Open source software for modelling using agro-environmental georeferenced data.

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Abstract—**In Agro-Environment, due to the increasing number of automatic sensors and devices, there is an emerging need to integrate georeferenced and temporal data into decision support tools, traditionally based on expert knowledge. Soft computing techniques and software suited to these needs may be very useful for modelling and decision making. This work presents an open source framework designed for that purpose. It is based upon open source toolboxes, and its design is inspired by the fuzzy software capabilities developed in *FisPro* for ordinary non georeferenced data. A real world application is included, and some perspectives are given to meet the challenge of using soft computing for georeferenced data.**

I. Introduction

Management of complex systems, particularly so in Agriculture or Environment, does not generally rely on a thorough mathematical modeling. Nevertheless, decision support systems are necessary to assist the decision maker, and system design should benefit from all the available knowledge, including expert knowledge and data.

In Agro-Environment, the considered data are more often georeferenced and temporal data. They come from measurements (satellite or aerial images, embedded sensors e.g. yield, contents), manual sampling (soil analyzes) or may be given by experts (flood-risk area). There is a need for aggregating heterotopic data of various kinds (expert, measurements), from different sources, with various spatial resolutions, protocols and assessments. Imprecision, partial truth, and uncertainty are a recurring characteristic.

Much effort has been made to design dedicated software for spatial data management, mainly Geographic Information Systems (GIS) used to handle and display georeferenced data, and geostatistical methods for data processing end estimation. Nevertheless, there have been relatively few soft computing developments to address the specific characteristics of georeferenced data. Even if some GIS propose fuzzy methods, like the popular fuzzy clustering algorithm, fuzzy c-means, these methods are not designed specifically for georeferenced data.

Soft computing techniques, especially fuzzy logic and fuzzy inference systems, proved to be efficient to cope with imprecise data and uncertainty attached to expert judgment and have already been used in agronomy and environment [2], [4], [5], [8], [10], [14], [16]. Spatial data specificities are likely to open novel research topics in soft computing. For instance, the notion of zone is not clearly defined in GIS, it is often mistaken for a projection of a classification achieved in the attribute space without considering geographic continuity. This concept is central in spatial reasoning and essential in decision making, particularly in Agro-Environment, as in practice, decisions need to be applied to management zones, satisfying geographical contiguity and shape criteria. For realistic decision support, zones must be defined with respect to the imprecision and uncertainty of available data and knowledge.

This work presents the outline of a decision support system framework for spatial data. It is based upon available open source toolboxes as well as on the authors' experience in soft computing software, through the former development of *FisPro*[1], that offers a high level of semantics and human-machine interaction. It could be part, as a spatial package, of a wider project like the GNU Fuzzy one proposed in the 2007 Fuzz'Ieee Conference [9].

The paper organization is as follows. Next section presents a state of the art of the available open source software environments for spatial data. The architecture, including *FisPro* and the *GeoFIS* framework, is introduced in Section III. The framework potential is illustrated with a real world application in Section IV. Finally, Section V summarizes the main conclusions and the open challenges.

II. State of the art and need for specialized software

GIS are powerful systems designed to capture, store, manipulate, analyze, manage, and display geographically referenced data. They are used in many application areas, archaeology, resource management, disease surveillance...

The most popular GIS include commercial software such as ArcGIS, JMap, MapInfo, SmallWorld, or open source library and software, such as GeoServer, GRASS, gvSIG, GeoTools[2], OpenMap, Quantum GIS or Udig.

GIS use digital data and a spatio-temporal (space-time) location as the key index variable for all information, allowing information from different sources to be related by accurate spatial information. They include a vast range of spatial analysis techniques, among them contour lines, topological and hydrological modelling, map overlay, geocoding, geostatistics and classification. In a GIS, geographical features are often expressed as vectors, by considering those features as

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[1] http://www.inra.fr/mia/M/fispro/

[2] http://geotools.org/

geometrical shapes: points, lines or polygons. A spatial data set with a given geometry constitutes a layer. Alternatively, a layer can also be constituted by a raster data set. Map overlay uses the combination of several of these layers to create a new output, visually similar to stacking several maps of the same region. Elementary operators are available, such as union, intersection and symmetric difference.

Geostatistics relies on statistical models based on random variable theory to produce field estimations from data points, by modelling the uncertainty associated with spatial estimation and simulation. It involves interpolation methods to complete the input data collected at a number of sample points.

Despite these powerful tools, GIS lack some functionalities for modelling and reasoning using georeferenced data. Geographic information is displayed for informing decision making, but there is no clear definition nor handling of some concepts, for instance the zone concept, often confused with the class concept. GIS focus on providing tools for multi criteria decision making, for instance for site selection and suitability. However the concept of learning from data is not explicit. To our knowledge, zone learning, zone operators, dynamic evolution of zones seem not to be available.

