



A technical opportunity index adapted to zone-specific management

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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, ε , 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 (β) and the distance required to
152 alter the input control (given by the product of the cruising speed ν and the time τ 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 (δ_{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_ϵ 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_ε 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 (ε
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 100×100 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.

435 **References**

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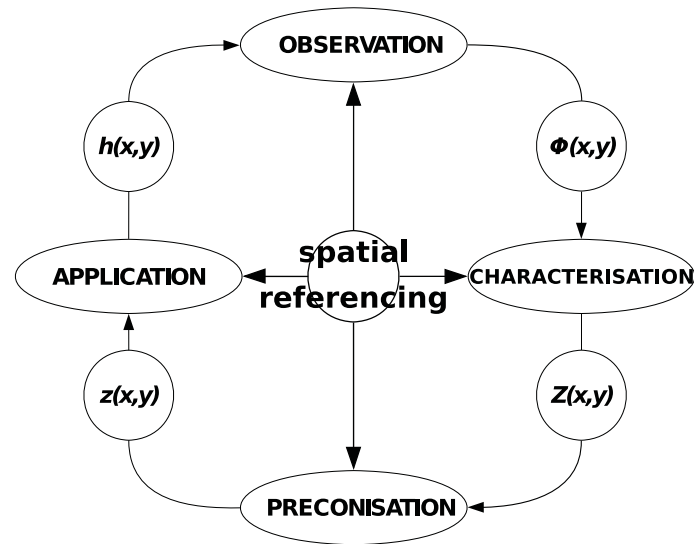
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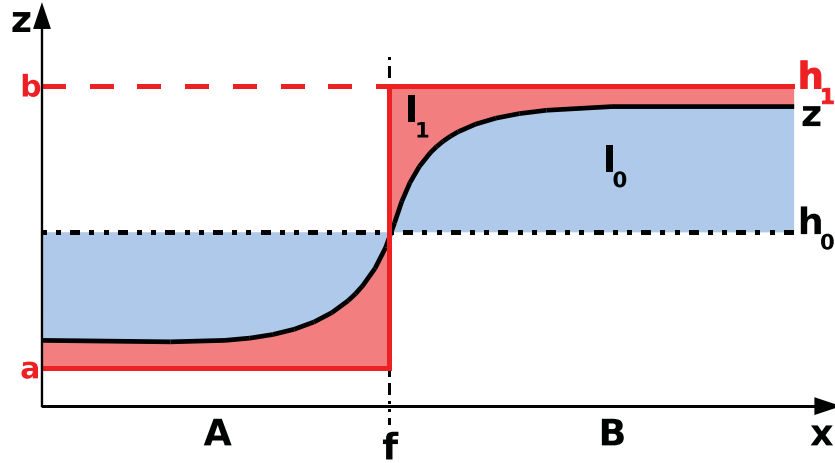
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491 **Fig. 1.** The 'PA wheel' representation of decision support systems for precision agriculture
492 (after McBratney and Taylor, 2000), where Φ is the physical quantity recorded by the sensor
493 (*observation*), Z is a variable describing the 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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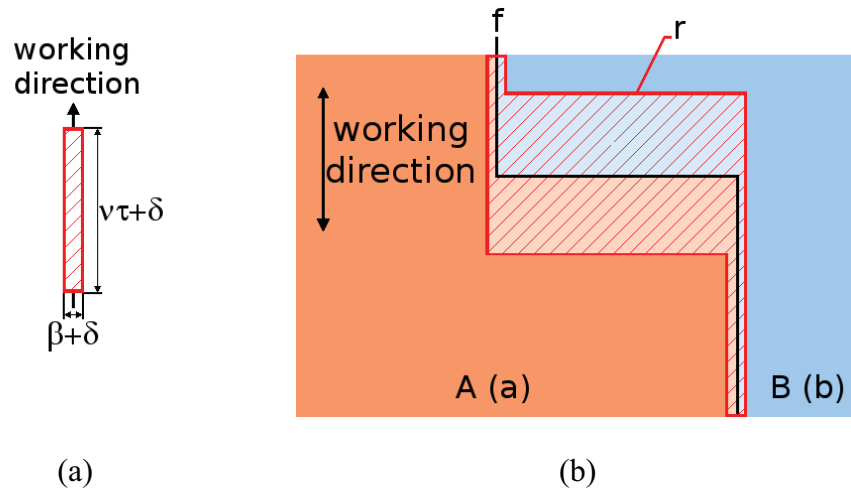
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Fig. 2. One-dimensional illustration of the situation around a boundary, f , between two zones A and B . Two treatments h_0 and h_1 can be considered to apply a recommendation z . In this example h_0 is a uniform treatment, whereas h_1 is a zone-based 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 .

