

Research Article

Interactive and visual fuzzy classification of remotely sensed imagery for exploration of uncertainty¹

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Abstract. In this study, we propose, describe, and demonstrate a new geovisualization tool to demonstrate the use of exploratory and interactive visualization techniques for a visual fuzzy classification of remotely sensed imagery. The proposed tool uses dynamically linked views, consisting of an image display, a parallel coordinate plot, a 3D feature space plot, and a classified map with an uncertainty map. It allows a geoscientist to interact with the parameters of a fuzzy classification algorithm by visually adjusting fuzzy membership functions and fuzzy transition zones of land-cover classes. The purpose of this tool is to improve insight into fuzzy classification of remotely sensed imagery and related uncertainty. We tested our tool with a visual fuzzy land-cover classification of a Landsat 7 ETM+ image of an area in southern France characterized by objects with indeterminate boundaries. Good results were obtained with the visual classifier. Additionally, a focus-group user test of the tool showed that insight into a fuzzy classification algorithm and classification uncertainty improved considerably.

1. Introduction

Geospatial data quality is a topic frequently covered in recent scientific literature on GIS and remote sensing (Foody and Atkinson 2002). With increasing use of remotely sensed data as input to a GIS, uncertainty in remotely sensed image classification is also receiving more attention. In recent years, much research has focused on modelling uncertainty in remotely sensed image classification (van der Wel 2000, Zhang 2001, Foody and Atkinson 2002). Uncertainty can arise from poor class definition, mixed pixels, and transition zones (fuzzy boundaries). Both fuzzy and probabilistic classification techniques can help to model and quantify uncertainty. Most proprietary GIS and remote-sensing software provide numerous conventional and advanced classification algorithms. However, most if not all of these packages do not offer tools to model, visualize, and manage uncertainty in classifications. Many of these packages can produce good thematic maps, but

¹A web supplement with colour figures and a demo version of the software can be found at <http://parbat.lucieer.net>

nowadays users want to be presented with information about the quality of these maps. Uncertainty in classification is an important aspect of the data quality and usability or 'fitness for use' of a classified map. Therefore, modelling and communication of uncertainty is becoming more important. An appropriate way to present spatial and thematic behaviour of uncertainty is via visualization. In recent years, visualization prototypes have been proposed, which focus on presentation and exploration of uncertainty in a remotely sensed image classification (van der Wel *et al.* 1997, Blenkinsop *et al.* 2000, Bastin *et al.* 2002). However, none of these tools provides a way of interacting with the classification algorithm itself. Visual interaction with the classification algorithm could greatly improve insight into classification and related uncertainty.

In this paper, we propose, describe, and demonstrate a novel visualization tool, which allows interaction with a supervised fuzzy classification algorithm. The objective of this study is to develop and implement a geovisualization tool by which a geoscientist can interact with the parameters of a fuzzy classification algorithm in order to gain insight into the working of a fuzzy classification and related uncertainty, and to possibly refine the classification result. For this study, we selected a Landsat 7 ETM+ image of an area characterized by semi-natural vegetation types. Transition zones between these vegetation types are known to be problematic in image classification. We evaluate the prototype with a focus group user test.

2. Methods

2.1. Fuzzy classification

Supervised image classification is a commonly performed analysis of remotely sensed data. The result of such a classification is a thematic map with a label for each pixel of the class with which it has the highest strength of membership. This hard or crisp classification is based on conventional crisp set theory. A conventional classification of remotely sensed imagery models the study area as a number of unique, internally homogeneous classes that are mutually exclusive. However, these assumptions are often invalid, especially in areas where transition zones and mixed pixels occur. Land-cover types are rarely internally homogeneous and mutually exclusive, so classes can seldom be separated by sharp or crisp boundaries, in feature space as well as geographic space. Furthermore, complex relationships exist between spectral responses recorded by the sensor and the situation on the ground, where similar classes, pixels, or objects show varied spectral responses, and similar spectral responses may relate to dissimilar classes, pixels, or objects. Moreover, remotely sensed images contain many pixels where boundaries or sub-pixel objects cause pixel mixing, with several land covers occurring within a single pixel. Finally, classes are often hard to define, resulting in vagueness and ambiguity in a classification scheme. Most, if not all, geographical phenomena are poorly defined to some extent and, therefore, fuzzy set theory as an expression of concepts of vagueness is an appropriate model for working with remotely sensed imagery (Fisher 1999, Zhang and Foody 2001). To adapt to the fuzziness characteristic of many natural phenomena, fuzzy classification approaches have been proposed (Wang 1990, Foody 1996, Zhang and Foody 2001).

Fuzzy classification is based on the concept of fuzzy sets (Zadeh 1965). In the fuzzy set model, the class assignment function attributes to each element a grade of

membership in the real interval $[0,1]$ for every defined set. This grade of membership corresponds to the degree to which the element is similar to the concept or prototype represented by that set. Accordingly, fuzzy sets enable representation of imprecisely defined classes such as land-cover classes. Several techniques exist to derive fuzzy memberships. These techniques can be divided into two groups (Burrough and McDonnell 1998):

1. The Similarity Relation Model is data-driven. It involves searching for patterns within a dataset similarly to traditional clustering. The most widespread method is the Fuzzy c -means algorithm (Bezdek 1981).
2. The Semantic Import Model is user-driven. An expert defines the membership functions (Evans 1977).

The fuzzy c -means classifier (FCM) uses an iterative procedure that starts with an initial random allocation of the objects to be classified to c clusters. Given the cluster allocation, the centre of each cluster (in terms of attribute values) is calculated as the weighted average of the attributes of the objects. In the next step, objects are reallocated among the classes according to the relative similarity between objects and clusters based on a well-known distance measure: the Euclidian, Diagonal (attributes are scaled to have equal variance), or Mahalanobis (both variance and covariance are used for distance scaling) metrics are frequently used. Reallocation proceeds by iteration until a stable solution is reached where similar objects are grouped together in a cluster. Their membership value gives their degree of affinity with the centroid of the class (Bezdek 1981).

Fuzzy clustering techniques like the FCM are unsupervised. This means that the data are unlabelled. In some applications, however, a part of the data set has labels. For example, an expert in the training stage of a supervised remotely sensed image classification could obtain these labels. Zhang and Foody (2001) apply a modified version of the fuzzy c -means algorithm in order to develop a fully fuzzy supervised classification method. In the supervised fuzzy c -means, the class centroids are determined from the training data. This reduces the clustering algorithm to a one-step calculation, resulting in fuzzy membership values for each pixel in each of the defined classes.

The fuzzy exponent, fuzziness, or overlap parameter determines the amount of fuzziness or class overlap. If this parameter is close to 1, allocation is crisp, and no overlap is allowed. For large values, there is complete overlap, and all clusters are identical. The fuzziness of the classification can be modulated by varying the magnitude of the fuzziness parameter. Ideally, it should be chosen to match the actual amount of overlap. However, class overlap is generally unknown. Although the fuzziness parameter is often set between 1.5 and 3.0, no clear arguments for the choice of these values are presented (Foody 1996, Burrough and McDonnell 1998, Zhang and Foody 2001).

Alternatively, expert knowledge of the area can be used to define the shape, width, and overlap of the membership functions for each class in a semantic import approach. However, a well-defined and functional classification scheme should exist.

Visualization could be helpful in determining fuzziness between classes. If we picture a classification of remotely sensed imagery, we could visualize the procedure in a feature space plot. In fact, classification is a clustering procedure in which

unclassified pixels are labelled according to their position in relation to the position of class clusters in feature space. Visualization of reference classes, their overlap, and the position of pixels relative to the class clusters could greatly improve insight into classification. Visualization could also help in exploring and adjusting overlap between classes. Thus, visualization might improve the result and understanding of a fuzzy classification by interaction with its parameters.

