) value. The CV values were interpreted using the criteria introduced by Wilding (1985), who defined the CV in the most (CV>35%), moderate (CV:15-35%) and least (CV<15%) variable classes. The variability of P (CV: 45.7%) and K (CV: 37.3%) content in herbicide applied plots was higher than those in non-herbicide plots (Table 1 and 2). In contrast to the findings of Sylvester-Bradley et al. (1999) and (Goulding., 2016) who reported a high heterogeneity of soil pH within a field, the variability of soil pH indicated by the CV values in both plots was very low (CV: 0.9 and 1.0% for herbicide applied and not applied plots). The variability of lime, EC, OM, N, exchangeable Ca, bulk density and moisture content were low in both experimental plots (Table 1 and 2).

Figure 3. Weed density in non-herbicide and herbicide applied plots from the experiment

Within Field Variability of Soil Characteristics and Silage Corn Yield

The experiment has been designed as a complete randomized block. Considering the spatial variability of soil properties, the blocks have been randomly placed within the experimental site. Data on soil characteristics and silage yield for herbicide applied and not applied plots have been separately analyzed for spatial variability. Two different maps were produced from each of the data set for the experimental site (Figure 4 and 5).

Reliable models for silt, lime, organic matter, EC, P and N concentrations could not be obtained by using the data from weedy plots. The longest range (168.4 m) value of weedy plots was obtained for K content and the shortest range value (4.7 m) was obtained for P content (Table 3). The range value of P content in herbicide applied plots was 17.2 m, while in contrast to weedy plots the range value of K content in herbicide applied plots was shorter (23.4 m) (Table 4). Low range value of P concentration in weedy plots compared to herbicide applied plots could be attributed to the high density of weeds between the rows in weedy plots. The patchy distribution of weeds within the plots caused a decrease in the range value of P content. In non-herbicide plots, available K and exchangeable Ca contents of soils had contrasting pattern with the silage yield. The highest K and exchangeable Ca concentration in non-herbicide applied block was on the northern part of the study area and gradually decreased towards the south. In contrast to K and exchangeable Ca contents, silage yield in herbicide applied plots was at the highest level on the south and decreased towards the north section of the study area (Figure 4). Hausherr-Lüder et al. (2019) who investigated the effects of tillage intensity on small-scale spatial variability of soil and winter wheat parameters in three different location stated that spatial relationships between soil properties and winter wheat parameters

Table 1. Descriptive statistics of soil characteristics and silage yield in non-herbicide plots

Attribute	Unit	Min	Max.	Mean	Std. Dev.	CV	Skewness
Clay	%	32.4	56.7	44.0	5.48	12.5	0.08
Sand	%	7.6	25.0	14.7	4.69	31.9	0.55
Silt	%	32.8	46.7	41.2	2.76	6.7	-0.71
Lime	%	6.13	8.13	7.15	0.40	5.6	0.11
pH	1:2	8.28	8.64	8.43	0.09	1.0	0.54
EC	mmhos cm^{-1}	261.7	526.0	330.0	48.61	14.7	2.07
P_2O_5	kg ha^{-1}	193.4	900.4	459.0	175.2	38.2	0.48
OM	%	1.24	2.12	1.71	0.19	11.2	-0.01
N	%	0.10	0.16	0.13	0.01	9.6	-0.17
K_2O	kg ha^{-1}	207.3	881.2	327.5	100.2	30.6	3.92
Ca	me $100g^{-1}$	13.63	19.84	17.36	1.24	7.2	-0.48
Na	me $100g^{-1}$	0.33	0.71	0.47	0.09	19.3	1.04
Moisture	%	23.28	29.14	26.33	1.21	4.6	-0.12
Bulk Density	g cm^{-3}	1.34	1.53	1.43	0.05	3.6	-0.06
Silage Yield	kg ha^{-1}	15857.1	59083.3	36987.0	10757.3	29.1	0.26

CV: Coefficient of variability

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Table 2. Descriptive statistics of soil characteristics and silage yield in herbicide applied plots