Another notable point is the limited use of soft computing techniques in GIS, though reasoning about space often has to deal with some form of uncertainty or imprecision. Recent add-ons to ArcGIS include fuzzy operators for map overlay and fuzzy classification. The concept of linguistic variable is used to model the inaccuracies in attributes and in the geometry of spatial data. Data are fuzzified through membership functions and overlay operators are applied on membership values instead of raw data. An add-on to GRASS provides fuzzy membership functions, fuzzy operators and fuzzy rules to implement fuzzy inference systems for classification tasks.

Fuzzy c-means clustering may be used for mining GIS data. In [3] the authors propose an extended fuzzy c-means method for GIS, that allows cluster centers to be hyperspheres, and apply it to find fire-point event hotspots from georeferenced data. Recent publications, for instance [1] which uses a fuzzy GIS-based spatial multi criteria framework for irrigated agriculture, take place in the application fields of agriculture and environment.

On a different note, several advanced packages (*spatial, geoR, gstat*...), are available for the open source R [13] software. They provide multivariate geostatistical functions for kriging, analysis and simulation, and often include GIS support (GRASS for gstat) for querying data and executing scripts. They are intended for researchers or engineers having a good background in Statistics. SAGA (System for Automated Geoscientific Analyses)[3] offers an open source comprehensive set of geoscientific methods.

The need for modelling using georeferenced data is increasing, in many application fields, but particularly so in agriculture and environment. The great amount of available spatial data has begun to open new avenues of scientific inquiry into behaviors and patterns of previously considered unrelated information. However, the software tools presented above, including GIS and R, are complex and require lengthy training and specialised skills to be taken over. This is a limiting factor for the practical use of spatial modelling in some domains, such as Agro-Environment where the stakeholders are not specialists of spatial data. Moreover, they lack an easy way to introduce expert knowledge, and are poor in soft computing tools.

New software, designed to facilitate modelling using expertise as well as georeferenced data, would be most useful to stakeholders intervening at different levels of decision. Ideally it should provide some of the basic viewing functionalities of GIS and interaction with maps. Expertise and data are available, and Decision Support Systems (DSS) must integrate them. The software should be easy to use with a quick and progressive learning, and a friendly interface so that decisions can be made and updated from map viewing, learning using expert knowledge and data, and map evolution. The concept of management zones, not limited to classes, is required. To limit the necessary work, the DSS software must be open, be based on existing GIS components through available libraries, include elementary geostatistical techniques through calls to R. It can then become an open platform for adding soft computing new developments, adapted to spatial data.

III. Proposed Architecture

The DSS architecture is shown in Figure 1.

The figure is divided by a dashed line: the upper part includes the components involved in the GeoFIS design while the lower one illustrates how they are used.

The data under consideration are georeferenced data. Another characteristics of the data available for the decision maker, especially in life science like environment or agronomy, is their uncertainty. This is due to biological variability but also to the necessity of using not well defined concepts such as flood-risk area.

Expert knowledge is central in decision making. The DSS should be oriented towards the service of the decision maker, his/her knowledge being given the leading part.

In the proposed architecture, various open source toolboxes and libraries are used for the cooperation between expert knowledge and data. Statistical and geostatistical functions are implemented in the R project [13] and, among the available GIS libraries, GeoTools is chosen because it includes all of the necessary concepts and the interface is written in Java. CGAL (Computational Geometry Algorithms Library)[4] provides efficient and reliable geometric algorithms in the form of a C++ library.

The FisPro environment offers a high level of interaction between expertise and data for designing and optimizing fuzzy inference systems. Even if it is not designed to handle geographic data it can be used to cope with uncertainty and to implement approximate reasoning. Available on line since

[3] http://www.saga-gis.org/

[4] http://www.cgal.org/

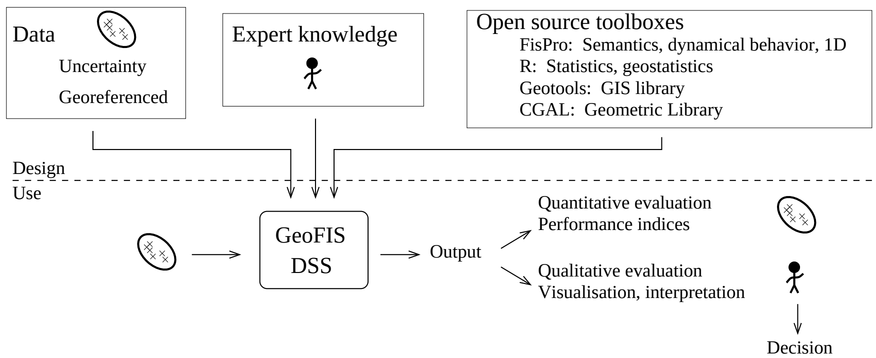

Fig. 1. GeoFIS architecture

2002, it is widely used in different fields and for various purposes (education, research, applications).

