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1 **Comparison between thermal airborne remote sensing, multi-depth electrical resistivity**  
2 **profiling and soil mapping: an example in Beauce (Loiret, France)**

3

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11

12

13 **Abstract**

14 A wide variety of remote sensing and ground-based (proximal sensing) methods have  
15 been developed to describe soil's physical properties and their lateral variations. Remote  
16 sensing enables the estimation of soil properties over large areas, but the information is often  
17 limited to the soil surface. Ground-based methods enable the derivation of soil properties for  
18 the whole soil thickness, although these methods cannot be conducted over large areas. The  
19 aim of the present study is to contribute to the assessment of the efficacy of airborne thermal  
20 prospection over bare soils in soil mapping. This study focuses on a comparison between this  
21 technique, which can investigate over the whole soil thickness after a sufficiently long  
22 transient heat exchange period, and pedological and electrical resistivity data that were  
23 recorded for three different depths of investigation.

24 The study area is located in the Beauce region, where the soils (haplic Calcisol or  
25 calcareic Cambisol) consist of a loamy-clay layer that is 0.3 to 1.4 m thick and overlies  
26 Tertiary Beauce limestone. Thermal measurements were recorded by ARIES radiometer in

27 December after 6 days of heat loss from the ground. The investigation depth could thus be  
28 considered to be larger than the thickness of the ploughed layer. Comparisons using statistical  
29 analyses between the thermal measurements, electrical resistivity and pedological data  
30 demonstrated that i) the spatial organization of the thermal inertia map is similar to the spatial  
31 organization of the 0-1.7 m resistivity map and ii) the thermal apparent inertia values were  
32 significantly different between the haplic Calcisols and the calcare Cambisols and can thus be  
33 mapped with a high spatial resolution over large areas.

34 The applicability of thermal prospecting in soil mapping opens large perspectives  
35 considering the present advances in light infrared radiometers. Beside agronomical concerns  
36 this methodology will also facilitate important progresses in engineering applications among  
37 which the cross estimation of electrical and thermal properties.

38

39

40 **Keywords:** Thermal infrared airborne remote sensing, soil physical property mapping,  
41 thermal inertia, electrical resistivity, ARP

42

43

#### 44 **Introduction**

45 Knowledge of the spatial variability of soils is of major importance for a wide variety  
46 of agronomic, industrial and environmental applications. The classification of soils is based  
47 on soil properties materials, which are defined in terms of diagnostic horizons (FAO, 2006).  
48 The properties that characterize soil classes play a significant role in the agronomic  
49 potentiality of cultivated fields and in most geotechnical engineering projects, such as the  
50 installation of buried pipes or high power electrical cables or the delineation of polluted areas.  
51 In all these cases, the soil classes and matched properties must be spatially described at a high

52 resolution, metric or decametric. For this purpose, the use of non-destructive geophysical  
53 methods is of major interest. Indeed, geophysical methods enable the measurement of soil  
54 physical properties rapidly and with a quasi-exhaustive covering. A wide variety of airborne  
55 and ground based geophysical methods have been developed.

56         Airborne techniques enable the estimation of soil properties over large areas, but most  
57 of them, for example, visible near-infrared (VNIR) reflectance data or radar backscattering,  
58 are often limited to the soil surface; in particular, the latter is limited to several centimeters  
59 (Nichols *et al.* 2011). In contrast, ground-based methods enable the derivation of soil  
60 properties over the whole soil thickness of pedological/agronomical interest (Viscarra Rossel  
61 *et al.* 2010) and to characterize the parent rock, but these methods cannot be conducted for  
62 large areas. Despite this limitation, the electrical resistivity of soils has been measured for  
63 twenty years (e.g. Samouelian *et al.* 2005), notably in the context of precision agriculture. The  
64 electrical resistivity of the soil is related to several soil properties, mainly porosity, clay  
65 content and water content: a wet soil is more electrically conductive than a drier soil  
66 (Samouëlian *et al.* 2005, Cousin *et al.* 2009). Because of the wide range of values exhibited by  
67 this property, which is associated with the easiness and reliability of its measurement, the DC  
68 resistivity technique is considered as a reference for testing the efficacy of other methods  
69 (Gebbers *et al.* 2009). Among airborne techniques, thermal prospection can be used to  
70 investigate the whole soil thickness (Scollar *et al.* 1990) and over large areas. This method is  
71 ancient (Kappelmeyer 1957, Krcmar and Masin 1970), but its ground-level applications have  
72 been rather limited by the necessity to correct diurnal soil temperature variations during the  
73 implementation of the survey. Fortunately, this limitation is overcome by remote infrared  
74 radiometric measurements, where the duration for measuring the whole area remains small  
75 against the soil surface temperature time variations. Satellite-borne scanner radiometers  
76 currently do not offer sufficient ground resolution, but airborne archaeological prospection

77 was initiated forty years ago (Périsset and Tabbagh 1981), taking advantage of favorable heat  
78 exchange conditions at the ground surface that correspond to transient, several-day-long  
79 weather changes. The experience that is acquired in archaeological prospection can be  
80 transferred to agronomy-driven soil management studies. Additionally, the development of  
81 new light thermal cameras that can be borne either by small planes or even by unmanned  
82 aerial vehicles has revived interest in thermal prospection (Schlerf *et al.* 2012).

83         The physical parameter that is measured by radiometers, the brightness temperature,  
84 depends on the soil emissivity and the thermometric temperature (see definitions in  
85 Appendix). Both can be of interest for geophysical exploration in the thermal infrared  
86 atmospheric window, which corresponds to the 8-14  $\mu\text{m}$  wavelength range. The soil  
87 emissivity provides information about the soil surface mineralogy. The lateral changes in the  
88 heat exchange balance and/or in the soil thermal properties modify the thermometric  
89 temperature. Soil emissivity can be directly used to map rocks or regoliths in arid climatic  
90 zones where pedogenesis is not active (Kahle and Rowan 1980, Salisbury *et al.* 1994, Watson  
91 *et al.* 1996, Kato *et al.* 2014), but it has no direct application in temperate humid climates,  
92 where soil moisture and organic matter make this parameter uniform. In the presence of  
93 vegetation, the plant temperature is governed by its evapotranspiration, and this predominant  
94 term of the heat exchange balance can consequently be assessed (Choudury *et al.* 1986, Hilker  
95 *et al.* 2013, Mallick *et al.* 2014). For bare soils, the lateral variations in the soil surface  
96 temperature depend either on modification to the heat balance terms because of the surface  
97 slope (Fourteau and Tabbagh 1979) or on changes in underground thermal properties  
98 (Gauthier and Tabbagh 1994) reflecting the ease with which heat (positive or negative) can be  
99 moved downward into the ground. For a homogeneous solid and unsteady heat inputs/outputs,  
100 the temperature changes are inversely proportional to the thermal inertia, which is expressed  
101 by  $P = \sqrt{KC_v}$ , where  $K$  is the thermal conductivity and  $C_v$  is the volumetric heat capacity

102 (see appendix for de definition of thermal properties). Thus, the results of a thermal  
103 prospection can be expressed in terms of variations in the soil's apparent thermal inertia  
104 (Price 1977): the thermal inertia of a homogeneous ground having the same surface  
105 temperature in the same flux conditions. However, in presence of a tilled layer it is more  
106 relevant to consider a two layer model with topsoil (*i.e.* the surface soil or the tilled layer)  
107 above homogeneous subsoil beneath. The reason for this is because the topsoil's properties  
108 (namely the bulk density) are homogenized by tillage and fauna activity at the plot scale  
109 (Tabbagh 1976). The inversion used hereafter will transform the brightness temperature  
110 variations in subsoil's thermal inertia variations.