2.2. Uncertainty visualization

In the past, one had to rely on traditional methods of cartographic expressions for visualization of uncertainty. Today, it is possible to work in an interactive and dynamic visualization environment that incorporates new methods, like those proposed here, alongside traditional methods. Traditional methods were mainly based on the theory of semiology of graphics of Bertin (1967). For example, MacEachren (1992) investigates the use of these graphic variables for uncertainty depiction, noting the crucial importance of logically coupling visual variables with data scale. Of the extended set of Bertin's variables, MacEachren suggests colour saturation as the most logical for uncertainty visualization. Van der Wel *et al.* (1998) propose four static visualization variables for conveying the quantitative character of uncertainty in remotely sensed image classification using probability vectors of individual pixels. These variables are: value (grey-scale maps), colour saturation (bivariate maps), colour hue (associative ranking maps), and a combination of the latter two variables (dichotomy maps). An example is the traffic light principle: red, orange, and green convey to a user prohibition, alertness, and permission, respectively. Hootsmans (1996) proposes colour lightness and saturation to visualize uncertain information derived from fuzzy sets. Hootsmans combined colour hue to depict thematic class information and colour saturation or lightness to visualize uncertainty in one static map.

Techniques like those described above focus on the extraction of uncertainty information from a classification, as either a probability vector or a membership vector per pixel, and presentation of this information to a user. The probability or membership vectors are summarized in a single uncertainty number, for example by computing the maximum membership or probability, confusion index, or entropy from these vectors. These uncertainty values are then visualized with one of the techniques describe above, as either an uncertainty map or a thematic map combined with uncertainty information. These types of visualizations can help in communicating uncertainty in the final classification product, but they do not allow for interaction with the classification.

Developments in computer graphics technology introduced dynamic visualization techniques in cartography. For example, animation techniques were implemented to improve interpretation of large amounts of data, as is the case in visualization of (classification) uncertainty. MacEachren (1994) distinguishes between different uses of temporal graphic variables: to animate maps and to depict dynamic processes in time. Sequential display of different uncertainty maps and different thematic maps derived from the same image may make up an animation. For example, probabilities can be visualized sequentially, according to their ranking, thereby enabling the representation of all probabilities underlying a classification. This animation can follow different schemes, such as simply sequential, progressive, cyclic and back-and-forth. Fisher (1994) proposes duration

as a variable to depict uncertainty: the higher the probability, the longer the period of time the class colour is displayed. Van der Wel *et al.* (1997) propose a method to toggle a thematic map and associated uncertainty map to result in a combined sensation of classes and uncertainty. Hootsmans (1996) uses animation techniques to represent uncertainty related to fuzzy series analysis. A sequence of maps is generated by processing a fuzzy series for a set of alpha cuts. Ehlschlaeger *et al.* (1997) describe a technique of visualizing uncertainty in elevation data using animation.

These dynamic visualization techniques offer a more advanced and flexible solution to visualizing uncertainty information. They provide insight into (per-pixel) uncertainty in the classification result by means of visualizing the entire vector of probabilities or memberships. Most, if not all, of the mentioned techniques focus on visualizing uncertainty in the classification result and do not allow for interaction with the classification. Another disadvantage of these techniques is that visualization and interpretation of uncertainty become difficult when we have a large number of classes.

An interactive visualization environment might be required to be able to improve the exploration of a classification and related uncertainty. The choice of a specific visualization technique also depends on the user group. For decision-makers, visualization of uncertainty in the form of static maps might be sufficient, but a scientific expert needs more to be able to improve the classification process. Geographic visualization (geovisualization or GVis) techniques might be helpful in this sense (MacEachren and Kraak 2001). These techniques are focused on exploration instead of presentation. Interactive visualization techniques such as dynamically linked views (MacEachren 1994, Dykes 1997) and geographic brushing (Monmonier 1989) are essential for exploration of geospatial information. A special issue of the *International Journal of Geographical Information Science* was devoted to visualization for exploration of spatial data (Kraak and MacEachren 1999). Several authors show that geovisualization tools with dynamically linked views facilitate exploratory analysis and 'visual thinking' (Andrienko and Andrienko 1999, MacEachren *et al.* 1999). Therefore, we suggest that uncertainty visualization is not just to present expert users with meta-information on data quality but also to enable them to explore uncertainty and its relation to the original data.

Recent studies (Blenkinsop *et al.* 2000, Bastin *et al.* 2002) show that exploratory geovisualization tools can help to improve the expert's understanding of uncertainty in a classified image scene. They propose a combination of static, dynamic, and interactive visualizations for exploration of classification uncertainty. Again, dynamically linked views and brushing functionality play a key role in these prototypes. The focus of these tools is on visual exploration of uncertainty in a classification result using linked displays of the original image, a parallel coordinate plot, a 2D feature space plot, the classified image with thematic classes, the uncertainty image displaying an uncertainty summary statistic per pixel, and animation of alternative classifications. These tools provide better insight into classification uncertainty, but they do not allow for interaction with the parameters of a classification algorithm. We argue that a user should be able to interact visually with a classification algorithm to improve their knowledge of the nature and effects of the algorithm. Improved understanding may contribute to a superior classification. We suggest that a feature space plot, dynamically linked with an

image display and the classification result, provides the best technique to visualize a classification. A user should be able to adapt the reference class clusters in a feature space plot to change the parameters of a fuzzy classification algorithm. Visual interaction with these parameters can help to gain insight into the origin and effect of uncertainty in a classification. Another advantage is that it can help to fine-tune the classification result.

2.3. Components of the visual classifier

We apply the visualization design of MacEachren *et al.* (1999), who propose three dynamically linked representation forms that facilitate data exploration. Their prototype consists of:

- geoviews in which geographic space is mapped;
- parallel coordinate plots which display several parallel axes, one for each variable in the data set with a line connecting individual records from one axis to the next, producing a signature;
- 3D scatterplots, which represent the relationships between three variables.

In our prototype, we adopt these different representation forms to facilitate visual classification. Our initial geoview is an image display with a colour composite of three image bands or a single image band in grey scale. It contains two windows: the main image window with a size of 500 by 500 pixels and a pan window if the image is larger than the main window size. The image display provides basic image exploration functionalities such as an enhancement tool for contrast stretching, a zoom tool (with a variable zoom factor) floating over the main image window, and a geographic brushing tool to derive information about pixel reflectance values or digital numbers (DN) and geographic location (figure 1(a)).

The parallel coordinate plot (Inselberg 1985, 1998) offers a technique by which a multidimensional space can be visualized in two dimensions. In our prototype, we adopted the ‘Parvis’ parallel coordinate plot designed and implemented by Ledermann (2002). All image bands are plotted in the parallel coordinate plot (PCP). Axes can be reordered, scaled, and translated by simple drag operations. Records can be selected in the display by dragging over them with a ‘brush’. We can select individual pixels and display their signature and a DN value label on each axis. Since real-time high-quality rendering of large datasets, like remotely sensed imagery, can become very time-consuming, the PCP provides the user with a fast preview rendering of the data. On each axis, a transparent histogram can be plotted to obtain information about the mean DN value and variance per band for a better understanding of the data density (figure 1(b)).

