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A technical opportunity index based on the fuzzy footprint of a machine for site-specific management: an application to viticulture

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Abstract This paper describes a method that allows farmers to (i) decide whether or not the spatial variation of a field allows a reliable variable-rate application, (ii) discover if a particular threshold (field segmentation) based on within-field data is technically feasible according to the application machinery and (iii) make an appropriate application map. Our method aims to improve on a previous technical opportunity index (Oi) with a fuzzy technical opportunity index (FTOi). The FTOi considers (i) a fuzzy footprint model of a variable-rate application controller (VRAC), which describes the area within which the VRAC can operate reliably, (ii) the location inaccuracy of the data and (iii) the ability (accuracy) of the VRAC to perform distinct levels of treatments. The originality of our approach is based on the use of a fuzzy estimation process to decide if a level of treatment is reliable or not for each area over which the VRAC operates. A unique feature of the approach is that it does not require data on a regular grid. Only characteristics of the machinery and the treatment to be applied are necessary; interpolation of the data and geostatistics are not required by the end user. Tests on theoretical fields, obtained from a simulated annealing procedure, showed that the FTOi was able to assess the technical manageability of variation in the field. Tests also showed that our approach could take into account problems related to low resolution data. Finally, the approach has been applied to a real situation in a vineyard block. This has highlighted the practical implementation and

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the ability to generate useful information for managing the within-field variation (optimal thresholding, and application and error maps).

Keywords Site-specific management (SSM) · Opportunity index (Oi) · Viticulture · Fuzzy logic · Possibility theory

Introduction

The problem of deciding whether or not the spatial variation of a field allows for reliable variable-rate application (VRA) is of critical importance for farmers that use this technology. Another critical issue is to establish if there is a particular threshold value in the field data (field segmentation) that enables minimization of the error of site-specific application. Therefore, decision-support tools need to be able to indicate to farmers whether it is feasible and useful to manage the spatial variation of a particular field. Two original approaches have been proposed to solve this problem. The first one was defined by Pringle et al. (2003). They suggested that a relevant opportunity index (Oi) has to take into account both the magnitude in variation of yield and the spatial arrangement of this variation. These considerations lead to the definition of a site-specific management (SSM) opportunity index, which was shown to be reasonably successful in ranking the fields from the most to the least suitable for SSM. Modifications of this Oi were proposed by de Olivera et al. (2007), but the principles underlying this index remained the same. The main difficulty in using the Oi is that (i) it relies on a step that requires skill to fit variograms to the data, (ii) this may be incompatible with the analysis of a large database and (iii) it does not provide application maps to show how to manage the within-field variation. To deal with these drawbacks, a second approach was proposed by Tisseyre and McBratney (2008). The originality of this latter approach was to process yield data (or other within-field of sources information) with a mathematical morphology filter. This filter allows the user to take into account how the variable-rate controller operates in the field and especially the minimum area within which it can operate reliably (the kernel). Knowing this minimum area, the TOi is based on the calculation of (i) the proportion of the field that can be managed specifically and (ii) the error involved. In spite of its relevance, the TOi still has significant drawbacks: (i) it requires data on a regular grid and interpolation by a method such as kriging and (ii) the filter takes no account of the inaccuracy of the data on which the decision is based. The fuzzy technical opportunity index (FTOi) that we propose in this paper should solve these two problems. It should also provide a practical decision-support system to help the farmer to manage within-field variation. In the first part of this paper we describe our FTOi. In the second part, we present and discuss the results obtained on hypothetical fields with known variation to check the relevance of our approach. Finally, we apply the FTOi to a case study in precision viticulture.

Theory

Fuzzy definition of two management strategies *A* and *B*

Site-specific management leads to at least two different management strategies (or two application rates) *A* and *B* for the same field. The proposed approach is general enough to

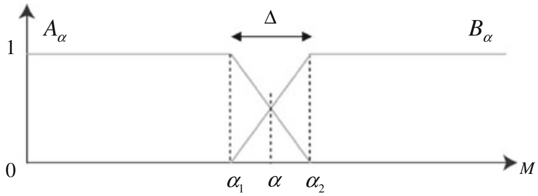


Fig. 1 Fuzzy definition of two management strategies A_α and B_α for a threshold α on the values of a field variable (M) and the inaccuracy Δ of the variable-rate application controller

consider more than two management strategies, however, for simplicity two management strategies only will be considered here.

Let M be the variable measured at the within-field level. The opportunity of each strategy has to be defined for all the values of M. Usually, a threshold, $\alpha \in M$, is chosen to separate the within-field data into two classes corresponding to strategies A and B. The choice of this threshold is somewhat arbitrary, however, mainly because of the inaccuracy of the VRAC.

To take account of the inaccuracy of the VRAC, we define fuzzy management strategies A_α and B_α (Fig. 1). This leads to two thresholds: α_1 below which treatment B can be excluded and α_2 above which treatment A can be excluded. These thresholds can be computed from the threshold, α, and from the inaccuracy of the VRAC, Δ, as defined in Eq. 1

$$\begin{aligned} \alpha_1 &= \alpha - \frac{\Delta}{2}, \\ \alpha_2 &= \alpha + \frac{\Delta}{2}. \end{aligned} \tag{1}$$

Note that Δ enables the inaccuracy between the settings of the VRAC (level of desired input) and the actual application over the field to be taken into account. This reasoning assumes that the expected response of a plant to the planned strategy (level of input) is fully known. The imprecision associated with the response of the plant (and the underlying agronomic model) is not taken into account in our approach.

The A_α and B_α are the fuzzy parts of M, which are defined by the following membership functions, Eq. 2

$$\begin{aligned} &\mu_{A_\alpha} : M \to [0,1], \\ &\mu_{B_\alpha} : M \to [0,1], \\ &\forall m \in M, \mu_{A_\alpha}(m) + \mu_{B_\alpha}(m) = 1. \end{aligned} \tag{2}$$

These are trapezoidal functions that are defined by two thresholds and a linear transition from 0 to 1. Shapes of fuzzy sets membership functions are usually simple, and trapezoidal ones are used extensively (Dubois and Prade 1988).

Fuzzy footprint of the VRAC (K)

The footprint is the minimum area within which VRA is technically possible. It is a function of the dimensions of the machine and of the time required to adjust the application rate. Some definitions have been proposed by Pringle et al. (2003) and Tisseyre et al. (2008). We attempt to improve these definitions to take into account (i) the inaccuracy of the positioning system used to locate the vehicle within the field and (ii) the inaccuracy arising from the action of the machine. This leads to a fuzzy definition of the machine's footprint, K.

