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Improved evaluation of field experiments by accounting for inherent soil variability

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ABSTRACT

Well-controlled field experiments are used to test agronomic management practices and evaluate the performance of cultivars in highly managed plots at experimental stations, in breeding nurseries or on-farm. However, the performance of crops and therefore the interpretation of experiments is affected by the inherent soil variability. To avoid large residual errors, replicate measurements or optimized designs are usually helpful but seldom adequately consider the unknown soil variability. The use of spatial covariates, such as proximally sensed data, in the statistical modelling of the target variable may provide a better estimate of such experimental residual variations (errors). Therefore, the purpose of this study was to determine whether the apparent soil electrical conductivity, topographical parameters and location information (expressed as Gauß-Krüger coordinates) could be used for an enhanced spatial and temporal characterization of the long-term and annual wheat yields within a static, long-term nitrogen fertilizer experiment that included six different forms of nitrogen and three levels of nitrogen fertilizer. Furthermore, this investigation aimed to propose statistical strategies for analysing this background variation by testing ANOVA (Analysis of variance) and ANCOVA (Analysis of covariance). ANCOVA with soil EC_a, location information and topographic parameters as covariates improved the accuracy of the yield estimates of the multi-annual means for all treatments. Without these independent variables in ANOVA, the coefficient of determination (R^2) was smaller and the root mean square difference (RMSD) was larger than those of ANCOVA (fertilized plots ANOVA: R^2 = 0.19, RMSD = 3.26 dt ha^{-1}; ANCOVA: R^2 = 0.87, RMSD = 1.29 dt ha^{-1}). In addition to the factor level of fertilization and form of nitrogen fertilizer, EC_a was the dominant covariate for the averaged long-term and annual yields. The EC_a was measured with different sensors and configurations and represented a significant independent variable. Of the topographic relief parameters, the predictor plancurvature was the dominant independent variable. The inclusion of plot-wise, time-invariant soil and relief parameters significantly improved the discrimination of testing the treatment performance within the long-term field trial. A further application of this approach to other experimental sites and breeding nurseries would likely be highly rewarding.

1. Introduction

Field experimentation is the common practice to test hypotheses in agronomy, breeding, physiology and ecology. Within agricultural field experiments, exact comparisons of treatments are the primary objective. Nevertheless, spatial site variability among different plots can negatively affect the accuracy and efficiency of such trials. To avoid bias in estimating the influence of tested variables, replications are mandatory, and optimized designs are adopted for the interpretation of results. However, even with the best design, soil variability can only be partially accounted for, even when it is considered.

Whereas large contrasts are relatively easy to detect, many research questions concern variations that are relatively small. For example, when comparing different forms of nitrogen at given levels of nitrogen or the effects of different herbicide or pesticide applications or alternatively, relatively uniform lines or cultivars, relatively small differences can prevent distinguishing among treatments or cultivars. Ultimately, soil variability, frequently unknown, affects all experimentation to some significant degree. This soil variability is of enormous relevance; for example, different forms of mineral nitrogen may cause only slight differences in plant growth and final yield (Hu et al., 2014) or cultivars tested in registration trials may differ by only a few percentages in their yields (Erdle et al., 2013). Therefore, soil variability that is not accounted for is clearly an obstacle towards improved assessments.

Intensive measurements of soil parameters are expensive, and even

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after interpolation; marked point-wise estimation errors may remain. The spatial variability of soils and yields has largely contributed to the development of site-specific farming activities, and enormous gains in information have been obtained and powerful new tools and technologies to assess the soil and crop variability at the level of the farm field have emerged (e.g., Schmidhalter et al., 2008; Adamchuk et al., 2004; Geesing et al., 2014). However, the investigation of the site-specific variability in dedicated field trials on experimental stations or in breeding nurseries has largely stagnated, and until recently, soil variability was only accounted for by optimized field trial designs. In the literature to date, relatively few reports have used the information gained from improved detection in dedicated field trials to improve the understanding of the tested factors or variables.

For that reason, soil conductivity (EC_a), topographical parameters and coordinates are increasingly used as a proxy for soil conditions. These variables are relatively easy and inexpensive to derive and produce area-wide, high-density data sets.

Kravchenko et al. (2005) used EC_a as an additional variable to increase the accuracy of estimates of phosphorus values in fields with different levels of manure application, and standard errors for the means of P concentrations without EC_a as a covariate were larger than those with EC_a. In the plots that received no manure and had higher soil EC_a readings, the concentrations of P were significantly lower.

According to Johnson et al. (2005), EC_a classification can be used as a basis for creating block plots only when EC_a and yield are correlated. At the investigated sites, the dominant factors were salinity and clay content, and the authors described the application of EC_a as a "compelling tool in statistical design".

Lawes and Bramley (2012) explored a new and simple method in the analysis of strip experiments that combined the spatial variability of treatment response. The authors applied the spatial distribution of yield data and a moving pairwise comparison of treatments. The results indicated that the pairwise comparisons adequately identified treatment differences and their significance. This method can be readily applied and also used with EC_a values and therefore, offers an important advance to establish in on-farm experimentation.

Brevik, (2012) investigated the use of EC_a readings in fields with more homogeneous soil properties and selected a field of lacustrine-derived soils with only weak spatial variability in soil properties. Although the highly uniform EC_a readings did not differentiate among soil map units, the EC_a results confirmed the uniform status of the soils in the field, thereby meeting a critical criterion for precision agriculture applications.

Tarr et al. (2003, 2005) used stratification of EC_a and terrain attributes to derive a heterogeneous pasture in relatively homogeneous sampling zones with fuzzy k-means clustering. The five zones identified had significant differences in the target variables (i.e., P, K, pH, organic matter and soil moisture).

Topography is closely related to soil development and soil types and therefore, is related to the distribution of yield. However, the precision and direction (Kravchenko et al., 2003) of this relationship differ strictly with the soil types and their positions on the landscape. On a site in Andalucía, southern Spain (Lozano-García et al., 2016), the organic carbon content was higher in the north-position than that in the other topographic aspects. The topography (primarily elevation, slope, and aspect) plays a significant role in affecting temperature and moisture regimes (Bale et al., 1998; Griffiths et al., 2009), and the differences in microclimate affect the distribution of plant communities and soil processes (Lenka et al., 2013; Bochet, 2015). Therefore, topographic aspects should be included in models (Meier and Leuschner, 2010; Ping et al., 2015; Scowcroft et al., 2008) and in estimations at local and regional scales.

The objective of this research was a comprehensive analysis of a long-term fertilizer experiment with treatments that included six different forms of N-fertilizer applied at three levels of nitrogen fertilization, which included control plots. The principal goal of this paper was to delineate yields of wheat as influenced by the nominal factors of fertilization level and fertilizer form and in a second step, by the additional metric parameters of EC_a, topographic variables and coordinates. Statistical analyses were conducted with ANOVA and ANCOVA to predict annual and multi-annual means of yields. In this paper, the evaluation of this 36-year, continuous N-fertilizer experiment is presented.

2. Materials and methods

2.1. General description, soil, and physiography of the Dürnast long-term study area

The study area is approximately 0.31 ha and is located in Freising, 30 km north of Munich, Germany (4477221.13 E, 5362908.78 N), in a hilly, Tertiary landscape. The study is a part of the long-term experiment of the Chair of Plant Nutrition from the Technical University of Munich. The average annual temperature is approximately 7.8 °C, and the average annual precipitation is 800 mm.

Tertiary sediments with secondary deposits of Pleistocene loess were the predominant soil material. The composition of the area is a consequence of Pleistocene loess deposition and subsequent erosion in the periglacial time period and Holocene erosion and deposition. According to the German Soil Survey (Bodenkundliche Kartieranleitung, 2005), fine-silty Dystric Eutrochrept and fine-loamy Typic Udifluvent are the dominant soil types.

The primary characteristics of the relief and soil parameters are listed in Table 1. The area has a slight slope in the south direction with a silt content of approximately 60%. The trend was for clay, C and N to increase from the south to the north-west of the area. The relatively high content of C and N in soil layers deeper than 25 cm is evidence of the erosive processes that formed this area.

2.2. Experimental design

The basic features (i.e., fertilizer amount and form, crop rotation, and plot size) of the N fertilizer experiment are listed in Table 2. In Table 3, the years of cultivation with wheat, the cultivars, the amount of fertilizer applied and the number of replications are presented. In Figs. 1 and 2, the layout of the experimental field is presented.

Of note, CAN (Calcium ammonium nitrate) was tested twice, and the control plots that did not receive N-fertilizer were located within the rows with low and high fertilization. In both cases, the result for each single plot was used as an independent value in the calculations.

Furthermore after 2006, the experiment was reduced to four replications, identified as a–d.

Table 1
Site description of the long-term nitrogen fertilization experiment in Dürnast.

Site description				
Elevation [m]		470 (469–472)		
Slope [rad]		0.05 (0.05–0.09)		
Aspect [rad]		2.64 (1.97–3.46)		
		0–25 cm	25–50 cm	50–75 cm
Soil texture [kg kg^{-1}]	Clay	20.8 (15.7–27.3)	23.3 (15.2–34.9)	26.2 (13.6–34.8)
	Silt	61.5 (54.4–67.5)	61.7 (35.7–72.9)	60.7 (32.8–76.8)
	Sand	16.6 (11.9–21.3)	14.4 (8.5–40.5)	12.4 (5.3–46.8)
	Skeleton	1.2 (0–3.0)	0.6 (0–7.0)	0.4 (0–3.0)
pH		6.44 (5.94–6.84)	6.36 (5.96–7.12)	6.31 (5.98–7.18)
C-content [%]		1.18 (0.94–1.38)	0.56 (0.35–1.14)	0.4 (0.22–1.11)
N-content [%]		0.1 (0.08–0.12)	0.06 (0.03–0.12)	0.04 (0.02–0.12)

Table 2
Basic features of the long-term N-fertilization experiment.

