



ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA

ARCHIVIO ISTITUZIONALE
DELLA RICERCA

Alma Mater Studiorum Università di Bologna Archivio istituzionale della ricerca

Soil and climate factors drive spatio-temporal variability of arable crop yields under uniform management in Northern Italy

This is the final peer-reviewed author's accepted manuscript (postprint) of the following publication:

Published Version:

Ali, A., Martelli, R., Scudiero, E., Lupia, F., Falsone, G., Rondelli, V., et al. (2023). Soil and climate factors drive spatio-temporal variability of arable crop yields under uniform management in Northern Italy. ARCHIVES OF AGRONOMY AND SOIL SCIENCE, 69(1), 75-89 [10.1080/03650340.2021.1958320].

Availability:

This version is available at: <https://hdl.handle.net/11585/865858> since: 2024-03-01

Published:

DOI: <http://doi.org/10.1080/03650340.2021.1958320>

Terms of use:

Some rights reserved. The terms and conditions for the reuse of this version of the manuscript are specified in the publishing policy. For all terms of use and more information see the publisher's website.

This item was downloaded from IRIS Università di Bologna (<https://cris.unibo.it/>).
When citing, please refer to the published version.

(Article begins on next page)

1 **Soil and Climate Factors Drive Spatio-temporal Variability of Arable Crop**
2 **Yields under Uniform Management in Northern Italy**

3 Abid Ali^a, Roberta Martelli ^{a*}, Elia Scudiero^b, Flavio Lupia^c, Gloria Falsone^a,
4 Valda Rondelli^a and Lorenzo Barbanti^a

5 *^aDepartment of Agricultural and Food Sciences, University of Bologna, Viale Fanin 50, 40127*
6 *Bologna, Italy; ^bDepartment of Environmental Sciences, University of California, Riverside, 450*
7 *West Big Springs Road, Riverside, 92507, California, USA; ^cCREA Research Centre for*
8 *Agricultural Policies and Bioeconomy, via Po, 14, 00198 Rome, Italy.*

9 **Correspondence: roberta.martelli@unibo.it*

10 **Soil and Climate Factors Drive Spatio-temporal Variability of Arable Crop** 11 **Yields under Uniform Management in Northern Italy**

12 Soil and weather data were used to analyse spatio-temporal yield patterns of winter cereals
13 (wheat) and spring dicots (sunflower and coriander) in a 11-ha field in Northern Italy (44.5°
14 N, 12.2° E), during 2010-2014. Three yield stability classes (YSCs) were established over
15 multiple years, based on spatio-temporal characteristics across the field: high yielding and
16 stable (HYS), low yielding and stable (LYS), and unstable. The HYS class (46% of field
17 area) staged a 122% relative yield with low temporal variability. The unstable class (24% of
18 field area) was slightly more productive (83% relative yield) than the LYS class (30% of
19 field area, and 80% relative yield), but less consistent over time. Crop yields evidenced
20 negative correlations with sand content; positive correlations with silt and clay content. Soil
21 properties were quite consistently classified among YSCs: the LYS and unstable classes
22 were associated with higher sand content and lower cation exchange capacity, suggesting
23 that these characteristics lead to fluctuation and depression of final yield. Establishing
24 YSCs based on spatio-temporal yield appears a sound approach to appraise field potential.
25 It results in strategic and tactical decisions to be taken, depending on the profile of spatial
26 and temporal productivity in different field areas.

27 **Keywords:** Apparent soil electrical conductivity; crop yield; field spatio-temporal
28 variability; geostatistics; soil properties

29 **Introduction**

30 Precision agriculture (PA) has a great potential to increase crop growth and final yield through
31 the application of variable crop inputs (Basso et al. 2017). Specific crop inputs at the right time
32 and place is highly encouraged in today's agriculture. Therefore, the focus of this study is to
33 analyse spatial and temporal variability of field crops, in-season climate conditions, and soil
34 nutrient status for optimizing crop productivity and sustaining the most efficient use of finite
35 natural resources (Blackmore 2000; Maestrini and Basso 2018). Soil physical-chemical
36 properties vary in space and time depending on their interaction with factors such as climate,

37 topography and anthropogenic activities (Corwin et al. 2003). Bullock and Bullock (2000)
38 stressed the importance of adopting efficient methods to characterize soil spatial variability.
39 Among them, apparent soil electrical conductivity (ECa) directed to soil sampling has been
40 shown a rapid and reliable method to characterize field variability (Corwin and Lesch 2003).
41 However, ECa has not always staged consistent results with crop yield, due to its complex
42 interactions with soil properties and external factors (Corwin et al. 2003).

43 Climatic factors exert a strong influence on crop productivity under rainfed conditions
44 (Iizumi and Ramankutty 2015; Asfaw et al. 2018), being responsible for consistently low
45 yielding areas where insufficient moisture is the most limiting factor. Several studies demonstrate
46 that the two main climatic factors, precipitation and temperature, significantly influence yield
47 stability across growing seasons (Kukul and Irmak 2018; Maestrini and Basso, 2018;
48 Mohsenipour et al. 2018; Shiru et al. 2018). Precipitation is seen to be more impacting than the
49 temperature on final crop yield (Kang et al. 2009)

50 During the 21st century, it is expected that higher temperatures influence the regime of
51 precipitation, and the ultimate availability of water (Mishra et al. 2014). Therefore, registering the
52 weather course during the crop season stimulates farmers to think critically regarding crop
53 management (Cuculeanu et al. 2002; Asfaw et al. 2018).

54 Furthermore, biotic and abiotic factors equally contribute to influence crop growth and
55 development, and final yield. Among abiotic factors, low water availability and heat exert an
56 influence on final crop yield (Mariani and Ferrante 2017), also depending on genotype adaptation
57 to specific adversities (Zandalinas et al. 2018).

58 In this complex situation, many studies addressed different methods of delineating site-
59 specific crop management (SSCM) zones within a field, by relating yield data with soil properties
60 and external factors. Da Silva (2006) produced classified zones based on spatio-temporal yield

61 maps. Lark and Stafford (1996) used an unsupervised fuzzy clustering method over multiple
62 years' yield data. Swindell (1997) analyzed the spatial variability by using several crop harvest
63 indices. Fraisse et al. (1999) combined topographical variables and ECa through unsupervised
64 cluster analysis. Maestrini and Basso (2018) produced zones based on spatio-temporal yield of
65 several crops with soil, crop reflectance and weather data during the growing seasons.

66 This research was aimed at identifying homogeneous areas for site-specific management,
67 using soil and crop yield data. The following steps were carried out: i) establishment of spatio-
68 temporal yield stability classes (YSCs) (Blackmore, 2000; Panneton and Brouillard 2002;
69 Blackmore et al. 2003), based on the yield data of a five-year crop rotation under uniform, rainfed
70 management; ii) assessment of the spatial variability of soil properties determined in samples
71 taken according to an ECa; iii) establishment of spatio-temporal YSCs based on soil properties;
72 iv) analysis of the weather effects on temporal yield variability in the five crop seasons.

73 **Materials and Methods**

74 *Study site description*

75 The experimental site was an 11.07-ha field of the Agrisfera Cooperative, located near Ravenna,
76 Italy, at N 44° 29' 26", E 12° 07' 44", 0 m above sea level (Figure S1). The area falls in the
77 Mediterranean North Environmental Zone (Metzger et al. 2005). The field was managed in a
78 uniform rotation system with winter cereals Durum Wheat in 2010 (DW 2010) and Bread Wheat
79 in 2012 and 2014 (BW 2012 and 2014), and spring dicots, Sunflower in 2011 (SF 2011) and
80 Coriander in 2013 (CO 2013). Cultivation was based on the good practices for each specific crop,
81 depending on the local conditions. The previous field history from 1976 to 2005 (Figure S2)
82 shows three separate parts of approximately equal length (200 m each in the north-south axis),

83 cultivated with fruit orchard and vineyard (upper, i.e. northern, part), and arable crops (lower, i.e.,
84 southern, part). In 2006, the three fields were merged into a single arable field (Figure S2).