Let G be the geographical reference associated with the positioning system of the VRAC, and K is a fuzzy subset of G defined by the membership function Eq. 3

$$\mu_K : G \rightarrow [0; 1]. \tag{3}$$

The shape of K is shown in Fig. 2. It can be seen as an extension of the trapezoidal functions, usually used for one-dimensional fuzzy subsets, to two-dimensional fuzzy subsets. It is defined according to (i) v the speed of the vehicle (in m s^{-1}), (ii) τ the time required to alter the application rate (in s), (iii) d the inaccuracy of the positioning system (in m) and (iv) β the width of the machine.

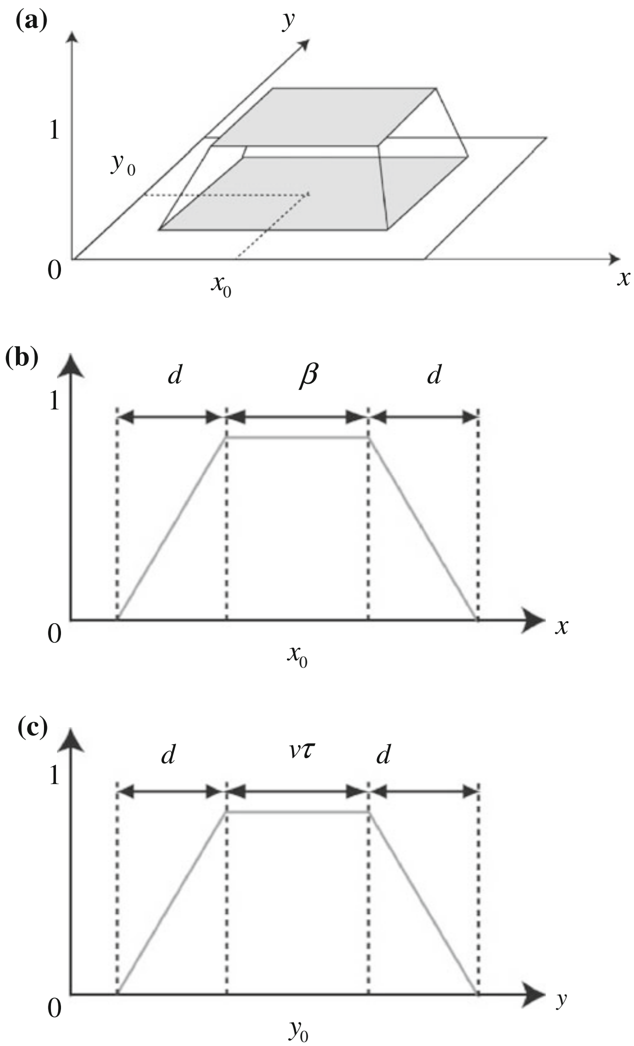


Fig. 2 **a** Shape of the fuzzy footprint K at the geographical location G, **b** length definition of the fuzzy footprint and **c** width definition of the fuzzy footprint

Opportunity of each strategy (A_α or B_α) for a fuzzy footprint K

We aim to determine the opportunity of each strategy, A_α or B_α, for a fuzzy footprint, K, using all the measurements available. The membership degree of each measurement, m, in each fuzzy part of M can be interpreted as a degree of confidence (Dubois and Prade 1988).

These degrees of confidence are denoted $\Pi(A_\alpha, m)$ and $\Pi(B_\alpha, m)$. They are called the possibilities of A_α and B_α restricted to m. They can be associated with the location (x_m, y_m) of the measurement m, defining an information element (denoted I). The definition of I is provided by Eq. 4

$$\begin{aligned} &I = ((x_m, y_m);\ \Pi(A_\alpha, m);\ \Pi(B_\alpha, m)),\\ &\Pi(A_\alpha, m) = \mu_{A_\alpha}(m),\\ &\Pi(B_\alpha, m) = \mu_{B_\alpha}(m),\\ &(x_m, y_m) \in G^2,\\ &m \in M. \end{aligned} \tag{4}$$

The combination of information elements, $I_i, i \in [1, n]$, leads to an estimate of the possibilities of A_α and B_α restricted to K (the footprint), denoted $\hat{\Pi}(A_\alpha, K)$ and $\hat{\Pi}(B_\alpha, K)$, respectively.

Paoli et al (2007) defined a method to perform this combination that aims to provide an assessment of fuzzy regions (such as fuzzy footprints):

1. Select the relevant information elements according to their locations. The weight of each I_i is computed from the geographical intersections between the information elements and the footprint.
2. Compute degrees of possibility from the values provided by the data and aggregate them to assess the fuzzy region. This aggregation is performed by a percentile like operator based on a Choquet integral. Equations of the process and a detailed description of the operator are given in Paoli et al. (2007).

Compared to usual fuzzy aggregation processes, in this approach (i) the outliers are filtered, (ii) the information elements do not have the same weight in the aggregation process over K and (iii) the estimated values, $\hat{\Pi}(A_\alpha, K)$ and $\hat{\Pi}(B_\alpha, K)$ conform to all the usual properties of degrees of possibility.

The use of this aggregation process requires the definition of two parameters: (i) the fraction of information elements considered as outliers and (ii) the amount of spatial information required for an accurate estimate of K. The choice of these parameters depends on the quality of information and the spatial resolution of the data. Default values can be used, for instance, an upper quartile operator can be defined by setting the fraction of outliers to 25%. The parameter corresponding to the amount of spatial information is set to 1, which means that at least one information element (I) is required about K to take a decision.

Note that the aggregation process neither introduces a model of spatial structure (based on variograms) nor an associated hypothesis such as spatial continuity. It provides only an expert interpretation of the available data set, whatever its size. With low resolution data, our approach necessarily leads to fuzzy regions (K) without information elements (I). A void fuzzy region implies that both strategies A and B are possible (i.e. both strategies are associated with K with a high degree of possibility).

Kriging could be used to predict values from sparse data and so increase the quantity of information. However, there is uncertainty associated with the estimated values, which could be derived from the kriging variance. Such uncertainty could be included in our approach (Paoli et al. 2007), but this idea is not tested in this research.

