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► **To cite this version:**

P. Roudier, Bruno Tisseyre, H. Poilvé, J.M. Roger. A technical opportunity index adapted to zone-specific management. *Precision Agriculture*, 2010, 12 (1), p. 130 - p. 145. 10.1007/s11119-010-9160-y. hal-00602346

**HAL Id: hal-00602346**

**<https://hal.science/hal-00602346>**

Submitted on 22 Jun 2011

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## A technical opportunity index adapted to zone-specific management

Pierre Roudier<sup>\*,†,‡</sup>, Bruno Tisseyre<sup>§</sup>, Hervé Poilvé<sup>‡</sup> and Jean-Michel Roger<sup>†</sup>

**Abstract** Ten years after the introduction of zone-based management to take into account within-field phenomena in agronomic practices, several methodological developments have progressed to the operational level. However, this raises a new scientific question: how can the relevance of this type of management be evaluated? This paper adapts the concept of a technical opportunity index to zone-specific management. Based on the characteristics of machinery, zoning opportunity is introduced through a new index (*ZOI*) adapted specifically to zone-based management. This index takes into account the operational conditions in which zoning is applied, together with its associated risks. The results obtained on simulated and real field data highlight the relevance of this index.

**Keywords** Opportunity index · Management zones · Precision agriculture · Decision support tools

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## 22 **Introduction**

23 Within-field delineation of zones aims at simplifying the spatial representation of within-field  
24 variability. Its principle is to divide a field into a small number of regions. Those regions must  
25 be contiguous (a region is a set of connected points), homogeneous (intra-zone variability is  
26 low) and distinct (inter-zone variability is high). This process allows the farmer to adapt field  
27 management to allow for differences between the main zones that can exist within a field. Ten  
28 years after the introduction of this concept (McCann et al.; 1996, Stafford et al. 1998), several  
29 methods of zoning have been published (Vrindts *et al.* 2005) and are now implemented into  
30 commercially available management solutions (Roudier *et al.* 2008; Douche *et al.* 2008).

31 The availability and diffusion of such tools introduced a new technical choice for the manager.  
32 It is now possible to apply a given recommendation according to different management  
33 options: classical uniform management (reference management option) and zone-based  
34 management (alternative management option). Such a decision is case-specific, and depends  
35 on a combination of several factors: field, type of recommendation, date of recommendation,  
36 proposed treatments and machinery used to apply the treatments, etc.

37 With the development of within-field management tools comes the need to characterize the  
38 potential for a given field to be treated using zone-specific treatments. As a consequence,  
39 Whelan and McBratney (2000) proposed a method to quantify the relevance of a site-specific  
40 treatment compared to a classical uniform one taken as a reference (or null hypothesis).

41 Several criteria are taken into account and analysed:

- 42 • Economic criterion *Ec*: ability of a treatment to maximize economic profitability of the  
43 farm
- 44 • Environmental criterion *En*: quantifying environmental impacts of cropping practices
- 45 • Technical criterion *T*: ability of a treatment to maximize the agronomic performance of

46 a field

47

48 While economic and environmental criteria  $E_c$  and  $E_n$  have been discussed already in the  
49 literature (Wu *et al.* 2005; Rider *et al.* 2006; Tozer and Isbister 2007; Delgado *et al.* 2008), the  
50 technical criterion  $T$  has been studied much less (Tisseyre and McBratney 2008). Its study is  
51 an important requirement in the application of within-field management tools. A major step in  
52 the adoption of these technologies is to decide whether or not the degree of variation of a  
53 given field is important and spatially structured enough to justify the application of a site-  
54 specific treatment. The concept of technical opportunity describes the technical aptitude of a  
55 field for a site-specific treatment (Tisseyre and McBratney 2008). This aptitude depends on  
56 the within-field variability of the recommendations to be applied and of the capability of  
57 machinery used to apply it.

58

59 The concept of technical opportunity is relatively new in the literature, and few estimators of  $T$   
60 have been proposed. Two kinds of methods exist at present. The first is based on the use of  
61 geostatistical tools to compare the average area within which data are autocorrelated with the  
62 spatial footprint of the machinery (Pringle *et al.* 2003). However, the steps required to model  
63 the autocorrelation are computationally demanding and difficult to automate. Despite recent  
64 efforts to simplify this formalism (de Oliveira *et al.* 2007), estimation of the average extent of  
65 autocorrelation is not compatible with the processing of a large amount of data. The second  
66 method makes use of morphological operators to simulate the path of the machinery through  
67 the field (Tisseyre and McBratney 2008). The potential to apply a treatment site-specifically  
68 using a given machine is estimated using morphological filtering of an application map. The  
69 index obtained from this method is, however, limited to the study of two different treatments  
70 and does not take into account the magnitude of within-field variability. Neither method is

71 adequate to evaluate zone-specific management. The first method focuses on the combined  
72 study of the magnitude and spatial structure of within-field variation, but does not assess the  
73 performance of the zone-based model. The second method evaluates the technical opportunity  
74 in part only.

75

76 There is a marked absence in the literature of a method to estimate the technical opportunity in  
77 relation to the various risk factors, under operational conditions and without expert or manual  
78 intervention. This study introduces an opportunity index adapted to the specific case of zoning.  
79 The aims of this index are (i) to help the end-user to decide between a uniform treatment and  
80 its zone-specific alternative and (ii) to be implemented into an operational precision  
81 agriculture solution (i.e. matching strong industrial constraints such as automation, robustness  
82 and simplicity of analysis).

### 83 **Theory**

84 Decision support systems for precision agriculture can be represented by a wheel with four  
85 successive steps organized around a central process, i.e. spatial referencing (Fig. 1, McBratney  
86 and Taylor 2000). This study focuses on the application step. The recommended rate,  $z(x,y)$ ,  
87 with its associated uncertainty, is produced from the preconisation step. The recommended  
88 rate is adapted to be applied technically: this is the prescribed rate,  $h(x,y)$ , that goes into the  
89 applicator.

90

FIGURE 1 HERE

91

92 Quantifying the performance of a zoning model

93 The zoning opportunity index (*ZOI*) proposed in this study quantifies the relevance of  
94 applying a given zone-based treatment instead of the reference treatment. On a given field,  $P$ ,  
95 two ways to apply a given recommendation  $z$  exist:

- 96 • ( $H_0$ ): Null hypothesis. Zone-based application is rejected, and the reference treatment is  
97 applied.
- 98 • ( $H_1$ ): Alternative hypothesis. Zone-based application is accepted in preference to the  
99 reference treatment.