85 *Crop data management*

86 Five years' georeferenced grain yield (GY) data was collected by a New Holland CR 9080 (CNH
87 Industrial N.V., Basildon, UK), equipped with an assisted guiding system based on real-time
88 kinematic GPS, yield mapping system consisting of a Pektron flow meter (Pektron Group Ltd,
89 Derby, UK), and Ag Leader moisture sensor (Ag Leader Technology, Ames, IA, USA).

90 Raw yield data were processed and filtered using Yield Editor software (Version 2.0.7;
91 USDA-ARS Cropping Systems and Water Quality Research, Columbia, Missouri). An average of
92 6170 GY data points per crop were retained in the experimental area. The sowing and harvesting
93 dates were: DW 2010, Oct. 30 (2009) – Jul. 10; SF 2011, Apr. 5 – Sep. 7; BW 2012, Oct. 14
94 (2011) – Jul. 1; CO 2013, Apr. 11 – Jul. 10; BW 2014, Nov. 9 (2013) – Jul. 7.

95 Thereafter, a geostatistical analysis was performed on GY data to i) examine the degree of
96 spatial dependence (SpD) in terms of semivariogram; ii) produce continuous grid points over the
97 entire field before mapping; iii) combine the interpolated data intersected on the regular grid.
98 Three main parameters describe semivariogram characteristics: i) nugget (C_0), the measurement
99 error at 0 distance ($h=0$); ii) sill ($C_0 + C$), the maximum y-axis value that increases with
100 increasing lag distance (h), and remains constant at a higher distance; iii) range (a), the maximum
101 distance at which data points are still correlated, i.e. the lag distance at sill value. The degree of
102 SpD as given by Cambardella et al. (1994) explains the nugget to sill ratio ($C_0/(C_0 + C)$): < 25 %,
103 indicates strong SpD; (ii) 25-75 %, moderate SpD; (iii) >75 %, weak SpD.

104 We employed the iterative cross-validation technique seeking the highest coefficient of
105 determination (R^2) and minimum mean absolute error (MAE) to choose the best fitting

106 semivariogram model among Circular, Spherical, Exponential, Gaussian, and Stable (Xiao et al.
 107 2016). Spatial variability maps were computed by simple kriging (SK) with 10 m cell size,
 108 resulting in 24 columns and 72 rows (Moral et al. 2010; Ali et al. 2019). SK was chosen as it
 109 provides, normally, maximum R² and minimal error parameters (Xiao et al. 2016).
 110 For each crop, standardized interpolated data with 1156 regular grid points were used for
 111 comparison among years, by replacing the actual GY (t/ha) with a relative GY where 100 %
 112 equals field average. This allowed data from different crops to be jointly analyzed. The Equation
 113 (1) was used to characterize the spatial variability maps over a single crop:

$$S_i = \left(\frac{y_i}{\bar{y}} \right) \times 100 \quad (1)$$

114 Where, S_i =standardized yield (%) over 100 % field average at point (i), y_i =interpolated yield at
 115 point i (t/ha), and \bar{y} =mean interpolated yield over the entire field (t/ha).

116 For multiple crops, a spatial variability map was produced by simply calculating the mean
 117 standardized yield, laid over the five years according to Equation (2).

$$\bar{S}_i = \frac{\sum_{t=1}^n S i_t}{n} \quad (2)$$

118 Where, \bar{S}_i = mean interpolated yield over 100% field average over n years, $S i_t$ = interpolated
 119 standardized yield (%) at point (i).

120 For multiple crops, a temporal variability map was produced to assess the stability of
 121 standardized GY over the five crop years. The coefficient of variation (CV) of each grid point
 122 over the five years was calculated based on Equation (3) (Blackmore 2000).

$$CVS_i = \frac{\left(\frac{n \sum_{t=1}^{t=n} Si_t^2 - (\sum_{t=1}^{t=n} Si_t)^2}{n(n-1)} \right)^{0.5}}{\bar{S}_i} \times 100 \quad (3)$$

123 Where, CVS_i = coefficient of variation of standardized yield at point (i) over n years; Si_t =
 124 standardized yield (%), at point (i); \bar{S}_i = mean standardized yield at point (i).

125 To define the threshold levels in spatial maps, four classes were established in both
 126 single- and multiple-year yield, based on the natural break classification method (Toshiro 2002):
 127 very low (VL), medium-low (ML), medium-high (MH) and very high (VH). Each class showed
 128 maximum difference with other classes, while the within-class variability was minimized.
 129 Likewise, four classes were defined for temporal variability map across CV ranges between 2%
 130 and 73%.

131 *Spatio-temporal yield variability analyses*

132 Three yield stability classes (YSCs) were produced by combining the spatial and temporal maps
 133 over multiple crops (Table S1): high yielding and stable (HYS) ($\bar{S}_i > 100$, $CV_{Si} < 30$), low yielding
 134 and stable (LYS) ($\bar{S}_i < 100$, $CV_{Si} < 30$), and unstable ($CV_{Si} > 30$). Each class was derived from
 135 spatio-temporal yield data of multiple crops (equations 2 and 3), by applying the combinational
 136 logic statement (Blackmore 2000).

137 *Soil sampling*

138 The positions for soil samples were based on the procedure developed by Corwin and Lesch
 139 (2005). First, a soil ECa survey was conducted using an on-the-go sensor CMD Tiny
 140 Electromagnetic Conductivity Meter (GF Instruments, s.r.o., Brno, Czech Republic) along a 8 m

141 transect over the field area (Figure 1), removing outliers from raw ECa values, which left a total
142 of 2651 data points (Figure 1). Then, the ECa-directed Response Surface Sampling Design
143 module in ESAP-95 version 2.01 (Lesch et al. 2000) was used to delineate the scheme for 20 soil
144 samples to be taken (Figure 1). Soil cores were taken at the 0-30 and 30-60 cm soil depth. The
145 samples were air-dried at 40 °C and sieved at 2 mm diameter.

146 **Figure 1**

147 *Soil physico-chemical analysis, and spatial variability*

148 The twenty soil samples (200-250 g) at 0-30 and 30-60 cm depth were subjected to determination
149 of the following properties: particle size distribution (sand, silt, and clay content), pH, total
150 carbonates (CaCO₃), total organic carbon (C), total nitrogen (N), available P (P Olsen),
151 exchangeable cations (K, Ca, Mg, Na), cation exchange capacity (CEC), and electrical
152 conductivity of a soil extract with a 1:2.5 (w/w) soil-to-water ratio (EC_{1:2.5}). The particle size
153 distribution was determined by the pipette method (Gee and Bauder 1986). Soil pH was
154 measured at 1:2.5 (w/w) soil-to-water ratio. The total carbonate content (CaCO₃) was
155 volumetrically determined (Loeppert and Suarez 1996). Total organic C and total N
156 concentrations were determined by a CHN elemental analyzer (EA 1110 Thermo Fisher,
157 Waltham, MA, USA). The available P was extracted according to Olsen et al. (1954) and was
158 measured by inductively coupled plasma optical emission spectrometer (ICP-OES, Ametek,
159 Spectro Arcos, Kleve, Germany). The cation exchange capacity (CEC) and the exchangeable
160 cations were determined according to the method proposed by Orsini and Rémy (1976) and
161 modified by Ciesielski and Sterckeman (1997), and the amounts of Co and exchangeable cations
162 were measured by ICP-OES. Soil electrical conductivity (EC) was determined on 1:2.5 (w/w)

163 soil-to-water ratio aqueous suspension and then reported as EC on the saturation extract (EC_e).

