Combining Spatial Data Layers using Fuzzy Inference Systems: Application to an Agronomic Case Study

Serge Guillaume[1][a], Terry Bates[2][b], Jean-Luc Lablée[1], Thom Betts[3] and James Taylor[1][c]

[1] *ITAP, Univ Montpellier, INRAE, Montpellier SupAgro, Montpellier, France*

[2] *Cornell Lake Erie Research and Extension Laboratory, Cornell University, New-York, U.S.A.*

[3] *Betts Vineyard LLC, New-York, U.S.A.*

Keywords: Fusion, Multicriteria, Preference, Decision.

Abstract: This paper presents an application of Fuzzy Logic, well known for its linguistic modeling ability, in a multi-criteria decision making framework applied to spatial data sets. The Fuzzy Logic is integrated in two different ways. First, fuzzy sets are used to model an expert preference relation for each of the individual spatial information sources to turn raw data into satisfaction degrees. Second, fuzzy rules are used to model the interaction between sources to aggregate the individual degrees into a global score. The whole framework is implemented in an open source software called *GeoFIS*. The potential of the method is illustrated using a typical farming decision: the design of a nitrogen fertilization map within a vineyard. The vineyard is a Concord (*Vitis labrusca*) juice grape vineyard in the Lake Erie region of New York state. The vineyard manager and a local research/extension viticulturist both used the tool to generate a prescription nitrogen map based on their knowledge and spatial crop and soil information. The process captured different preferences between the two users (industry vs. research) and generated different prescription maps that reflected their differing objectives, knowledge and risk perception in vine management. Although applied to vineyard data, this decision tool has a wide potential application to agri-environmental (and other) spatial data sets.

1 INTRODUCTION

Complex systems, such as agricultural production systems, are characterized by several interrelated dimensions, for instance agronomic, social and economic. The production process includes different steps performed systematically, from initial selection of the product type right the way through to product marketing. Decisions are made at each step of this process that may degrade or support the sustainability of the production system.

Decision making often involves several, potentially conflicting, attributes. Multicriteria decision analysis (MCDA) has been indicated as an appropriate set of tools. In a recent paper (Cinelli et al., 2014) five MCDA methods were evaluated for their ability to handle sustainability problems using ten comparison criteria. The methods were from three main families: i) utility-based theory: Multi-Attribute Utility Theory (MAUT) and Analytical Hierarchy Process (AHP), ii) outranking relation theory: elimination and choice expressing the reality (ELECTRE) and preference ranking organization method for enrichment of evaluations (PROMETHEE) and, iii) the sets of decision rules theory: Dominance-based Rough Set Approach (DRSA). The latter uses crisp *"if ... then"* rules where the satisfaction degree for each criterion is compared to a defined threshold and the conclusion is a category or a set of categories.

In this work, a generic methodology, implemented as an open source software is introduced. The proposed framework first converts raw data into satisfaction degrees according to the decision to be made and then aggregates these degrees to compute a global score. The first step is carried out using fuzzy sets: they are used to model the expert preference relation for each individual information source. The second step usually involves numerical operators of aggregation, including the well known Weighted Arithmetic Mean (WAM), as well as the Ordered Weighted Average (OWA). An introduction to these operators can be found in (Bloch, 1996; Dujmović et al., 2009). Few

[a] https://orcid.org/0000-0002-3546-5276
[b] https://orcid.org/0000-0002-6719-9435
[c] https://orcid.org/0000-0001-9709-8689

Guillaume, S., Bates, T., Lablée, J., Betts, T. and Taylor, J.
Combining Spatial Data Layers using Fuzzy Inference Systems: Application to an Agronomic Case Study.
DOI: 10.5220/0009356000620071
In *Proceedings of the 6th International Conference on Geographical Information Systems Theory, Applications and Management (GISTAM 2020)*, pages 62-71
ISBN: 978-989-758-425-1

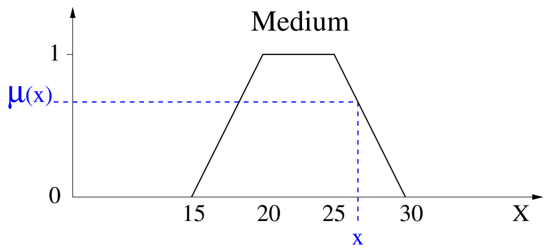


Figure 1: A Trapezoidal Shaped Fuzzy Set.

papers from the GIS community have utilized these kind of operators (Shorabeh et al., 2019), and the most popular technique for multicriteria decision making remains the AHP (El Jazouli et al., 2019; Seyedmohammadi et al., 2019; Graff et al., 2019; Konstantinos et al., 2019; Giamalaki and Tsoutsos, 2019).

An alternative to numerical operators is proposed here to aggregate the satisfaction degrees: a set of fuzzy rules within a fuzzy inference system. Fuzzy rules are suitable, and easy to define, to model the interactions between individual variables.

The potential of the method is illustrated using an agronomic case study: how much nitrogen fertilizer should be applied according to the production target, the expert knowledge and the data?

The paper is organized as follows. The basics of fuzzy logic and linguistic modeling are recalled in Section 2. The different steps and options of the multicriteria methodology are introduced in Section 3. Section 4 describes the agronomic case study and discusses the results. Finally, the main conclusions are summarized in Section 5.