111         The key point of thermal prospection is the evaluation of the weather conditions under  
112 which the investigation depth would be larger than the ploughed layer. Contrary to other  
113 prospection techniques, this depth does not depend on the choice of a frequency or other  
114 instrument parameters but on the history of the heat exchange at the ground surface before the  
115 measurement time. The daily heat flux variation is too rapid to significantly influence subsoil  
116 temperature, and longer transient variations must be considered: if the duration of a transient  
117 input (or output) of heat lasts one or two days, the investigation depth would be limited to  
118 approximately 25 cm, while the depth would reach 1 m if the transient input (or output) lasts  
119 one week or more (Périsset and Tabbagh 1981).

120         The present study focuses on the ability of thermal airborne remote sensing techniques  
121 - thermal prospection for exploration geophysicists - to discriminate soil classes. The  
122 experiment was conducted on a cultivated field in the Beauce region, France. The soil classes  
123 and their spatial variability in this field were widely known because a soil map had been  
124 drawn before the experiment (Nicoullaud *et al.*, 2004). The study zone consists of haplic  
125 Calcisols and calcareic Cambisols (IUSS Working Group WRB, 2006). The surface  
126 temperature variations were recorded by using an airborne radiometer, and then the thermal

127 inertia of the subsoil layer was calculated by using the transient heat flux values, which were  
128 determined at the nearby Bricy meteorological station. A geoelectrical prospection was  
129 conducted on the same field to compare the two types of geophysical methods and their  
130 investigation depths. First, the thermal inertia and electrical resistivity are compared to the  
131 soil properties, which were locally measured by auger drilling, and then to the soil classes,  
132 which were described on the soil map. Finally, a statistical methodology is proposed to  
133 transform the thermal inertia map into a map of soil types.

134

## 135 **Materials and methods**

### 136 *Study site and soil description*

137 The study area consists of one 39 ha plot (plot A) in the Beauce region (Villamblain,  
138 Loiret, France), where the soil thickness varies from 0.3 to 1.4 m over Tertiary Beauce  
139 limestone (Fig. 1). Figure 1 presents the soil map - realized in 2000 before and independently  
140 of the airborne prospection described here - that was made from the description of 110 auger  
141 soil samples. Soil auger hole sampling was conducted on transects that were spaced every 100  
142 m. Soil scientists selected samples from the transects based on previous surveys, surface  
143 observations and topography. Sometimes, a soil sample was added between transects when  
144 observations were different between two nearby auger holes.

145 The two soil types that were found (haplic Calcisol and Calcaric Cambisol) consist  
146 of a loamy-clay layer that developed on a lacustrine limestone deposit. The difference  
147 between these two soil types is the calcareous content in the topsoil: haplic Calcisols are soils  
148 with a significant accumulation of secondary calcium carbonates but are non-calcareous (less  
149 than 10%  $\text{CaCO}_3$ ), while calcaric Cambisol topsoil is calcareous. The soil units were  
150 determined by simple observation, without soil analysis. Three sub-units were described for  
151 the haplic Calcisols and eight sub-units for the calcaric Cambisols, which depended on the

152 thickness of the loamy-clay layer, the carbonate content, the stone content, the type of  
153 calcareous content (cryoturbated or not) and the depth of the bedrock (Nicoullaud *et al.* 2004).  
154 These two soil types may differ in terms of agronomy: an abundance of calcium can block  
155 elemental nutrients, and high limestone content in soils is unfavorable for rooting. Most  
156 Calcisols have a medium or fine soil texture and good water-holding properties.

157

### 158 ***DC electrical prospection***

159 A multi-depth resistivity map was created by an ARP© device in August 2012 over a  
160 9 ha study area (zone B), a part of plot A. This ARP© system (Figure 2) is a mobile, multi-  
161 depth soil electrical resistivity mapping system that comprises one injection dipole (AB) and  
162 three V-shaped measuring dipoles (M1 N1, M2 N2 and M3 N3) (Panissod *et al.* 1997, Dabas,  
163 2009). The distance between the injection dipole and the measuring dipoles is 0.5 m for the  
164 V1 array (A B- M1 N1), 1 m for the V2 array (A B-M2 N2) and 1.7 m for the V3 array (A B-  
165 M3 N3). The investigation depths roughly correspond to the distance between the AB dipoles  
166 and MN dipoles (Figure 3: 0.5 m, 1.0 m and 1.7 m for V1, V2 and V3, respectively).  
167 Resistivity measurements were recorded every 20 cm along profiles spaced 6 m apart. After  
168 filtering the measurements, the resistivity data were interpolated on regular grids by the  
169 inverse distance weighted method.

170 To compare with the subsoil's thermal inertia variations, the three apparent electrical  
171 resistivity values were interpreted by using a 1D two layer model (Meheni *et al.* 1996) to  
172 estimate the resistivity of the subsoil layer (depth > 0.25 m). The following parameters were  
173 used to process the inversion: the ploughed surface had a thickness equal to 0.25 m according  
174 to the 21 auger hole prospection, and its resistivity was estimated to be equal to 40  $\Omega$ .m. This  
175 resistivity value was estimated from the established relationship between the interpreted  
176 electrical resistivity and the volumetric water content of the topsoil, which was recorded by



177 TDR probes at the same study site, according to the formula for this pedological context  
178 (Cousin *et al.* 2009),  $\rho = -129 \ln(\theta) + 456$ , where  $\rho$  is the resistivity value and  $\theta$  is the  
179 volumetric water content. Indeed, calibrated TDR probes were installed at North-East from  
180 plot A. The interpreted electrical resistivity and water content were recorded at two depths of  
181 the topsoil layer (12 and 20 cm depth, respectively) at 23 dates during a year at 2  
182 measurements positions. Thus, the relationship mentioned above was established on 92  
183 measurements.  $\theta$  in the relationship by Cousin *et al.*, 2009 was inferred on the base of the  
184 volumetric water content measured during the acquisition period of the electrical resistivity  
185 data.  $\theta$  was equal to  $0.355 \text{ m}^3 \text{ m}^{-3}$  (mass water content x bulk density:  $0.25 \text{ g g}^{-1} \times 1.42 \text{ g cm}^{-3}$ ).  
186 The resolution of the grid map was 1.7 m (Figure 3).

187

### 188 ***Auger soil sample information***

189 A total of 21 auger holes were regularly dug during the electrical prospection  
190 (Figure 3) to describe and sample the successive horizons. The auger hole depths range from  
191 30 to 120 cm. The soil horizons were classified into the A horizon (topsoil, LA, tilled layer,  
192 usually 0.25 m thick), B horizon (subsoil, Sci or Sca, horizons under the tilled layer) and C  
193 horizon (corresponding to the bedrock). Depending on the location, the soil profiles were  
194 characterized by an A/B sequence, an A/C sequence, or an A/B/C sequence. All of the soil  
195 samples were analyzed at the INRA Arras Laboratory (Arras, Pas de Calais, France) to  
196 determine (1) the soil texture by using ISO 10693 method (5 particle size fractions with no  
197 decarbonization) and (2) the soil  $\text{CaCO}_3$  content by using the NF ISO 10693 volumetric  
198 method. Each of the 21 auger holes was affiliated to a soil type according to the soil map of  
199 the study area.