164 For soil spatial variability, we produced the maps of soil properties in the 0-60 cm soil
165 depth (average of the 0-30 and 30-60 cm layers), by using ordinary kriging with 10 m grid
166 resolution. Kriging outperforms normally the inverse-distance weighted method in spatial soil
167 mapping (Kravchenko and Bullock 1999; Reza et al. 2010; Daniel et al. 2017).

168 *Relationship between spatio-temporal YSCs and soil data*

169 Thirty m wide buffers around the 20 positions determined by the ESAP software were created for
170 statistical correlations between spatio-temporal yield and soil properties. The values of
171 interpolated GY and selected soil properties falling within the range of each buffer were averaged
172 for Pearson's correlations (r) involving the 20 data points. Thereafter, it was evaluated if multi-
173 years spatio-temporal yield could effectively be described by the differences in soil properties
174 within YSCs. To this aim, interpolated soil data were associated with the YSCs, then the
175 statistical differences of soil properties among YSCs were assessed in the same way as described
176 by Li et al. (2008) and Scudiero et al. (2018).

177 The weather information during the five growing seasons (Hydro-meteorological Service
178 of the Emilia-Romagna region) was used to interpret temporal yield variability. The wet and dry
179 periods from initial to maturity stages of the surveyed crops were represented by the balance
180 between precipitation (P) and crop evapotranspiration (ET_c), this latter determined according to
181 Allen et al. (1998). In the supplementary materials, total precipitation and the average
182 temperature were computed monthly according to Bagnouls and Gausson (1953), to indicate wet
183 and dry periods during the five crop seasons.

184 Map production and geostatistical data analysis were carried out with the ArcGIS
185 software (Version 10.3, ESRI, Redlands, CA, USA) under the reference system WGS 84/UTM

186 zone 32 °N. Statistical analyses were performed with the Statistica 10 software (StatSoft Corp.,
187 Tulsa, OK, USA).

188 *Statistical analysis*

189 Crop yields and soil data were subjected to descriptive statistics. Pearson's correlation (r) was
190 used to evaluate the relationships of soil properties and spatio-temporal relative yield in single
191 and multiple crops. One way analysis of variance (ANOVA) was run to assess the differences in
192 soil and yield traits among the three YSCs. The least significant difference (LSD) at $P \leq 0.05$ was
193 used to indicate significantly different levels.

194 **Results**

195 *Descriptive statistics of crop yields*

196 Table 1a summarizes the characteristics (mean, minimum, maximum, SD, kurtosis, and
197 skewness) of standardized GY data in the five years. Crop yield varied greatly across the field.
198 The widest min.-max. range (183) was found in BW 2012, whereas the tightest range (143) was
199 shown in DW 2010. Standardized GY variability was generally high, as indicated by SD ranging
200 from 29 % for DW 2010 to 38 % (SF 2011 and CO 2013).

201 **Table 1**

202 *Geostatistics of crop yields*

203 The spatial patterns of crop yields were evaluated in terms of semivariograms and the respective
204 model fittings (Table 1b). DW 2014 showed a zero nugget effect, followed by SF 2011 and DW
205 2010 with very low nugget values. All crops exhibited a quite similar total variance (sill variance

206 (C_0+C) ranging from 0.92 to 1.17), whereas the range (a) varied noticeably between 38 and 121
207 m. A high/low range indicates high/low continuity, respectively, within the dataset. Based on the
208 degree of SpD (Cambardella et al. 1994), crop data showed a ‘strong’ continuity in their SpD in
209 all cases except BW 2012. The results of semivariogram model fitting (R^2 and MAE) confirmed
210 the good performance of the stable and exponential variogram, depending on years, over the
211 empirical data (Xiao et al. 2016; Bhunia et al. 2018).

212 *Yield maps and spatio-temporal variability*

213 Spatial maps of standardized GY were traced depicting the four yield classes in the five years
214 (Figure 2a, 2b, 2c, 2d, 2e). Spatial variability map over multiple crops (Figure 2f) exhibited
215 higher minimum (27) and lower maximum (148) relative GY, resulting in a narrower range (121)
216 compared to single crops. Nevertheless, spatial variability maps in single vs. multiple crops were
217 quite consistent, i.e. areas at high or low GY tended to repeat in the same position. The upper
218 field portion (4.12 ha) always showed low and below-average yield, whereas the middle and
219 lower field portions (6.95 ha) always featured above average and high yield.

220 In the spatial map over multiple crops (Figure 2f), an area of 1.30 ha (11.7 % of the field
221 surface) lay in the VL area, 3.86 ha (34.8 %) in the ML area, 3.10 ha (28.1 %) in the MH area,
222 and 2.81 ha (25.4 %) in the VH area. In the temporal map (Figure 2g), high stability (CV up to 30
223 %) covered an area of 8.27 ha (76 %) across the field, while the unstable area (CV = 30-73 %)
224 covered the remaining 2.8 ha (24 %) (Figure 2g). Lastly, the three yield stability classes (HYS,
225 LYS and unstable) depicted the features of spatio-temporal yield over multiple years (Figure 2h).

226 **Figure 2**

227 *Yield data distribution within spatio-temporal yield stability classes*

228 Data distribution within the classes of spatio-temporal maps is reported in Table 2.

229 **Table 2**

230 For spatial variability classes, in DW 2010 GY data distribution was more skewed
231 towards high yielding classes, meaning that more grid points belonged to the MH and VH
232 classes. The same occurred, to a lesser extent, in all the other years except SF 2011. Also the
233 multiple crops combined showed a slight prevalence of the MH and VH classes. The differences
234 between the relative GY values in single and multiple crop maps indicate that class limits and
235 width are not the same between single and multiple datasets.

236 For temporal variability classes, 334 data points out of 1156 (28.9 % or 3.3 ha) were in
237 the highly stable class (2-14 % CV), 310 points (26.8 % or 3.1 ha) were in the medium stable
238 class (14-22 % CV), 235 points (20.3 % or 2.4 ha) in the lowly stable class (22-30 % CV), and
239 finally 277 data points (24 % or 2.8 ha) were in the unstable class (30-73 % CV).

240 For yield stability classes, 527 data points (46 % or 5.3 ha) were found in the HYS class,
241 352 (30 % or 3.5 ha) in the LYS class, and 277 points (24 % or 2.8 ha) in the unstable class.

242 *Spatial variability of soil properties*

243 The descriptive analysis of soil physico-chemical properties in the average of the two depths (0-
244 60 cm) is reported in the supplementary material (Table S2). The soil was loamy, moderately
245 alkaline, rich in carbonates, poor of organic carbon (< 10 g/kg), and with a low C:N ratio (< 10).

246 Available P and exchangeable K were also quite low (< 10 mg/kg and < 0.3 cmol₊/kg,
247 respectively). Exchangeable Ca was relatively high (almost 80% of the CEC). EC_e denoted a
248 negligible salinity across the field. Lastly, the three particle size classes (sand, silt, and clay) were

249 more heterogeneous (higher SD in proportion to mean data) than the rest of the soil properties.

250 *Spatial soil maps*

251 Spatial maps of soil properties interpolated with ordinary kriging are reported in Figures 3a, 3b,
252 3c, 3d. Sand exhibited low values in the lower (south) field portion, in exchange for high values
253 in the upper (north) portion (Figure 3a). Furthermore, sand variability depicted inverse spatial
254 trends to silt, clay, and CEC (figure 3b, 3c, and 3d, respectively). Silt, clay, and CEC values
255 exhibited similar trends, showing high values in the south and low values in the north side of the
256 field. Therefore, silt, clay, and CEC displayed a pattern similar to spatio-temporal yield (Figure
257 2a, 2b, 2c, 2d, 2e, 2f), whereas sand displayed a pattern in the opposite direction.