2 LINGUISTIC MODELING

Fuzzy logic is widely used as an interface between symbolic and numerical spaces, allowing the implementation of human reasoning in computers. Fuzzy sets are used to implement approximate concepts, e.g. *Medium*. They are defined using a function that assigns to any value, x, in the universe of the variable, e.g. *Temperature*, a membership degree, $0 \leq \mu(x) \leq 1$, as shown in Figure 1. Therefore, in this example, these degrees would be interpreted as the level to which x should be considered as a *Medium Temperature*.

The core of the fuzzy system, Figure 2, is a set of fuzzy *"if... then"* rules in the form: If *Temperature* is *Medium* then... When several variables are involved in the rule description, the membership degrees can be combined using an 'AND' operator (the most common are the minimum and the product) to weight the rule conclusion. The inferred output results from the aggeregation of all rule conclusions. The rule base may include expert rules and rules learned from data, making fuzzy inference systems a suitable environment for cooperation between expert knowledge and data mining/learning techniques (Guillaume and Charnomordic, 2012). As a consequence of overlap in the fuzzy partition, several rules are likely to be called by the same input data. The inferred output is the result of the combination of all these weighted conclusions.

3 DATA FUSION AND MULTICRITERIA DECISION MAKING

The objective here is to ensure that the process of data fusion for decision making is driven by expert knowledge. Information fusion is done with a specific goal, for instance risk level evaluation or variable rate application in agriculture. The selection of the relevant and available information sources is done by the decision maker. The next step is to evaluate the possible level of decision, e.g. risk or rate, according to each of the sources for a given entity defined by its spatial coordinates. The final step comes down to aggregating these partial levels, or degrees, to make the final decision. The aggregation *function* models the decision-maker's preferences: Are some attributes more important than others? How to combine conflicting information sources?

The whole framework can be illustrated as follows:

$$\begin{array}{ccc} (\mathbf{a_1},\ldots,\mathbf{a_n})\ ,\ (\mathbf{b_1},\ldots,\mathbf{b_n}) & \xrightarrow{\mathbf{A}} & \mathbf{f}(\mathbf{a})\ ,\ \mathbf{f}(\mathbf{b}) \\ \uparrow & & \mathbf{c}\downarrow \\ (\mathbf{x_1},\ldots,\mathbf{x_n})\ ,\ (\mathbf{y_1},\ldots,\mathbf{y_n}) & & \precsim (\mathbf{a},\mathbf{b}) \end{array}$$

There are two steps to formalize expert knowledge and preferences in the decision process. The first deals with each individual variable, or information source. The second addresses the interaction between sources.

The first step aims to turn **raw data** into **satisfaction degrees**. This is done by defining a preference relation for the considered attribute: What are the preferred values for the decision for this variable? Do some of these values have a similar meaning for the decision to be made? Once the values are commensurable, i.e. they have the same scale with the same meaning, they can be aggregated in a second step to compute a global **score**. Items can be compared according to their score. These two steps are now de-

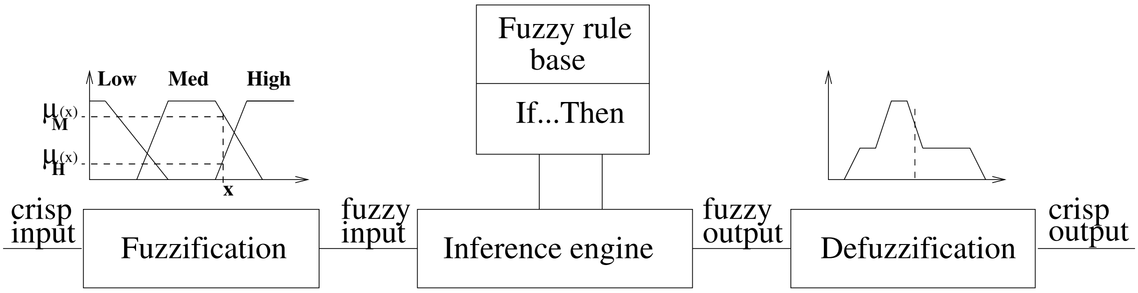


Figure 2: A Fuzzy Inference System.

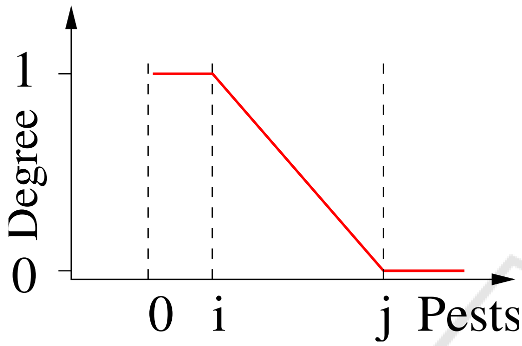


Figure 3: A Membership Function Indicating the Number of Plant Pests Present and the Corresponding Degree of Plant Health.

tailed.

3.1 From Raw Data to Satisfaction Degrees

A common scale with a common meaning is required by the aggregation process. This step is thus mandatory to aggregate information sources with different scales and different units. It is carried out by associating a preference relation to a variable to define a criterion. The preference depends on the decision to be made and on the attribute used in the decision-making. For example, if crop health is evaluated using the number of plant pests present, then the lower the number of pests the better the health state. In this work, the scale is the unit interval, $[0,1]$ with zero meaning the criterion is not satisfied and that it is fully satisfied with one. The preference relation can be modeled, or implemented, using a fuzzy set as shown in Figure 3 for this example.