Possibility of making an error

For each spatial footprint (K), the aggregation process described in the previous section, provides two degrees of possibility $\hat{\Pi}(A_\alpha, K)$ and $\hat{\Pi}(B_\alpha, K)$, which can be interpreted as the degree of confidence that the strategy A (or B, respectively) is the correct strategy to apply over K. The strategy applied to the spatial footprint (K) is then logically the one associated with the highest degree of possibility. The degree of possibility associated with the other strategy can then be considered as the possibility of making an error $\left(\hat{\Pi}(E_\alpha, K)\right)$. It is then defined by Eq. 5

$$\hat{\Pi}(E_\alpha, K) = \min\left(\hat{\Pi}(A_\alpha, K); \hat{\Pi}(B_\alpha, K)\right). \tag{5}$$

This definition can be generalized easily to more than two strategies. Let $J_1,\ldots,J_j$, be fuzzy sets corresponding to more than two strategies (Eq. 2), it is then possible to define $\overline{J_1}, \ldots, \overline{J_j}$ as complementary fuzzy sets. The $\bar{J}_j$ then corresponds to all possible strategies except for J_j. Complementary strategies are defined according to Eq. 6

$$\begin{aligned} &\Pi(J_i, m) = \mu_{J_i}(m), \\ &\Pi\left(\overline{J_i}, m\right) = 1 - \mu_{J_i}(m), \\ &i \in \{1, j\}. \end{aligned} \tag{6}$$

The possibility of making an error is the smallest possibility associated with a complementary strategy. It is then defined by Eq. 7

$$\begin{aligned} &\hat{\Pi}(E, K) = \min\left(\hat{\Pi}\left(\overline{J_i}, K\right)\right), \\ &i \in \{1, n\}. \end{aligned} \tag{7}$$

Computation of a fuzzy technical opportunity index at the field level

The field will be viewed as a succession of machine positions (x_j, y_j) that correspond to all the possible positions of the VRAC. This leads to a grid in the field based on K as shown in Fig. 3.

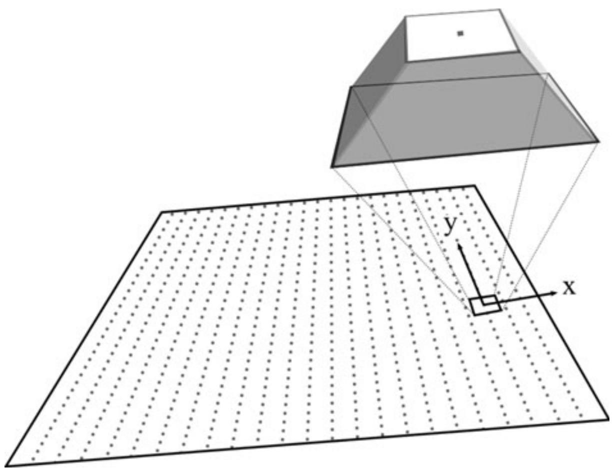


Fig. 3 A fine grid is superimposed on the field—the fuzzy footprint (defined in Fig. 2) is then centred on each grid point and the possibilities are calculated for each footprint position

At the end of the process, a decision will have to be taken as to how each particular location will be managed, i.e. with strategy A_α or B_α. Each grid cell in Fig. 3 corresponds to a location of K.

The aim of our method is to aggregate the results obtained at each machine location to assess the possibility of managing the field specifically and properly. Several aggregation operators are available depending on the reasoning at the field level. In this study, the information for each machine position was aggregated using a mean arithmetic operator.

Let $\{(x_j, y_j)/j \in [1, p]\}$ be the set of all the possible locations of the VRAC. We compute:

$$\begin{aligned} \hat{\Pi}(A_\alpha) &= \frac{1}{p}\sum_{j=1}^{p}\hat{\Pi}\left(A_\alpha, K_j\right), \\ \hat{\Pi}(B_\alpha) &= \frac{1}{p}\sum_{j=1}^{p}\hat{\Pi}\left(B_\alpha, K_j\right), \\ \hat{\Pi}(E_\alpha) &= \frac{1}{p}\sum_{j=1}^{p}\hat{\Pi}\left(E_\alpha, K_j\right). \end{aligned} \tag{8}$$

It is relevant to manage the field site-specifically if the possibility of making an error is small and of applying treatments A and B is large. If the possibility of an error is large, then the spatial variation of the field cannot be managed with the footprint K. Therefore, for a given value of α, our FTOi can be defined by Eq. 9

$$\mathrm{FTOi}_\alpha = \min\left(\hat{\Pi}(A_\alpha); \hat{\Pi}(B_\alpha); 1 - \hat{\Pi}(E_\alpha)\right). \tag{9}$$

Determination of the optimal threshold

Values of the FTOi depend logically on the value of the threshold α, therefore, the FTOi can also be used to determine the optimal threshold α_{opt} from the field values. The determination of α_{opt} is based on a test of all the possible values and selection of the one that (i) maximizes the opportunity of managing the field according to A or B and (ii) minimizes the possibility of making an error. It is determined by the following Eq. 10

$$\mathrm{FTOi} = \sup_{\alpha \in M}\left(\min\left(\hat{\Pi}(A_\alpha); \hat{\Pi}(B_\alpha); 1 - \hat{\Pi}(E_\alpha)\right)\right). \tag{10}$$

Materials and methods

Data

We tested our approach on hypothetical fields of known spatial variability obtained from a simulated annealing procedure (Goovaerts 1997). Properties of the hypothetical fields were chosen based on information from vineyards already harvested with real-time yield monitors (Taylor et al. 2005). Five fields were generated by an exponential function with a nugget effect that was approximately one third of the sill [the nugget effect was 5 and the sill was 16 (in arbitrary units)]. The fields differ in terms of the variogram range only; the practical ranges of the exponential model used were 9, 18, 27, 36 and 45 m. One field with no spatial structure, i.e. a pure nugget effect, was also considered. All of the fields have a notional area of 1 ha (100 × 100 m). The theoretical fields generated in this study show the same characteristics as those in Tisseyre and McBratney (2008). The spatial distribution of data within each field was different from the previous work. The values were generated to appear similar to the spatial distribution of data resulting from a yield monitoring system, i.e. (i) not on a regular grid and (ii) a spatial resolution of around 2000 points ha^{-1}.

In addition to the hypothetical data described above, real data were used to validate our approach. These are yield monitor data obtained from a sensor mounted on a grape harvesting machine (Pellenc S.A.). The field is 1.4 ha and planted with the Bourboulenc variety and was harvested in 2001 in Provence (France). The theoretical average sampling rate is about 2400 measurements per ha. This is an interesting example because the field was harvested with two machines one of which was fitted with a yield monitoring system. This resulted in a significant proportion of missing data in rows that were not measured (Fig. 12a).