258 **Figure 3**

259 *Quality control of spatio-temporal YSCs*

260 Significant correlations were evidenced between soil properties and the spatio-temporal yield
261 data (Table 3). The sand content showed negative correlations with silt and clay, CEC, and
262 spatio-temporal yield data (except for SF 2011). The silt and clay contents showed a positive
263 correlation with each other and CEC, and they had positive correlations with crop yields, except
264 for SF 2011. The CEC was positively correlated with single and multiple crop yields, except for
265 SF 2011 and BW 2014. Additionally, high correlations were evidenced between spatio-temporal
266 yields over single and multiple years: DW 2010, CO 2013 and BW 2014 yields showed the
267 strongest relationship with multiple crop yield ($r = 0.97^{**}$ all) followed by BW 2012 ($r = 0.78^{**}$)
268 and SF 2011 ($r = 0.73^{**}$).

269 **Table 3**

270 Classification of stable soil physico-chemical properties within the three spatio-temporal
271 yields classes depicted statistical differences of soil properties (Table 4).

272 **Table 4**

273 The lowest mean value of sand (47.9 %) was associated with the HYS class, resulting in
274 maximum yield over multiple crops (YSCs). Higher sand content was found in LYS (56.8 %) and
275 unstable class (57.4 %), which featured a similar but statistically different yield (80 % and 83 %,
276 respectively). Conversely, silt, clay, and CEC had higher values in the HYS class, compared to
277 LYS and unstable class.

278 *Ambient conditions during the five cropping seasons*

279 The balance of ambient moisture in the five crop seasons is reported in Table 5.

280 **Table 5**

281 During DW 2010, the crop growing period from tillering to heading (initial to mid-
282 season) received a surplus of 206 mm as P-ETc difference and was considered a wet period,
283 whereas late-season (ripening stage) staged a 68 mm deficit. BW 2012 and 2014 also received
284 enough precipitation from tillering to stem elongation (28 and 212 mm surplus in the two
285 respective years), whereas a dry period occurred from heading to ripening in both years. It
286 resulted in a respective deficit of 298 and 249 mm. Compared to winter cereals, spring dicots SF
287 2011 and CO 2013 suffered an increasing water deficit across growth stages. At ripening, a
288 cumulated deficit of 433 and 219 mm was attained in the two respective crops.

289 The representation of temperature and precipitation during the five growth seasons
290 according to Bagnouls and Gaussen (1953) exhibits a similar picture (Figures S3 and S4).

291 The stronger drought experienced by the spring dicots vs. autumn cereals reflected in a

292 stronger variation of yield data (Table 1a). Standard deviation was 38% of the mean GY in both
293 SF 2011 and CO 2013, whereas it was 31%, averagely, in DW 2010, BW 2012, and BW 2014.

294 **Discussion**

295 The geostatistical analysis of the five crop yields featured quite similar parameters, despite using
296 two different semivariogram models (Table 1b). BW 2012 represents the only partial exception,
297 having a far more extended range than the rest of crops, associated with less spatial dependence.
298 However, negligible nugget or barely exceeding 25% of the total sill, as in the case of BW 2012,
299 indicates high spatial continuity between data points. This is a circumstance strengthening the
300 value of the spatial variability maps obtained through kriging interpolation.

301 In these maps, the differences among the four yield classes that are evidenced in
302 individual crops (Figure 2a, 2b, 2c, 2d, 2e) are softened in the multiple crops (Figure 2f).
303 Therefore, the multiple crops play a buffering role vs. single crops, meaning that operating with
304 the former data is as a sounder basis for crop management decisions to be taken.

305 The three YSCs proposed by Blackmore (2000) set themselves one step beyond spatial
306 variability maps, as they combine spatial and temporal variability into a single indicator. The
307 unstable class is that deserving most attention, as it is an area with a potential for improving crop
308 yields. In our case, this area covers almost one-fourth of the total field surface (Table 2).
309 Additionally, the unstable class has a patchy distribution across the field, whereas the two stable
310 classes, HYS and LYS, have a more consistent shape and distribution (Figure 2h). Lastly, the
311 unstable and LYS classes denote an increase in sand content and a parallel decrease in silt and
312 clay content, and CEC (Table 4). Hence it is sensed that sharper values in soil properties lead to
313 fluctuation and depression of final yield, whereas more balanced values conduct to consistently
314 higher crop yields (Table 4).

315 The ECa survey directs soil sampling towards field areas more prone to indicate
316 variations in soil properties, in contrast to regular grid sampling (Corwin et al. 2003). In our case,
317 it is perceived that a higher density of sampling points was placed in the upper field portion
318 (Figure 1), where the multiple-year data indicate systematic yield loss vs. the rest of the field
319 (Figure 2f). Therefore, the ECa survey was shown able to predict soil constraints for plant
320 growth. However, sampling and analysis were needed to detect the underlying causes, as premise
321 for taking decisions to deal with constraints.

322 Overall, the mean values of spatial soil properties across the three YSCs show
323 considerable differences and align with the multiple year yield map (Figure 2h). The considerable
324 variations of crop yield across the whole field were quite well correlated with the variations of
325 soil properties (Table 3); SF 2011 was a partial exception, but CO 2013, the other spring sown
326 crop, behaved as the three winter wheat crops (DW 2010, BW 2012 and 2014). The general good
327 correlations between crop yield and soil properties are in accordance with the findings of Corwin
328 et al. (2003). It is evinced from their work and ours how much it is important to understand the
329 causes of yield variation through soil factors that are expected to contribute to crop productivity.

330 Temporal stability is seen as a relevant property in multiple crops across multiple years.
331 The unstable is made a class of its own in the YSC system (Blackmore 2000), to account for
332 fluctuations which are due to crop type, weather, and undefined factors interacting with them
333 (Figure 2g). We believe that this field portion that gave a slightly higher yield (83 %) than the
334 LYS class (80 %) (Table 4), averagely, may require separate cultivation practices, depending on
335 in-season weather conditions during the specific crop season. The unstable class was
336 characterized by similar values of soil properties as the LYS class (Table 4), indicating that these
337 levels of soil properties are prone to reduce crop yield. Therefore, the unstabilizing effect
338 associated with these properties is responsible for reducing crop yield in areas that could

339 potentially give a high yield. Separate cultivation practices aimed at reducing the negative effects
340 of soil constraints in such areas should provide a gain in crop yields.

341 The weather pattern during the five growing seasons (Table 5, Figures S3 and S4)
342 provides some clues to understanding why some field areas gave higher yield than others, and
343 why some other areas behaved differently over time. The five rainfed crops were exposed to
344 irregular weather, and the erratic pattern of water availability is acknowledged as one of the
345 main determinants of crop yield and its variability (Kang et al. 2009; Kukal and Irmak 2018).
346 Yield losses consequential to drought are commonly reported in the literature for wheat (Karim et
347 al. 2000; Mirzaei et al. 2011), as well as sunflower (Nel et al. 2001) and coriander (Unlukara et
348 al. 2016). However, the effect of ambient moisture that we noticed on yield spatial variability
349 cannot be ascertained in small plot experiments and is relatively novel in the literature.

350 Additionally, our study suggests that, under favorable weather in a specific year, unstable
351 field zones could be managed as high yielding ones, i.e. supplying a non-limiting amount of
352 inputs to harness the favourable conditions conducive to high yield. Conversely, under
353 unfavourable weather, savings could be made to avoid inefficient use of crop inputs.