100 Management options  $H_0$  (reference management option) and  $H_1$  (zone-based management  
101 option) are represented by their prescribed rates,  $h_0$  and  $h_1$ , which are two different ways to  
102 model a recommendation  $z(x,y)$  on  $P$  with regard to its application. The zoning opportunity  
103 index aims to compare the performances of prescribed rates  $h_0$  and  $h_1$  on field  $P$ , where  $h_0$  is  
104 the rate that is applied if the zone-based management hypothesis is rejected. The most  
105 common example is uniform management, e.g. using the mean recommendation on the  
106 field ( $h_0(x,y) = \bar{z}$ ). The alternative treatment,  $h_1(x,y)$ , is a piecewise constant function on  $P$   
107 resulting from a given zoning method (either automated or manual, empirical or expert).

108

109

FIGURE 2 HERE

110

111 Figure 2 illustrates for a part of  $P$  the estimation and comparison of the respective  
112 performances of management options  $H_0$  and  $H_1$  for application of the recommendation  $z$ . This  
113 one-dimensional example is around a boundary,  $f$ , between two zones  $A$  and  $B$  proposed by a

114 zoning model  $h_1$  so that  $h_1(x \in A) = a$  and  $h_1(x \in B) = b$ . Reference management option  $H_0$  is a  
 115 uniform treatment over the field, and is described by a uniform rate  $h_0 = \bar{z}$ . The less the  
 116 difference there is between the recommendation ( $z$ ) and its model ( $h$ ), the better a given  
 117 management option  $H$  is. This difference corresponds to the modelling error of  $z$  by  $h$ , which  
 118 shown in Fig. 2 by the area  $I_0$  for management option  $H_0$ , and by the area  $I_1$  for management  
 119 option  $H_1$ . In practice, those areas can be estimated by the sum of the squared error (SSE)  
 120 between recommendation  $z$  and each prescribed rate  $h$ :

$$121 \quad I_0 = \sum_{x,y \in P} (h_0 - z(x,y))^2, \quad (1)$$

$$122 \quad I_1 = \sum_{x,y \in P} (h_1(x,y) - z(x,y))^2. \quad (2)$$

123

124 The  $I_0$  and  $I_1$  enable the model performance of a recommendation,  $z$ , by each treatment  $h_0$  and  
 125  $h_1$  to be estimated. To characterize a zoning model, we propose to compare its performance  
 126 with the reference treatment. To formulate an index in which the order depends on the  
 127 relevance of applying the zone-based treatment, the zoning opportunity index  $ZOI$  is computed  
 128 as:

$$129 \quad ZOI(h_1 | h_0) = 1 - \frac{I_1}{I_0}, ZOI \in ]-\infty, 1], \quad (3)$$

130 where  $h_1$  is a zone-based application model of recommendation  $z$  and  $h_0$  is the reference  
 131 treatment. The decision as to whether or not to apply the proposed zoning model can be  
 132 determined by a simple decision rule:

- 133 • If  $ZOI(h_1 | h_0) > 0, I_1 < I_0$ . The alternative hypothesis  $H_1$  is accepted.
- 134 • If  $ZOI(h_1 | h_0) \approx 0, I_1 \approx I_0$ .  $H_1$  could be accepted, but in most cases it will be rejected as it

135 does not bring significant advantages to justify setting it up.

136 • If  $ZOI(h_1 | h_0) < 0, I_1 > I_0$ . Alternative hypothesis  $H_1$  is rejected.

137

138 Integration of the zoning application risks

139 The application of a recommendation  $z$  by a prescribed rate  $h$  can be affected by errors that  
140 generate a difference between the treatment's prescribed rate  $h(x,y)$  and the rate that is actually  
141 applied *in situ*. Such errors affect the modelling of  $z$  by  $h$  and are related to the technical  
142 characteristics of the machinery. Two sources of error can be identified:

143 • Spatial errors, related to the spatial footprint of the machinery (and associated  
144 uncertainties).

145 • Discretization errors, related to the differences between prescribed rate and fixed  
146 increments in application rates that the machinery can achieve (and associated  
147 uncertainties).

148 *Risks related to the spatial footprint of the machinery*

149 The spatial footprint,  $\varepsilon$ , of the machinery represents the maximum spatial resolution of a  
150 within-field treatment (Pringle *et al.* 2003; Tisseyre and McBratney 2008). It is defined by  
151 characteristics of the machinery, i.e. the width of application ( $\beta$ ) and the distance required to  
152 alter the input control (given by the product of the cruising speed  $\nu$  and the time  $\tau$  required to  
153 alter the command, Fig. 3):

154

$$155 \quad \varepsilon = \beta \nu \tau. \quad (4)$$

156



157 The uncertainty of the positioning system ( $\delta_{geo}$ ) can also be integrated into Eq. 4:

158

$$159 \quad \varepsilon = (\beta + \delta_{geo})(v\tau + \delta_{geo}). \quad (5)$$

160

161 The spatial footprint of the machinery used to apply a zone-based treatment  $h_1$  defines a  
 162 risk of error in the application of this treatment. This risk expresses itself in the neighbourhood  
 163 of a boundary, i.e. a change in the prescribed rate. While passing from one rate,  $a$ , to another,  
 164  $b$ , the spatial footprint of the machinery represents the area below it where the actual amount  
 165 of input applied is unknown. The convolution of this spatial footprint on the zone boundaries  
 166 of treatment  $h_1(x,y)$  defines the set of points in  $P$  for which the amount of input that is actually  
 167 applied is uncertain. This set defines the risk area of treatment  $h_1$  and is known as  $r$  (Fig. 3b).

168

FIGURE 3 HERE

169 For each boundary between two management zones  $A$  and  $B$  with respective rates  $a$  and  $b$ , the  
 170 risk of applying a zone-based management model  $h_1$  expresses itself by an error in the rate that  
 171 is actually applied inside the risk area  $r$  that exists between two adjacent zones (Fig. 5). In the  
 172 example in Fig. 4, field  $P$  can be decomposed as follows:

$$173 \quad P = A + B, \quad (6)$$

$$174 \quad A = n_A + r_A, \quad (7)$$

$$175 \quad B = n_B + r_B, \quad (8)$$

$$176 \quad r = r_A + r_B, \quad (9)$$

177 where  $r_A$  and  $r_B$  are the areas of zone  $A$  and  $B$ , respectively, where a technical risk of  
 178 application exists, and  $n_A$  and  $n_B$  are the areas of zone  $A$  and  $B$ , respectively, without any

179 technical risk of application. The risk of applying zone-based model  $h_1$  is given by an  
180 uncertainty on the rate applied in  $r$ :