Standard operations in the vineyard and resulting kernels

The kernels were chosen according to standard operations performed in a vineyard. A plantation density of 4000 vine stocks per ha was considered. The width of the machine (β) is related to the number of rows that are treated at the same time (1 for pruning or harvesting to 4 for fertilizing). The speed (v) varies from 1 m s^{-1} (for pruning or harvesting) to 2 m s^{-1} (for spraying or fertilizer application). The time rate (τ) (i.e. the time needed to alter the application rate) is estimated as 1–3 s. The inaccuracy of the positioning system is 0.5 m, which is the standard deviation usually observed with a differential GPS. The resulting kernels are given Table 1.

We chose to express the inaccuracy of the VRAC (Δ) as 2% of the threshold α. As mentioned above, Δ represents the inaccuracy between the planned strategy (i.e. level of input) and the level of treatment actually made by VRAC over the field. The value of Δ will depend on the characteristics of the machine and the accuracy with which it applies the expected level of input. From a practical standpoint, Δ may be set according to technical reference documentation or based on local expertise of the farmer or technician. The larger the value of Δ, the greater is the error associated with the strategy and the smaller the resulting Oi.

Results

Optimal threshold

Figure 4 presents the results obtained for a theoretical field (variogram range of 18 m) with three different thresholds ($\alpha_1 > \alpha_2 > \alpha_3$). The maps are ranked from the lowest threshold

Table 1 Standard operations for the vineyard and resulting parameters of the kernels

Operation	Speed (m s^{-1}) v	Width (m) β	Time rate (s) τ	Location inaccuracy (m) d	Kernel (m^2) $(v\tau + 2d) * (\beta + 2d)$
Summer pruning	1	2 (1 row)	1	0.5	$K1 = 6$
Harvesting	1	2 (1 row)	3	0.5	$K2 = 12$
Spraying	2	4 (2 rows)	2	0.5	$K3 = 25$
Fertilizer application	2	8 (4 rows)	2	0.5	$K4 = 45$

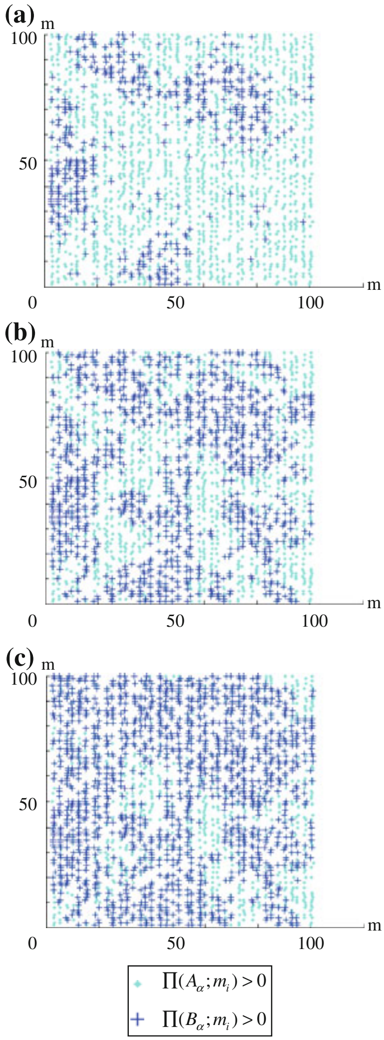


Fig. 4 Map of a hypothetical field, the axes are in metres. Results obtained (variogram range of 18 m) with three different thresholds: **a** $\alpha_1 = 0.2$, **b** $\alpha_2 = 0.5$, and **c** $\alpha_3 = 0.8$. Thresholding values are defined on standardized data. The thresholds correspond to quantiles, for example, 0.5 corresponds to the median. Data points are represented by light dots (when the strategy A is possible) and dark crosses (when the strategy B is possible)

(Fig. 4a) to the highest (Fig. 4c). To simplify the representation, each figure shows the points that can be treated as A and B such that $\prod(A_\alpha;\ m_i) > 0$ and $\prod(B_\alpha;\ m_i) > 0$. This representation leads to some points that have to be treated simultaneously as A and as B. Figure 4 shows also the result of different thresholds (α). Logically, as the threshold increases (according to our representation) the number of A points increases and the number of B points decreases.

The values provided by our aggregation process are shown in Fig. 5. Figure 5a shows how $\hat{\Pi}(A_\alpha)$ and $\hat{\Pi}(B_\alpha)$ (the possibilities of managing the field as A and B) vary with the threshold (α). Logically $\hat{\Pi}(B_\alpha)$ increases as α increases and $\hat{\Pi}(A_\alpha)$ decreases. Figure 5b shows the possibility, $\left(1 - \hat{\Pi}(E_\alpha)\right)$, of treating the fields correctly as A and B. The α_{opt} is the threshold that maximizes the possibility of treating the field as A or B correctly.

Figure 6 shows both maps of $\hat{\Pi}(A_\alpha; K_j)$ and $\hat{\Pi}(B_\alpha; K_j)$ for $\alpha = \alpha_{opt}$ after aggregation for each K_j. There are locations where both treatments are possible, especially in the transition

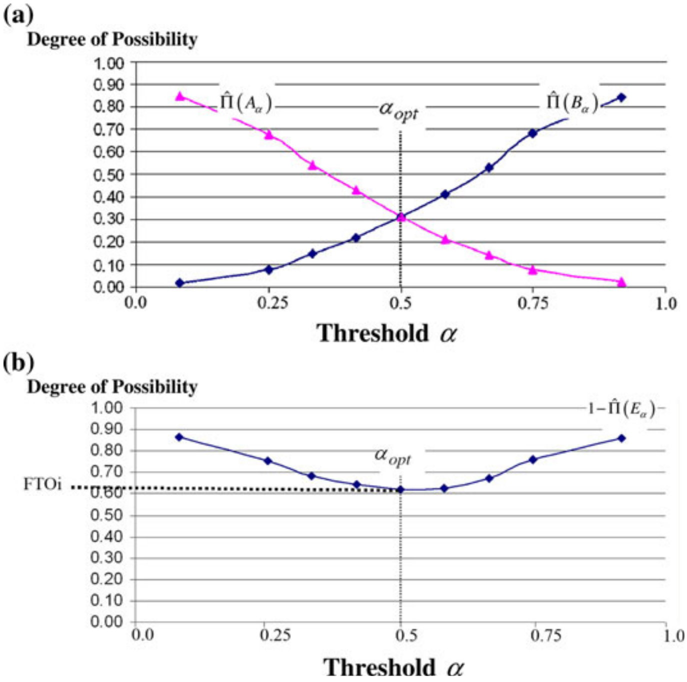


Fig. 5 The abscissa is the quantile of the spatial variable on which the decision is being made and the ordinate is a possibility value. **a** $\hat{\Pi}(A_\alpha)$and $\hat{\Pi}(B_\alpha)$ versus the different thresholds (α) and the optimal threshold (α_{opt}) and **b** $1 - \hat{\Pi}(E_\alpha)$ versus the different thresholds (α) (variogram range of 18 m, *K*3)