The 3D feature space plot is generated from three image bands. These bands can be selected from the colour composite in the image display, from the PCP based on their histograms, or any of the bands in the image. The unit on the axis in the 3D plot is reflection in digital numbers ranging from 0 to 255. Initially, all pixels are plotted in the 3D plot as small dots. In this mode, individual pixels cannot be selected. For selection purposes, the user can choose to plot small (grey) spheres that represent pixel values. If the image contains more than 2000 pixels, the pixels are sampled from the image either randomly or on a regular grid. To display the scatter cloud more accurately, the user can also choose to calculate and visualize a

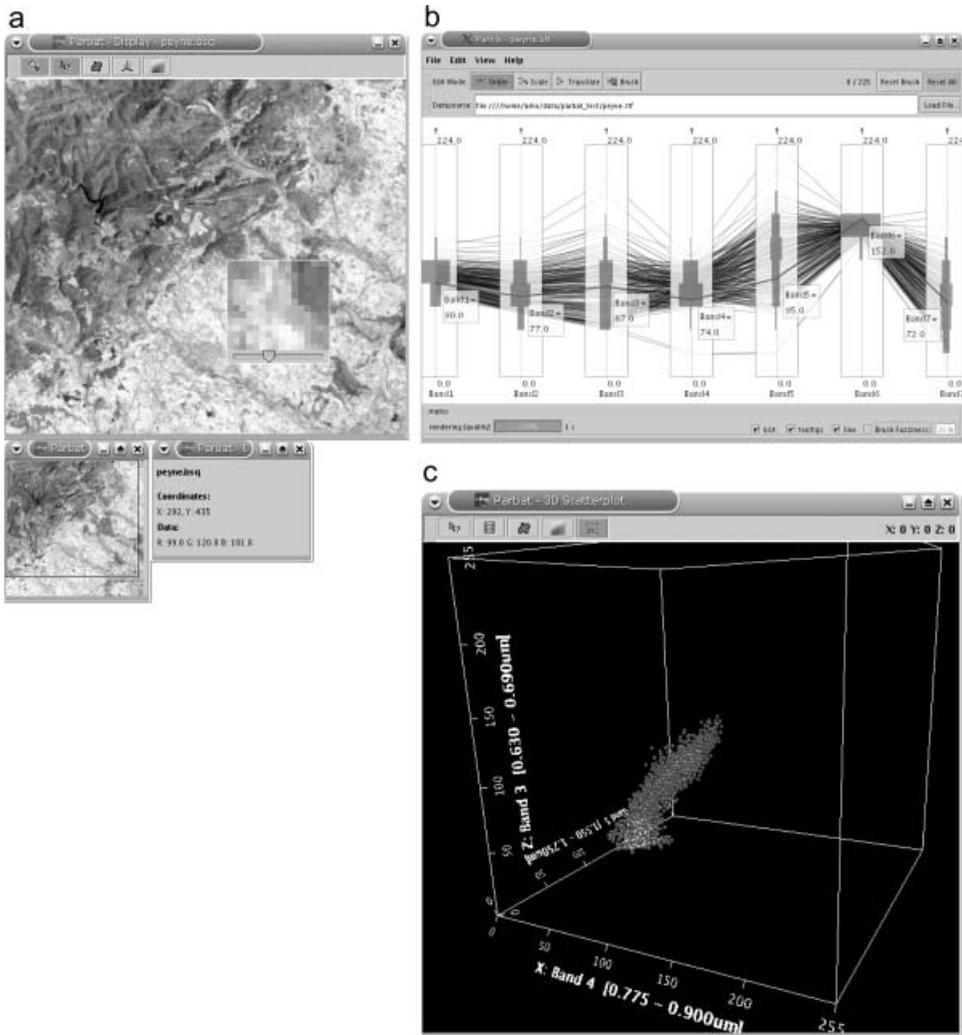


Figure 1. Three basic representation forms implemented in our prototype. (a) Image display showing band 4. For large images, a pan window is used to pan the main image display. The image display contains a zoom window with a slider to set the zoom factor. A separate information window shows the location and values of a selected pixel. (b) Parallel coordinate plot (PCP) showing the signatures of pixels in all seven bands. Transparent histograms provide information on the density of pixel values on each axis. The thick line shows a brushed pixel signature with labels containing the DN values per band. (c) 3D feature space plot showing the scatter cloud of pixels in band 4 on axis X, band 5 on axis Y, and band 3 on axis Z (XYZ). In this density scatter cloud, 2000 of the most occurring pixel values are shown. The pixel grey-scale depicts their frequency, where bright values are used for the most occurring pixel values, and dark values are used for the least occurring pixel values. The plot can be navigated (zoom, pan and (auto)rotate) with the three mouse buttons. This plot can be linked to the image display in (a).

density plot, in which the values/locations of the 2000 most frequent occurring pixels are displayed. The pixel spheres are coloured according to their frequency using a grey scale with bright values as the most and dark values as the least

occurring pixel value. To explore the location of pixels in feature space, the 3D plot can be navigated by (auto-)rotation, translation, and zoom. Individual pixels can be selected to derive their DN values. When a pixel is selected, it is highlighted, and it flashes for 5 s to attract attention; its value is then shown in the plot window. The position of the viewer changes automatically to an optimal viewing angle. Band names and DN labels are shown on the three axes in the plot (figure 1(c)).

The 3D feature space plot is dynamically linked with the image display, i.e. the result of a selection in one view is also shown in other views by highlighting, and the views are updated upon user action. In the image display, the selection colour used for highlighting a selected pixel can interfere with the original pixel colours in the image. Therefore, selection colours can be changed in both views.

2.4. Visualization of classes

An important step in a supervised classification is the choice of reference pixels (also known as regions or areas of interest) for the representation of different land-cover classes. Usually, reference pixels are identified in the image or derived from external data like aerial photography or field observations. Groups of class reference pixels represent a land-cover class. These pixels can be imported and visualized in the image display in their unique class colour. Statistical information from these reference pixels, like the minimum and maximum values, mean vector, and (co)variance matrix, is used in many classification algorithms.

The focus of this study is an interactive visual fuzzy classification based on the visualization of these reference class clusters in the 3D feature space plot. The user can add all reference classes or individual classes to the 3D plot. These class clusters are depicted by (semi-transparent) spheres (figure 2). The centroid of a sphere (i.e. position in the 3D plot) is based on the mean vector of the class's reference pixels. Initially, the radius of a sphere is based on twice the maximum standard deviation. The spheres are coloured according to their unique class colour. Moreover, transparency can be changed interactively so that pixels inside the spheres become visible. Lighting and shading are applied to improve visibility of pixels and class spheres and to facilitate the '3D feeling'. Class overlap is clearly visible in places where spheres intersect (figure 2). Class spheres can be selected, showing a popup window with information about class label, class colour, mean DN value in each band, and maximum standard deviation (i.e. sphere radius). Exploration of this 3D plot provides valuable information about classes, class overlap, and pixel positions. By selecting a pixel in the 3D plot inside or outside one of the spheres, a user can see the locations of pixels with the selected value highlighted in the image display. In addition, when a pixel is selected in the image, a user can see whether it is included in a class cluster or not. The distance in feature space between a pixel and a class cluster or centroid reveals a large amount of information about its uncertainty. Additionally, when a pixel is located in between class spheres, uncertainty is most likely high. Especially, in the regions where class spheres overlap, uncertainty values are high. The position and radius of the class spheres provide an initial condition for a fuzzy classification of the image. However, interaction with these spheres could improve a classification and could help us to fine-tune a classification result and discover relations between classes in feature space and a resulting thematic map and uncertainty map.