181 
$$h_1(x, y \in r_A) \in [a, b]. \quad (10)$$

182 
$$h_1(x, y \in r_B) \in [a, b]. \quad (11)$$

183

184 **FIGURE 4 HERE**

185

186 The formulation of this risk can be used to take into account the machinery effects in *ZOI*.  
187 There are several ways of integrating this uncertainty, for example an applicator response  
188 function to a change in rate. In this study, we decided to consider the maximum risk  
189 systematically. Thus, for the first possible error (Eq. 10), the risk area  $r_A$  is treated with the  
190 rate  $b$ , whereas it has been prescribed the rate  $a$ . A symmetrical reasoning in relation 11 allows  
191 us to formulate the two possible risks in the neighbourhood of a given boundary:

192 
$$h_1(x, y \in r_A) = b. \quad (\text{Fig. 5b}) \quad (12)$$

193 
$$h_1(x, y \in r_B) = a. \quad (\text{Fig. 5c}) \quad (13)$$

194

195 **FIGURE 5 HERE**

196

197 Consequently, it is necessary to correct the value of  $I_1$  in Eq. 2 for *ZOI*. The  $I_1$  must be

198 replaced by a corrected SSE  $I_{1c}$  that takes into account the two application errors that can  
 199 occur around a given boundary (Eqs. 12 and 13, Figs. 5b and 5c). In practice, only one of the  
 200 two errors can occur at one time. If the application error occurs in the risk area  $r_A$ , then the  
 201 application is correct in  $n_A$  ( $h_1(x, y \in n_A) = a$ ) and incorrect in  $r_A$  ( $h_1(x, y \in r_A) = b$ ). Moreover,  
 202 there is no application error in  $r_B$  as the same rate is applied to the risk area  
 203 ( $h_1(x, y \in \{r_A, r_B\}) = b$ ). As for  $n_A$ , the application is always correct in  $n_B$ , and consequently the  
 204 treatment in  $B$  is correct ( $h_1(x, y \in n_B) = b$ ).

205

$$\begin{aligned}
 206 \quad I_{1c}(A) &= \sum_P (h_1 - z)^2 \\
 207 \quad &= \sum_{n_A} (h_1 - z)^2 + \sum_{r_A} (h_1 - z)^2 + \sum_{r_B} (h_1 - z)^2 + \sum_{n_B} (h_1 - z)^2 \\
 208 \quad &= \sum_{n_A} (a - z)^2 + \sum_{r_A} (b - z)^2 + \sum_B (b - z)^2 \quad (14)
 \end{aligned}$$

209

210 A similar reasoning allows us to define  $I_{1c}(B)$ :

211

$$212 \quad I_{1c}(B) = \sum_A (a - z)^2 + \sum_{r_B} (a - z)^2 + \sum_{n_B} (b - z)^2 \quad (15)$$

213

214 As we have decided to consider the maximum risk, the less favourable case is chosen to  
 215 compute  $I_{1c}$ :

216

$$217 \quad I_{1c} = \max(I_{1c}(A), I_{1c}(B)) . \quad (16)$$

218 The zoning opportunity index then takes into account the operational conditions of the  
 219 application of the zoning (Eq. 17):

220 
$$ZOI(h_1 | h_0) = 1 - \frac{I_{1c}}{I_0} . \quad (17)$$

221

222 *Risks related to the discretization of input rates by the machinery*

223 The application constraints that can be taken into account are not limited to the spatial  
224 footprint of the machinery and uncertainties that can affect the positioning system. In addition,  
225 errors related to the discretization of the prescribed rates by the applicator can be integrated  
226 using the same formalism.

227 A discretization of the prescribed rates by the controller of the applicator is necessary for  
228 the technical implementation of a zone-based treatment  $h_1$ . Thus, errors can occur between the  
229 prescribed rates  $h_1$  and the rates that are actually handled by the controller:

- 230 • Most of the time, controllers have a discrete and finite range of rates (e.g. steps of 10  
231 units in the case of a nitrogen spreader). Thus it is necessary to adapt the prescribed rate  
232  $h_1$  so that every prescribed value can be handled by the controller.
- 233 • There are always uncertainties between the prescribed rate and the rate actually applied  
234 that are related to the accuracy of the application system.

235 Uncertainties also affect the recommendation  $z$  through the errors of predicting the crop's  
236 needs. However, the aim of this study is the integration of operational constraints during the  
237 application step in Fig. 1. Integration of the uncertainties on  $z$  are considered in the  
238 Discussion.

239

240 FIGURE 6 HERE

241 To take into account these risks there is a need to correct the prescribed rate  $h_1$  by a prescribed  
242 rate  $h'_1$  so that (i)  $h'_1$  values are in the range of the applicator and (ii) the uncertainties on the

243 applied rate are taken into account (Fig. 6). Once the prescribed rate is corrected, the  
244 computation is the same as the one described above.

245

## 246 **Material and methods**

### 247 Theoretical data

248 To characterize the behaviour of the zoning opportunity index, three theoretical fields  
249 simulated by Tisseyre and McBratney (2008) to provide values at a resolution of 1m in a 1ha  
250 field plot were tested. These fields were derived from a Gaussian distribution. The values for  
251 fields  $r_{27}$ ,  $r_{36}$  and  $r_{45}$  were simulated with variogram models with increasing ranges of  
252 spatial dependence, 27, 36 and 45 m, respectively. As a consequence, the spatial organisation  
253 of the data increases from field  $r_{27}$  to field  $r_{45}$ . The fields tested were obtained after  
254 elimination of the white noise that affected the initial simulated fields using the  
255 *GREYCstoration* algorithm (Tschumperlé 2006, Fig. 7). The aim of this was to eliminate the  
256 high frequency noise resulting from the nugget effect in the variogram models, while retaining  
257 the differences in spatial organisation of the data.

258

259 **FIGURE 7 HERE**

260

261 To test the behaviour of the zoning opportunity index in relation to the spatial structure in each  
262 of the three theoretical fields, an agronomist delineated zones based on expertise. Prescribed  
263 rates were determined using the mean value in each zone. To test the behaviour of the index  
264 when the number (and therefore the area) of the zones varies, an increasing number of zones  
265 (from 2 to 6 zones) were delineated in field  $r_{36}$  (Fig. 8a) as shown in Fig. 8b–f.

266

267

FIGURE 8 HERE

268

269 For each zoning, the *ZOI* was computed using a circular spatial footprint. The radius of the  
270 spatial footprint  $r_\epsilon$  ranged from 0 to 5 m.

271

272 Real data

273 To ensure the relevance of our approach in an operational context, nitrogen recommendation  
274 data for wheat from the Farmstar service (Douche *et al.* 2008) were also considered. Two  
275 fields on commercial farms in Northern and Central France were studied. Figure 9a-b shows  
276 the maps of recommendations, and Table 1 summarizes the characteristics of each field tested.