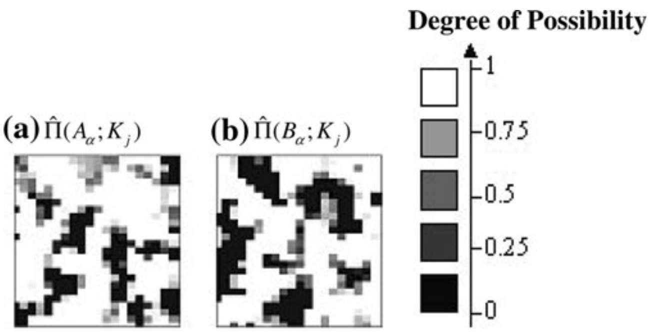


Fig. 6 Maps resulting from the application of the fuzzy footprint (*K*3) for a hypothetical field (variogram range of 18 m), maps of $\hat{\Pi}(A_\alpha; K_j)$, $\hat{\Pi}(B_\alpha; K_j)$, with $\alpha = \alpha_{opt}$. The grey scale on the right indicates the level of possibility (0—black to 1—white). The white areas would definitely be treated with treatment A in map (**a**) and treatment B in map (**b**)

zones of the map. These situations arise where several information sources lead simultaneously to two strategies at a location, and are sources of uncertainty. Our approach leads to an increased possibility of making an error (the possibility of applying the wrong strategy) when (i) the sources of information are inconsistent because there is too much spatial variation in relation to the footprint of the VRAC and or (ii) when the inaccuracy (Δ) associated with the VRAC is too great.

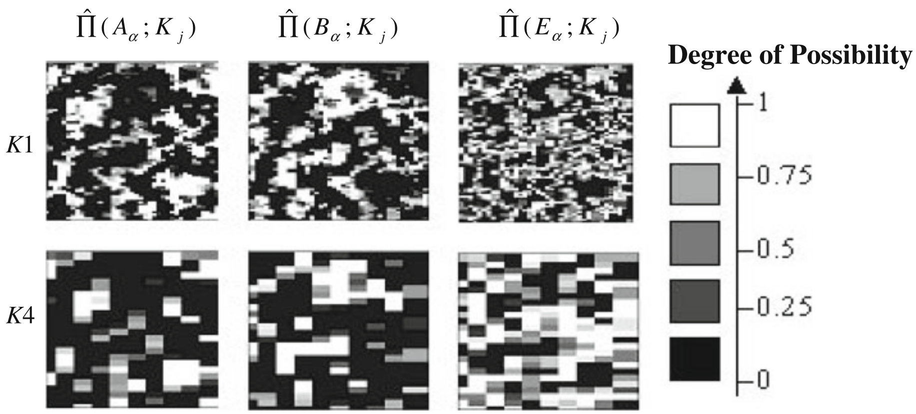


Fig. 7 Maps of $\hat{\Pi}(A_\alpha, K_j)$, $\hat{\Pi}(B_\alpha, K_j)$ and $\hat{\Pi}(E_\alpha, K_j)$, obtained for the same hypothetical field (variogram range of 18 m with the same threshold (α_{opt}) and two different machine footprints (*K*1 and *K*4)

Effect of the different parameters

Footprint of the VRAC

This is illustrated in Fig. 7 with two different footprints (*K*1 and *K*4) on the same theoretical field and with the same threshold. The largest footprint, *K*4, leads to machine positions where conflicts between treatments *A* and *B* occur especially in the transition zones. The possibility of making an error with footprint *K*4 is high (i.e. the map of $\hat{\Pi}(E_\alpha, K_j)$ has more white). On the contrary, the smallest footprint, *K*1, can manage the variation at a finer scale. With *K*1 there is less conflict at each K_j, and the map of $\hat{\Pi}(E_\alpha, K_j)$ has less white for this footprint.

Spatial distribution of the data

Figure 8 shows two theoretical fields (one has a pure nugget effect and the other has a variogram range of 18 m). Figure 6 shows the maps of $\hat{\Pi}(A_\alpha, K_j)$, $\hat{\Pi}(B_\alpha, K_j)$ and $\hat{\Pi}(E_\alpha, K_j)$ and for the same threshold (α_{opt}) and the same machine footprint (*K*2).

The random spatial distribution of the data in the pure nugget effect field leads to an error map (almost white) where the possibility of applying the wrong treatment at each K_j is large. For this field, the VRAC footprint (*K*2) is too large to manage the within-field variation (or the scale of variation of the field is too fine for the footprint). Conversely, our method leads to an error map (almost black) for the other field, where the possibility of applying the wrong treatment at each K_j is small. This means that the scale of variation in the field is large enough for the footprint considered (or that the footprint is small enough).

This result is logical, but significant; it highlights the relevance of our approach and its ability to assess the technical opportunity to manage each machine position, K_j, site-specifically.

The FTOi was determined for all the hypothetical fields with all the footprints. The results are summarized in Fig. 9, which shows that whatever the spatial range of the field, the larger is the footprint the smaller is the FTOi. This result was expected if we consider that management of the within-field variation is easier with a VRAC with a small footprint. Figure 9 also shows that whatever the footprint, the larger the spatial