FisPro main functionalities, which are detailed below, inspire the GeoFIS framework. The goal is to provide the decision maker not only with useful indices for a quantitative evaluation but with a user friendly interface to make a qualitative evaluation of the whole model. Interactive modelling capabilities are a must. Specific tools needed for spatial data visualization, spatial reasoning and to investigate the spatial system behavior are under development and introduced in the GeoFIS section.

A. *FisPro*

FisPro allows Fuzzy Inference System (FIS) design from expert knowledge or data. Among the available fuzzy software toolboxes, FisPro stands out for system interpretability, which is a necessary condition for cooperation between expert knowledge and data.

FIS can be completely, and automatically, designed from data [6]. In the latter case, semantics is guaranteed at each step. Variable partitioning only involves strong fuzzy partitions, as the one shown in Figure 2 and the rules share the same linguistic terms. The optimization module does not modify the FIS structure and semantics is preserved after parameter tuning.

FisPro efficient approach in exploratory analysis and system modeling has been used to deal with agricultural applications [5]. Special attention has been put on the dynamical behavior of a FIS following user modifications. Each variable, rule or data item can be activated/deactivated. The system parameters (operators, partitions, rule description) can be edited. All changes are dynamically handled and all current windows are updated, including the inference result ones. Response surfaces are also available for an analysis of the system behavior.

To help the user to assess the rule representativeness, an option that evaluates the *links between rules and examples* is available. An accessible detailed cross-summary gives for each rule, the samples that fire this rule above a given matching degree, and for each sample, the rules that are fired.

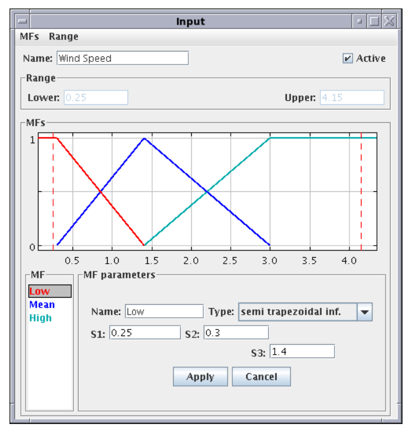

Fig. 2. A strong fuzzy partition

Inference can be done manually or on the current data file, with evaluation criteria which take into account the numerical accuracy as well as the significance of data items regarding the FIS.

Figure 3 shows two distinct windows. The upper one shows the data as a table: a row corresponds to a data item, a column to a variable. The output variable is in the last column. A double-click on a given row opens the inference window with the corresponding input values, as shown in the bottom part of the figure. Each row corresponds to a rule. For each rule, the four first columns correspond to the input variables. The fuzzy set is shaded up to the corresponding membership degree for the given input value. The second input variable is not involved in any rule. The last column displays the rule outputs. This being a Sugeno FIS, the rule conclusion is given in parenthesis below the rule matching degree for the current input data. The inferred output value, which results from rule output aggregation, appears in the top right corner (5.249). Any system modification would update this window.

Fuzzy inference systems are useful for building composite variables to be used in DSS. Fuzzy partitioning can be used to model uncertainties through linguistic variables, and an

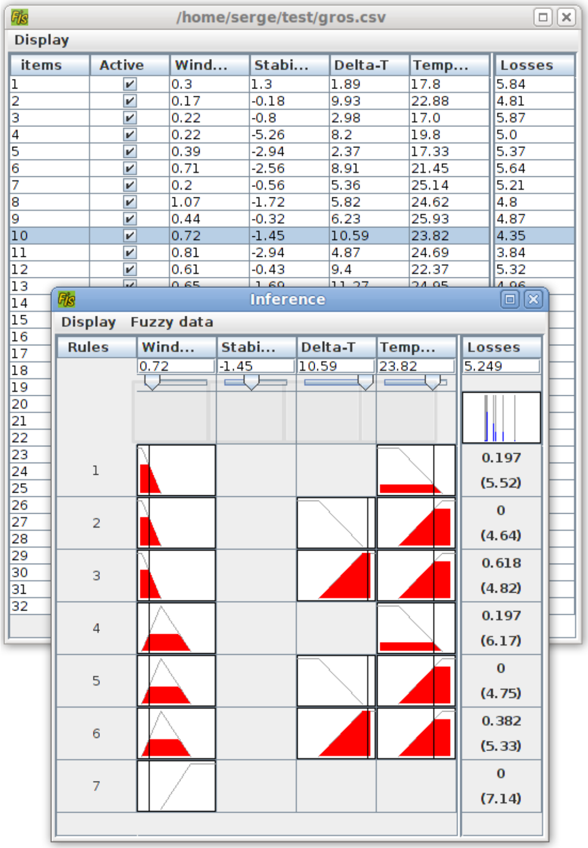

Fig. 3. Inference using an input row from the data table

example will be given in Section IV.