Begin	1979
N-Fertilizer Form	Calcium ammonium nitrate (CAN; twice)
	Urea (Ur)
	Calcium cyanamide (CC)
	Ammonium sulphate (ANS)
	Urea ammonium nitrate (UAN)
	Ammonium sulphate + nitrification inhibitor (AS + NI)
Crop rotation	Potato
	Wheat
	Barley
Plot size	4 * 8 m

Table 3
Cultivars, amount of fertilizer and number of replicates.

Year	Wheat	Cultivar	N-fertilizer [kg ha^{-1}]		No. of replications	
			Low	High	Control	Fertilized plots
1980	Winter	Caribo	100	150	12	6
1983	Winter	Caribo	100	150	12	6
1986	Winter	Kronjuwel	100	150	12	6
1989	Winter	Obelisk	100	150	12	6
1992	Winter	Orestis	100	150	12	6
1995	Winter	Astron	100	150	12	6
1998	Winter	Astron	100	150	12	6
2001	Winter	Ludwig	100	150	12	6
2004	Winter	Tommi	140	180	12	6
2007	Winter	Tommi	140	180	8	4
2010	Winter	Tommi	140	180	8	4
2012	Spring	Kadrilj	120	180	8	4

2.3. Data collection

For the derivation of the yield, the following independent parameters were used:

(i) experimental cultivation parameters:

- number of fertilizer (control = 0, fertilizer no. 1–6) (Table 2),
- level of fertilization (control = 0, low = 1, high = 2) (Table 3);

(ii) EC_a (EM38-v, EM38-h, MK2-v-1.0, MK2-h-1.0, MK2-v-0.5 and MK2-h-0.5);
(iii) parameters from digital terrain model; and
(iv) position of the plots (expressed as Gauß-Krüger coordinates).

2.4. Yield data

The yield of wheat was determined per plot with a combine harvester.

2.5. Apparent electrical conductivity

The EC_a was measured with the sensors EM38 and EM38-MK2 on 1st April 2011 in the vertical (v) and in the horizontal (h) configuration in the experimental field, in addition to in the adjoining experimental areas. The two sensors differed in their coil spacing, with narrower spacing allowing for shallower measurements in the soil profile. Shallower measurements were also obtained with the horizontal mode, compared with the vertical mode. For further details, see Heil and Schmidhalter (2015).

The measurements were used to construct six maps that showed EC_a distributions (EM38-v, EM38-h, MK2-v-1.0, MK2-h-1.0, MK2-v-0.5 and MK2-h-0.5). Based on the recommended practice for conducting such measurements, the soil water contents were close to or near field

Fig. 1. Schematic representation of the experimental area with the distribution of the fertilized and control plots per replication.

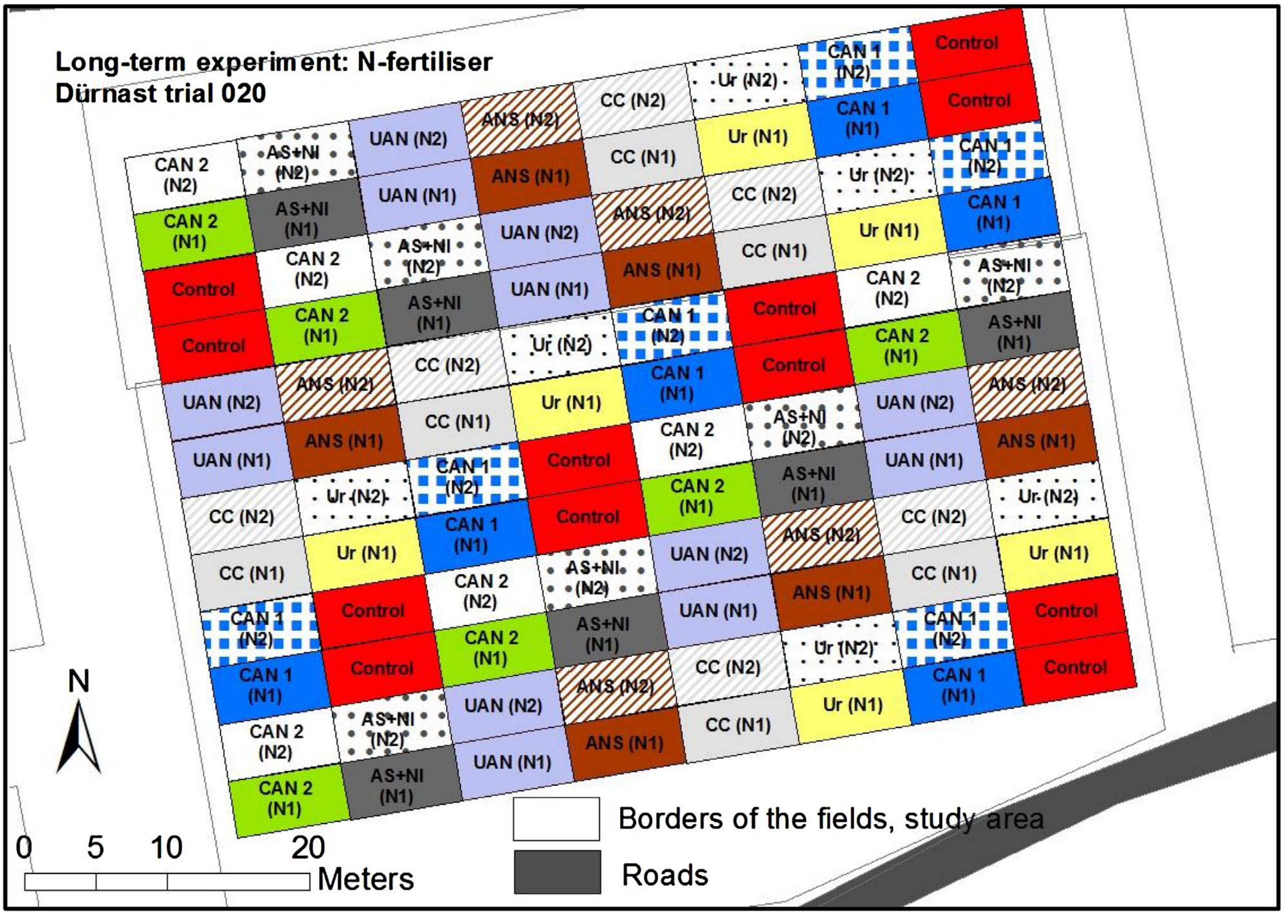


Fig. 2. Georeferenced arrangement of the experimental area showing the distribution of the N-fertilizer treatments (Abbreviations, see Table 2) and indicating the low (N1) or high (N2) fertilized treatments.

capacity, as determined by the German Weather Service data for the region (unpublished data from the station Weihenstephan). The EC_a values were recalculated to electrical conductivity values at 25 °C using the equation developed by Sheets and Hendrickx (1995).

In the next step, the EC_a data were interpolated using a GIS software. Continuous maps of all EC_a values were obtained using experimental omnidirectional semivariograms and ordinary kriging (OK) (Table 4).

The semivariogram models were also evaluated for anisotropy (direction-dependent trend in the data) and hole effects. Although directional semivariograms and visual inspections did not reveal detectable trends and drifts, the occurrence of hole effects was obvious. Therefore, the range of the semivariograms was limited to the first ridge of the curve progression.

With the kriging method and appropriate semivariogram models, EC_a readings were interpolated in maps with 2-m grids (Fig. 3).

2.6. *Digital terrain model*

Elevation grid data of the area (approximately 400 ha) with a grid size of 2 m was obtained from the Agency for Digitisation, High-Speed Internet and Surveying (Munich).

Additional different primary and secondary complex relief attribute parameters were calculated with the software package System for Automated Geoscientific Analyses (SAGA, produced by Scilands GmbH Göttingen, www.scilands.de). The following variables were used in the statistical calculations:

elevation (ELEV) [m]; slope gradient (SG) [radian]; aspect (ASP) [radian]; upslope catchment area (CA) [m2]; topographical wetness index (TWI) [−]; plancurvature (PLC) [−]; profilecurvature (PRC) [−]; convergence (CON) [%]; LS-factor (LSF) [−]; channel network base level (CNBL) [−]; vertical distance to channel network (VDCN) [−]; valley depth (VD) [m]; and relative slope position (RSP) [−].

Table 4
Results of the semivariance analysis indicating the EC_a spatial variability by showing the variogram model selected and the model parameters determined (nugget (C_0), sill (partial C), and range for the v- and h-mode measurements of EM38 and EM38-MK2) (Time of measurement: 1st April 2011). Averaged EC_a values of each plot are indicated in Fig. 4.