354 In other words, while the stable yield zones of a field should be managed by strategic
355 planning, the unstable zones shall better be managed by tactical approach, e.g., based on crop
356 growth status and soil moisture conditions, which are a key factors for final yield in many
357 agricultural areas around the world. Therefore, it is of paramount importance for the farmers to
358 monitor their crop and receive timely weather information for alternative decisions to be
359 taken (Basso et al. 2011).

360 One last point concerns the management of fields that become larger and larger by
361 merging previously separated fields, under the urge to increase the efficiency in agricultural
362 practice. In the surveyed case, three consecutive fields, each approximately 200 m long in the

363 north-south axis, were combined into a single field approximately 600 m long in 2006 (Figure
364 S2). The result is that the northern third, which was planted with deep rooted tree crops, is
365 scarcely productive, once converted to annual crops: in the multiple year average, a relative
366 yield of 76 % can be calculated for the upper third, compared to 104 % and 124 % for the
367 central and lower third.

368 There is no univocal answer to the dilemma whether to pursue the enlargement of crop
369 fields, to the expenses of crop advocacy, or save advocacy, to the expenses of efficiency. In
370 the former case, the assessment of the causes for low productivity in a field portion provides
371 the grounds for applying the most suited crop husbandry in a site specific manner.

372 **Conclusions**

373 Site-specific zones are the basis in precision agriculture by understanding where variable crop
374 inputs are needed, based on the spatial and temporal variability of field characteristics. This paper
375 defines the concept of classified zones by delineating the potential yield stability classes based on
376 spatio-temporal maps over a five-year series of yields obtained with different crops.

377 It is evinced that the field areas featuring unstable yield across years should be managed
378 by considering the in-season weather information to predict whether the unstable field part will
379 behave as high yielding or low yielding in a specific year. This will provide farmers with
380 valuable support to decide the appropriate level of crop intensity, e.g., fertilizers or water supply,
381 in a site-specific way.

382 Our work concludes that multi-year yield stability classes are a more practical and cost-
383 effective approach than uniform management, as they set the premise for variable inputs to
384 optimize crop productivity. Based on yield stability classes, strategic and tactical decisions must
385 be taken in different field areas, depending on the spatial and temporal profile of productivity

386 owned by these areas.

387 However, despite encouraging results based on a five-year data from a mixed cropping
388 system, it is quite likely that the surrounding conditions play a relevant role in each specific case.
389 This makes the approach described in this work reproducible, not simply generally valid, in
390 different crop conditions.

391 Acknowledgements, The Agrisfera Cooperative is kindly acknowledged for the support during the field
392 experiment.

393 In accordance with Taylor & Francis policy and my ethical obligation as a researcher, I am reporting that
394 this research did not receive any specific grant from funding agencies in the public, commercial, or not-
395 for-profit sectors.

396 Table 1. Descriptive statistics of (1a) and semivariogram analysis (1b) of relative yields (average
397 = 100) over the five years

398

1a						
Crop year	Min.	Max.	SD	Kurtosis	Skewness	K-S
DW 2010	13	156	29	-0.1	-0.6	**
SF 2011	12	190	38	-0.7	0.2	**
BW 2012	14	197	32	0.1	-0.1	**
CO 2013	19	181	38	-1.0	-0.3	**
BW 2014	21	178	33	-0.9	-0.2	**

1b						
Crop year	Model	C ₀	C ₀ +C	a (m)	C ₀ /(C ₀ +C) (%)	SpD
DW 2010	Stable	0.03	1.05	64	2.5	S
SF 2011	Exponential	0.01	1.01	38	1.0	S
BW 2012	Exponential	0.31	1.17	121	26.5	M
CO 2013	Stable	0.13	0.96	66	13.5	S
BW 2014	Stable	0.00	0.92	51	0.0	S

399 DW, durum wheat; SF, sunflower; BW, bread wheat; CO, coriander. Min., minimum; Max., maximum; SD, standard
400 deviation; K-S, Kolmogorov-Smirnov test for normal distribution; **, significant at $P \leq 0.01$. C₀, nugget; C, partial
401 sill; C₀+C, sill; a, range; C₀/(C₀ + C), nugget to sill ratio; SpD, spatial dependence; S, strong; M, moderate; MAE,
402 mean absolute error.

403

404 Table 2. Relative yield (average = 100) and CV data in spatio-temporal and yield stability
 405 classes.

Variables	Relative yield or CV	Yield or CV classes	Grid points	Area (%)
DW 2010	13-61	VL	134	11.6
	62-95	ML	317	27.4
	96-116	MH	301	26
	117-156	VY	404	35
SF 2011	12-61	VL	161	13.9
	62-95	ML	439	38
	96-134	MH	293	25.3
	135-190	VY	263	22.8
BW 2012	14-67	VL	176	15.2
	68-99	ML	374	32.4
	100-138	MH	506	43.8
	139-197	VY	100	8.6
CO 2013	19-60	VL	213	18.4
	61-99	ML	323	27.9
	100-131	MH	335	29
	132-181	VY	285	24.7
BW 2014	21-64	VL	176	15.2
	65-99	ML	387	33.5
	100-127	MH	304	26.3
	128-178	VY	289	25
Spatial map	27-66	VL	135	11.7
	67-99	ML	402	34.8
	100-120	MH	325	28.1
	121-148	VY	294	25.4
Temporal map (CV data)	2-14	Highly stable	334	28.9
	14-22	Medium stable	310	26.8
	22-30	Lowly stable	235	20.3
	30-73	Unstable	277	24
Yield stability classes		HYS	527	46
		LYS	352	30
		Unstable	277	24

406 DW, durum wheat; SF, sunflower; BW, bread wheat; CO, coriander; CV., coefficient of variation; VL, very low;

407 ML, medium-low; MH, medium-high; VH, very high; HYS, high yielding and stable; LYS, low yielding and stable.

408

409 Table 3. Pearson correlations (r) between relevant soil properties and spatio-temporal relative
 410 yields in single and multiple crops.

Traits	Sand	Silt	Clay	CEC	DW 2010	SF 2011	BW 2012	CO 2013	BW 2014
Silt	-1.00**								
Clay	-0.96**	0.93**							
CEC	-0.91**	0.90**	0.91**						
DW 2010	-0.58**	0.59**	0.50*	0.52*					
SF 2011	-0.40	0.40	0.36	0.35	0.61**				
BW 2012	-0.63**	0.63**	0.57**	0.56**	0.72**	0.36			
CO 2013	-0.54*	0.57**	0.41	0.46*	0.96**	0.61**	0.72**		
BW 2014	-0.47*	0.49*	0.39	0.35	0.94**	0.68**	0.69**	0.94**	
Multiple crops	-0.58**	0.60**	0.49*	0.50*	0.97**	0.73**	0.78**	0.97**	0.97**

411 * and ** indicate r values significant at $P \leq 0.05$ and $P \leq 0.01$, respectively (n = 20).