Attribute	Unit	Min	Max.	Mean	Std. Dev.	CV	Skewness
Lime	%	6.50	8.25	7.30	0.43	5.9	0.15
pH	1:2	8.21	8.60	8.43	0.07	0.9	-0.68
EC	mmhos cm^{-1}	275.3	489.3	336.3	46.37	13.8	1.97
P_2O_5	kg ha^{-1}	174.4	1205.3	477.4	218.2	45.7	1.62
OM	%	1.40	2.27	1.66	0.18	10.8	0.78
N	%	0.10	0.18	0.13	0.02	13.2	0.45
K_2O	kg ha^{-1}	184.3	886.6	347.5	129.7	37.3	2.58
Ca	me $100g^{-1}$	14.93	19.46	17.88	0.97	5.4	-0.89
Na	me $100g^{-1}$	0.25	2.22	0.50	0.27	55.1	5.92
Moisture	%	22.31	28.06	25.53	1.30	5.1	-0.15
Bulk Density	g cm^{-3}	1.31	1.52	1.45	0.04	2.9	-1.18
Silage Yield	kg ha^{-1}	23178.6	62631.0	40152.4	9929.6	24.7	0.08

CV: Coefficient of variability

Table 3. Parameters of semivariance models for soil characteristics and silage yield of non-herbicide plots

Attribute	Model[a]	A[b] (m)	Co[c]	Sill (Co+C)[d]	Spatial Dep	R^2[e]	RSS[f]
Clay	Sph	102	6.4	42.80	14.95	0.918	30.2
Sand	Sph	134	5.8	37.40	15.51	0.933	18.2
Silt	Sph	37	4.28	9.47	45.20	0.484	16
$CaCO_3$	Sph	12.2	0.0086	0.16	5.24	0.212	8.048E-03
pH	Sph	41.6	0.0027	0.01	32.93	0.668	1.11 E-05
EC	Exp	10.7	959	2432.00	39.43	0.141	3.918 E+06
P_2O_5	Exp	4.7	54.6	329.30	16.58	0.069	13033
OM	Exp	4.7	0.008	0.04	21.80	0.049	7.332 E-04
N	Not modelled						
K_2O	Exp	168.4	15.8	52.60	30.04	0.632	126
Ca	Exp	147.5	0.839	2.46	34.13	0.672	0.212
Na	Sph	20.1	0.0012	0.01	12.77	0.648	5.012 E-06
Moisture	Sph	128.2	0.829	2.18	38.10	0.744	0.52
Bulk Density	Sph	135.5	0.0016	0.00	34.04	0.941	1.323E-07
Silage Yield	Exp	224.2	719000	1866000	38.5	0.628	5.44E+11

a: Model, sph: Spherical, exp: Exponential, b: A, Range, Spatial Correlation Distance, c: Co, Nugget Variance, d: Sill (Co+C): Structural Variance, e: R^2 Value of Semivariance Model, f: RSS, Residual Sum of Squares

were in the herbicide applied plots, the shortest range distance (8.9 m) was obtained for pH and the longest range distance (211.9 m) was obtained for moisture content, followed by silage yield (210.9 m) and organic matter (176.2 m). Moisture content, pH, P and exchangeable Ca contents had strong spatial dependency and all other characteristics had a moderate level spatial dependency (Table 4). All soil characteristics other than pH and Ca had similar spatial distribution patters (Figure 4).

Spatial distribution of silage corn yield clearly differentiated the location of silage varieties used in the experiment (Figure 4g and 5g). The main reason to distinguish the three corn varieties was the length of vegetation period for each of corn varieties required to be matured. The corn with FAO450 code was enough mature when harvested, whereas the harvest was little early for the corn with FAO550 code. Therefore, the differences in silage yield of different corn hybrids can be attributed to the differences in the maturation period. Another reason in variability of silage corn yield was spatial variability of soil properties within the blocks in which the corn hybrids grown. The variation of clay and sand content in the study area will significantly affect the cation exchange capacity, water holding capacity and some of other important soil characteristics, which have a significant impact on plant growth. High variability of P and N content indicated the need for variable rate application of nutrients. The variable-rate fertilizer application will cause an increase in silage yield compared to the uniform application of N and P. In a two-year study, (Yang et al., 2001) obtained significantly higher grain yields in variable rate application of nutrients compared to the uniform applications.