Instru-ment	Mode, Coil orienta-tion	Kriging	Model	Trans-formation	C_0	Partial C	Range	Lag size	Number of lags
EM38	v	Ordinary	Gaussian	None	5.2	65.4	56	2	28
	h	Ordinary	Gaussian	None	0.002	0.0004	76	4	19
EM38-MK2	v-1.0	Ordinary	Gaussian	None	5.18	63.64	76	4	19
	h-1.0	Ordinary	Gaussian	ˆ−1.1	2.08E-6	2.1E-5	62	2	31
	v-0.5	Ordinary	Gaussian	None	6.5	51.53	71.64	4.2	19
	h-0.5	Ordinary	Gaussian	ˆ−1.8	2.84E-8	1.1E-7	54	2	27

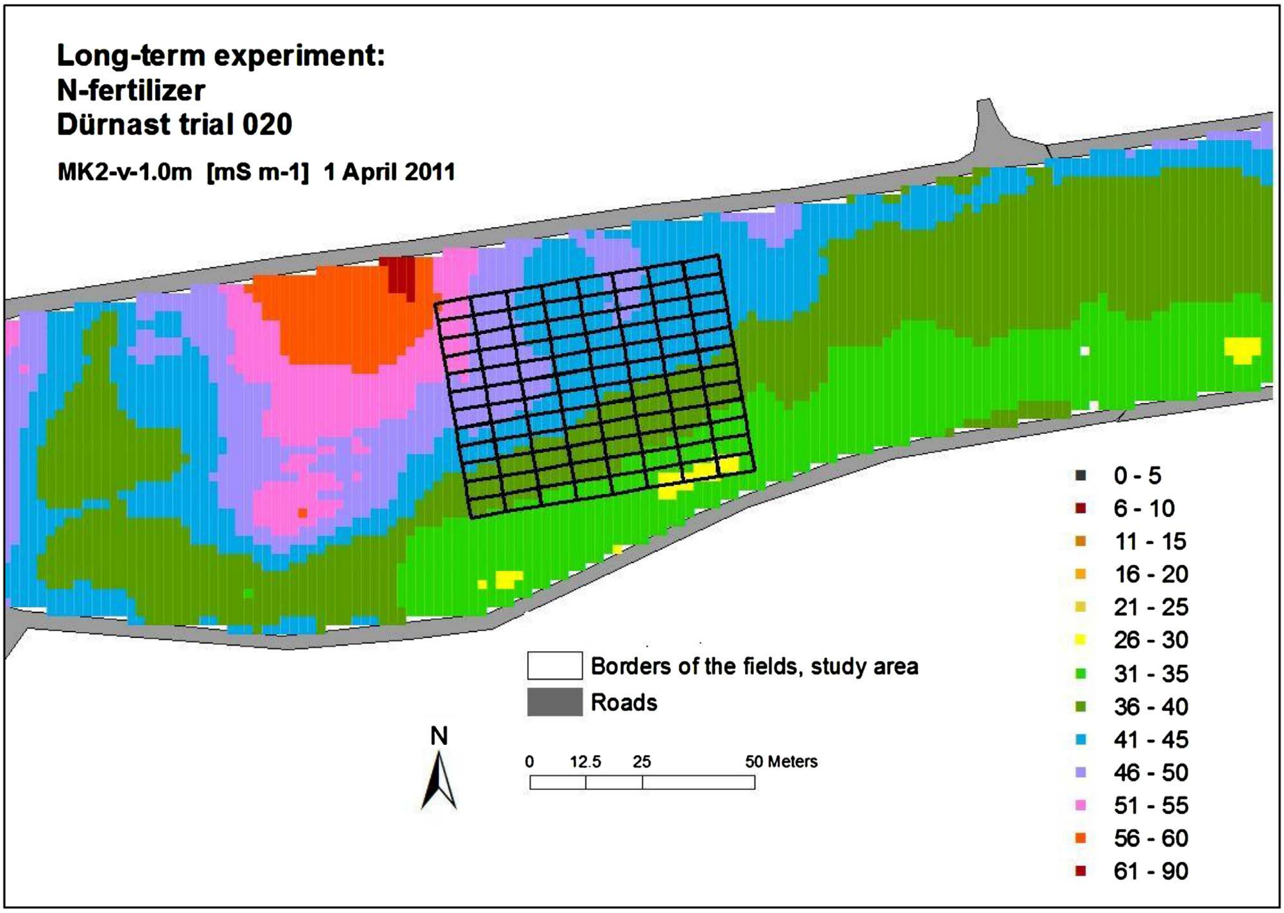


Fig. 3. Map of interpolated EC_a readings (mS m^{-1}) obtained from the MK2-v-1.0 in a 2-m grid and the borders of field experiment 020.

2.7. Construction of the data set for calculations

Within the border of each plot, EC_a (Figs. 3 and 4) and terrain variables were averaged. The position parameter Gauß-Krüger was determined for each plot.

Yield values, experimental cultivation parameters, EC_a readings, terrain variables and position (Gauß-Krüger coordinates) were combined into one data set as a final step.

From the beginning of the experiment in 1979 until 2006, each experimental treatment receiving different fertilizer forms had six replications (replications a–f; Fig. 1). In 2007, the number of replications was reduced to 4 (replications a-d; Fig. 1), and the number of control plots was reduced from 12 to 8.

2.8. Statistical analyses

Statistical analyses were conducted with the SPSS 21.0 statistical software package. To address the objectives of the study, linear multivariate regression (REG), analysis of variance (ANOVA) and analysis of covariance (ANCOVA) were used.

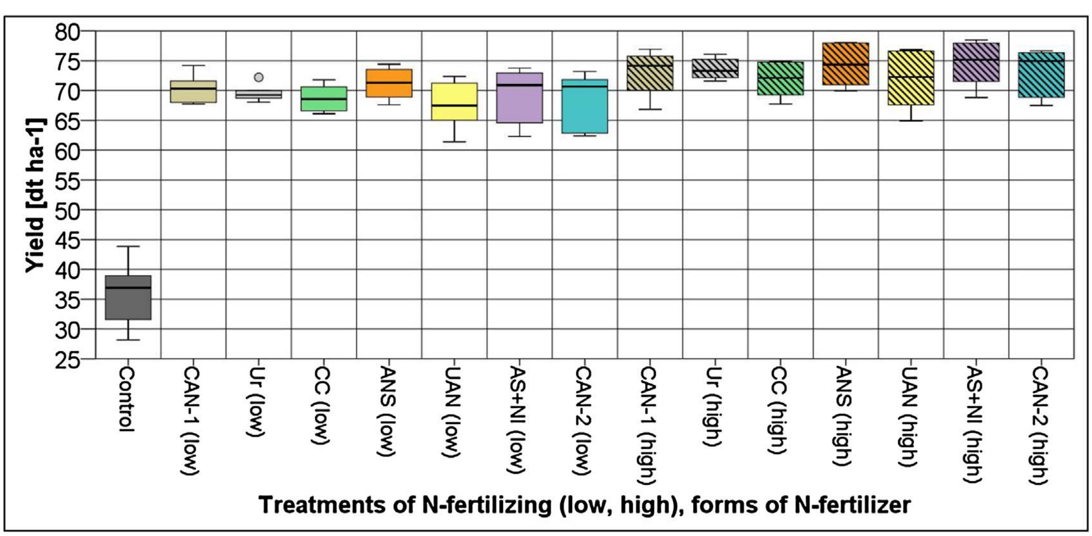


Fig. 4. Boxplots of the multi-annual yields (averages from 1980 to 2012) separated for control plots (0 N) and fertilizer level and fertilizer form.

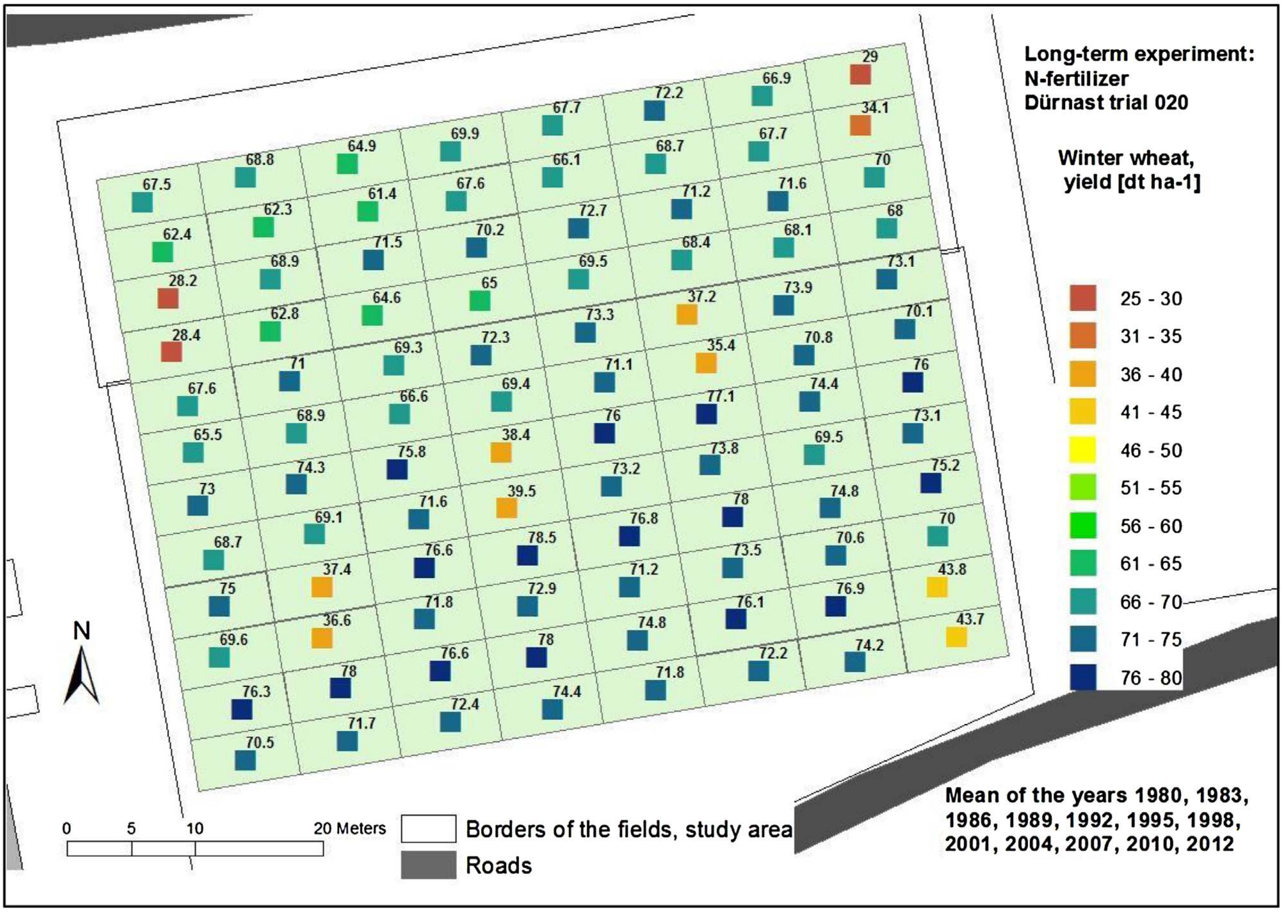


Fig. 5. Spatial distribution of the multi-annual yields of wheat according to the experimental design (Figs. 1 and 2).