277

278

FIGURE 9 HERE

279

280

TABLE 1 HERE

281 A zoning of each of the agricultural fields was generated by the method proposed by Roudier  
282 *et al.* (2008): an initial segmentation step is followed by a hierarchical fusion of the zones  
283 obtained, until constraints related to the size and morphology of the zones are satisfied. The  
284 zoned maps are shown in Fig. 9c-d. To compute the *ZOI* for these fields, the spatial footprint  
285 of the machinery was modelled by a 12 m-radius disc ( $\epsilon=452.4 \text{ m}^2$ ), corresponding to the  
286 average width of a nitrogen spreader on the farms where the fields are located. We have also  
287 considered that the controller can accept only a limited set of commands, corresponding to the

288 rates that can be accepted by the fertilizer spreaders. This set of values was determined by the  
289 Farmstar agronomist as 0, 30, 40, 50, 60, 70, 80 and 100. Thus, values of the prescribed rates  
290 in each zone have been modified and given the nearest value in the spreader's range.

## 291 Implementation

292 Risk areas were determined by morphological dilation of the zone boundaries (Serra 1982).  
293 The morphological dilation is an operator whose effect is to enlarge the width of the  
294 boundaries to the detriment of the neighbouring pixels. This neighbourhood used in the  
295 dilation process is defined on the basis of the spatial footprint of the machinery used to apply  
296 inputs to the zones, i.e. a disc with a radius  $r_\varepsilon = \max(\beta + \delta_{\text{geo}}, \nu\tau + \delta_{\text{geo}})$ . The methods described  
297 in this paper were implemented in the IDL language (Research Systems, Inc. 2005), on a PC-  
298 platform.

299

## 300 Results

### 301 Characterisation of the index

#### 302 *Spatial structure of the within-field variability*

303 The first experiment aims to study the sensitivity of the proposed zoning opportunity index in  
304 relation to the characteristics of the machinery. To do so, the *ZOI* was computed for each  
305 theoretical field (Fig. 7) for a circular spatial footprint of radius  $r_\varepsilon$  varying from 0 to 10 m.

306

307

FIGURE 10 HERE

308

309 Figure 10 presents the results of these experiments graphically. Figure 10a shows the  
310 evolution of areas of risk with the change in spatial footprint of the machine. For each of the  
311 three simulated fields, the risk area increases with the size of the machine's footprint. Figure  
312 10 also shows that whatever the size of the footprint, the risk area decreases with increasing  
313 spatial structure (i.e. variogram range) of the data. Figure 10b shows the evolution of the  
314 zoning opportunity index with the size of machine's footprint, for each of the three simulated  
315 fields. Zoning opportunity is affected by the increase in the footprint because this increase  
316 implies a bigger uncertainty in the rate that is really applied by the applicator. Similarly, for a  
317 given spatial footprint, zoning opportunity increases with greater spatial structure in the data.  
318 These results are consistent with the definition of opportunity in the PA context.

319 As shown by Fig. 10a and b, the ratio of the area of risk to the total area of the field is a  
320 good indicator of zoning opportunity. However, this notion is not sufficient to assess zoning  
321 opportunity because it does not take into account the differences in the rates required on both  
322 sides of a boundary. The greater the difference between two adjacent zones, the greater is the  
323 risk of application error, which diminishes zoning opportunity.

324

325 The results of Fig. 10b allow us to estimate explicitly the opportunity for zone-based treatment  
326 according to the spatial footprint of the machinery. Zone-specific treatment for a field will be  
327 opportune if  $ZOI > 0$ . This means having a spatial footprint smaller than a limiting value,

328  $\varepsilon_{lim} = \pi \times R^2$ , where  $R$  is the radius of the machinery footprint. This value is

329  $\varepsilon_{lim} = \pi \times 4^2 \approx 50.3m^2$ ,  $\varepsilon_{lim} \approx 28.3m^2$  and  $\varepsilon_{lim} \approx 7.1m^2$  for fields  $r47$ ,  $r36$  and  $r27$ , respectively.

330 These results highlight the relevance of our approach for the theoretical fields. They show  
331 logically that the more the field is spatially structured, the more suitable it is for zone-based  
332 treatment.



333 *Number and area of zones*

334 The second experiment tests the behaviour of the zoning opportunity index when the number  
335 (and area) of management zones varies. The number and area of the zones depend both on the  
336 spatial structure of the data and on the operational constraints. They can also be affected by the  
337 zoning method that has been used. Five different zonings of theoretical field  $r36$  were  
338 generated manually by an expert (Fig. 8). The relation between the *ZOI* for each possible  
339 zoning of field  $r36$  to the size of the machine's spatial footprint is given in Fig. 11.

340

341

FIGURE 11 HERE

342

343 The results show that zoning opportunity decreases systematically when the spatial footprint  
344 of the machinery increases. The change in zoning opportunity with the number of zones also  
345 varies according to the spatial footprint of the machinery. An increase in the number of  
346 management zones improves the modelling performance of a zone-based treatment because it  
347 reduces the difference between the recommendation rates and the prescribed rates in each  
348 zone. However, this advantage can be offset by the presence of risk areas, for which there is a  
349 risk of applying an inappropriate rate. The areas at risk increase with the number of zones.

350 Therefore, when the spatial footprint of the machinery is small (from  $\varepsilon = 0 \text{ m}^2$  to  $\varepsilon = 12.57 \text{ m}^2$ ),  
351 zoning opportunity increases with the number of zones because the ratio of risk areas to total  
352 field area remains low. On the contrary, when the spatial footprint becomes more important ( $\varepsilon$   
353  $= 78.54 \text{ m}^2$ ), increasing the number of zones systematically penalizes the zoning opportunity.

354 Between those two categories ( $\varepsilon = 28.27 \text{ m}^2$  and  $\varepsilon = 50.27 \text{ m}^2$ ), an optimal number of zones  
355 exists.

356 *Application example*

357 The application of the zoning opportunity index in an operational context was tested for  
358 nitrogen recommendations on two wheat fields (Fig. 9a-b). For each field, the decision-maker  
359 must choose between an application following either a zoned or a uniform application map.