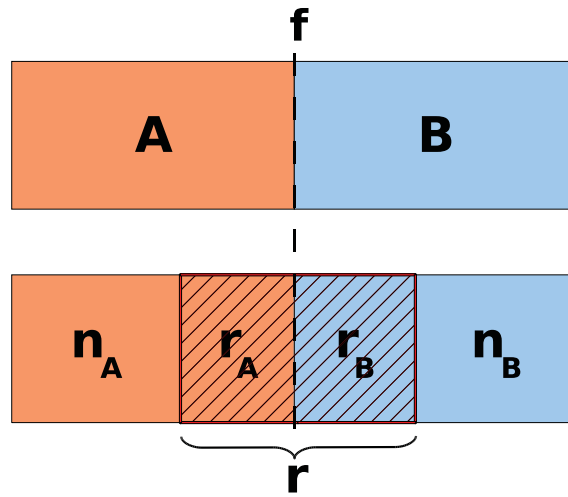


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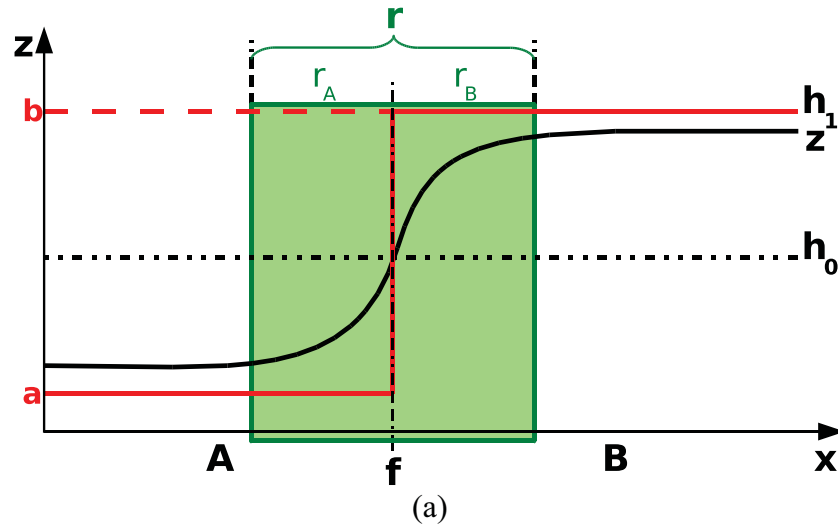
506 **Fig. 3.** Spatial footprint of the machinery and area of risk on a field plot P : (a) spatial
507 footprint of the machinery and (b) risk area r corresponding to the convolution of the spatial
508 footprint (a) on the boundary f between zones A and B , according to a working direction given
509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

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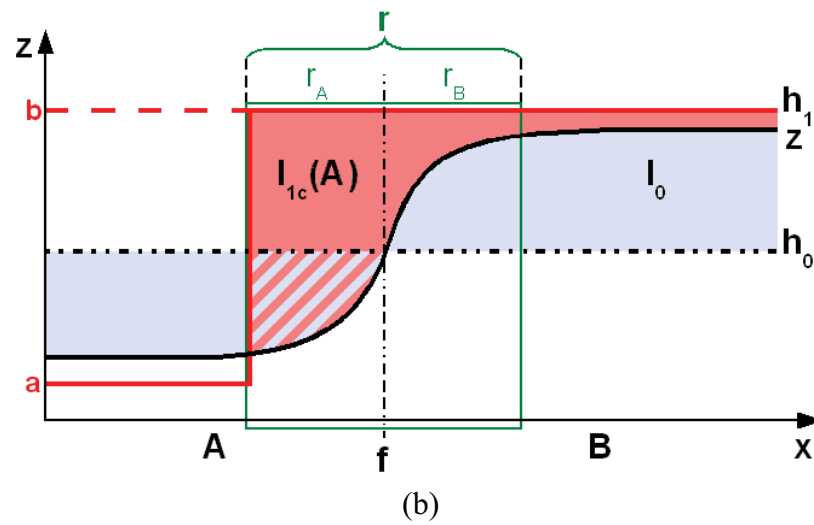