The degrees are computed for any $x \in [0,+\infty[$ according to Equation 1.

$$deg(x) = \begin{cases} 1 & if \quad x \leq i \\ \frac{j-x}{j-i} & if \quad i \leq x \leq j \\ 0 & if \quad x \geq j \end{cases} \tag{1}$$

This is another way of using the fuzzy set concept. The transformation function includes the part of the expert knowledge related to each individual variable, without considering its interaction with the other variables.

3.2 Numerical Operators

The most popular techniques to aggregate commensurable degrees are numerical operators. The two main families of such operators, with suitable properties, are the Weighted Arithmetic Mean (WAM) and Ordered Weighted Average (OWA).

The WAM aggregation is recalled in Equation 2.

$$WAM(a_1,\ldots,a_n) = \sum_{i=1}^{n} w_i a_i \tag{2}$$

with $w_i \in [0,1]$ and $\sum_{i=1}^{n} w_i = 1$. The weights are assigned to the sources of information. Unfortunately, WAM cannot model compromise as shown in this example. Let's consider three items described by two attributes with the following satisfaction degrees:

	a_1	a_2
It 1	0.7	0.7
It 2	0.4	1
It 3	1	0.4

Item 1 is preferred to the other two. This leads to the two conditions for the weights to fulfill:

- $Score(It1) > score(It2) \quad \Longrightarrow \quad w_1 > w_2$
- $Score(It1) > score(It3) \quad \Longrightarrow \quad w_2 > w_1$

These two conditions are contradictory, and there is no combination (w_1, w_2) that can model the decision maker preference.

The OWA (Yager, 1988) is computed as shown in Equation 3.

$$OWA(a_1,\ldots,a_n) = \sum_{i=1}^{n} w_i a_{(i)} \tag{3}$$

where $(.)$ is a permutation such as $a_{(1)} \leq \cdots \leq a_{(n)}$.

In this case, the degrees are ordered and the weights are assigned to the locations in the distribution, from the minimum to the maximum, whatever

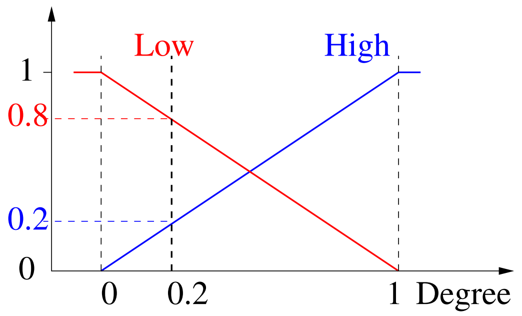


Figure 4: A Regular Fuzzy Partition with Two Linguistic Labels.

the information sources. Using the OWA, the two contradictory conditions above can be solved. WAM and OWA can be combined in the Weighted OWA operator, WOWA (Torra, 1996).

These operators are easy to use, the number of parameters is the number of information sources to aggregate, but their modeling ability is limited. The Choquet integral (Choquet, 1954) proved to be useful in multi-criteria decision making (Grabisch and Labreuche, 2008). It is computed according to Equation 4.

$$C(a_1, \dots, a_n) = \sum_{i=1}^{n} (a_{(i)} - a_{(i-1)}) w(A_i) \tag{4}$$

where $(.)$ is a the permutation previously defined with $a_{(0)} = 0$ and $A_i = \{(i), \dots, (n)\}$, meaning the set of sources with a degree $a \geq a_{(i)}$.

The weights are not only defined for each of the information sources but for all their possible combinations. Specific configurations include WAM and OWA modeling. In the general case, the aggregation of n information sources requires 2^n coefficients. These are usually set by learning algorithms (Murillo et al., 2013).

3.3 Fuzzy Inference Systems

A fuzzy inference system usually requires more parameters than the former numerical aggregators but, in this particular case of data fusion, the design can be simplified as all the input variables are satisfaction degrees that share the same scale, unit interval, and the same meaning. Strong fuzzy partitions with regular grids are used to ensure semantic integrity. The unique parameter left to the user is the number of linguistic terms for each input variable. In this work it was set at 2, *Low* and *High*, for each variable. The automatically generated input fuzzy partition is shown in Figure 4. Thus, any degree $0 < x < 1$ partially belongs to the two sets with a complementary level.

With two linguistic labels per variable, the number of rules is 2^n, i.e. the equivalent number of coefficients required by the Choquet integral. A rule describes a local context that the domain expert, the decision maker, is able to understand. In this way, the rule conclusions are easier to define than the Choquet integral coefficients.

Table 1: Functions to Turn Raw Data into Satisfaction Degrees.

Name	Shape	Preference
Semi Trapezoidal Inferior	:	low values
Semi Trapezoidal Superior	:	high values
Trapezoidal	:	an interval
Triangular	:	a value

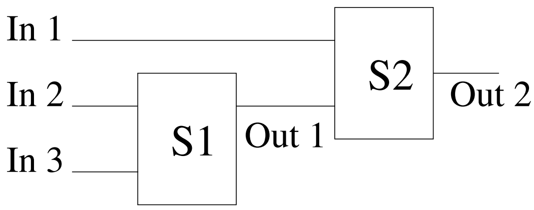


Figure 5: A Hierarchical Structure to Decision-Making Where the Scaled Output from the First Decision (S1) Is an Input for the Second Decision (S2).