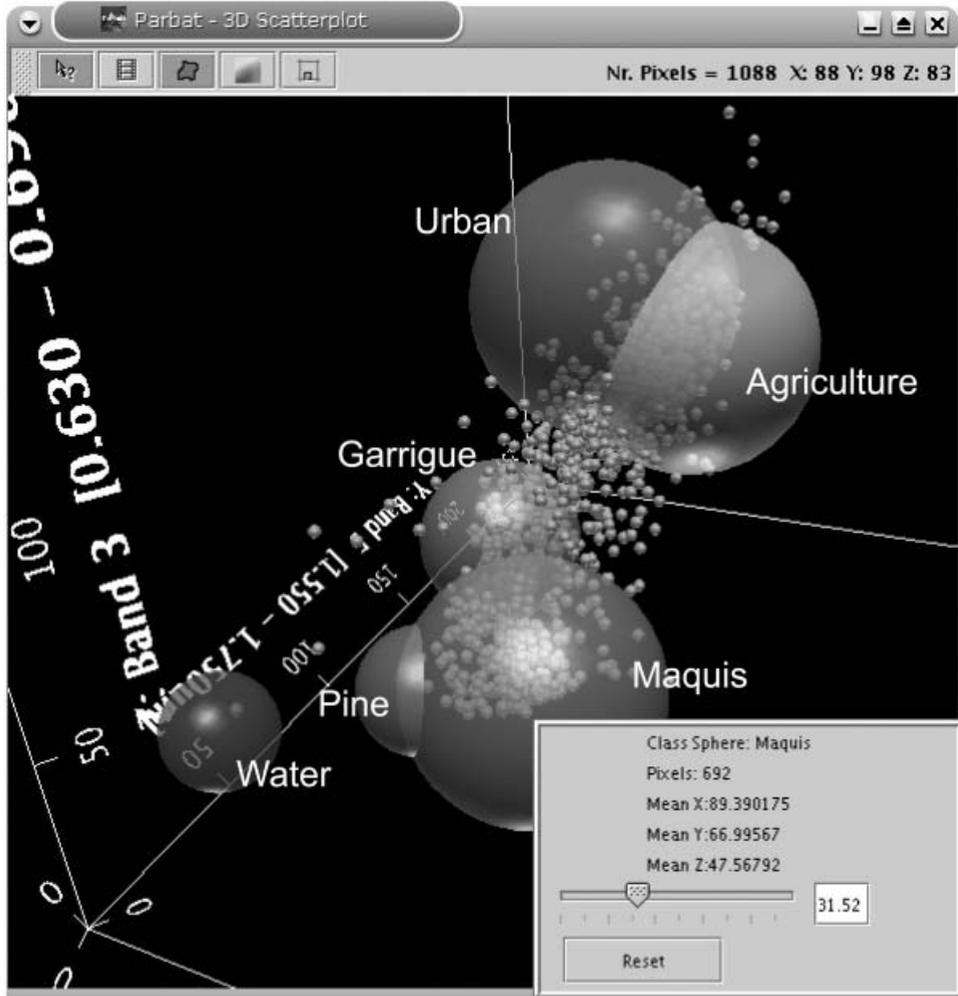


Figure 2. 3D feature space plot showing the class spheres of the reference classes. Overlap occurs between class maquis and pine, maquis and garrigue, and agriculture and urban. The class sphere of the maquis class is selected. The popup window shows the class label, colour, the number of pixels in the reference area, the mean value in each of the bands, and the radius of the class sphere. The value of a selected pixel is shown in the upper-right corner of the plot window. Additionally, the number of pixels with the selected value in the image is shown. These image pixels are highlighted in the image display.

2.5. Visual fuzzy classification

We use the class spheres as described in the previous section to define the membership functions for a fuzzy classification. In traditional fuzzy classification, the fuzziness parameter is set to a specific value. This decision is often relatively arbitrary. In addition, in a semantic import model, the membership function is seldom based on well-founded data. We argue that visual information on class overlap and class range is invaluable for determining the width and overlap of membership functions.

A class sphere depicts a membership function with the centroid as the point where membership is equal to 1, and the outside of the sphere itself is the point where membership is equal to 0. Pixel memberships range between 0 and 1 in the area inside the sphere, between the border and the centroid (figure 3). The shape of the membership function is triangular. The initial radius of a sphere (width of the membership function) is based on twice the maximum standard deviation of the

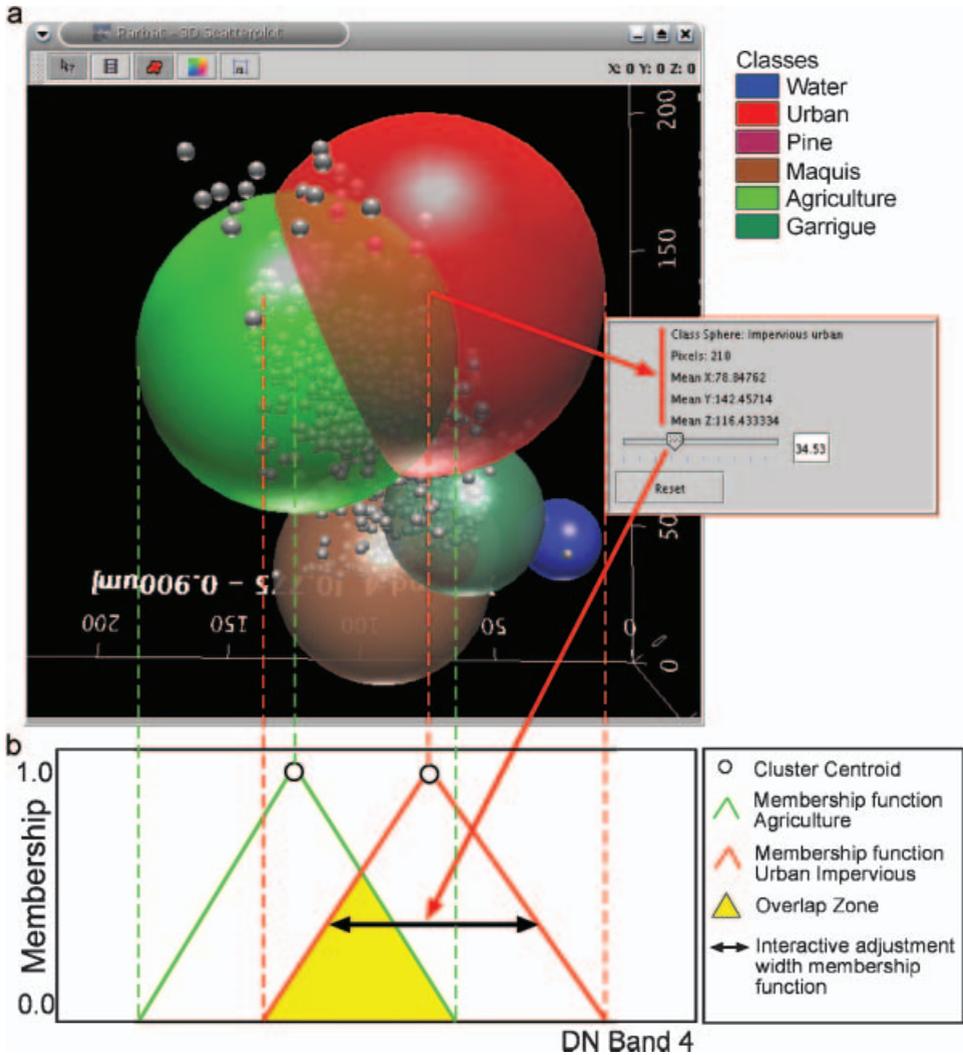


Figure 3. (a) Schematic representation of interactive visual fuzzy classification. The classes agriculture and urban overlap in the 3D feature space plot. The class spheres depict the triangular membership functions, which are used for classification. Membership values for unclassified pixels are calculated based on these membership functions. (b) Membership functions of the two overlapping classes projected onto band 4. When selecting one of the spheres, a user is presented with a popup window including a slider. This slider is used to adjust the radius of the sphere, thereby changing the width of the membership function and possibly changing the overlap with another class/membership function.

class under consideration. When the user selects a class sphere, they are presented with a popup window with information about the class label, colour, mean values, and the radius. The radius can be adjusted with a slider, increasing or decreasing the size of the sphere. The exact value for the radius of the changing sphere is shown in the popup window. By changing the radius of a class sphere, the user changes the width of the triangular membership function of a class (figure 3). Class overlap zones can be resized to increase or decrease the fuzziness, effectively changing the fuzziness parameter in a fuzzy *c*-means classification for those particular classes.