360 **FIGURE 12 HERE**

361 The zoning proposed for field Fort (Fig. 9c) results in a large *ZOI* of 0.935 in relation to the  
362 machinery constraints considered. As Fig. 12 shows, the nitrogen recommendations are  
363 significantly different for each delineated zone; as a consequence, the modelling of the  
364 recommendation by the prescribed rate is significantly better for zone-based treatment than  
365 with the uniform recommendation. Figure 9a also shows that the within-zone variation is also  
366 small. Moreover, the total length of zone boundaries is not important, which reduces the areas  
367 of risk. Therefore, zone-based treatment of nitrogen would be applied in this field. By contrast,  
368 the zoning proposed for field Mont (Fig. 9d) and for the machinery constraints considered, the  
369 *ZOI* is low ( $ZOI=0.099\approx 0$ ). The boxplot in Fig. 12 shows that the two zones proposed by the  
370 zoning model are not significantly different, and Fig. 9b shows that both have considerable  
371 within-zone variation. As a result, there is no significant advantage of applying zoned-based  
372 treatment in this field; a uniform nitrogen application would be made in field *Mont*.

373

374 **Discussion**

375 This study has aimed to apply within-field modulation tools in a commercial service. The  
376 context implies taking into account some specific constraints (e.g. computing efficiency,  
377 automation), while integrating knowledge about the operational conditions for zoning. The  
378 method that has been proposed answers those requirements, since computing of the proposed

379 index is based on operations that are simple from a computing point of view (sum of squares,  
380 morphological dilation). Computing *ZOI* takes <0.005 s on a standard desktop computer for a  
381 field of  $100 \times 100$  pixels. Moreover, the *ZOI* can be computed for any continuous variable.  
382 The only requirements are, in addition to machinery-based information, that both the  
383 recommendations and the zoned data are on a regular grid. Finally, when the spatial footprint  
384 of the machinery can be specified, computation of the *ZOI* is fully automated. Opportunity can  
385 be computed by defining a standard spatial footprint for the machinery, i.e. an area defined by  
386 the radius of influence of the machinery. If the working direction is specified, an oriented  
387 spatial footprint of the machinery can be defined.

388 The proposed *ZOI* gives a means of comparing the performance of two concurrent  
389 treatments by taking into account the technical conditions of application. The index can  
390 support the choice of a treatment for applying a given recommendation and can determine an  
391 optimal number of management zones. We think that, if the zoning is regarded as a means of  
392 simplifying the spatial representation of within-field variation, several other uses are possible,  
393 e.g. it could guide the choice of zoning method to maximize the resulting opportunity.

394 Several improvements to the methodology presented in this paper are suggested. As  
395 mentioned above, there is always an uncertainty on the recommendation  $z$  the farm manager  
396 has to apply. We propose two different approaches to integrate the uncertainty. The first uses a  
397 Bayesian approach that requires the distribution of the recommendation  $z$  to be modelled. The  
398 second approach is based on possibility theory (Zadeh 1978), which can model different  
399 sources of uncertainty using the same formalism. The approach we have proposed in this study  
400 is a first step towards an index that could be more exhaustive, for example using fuzzy  
401 formalism to define the spatial footprint of the machinery (Paoli 2009). The latter is more  
402 flexible than our Boolean representation of the risk areas and closer to technical reality.

403 Finally, it would also be of interest to consider the notion of zoning opportunity beyond its

404 technical component by integrating environmental and economic risks of a treatment through  
405 cost functions. However, this raises the question of the aggregation of different types of data,  
406 which might be possible with methods based on fuzzy logic.

## 407 **Conclusion**

408 Computation of the opportunity of a given zoning takes into account the technical  
409 characteristics of the machinery that is used to apply the recommendations zone-specifically,  
410 and estimates the relevance of its application by modelling the effects of several risks  
411 (positioning errors, errors in the rates that are actually applied). Experiments enabled us to  
412 highlight the main characteristics of the zoning opportunity index proposed in this paper as  
413 follows:

- 414 • it can be computed whatever zoning operator has been used (automated or manual,  
415 empirical or expert),
- 416 • it integrates the technical risks of zone-specific applications by determining the risks  
417 related to uncertainties in the rates applied and through the notion of spatial footprint of  
418 the machinery,
- 419 • it depends on the number of zones proposed by the zoning method.

420 The proposed method addresses the different requirements of use within the framework of a  
421 commercial PA service (computing efficiency, automation, robustness).

422

423 Finally, a major aim of this study was to propose a method that can integrate the technical  
424 conditions of applications by zone. The method enables the integration of different kinds of  
425 expert knowledge:

426 **Knowledge on data:** The expert can give knowledge on the zoned data (range of rates  
427 specific to a particular machine, uncertainty on the applied rates) to correct the rate

428 value for each zone.

429 **Knowledge on operational constraints:** The definition and use of the spatial footprint of  
430 the machinery used to apply the recommendations zone-specifically enables the real  
431 risks of application by a given zoning to be determined.

432 **Knowledge and automation:** Finally, the methods make it possible to integrate detailed  
433 information on operational zoning constraints, without making concessions on  
434 automation.

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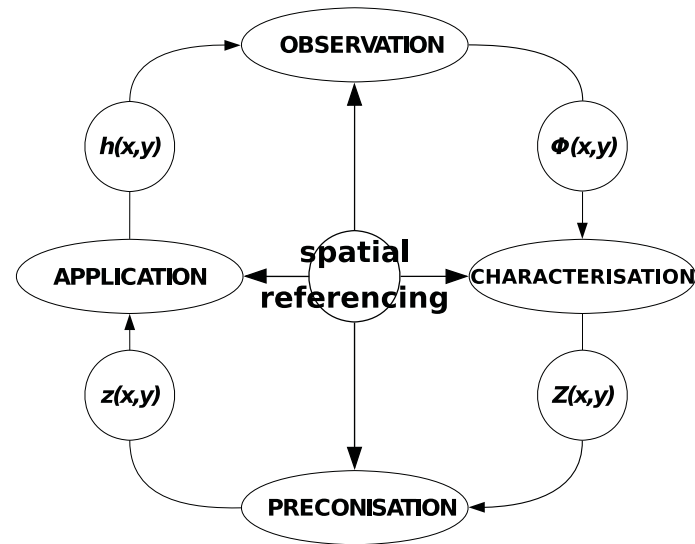
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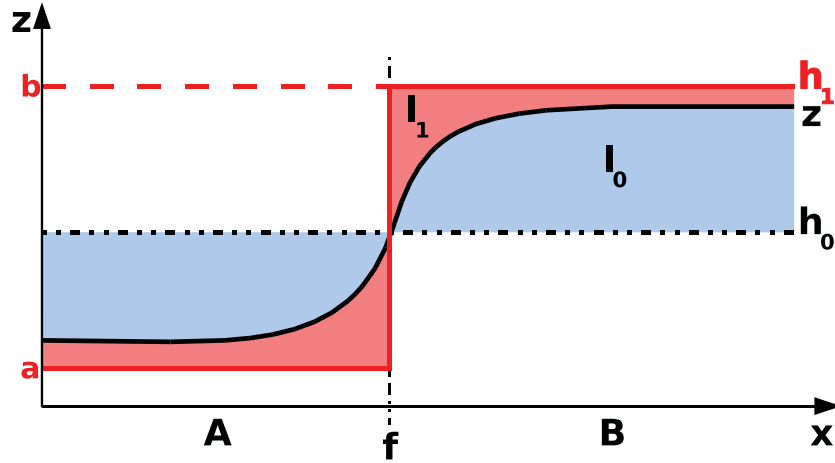


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491 **Fig. 1.** The 'PA wheel' representation of decision support systems for precision agriculture  
492 (after McBratney and Taylor, 2000), where  $\Phi$  is the physical quantity recorded by the sensor  
493 (*observation*),  $Z$  is a variable describing the characteristics of the observed crop and or soil  
494 (*characterization*),  $z$  is the recommendation proposed by the decision support system given  $Z$   
495 (*recommendation*) and  $h$  is the way recommendation  $z$  is applied on the field (*application*).