3.4 Implementation

The fusion module is implemented as an open source software in the *GeoFIS* program. The data must be co-located, i.e. a record includes the spatial coordinates, from a point to a zone, and the corresponding attributes.

The available functions to turn raw data into degrees are summarized in Table 1.

Three aggregation operators are currently available: WAM, OWA and a fuzzy inference system (FIS) that can use linguistic rules.

For WAM and OWA the weights can be learned provided a co-located target is available. Rule conclusion can also be learned using the *FisPro* software (Guillaume and Charnomordic, 2011).

Rule conclusion can be either a linguistic term, fuzzy output, or a real value, crisp output. Using a fuzzy output, it would be necessary to define as many labels as there are different suitable rule conclusions. As a crisp conclusion may take any value in the output range, it allows for more versatility.

The output should also range in the unit interval. This constraint ensures that the output can feed a further step of the process as shown in Figure 5.

In this way, the intermediate systems can be kept small, making their design and interpretation easier.

The *GeoFIS* program includes a distance function based on a fuzzy partition that allows for integrating expert knowledge into distance calculations (Guillaume et al., 2013) as well other functionalities, such as a zone delineation algorithm (Pedroso et al., 2010). An illustration of its potential use in Precision Agriculture can be found in (Leroux et al., 2018).

4 CASE STUDY

In this section a short case study is presented of the spatial decision support model. It is not possible to provide an exhaustive case study within the restrictions of a conference paper. It is therefore primarily illustrative in nature but based on a typical farming decision, the application of nitrogen within a vineyard. The vineyard is a Concord (*Vitis labrusca*) juice grape vineyard in the Lake Erie region of New York state. The decision process followed by both a grower and an academic are presented to illustrate how the different knowledge bases and risk perceptions are captured in the process. For this illustration, only the FIS approach is considered and the OWA and WAM operators are not used. Although a relatively simple example, the following case study utilizes three different types membership functions to derive satisfaction degrees (both inferior and superior semi-trapezoidal functions and a trapezoidal function, Table 1). The degrees are aggregated using a fuzzy rule base.

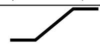
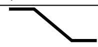
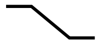
4.1 The Decision

How much nitrogen fertilizer should be applied to the vineyard and should this be site-specific?

The amount of fertilizer applied will be dependent on the intended vine size management and the production target, which is likely to differ between growers. In general terms, larger vines should be more productive and ripen more grapes. Management, including nutrition, should aim to enable crop maturity and to maintain vine size. Smaller vines risk being overstressed with a large fruit load and will have lower long-term productivity. They are also more susceptible to cold and disease damage. The intent with smaller vines is to manage the fruit load and nutrition so that the vine can put more effort into vegetative development in the short-term to increase its size and so become more productive in the longer-term.

Information was available on soil variability in the form of an apparent soil electrical conductivity (EC_a) map that is a surrogate for soil texture and to some extent soil fertility. Crop information was available as vine size (measured as pruning mass) and Crop Load (the ratio of the mass of fruit to pruning mass). These data were obtained from various sensors (see

Table 2: Membership Functions Defined by a and B to Standardize the Input Variables into a $[0,1]$ Range and to Identify What Constitutes a Good (1) and Bad (0) Score. The Soil EC_a Variable Was Defined Jointly by the Two Decision-Makers and Is Constant. The Pruning Mass and Crop Load Were Defined Independently and Illustrate a Difference in Opinion between the Two on What Is the Minimum Value for a Good Vine Size and a Bad Crop Load.

	Soil conductivity EC_a (mS/m)	Pruning Mass (lbs/vine)	CropLoad (Ravaz Index)
A		 1 - 2	 10 - 18
B	2, 10, 15, 33	 1 - 2.5	 10 - 15

(Bates et al., 2018) for further details) and mapped onto a common grid. The interpolated data are shown in Figure 6 to illustrate general (and differing) trends between the variables.

Within this case study, the thought process of two decision-makers was used to illustrate the flexibility in the decision systems and the potential to arrive at different outcomes from identical inputs based on the specific objectives of each individual decision-maker. The first decision-maker, denoted “A”, is the vineyard owner/manager, who routinely makes decisions in the vineyard to ensure the viability of the production system. Their decision-making is strongly influenced by the accumulated knowledge of 3 generations of vineyard management in the region.

The second decision-maker is a trained viticulturist, denoted “B”, who is involved in research and extension activities in the district. B is also a vineyard manager, but their knowledge is strongly informed from the scientific literature, rather than a family history in vineyards.

4.2 The Aggregation System

The first step is to allow each decision-maker to impose their knowledge onto the input variables. The decision is based on managing larger and smaller vines; but what is a large and small vine? Similarly, what soil EC_a response is considered good or bad from a nutritional perspective? To define this, membership functions were generated (Table 2) to transfer the decision-makers preferences into the analysis and also to standardized inputs to a [0,1] range for future analysis.