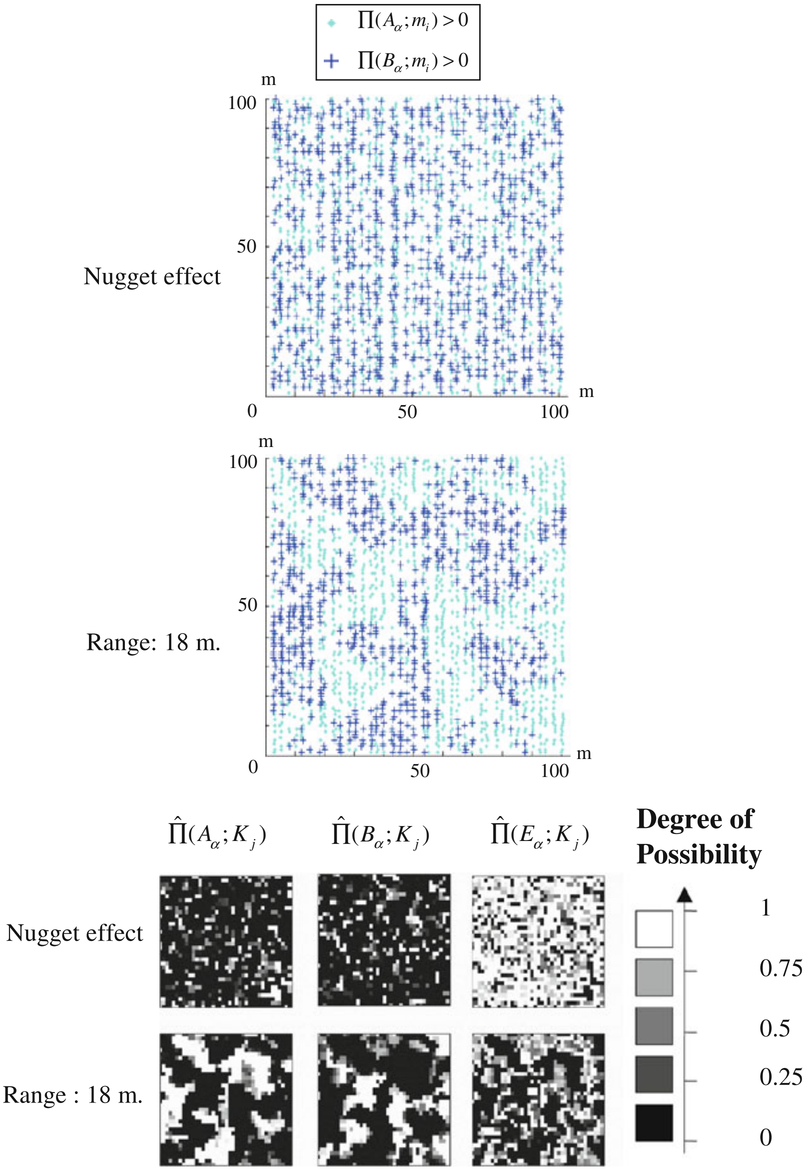


Fig. 8 Maps of $\hat{\Pi}(A_\alpha, K_j)$, $\hat{\Pi}(B_\alpha, K_j)$ and $\hat{\Pi}(E_\alpha, K_j)$, obtained for two theoretical fields (pure nugget effect and variogram range of 18 m) with the same threshold α_{opt} and the same machine footprint ($K2$)

range of the field, the larger is the FTOi. Once again this result was expected because it is easier to manage a field with large patterns of variation (large variogram range).

Data resolution

Figure 10 shows the results of our method on three different hypothetical fields with a decreasing resolution (1000, 250 and 100 points ha^{-1}). Note that (i) almost all the K_j are

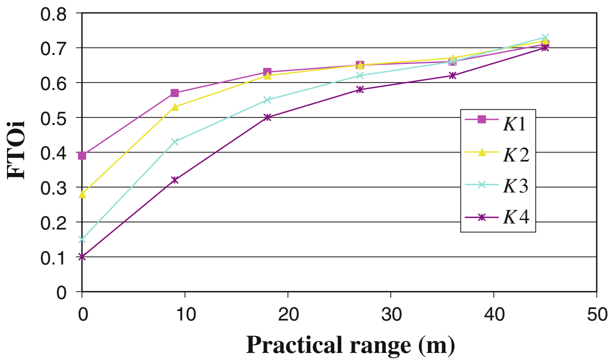


Fig. 9 Values of fuzzy technical opportunity index (FTOi) obtained for six hypothetical fields with different spatial patterns (range of variogram) and four different footprints

filled with at least one data point for 1000 points ha^{-1}, (ii) a lack of spatial information occurs at some K_j for 250 points ha^{-1} and (iii) the lack of information becomes significant at 100 points ha^{-1}. The maps of $\hat{\Pi}(A_\alpha, K_j)$ and $\hat{\Pi}(B_\alpha, K_j)$ for the three fields show that whatever the number of points and the conflict that may occur at each K_j, our method can give the possibility that a machine position has to be treated as A or B. When no information is available within the footprint at a given machine position, K_j, the possibility of making an error is maximal. This situation is evident in the maps of $\hat{\Pi}(E_\alpha, K_j)$ where the increasing lack of information leads to an increasing number of K_j with a large possibility of making an error (shown as white on the maps). For lower resolutions, the FTOi decreases significantly because of the lack of data and the resulting uncertainty about which treatment to apply at each K_j.

Our method provides a new approach to VRA in precision agriculture that could take into account problems of resolution and lack of information. Methods such as kriging or stochastic simulation can improve data sets by estimating values and associated confidence intervals where there are no values. These methods, however, are not widely used by farmers and advisors. Our approach can treat raw data and select all the possible strategies according to the available information.

Accuracy of the VRAC versus the magnitude of variation in the data

The magnitude of variation in values is a significant problem in assessing whether or not it is of value to shift from uniform to SSM. Accuracy of the VRAC is important, and our aim is to show that our method and the resulting FTOi deals with this problem. Figure 11 shows the FTOi of 8 VRACs that differ only in their accuracy, from 1% (of the mean data value of the field) to 10%. Figure 11 shows that our FTOi decreases when inaccuracy of the VRAC increases (from FTOi = 0.6 for 1% to FTOi = 0.5 for 10%). We obtained a similar result by increasing the magnitude of variation in the data with a constant VRAC accuracy. This result is relevant if we consider that site-specific field management is more difficult with an inaccurate VRAC. Then, the possibility of making an error increases which leads to a decrease in the FTOi. This result shows that our FTOi is also relevant for assessing whether accuracy of the VRAC is compatible with the magnitude of variation in the field.