B. GeoFis

GeoFIS provides a simple evolutive framework to visualize and analyze spatial data. Based on open source libraries, it is written in Java and uses GeoTools to display existing data layers or generate them from raw text files. It also implements calls to R to provide one-dimensional spatial analysis. It is relatively easy to implement new geostatistical techniques through calls to R spatial packages. *GeoFIS* includes an elementary zone learning module. Add-ons will allow to introduce new learning methods into the framework, in particular soft computing ones.

Figure 4 shows an example of a two layer map. The first layer displays the data points while the second one corresponds to their Voronoi tessellation.

1) One-dimensional statistical analysis: All these functionalities are implemented using the R software [13] with the *gstat*[5] package. The R functions are used by a large research community and are well tested. The interface implemented here uses the *Rserver*[6] developments, which allow to directly transfer objects between R and Java.

[5]http://www.gstat.org/
[6]http://www.rforge.net/Rserve/

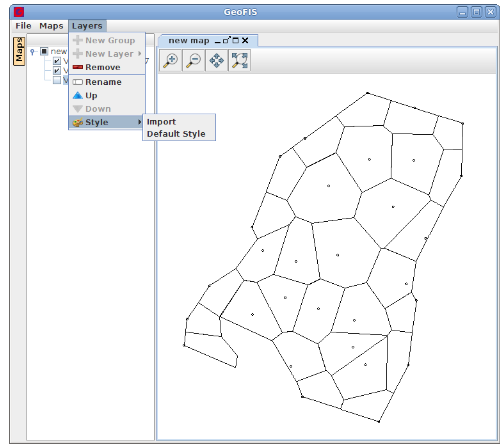

Fig. 4. GeoFIS framework

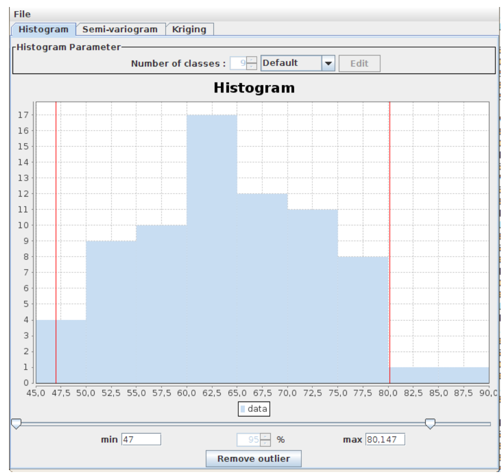

Fig. 5. GeoFIS histogram window

The histogram window shows the distribution of data values for the selected variable. The number of classes and the class bounds can be customized. Different choices are possible, including equally spaced containers, bins with an equal number of elements, or Sturges algorithm for selecting the best number of classes.

Given the distribution, data can be automatically or manually filtered, to define a validity range, for instance one that holds 95% of the data, or by selecting the bounds, and so remove outliers.

The histogram window and the map viewing one are dynamically linked, so that the valid and removed data points are plotted in the latter window in two distinct colors, and updated according to the user edits in the former one.

The variogram window prepares for kriging, i.e. interpolation using a defined model. The variogram model often needs expert tuning to fit the model taking into account the data set specifities (spatial resolution, shape ans size of the area under study . . .). All of the model parameters can be adjusted and the theoretical model (exponential, Gaussian, linear with sill and spherical), as well as the data fit, are updated accordingly.

The variogram model can be saved in standard format (xml) for reuse on new data or exporting to other software.

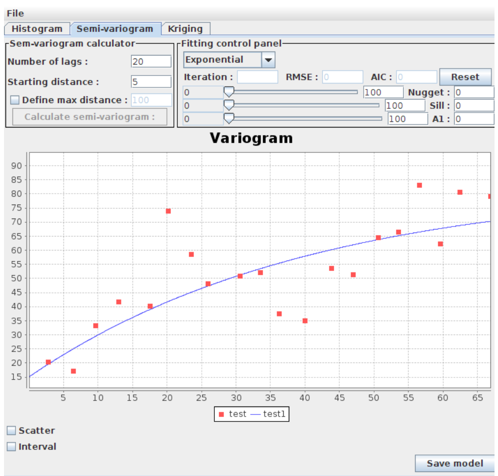

Fig. 6. GeoFIS variogram window

2) Learning module: The zone learning module is based on a segmentation algorithm, inspired from an image-processing region merging algorithm. It allows the delineation of discrete contiguous management zones. Management in agricultural systems is dependent on both the magnitude of variation and how it is partitioned [12]. Segmentation algorithms differ from classification algorithms in that they are object-oriented (note: the term "object-oriented" here is used in its image analysis context, not a software engineering context). This focus leads to the production of discrete zones rather than classes and the output is spatially structured. One of the disadvantages with many object-oriented segmentation algorithms is a reliance on regular grid data for determining segment morphology. This is probably an artefact from their primary application in image analysis and has restricted the use of these algorithms on irregular agro-environmental data sets.