There was agreement between A and B on the EC_a function so it is common for both decision paths. Note that in the EC_a layer, very low and very high values are both considered poor for production, and this is permissible in the analysis. The two decision-makers

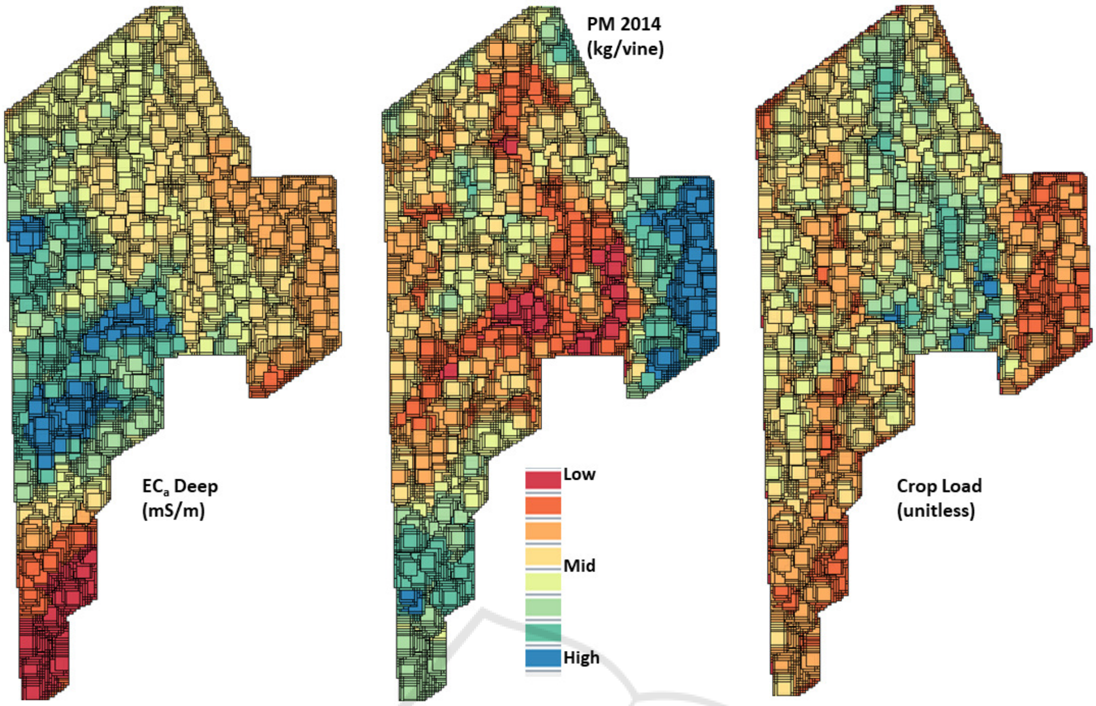


Figure 6: Images Illustrating the Spatial Patterns of the Three Input Variables - Apparent Soil Electrical Conductivity (Left, EC_a) to a Depth of 1.5 M Using a Dualem 1s (DUALEM, Mississauga, ON, Canada); Pruning Mass (Centre, PM 2014) from 2014 Predicted from a Calibrated Canopy Sensor ((Taylor et al., 2017) and Crop Load (Ravaz Index) in 2014 Using the Pruning Mass and Grape Yield Monitoring Data (Yield Data Not Shown).

differed in their interpretation of good vine size (pruning mass) and desired Crop Load. The vineyard manager (A) considered 2 lbs (0.91 kg) vines as a good vine size, while the researcher (B) defined 2.5 lbs (1.13 kg) as the minimum for a good vine size. Similarly, A did not consider the vines over-cropped until a higher Crop Load value was achieved, i.e. A, the commercial grower, was more content to have more fruit in the vineyard, effectively pushing the vines harder than B through this step. This may stem from a better understanding of what the vineyard can produce and/or a need to ensure sufficient short-term production to remain economically viable.

Following the specification of the membership functions, a fuzzy inference system can be used to define the decisions for A and B. For the three inputs, 2 levels of operation [High/Low] were defined. This gave 8 potential linguistic rules (Table 3). Again, these rules were defined jointly by A and B in agreement with the relative amount of nitrogen fertilizer needed in each situation. Of course, this may not always be the case, and producers with differing objectives could generate different "if-then" statements at this point. However, in this case, the rules were common for both A and B to simplify the example. Crisp numerical values were used for the rule conclusions,

Table 3: The Linguistic Rule Base. Abbreviations Refer to the Variables Presented in Figure 6.

	CropLoad	EC_a	*PM*	*Nitrogen*
1	Low	low	Low	0.7
2	Low	low	High	0.5
3	Low	High	Low	0.5
4	Low	High	High	0.3
5	High	low	Low	0.9
6	High	low	High	0.7
7	High	High	Low	0.7
8	High	High	High	0.5

such that Line one (Table 3) reads If *CropLoad* is Low AND EC_{Deep} is Low AND *PM* is Low then *Nitrogen* is 0.7 (i.e. 70% application). As indicated previously, linguistic or fuzzy outputs could also be possibly used here for the rule conclusions.

4.3 Results and Discussion

The raw output maps are noisy and difficult to directly interpret (inset of Figure 7). Of course a variable rate controller may not have difficult in reading and interpreting these maps, although the potential levels of application may need to be simplified to account for the application resolution of the variable rate equipment.

For human intervention, and often for simplicity of application, the data can be aggregated into zones. In this case they are specific nitrogen application zones. Figure 7 shows the simplified output for the decision process of A and B on a common legend. Note that the legend has yet to be transformed into actual N values and shows the output (between 0 and 1) from the FIS. The zoning algorithm was performed using a segmentation approach (Pedroso et al., 2010) in *GeoFIS* (Leroux et al., 2018).