The theoretical model of the REG is

$$y = b_o + b_1 * x_1 + b_2 * x_2 + b_n * x_n + e,$$

where the response variable (y) represents the yield of wheat; b_n is the empirical regression model coefficient; x_n represents terrain attributes, EC_a, and fertilizing parameters and e is the residual error component associated with the model.

The 0.05 level of significance (Kolmogorov–Smirnov, with the significance correction after Lilliefors) was used with normally distributed (partly with transformations) parameters. For non-normal data, the variables were transformed (Box–Cox transformations). Multiple regression models require that the following four primary assumptions be met: homoscedasticity (homogeneity of variance), no multicollinearity (two independent variables are highly correlated), normally distributed residuals, and independence of the residuals (no autocorrelation in regression residuals). All regression formulas met these criteria. These assumptions were tested with the following procedures:

– autocorrelation of regression residuals: Durbin–Watson test;
– homoscedasticity: plot of residuals against predicted values;
– normally distributed residuals: p–p plot; and
– multicollinearity: tolerance, variance inflation factor (VIF).

The theoretical model of ANOVA is

$$F = \frac{variancebetweentreatments}{variancewithintreatments}$$

$$F = \frac{\frac{1}{l-1} SS_A}{\frac{1}{n-1} SS_R} = \frac{\frac{1}{l-1}}{\frac{1}{n-1} * \sum_{i=1}^{l}} \frac{* J \sum_{i=1}^{J} (\overline{x_i} - \overline{x})^2}{* \sum_{j=1}^{J} (\overline{x_{ii}} - \overline{x_i})^2}$$

SS_A sum of squares of the treatments
SS_R sum of squares of the error
l number of treatments (no. of fertilizer form, N-fertilizer level = 2)
n number of cases (control plots and fertilized plots = 96)
$\overline{x}$ mean of the data set (mean of all 96 plots)
$\overline{x_i}$ mean of the i-group (mean of each single group)
i number of groups (= 16 groups)
J number of measurements (= 1, measurement in the case of multi-annual mean yield)
j j-measurement (= 1, first measurement in the case of multi-annual mean yield)

When the SSA is higher than the SSR, the F-value is higher, and high F-values indicate significant differences among effects.

Analysis of covariance (ANCOVA) combines features of both ANOVA and REG. ANCOVA combines the ANOVA model with one or more additional quantitative variables (covariates), which are related to the target variable. The covariates are included to reduce the variance in the error terms and provide a more precise measurement of the treatment effects.

Continuous variables (EC_a, relief parameters) are not part of the primary experimental manipulation but have an influence on the target variable.

The following five assumptions underlie the use of ANOVA and ANCOVA (Kutner et al., 2005):

– The residuals (error terms) are normally distributed (KS-test).
– The error variances are equal for different treatment classes (homogeneity of variances, tested with the Levene test).
– The relationship between the dependent and independent variables must be linear (plotting a grouped scatterplot of the covariate and the dependent variable).

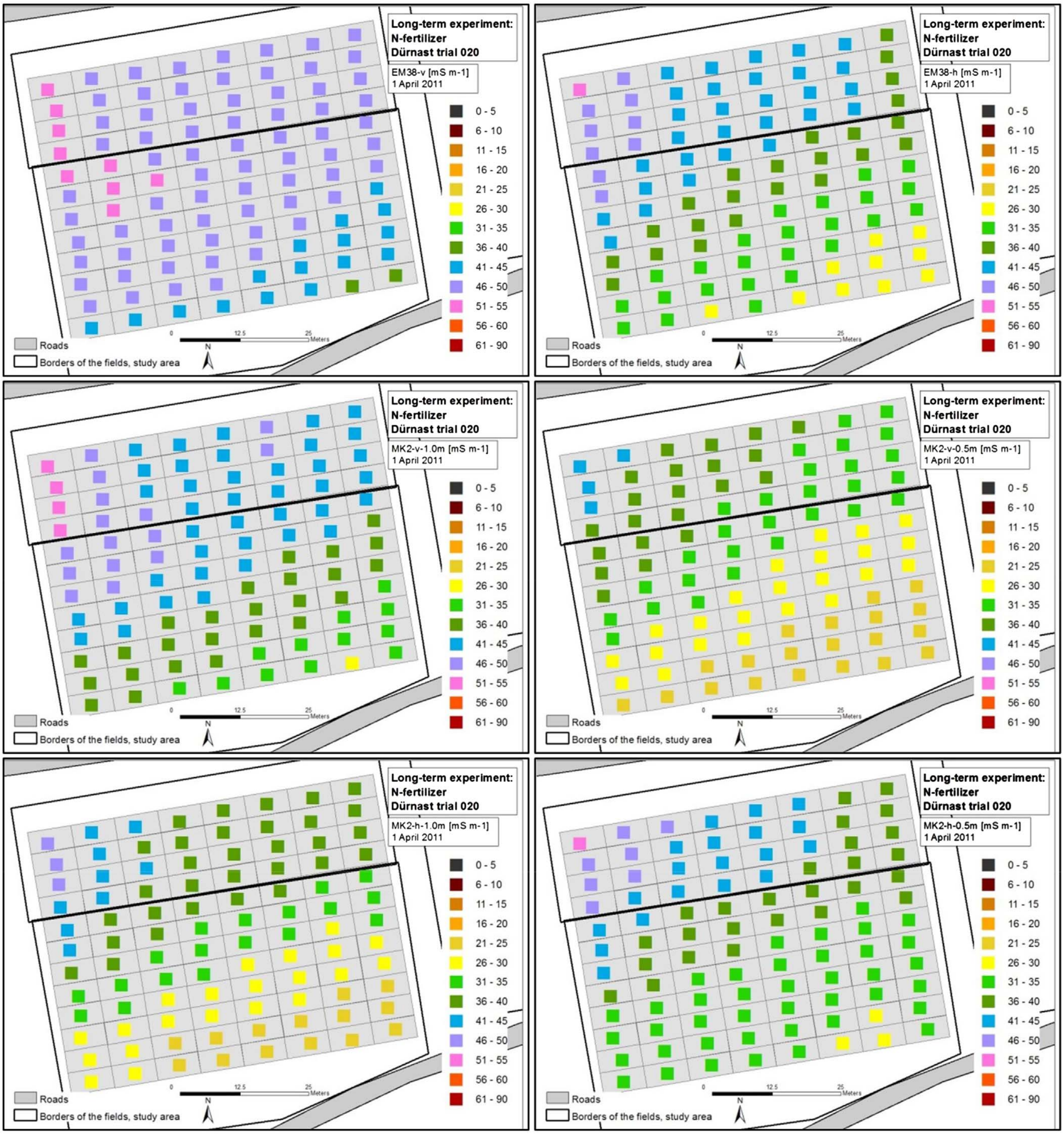


Fig. 6. Map of plot wise EC_a readings (mS m^{-1}) obtained from the EM38 and MK2 in all configurations of the field experiment 020.

– The error terms are uncorrelated (independent; plotting a scatterplot of the standardized residuals against the predicted values).

ANCOVA has two additional important requirements:

– Homogeneity of regression slopes is required, i.e., the slopes between covariates and dependent variables within groups must be similar (parallel among groups for homogeneity of regression slopes), with the best test of this assumption to plot a scatterplot for each experimental condition between the covariate and the outcome (Field, 2012).
– Independence of the covariate and treatment effects, i.e., no difference occurs in the covariates among the groups in the analysis.

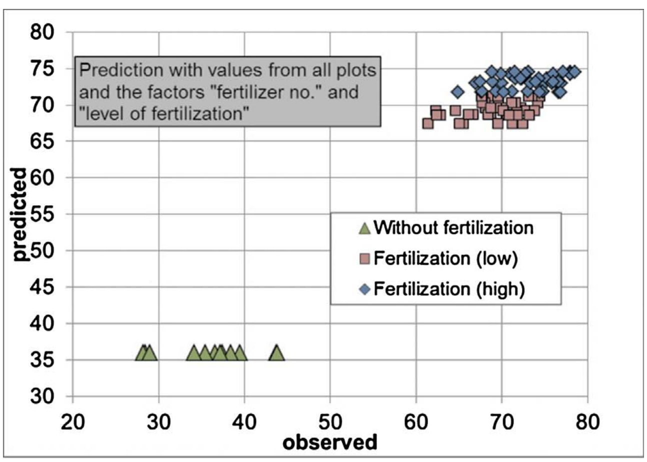
In the calculations for this study, the ANOVA procedure was as follows:

$$y = \mu + Factor\,(N - level) + Factor\,(N - fertilizerform) + Factor\,(N - level)*Factor\,(N - fertilizerform) + e$$

The extension to the ANCOVA procedure was the following:

Table 5
Results of ANOVA and ANCOVA for the multi-annual means of yield.