Tests on real data

Figure 12a shows the yield map of grapes used for this study [this map has already been used and described by Tisseyre and McBratney (2008)]. We recall the main features that

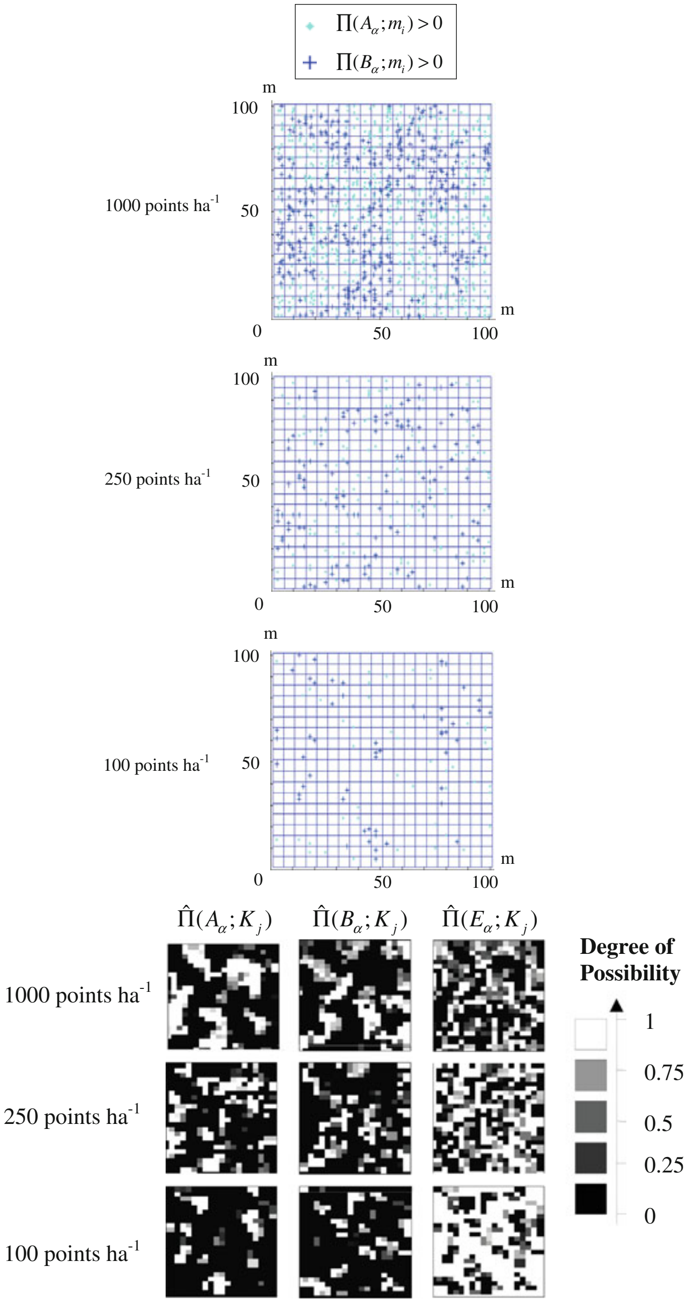
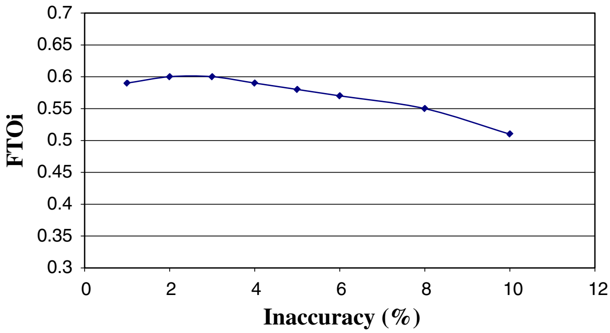


Fig. 10 Maps of $\hat{\Pi}(A_\alpha, K_j)$, $\hat{\Pi}(B_\alpha, K_j)$ and $\hat{\Pi}(E_\alpha, K_j)$, for three theoretical fields (variogram range of 18 m) with different data densities (1000, 250 and 100 points/ha). The threshold (α_{opt}) and the footprints ($K2$) remained the same for the calculation of the maps

Fig. 11 The FTOi with different inaccuracies (Δ) of the VRAC (the accuracy is defined as ±Δ in % of the mean value of the spatial decision-making variable for the field). Same field (variogram range of 18 m), same footprint (K4)



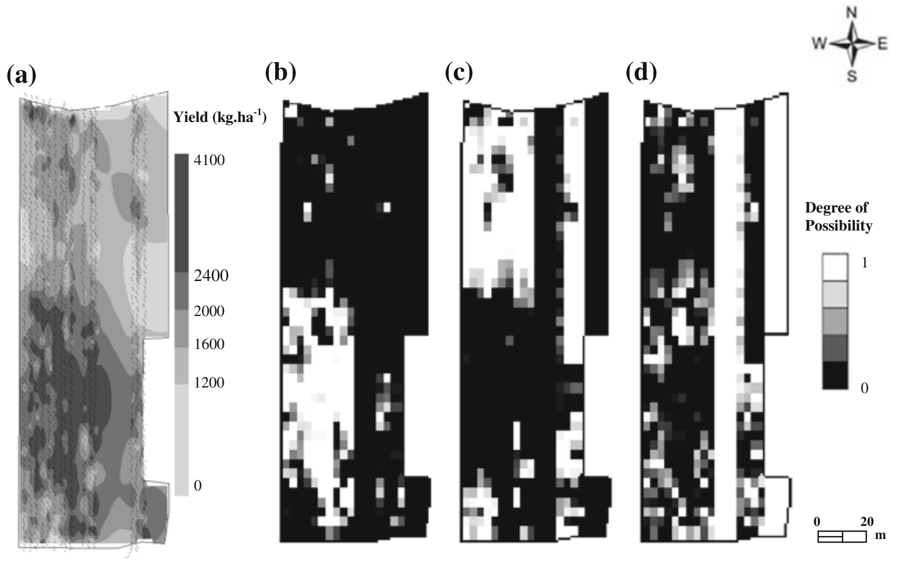


Fig. 12 **a** Kriged map of yield of the Bourboulenc variety and location of the measurements. Two management strategies proposed for the field according to the threshold α on the yield values (points are locations of yield measurements): **b** the result for strategy A, **c** the result for strategy B and **d** the error map. Application maps were computed with a kernel $K = 12\ m^2$

explain the observed spatial variation in order to understand the SSM that may be considered. The field shows a considerable change in yield from north to south. Other observations (vigour, electrical resistivity, soil depth, etc.) on this particular field have shown that the variation in yield was mainly due to variation in the soil and soil–water availability (Tisseyre 2003). Tisseyre et al. (2008) and Acevedo-Opazo et al. (2008) have shown that in non-irrigated vineyards, these differences in yield (and the related vigour of the plants) induced by differences in soil–water availability were stable over time. This characteristic of perennial crops such as grapes enables us to use yield maps to identify relevant site-specific practices. In this example, high yields indicate sites of vigorous growth where water availability is not limiting. These sites correspond to grapes of low quality. Deloire et al. (2004) showed that water restriction improved grape quality. To simplify, water restriction reduces yield, reduces the berry size and increases the concentration of colour and flavour compounds.