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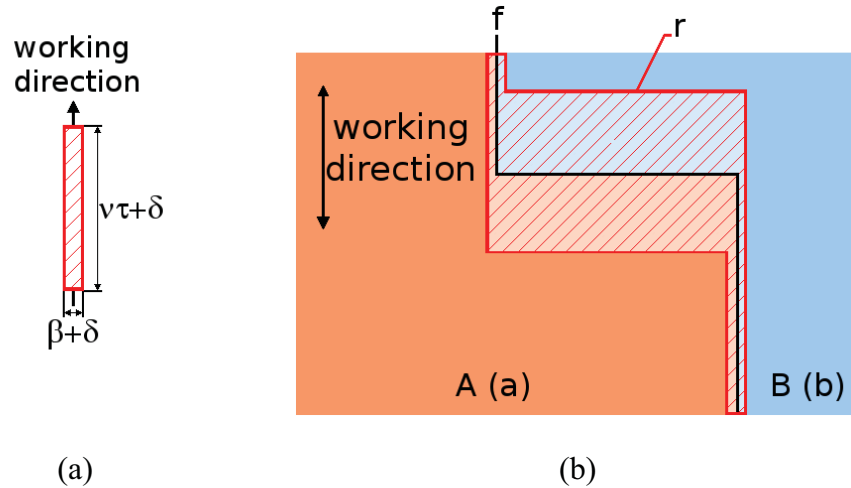
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**Fig. 2.** One-dimensional illustration of the situation around a boundary,  $f$ , between two zones  $A$  and  $B$ . Two treatments  $h_0$  and  $h_1$  can be considered to apply a recommendation  $z$ . In this example  $h_0$  is a uniform treatment, whereas  $h_1$  is a zone-based treatment with prescribed rates  $a$  and  $b$  for zone  $A$  and  $B$ , respectively. The relative performance of those treatments for modelling recommendation  $z$  is estimated by comparing areas  $I_0$  and  $I_1$ .

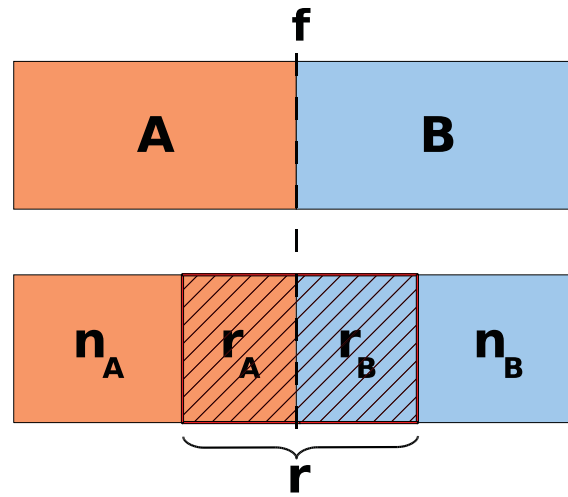


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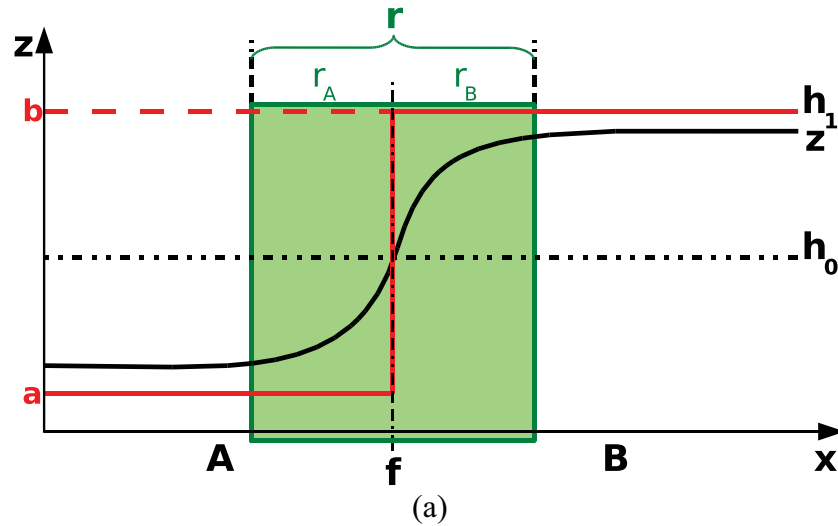
506 **Fig. 3.** Spatial footprint of the machinery and area of risk on a field plot  $P$ : (a) spatial  
507 footprint of the machinery and (b) risk area  $r$  corresponding to the convolution of the spatial  
508 footprint (a) on the boundary  $f$  between zones  $A$  and  $B$ , according to a working direction given  
509 by the black arrow.

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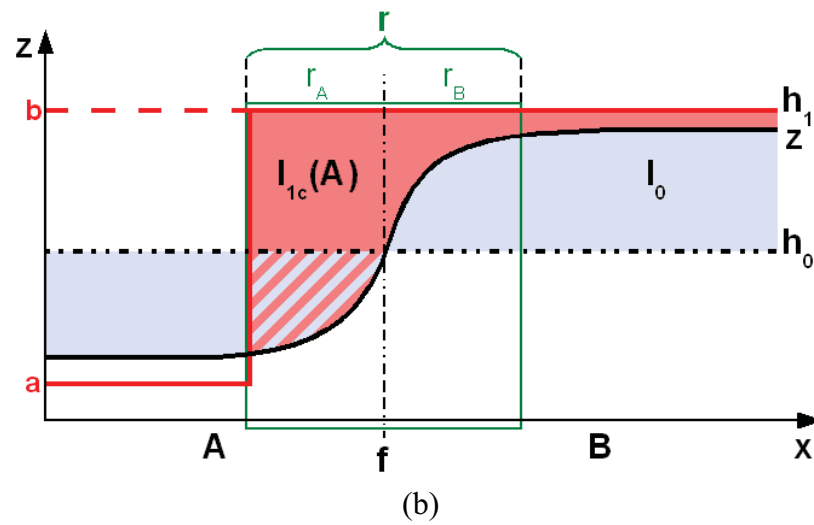