The zone learning algorithm implemented in *GeoFIS* is able to process irregular grid data, or high resolution regular grid data. It is inspired from a region-merging algorithm and all details can be found in [11]. A fundamental point is the way the spatial coordinates are used here. They are not involved in any distance calculation, but are only used to define point and zone neighbourhood. The algorithm works on two spaces simultaneously (attribute space and geographic space). The proximity criterion used for zone merging is based on a distance in the attribute space, and it is only calculated within a given neighbourhood. Spatial interpolation of data is not necessary for the algorithm to run. This is an asset, as interpolation makes up synthetic data, whose artificial nature is often forgotten in the interpretation of the results.

Figure 7 shows the main parameters of the zone learning algorithm. It presently works on a single dimension in the attribute space, which is referred to by *Attribute column number*. Stop criteria include the number of zones to generate and a zone spatial heterogeneity based criterion. Intermediate maps may be required to allow users to see the evolution of the zone merging process. An auxiliary variable can be specified to recursively re-run the algorithm on a zone, using that auxiliary feature to guide the new zoning.

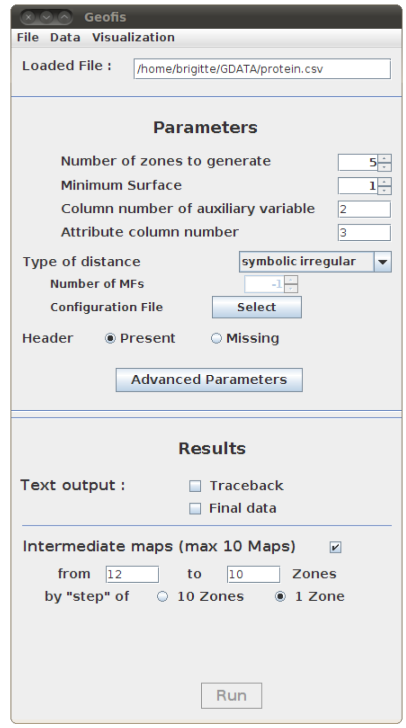

Fig. 7. GeoFIS zone learning parameters

As all segmentation or classification methods, the algorithm is sensitive to the choice of the distance in the attribute space. Options include the Euclidean distance, as well as a fuzzy partition based distance, allowing to introduce expert knowledge in the algorithm [7]. The latter distance combines numerical and symbolic elements. Its numerical part allows to handle multiple membership in transition zones, while the symbolic one takes into account the granularity of the concepts associated to the fuzzy sets. All details can be found in [7].

Figure 8 shows an example of rank inversion of the fuzzy partition based distance results compared with the Euclidean distance ones. With the univariate fuzzy partition based distance d_P^u, x and y are further apart than y and z, while they would be closer than y and z, were the Euclidean distance used. This rank inversion is due to the fact that all elements within a given fuzzy set kernel have a null distance.

More sophisticated methods can be added for zoning, in particular soft computing new developments. The concept of fuzzy zone needs to be developed and proper visualization tools are required to display fuzzy zones.

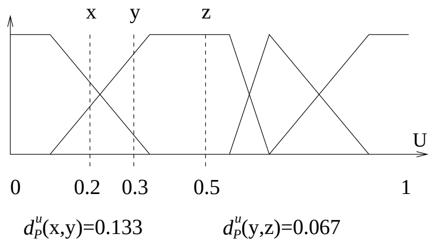

Fig. 8. Example of fuzzy partition based distance behavior(d_P^u)

IV. CASE STUDY

This section presents a real world wine growing application involving spatial data and expert knowledge.

The georeferenced data are yield data [15], coming from an embedded sensor on a grape-harvesting machine. The 1.4 ha field is planted with the Bourboulenc variety and was harvested in 2001 in Provence (France). The average sampling rate is about 2400 measurements per ha. But, due to a data acquisition problem, some records are missing.

The objective of the study is to find suitable management zones from the information found in the yield data and the domain knowledge. Several operations could then be adapted including, for example, fertilization, winter pruning and grassing. In this case, the grower was considering the establishment of grass on the rows located in zones of high production to introduce a competition with the vines and reduce their vigour and the resulting yield.