In Figure 7 the different satisfaction degrees for vine size and Crop Load for the two decision makers have clearly generated some differences in the potential nitrogen application zones. The inputs were common, as was the rule set used, so it is not surprising to see that the pattern of N required is similar in the two maps. However, seemingly small alterations to the the idea of a good vine size or an overcropped vine has clearly affected the final zoning. It is not possible to say which of the maps is preferable, as each was tailored to the preferences of each decision-maker.

It is important to note that since the output is standardized, there does exist another potential point of difference between A and B in their determination of how much nitrogen equates to a value of 1 and 0 (and all values in between) in this situation, or rather, how much N would each user apply in the red zone, the yellow zone etc... There is no need for this amount to be fixed for a particular output score.

As indicated in Section 3.4, the rule conclusions can be specified as a linguistic term (as well as a numerical value. Figure 7 was derived from the numerical rule conclusions in Table 3. However, many producers may be more comfortable providing ‘fuzzy’ indications of rates, rather than hard numerical values. To quickly illustrate this alternative approach, Table 4 shows the same “if-then” statements as Table 3, but with linguistic rule conclusions. In this case, the rule conclusions have been specified simply as either a ‘High’, ‘Average’ or ‘Low rate’. The decision process was then rerun, using the same input layers and the same satisfaction degrees (membership functions) as before, but with the linguistic rule conclusions (Table 4). These were again common for both A and B. The zoned outcome, for both A and B, is shown in Figure 8. The output has been defuzzified and expressed in numerical form ([0,1]).

The two maps in Figure 8 can be compared to each other (illustrating again the difference in the determination of satisfaction degrees for Crop Load and vine size between A and B), or compared to Figure 7. The

Table 4: The Linguistic Rule Base with ’fuzzy’ Linguistic Rule Conclusions.

	CropLoad	EC_a	*PM*	*Nitrogen*
1	Low	Low	Low	High
2	Low	Low	High	Average
3	Low	High	Low	Average
4	Low	High	High	Low
5	High	Low	Low	High
6	High	Low	High	High
7	High	High	Low	High
8	High	High	High	Average

difference between Figures 7 and 8 lies in the use of the numerical or linguistic rule conclusions (Tables 3 and 4 respectively). The patterns again remain similar, i.e. areas of higher and lower N application, although the size and shape of the zones, and the location of boundaries, is changed. The simpler (3-level) linguistic rule conclusions have generated smoother zones than the numerical rule conclusions (with 4 levels). Again, there is no perfect answer here. All four maps present a solution based on slightly differing input knowledge related to the satisfaction degrees or the FIS rules. The red zone in the eastern part would receive the same amount of Nitrogen after the output maps were translated to actual Nitrogen rates.

This case study has shown the steps involved in a fertilizer decision process using the data-fusion module in *GeoFIS* and the fuzzy logic option. It illustrates how even a slight change in the process between users A and B (with only 2 of the 3 membership functions varying), generated different prescription levels of N to be spatially applied in the vineyard. Altering the if-then rules, and possibly also the types of input information preferred by different users for the same decision, will generate even more pronounced differences. It is impossible to identify which solution is best, or if there is an actual optimal solution, as for each case the outcome is adapted to the perception, risk and objectives of the user. While the example here is with fertilizer application, the decision process can be applied to any decision, provided relevant input layers and expert knowledge is available.

Finally, it is important to note that although the software and decision support tool is capable of using OWA and WAM operators for aggregation, the agronomic decision selected here (nitrogen application) dictated the use of the FIS approach in this instance. The OWA and WAM approaches require well-structured and logical decision processes i.e. an aggregation of ‘low’ satisfaction degrees should generate a ‘low’ output response. Agronomic decisions are not always so linear or straight-forward. In this case, both small and large vines could receive high applica-