Calculation data, N	Target variable	Model and effects	F	Sig.	Partial eta-quadrat	Adj. R^2	RMSD
Data from all plots;	Yield	Adjusted model	64.317	0.000	0.917	0.903	3.55
Independent	[dt ha $^{-1}$]	Constant	25623.09	0.000	0.997		
variables: factors ,	mean	Fertilization level	20.895	0.000	0.205		
fertilization level	1980–2012	Fertilizer no.	0.882	0.512	0.061		
fertilizer no.		Fertilization level * Fertilizer no.	0.184	0.981	0.013		
Data from all plots; , N = 96	Yield	Adjusted model	347.917	0.000	0.986	0.98	1.46
Independent	[dt ha $^{-1}$]	Constant	4468.768	0.000	0.983		
variables: factors	mean	EC_a (MK2-h-0.5)	329.344	0.000	0.807		
fertilization level	1980–2012	Catchment	6.974	0.010	0.081		
fertilizer no., and		Fertilization level	165.877	0.000	0.677		
covariates (EC_a,		Fertilizer no.	4.492	0.001	0.254		
topographic		Fertilization level * Fertilizer no.	1.013	0.423	0.071		
parameters, location (Gauß-Krüger coordinates) N = 96							



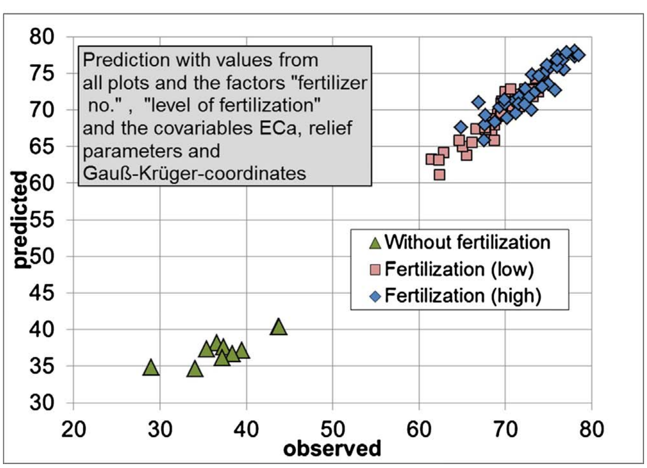


Fig. 7. Comparison of measured and modelled ANOVA (left) and ANCOVA (right) yields.

$$y = \mu + Factor(N - level) + Factor(N - fertilizerform) + Factor(N - level) * Factor(N - fertilizerform) + \mathrm{ECa} + \mathrm{relief}^* + \mathrm{Position} + \mathrm{e},$$

where y is the yield, μ is the overall mean of the yield, factor (N-level) and (N-fertilizer form) reflect the effects of quantity and form of the fertilizer and e is the error term.

The term relief* includes the topographical parameters listed above. Position describes the Gauß-Krüger coordinates of the plots.

First, the calculations were conducted with the multi-annual means of the yields (averages from 1980 to 2012) within the following scheme:

1. Overall derivation of yields for all plots with ANOVA and ANCOVA.
2. Derivation of yields only for the control areas with REG.
3. Derivation of yields for the fertilized plots with ANOVA and ANCOVA.

Second, steps 2 and 3 were used for the calculation of the respective annual yield.

In the last step, the predicted values were tested against the measured values with RMSD (root mean square difference):

$$RMSD = \left[1/N \sum_{i=1}^{N(h)} (Z_{si} - Z_{si}^{*})^2 \right]^{0.5}$$

where N represents the site, z_{si} represents the observed value, and z^*_{si} represents the predicted value.

The RMSD is a measure of the accuracy of the prediction calculation, and this value is small for an unbiased prediction.

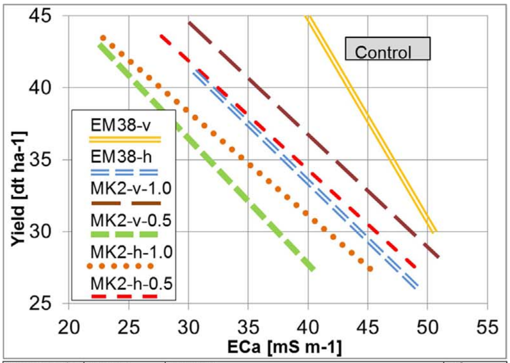
3. Results

3.1. Modelling of averaged multi-annual means of yield

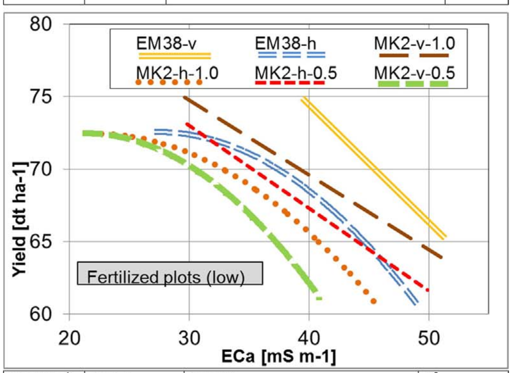
The evaluation concentrated first on the multi-annual yield. An overview is given in Fig. 4 with boxplots calculated for each level of fertilizer and fertilizer form and in Fig. 5, which shows the spatial distribution of the yields in the 96 plots. The high level of N fertilization did not produce considerably higher yields. The yield of non-fertilized plots was 35 dt*ha^{-1}, which was approximately half of the yield of fertilized treatments. The map of the yields shows a weak spatial increase (both control and fertilized plots) from the south border to the northwest corner. A contrasting trend is identifiable for the EC_a readings of both devices and for all configurations (Fig. 6). Values were decreased by about 22 mS m^{-1} and were nearly on the same level. Only in the case of the EM38-v the decrease was with 11 mS m^{-1} less pronounced.

The average values are characterized by a decrease from EM38-v, MK2-v-1.0m, EM38-h, MK2-h-0.5m, MK2-h-1.0 m to MK2-v-0.5m.

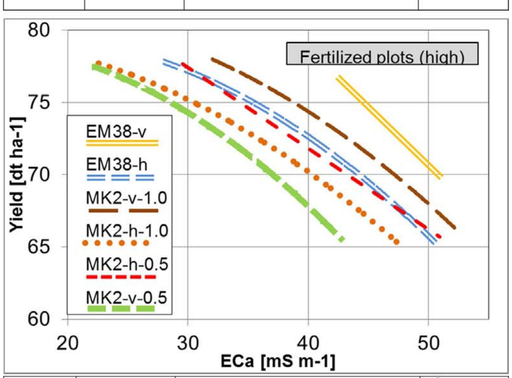
According to the ANOVA results in Table 5, only the level of



Yield [dt ha⁻¹]	Sensor	Equation	R^2
	EM38-v	101.33-1.411*EC_a	0.67
	EM38-h	64.61-0.758*EC_a	0.81
	MK2-v-1.0	68.06-0.783*EC_a	0.79
	MK2-v-0.5	62.76-0.875*EC_a	0.79
	MK2-h-1.0	59.93-0.72*EC_a	0.82
	MK2-h-0.5	65.708-0.806*EC_a	0.75



Yield [dt ha⁻¹]	Sensor	Equation	R^2
	EM38-v	106.85-0.81*EC_a	0.36
	EM38-h	53.466+1.394*EC_a -0.025*EC_a^2	0.76
	MK2-v-1.0	48.603+1.598*EC_a -0.026*EC_a^2	0.68
	MK2-v-0.5	58.94+1.268*EC_a -0.03*EC_a^2	0.77
	MK2-h-1.0	62.05+0.94*EC_a -0.21*EC_a^2	0.79
	MK2-h-0.5	79.807-0.018*EC_a -0.07*EC_a^2	0.82



Yield [dt ha⁻¹]	Sensor	Equation	R^2
	EM38-v	111.2-0.811*EC_a	0.22
	EM38-h	76.853+0.361*EC_a -0.012*EC_a^2	0.67
	MK2-v-1.0	96.968-0.57*EC_a	0.57
	MK2-v-0.5	77.522+0.3*EC_a -0.014*EC_a^2	0.68
	MK2-h-1.0	79.16+0.145*EC_a -0.009*EC_a^2	0.72
	MK2-h-0.5	94.227-0.561*EC_a	0.75

Fig. 8. Relationships between EC_a and yields for the control and the fertilized plots with low and high levels of N fertilizer.

fertilization was a significant influencing factor, and the interaction between the factors fertilizer amount and fertilizer form was not significant. Nevertheless, a high R^2 was reached, although with a relatively high RMSD (3.55 dt ha^{-1}).

The significant components of the ANCOVA procedure showed a modified picture. With ANCOVA, both factors in combination with EC_a (MK2-h-0.5) and the catchment attribute (CA) produced a very high R^2 and a low RMSD (1.46 dt ha^{-1}). In Fig. 7, the measured and the modelled values are compared (1:1 relationship). As the figures clearly demonstrate, the high R^2 for both procedures was produced by the low values of the control plots. In contrast to ANOVA, ANCOVA, which included continuous variables, showed a more realistic picture, in addition to a low RMSD.

According to the partial eta^2, the primary parameters of influence in ANCOVA were EC_a, followed by the level of fertilization. At lower EC_a values, the yields were higher, and this negative relationship (Fig. 8) was detected with the different configurations of both sensors. Remarkably, the curves had similar slopes; therefore, EC_a (MK2-h-0.5) could be replaced by the other measurements of conductivity. However, this does not apply to EM38-v because of a lower R^2 and divergent slope, which is caused, at least in part, by the smaller range of the EC_a readings.

For more detailed insight into the variables that influenced yield, the multi-annual data set was divided into control (non-fertilized) and fertilized data.

The modelling of the yield of the control plots (N-level = 0, no. of fertilizer = 0) was performed with REG in two forms, with all continuous independent variables and only with EC_a.

For both models, the R^2 and RMSD indicated that the results were acceptable. In the first calculation, the significant variables were CNBL and PLC. However, the prediction of the yield was also satisfactory for the non-fertilized treatment with only EC_a (MK2-h-1.0) (Table 6).