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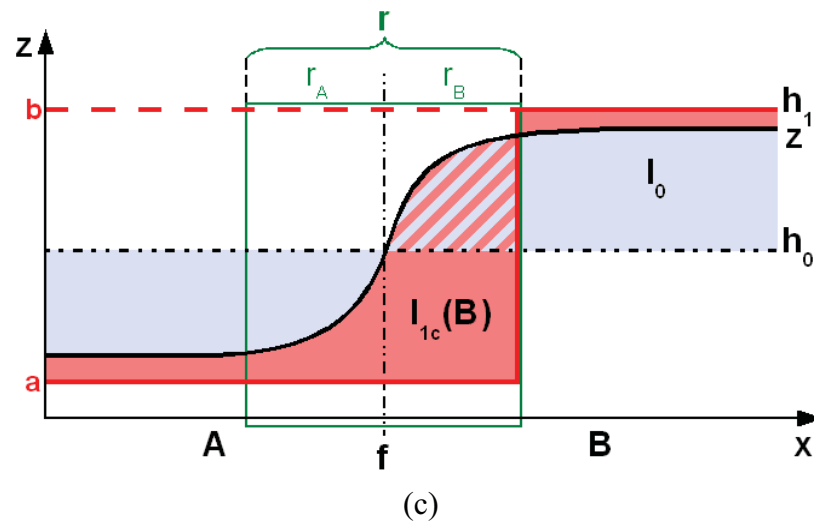
513 **Fig. 4.** Decomposition of a field according to the existence of a risk of application error (r_A
514 and r_B) or not (n_A and n_B).



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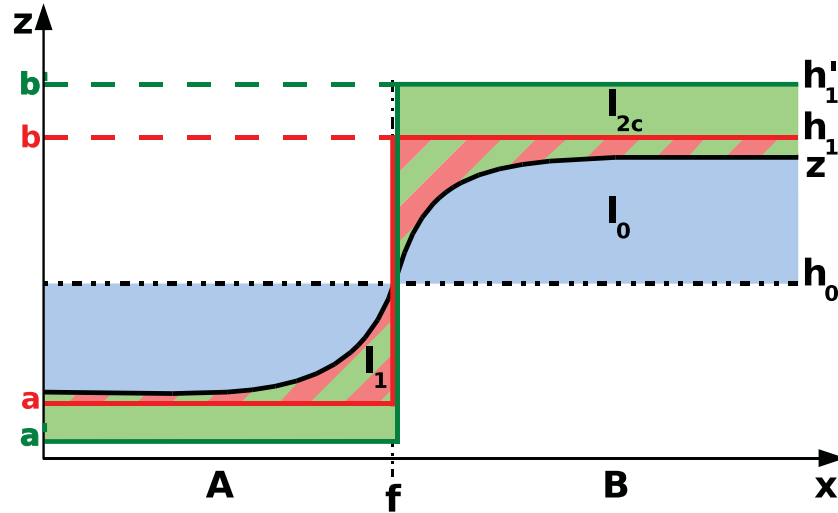


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521 **Fig. 5.** Consideration of the errors related to the footprint of the machinery when computing
 522 the technical risk of application by zones in the neighbourhood of a boundary f : (a) risk area r
 523 is a transition zone between two different management zones (two errors are possible within
 524 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
 525 the zone-based model (I_1) must be corrected by $I_{1c}(A)$ or $I_{1c}(B)$ that take those risks into

526 account.

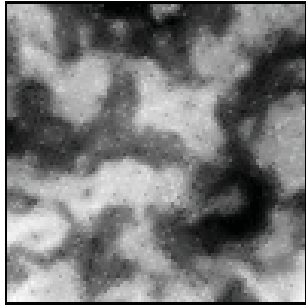
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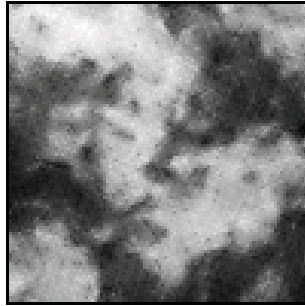
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Fig. 6. Implementation of the errors related to discretization of the prescribed rates by the applicator in computing the technical risk of application of zone-based treatment around a boundary f . In this example, h_1 is the prescribed rate, whereas h'_1 is the rate actually applied. The controller applies the rate $a' \neq a$ in zone A and the rate $b' \neq b$ in zone B . The SSE of the zone-based treatment (I_1) must be corrected by the SSE I_{2c} , which takes into account the discretization effect.