412

413 Table 4. Statistical differences in soil properties and spatio-temporal relative yield among the
 414 three YSCs.

Variables	YSCs	Data points	Mean	Min	Max	SD
% sand	HYS	527	47.9 b	34.0	73.4	10.6
	LYS	352	56.8 a	33.6	75.6	10.6
	Unstable	277	57.4 a	37.1	73.5	9.4
% silt	HYS	527	40.2 a	20.0	50.6	8.2
	LYS	352	32.8 b	17.5	52.4	8.5
	Unstable	277	32.3 b	19.6	48.4	7.4
% clay	HYS	527	11.9 a	6.1	16.9	2.5
	LYS	352	10.4 b	6.2	15.0	2.3
	Unstable	277	10.4 b	6.3	14.8	2.1
CEC (cmol ₊ /kg)	HYS	527	10.8 a	7.6	13.4	1.1
	LYS	352	10.0 b	6.7	13.4	1.5
	Unstable	277	10.0 b	6.6	12.7	1.2
Rel. yield (multiple crops)	HYS	527	122 a	100	148	11.5
	LYS	352	80 c	27	100	15.4
	Unstable	277	83 b	29	136	26.4

415 YSCs, yield stability classes; HYS, high yielding and stable; LYS, low yielding and stable; SD, standard deviation.

416 Different letters indicate significantly different mean values (LSD test at $P \leq 0.05$).

417

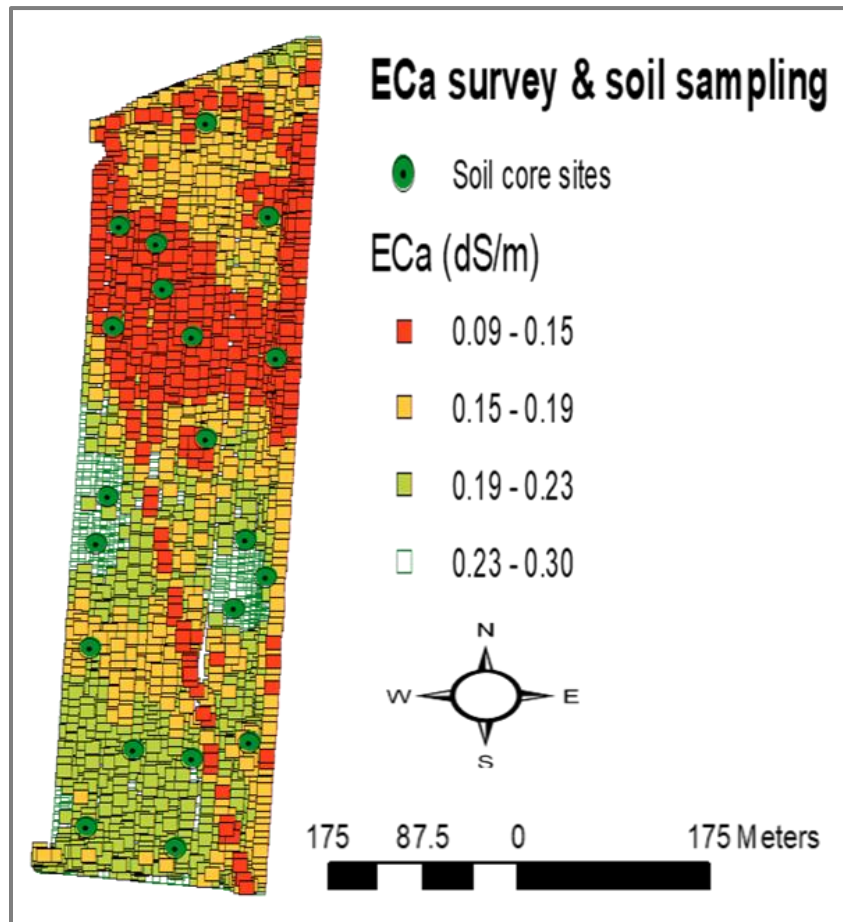
418 Table 5. Weather conditions during the five crop seasons.

Crop and year	Growth period	Time (days)	P (mm)	ETc (mm)	P-ETc (mm)	Moisture condition
DW 2010	Ini	24	17	9	8	Wet
	Dev	65	180	26	154	Wet
	Mid	100	265	221	44	Wet
	Late	64	127	195	-68	Dry
SF 2011	Ini	35	31	41	-10	Dry
	Dev	40	29	142	-113	Dry
	Mid	50	67	278	-211	Dry
	Late	30	2	101	-99	Dry
BW 2012	Ini	19	35	10	25	Wet
	Dev	68	43	40	3	Wet
	Mid	116	77	245	-168	Dry
	Late	58	50	180	-130	Dry
CO 2013	Ini	20	22	23	-1	Dry
	Dev	30	36	83	-47	Dry
	Mid	25	5	141	-136	Dry
	Late	15	17	52	-35	Dry
BW 2014	Ini	44	96	13	83	Wet
	Dev	74	188	59	129	Wet
	Mid	79	86	273	-187	Dry
	Late	43	77	139	-62	Dry

419 DW, durum wheat; SF, sunflower; BW, bread wheat; CO, coriander; CV., coefficient of variation; P, precipitation;

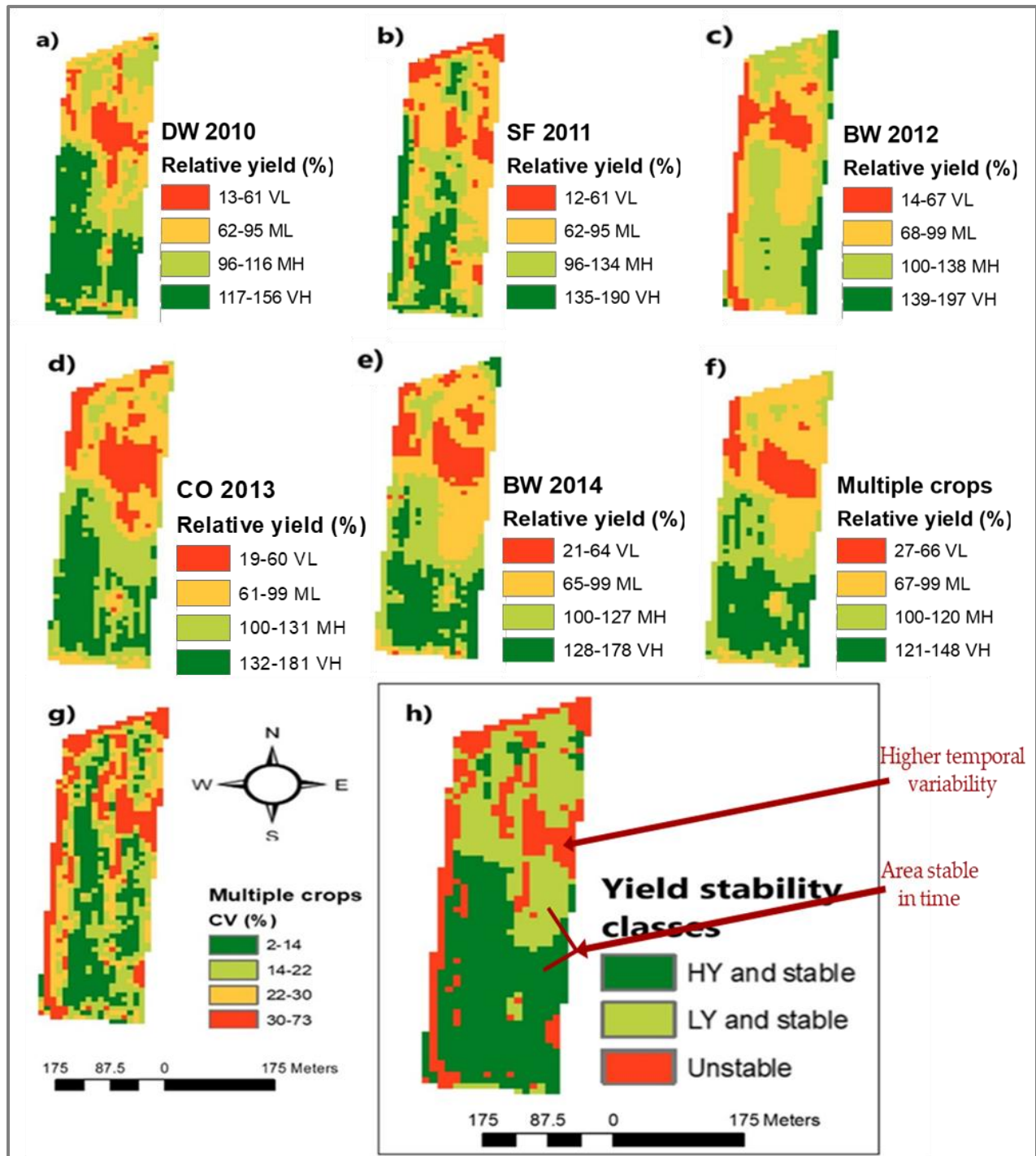
420 ETc, crop evapotranspiration; Ini, Initial; Dev, crop development; Mid, mid-season; Late, late-season.