When all membership functions are adjusted based on the visual interpretation of class spheres, all unclassified pixels in the image can be classified. First, the user has to decide on the type of output products of the classification. Users are likely to be interested in a crisp classification product to see the geospatial distribution of classes in the image or to see a generalized, classified version of the image. Therefore, a hard (i.e. 'defuzzified') land-cover image is one of the main outputs of the classification. It gives the class label and class colour per pixel (figure 4(a)). A membership image with a membership layer for each class is the second product (figure 4(b)). Information about transition zones can be obtained from these membership images. A third output is an image depicting the maximum membership per pixel. This image gives an indication of the uncertainty of the classification; the lower the maximum membership, the higher is the uncertainty (figure 4(c)). Another measure for uncertainty is the confusion index (Burrough and McDonnell 1998). As a final output, an image with the pixel confusion index is produced. This image gives an excellent overview of the areas where uncertainty is highest and classes overlap (figure 4(d)). When the actual classification is performed, the selected classification outputs are shown on screen and automatically linked to the 3D feature space plot. Pixels that fall outside any of the class spheres are unclassified. They are shown in black in the hard class image (figure 4(a)). The resulting image displays have the same functionality as the original image display. The user can navigate, zoom, and query pixels in the image (as shown in figure 1(a)).

The dynamic links between the class image display and the 3D plot are very powerful. This gives the user the possibility to explore and discover relations between the class of a certain pixel, its uncertainty and the location in feature space. Based on the visual information, a user can get a much better impression of where uncertainty arises. Insight into the actual classification can be improved, because the user can 'play' with the parameters of the algorithm by adjusting the class spheres in feature space. The new result is shown as a class image with related uncertainty information. Changes in class membership functions are immediately depicted in the output images. In this way, the user will get a better feel of the functioning of a fuzzy classification. Another advantage of this tool is that it also enables a user to fine-tune the classification result.

2.6. Implementation of the prototype 'Parbat'

The prototype, named 'Parbat', is programmed in JavaTM, using the JavaTM Advanced Imaging library (JAI) for advanced image processing and the Java 3DTM library for 3D graphics (Sun Microsystems Inc. 2002). One advantageous property

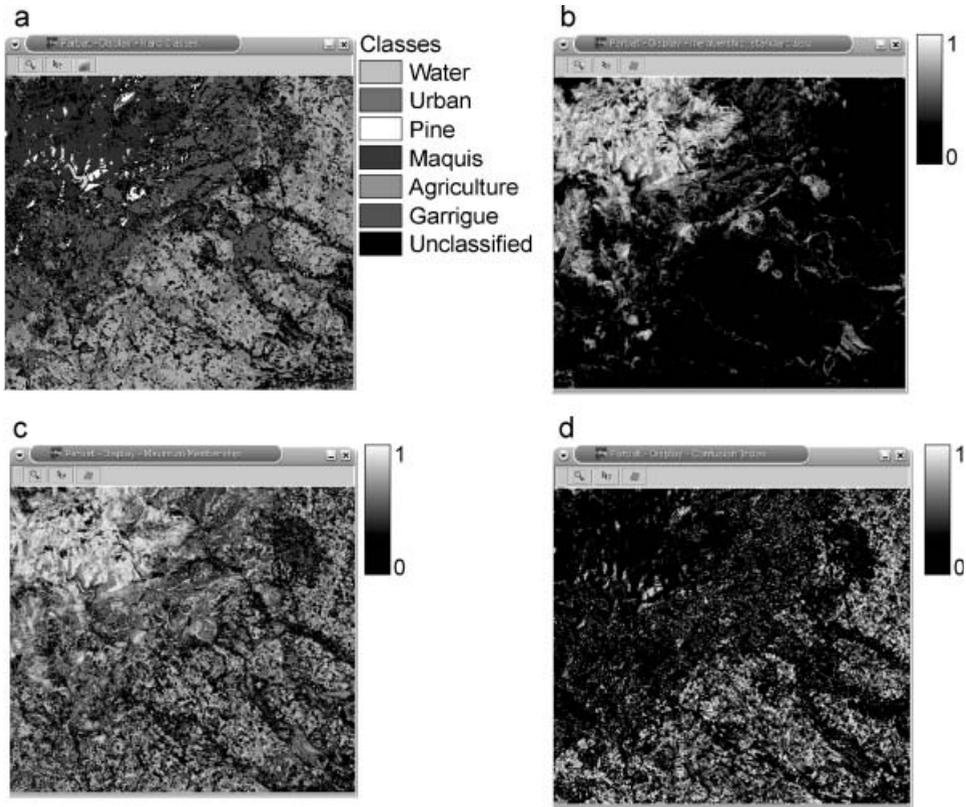


Figure 4. Classification result after an initial visual fuzzy classification based on the default radii of the class spheres. (a) Hard landcover class image display with class labels based on the maximum membership. The colours of the classes are the same as the colours used in the 3D plot. The following classes occur: water, pine, maquis, garrigue, agriculture, and urban. Black pixels are unclassified, because these pixels occur outside any of the class spheres in the 3D feature space plot. (b) Membership image display for the class maquis showing high membership values for pixels in the north-west, hilly part of the area (bright values depict high membership values). (c) Maximum membership map showing, for every pixel, the maximum membership from the membership vector. High values depict a low uncertainty (bright), whereas low values depict a high uncertainty (dark). The maquis and water pixels are classified with a low uncertainty, whereas maquis, urban, and agricultural areas are classified with higher uncertainty values (note: high uncertainty=low membership=dark value). (d) Confusion image display showing areas where confusion in classification occurs (bright areas). These are the pixels with values within the overlap zone of two or more membership functions. Urban and agricultural areas overlap in feature space, as can be seen in figures 2 and 3. Pixels in this overlap zone show high confusion values in the image display (note: high uncertainty=high confusion=bright value). In future versions, an interactive legend will be implemented to avoid confusion between uncertainty maps.

of Java is its platform independency, meaning that 'Parbat' can be used on any operating system. The prototype can be downloaded at <http://parbat.lucieer.net>.