200

### 201 ***Thermal prospection***

202           The thermal prospection was conducted with the ARIES radiometer, which included  
203 two numerical channels: one in the visible and near infrared ranges (0.5-1  $\mu\text{m}$ ), and the other  
204 in the thermal infrared range (10.5-12.5  $\mu\text{m}$ ) (Monge and Sirou 1975, Beaufrère *et al.* 1999)  
205 with an Hg-Cd-Te photoconduction detector. Two internal blackbodies allowed the translation  
206 of the recorded video signal into the brightness temperature. The data were acquired on  
207 December 11, 2002 at 10 h 40 U.T. at a flight altitude of 1006 m and an IFOV (Instantaneous  
208 Field Of View) of 6.25  $\text{m}^2$  at nadir, while the sampling step along the line was 1.75 m. The  
209 mirror rotated at 36.4 Hz, and the speed of the plane was 56.6  $\text{ms}^{-1}$ . In the temperature signal,  
210 the least significant bit (LSB) corresponded to 0.044 K resolution. The data were corrected for  
211 pitch and roll (with data from the gyroscope) and anamorphic distortion before a last  
212 geometric rectification in the GIS. Finally, the measurements were represented on a 1.6 m by  
213 1.6 m grid.

214           The heat flux variations at the soil surface were calculated from soil temperature data  
215 that were recorded at the nearby (20 km east) Bricy meteorological station at 10, 20, 50 and  
216 100 cm depths by using the algorithm that is described in Scollar *et al.* (1990), which is  
217 recalled in Appendix III. These values are presented in Figure 6 from the 15<sup>th</sup> of November to  
218 the 15<sup>th</sup> of December. The soil cooling was significant, especially during the six days that  
219 preceded the flight. The investigation depth can thus be considered to be greater than the  
220 thickness of the ploughed layer (Scollar *et al.* 1990) and qualitatively the thermal inertia of  
221 the subsoil is higher where the measured ground surface temperature is higher and lower  
222 where the temperature is lower. Under the hypothesis that the observed temperature lateral  
223 variations originate in variations of the subsoil thermal inertia it is possible to establish a  
224 quantitative correspondence between the brightness temperature and this thermal inertia using  
225 a two layer forward model. In this calculation, the heat flux variations are considered as series

226 of successive  $\frac{\partial Q}{\partial \tau}$  variations, so that the resultant ground surface temperature  $T(t)$  on time  $t$   
 227 can be expressed by:

$$228 \quad T(t) = \int_0^t \frac{\partial Q}{\partial \tau} \text{Step}(t - \tau) d\tau .$$

229 The two layers step response has for expression (Tabbagh 1973):

$$230 \quad \text{Step}(t - \tau) = \frac{2\sqrt{t - \tau}}{P_1} \left[ \frac{1}{\sqrt{\pi}} + 2 \sum_{n=1}^{\infty} (-C)^n \text{ierfc}\left(\frac{nh}{\sqrt{\Gamma_1(t - \tau)}}\right) \right],$$

231 where  $P_1$  is the thermal inertia of the first layer (topsoil),  $h$  its thickness,  $\Gamma_1$  its thermal  
 232 diffusivity,  $\text{ierfc}$  is the integral of the complementary error function and  $C = \frac{P_2 - P_1}{P_2 + P_1}$  is the  
 233 contrast coefficient between the thermal inertia of the first layer ( $P_1$ ) and second layer ( $P_2$ ).

234 When  $P_2 = P_1$ , the step response reduces to:

$$235 \quad \text{Step}(t - \tau) = \frac{2}{P_1} \sqrt{\frac{t - \tau}{\pi}} .$$

236 For this correspondence calculation we assumed the uniform topsoil layer has a  
 237 thickness  $h = 25$  cm, a thermal diffusivity of  $\Gamma_1 = 0.48 \text{ m}^2 \text{ s}^{-1}$  and a  $P_1 = 1732$  S.I. thermal inertia  
 238 and we fixed the 128 signal value at  $5.63 \text{ }^\circ\text{C}$  (using both in-flight radiometer calibration and  
 239 ground control points). The resulting apparent thermal inertia of the subsoil map is shown in  
 240 Figures 3 and 7.

241

## 242 **Data analysis**

243 The approach that was developed to assess the information from the thermal survey is  
 244 summarized in Figure 8. The approach involves 4 steps.

245 First, Principal Component Analysis (PCA) was used to analyze the overall variation  
 246 in the data (soil properties, thermal inertia and electrical resistivity, step 1). The effect of soil

247 type on the thermal inertia response and electrical resistivity response was assessed by using  
248 analysis of variance (ANOVA) (step 2). ANOVA tests the null hypothesis that samples in two  
249 or more groups are drawn from populations with the same mean values. ANOVA produces an  
250 F-statistic, which is the ratio of the variance that is calculated among the means to the  
251 variance within the samples. If the group means are drawn from populations with the same  
252 mean values, the variance between the group means should be lower than the variance of the  
253 samples. A higher ratio therefore implies that the samples were drawn from populations with  
254 different mean values.

255 Factorial discriminant analysis (FDA, step 3) was used to establish a classification  
256 model of the soil types in the study area according to the thermal inertia and electrical  
257 resistivity, respectively. For a detailed presentation, the reader can refer to books or papers on  
258 the subject, such as Tomassone *et al.* (1988), Tabachnick and Fidell (1996), and Bourennane  
259 *et al.* (2014). FDA is a statistical method for describing and forecasting. Its purpose is to study  
260 the relationship between a qualitative variable and a set of quantitative variables. The FDA  
261 can be considered as an extension of the regression problem, where the dependent variable is  
262 qualitative. The data consist of  $n$  observations that are divided into  $k$  classes or categories and  
263 described by  $p$  variables. Traditionally, one can distinguish two aspects in discriminant  
264 analysis:

- 265 1. A descriptive aspect, which consists of finding linear combinations of variables that  
266 separate the  $k$  categories and provide a graphic representation that adequately reflects this  
267 separation;
- 268 2. A decisional aspect, where a new individual arises for which we know the values of  
269 the predictors; this aspect decides which category it should be allocated to. In such cases, this  
270 is a classification problem.

271 Two FDA models are possible based on a fundamental assumption: if we assume that  
272 the covariance matrices are identical, one can be used for linear factorial discriminant  
273 analysis. If we assume that the covariance matrices are different for at least two categories, we  
274 have a quadratic model. The box test allows testing of this hypothesis (Bartlett's  
275 approximation allows the use of a chi-square law for the test).

276 Finally, the discriminant function from step 3 was applied to map the soil types over  
277 the whole study area (step 4).

278

## 279 **Results and discussion**

### 280 ***Soil data: descriptive statistics***

281 The soil textures (Figure 4) are represented in the CEC85 triangle (Commission of the  
282 European Communities 1985). A particle size analysis of the samples shows that the Calcisols  
283 have mainly medium/fine texture, whereas the Cambisols have more variable textures (“fine”,  
284 “medium/fine” or “medium”). The Cambisols appear to have some sandy particles, from 5 to  
285 30%, while the sandy content in the Calcisols does not exceed 4% in the A horizon. The  
286 sandy soil texture is probably explained by the amount of coarse limestone particles. The  
287 boxplot (Figure 5) analysis that was performed on the 21 soil samples shows that the Calcisols  
288 have low CaCO<sub>3</sub> content, specifically, less than 10 g.kg<sup>-1</sup>, conversely to the Cambisols. The  
289 soil types can be differentiated according to their texture and CaCO<sub>3</sub> content.