Table 4. Parameters of semivariance models for soil characteristics and silage yield of herbicide applied plots

Attribute	Model[a]	A[b] (m)	Co[c]	Sill (Co+C)[d]	Spatial Dep	R^{2e}	RSS[f]
$CaCO_3$	Exp	32	0.1221	0.25	49.80	0.661	4.226 E-03
pH	Sph	8.9	0.0004	0.01	7.27	0	4.274 E-05
EC	Exp	125.6	1736	4242.00	40.92	0.566	1.28 E+06
P_2O_5	Sph	17.2	22.6	230.20	9.82	0.271	7918
OM	Sph	176.2	0.0166	0.04	38.88	0.499	1.063 E-04
N	Not modelled						
K_2O	Sph	23.4	18.1	57.68	31.38	0.449	344
Ca	Sph	9.5	0.106	1.01	10.45	0	0.386
Na	Sph	20.9	0.0023	0.01	35.94	0.289	5.033 E-06
Bulk Density	Sph	20.2	0.0005	0.00	29.41	0.319	8.096 E-07
Moisture	Sph	211.9	0.679	3.47	19.58	0.901	0.279
Silage Yield	Sph	210.9	281000	2527000	11.12	0.87	1.604 E+11

a: Model, sph: Spherical, exp: Exponential, b: A, Range, Spatial Correlation Distance, c: Co, Nugget Variance, d: Sill (Co+C): Structural Variance, e: R^2 Value of Semivariance Model, f: RSS, Residual Sum of Squares

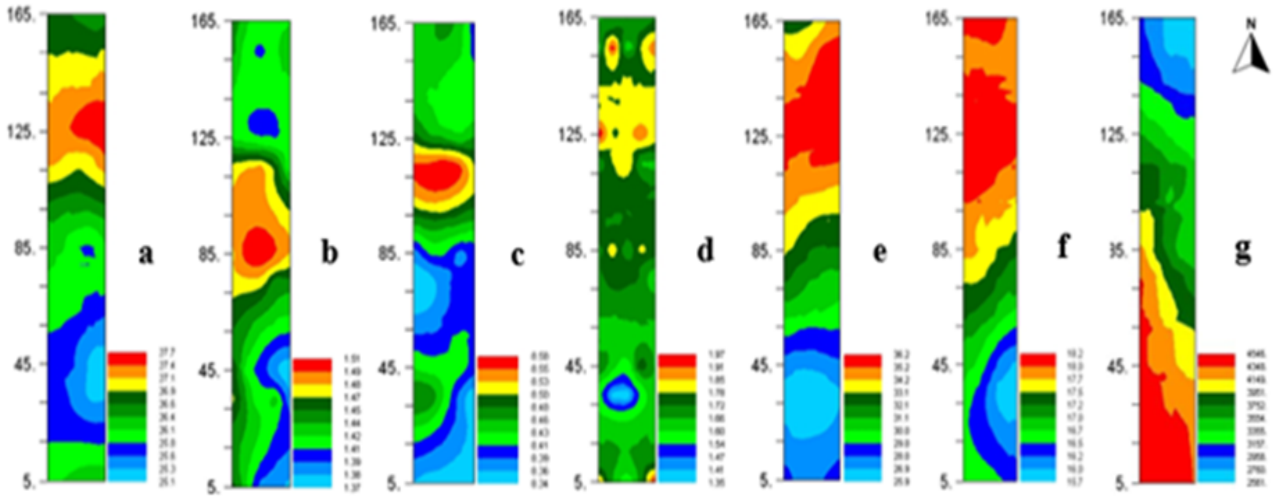

Figure 4. Spatial distribution of some of soil characteristics and yield for non-herbicide plots (a: moisture (%), b: bulk density (g cm^{-3}), c: pH, d: organic matter (%), e: available potassium (K_2O, kg ha^{-1}), f: exchangeable calcium (me $100g^{-1}$), g: silage yield (kg ha^{-1}))