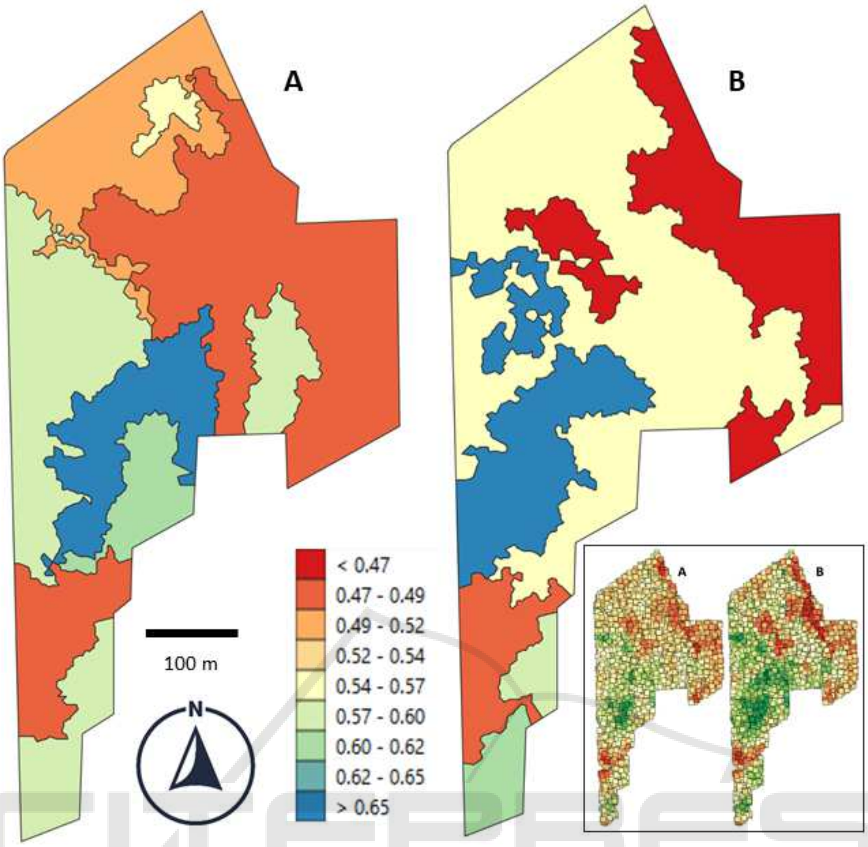


Figure 7: Simplified Zoned Maps (9 Zones Each) of the Nitrogen Decision Generated by the Two Decision-Makers – a = Vineyard Manager and B = Research Viticulturist. The Raw Output Is Shown in the Inset Image. The Trends Are Similar for Both, but Boundaries and Output Levels Do Differ.

tions of nitrogen, for differing reasons (see lines 1 and 6 in Tables 3 and 4). For smaller vines, additional nitrogen may be needed to promote vegetative vigor to grow larger, more sustainable vines, while with larger vines, additional nitrogen will be needed to maintain a higher level of production under poorer soil conditions. Therefore, the system has two very different reasons to arrive at the same nitrogen application rate decision. This is a limitation for the OWA and WAM operators and a strength for the FIS approach.

5 CONCLUSIONS

This paper has introduced a novel spatial decision process and demonstrated it using a typical agronomic practice. The decision process used satisfaction degrees specified by the user to avoid the requirement for a large number of parameters to define input partitions and the inference operators. Since all the input variables in the decision process were satisfaction degrees, with a common scale and common meaning, the automatic setting of the decision rules was possible using a strong fuzzy partition with linguistic terms (in this case, Low and High). As a consequence, only the rule conclusions had to be specifically defined by the user. This was a relatively quick and easy activity, using both numerical and linguistic rule conclusions, to allow the expert knowledge (grower, advisor, etc…) of the variables and their interactions to be modeled. Fuzzy inference systems, thanks to their proximity with natural language and expert reasoning, are a good alternative framework for modeling preferences and for use in multi-criteria decision making under uncertainty.

Field cropping systems operate under a large amount of uncertainty and variability imposed by variable biotic and abiotic stresses and a grower's risk and market preferences. As such, no decision is absolute. This simple case study illustrated that a difference in perception of good and bad vine size and Crop Load (fruit:leaf ratio) generated a difference in target nitrogen application. The particular novelty of this decision system was in its ability to provide a spatial decision that captured the user's intentions and

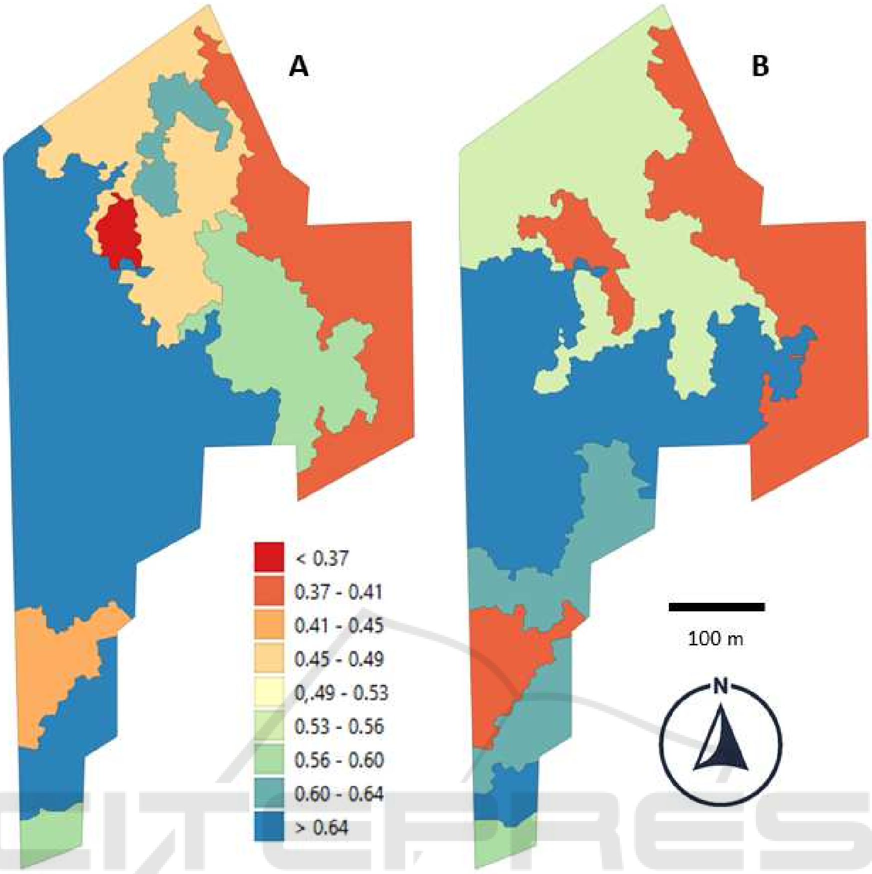


Figure 8: Alternative Nitrogen Application Zones (9 Zones Each) Derived using the Same Satisfaction Degrees and Inputs as Figure 7, but with Linguistic Rule Conclusions. It Again Shows the Output for Both Users a and B, Illustrating Differences between Their Choice of Satisfaction Degrees (Table 2). the Use of 'less Crisp' Linguistic Rule Conclusions (and Fewer Levels) Generates More Regular and Larger Zones Compared with the Equivalent Nitrogen Zone Maps in Figure 7.

knowledge without needing the user to understand all the local, varying interactions in the multi-variate spatial data. The system modeled and spatially differentiated what a grower would do vs. what an advisor would recommend.