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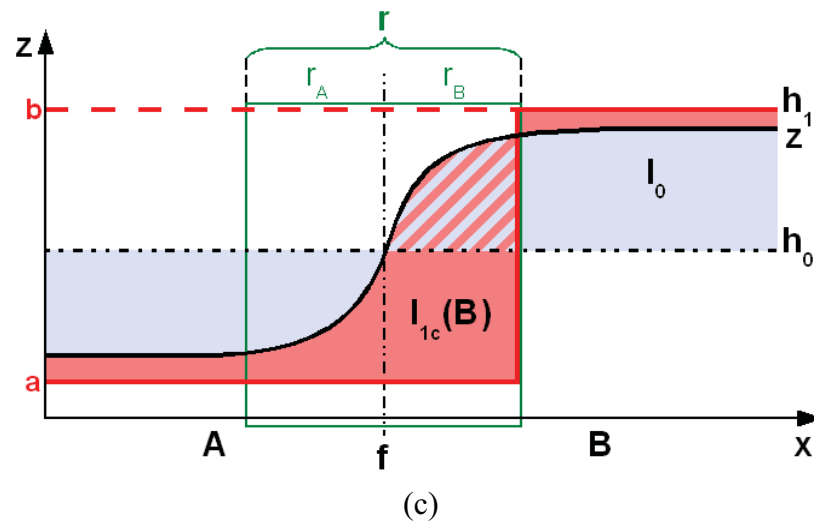
513 **Fig. 4.** Decomposition of a field according to the existence of a risk of application error ( $r_A$   
514 and  $r_B$ ) or not ( $n_A$  and  $n_B$ ).



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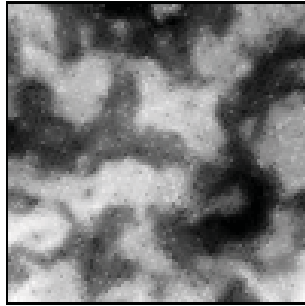


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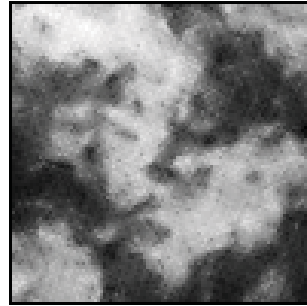
**Fig. 5.** Consideration of the errors related to the footprint of the machinery when computing the technical risk of application by zones in the neighbourhood of a boundary  $f$ : (a) risk area  $r$  is a transition zone between two different management zones (two errors are possible within  $r$ ), (b) the control applies the rate  $b$  in  $r_A$  or (c) the control applies the rate  $a$  in  $r_B$ . The SSE of the zone-based model ( $I_1$ ) must be corrected by  $I_{1c}(A)$  or  $I_{1c}(B)$  that take those risks into



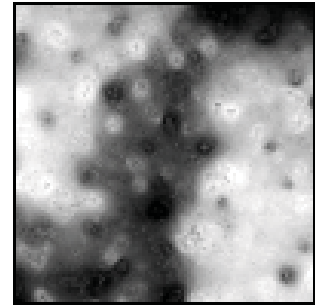
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(a) Field  $r_{27}$



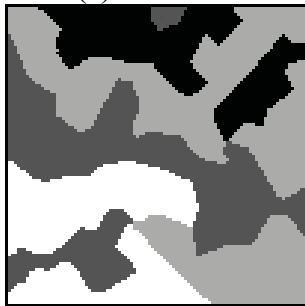
(b) Field  $r_{36}$



(c) Field  $r_{45}$

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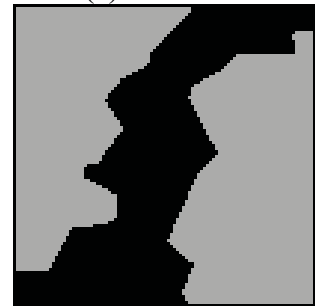
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(d) Expert zoning of field  $r_{27}$



(e) Expert zoning of field  $r_{36}$



(f) Expert zoning of field  $r_{45}$

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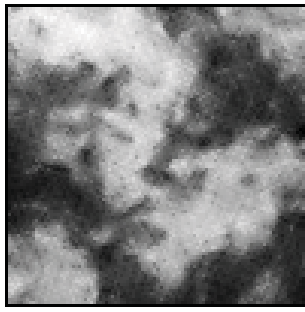
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**Fig. 7.** Study of the relations between zoning opportunity and spatial organization of the within-field variation. (a-c) Theoretical fields showing increasing spatial organisation and (d-f) corresponding zoning models.

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(a) Field *r36*



(b) 2 zones



(c) 3 zones



(d) 4 zones



(e) 5 zones

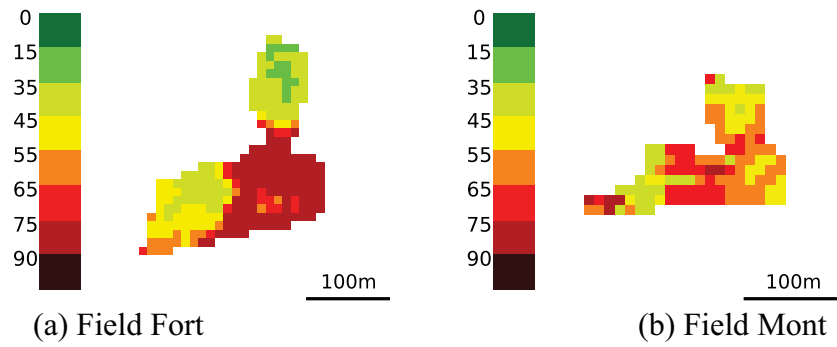


(f) 6 zones

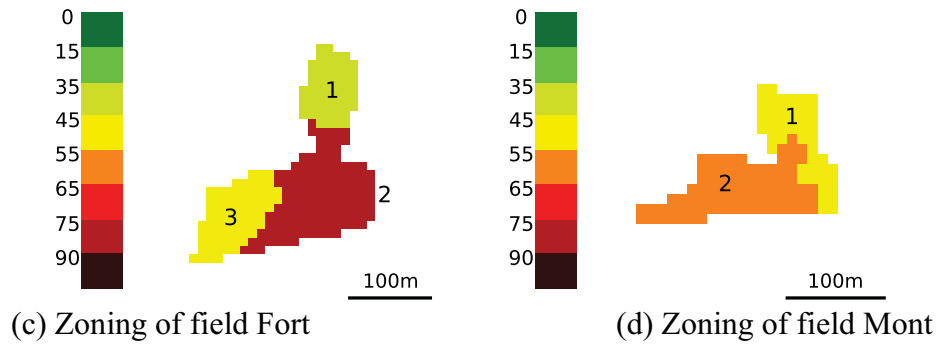
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**Fig. 8.** Zoning of field *r36* with an increasing number of zones.