290

### 291 ***Thermal inertia and electrical resistivity maps***

292 The apparent thermal inertia of the subsoil in the study area varied between 916 and  
293 2082 S.I. This value was lower in the western part of the studied plot and higher in the south-  
294 eastern part (Figure 7). The apparent electrical resistivity over the 9 ha B plot varied between  
295 11 and 68 Ω.m for the V1 array, between 17 and 90 Ω.m for the V2 array and between 14 and  
296 127 Ω.m for the V3 array (Figure 3). For all the arrays, the spatial organization of the

297 electrical resistivity was the same, with lower resistivity values to the northwest and higher  
298 resistivity values to the southeast. A low resistivity value band (oriented from northeast to  
299 southwest) crossed over the south-eastern part, which corresponds to a calcareous Cambisol that  
300 developed over a grey limestone soil unit. The inverted subsoil (using the same two-layer  
301 model geometry as for the thermal data) resistivity values were between 17 and 167  $\Omega$ .m and  
302 exhibited a similar spatial pattern to the apparent resistivity values.

303 On the 9 ha B plot, the spatial pattern of the thermal inertia map was also very  
304 similar to the spatial pattern of the resistivity maps: areas with low resistivity corresponded to  
305 low thermal inertia areas and vice versa, except for the Cambisol that developed over the grey  
306 limestone soil unit to the south. In this soil unit, the inverted subsoil resistivity approximately  
307 was 35  $\Omega$ .m, the thermal inertia was high., the soil depth was approximately 40 cm. This soil  
308 unit likely was wet during the electrical prospecting (due to heavy rain).

309 In addition, Figure 7 shows that the airborne technique depends on any obstacles  
310 that are located between the soil and the sensor, unlike the ARP method. Indeed, we can spot  
311 ground cover, sprinkler lines, hedges and buildings.

312

### 313 *Principal Component Analysis between geophysical measurements and soil properties at* 314 *auger holes*

315 The first principal component (Fig. 9 a and b) accounts for more than 80% of the  
316 total variation. Except for the clay content in the subsoil, this component is strongly correlated  
317 with all the original variables and is inversely correlated with the silt content, thermal inertia,  
318 electrical resistivity and  $\text{CaCO}_3$  contents. The  $\text{CaCO}_3$  and sand contents are strongly  
319 positively correlated in both layers (Figure 9 a and b). Previous results have shown that no  
320 difference in clay content exists between Calcisols and Cambisols, thus, we can conclude that  
321 these soil properties (sand content and  $\text{CaCO}_3$ ) are well correlated and explain the higher

322 electrical resistivity and thermal inertia in accordance with the general knowledge about these  
323 properties.

324

325 *Effect of soil type on the thermal inertia response and electrical resistivity at the auger*  
326 *holes*

327 We studied the effect of soil type, a more inclusive variable than soil texture or CaCO<sub>3</sub>  
328 content, on the geophysical measurements. An ANOVA analysis (performed on auger sample  
329 measurements N = 21), which used the Tukey pairwise means comparison method on the  
330 thermal inertia signal, showed a highly significant influence from the soil type (Table 1). An  
331 ANOVA test on the resistivity data provided similar results (Table 2), which means that both  
332 thermal and resistivity methods are efficient tools to differentiate soil types.

333 Thus, a quadratic factorial discriminant analysis (FDA) was performed to obtain a  
334 model that can map soil types by using exhaustive geophysical information. Confusion  
335 matrices (Table 3a) showed that the thermal inertia values enabled the accurate classification  
336 of 85% of the 21 soil samples in the correct soil class, while the resistivity values, particularly  
337 the inverted subsoil resistivity, enabled the accurate classification of 81% of the samples.  
338 According to the data that were used to elaborate the FDA in Table 3a, two soil samples that  
339 were not adequately assigned by the FDA were classified by the soil scientist in the Calcisol  
340 map unit, while they should be classified as calcareous Cambisols according to the chemical  
341 analyses. Thus, only one sample was incorrectly classified by the FDA with the thermal  
342 inertia values.

343 The study also showed that the V2 array can better discriminate the soil type than the  
344 other arrays. Indeed, the V1 array's measurements were influenced by the topsoil horizon, in  
345 which structural heterogeneity from plant growth, tillage and the climate can affect electrical  
346 measurements (e.g., Seger *et al.*, 2009; Besson *et al.*, 2013). The electrical resistivity

347 measurements from the V3 array were more affected by the substrate. Indeed, the soil depth  
348 investigation of the V3 array was approximately 0-170 cm, which includes a larger part of the  
349 resistant limestone layer than the V2 array. For these two reasons, the V2 array seems to  
350 provide the best support for soil mapping in this pedological context, as demonstrated by  
351 Moeys *et al.* 2006.

352

### 353 *Extrapolation to the study area and validation*

354 We used the coefficients of the FDA ranking function (Table 4) to predict the soil  
355 type at the plot's extent (Figure 10). The coefficients of the two ranking functions were  
356 applied to the thermal inertia grid to obtain two grids values. Then, each pixel was assigned to  
357 the category for which the ranking function is highest. We obtained the spatial distribution of  
358 the two soil types through the study area. The classification results show an overall percentage  
359 of correct classification of 91% for the 9 ha subplot (Table 5a) and 83.5% for the whole study  
360 area (Table 5b). The decrease in the classification rate with the extension of the area can be  
361 explained by the underlying extrapolation of the auger hole soil observations, from which soil  
362 scientists usually interpolate the observed characteristics.

363

### 364 **Conclusion**

365 This paper focuses on the assessment of the ability of thermal prospection to  
366 discriminate between soil classes. Our findings indicate that thermal inertia data allow the  
367 discrimination between two bare soil types in the Beauce region. In addition, the thermal  
368 inertia and statistical methodology that was proposed, specifically factorial discriminant  
369 analysis, allows an efficient extrapolation of the mapping model beyond the area where it was  
370 established. This study provides insights for the spatial mapping of soil types by focusing on  
371 thermal airborne remote sensing as an ancillary variable for mapping over large areas. Indeed,



372 thermal airborne remote sensing presents the advantages of both airborne and ground methods  
373 and should be considered and developed in soil studies: in terms of the extent of the  
374 investigated surface, this approach fills the gap between ground-based (proximal soil sensing)  
375 and satellite techniques.

376           The results of this paper are, to our knowledge, the first direct field-scale comparison  
377 between electrical resistivity and thermal inertia data to be published. This paper  
378 complements and facilitates the laboratory results in this domain (Singh *et al.* 2001). These  
379 new perspectives in thermal prospecting with new light infrared radiometers will facilitate the  
380 cross estimation of electrical and thermal properties, which is very important for engineering  
381 applications.

382

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479

480

481 **Figure captions**

482

483 Figure 1: Soil map of plot A with the location of the zone B

484

485 Figure 2: View of the ARP© system, with the geometrical scheme of the location of the 8  
486 electrodes.

487

488 Figure 3: Zone B: apparent resistivity maps for the three ARP© channels, with the location of  
489 the auger-drilled holes, the data of which are used in the statistical analyses. The resistivity of  
490 the subsoil layer is calculated assuming the topsoil has a 40  $\Omega\text{m}$  resistivity and a 0.25 m  
491 thickness, the apparent thermal inertia of the subsoil layer is calculated assuming the same  
492 thickness, a  $0.48 \cdot 10^{-6} \text{ m}^2\text{s}^{-1}$  diffusivity and a 1732 S.I. thermal inertia.

493

494 Figure 4: Localization of the auger holes' soil textures in CEC85 triangle.

495

496 Figure 5: Variation in the auger holes  $\text{CaCO}_3$  content.

497

498 Figure 6: Heat flux in the ground at the Bricy meteorological station from November 15, 2002  
499 to December 15, 2002. The arrow corresponds to the measurement time.