Let us discuss the different modelling steps made possible by the software framework.

The first stage is to view the spatial distribution of the yield attribute, by splitting it into classes, and projecting it into a two dimensional map. Various methods can be used: expert definition of classes or automatic definition from data. We present here three different choices for clustering in the attribute space: a) *crisp* clustering using expert bounds, b) *automatic* k-means with three groups, and c) clustering into three *equi populated* groups. Figures 9, 10 and 11 show the corresponding respective maps.

The interpolation is used to represent a continuous map, so even if the sampling is irregular (see data point layer in Figure 9), it is possible to visualize the main spatial patterns of the field. Each of the different types of maps presented in Figures 9, 10 and 11 is important for operational data analysis. The map in Figure 9 provides expert classes. It allows to view the response of the field in relation with technical goals of the grower. The central class corresponds to yield target, the lower and upper classes are the yields for which the vineyard operations (pruning, fertilization, etc.) are probably not appropriate. Figure 9 shows a northern zone that matches the yield goal and a southern zone for which the vine management does not seem appropriate because the yield is too high. Other representations are however necessary for operational purposes. The *k-means* classification (Figure 10) helps to identify whether there is a particular distribution of data on the plot. Equiprobable classification (Figure 11)

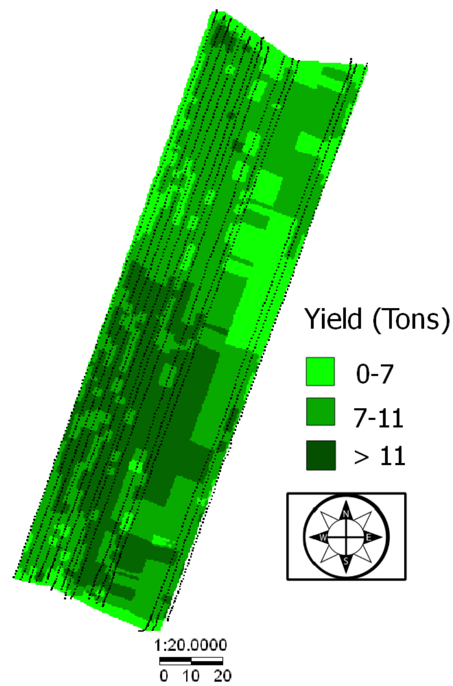

Fig. 9. Two layers: 1- data points, 2- clustering yield data with three expert groups: yield<7, $7 \leq$ yield ≤ 11, yield >11