Based on the yield map, the objective of the grower is to improve the quality of his field. Because the vineyard is not irrigated, only two solutions were possible: (i) manage the field in the same way, but consider differential harvesting to manage harvest quality specifically that relates to sites with high and low yields and (ii) consider site-specific remedial action according to information provided by the yield map. This last solution was chosen by the grower.

The management strategy chosen by the grower was to grass some parts of the field so that the grass will decrease the water available to the vine. This would reduce the yield and vigour of the plants, which would consequently increase the quality (sugar content, flavour compounds, etc.). Based on the yield values, the site-specific treatments considered are summarized by Eq. 11

$$\begin{array}{ll} \text{If yield } > \alpha & \text{Then strategy } A \text{ (grassing)}, \\ \text{If yield } < \alpha & \text{Then strategy } B \text{ (nothing)}. \end{array} \tag{11}$$

The FTOi would be a good tool to decide whether or not this SSM approach should be adopted to improve the quality of the harvest. The FTOi was computed with a kernel of 12 m^2 corresponding to the characteristics of the machine (speed, width of application, estimated time to change the application rate, etc.) used by the grower. The FTOi for this field with $K = 12$ m^2 is 0.60. This value means it is possible to do two treatments correctly on 60% of the field area with the best possible threshold. It shows a significant opportunity of managing this field site-specifically. The threshold yield value was $\alpha = 2\ 035$ kg ha^{-1}. It was determined by Eq. 11. It corresponds to the maximum ability of the machine to manage the field site-specifically and correctly according to the observed within-field variation and the fuzzy footprint of the machine. This threshold leads to the two management strategies shown in Fig. 12b and c. Management zones identified by our approach correspond to two large patterns in the field, one in the north and one in the south.

Figure 12d shows the map of error possibilities. A comparison of Fig. 12a and d shows that a significant proportion of the error has two sources:

1. Lack of information, for example, for the central rows where no information (yield data) is available to decide whether treatment *A* or *B* is required. Both treatments are then possible leading to a maximum possibility of making an error.
2. The conflict between information sources at some machine positions can be seen to the west side of the field where the machine is in the transition zone between the high and low yielding zones. This can also be seen when the size of yield patterns is smaller than the footprint of the machine (in the southern part of the field).

This example corresponds to a context where the grower does not necessarily know the optimal threshold to apply. The example enables us to know whether the application is technically possible given the observed spatial variation and the accuracy of the machinery. Our approach provides an optimal threshold, an index that rates the technical relevance of the SSM and a map to show the treatment to be performed and possible errors. When the grower knows what threshold to apply, then he can refer to an agronomic model or to experiments. Our approach can be used with the selected threshold. It will then provide an application map and an index to indicate the opportunity to manage the field according to the selected threshold, the observed spatial variation and characteristics of the machinery.

Discussion on the practical implementation

The example on a real field shows that our FTOi can be used for decision-support to: (i) assess the opportunity of managing the field site-specifically with the machine under consideration, (ii) discover the threshold (in terms of yield values in this particular case) that minimizes errors of application, (iii) make an appropriate application map, (iv) visualize the field as it could be treated and (v) visualize the possibility of making an error at each machine position.

From a practical standpoint, our approach requires no operational skills and no knowledge of data processing. Only knowledge on the characteristics of the machine and operating conditions are necessary. The farmer can easily obtain such information. High level parameters required in the aggregation process can be set by default (25% for outliers and 1 for information quantity), nevertheless, their role is easy to understand. Depending on the quality and resolution of the data, they can be changed.

The proposed approach does not need data to be interpolated. From an operational perspective, this is important because it can be used by people who have technical knowledge about machinery, but not necessarily of geostatistics. Our approach does not preclude data interpolation, however. Rather, the two approaches may by quite complementary when the data resolution is low. Nevertheless, a method to determine the uncertainty of the interpolated data should be used in that case (i.e. kriging variance or stochastic simulation).

A unique feature of our method is that it generates an error map that shows areas where SSM may cause problems and that can be used in different ways. A decision to apply treatment *A* or *B* at places with a large possibility of error may depend on the operation and the environmental and or economic context. It may also result in a decision to apply an average treatment at these locations, i.e. the one that would be applied to the whole field if no SSM was considered.

Our approach can also be used by the farmer for decision support to simulate the SSM of a field with a particular threshold. If the threshold is imposed by agronomic considerations or by practical constraints, it is possible to determine the FTOi for such thresholds. In such a case, our approach can still be used to generate the error map and the application maps, which may be of help for assessing the advantage of the SSM.

Finally, when used expertly, our approach can take several thresholds into account. In this case, as shown by Eqs. 6 and 7, several strategies $J_1,\ldots,J_j$ (i.e. rate of fertilizer) can be considered over the field. Our approach can then compute the possibility of managing the field correctly according to each strategy $\left(\hat{\Pi}(J_1);\hat{\Pi}(J_2);\hat{\Pi}(J_3);\ldots;\hat{\Pi}\left(J_{j+1}\right)\right)$ and the possibility of making an error $\left(\hat{\Pi}(E)\right)$. The opportunity to manage the field according to the $J+1$ strategies can be computed by Eq. 10. The approach, however, cannot compute the optimal set of thresholds to minimize the possibility of making an error of application. This aspect will be considered in further improvements of the index.

Conclusion

The aim of this work was to develop a new SSM technical opportunity index. The relevance of our approach was illustrated on theoretical fields with known spatial variability as well as on real data. The unique feature of our method is the use of fuzzy set theory to take into account simultaneously the spatial inaccuracy (fuzzy footprint) and the ability of the VRAC to apply the expected rate of input (inaccuracy of the application rate). Our approach is also unique because problems of over resolution as well as lack of information are considered in the same formalism.

When two strategies are considered, our method is able to compute an optimal threshold that minimizes the error of application. An optimal application map is then generated with an assessment of the possibility of being wrong at each machine position. The next steps of this study will focus on the consideration of more than two strategies. The proposed approach makes it easy to consider more than two treatment strategies. However, the determination of optimal thresholds requires a different optimization process. This aspect will be the subject of future research.

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