500

501 Figure 7: Apparent thermal inertia of the subsoil layer as deduced from the brightness  
502 temperature in the 10.5 – 12.5  $\mu\text{m}$  channel (left), and the limits of plot A and zone B.

503

504 Figure 8: Flowchart of the developed approach.

505

506 Figure 9a: PCA on topsoil data.

507

508 Figure 9b: PCA on subsoil data.

509

510 Figure 10: Soil types that were inferred from the ranking functions of the FDA.

511

512

513 **Table captions**

514

515 Table 1: ANOVA results of thermal inertia and soil type (haplic Calcisol and calcareic  
516 Cambisol) punctual data (21 soil auger holes).

517

518 Table 2: ANOVA results of subsoil resistivity and soil type (haplic Calcisol and calcareic  
519 Cambisol) punctual data (21 soil auger holes).

520

521 Table 3: Confusion matrix from factorial discriminant analysis between the two soil types and  
522 the subsoil thermal inertia values (a), subsoil inverted resistivity values (b) and apparent  
523 resistivity (c to e).

524

525 Table 4: Factorial discriminant analysis: coefficients of the ranking functions.

526

527 Table 5: Discrepancy between soil types from discriminant functions and the reference soil  
528 map: (a) zone B, (b) plot A.

529



530

## 531 **Appendix I: Glossary**

### 532 *Statistical methods*

533 **ANOVA:** Analysis of variance, a test that verifies whether several samples belong to the same  
534 population.

535 **DF:** The degrees of freedom for the model, equal to one less than the number of categories

536 **F ratio,  $P_r > F$ :** The test statistic that is used to decide whether the sample means are within  
537 the sampling variability.

538 **Sum of Squares:** Sum of the squared differences between each observation and the overall  
539 mean.

540 **Mean Squares:** Sums of Squares divided by the corresponding degrees of freedom.

541 **FDA:** Factorial discriminant analysis, assigns to pre-defined classes by using discriminant  
542 variables.

543 **PCA:** Principal Component Analysis, uses an orthogonal transformation to convert a set of  
544 observations of correlated variables into a set of values of linearly uncorrelated variables  
545 called principal components.

### 546 *Thermal instrument and parameters*

547 **Radiometer:** An instrument that measures the radiant flux of electromagnetic waves - in this  
548 case, the infrared band - from the photo-conductive effect.

549 **Brightness temperature:** temperature of the black body emitting the same radiation intensity.

550 **Thermometric temperature:** temperature which would be measured by a thermometer in  
551 close contact with the soil surface (in other words the brightness temperature if the emissivity  
552 is 1.)

553 **Emissivity:** ratio between the radiance emitted by a given surface to the radiation that would  
554 be emitted by the black body surface at the same thermometric temperature. In the present  
555 case the emissivity is considered for the thermal infrared spectrum band 10.5 – 12.5  $\mu\text{m}$ .

556 **Thermal conductivity,  $K$ :** This property is defined by the Fourier law as the opposite of the  
557 ratio of the heat flux to the temperature gradient. Its SI unit is  $\text{Wm}^{-1}\text{K}^{-1}$ .

558 **Volumetric capacity,  $C_v$ :** This property expresses the ability of heat storage. It is defined as  
559 the ratio of the variation in the stored heat to the corresponding temperature variation. Its SI  
560 unit is  $\text{Jm}^{-3}\text{K}^{-1}$ .

561 **Thermal diffusivity,  $\Gamma$ :** This property is defined by  $\Gamma=K/C_v$  and governs the temperature  
562 behavior in unsteady regimes. Its SI unit is  $\text{m}^2\text{s}^{-1}$ .

563 **Thermal inertia,  $P$ :**  $P = \sqrt{KC_v}$ . The unsteady temperature changes at the surface of a body  
564 are inversely proportional to  $P$ . Its SI unit is  $\text{Jm}^{-2}\text{K}^{-1}\text{s}^{-0.5}$ .

565

## 566 **Appendix II: Variable descriptions**

567 **clay:** Percentage of clay in the soil sample, parameter of soil texture, particle diameter below  
568 0.002 mm

569 **silt:** Percentage of silt in the soil sample, parameter of soil texture, particle diameter from  
570 0.002 to 0.05 mm

571 **sand:** Percentage of sand in the soil sample, parameter of soil texture, particle diameter from  
572 0.05 to 2 mm

573 **CaCO<sub>3</sub>:** Percentage of calcium carbonate in the soil sample

574 **V1:** Apparent resistivity in  $\Omega\cdot\text{m}$ , measured by the first channel (A B-M1 N1)

575 **V2:** Apparent resistivity in  $\Omega\cdot\text{m}$ , measured by the second channel (A B-M2 N2)

576 **V3:** Apparent resistivity in  $\Omega\cdot\text{m}$ , measured by the third channel (A B-M3 N3)

577 **ISR:** Inverted subsoil resistivity, calculated from the two layer 1D model with a 40  $\Omega\cdot\text{m}$   
578 resistivity and 0.25 m-thick first layer

579

## 580 **Appendix III**

581 To determine the flux  $Q(t)$  at the ground surface, it is split into a series of step functions  
 582 beginning at a regular interval  $\delta t$  so that at time  $t_i = i\delta t$  the temperature of a homogeneous soil  
 583  $T(z,t)$  is written as follows:

$$584 \quad T(z,t) = \frac{2}{P} \left\{ \sum_{l=2}^{i-1} (Q_l - Q_{l-1}) S(z, i-l) + Q_1 S(z, i-1) \right\}, \text{ where } S(z, m) = \sqrt{m\delta t} \cdot ierfc\left(\frac{z}{2\sqrt{\Gamma m\delta t}}\right),$$

585  $P$  is the thermal inertia and  $\Gamma$  the thermal diffusivity and  $Q_l$  the successive values of  $Q(t)$  and

586  $ierfc$  the integral of the complementary error function:  $ierfc(x) = \int_x^{\infty} erfc(u) du$ , and

$$587 \quad erfc(x) = \frac{2}{\sqrt{\pi}} \int_x^{\infty} e^{-u^2} du. \text{ These monotonous functions are calculated by their series}$$

588 development.

589 The successive values of the flux are then calculated step by step from the temperature  
 590 differences. The calculation can be applied with only one depth:

$$591 \quad Q_1 = (T(z, \delta t) - T(z, 0)) \frac{P}{2S(z, 1)}, \text{ then}$$

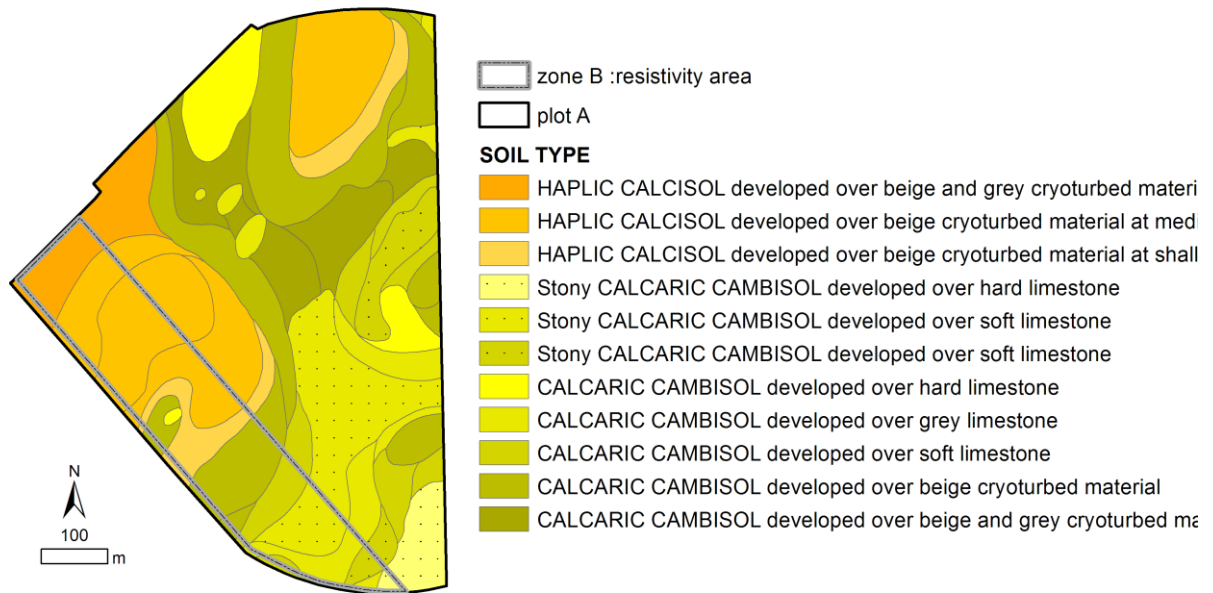
$$592 \quad Q_2 = \frac{(T(z, 2\delta t) - T(z, \delta t))P/2 - Q_1(S(z, 2) - S(z, 1))}{S(z, 1)}, \text{ and so on.}$$

593 Using  $J$  different depths one must apply the least squares method and one has:

$$594 \quad Q_1 = \frac{P \sum_{j=1}^J (T(z_j, \delta t) - T(z_j, 0)) S(z_j, 1)}{2 \sum_{j=1}^J S^2(z_j, 1)}, \text{ and so on.}$$

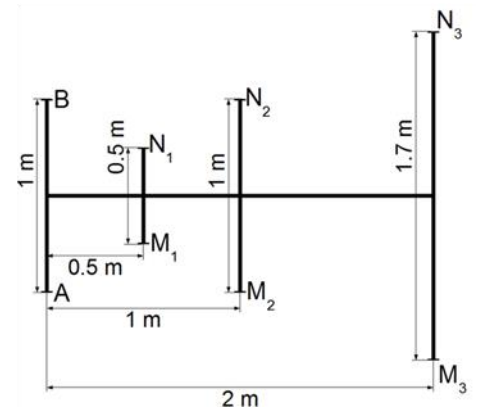
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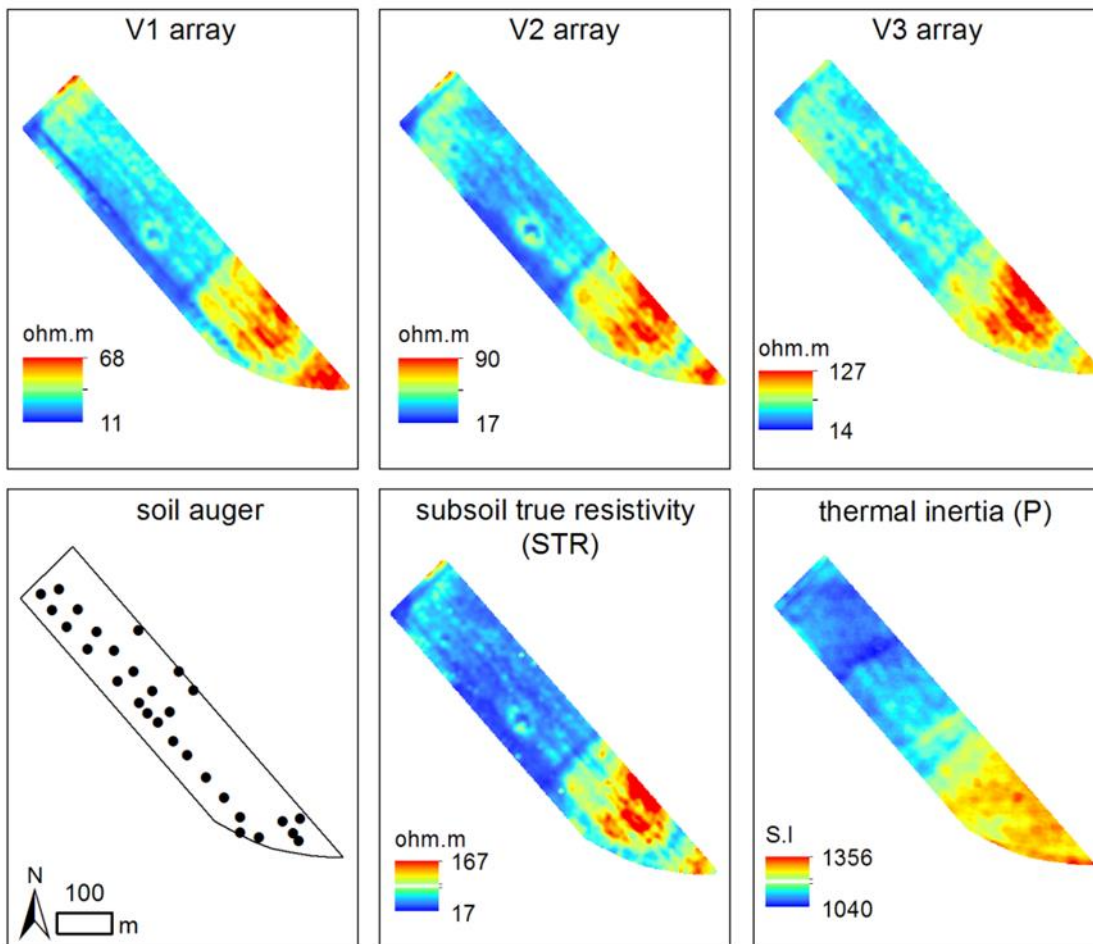
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599 Figure 1

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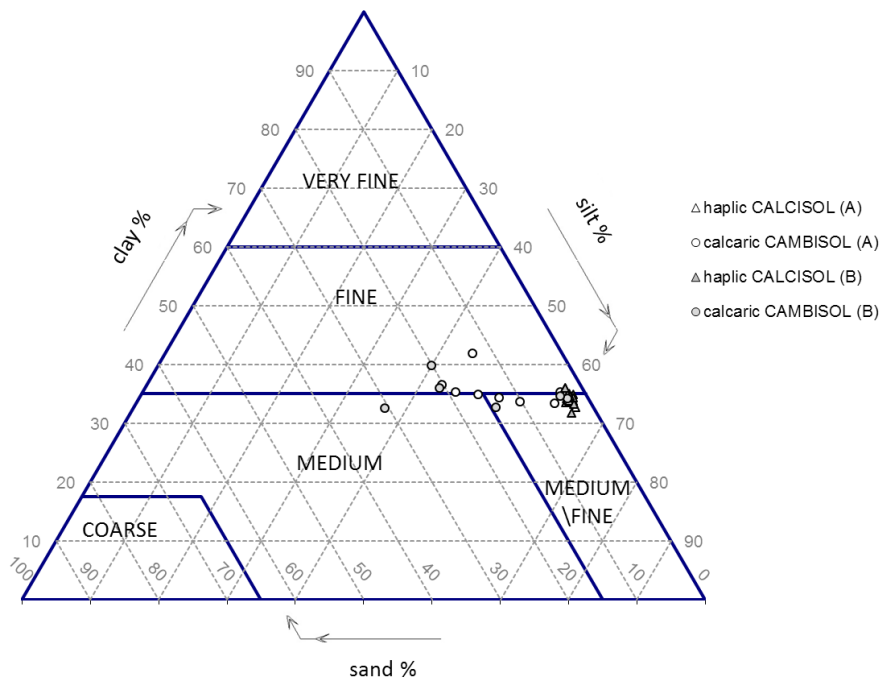
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604 Figure 2