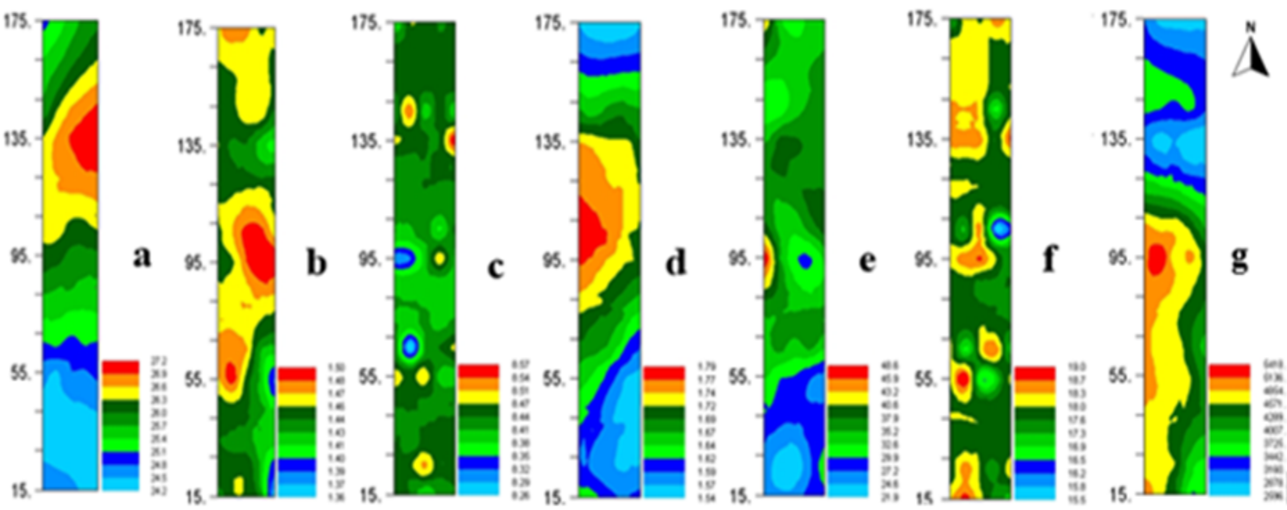

Figure 5. Spatial distribution of some of soil characteristics and yield for herbicide applied plots (a: moisture (%), b: bulk density (g cm^{-3}), c: pH; d: organic matter (%), e: available potassium (K_2O, kg ha^{-1}), f: exchangeable calcium (me $100g^{-1}$), g: silage yield (kg ha^{-1}))

Conclusion

In this study, variability of soil properties and silage yield of three corn hybrids grown under five different tillage systems with and without weed control was investigated. Within field variability of soil characteristics especially available phosphorus and potassium affected the silage yield of corn hybrids. High content of silt in some parts of the field caused formation of surface crust, which inhibited homogenous germination of corn seeds. Farmers should take variability in soil properties and crop yield within and between fields into account to adopt precision farming techniques, such as site-specific nutrient management, in order to increase productivity. Indeed, not only for the nutrient management, many of the agricultural practices such as soil tillage, irrigation and reclamation activities should be accomplished considering the spatial variability to improve economic returns and reduce the impacts on the environment. New technologies in variable rate application help to reduce the environmental impacts of agricultural production, while maintaining, or even improving, current levels of soil quality and crop productivity.

Funding Information

This study was a part Master Thesis of Murat BİROL, and funded by the Scientific and Technological Research Council of Turkey (TÜBİTAK) (Grant number, TOVAG 106 O 217).

Conflict of Interest

The authors declare that they have no known competing financial or non-financial, professional, or personal conflict that could have appeared to influence the work reported in this paper.

Author Contributions

MB: Data Curation, Formal Analysis, Investigation, Methodology, Writing Original Draft; **HG:** Supervision, Review and Editing.

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