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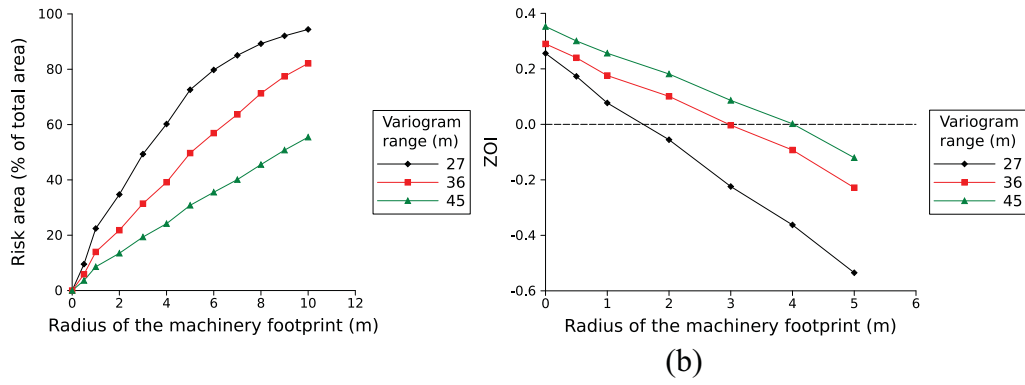


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**Fig. 9** Use of the zoning opportunity index to estimate the relevance of zone-specific applications: (a, b) nitrogen recommendation for wheat in fields Fort and Mont and (c, d) corresponding zonings.

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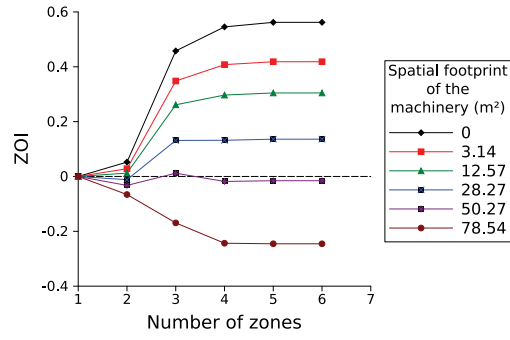


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592 (a)

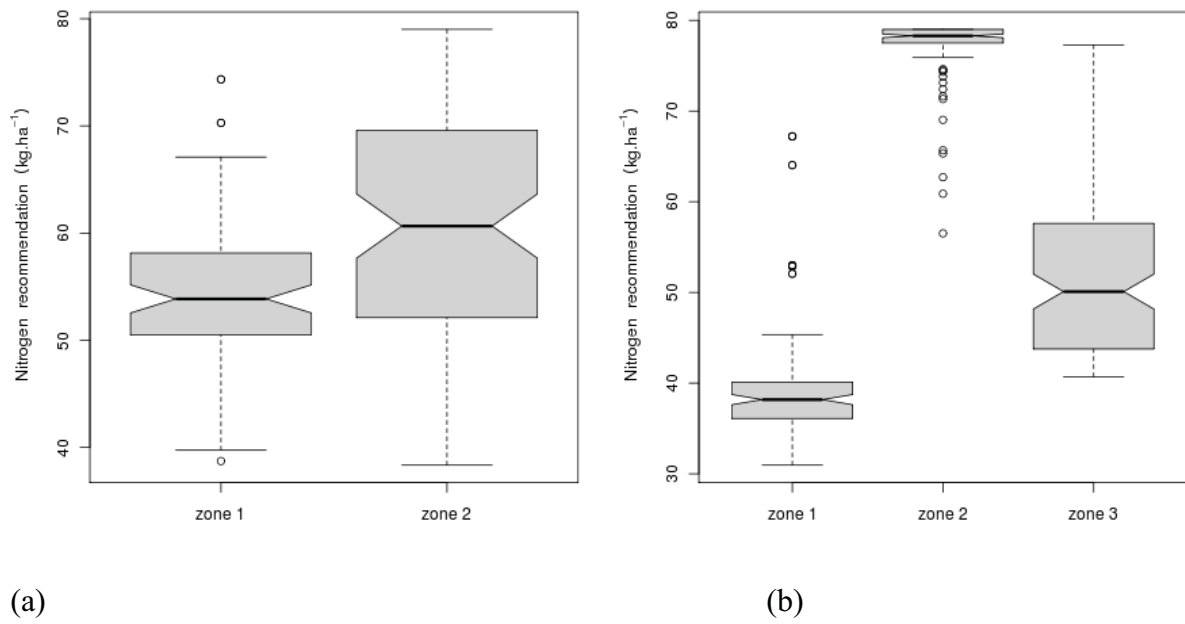
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594 **Fig. 10.** Effect of spatial structure of within-field variation on zoning opportunity: (a) Area of  
595 risk related to the spatial structure of within-field variation and the machine's spatial footprint  
596 and (b) zoning opportunity index (ZOI) in relation to the spatial structure of within-field  
597 variation and the machine's spatial footprint.



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**Fig. 11.** Relationship between the zoning opportunity index (*ZOI*), the number of zones and spatial footprint of the machinery ( $\epsilon$ ) on field *r36*.



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(a)

(b)

**Fig. 12.** Nitrogen recommendation in each zone for fields (a) Mont and (b) Fort.

606 Table 1: Details of the fields studied. The area of the zone, and the means and variances of the  
 607 nitrogen recommendations are shown for each delineated zone. The mean recommendation  
 608 can be compared to the rate that is entered to the spreader controller.  
 609

Field			Nitrogen rate (kg.ha <sup>-1</sup> )				Zones				
Name	Area (ha)	Variety	Min.	Max.	Mean	SD.	Id	Area (ha)	Nitrogen rate (kg.ha <sup>-1</sup> )		
									Mean	Rate	SD.
Fort	10.19	Hysun	26.18	79	60.60	17.44	1	2.20	39.55	40	6.89
							2	5.16	56.51	60	3.53
							3	2.84	52.17	50	9.82
Mont	5.29	Sankara	38.35	79	56.48	12.70	1	3.40	60.34	60	11.82
							2	1.92	53.44	50	7.46