The user interface contains a series of buttons, similar to ERDAS Imagine and ENVI, to access the main visualization and classification functions. Selection

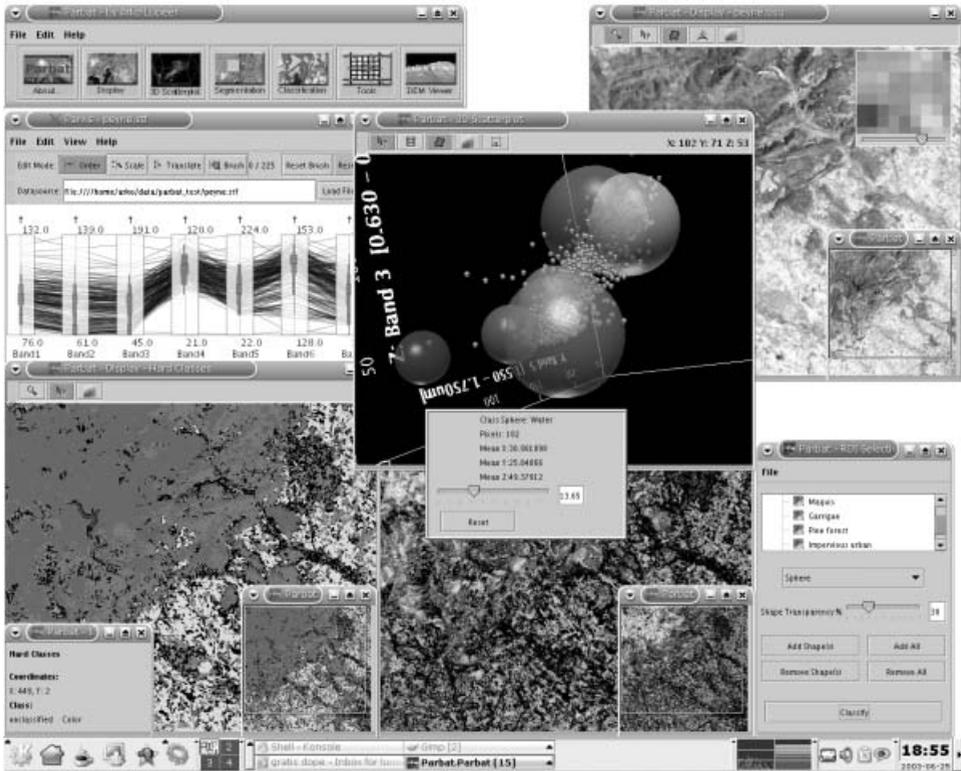


Figure 5. Screen capture of the 'Parbat' prototype, showing several selection, information, and display windows. 'Parbat' uses a multiple document interface without a backing window. The main window is the button bar in the upper-left corner, with buttons to access the main visualization and classification functions.

dialogs and displays are opened in new windows. Thus, 'Parbat' implements a multiple document interface (MDI) without a backing window; the main window is the button bar (figure 5). Currently, 'Parbat' can read band sequential files based on the standard ENVI format. Both input and output functions use this file format. A band sequential file (often with the extension .bsq) is a generic binary file with an ASCII header describing the number of rows, columns, bands, band names, data type, projection, description, and sensor. Reference pixels for classification are selected from regions of interest (ROIs) digitized in ENVI. The ENVI ROI ASCII export format is used as input in 'Parbat' for visualization of reference class pixels in the image display and class spheres in the 3D plot. Information about these ROIs is used in subsequent classification.

Currently, this prototype is tested and run on a Pentium III 800-MHz laptop with 512 Mb of RAM and a video card supporting OpenGL running a Linux operating system. Java 3DTM uses OpenGL in the background, and a video card supporting this 3D graphics standard greatly enhances the 3D visualization performance. A visual fuzzy classification based on three bands of an image of 512 by 512 pixels takes less than 3s on this machine. Navigation of both the image display and 3D feature space plot is fast and smooth, without jittering.

3. Prototype test case

3.1. Study area and data set

In order to test the prototype, we used a subset of a Landsat 7 ETM+ image of an area in southern France. Transition zones between vegetation types are known to be problematic in land-cover classification of remotely sensed images (Foody 1996). Therefore, classification uncertainty plays an important role in these images. A geovisualization tool like 'Parbat' can help to gain insight into classification uncertainty. An area in which these classification problems occur is the 'La Peyne' catchment located north-west of Montpellier, France. This area is chosen as the study area to demonstrate the use of a geovisualization tool for visual fuzzy classification and uncertainty. The area is situated at the fringe of the 'Massif Central' and is characterized by various geological and lithological substrates. The large variety in these substrates has caused a wide range of soil conditions and vegetation types. The northern part of the area is covered by a Mediterranean oak forest (also known as 'maquis') dominated by *Quercus ilex* and *Quercus pubescens* and lower 'garrigue' shrub lands. The southern part of the area is characterized by vineyards and agricultural crops (Lucieer *et al.* 2000, Sluiter 2001). A subset (225 km²) of a Landsat 7 (ETM+) scene covering the La Peyne area is used in this study (figure 1(a)). The image was acquired on 26 June 2001.

The study area is actively used as research area for modelling floods, erosion, and temperature balance. Information on basic land cover provides important input for these models. The following land-cover classes can be found in the study area: water (lake), maquis, garrigue, pine forest, agriculture (mostly vineyard) and urban area. Not all classes are likely to have similar spectral responses and overlap. Water, for example, is often a spectrally 'pure' class and usually does not overlap with other classes. However, maquis and garrigue are expected to show very similar signatures with significant overlap of clusters in feature space. Fieldwork showed that these classes often gradually change from one to the other. Urban areas are often a mix of roofs, gardens, cars, and streets. Thus, the urban class will probably show a high variance in its class cluster in feature space. The same applies to vineyards, showing a mix of vegetation and bare soil, with the percentage of vegetation cover depending on the season.

Fieldwork has been carried out to obtain ground reference data. Regions with 'pure' classes have been observed in the field and corresponding pixels digitized and extracted from the image to form reference class clusters. The mean and standard deviation from these class reference pixels are then used to plot the class spheres in the 3D feature space plot. Additionally, the reference areas are highlighted in their class colour in the image display. Individual classes can be added or removed from the 3D plot or image display. The locations and sizes of the class reference spheres in the 3D plot provide an initial setup for the fuzzy classification. Before the actual classification, a user is stimulated to explore overlap zones between classes by navigation in the 3D plot and to explore relations between pixels in the 3D plot and pixels in the image display, and their distance from the class reference clusters.