421



422

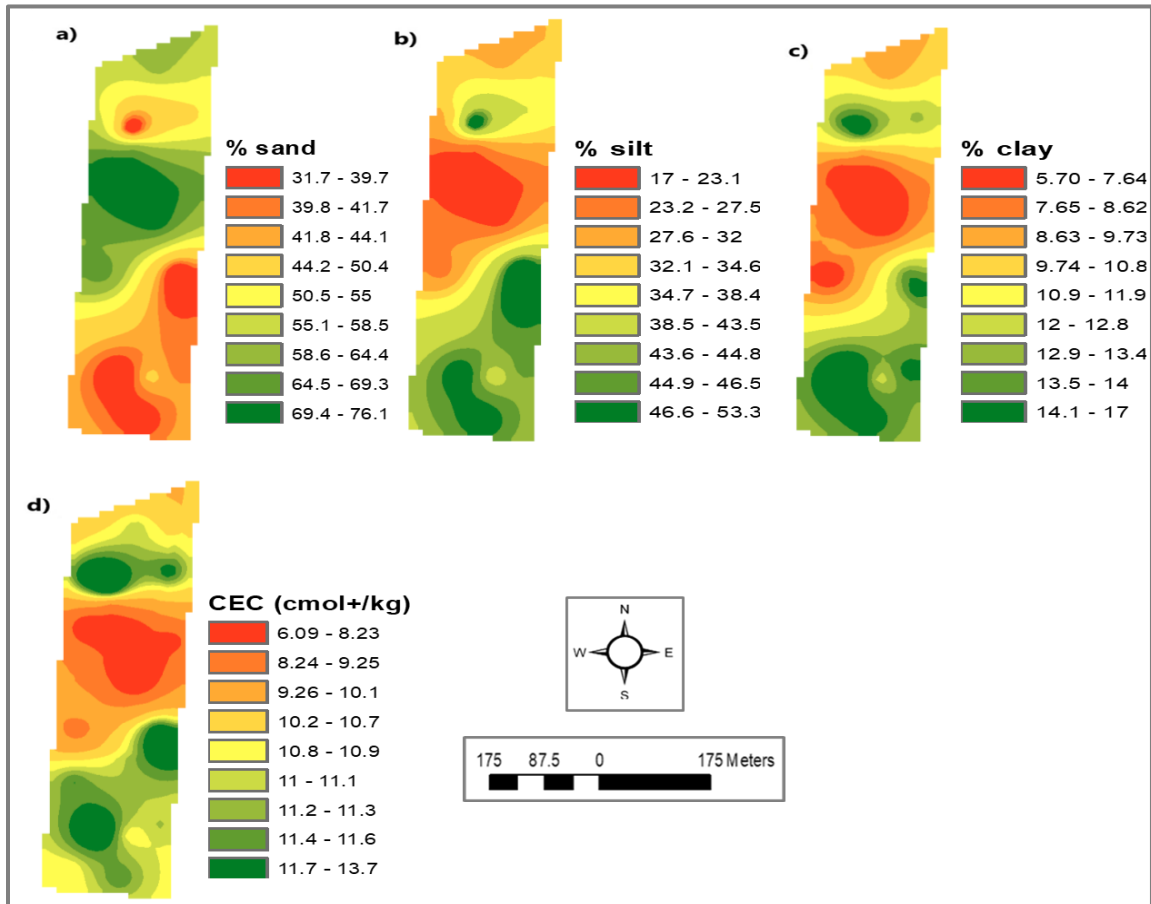
423 Figure 1. Map of the ECa distribution; green circles indicate the 20 soil sampling positions.



424

425 Figure 2. Consolidated spatio-temporal yield maps: VL, very low; ML, medium-low; MH,
 426 medium-high; VH, very high; 2a, spatial variability map of DW 2010; 2b, spatial variability map
 427 of SF 2011; 2c, spatial variability map of BW 2012; 2d, spatial variability map of CO 2013; 2e,
 428 spatial variability map of BW 2014; 2f, spatial variability map over 5 years' multiple crops; 2g,

429 temporal variability map over 5 years' multiple crops; 2h, yield stability classes over spatio-
430 temporal variability over 5 years' multiple crops.



431

432 Figure 3a, 3b, 3c, 3d. Spatial variability maps of soil properties.

433

434 References

435 Ali A, Martelli R, Lupia F, Barbanti L. 2019. Assessing multiple years' spatial variability of crop
436 yields using satellite vegetation indices. Remote Sens. 11(20):2384.

437 <https://doi.org/10.3390/rs11202384>

438 Allen RG, Pereira LS, Raes D, Smith M. 1998. Crop evapotranspiration-Guidelines for
439 computing crop water requirements-FAO Irrigation and drainage. FAO, Rome. Report

440 No.: 56; D05109.

441 Asfaw A, Simane B, Hassen A, Bantider A. 2018. Variability and time series trend analysis of
442 rainfall and temperature in northcentral Ethiopia: A case study in Woleka sub-basin.
443 *Weather Clim Extremes*. 19:29-41.

444 Bagnouls F, Gaussen H. 1953. Saison sèche et indice xérothermique. *Bull Soc His Nat Toulouse*.
445 88:193-239.

446 Basso B, Dobrowolski J, McKay C. 2017. From the dust bowl to drones to big data: the next
447 revolution in agriculture. *Georget J Int Aff*. 18(3):158–165.

448 Basso B, Ritchie JT, Cammarano D, Sartori L. 2011. A strategic and tactical management
449 approach to select optimal N fertilizer rates for wheat in a spatially variable field. *Eur J*
450 *Agro*. 35(4):215-222.

451 Bhunia GS, Shit PK, Maiti R. 2018. Comparison of GIS-based interpolation methods for spatial
452 distribution of soil organic carbon (SOC). *J Saudi Soc Agric Sci*. 17(2):114-126.

453 Blackmore S. 2000. The interpretation of trends from multiple yield maps. *Comput Electron*
454 *Agric*. 26(1):37-51.

455 Blackmore S, Godwin RJ, Fountas S. 2003. The analysis of spatial and temporal trends in yield
456 map data over six years. *Biosyst Eng*. 84(4):455-466.

457 Bullock DS, Bullock DG. 2000. Economic optimality of input application rates in precision
458 farming. *Precis Agric*. 2(1):71-101.

459 Cambardella CA, Moorman TB, Parkin TB, Karlen DL, Novak JM, Turco RF, Konopka AE.
460 1994. Field-scale variability of soil properties in central Iowa soils. *Soil Sci Soc Am J*.
461 58(5):1501-1511.

462 Ciesielski H, Sterckeman T. 1997. Determination of cation exchange capacity and exchangeable
463 cations in soils by means of cobalt hexamine trichloride. Effects of experimental
464 conditions. *Agronomie*. 17:1–7.

465 Corwin DL, Lesch SM. 2003. Application of soil electrical conductivity to precision agriculture.
466 *Agron J*. 95(3): 455-471.