Under these conditions, aggregation with the OWA and WAM operators was not possible. This is a limitation for the OWA and WAM operators and a strength for the FIS approach.

This framework is implemented as an open source software called *GeoFIS* available at: https://www.geofis.org. This is a strong asset as software support availability is a key factor for a method to be adopted.

ACKNOWLEDGEMENTS

The work is funded by the USDA-NIFA Specialty Crop Research Initiative Award No. 2015-51181-24393.

REFERENCES

Bates, T., Dresser, J., Eckstrom, R., Badr, G., Betts, T., and Taylor, J. (2018). Variable-rate mechanical crop adjustment for crop load balance in 'concord' vineyards. In *2018 IoT Vertical and Topical Summit on Agriculture - Tuscany (IOT Tuscany)*, pages 1–4.

Bloch, I. (1996). Information combination operators for data fusion: a comparative review with classification. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, 26(1):52–67.

Choquet, G. (1954). Theory of capacities. *Annales de l'Institut Fourier*, 5:131–295.

Cinelli, M., Coles, S. R., and Kirwan, K. (2014). Analysis of the potentials of multi criteria decision analysis methods to conduct sustainability assessment. *Ecological Indicators*, 46:138 – 148.

Dujmović, J., De Tré, G., and Dragićević, S. (2009). Comparison of multicriteria methods for land-use suitability assessment. pages 1404–1409.

El Jazouli, A., Barakat, A., and Khellouk, R. (2019). Gis-multicriteria evaluation using ahp for landslide susceptibility mapping in oum er rbia high basin (morocco). *Geoenvironmental Disasters*, 6(1).

Giamalaki, M. and Tsoutsos, T. (2019). Sustainable siting of solar power installations in mediterranean using a gis/ahp approach. *Renewable Energy*, 141:64–75.

Grabisch, M. and Labreuche, C. (2008). A decade of application of the choquet and sugeno integrals in multi-criteria decision aid. *4OR*, 6(1):1–44.

Graff, K., Lissak, C., Thiery, Y., Maquaire, O., Costa, S., Medjkane, M., and Laignel, B. (2019). Characterization of elements at risk in the multirisk coastal context and at different spatial scales: Multi-database integration (normandy, france). *Applied Geography*, 111.

Guillaume, S. and Charnomordic, B. (2011). Learning interpretable fuzzy inference systems with fispro. *Information Sciences*, 181:4409–4427.

Guillaume, S. and Charnomordic, B. (2012). Fuzzy inference systems: an integrated modelling environment for collaboration between expert knowledge and data using fispro. *Expert Systems with Applications*, 39:8744–8755.

Guillaume, S., Charnomordic, B., and Loisel, P. (2013). Fuzzy partitions: a way to integrate expert knowledge into distance calculations. *Information Sciences*, 245:76–95.

Konstantinos, I., Georgios, T., and Garyfalos, A. (2019). A decision support system methodology for selecting wind farm installation locations using ahp and topsis: Case study in eastern macedonia and thrace region, greece. *Energy Policy*, 132:232–246.

Leroux, C., Jones, H., Pichon, L., Guillaume, S., Lamour, J., Taylor, J., Naud, O., Crestey, T., Lablee, J.-L., and Tisseyre, B. (2018). Geofis: An open source, decision-support tool for precision agriculture data. *Agriculture*, 8(6):73.

Murillo, J., Guillaume, S., Tapia, E., and Bulacio, P. (2013). Revised hlms: A useful algorithm for fuzzy measure identificat ion. *Information Fusion*, 14(4):532–540.

Pedroso, M., Taylor, J., Tisseyre, B., Charnomordic, B., and Guillaume, S. (2010). A segmentation algorithm for the delineation of management zones. *Computer and Electronics in Agriculture*, 70(1):199–208.

Seyedmohammadi, J., Sarmadian, F., Jafarzadeh, A., and McDowell, R. (2019). Development of a model using matter element, ahp and gis techniques to assess the suitability of land for agriculture. *Geoderma*, 352:80–95.

Shorabeh, S., Firozjaei, M., Nematollahi, O., Firozjaei, H., and Jelokhani-Niaraki, M. (2019). A risk-based multi-criteria spatial decision analysis for solar power plant site selection in different climates: A case study in iran. *Renewable Energy*, 143:958–973.

Taylor, J. A., Link, K., Taft, T., Jakubowski, R., Joy, P., Martin, M., Hoffman, J. S., Jankowski, J., and Bates, T. R. (2017). A protocol to map vine size in commercial single high-wire trellis vineyards using "off-the-shelf" proximal canopy-sensing systems. *Catalyst: Discovery into Practice*, 1(2):35–47.

Torra, V. (1996). Weighted owa operators for synthesis of information. In *Proceedings of IEEE 5th International Fuzzy Systems*, volume 2, pages 966–971.

Yager, R. R. (1988). On ordered weighted averaging aggregation operators in multicriteria decisionmaking. *IEEE Transactions on Systems, Man, and Cybernetics*, 18(1):183–190.