3.2. Visual fuzzy classification of the study area

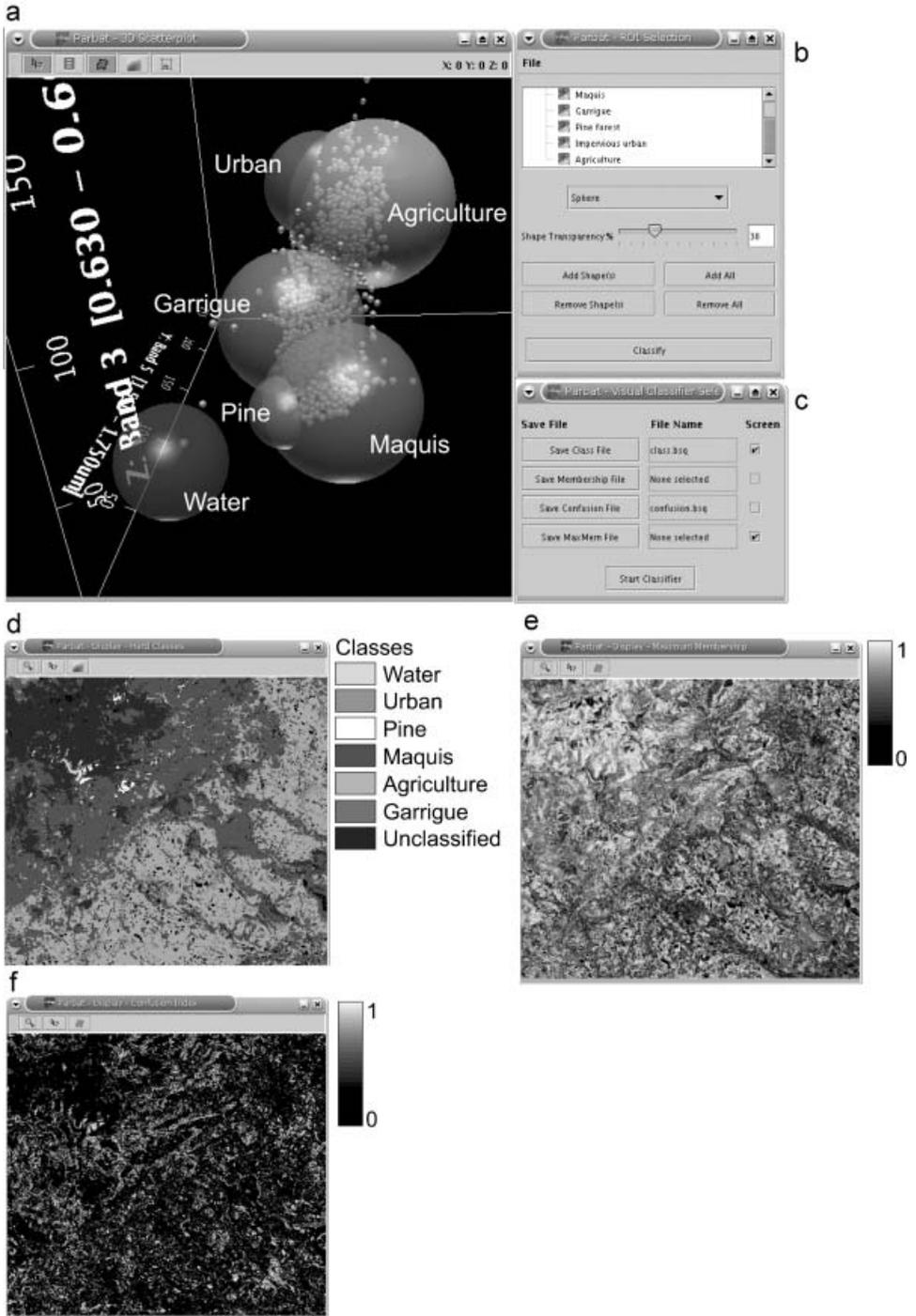
To test the visual fuzzy classification in the prototype, we use band 4 (NIR), 5 (MIR) and 3 (RED) from the Landsat 7 test image. These three bands explain most of the variability in the image and are expected to give good classification results.

When we plot the reference class spheres in the 3D plot, we can see that the classes agriculture and urban overlap considerably (figures 2 and 3). In addition, the maquis and garrigue class spheres, as well as the maquis and pine classes, overlap slightly. The water class sphere shows no overlap with other classes. An initial classification with the default membership functions (i.e. default sphere radius equals twice the maximum standard deviation) shows that many pixels remain unclassified (figure 4(a)). This is caused by the small width of the membership functions. It also shows that the urban class is overclassified, and the agricultural class is underclassified, compared with field observations. Furthermore, the image display with the confusion index visualizes the spatial distribution of uncertainty (figure 4(d)). It shows that there is considerable confusion in agricultural and urban areas. In addition, in regions affected by shadow, confusion is high. This observation corresponds to the overlapping class spheres in the 3D plot. We can test this by clicking on a pixel with high confusion in the confusion image display and study the position of this pixel in the feature space plot (it is highlighted, it flashes, and the position of the viewer changes to the optimal location). This exploration session shows that pixels with a high confusion index (i.e. high uncertainty) are located in the overlap zones between classes urban and agriculture. The maximum membership image display shows that in areas where maquis and water occur, membership is highest, and therefore, uncertainty values are low (figure 4(c)). When we select pixels in these areas in the image display, we see that these pixels are located inside the maquis and water class spheres in the 3D plot, close to the centroids, therefore with high membership values.

To fine-tune the classification, we return to the 3D plot (figure 6). A considerable number of pixels are unclassified because these pixels do not fall within any of the class spheres, so their membership equals 0. A first step is to increase the width of some of the membership functions (figure 3), but at the same time, we do not want classes to overlap completely. We can easily increase the radius of the garrigue class sphere without making the overlap zone with maquis too large. We also would like to reduce the width of the urban class, because it was overclassified in our initial classification. We select this class sphere in the 3D plot and decrease its radius using the slider. The radius is shown in the popup window, which gives us the width of the membership function. The agriculture class sphere is resized to a larger size, because it was underclassified in the initial classification. See figure 6(a) for the resulting class sphere configuration. A second classification based on this configuration shows that most of the unclassified pixels in the previous session are now classified (figure 6(d)). The area of the urban class is much smaller. This corresponds with the small number of villages present in the area. Agriculture, maquis, garrigue, pine, and water are accurately represented in the class image display. The confusion image display shows that confusion is highest in narrow transition zones between maquis and garrigue, and in agricultural parcels (figure 6(f)). These parcels are most likely bare soil patches, which are spectrally very similar to roofs of houses. A selection of pixels in these areas shows that these pixels are located in the overlap zone between the agriculture and urban classes in the 3D feature space plot.

Comparison of the visual classification result with a standard supervised fuzzy *c*-means classification with a fuzziness of 2.0 shows that the visual classifier outperforms the conventional fuzzy classifier (figure 7). The standard fuzzy classifier

overclassifies the urban area, i.e. too much urban area occurs in the classification result (figure 7(a)). However, the main gain of the visual classifier is the insight a user gains of the classification algorithm and related uncertainty by exploring the relations between classes and pixels and the relations between the spatial classification



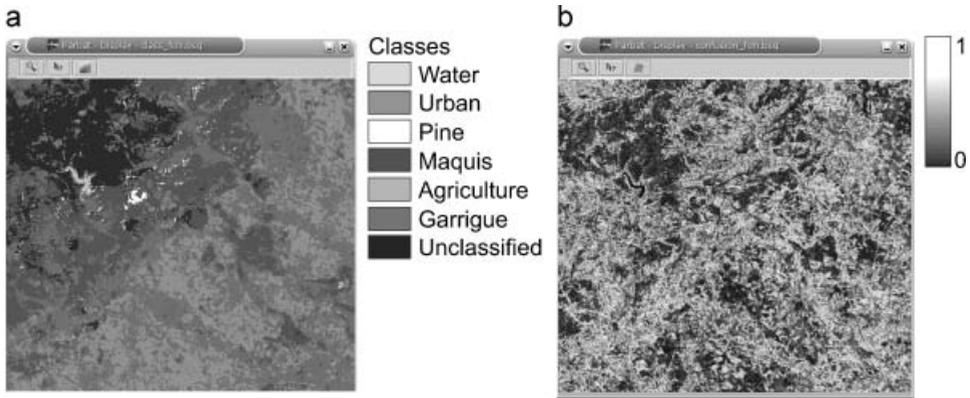


Figure 7. Standard supervised fuzzy c -means classification for comparison with the fuzzy visual classifier in figure 6. (a) Image display with hard classes showing that the urban class is overclassified, and the agricultural class is underclassified. (b) Image display with the confusion index for the standard fuzzy c -means, which depicts high confusion values in agricultural, urban, and garrigue areas.

result (image display) and uncertainty information (confusion and maximum membership display), and corresponding thematic or spectral information in the 3D feature space plot. Dynamically linked views and interaction with the class reference spheres are, therefore, crucial for the effectiveness of a visual classifier.

4. Evaluation of the prototype

4.1. Focus group user test

Evaluation is an important issue in considering the effectiveness of the prototype in improving understanding of a fuzzy classification and uncertainty. Initially, we are interested in a qualitative evaluation of the prototype. Focus groups are an excellent way of qualitative user testing (Morgan 1998, Kessler 2000). Harrower, MacEachren and Griffin (2000) describe focus groups as a ‘cost-effective way to generate qualitative evidence concerning the pros and cons of a geovisualization system’.