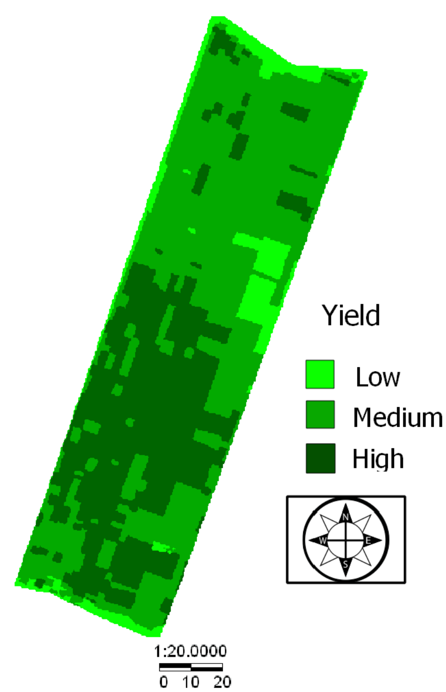

Fig. 10. Clustering yield data with *k-means* - three clusters

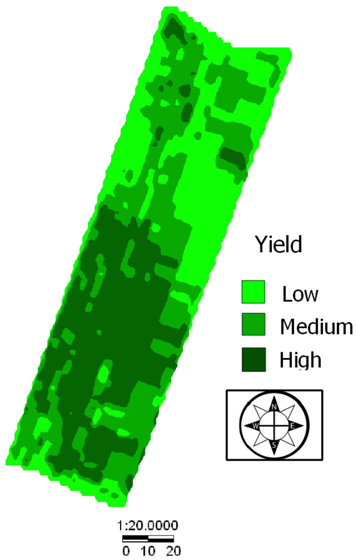

Fig. 11. Clustering yield data with three equi populated groups

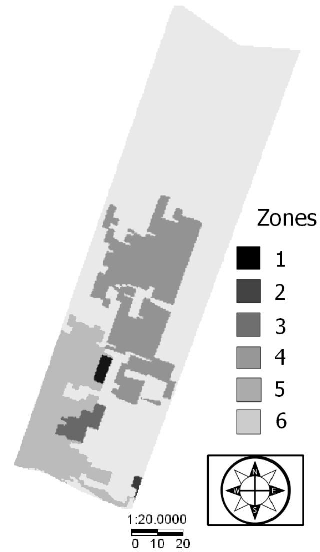

Fig. 12. Zoning yield data with a Euclidean distance criterion

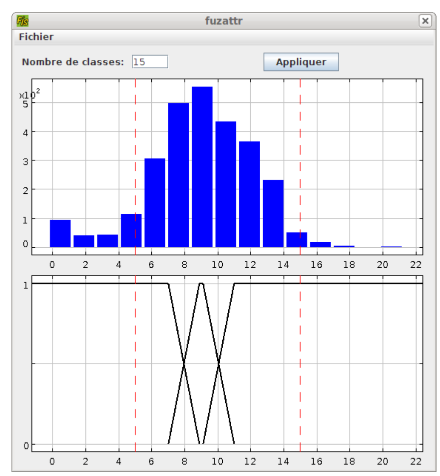

Fig. 13. Histogram and fuzzy partition for yield data

allows to visualize the data variability. Figure 11 shows for example that the northern zone consists of medium and very low yields. This map may be useful to highlight the effects of the environment factors (soil, altitude, etc..) which explain the observed spatial variability. In all examples, regardless of the classification methods used, the maps show discontinuous spatial patterns. Although classification is interesting for analysis purposes, the resulting maps can hardly be taken into account to propose site specific management of the field.

The second stage consists in a spatial zoning of the yield data, using a Euclidean distance in the attribute space. The merging algorithm mentioned in section III-B is used. It yields a series of maps with a decreasing number of zones. The six zone map is presented in Figure 12, that highlights the usefulness of zoning. It shows zones where site specific management may be considered. However, from a practical point of view, the map presented in Figure 12 remains difficult to use. Indeed, the high yield zone located in the southern part of the field (zone 5 in dark grey) is limited to very high yield values while medium-high yield sites have been associated with a low yield zone (zone 6 in light grey). This zoning method yields zones with complex borders and does not allow a simple view of the field. The third stage improves the spatial zoning of the yield data by incorporating expert knowledge through a fuzzy partition based distance (see section III-B). The fuzzy set breakpoints are 7,9,11, which are related to the choice made previously for the crisp classification. A *FisPro* snapshot is shown in Figure 13, allowing to view the fuzzy partition together with the data distribution. The six zone map obtained by running the zoning algorithm, guided by the fuzzy partition based distance, is shown in Figure 14. The introduction of fuzzy logic in the zoning method provides a map that simplifies the representation of the field. Two main management zones are highlighted, one corresponding to the northern low yield, one corresponding to the southern high yield. Note that a few specific zones of small size are also identified. They correspond to i) a zone of very high yield in the center of the plot and ii) two low yield zones located in the southern part of the field which correspond to border effects (beginning of the rows). Depending on the goal and the machinery of the grower, these small zones may not be considered for site specific management.

V. Conclusion

Cooperation between knowledge and data is still an open challenge in system modelling. Among soft computing meth-

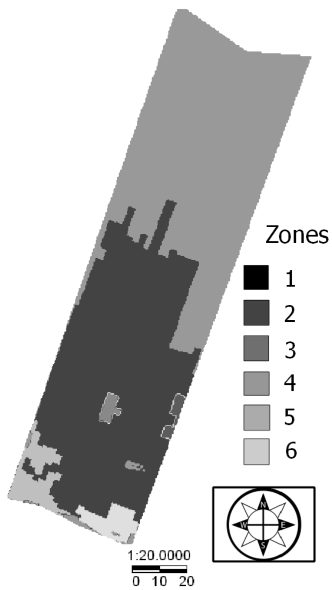

Fig. 14. Zoning yield data with a fuzzy partition based distance criterion

ods, fuzzy logic provides original efficient solutions. Its success stems from the ability to express the system behavior in a linguistic, highly interpretable way. An emerging ambitious challenge is the development of methods and software suitable for cooperation between domain knowledge and georeferenced data, also called spatial data, which are now becoming available in great quantities.

In this paper, we propose an open source framework, based on specialized toolboxes and software, to be used for modelling and decision support. We show how it can help practioners in a simple case study in Agro-Environment. It also aims to answer some educational needs of students in these application domains, including advanced programs for developing countries where the use of open source software is an asset.

This is only a first step. For instance, it is necessary to develop specific visualization tools, in order to represent a fuzzy zone, with uncertainties in two different spaces, the geographical space and the attribute space.

The interpretability constraints which have been implemented in fuzzy software for ordinary data, such as *FisPro*, are not so easy to define for georeferenced data. There is no trivial extension of strong fuzzy partitions to a two-dimensional space. The development of approximate map comparison techniques, in order to monitor the temporal evolution of zones on a map, or to compare maps for different attributes, constitutes another topic of interest. Image analysis techniques have to be extended to include irregularly spaced data, coming from manual measurements, and domain knowledge.