According to ANOVA, the fertilization level was the only factor of influence, but the result was poor (R^2 = 0.19, RMSD = 3.26 dt ha^{-1}). In contrast to this result, in ANCOVA, which included the factors fertilization level and fertilization no. and the covariate EC_a (MK2-h-0.5), EC_a was followed by fertilization level as dominant parameters. With R^2 = 0.87 and RMSD = 1.29 dt ha^{-1}, ANCOVA was a significant improvement in comparison with ANOVA (Table 7, Fig. 9).

3.2. Modelling of annual yields

A great range in R^2 and RMSD values characterized the regressions of the annual yields of the control plots (Table 8). With the 1992 and 2010 yields excluded, the R^2 values were higher than 0.65. The best fit was reached in 1989, 1991, 2001 and 2012, which were also characterized by more predictors.

Remarkably, in 11 of 12 calculations, EC_a values measured with different sensors and configurations represented significant independent variables (MK2-h-0.5, EM38-v, MK2-h-1.0). The plancurvature was the dominant predictor among the relief parameters.

The modelling of the yield of the fertilized plots resulted in the following observations (Table 9):

The ANOVA procedures resulted in relatively poor simulation results in most cases, with R^2 values ranging between 0.008 and 0.58 and those of RMSD ranging from 1.26 to 13.6 dt ha^{-1}.

- The significant predictors were primarily the fertilization level and to a minor degree, also the fertilizer form.
- The accuracies were higher when the fertilizer form was included in the models (1980, 1986, 1992, 2012).
- The introduction of the covariates clearly improved the quality of the simulations, particularly for 1995, 1998, 2001, 2004 and 2010. The R^2 increased to 0.43-0.85, and the RMSD decreased to approximately 1–5 dt ha^{-1}.
- The EC_a was included in nine calculations, primarily as MK2-h-0.5 but also as MK2-v-0.5, MK2-v-1.0, EM38-v and EM38-h.
- In addition to the aspect, the more three-dimensional parameters convergence, valley depth, and LS-factor also influenced the yield.

Table 6
Simulation of the yield (means of the years 1980–2012) with REG of the control plots.

Target variable	Predictors	Regression coefficients	Sig.	Standard. beta-coeff.	Adj. R^2 sig.	RMSD
Control, N = 12 (independent variables: EC_a, topographic parameters, location information(Gauß-Krüger))						
Wheat mean (1980–2012) [dt ha^{-1}]^2		65798.14	0.000		0.96***	1.04
	Channel network [m]^3	−0.000618	0.000	−0.885		
	Plancurvature [−]	30,766.741	0.009	0.218		
Control, N = 12 (independent variables: EC_a)						
Wheat mean (1980–2012) [dt ha^{-1}]^3		−43585.695	0.006		0.84***	2.15
	EC_a (MK2-h-1.0) [mS m^{-1}] (1/x)	29,79,297.639	0.000			

Table 7
Simulation of the yield (means of the years 1980–2012) with ANOVA and ANCOVA with the factors fertilization level and fertilizer no. and the covariates EC_a, relief parameters and coordinates.

Calculation data, N	Target variable	Model and effects	F	Sig.	Partial eta-quadrat	Adj. R^2	RMSD
Data from fertilized plots; Independent variables: factors fertilization level, fertilizer no.	Yield [dt ha^{-1}] mean 1980–2012	Adjusted model	2.451	0.008	0.313	0.185	3.26
		Constant	33,300.233	0.000	0.998		
		Fertilization level	24.398	0.000	0.258		
		Fertilizer no.	1.029	0.414	0.081		
N = 84		Fertilization level * Fertilizer no.	0.215	0,971	0.018		
Data from fertilized plots; Independent variables: factors fertilization level, fertilizer-no., covariates (EC_a, topographic parameters, location (Gauß-Krüger coordinates),	Yield [dt ha^{-1}]^3 mean 1980–2012	Adjusted model	42.6	0.000	0.896	0.875	1.29
		Constant	4.378	0.040	0.060		
		Fertilization level	221.457	0.000	0.762		
		Fertilizer no.	6.229	0.000	0.351		
		Fertilization level * Fertilizer no.	1.362	0.242	0.106		
N = 84		EC_a (MK2-h-0.5)	383.966	0.000	0.848		

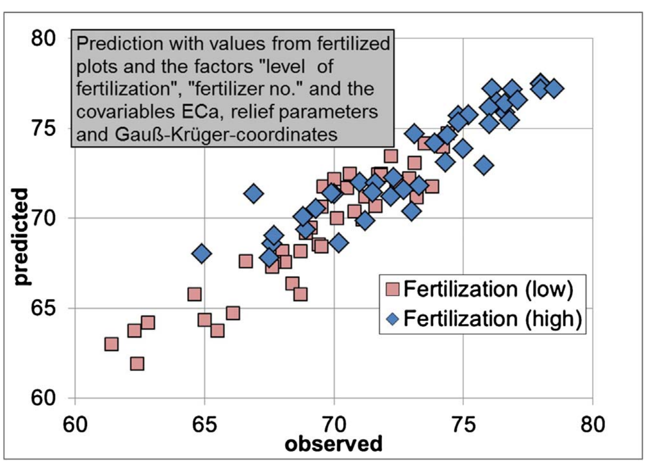


Fig. 9. Comparison of measured and modelled ANCOVA (Table 6) yields.

– The interaction (Fertilization level*Fertilizer no.) was a significant contribution to the simulations only in ANCOVA (1980, 1995, 2001).
– The variation in the yield in 1992, 2004 and 2007 corresponded with higher RMSD values.

With 1983 and 2010 excluded, the form of fertilizer was a significant contribution to the simulation of the yield; however, this factor was a significant influence only in ANCOVA. The influence of specific fertilizer forms must be analysed in subsequent work.

4. Discussion

Field experiments simultaneously investigate the effect of one or more input variables (factors) on one or more output variables (response) and consist of measurements for which purposeful changes (e.g., fertilization levels, cultivars) are part of the input variables. All the unrecognized and extraneous variation contribute to experimental errors, and the inherent soil variability tends to mask the outcome of such field experiments. Although it is frequently assumed that the field or parts of it are generally homogeneous, and therefore, the conditions for plant growth are similar, this assumption usually remains untested.

Conventional soil investigations are expensive and time-consuming, and therefore, experimental areas are arranged in a specific manner. Blocking of the experimental area is frequently used to account for experimental errors. The hypothesis is that the influence of soil heterogeneity should on average be similar in all treatment plots within the entire experiment. In some investigations, the use of a covariate in the statistical evaluation is possible to reduce the level of soil-related errors.

In this study, a conventional investigation was expanded by testing the added value of a non-invasive geophysical characterization of the field site of a long-term experiment. To the best of our knowledge, this study is the first to include such a geophysical characterization of a long-term study, which may also permit ex-post analysis of previous experiments. The static character of the tested factors, apparent electrical conductivity and topographical features was essential. Therefore, the soil conductivity (EC_a), coordinates of the plots and topographical parameters were used as proxies for soil conditions. These variables were relatively easy and inexpensive to derive and also remained more or less stable over time.

Based on the relationship between the yield and tested covariates for the non-fertilized plots, the data obtained from the geophysical sensor MK2-h-0.5, measured in the horizontal mode at the 0.5 m coil distance mode, and the topography attribute plan curvature (PC) were the primary predictors.

Compared with standard ANOVA, the R^2 and RMSD values of ANCOVA improved with soil EC_a and topographic parameters as

Table 8
Simulation of the annual yield from 1980 to 2012 with REG of the control plots and the independent variables EC_a and relief.

Control, N = 12 (independent variables: EC_a, topographic parameters, location (Gauß-Krüger coordinates))

Target variable	Year	Predictors	Regression coefficients	Sig.	Standard. beta-coeff.	Adj. R^2 sig.	RMSD
Yield [dt ha $^{-1}$] (1/x)	1980	Constant	0.015	0.000		0.76	3.36
		EC_a (MK2-h-0.5)^3	1.034e–007	0.000	0.987	***	
		Plancurvature^2	−165.123	0.006	−0.594		
Yield [dt ha $^{-1}$] (1/x)	1983	Constant	0.019	0.000		0.76	3.98
		EC_a (MK2-h-0.5)^3	2.801e-007	0.000	0.882	***	
Yield [dt ha $^{-1}$] (1/x)	1986	Constant	0.077	0.005		0.66	4.22
		EC_a (MK2-h-0.5) (1/x)	2.587e-007	0.001	0.859	**	
		Aspect (1/x)	−0.161	0.022	−0.510		
Yield [dt ha $^{-1}$] (log10)	1989	Constant	18.428			0.97	0.75
		Channel network base level	−1.56e-007	0.000	−1.538	****	
		1/ECa (EM38-v)	−24.77	0.000	−0.693		
		Profile curvature	1.144	0.039	0.128		
Yield [dt ha $^{-1}$]^3	1992	Constant	23735.88	0.423	0.737	0	8.83
		LS-factor	28628.03	0.006		0.50	
						**	
Yield [dt ha $^{-1}$] (1/x)	1995	Constant	−0.092	0.019		0.95	1.36
		sqrt(EC_a) (MK2-h-0.5)	0.016	0.003	0.952	***	
		Catchment area (1/x)	1.032	0.001	0.604		
		EC_a (MK2-v-0.5) (1/x)	0.827	0.017	0.646		
		Plancurvature ^3	−26850.9	0.045	−0.250		
Yield [dt ha $^{-1}$]^3	1998	Constant	−1,26,807.08	0.001		0.82	3.59
		1/ECa (EM38-v)	66,10,447.2	0.000	0.914	***	
Yield [dt ha $^{-1}$] (log10)	2001	Constant	1.862	0.000		0.93	2.21
		EC_a (MK2-h-0.5)^2	−0.000328	0.000	−1.113	***	
		ECa (EM38-v)^3	4.952e-006	0.002	0.693		
		Valley depth	−1.764	0.010	−0.328		
		Plancurvature	4,59,810.23	0.047	0.241		
Yield [dt ha $^{-1}$] log(10)	2004	Constant	3.3431	0.000		0.80	4.53
		EC_a (MK2-h-1.0)	−1.16	0.004	−0.655	**	
		LS-factor	−0.303	0.040	−0.396		
Yield [dt ha $^{-1}$]^3	2007	Constant	−5,81,865.19	0.009		0.74	6.68
		1/EC_a (EM38-v)	2,89,29,462.2	0.006	0.862	**	
Yield [dt ha $^{-1}$]^3	2010	Constant	130118.068	0.008		0.46	4.26
		EC_a (EM38-v)^3	−0.926	0.040	−0.73	*	
Yield [dt ha $^{-1}$]	2012	Constant	66.602	0.000		0.904	0.71
		EC_a (EM38-v)	−0.823	0.001	−0.959	**	

covariates (fertilized plots, ANOVA: R^2 = 0.18, RMSD = 3.26 dt ha^{-1}; ANCOVA: R^2 = 0.87, RMSD = 1.29 dt ha^{-1}). In addition to the factors of the fertilization level and fertilizer form, the dominant covariate in ANCOVA was EC_a (MK2-h-0.5). Similar results were obtained in the derivations of the single years, primarily for MK2-h-0.5 but also EM38-v and MK2-h-1.0. The predictor plancurvature was the dominant relief parameter.