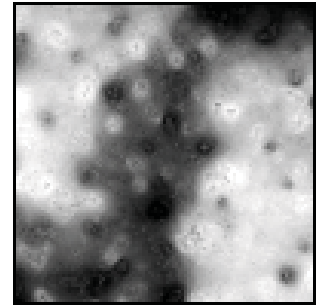
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(a) Field r_{27}



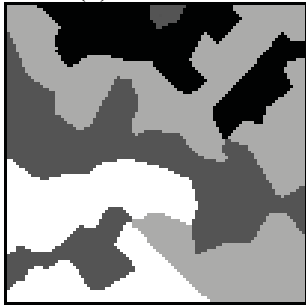
(b) Field r_{36}



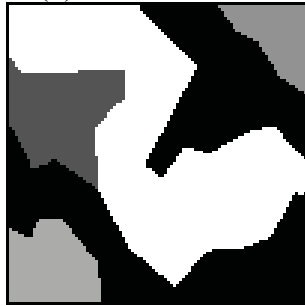
(c) Field r_{45}

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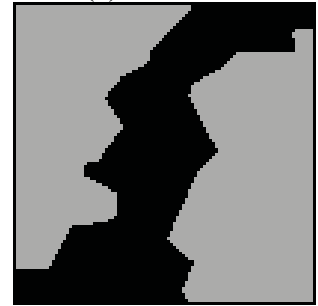
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(d) Expert zoning of field r_{27}



(e) Expert zoning of field r_{36}



(f) Expert zoning of field r_{45}

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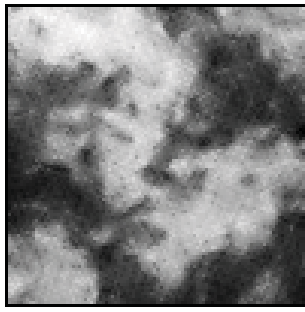
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Fig. 7. Study of the relations between zoning opportunity and spatial organization of the within-field variation. (a-c) Theoretical fields showing increasing spatial organisation and (d-f) corresponding zoning models.

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(a) Field *r36*



(b) 2 zones



(c) 3 zones



(d) 4 zones



(e) 5 zones

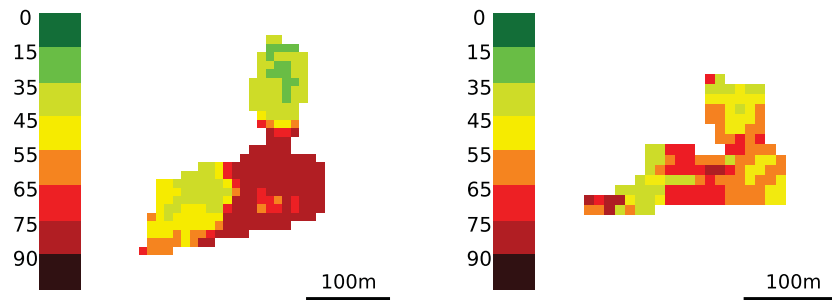


(f) 6 zones

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

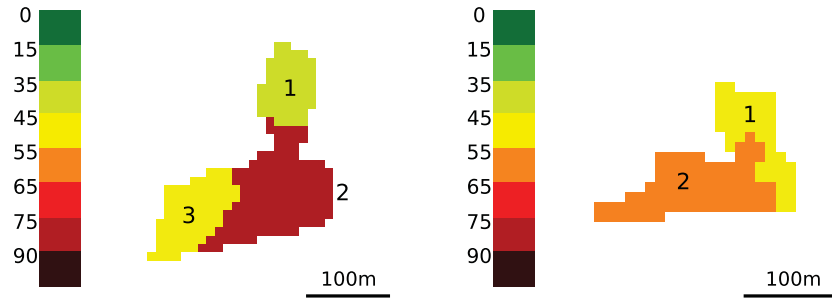
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(a) Field Fort