Applying fuzzy logic tools, or more generally soft computing tools, to spatial data is an attractive perspective that opens new research topics, both methodological and software related.

REFERENCES

[1] Y. Chen, S. Khan, and Z. Paydar, "To retire or expand? a fuzzy gis-based spatial multi-criteria evaluation framework for irrigated agriculture," *Irrigation and Drainage*, vol. 59, no. 2, pp. 174–188, 2010.

[2] F. Colin, S. Guillaume, and B. Tisseyre, "Small catchment agricultural management using decision variables defined at catchment scale and a fuzzy rule-based system: a mediterranean vineyard case study," *Water Resources Management*, vol. 25, pp. 2649–2668, 2011.

[3] F. Di Martino and S. Sessa, "The extended fuzzy c-means algorithm for hotspots in spatio-temporal gis," *Expert Syst. Appl.*, vol. 38, pp. 11 829–11 836, September 2011. [Online]. Available: http://dx.doi.org/10.1016/j.eswa.2011.03.071

[4] M. El Hajj, A. Bégué, and Guillaume, "Integrating spot-5 time series, crop growth modeling and expert knowledge for monitoring agricultural practices - the case of sugarcane harvest on reunion island," *Remote Sensing of Environment*, vol. 113, no. 10, pp. 2052–2061, October 2009.

[5] S. Guillaume and B. Charnomordic, "Interpretable fuzzy inference systems for cooperation of expert knowledge and data in agricultural applications using fispro," in *IEEE International Conference on Fuzzy Systems*, I. C. N. CFP10FUZ-DVD, Ed. Barcelona, Spain: IEEE, July 2010, pp. 2019–2026.

[6] ——, "Learning interpretable fuzzy inference systems with fispro," *International Journal of Information Sciences*, vol. 181, pp. 4409–4427, 2011.

[7] S. Guillaume, B. Charnomordic, and P. Loisel, "A numerical distance based on fuzzy partitions," in *Proceedings of the 7th conference of the European Society for Fuzzy Logic and Technology (EUSFLAT-2011) and LFA-2011*, S. Galichet, J. Montero, and G. Mauris, Eds., Annecy, France, July 2011, pp. 1000–1006.

[8] S. Matreata and M. Matreata, "Application of fuzzy logic systems for the elaboration of an operational hydrological warning system in ungauged basins," in *Uncertainties in the 'monitoring-conceptualisation-modelling' sequence of catchment research. 11th Conference of the Euromediterranean Network of Experimental and Representative Basins (ERB)*, L. Pfister and L. Hoffmann, Eds., Luxembourg, September 2006, pp. 157–162.

[9] D. D. Nauck, "Gnu fuzzy," in *IEEE International Conference on Fuzzy Systems*. IEEE, July 2007, pp. 1019–1024.

[10] J.-N. Paoli, O. Strauss, B. Tisseyre, J.-M. Roger, and S. Guillaume, "Spatial data fusion for qualitative estimation of fuzzy request zones: Application on precision viticulture," *Fuzzy Sets and Systems*, vol. 158, no. 5, pp. 535–554, March 2007.

[11] M. Pedroso, J. Taylor, B. Tisseyre, B. Charnomordic, and S. Guillaume, "A segmentation algorithm for the delineation of management zones," *Computer and Electronics in Agriculture*, vol. 70, pp. 199–208, 2010.

[12] M. Pringle, A. McBratney, B. Whelan, and J. Taylor, "A preliminary approach to assessing the opportunity for site-specific crop management in a field, using yield monitor data," *Agricultural Systems*, vol. 76, no. 1, pp. 273 – 292, 2003.

[13] R Development Core Team, *R: A Language and Environment for Statistical Computing*, R Foundation for Statistical Computing, Vienna, Austria, 2008, ISBN 3-900051-07-0. [Online]. Available: http://www.R-project.org

[14] T. Rajaram and A. Das, "Modeling of interactions among sustainability components of an agro-ecosystem using local knowledge through cognitive mapping and fuzzy inference system," *Expert Systems with Applications*, vol. 37, no. 2, pp. 1734–1744, 2010.

[15] B. Tisseyre and A. B. McBratney, "A technical opportunity index based on mathematical morphology for site-specific management: an application to viticulture," *Precision Agriculture*, vol. 9, pp. 101–113, 2008.

[16] N. Tremblay, M. Bouroubi, B. Panneton, S. Guillaume, P. Vigneault, and C. Bélec, "Development and validation of fuzzy logic inference to determine optimum rates of n for corn on the basis of field and crop features," *Precision Agriculture*, vol. 11, pp. 621–635, 2010.