Different conclusions were reached regarding the treatment effects and covariates:

– The position of the plots had no influence on the distribution of the yield.
– The relationships between EC_a and yield were negative; thus, high EC_a was an indication of low yield.
– The influence of EC_a and the relief parameters on the yields indicated that the site-specific growing conditions were not homogeneous in this relatively small investigation area.
– The dominance of EC_a (MK2-h-0.5) led to the conclusion that shallower soil layers contributed more to the variability in the yield than that of the deeper soil layers.
– The increased 3-dimensional relief parameters were a significant influence, which indicated that the slope character of this area increased the site heterogeneity.

The metric variable EC_a had significant explanatory power with respect to the variability of the wheat yields. The curve progressions between ECa and yield led to further interpretations:

– EC_a was the primary influence on the spatial distribution of the yield across the field. The treatment effects (fertilization level, fertilizer form) were overlaid on soil conditions with different EC_a values.
– The level of fertilization was a secondary influence on the size of the yield.
– The differences in yield among the forms of fertilizers were not significant, indicating the lower importance of the fertilizer form.

At the investigated site, the soil texture (primarily clay and sand), water content, bulk density and conductivity of the pore water (unpublished data) influenced the soil EC_a (EM38 and EM38-MK2). Lower EC_a values corresponded with lower elevations and higher catchment areas and soils with more silt (silt: 67 kg kg^{-1}; clay: 16 kg kg^{-1}; sand: 16 kg kg^{-1}; skeleton: 2 kg kg^{-1}; near the southern border), whereas higher EC_a readings were detected in soils at higher elevations with more clay (clay: 26 kg kg^{-1}; silt: 56 kg kg^{-1}; sand: 17 kg kg^{-1}; skeleton: 3 kg kg^{-1}; near the northern border). Additionally, soils with a lower EC_a value had higher contents of C and N.

The site-specific yield potentials increased in soils with a higher content of silt in combination with a higher content of organic matter. The positive influence of the increased plant available water holding capacity on the yield and yield potential is well known and has been derived as the primary explanatory factor for field site-specific yield differences (Geesing et al., 2014).

The close EC_a-yield relationships in this study were in contrast to a previous study in which only weak relationships between the apparent electrical conductivity and yield were observed for generally

Table 9
Simulation of the annual yield from 1980 to 2012 with ANOVA and ANCOVA with the factors fertilization level and fertilizer-no. and the covariates EC_a, relief parameters and coordinates.

Data from fertilized plots; Independent variables: factors fertilization level, fertilizer-no. N = 84

Target Variable	Year	Model and effects	F	Sig.	Partial eta-quadrat	Adj. R^2	RMSD
Yield [dt ha^{-1}]	1980	Adjusted model	4.109	0.000	0.433	0.328	3.08
		Constant	31,258.88	0.000	0.998		
		Fertilization level	9.847	0.002	0.123		
		Fertilizer no.	5.446	0.000	0.318		
		Fertilization level*Fertilizer no.	1.816	0.108	0.135		
Yield [dt ha^{-1}]	1983	Adjusted model	3.175	0.001	0.371	0.254	3.34
		Constant	24598.810	0.000	0.997		
		Fertilization level	27.356	0.000	0.281		
		Fertilizer no.	1.254	0.290	0.097		
		Fertilization level*Fertilizer no.	1.066	0.392	0.084		
Yield [dt ha^{-1}]^3	1986	Adjusted model	9.846	0.000	0.646	0.581	1.26
		Constant	17246.367	0.000	0.996		
		Fertilization level	25.353	0.000	0.250		
		Fertilizer no.	16.704	0.000	0.589		
		Fertilization level*Fertilizer no.	0.736	0.622	0.059		
Yield [dt ha^{-1}] ^3	1989	Adjusted model	3.139	0.001	0.368	0.251	4.70
		Constant	2635.926	0.000	0.974		
		Fertilization level	35.527	0.000	0.317		
		Fertilizer no.	0.920	0.486	0.073		
		Fertilization level*Fertilizer no.	0.458	0.837	0.038		
Yield [dt ha^{-1}]^2	1992	Adjusted model	3.270	0.001	0.378	0.262	4.11
		Constant	7675.400	0.000	0.991		
		Fertilization level	19.291	0.000	0.216		
		Fertilizer no.	3.549	0.004	0.233		
		Fertilization level*Fertilizer no.	0.321	0.924	0.027		
Yield [dt ha^{-1}] (1/x)	1995	Adjusted model	1.048	0.417	0.163	0.008	5.20
		Constant	8742.404	0.000	0.992		
		Fertilization level	5.530	0.022	0.073		
		Fertilizer no.	1.073	0.387	0.084		
		Fertilization level*Fertilizer no.	0.277	0.946	0.023		
Yield [dt ha^{-1}]	1998	Adjusted model	2.191	0.019	0.289	0.157	3.84
		Constant	25,119.760	0.000	0.997		
		Fertilization level	18.383	0.000	0.208		
		Fertilizer no.	1.372	0.238	0.105		
		Fertilization level*Fertilizer no.	0.313	0.928	0.026		
Yield [dt ha^{-1}]^3	2001	Adjusted model	2.675	0.004	0.332	0.208	13.6
		Constant	860.275	0.000	0.925		
		Fertilization level	19.851	0.000	0.221		
		Fertilizer no.	1.849	0.102	0.137		
		Fertilization level*Fertilizer no.	0.639	0.698	0.052		
Yield [dt ha^{-1}]	2004	Adjusted model	0.762	0.697	0.124	0.039	6.30
		Constant	14,937.152	0.000	0.995		
		Fertilization level	4.953	0.029	0.066		
		Fertilizer no.	0.704	0.648	0.057		
		Fertilization level*Fertilizer no.	0.121	0.994	0.010		
Yield [dt ha^{-1}]	2007	Adjusted model	1.808	0.074	0.359	0.160	6.30
		Constant	8234.419	0.000	0.995		
		Fertilization level	9.717	0.003	0.188		
		Fertilizer no.	2.078	0.076	0.229		
		Fertilization level*Fertilizer no.	0.219	0.969	0.030		
Yield [dt ha^{-1}]	2010	Adjusted model	0.799	0.657	0.198	0.050	3.00
		Constant	25,320.336	0.000	0.998		
		Fertilization level	3.477	0.069	0.076		
		Fertilizer no.	0.355	0.903	0.048		
		Fertilization level*Fertilizer no.	0.797	0.578	0.102		
Yield [dt ha^{-1}] (log10)	2012	Adjusted model	6.633	0.000	0.672	0.571	2.63
		Constant	3,51,125.040	0.000	1.000		
		Fertilization level	67.937	0.000	0.618		
		Fertilizer no.	2.503	0.037	0.263		
		Fertilization level*Fertilizer no.	0.546	0.770	0.072		

Data from fertilized plots; Independent variables: effects fertilization level, fertilizer-no., and covariates (EC_a, topographic parameters, location information (Gauß-Krüger coordinates)); N = 84

Target	Year	Model and effects	F	Sig.	Partial eta-	Adj. R^2	RMSD
Yield [dt ha^{-1}]	1980	Adjusted model	5.126	0.000	0.531	0.427	2.80
		Constant	1403.646	0.000	0.954		
		Fertilization level	9.658	0.003	0.148		

(continued on next page)

Table 9 *(continued)*

Data from fertilized plots; Independent variables: effects fertilization level, fertilizer-no., and covariates (EC_a, topographic parameters, location information (Gauß-Krüger coordinates)); N = 84