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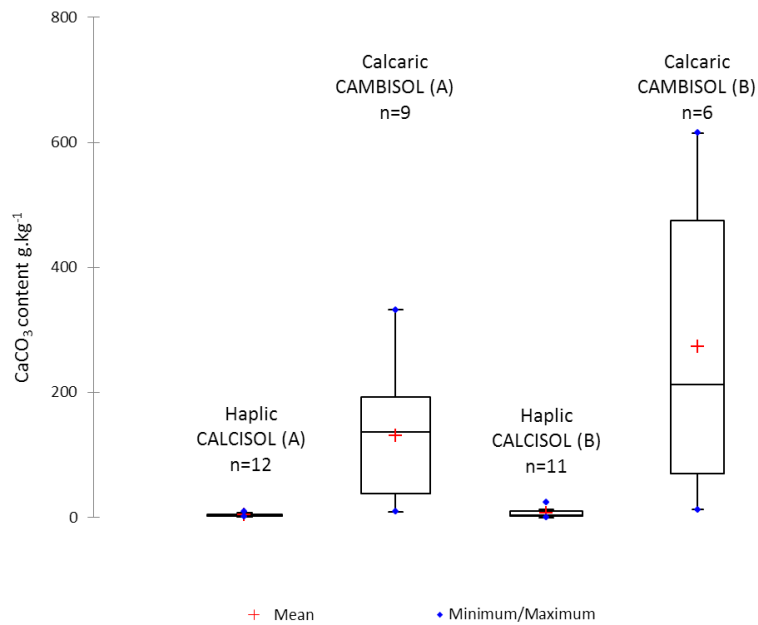
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607 Figure 3



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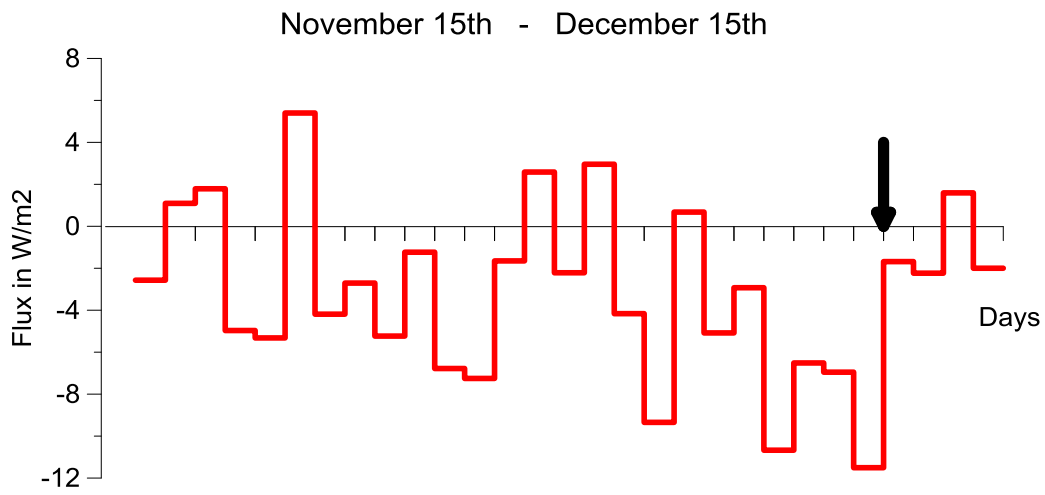
609 Figure 4



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611 Figure 5

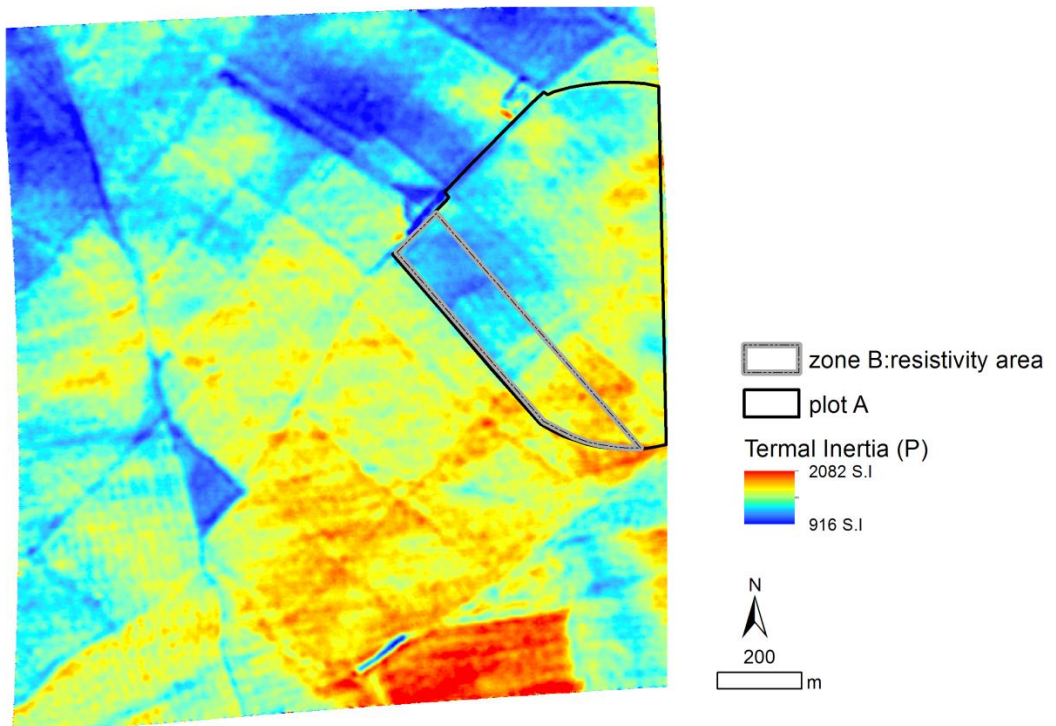
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614 Figure 6

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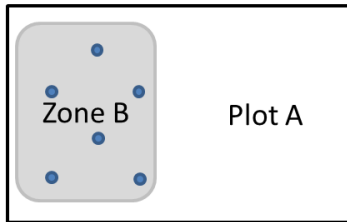
617 Figure 7

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Study sites :

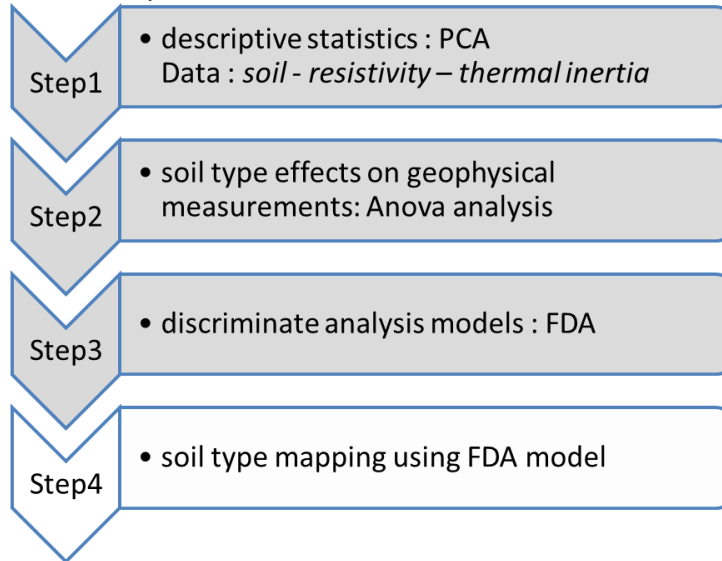


Data set :