(b) Field Mont



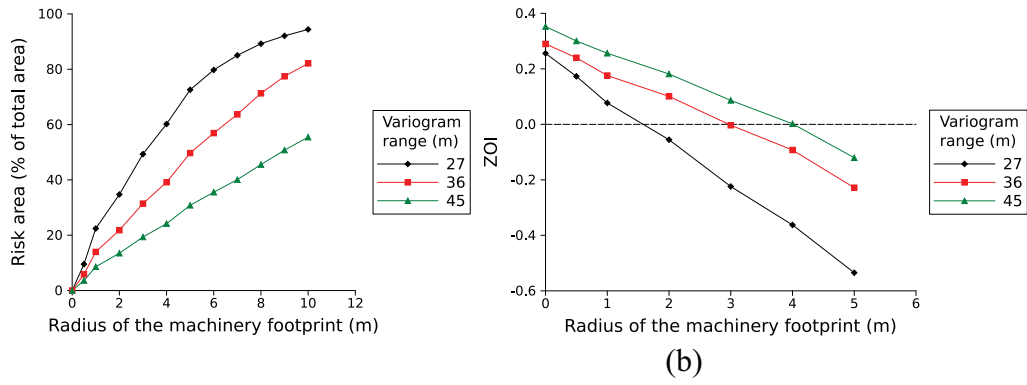
(c) Zoning of field Fort

(d) Zoning of field Mont

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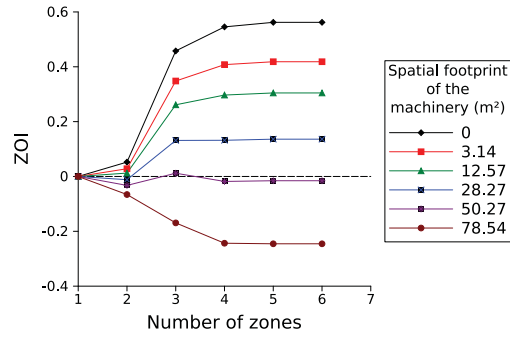
Fig. 9 Use of the zoning opportunity index to estimate the relevance of zone-specific applications: (a, b) nitrogen recommendation for wheat in fields Fort and Mont and (c, d) corresponding zonings.

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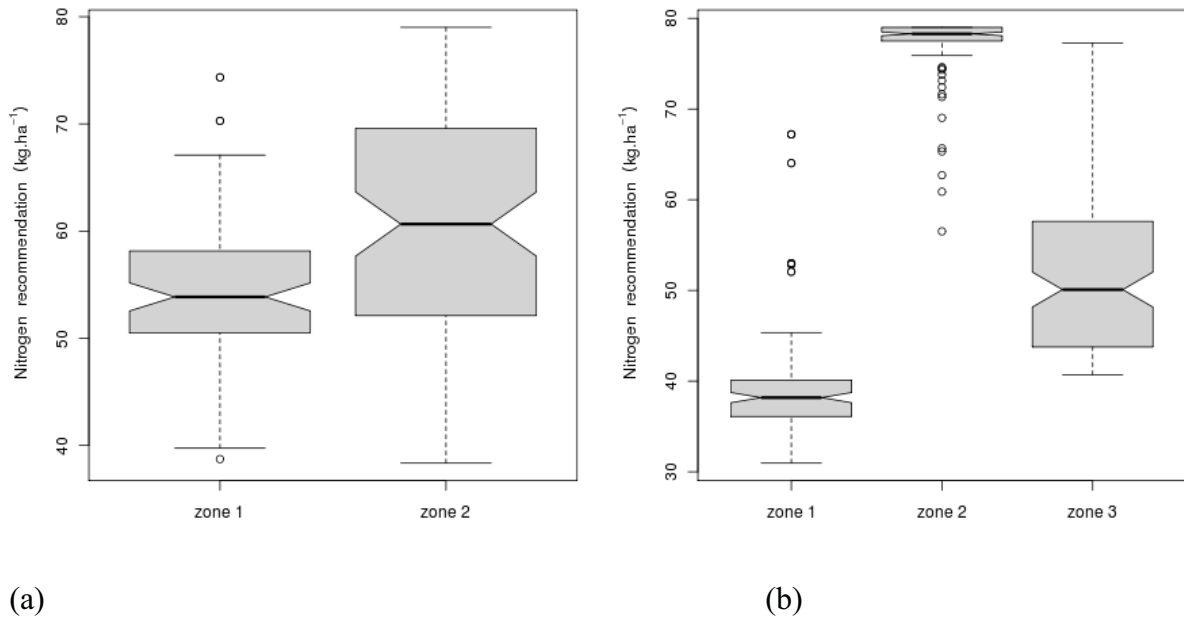
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(a) **Fig. 10.** Effect of spatial structure of within-field variation on zoning opportunity: (a) Area of risk related to the spatial structure of within-field variation and the machine's spatial footprint and (b) zoning opportunity index (ZOI) in relation to the spatial structure of within-field 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 (ϵ) 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 ⁻¹) | | | | Zones | | | | |
|-------|-----------|---------|--------------------------------------|------|-------|-------|-------|-----------|--------------------------------------|------|-------|
| Name | Area (ha) | Variety | Min. | Max. | Mean | SD. | Id | Area (ha) | Nitrogen rate (kg.ha ⁻¹) | | |
| | | | | | | | | | 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 |