Target	Year	Model and effects	F	Sig.	Partial eta-	Adj. R^2	RMSD
		Fertilizer no.	4.984	0.000	0.305		
		Fertilization level*Fertilizer no.	2.354	0.040	0.172		
		Aspectˆ3	11.805	0.001	0.148		
		Convergence (1/x)	1.814	0.050	0.026		
Yield	1983	Adjusted model	7.467	0.000	0.674	0.584	2.39
[dt ha^{-1}]ˆ2		Constant	84.666	0.000	0.566		
		Fertilization level	46.559	0.000	0.056		
		Fertilizer no.	0.637	0.700	0.236		
		Fertilization level*Fertilizer no.	1.298	0.271	0.107		
		Convergence (1/x)	5.399	0.023	0.077		
		Convergence ˆ3	5.852	0.018	0.083		
		Valley depth (1/x)	13.445	0.000	0.171		
		EC_a (EM38-v)ˆ3	5.439	0.023	0.077		
		EC_a (MK2-h-0.5) (log10)	33.075	0.000	0.337		
Yield	1986	Adjusted model	10.070	0.000	0.690	0.621	1.12
[dt ha^{-1}] (log10)		Constant	1,39,973.947	0.000	1.000		
		Fertilization level	28.995	0.000	0.299		
		Fertilizer no.	13.611	0.000	0.546		
		Fertilization level*Fertilizer no.	0.676	0.669	0.056		
		LS-factorˆ3	13.014	0.001	0.161		
		Aspectˆ3	8.146	0.006	0.107		
Yield	1989	Adjusted model	14.712	0.000	0.764	0.712	2.98
[dt ha^{-1}]ˆ2		Constant	443.109	0.000	0.867		
		Fertilization level	105.779	0.000	0.609		
		Fertilizer no.	2.755	0.019	0.196		
		Fertilization level*Fertilizer no.	1.170	0.333	0.094		
		Valley depthˆ3	75.18	0.000	0.525		
		Analytical hill hillschadingˆ3	10.81	0.002	0.137		
Yield	1992	Adjusted model	19.465	0.000	0.798	0.757	2.45
[dt ha^{-1}]ˆ3		Constant	253.965	0.000	0.786		
		Fertilization level	81.477	0.000	0.541		
		Fertilizer no.	9.634	0.000	0.456		
		Fertilization level*Fertilizer no.	1.195	0.319	0.094		
		EC_a (MK2-h-0.5) (log10)	142.533	0.000	0.674		
Yield	1995	Adjusted model	16.695	0.000	0.811	0.763	2.39
[dt ha^{-1}]ˆ3		Constant	196.478	0.000	0.749		
		Fertilization level	47.841	0.000	0.420		
		Fertilizer no.	3.489	0.005	0.241		
		Fertilization level*Fertilizer no.	2.576	0.027	0.190		
		EC_a (MK2-h-0.5)ˆ3	47.939	0.000	0.421		
		LS-factorˆ3	5.624	0.021	0.079		
		Aspectˆ3	29.705	0.000	0.310		
		LS-factor (1/x)	19.773	0.000	0.231		
Yield	1998	Adjusted model	22.934	0.000	0.835	0.799	1.85
[dt ha^{-1}]		Constant	135.277	0.000	0.665		
		Fertilization level	109.121	0.000	0.616		
		Fertilizer no.	3.496	0.005	0.236		
		Fertilization level*Fertilizer no.	1.504	0.190	0.117		
		EC_a (MK2-v-1.0) (1/x)	16.282	0.000	0.193		
		Channel network base levelˆ3	108.263	0.000	0.614		
Yield	2001	Adjusted model	27.412	0.000	0.881	0.849	2.47
[dt ha^{-1}] (1/x)		Constant	19.647	0.000	0.238		
		Fertilization level	103.829	0.000	0.622		
		Fertilizer no.	9.760	0.000	0.482		
		Fertilization level*Fertilizer no.	2.576	0.027	0.197		
		LS-factorˆ3	4.987	0.000	0.073		
		Aspectˆ3	32.861	0.000	0.343		
		EC_a (EM38-h) (1/x)	212.46	0.000	0.254		
		sqrt(EC_a) (MK2-h-0.5)	92.819	0.000	0.596		
Yield	2004	Adjusted model	29.365	0.000	0.866	0.837	2.48
[dt ha^{-1}]ˆ2		Constant	3.733	0.058	0.052		
		Fertilization level	63.126	0.000	0.481		
		Fertilizer no.	4.248	0.001	0.273		
		Fertilization level*Fertilizer no.	0.786	0.584	0.065		
		EC_a (MK2-h-0.5) (1/x)	44.151	0.000	0.394		
		sqrt(valley depth)	5.899	0.018	0.080		
Yield	2007	Adjusted model	4.580	0.000	0.610	0.477	5.27
[dt ha^{-1}]ˆ3		Constant	501.880	0.000	0.924		
		Fertilization level	25.718	0.000	0.385		
		Fertilizer no.	2.440	0.041	0.263		
		Fertilization level*Fertilizer no.	0.498	0.806	0.068		
		EC_a (MK2-v-0.5)ˆ3	22.187	0.000	0.351		

(continued on next page)

Table 9 *(continued)*

Data from fertilized plots; Independent variables: effects fertilization level, fertilizer-no., and covariates (EC_a, topographic parameters, location information (Gauß-Krüger coordinates)); N = 84

Target	Year	Model and effects	F	Sig.	Partial eta-	Adj. R^2	RMSD
Yield [dt ha $^{-1}$] (1/x)	2010	Adjusted model	6.647	0.000	0.714	0.606	1.83
		Constant	4705.381	0.000	0.992		
		Fertilization level	18.141	0.000	0.312		
		Fertilizer no.	0.980	0.451	0.128		
		Fertilization level*Fertilizer no.	2.141	0.070	0.243		
		EC_a (MK2-h-0.5)ˆ3	36.50	0.000	0.477		
		EC_a (MK2-v-1.0)ˆ3	14.066	0.001	0.260		
Yield [dt ha $^{-1}$]	2012	Adjusted model	10.792	0.000	0.802	0.728	2.04
		Constant	3419.743	0.000	0.988		
		Fertilization level	126.664	0.000	0.760		
		Fertilizer no.	2.769	0.024	0.293		
		Fertilization level*Fertilizer no.	0.833	0.552	0.111		
		EC_a (MK2-h-0.5)ˆ3	13.30	0.001	0.250		
		LS-factorˆ3	8.714	0.005	0.479		

homogeneous soil sites (Neudecker et al., 2003). However, by focusing on heterogeneous field sites as part of a Germany-wide study to delineate management and yield zones for site-specific management actions, generally close relationships between EC_a values and yields were observed, with R^2 values ranging from 0.15 to 0.71. Furthermore, notably, in this experimental area, the relationships were always negative, which indicated that sandy soils that typically have low EC_a readings in combination with low yields were absent.

Based on previous studies, various factors influence growth and may contribute to differences in yield on large heterogeneous field sites varying in size up to 100 ha; however, the influence of plant available water is the most influential factor (Selige and Schmidhalter 2001; Schmidhalter et al., 2008).

Furthermore, in particular, the terrain parameters CA, PLC, CON, VD and LSF were the most common significant predictors. With higher biomass produced in flat locations, attributes associated with water accumulation and water availability played an important role in wheat production.

ANCOVA analysed multiple direct and indirect relationships among the studied factors, and we expect that this approach has great potential for this type of evaluation in agricultural research because ANCOVA is an easy way to identify multiple factors interacting simultaneously.

In contrast to the site in this study, which was characterized by a modest slope, in flat fields, topographic attributes are not likely to be influential. In those fields, EC_a measurements should primarily be tested for their potential to explain site-specific differences that account for residual errors in statistical models.

As an alternative to the tested proxies, proximal or aerial remote sensing is also a feasible approach to delineate growth and the resulting yield differences on experimental field sites (Neudecker et al., 2001). Whereas this approach is frequently evaluated on heterogeneous field sites, the adoption to highly managed plots on experimental stations or in breeding nurseries is expected to also significantly enhance the analysis of such experimental data. In contrast to non-invasive soil mapping, which is performed before or during experimentation, previously uniformly managed field experimentation sites with historical data sets represent a good choice to unravel the inherent soil heterogeneity indirectly by proximal or aerial reflectance sensing of soil and plant properties. This latter approach is particularly suitable for either previously or subsequently uniformly managed fields and allows to derive important soil characteristics such as the varying plant available water capacity via plant reflectance characteristics at relevant time windows (Schmidhalter et al., 2008) or relevant top soil characteristics (Selige et al., 2006). Since in most cases where not dedicated changes in the soil nutrient status, other than nitrogen, or e.g. the pathogenic soil/plant status, have been established, the availability of water or nitrogen represents by far the most dominant properties determining differences in local plant yields (Geesing et al., 2014) and should therefore preferably be determined prior or following experimentation. In all cases possible interactions with the yearly climatic situation should be considered. Potentially limiting factors should be included in the choice of the most appropriate method.

In summary the inclusion of plot-wise, time invariant soil and relief parameters allows significantly improving the discrimination of the treatment performance in field trials. Therefore, we recommend to systematically collecting this information from all experimental sites prior or following the experimentation. The static character of this information depicts the local heterogeneity and remains as long-term information not requiring any further data collection. Regarding the choice of the different sensors it is difficult to arrive at a clear recommendation. The weaker influence of temperature on the readings represents an advantage of the MK2. On the other hand the regression analyses between ECa and texture indicates mostly higher R^2-values using the EM38 (Heil and Schmidhalter, 2015).

Deriving experimental field heterogeneities by means of remote or proximal sensing (satellite, drone, terrestrial sensing) represents also a viable alternative.

5. Conclusions

It is clear that not all differences in soils that account for yield differences can be assayed by proximal soil sensing as used in this study or, alternatively, by proximal or spectral remote sensing as outlined above. However, these approaches provide new and more comprehensive analyses for dedicated agronomic plot testing or breeding nurseries. Overall, significant advantages are expected beyond those of the established enhanced analysis based on optimized field layout experimental protocols with adapted statistical analyses. However, these approaches are not meant to replace well-established analytical protocols in field experimentation but to augment them with a plot-wise, non-invasive investigation of the inherent soil variability; thus, a highly likely outcome of this type of investigation is a more comprehensive analysis. Based on the required intensive further testing and validation, this might represent a new standard in field experimentation that also permits interpretation of subtle or minor differences in plant growth or yield.

Subsequent work, which is beyond the scope of this publication, will have to address the influence of specific forms of fertilizer on underlying structures, such as different growth patterns. Furthermore, weather conditions must be considered for further improvements in the models. Finally, the year-to-year climatic variation can be sufficiently high so that even the best predictors cannot adequately simulate the yield.

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