Zone B
Punctual analysis
<ul style="list-style-type: none"><li>• electrical resistivity prospection, 3 depths</li><li>• soil analysis (21 pits)</li></ul>

Plot A (zone B included)
Spatial analysis
<ul style="list-style-type: none"><li>• thermal prospection</li><li>• soil map</li></ul>

Data analysis :

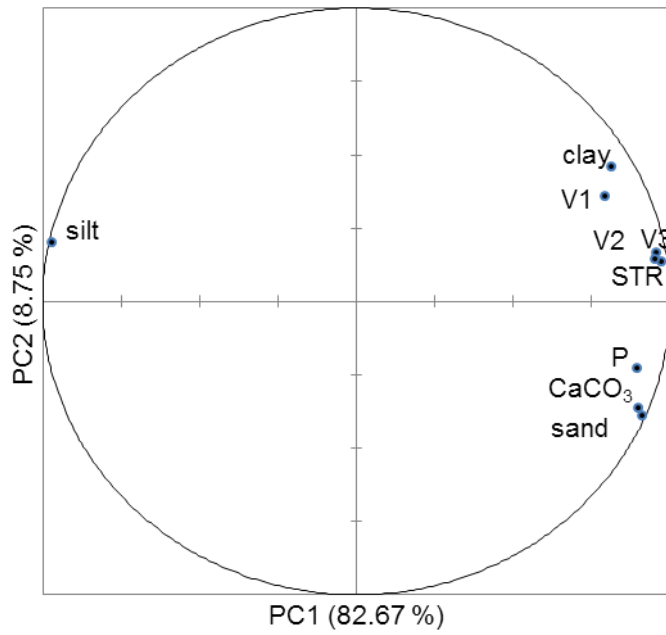


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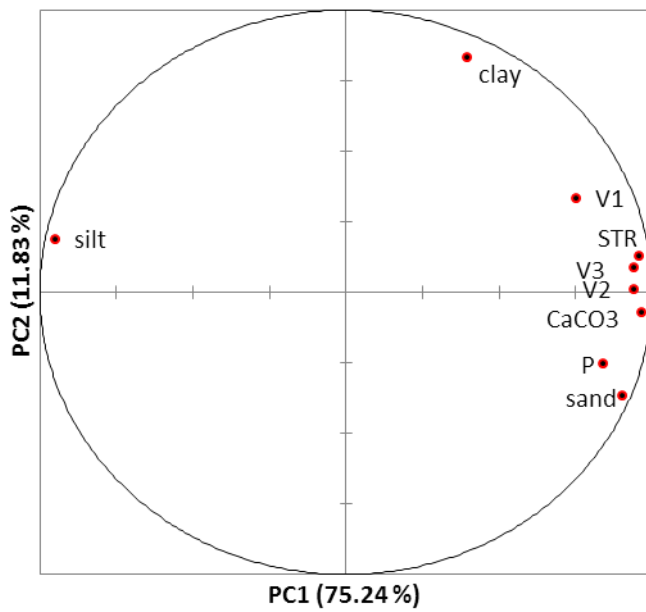
Figure 8



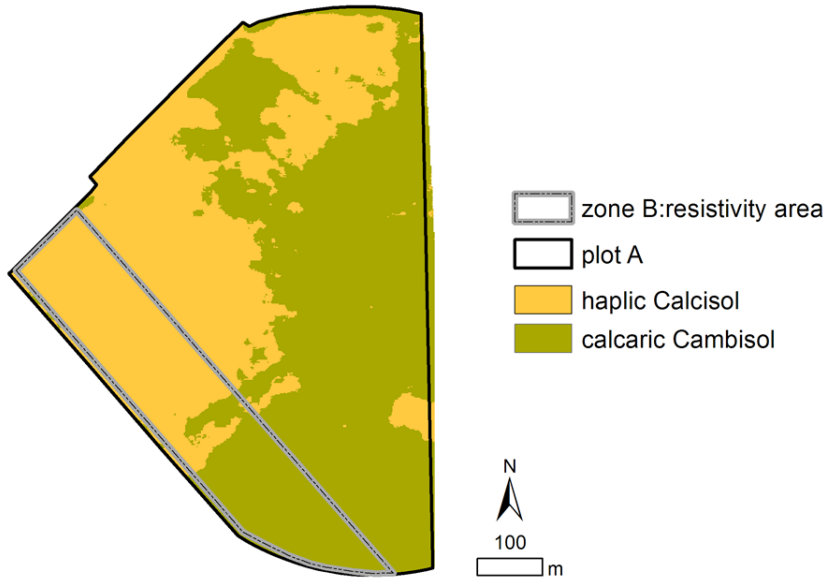
625  
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627  
628 Figure 9a  
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630  
631 Figure 9b  
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634

635 Figure 10

636

637  
638

ANOVA analysis

Source of variation	DF	Sum of squares	Mean square	F-ratio	Pr > F
Model	1	58188.011	58188.011	20.744	0.000
Error	20	56101.097	2805.055		
Total	21	114289109.000			

Modality	Estimated mean	Groups
calcaric Cambisol	1211.977	A
haplic Calcisol	1108.692	B

639

640

641 Table 1

642

ANOVA analysis

Source of variation	DF	Sum of squares	Mean square	F-ratio	Pr > F
Model	1	1743.219	1743.219	15.143	0.001
Error	20	2302.408	115.120		
Total	21	4045.627			

Modality	Estimated mean	Groups
calcaric Cambisol	48.776	A
haplic Calcisol	30.899	B

643 Table 2

644

645  
646

Category	h. Calcisol	c. Cambisol	total	% of correct classification
<i>(a) thermal inertia (P)</i>				
haplic Calcisol	11	1	12	91.7
calcaric Cambisol	2	7	9	77.8
total	13	8	21	85.7
<i>(b) subsoil interpreted resistivity</i>				
haplic Calcisol	12	0	12	100
calcaric Cambisol	4	5	9	55.6
total	16	5	21	80.9
<i>(c) apparent resistivity, V1</i>				
haplic Calcisol	10	2	12	83.33
calcaric Cambisol	4	5	9	55.56
total	14	7	21	71.43
<i>(d) apparent resistivity, V2</i>				
haplic Calcisol	10	2	12	83.33
calcaric Cambisol	2	7	9	77.78
Total	12	9	21	80.95
<i>(e) apparent resistivity, V3</i>				
haplic Calcisol	12	0	12	100
calcaric Cambisol	4	5	9	55.56
total	16	5	21	80.95

647 Table 3

648

	haplic Calcisol	calcaric Cambisol
Constant	-219.099	-259.660
P	0.394	0.429

649 Table 4

650

651

652

Category	haplic Calcisol	calcaric Cambisol	total	% of correct classification
<i>(a) zone B</i>				
haplic Calcisol	46256	5058	51314	90.1
calcaric Cambisol	2828	32893	35721	92.1
total	49084	37951	174070	90.9
<i>(b) plot A</i>				
haplic Calcisol	116246	53789	170035	68.4
calcaric Cambisol	11126	212627	223753	95.0
total	127372	266416	787576	83.5

653

654 Table 5

655

656