467 Corwin DL, Lesch SM. 2005. Characterizing soil spatial variability with apparent soil electrical
468 conductivity: I. Survey protocols. *Comput Electron Agric*. 46(1-3):103-133.

469 Corwin DL, Lesch SM, Shouse PJ, Sophe R, Ayars JE. 2003. Identifying soil properties that
470 influence cotton yield using soil sampling directed by apparent soil electrical
471 conductivity. *Agron J*. 95(2):352-364.

472 Cuculeanu V, Tuinea P, Bălteanu D. 2002. Climate change impacts in Romania: Vulnerability
473 and adaptation options. *GeoJournal*, 57(3):203-209.

474 Da Silva JM. 2006. Analysis of the spatial and temporal variability of irrigated maize yield.
475 *Biosyst Eng.* 94(3):337-349.

476 Daniel S, Gabiri G, Kirimi F, Glasner B, Näschen K, Leemhuis C, Steinbach S, Mtei K. 2017.
477 Spatial distribution of soil hydrological properties in the Kilombero floodplain, Tanzania.
478 *Hydrology.* 4:57.

479 Fraisse CW, Sudduth KA, Kitchen NR, Fridgen J. 1999. Use of unsupervised clustering
480 algorithms for delineating within-field management zones. St. Joseph: American Society
481 of Agricultural Engineers.

482 Gee GW, Bauder JW, Klute A. 1986. Methods of soil analysis, part 1, physical and mineralogical
483 methods. *Soil Sci Soc of Am, Am Soc Agro.*

484 Iizumi T, Ramankutty N. 2015. How do weather and climate influence cropping area and
485 intensity? *Glob Food Sec.* 4:46-50.

486 Kang Y, Khan S, Ma X. 2009. Climate change impacts on crop yield, crop water productivity and
487 food security—A review. *Prog Nat Sci.* 19(12):1665-1674.

488 Karim MA, Hamid A, Rahman S. 2000. Grain growth and yield performance of wheat under
489 subtropical conditions: II. Effect of water stress at reproductive stage. *Cereal Res*
490 *Commun.* 28(1-2):101-107.

491 Kravchenko A, Bullock DG. 1999. A comparative study of interpolation methods for mapping
492 soil properties. *Agron J.* 91(3):393-400.

493 Kukal MS, Irmak S. 2018. Climate-driven crop yield and yield variability and climate change
494 impacts on the US great plains agricultural production. *Sci Rep.* 8(1): 3450.

495 Lark RM, Stafford JV. 1996. Classification as a first step in the interpretation of temporal and
496 spatial variability of crop yield. *Asp Appl Biol.* 46:139–142.

497 Lesch SM, Rhoades JD, Corwin DL. 2000. ESAP-95 Version 2.01 R: User manual and tutorial
498 guide: Research Rpt. 146. Riverside (USA): USDA-ARS Salinity Laboratory.

499 Li Y, Shi Z, Wu CF, Li HY, Li F. 2008. Determination of potential management zones from soil
500 electrical conductivity, yield and crop data. *J Zhejiang Univ Sci B.* 9(1):68-76.

501 Loeppert RH, Suarez DL. 1996. Carbonate and gypsum. *Methods of Soil Analysis: Part 3*
502 *Chemical Methods.* Vol.5. p. 437-474.

503 Maestrini B, Basso B. 2018. Drivers of within-field spatial and temporal variability of crop yield
504 across the US Midwest. *Sci Rep.* 8(1):1-9.

505 Mariani L, Ferrante A. 2017. Agronomic management for enhancing plant tolerance to abiotic
506 stresses—drought, salinity, hypoxia, and lodging. *Horticulturae.* 3(4):52.

507 Metzger MJ, Bunce RGH, Jongman RH, Múcher CA, Watkins JW. 2005. A climatic
508 stratification of the environment of Europe. *Glob Ecol Biogeogr.* 14(6):549-563.

509 Mirzaei A, Naseri R, Soleimani R. 2011. Response of different growth stages of wheat to
510 moisture tension in a semiarid land. *World Appl Sci J.* 12(1):83-89.

511 Mohsenipour M, Shahid S, Chung ES, Wang XJ. 2018. Changing pattern of droughts during
512 cropping seasons of Bangladesh. *Water Resour Manag.* 32(5):1555-1568.

513 Moral FJ, Terrón JM, Da Silva JM. 2010. Delineation of management zones using mobile
514 measurements of soil apparent electrical conductivity and multivariate geostatistical
515 techniques. *Soil Tillage Res.* 106(2):335-343.

516 Nel AA, Loubser HL, Hammes PS. 2001. The effect of water stress during grain filling on the
517 yield and processing quality of sunflower seed. *S Afr J Plant Soil.* 18(3):114-117.

518 Olsen SR, Cole CV, Watandbe F, Dean L. 1954. Estimation of available phosphorus in soil by
519 extraction with sodium bicarbonate. *J Chem Inf Model.* 53(9):1689-1699.

520 Orsini L, Remy JC. 1976. Utilisation du chlorure de cobaltihexamine pour la détermination
521 simultanée de la capacité d'échange et des bases échangeables des sols. *Sci Sol.* 4:269-
522 275.

523 Panneton B, Brouillard M. 2002. Use of fuzzy mapping to extract management zones from yield
524 maps AIC 2002. CSAE/SCGR, Mansonville, QC, Canada.

525 Reza SK, Baruah U, Sarkar D, Das TH. 2010. Evaluation and comparison of ordinary kriging and
526 inverse distance weighting methods for prediction of spatial variability of some chemical
527 parameters of Dhalai district, Tripura. *Agropedology.* 20:38–48.

528 Scudiero E, Teatini P, Manoli G, Braga F, Skaggs T, Morari F. 2018. Workflow to establish
529 time-specific zones in precision agriculture by spatiotemporal integration of plant and soil
530 sensing data. *Agronomy.* 8(11):253.

531 Setia R, Gottschalk P, Smith P, Marschner P, Baldock J, Setia D, Smith J. 2013. Soil salinity
532 decreases global soil organic carbon stocks. *Sci Total Environ.* 465:267-272.

- 533 Shiru M, Shahid S, Alias N, Chung ES. 2018. Trend analysis of droughts during crop growing
534 seasons of Nigeria. *Sustainability*. 10(3):871.
- 535 Swindell JEG. 1997. Mapping the spatial variability in the yield potential of arable land through
536 GIS analysis of sequential yield maps. *Precision agriculture'97: papers presented at the*
537 *first European Conference on Precision Agriculture, Warwick University Conference*
538 *Centre; Sept 7-10; Oxford (UK).*
- 539 Toshiro O. 2002. *Classification Methods for Spatial Data Representation*. Center for Advanced
540 *Spatial Analysis*. London: University College London.
- 541 Unlukara A, Beyzi E, Ipek A, Gurbuz B. 2016. Effects of different water applications on yield
542 and oil contents of autumn sown coriander (*Coriandrum sativum* L.). *Turkish J Field*
543 *Crop*. 21(2):200-209.
- 544 Xiao Y, Gu X, Yin S, Shao J, Cui Y, Zhang Q, Niu Y. 2016. Geostatistical interpolation model
545 selection based on ArcGIS and spatio-temporal variability analysis of groundwater level
546 in piedmont plains, northwest China. *SpringerPlus*. 5:425.
547 <http://dx.doi.org/10.1186/s40064-016-2073-0>.
- 548 Zandalinas SI, Mittler R, Balfagón D, Arbona V, Gómez-Cadenas A. 2018. Plant adaptations to
549 the combination of drought and high temperatures. *Physiol Plant*. 162(1):2-12.