4.2. Focus group setup

Eight researchers within our institute were invited for a 2-h focus group session. The participants all have an academic background in remote sensing or visualization. We started the session with a 20-min presentation about the background of

Figure 6. Fine tuning of initial classification result. After an initial classification based on the default class sphere radii, we return to the 3D plot to fine-tune the classification result. (a) 3D plot with the adjusted class spheres. The size of the maquis class sphere, as well as the garrigue and agriculture class spheres, was increased and the radius of the urban class sphere was decreased. This configuration of class clusters better reflects the situation in the field. (b) Selection window to add and remove classes to and from the 3D plot. Transparency for the class spheres can be adjusted in this window. The ‘classify’ button initializes another window (c) to select the output of the classification. In this window, the classifier is finally started. (d) Hard classes, (e) maximum membership, and (f) confusion showing the classification result based on the new class sphere configuration.

fuzzy classification of remotely sensed imagery and about geovisualization. Then, we demonstrated the prototype by first showing the different displays and their basic functionality, followed by a visual fuzzy classification based on class clusters in the 3D feature space plot. Next, the participants worked with the prototype for 45 min with clear directions to focus on the visual fuzzy classifier. Finally, we discussed their experiences in a 40-min discussion.

4.3. Focus group comments

All participants felt that visualization helps in understanding a classification algorithm. Dynamic linking of the different representations greatly improved their insight. The 3D plot provides an excellent visualization for classification. Interaction with the class clusters helped in understanding the effect of changing membership function and class overlap on the classification and uncertainty. Some participants noted that a tool like this would be very helpful in teaching students remotely sensed image classification, to help them visualize the classification process. One of the main complaints about existing software was that ‘uncertainty tools’ are lacking in commercial remote sensing and GIS packages.

The prototype is not restricted to one type of application, like land-cover mapping. In other applications like geological, soil, or vegetation mapping, a tool like this might be very useful and helpful. In addition, the prototype is not restricted to one type of remotely sensed imagery.

The role of the parallel coordinate plot is small in this prototype. The PCP helps in choosing bands for the 3D plot (based on the histograms); however, the PCP is not linked to the image and 3D plot. Therefore, it is difficult to use it in classification. A dynamic link of the PCP with the other displays would be an improvement.

The classification products like the confusion and maximum membership image display give a good overview of the geographical distribution of uncertainty in the classification. Detailed exploration of individual pixel values gives good insight into thematic pixel uncertainty.

We can conclude from this focus group session that the prototype complies with the objectives. Although some detailed aspects of the user interface and functionality could be improved, the main objective of the prototype was clear. All participants found that the proposed geovisualization prototype helps in clarifying the functioning of a supervised fuzzy classification algorithm. It also helps in understanding uncertainty and fuzzy class overlap.

5. Discussion

The visual classifier as proposed in this study is based on three image bands. These bands are chosen from all image bands based on interpretation of the parallel coordinate plot or colour composites in the image display. In other words, only three dimensions of a seven-dimensional space are used in classification. Alternatively, we could apply techniques to reduce a seven-dimensional space to three dimensions. For example, a principal-components analysis (PCA) can be carried out to derive the three principal components that explain most variance in the data. The axis of the 3D plot can then be formed by the first three principal components. Likewise, the image display can contain a colour composite of these principal components. The bands in the PCP can be depicted by all principal

components in sequential order. A classification is then carried out in principal-component space. Alternatively, a projection of a hyper-dimensional feature space to three dimensions could be used. Other visualization techniques for visualization of hyper-dimensional spaces exist, such as the hyperbox or starplot. However, these techniques are not suitable for classification purposes. In future work, we will focus on the dynamic link between the PCP, the 3D plot, and image displays.

The membership function used in our prototype is a triangular-shaped function. A useful addition to the prototype would be an option to choose the shape of the membership function, either globally or per class. For example, the user should be able to select a trapezoidal or Gaussian membership function. This makes it possible to assess the effect of different membership functions on the classification result. Additionally, the centroids of the class spheres (i.e. centre of the membership functions, where membership equals 1) are fixed. A user might want to change the location of a class sphere to assess the effect of relocation of reference class clusters on fuzzy overlap, for example.

Class clusters in the 3D feature space plot are visualized by semi-transparent spheres. However, a sphere is a very rough approximation of the shape of a class cluster. By using a sphere, one assumes equal variance in every direction. In fact, the maximum standard deviation of the three bands is used to set the radius of a class sphere. A better approximation of the shape of a class cluster would be an ellipsoid. A 3D ellipsoid could be constructed from the mean vector and covariance matrix of a class. The mean vector gives the centre of the ellipsoid. From the covariance matrix, eigenvalues and eigenvectors can be calculated. Eigenvalues represent the lengths of the axis; eigenvectors represent the direction of the axis of the ellipsoid. In this way, for every reference class, ellipsoids can be constructed and visualized. However, an ellipsoid is also an approximation of the shape of a class cluster. Evaluation of the prototype showed that users would like to see the 'real' shape of a class clusters in feature space. They argued that it would help in the interpretation of reference classes and assessing their overlap. α shapes provide a technique for calculating a shape from a set of points in feature space. Therefore, α shapes provide a way of visualizing irregular and even concave clusters in a 3D feature space plot. Current and future research will focus on this direction.

Visualization of uncertainty in the final classification result is done by depicting maximum membership or confusion values in a separate grey-scale map. Alternatively, the map containing hard land-cover classes can be combined with the uncertainty map. Colour hue can be used to describe the classes, and colour saturation or lightness can be used to visualize uncertainty information. We could use one of the visualization techniques as described in Section 2.2. The focus of this study, however, is explorative visualization of a fuzzy classification and not presentation of uncertainty in a classification result.

It should be noted that the effectiveness of the geovisualization tool proposed in this paper depends not only on the visualization techniques used but also on the knowledge of the user (a geoscientist). The selection of reference or ground data pixels is an important step in the classification process. Sufficient knowledge of the area under consideration is essential for good classification results.

6. Conclusions

Uncertainty plays an important role in land-cover classification of remotely sensed imagery. Classification of areas where transition zones between vegetation types or mixed pixels occur usually results in a high classification uncertainty. Fuzzy classification provides a technique for quantifying this uncertainty. Visualization provides an excellent means of exploring the functioning of a fuzzy classification algorithm and related uncertainty. In this study, we proposed and described a geovisualization tool by which a geoscientist can visually interact with the parameters of a supervised fuzzy classification algorithm. Using this geovisualization tool, they can find an optimal classification result and gain an insight into classification uncertainty. The tool consists of three basic plots: an image display, a parallel coordinate plot, and a 3D feature space plot. The user can interactively adjust the membership functions of classes and fuzzy overlap zones between them in the 3D feature space plot. All plots are dynamically linked and have geographic brushing functionality to stimulate exploration and, consequently, improve insight into classification and uncertainty. To test the proposed prototype, we used a Landsat 7 ETM+ image of an area in southern France where transition zones between semi-natural vegetation types dominate. A visual fuzzy classification resulted in a hard landcover map and uncertainty maps showing the membership layers, maximum membership per pixel and the confusion index per pixel. Good classification results were obtained. The user can adapt the reference class sphere in the 3D feature space plot to fine-tune the classification. A focus-group user test showed that remote-sensing users find this geovisualization prototype 'Parbat' very valuable. Their insight into a fuzzy classification algorithm and classification uncertainty improved considerably by using this tool. Users noted that the main advantage of the visual classifier is their improved insight into the classification algorithm and related uncertainty. Exploring the relations between classes and pixels and the relations between the spatial classification result (image display) and uncertainty information (confusion and maximum membership display), and corresponding thematic or spectral information in the 3D feature space plot, provides important information for understanding a fuzzy classification and related uncertainty.

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References

- ANDRIENKO, G. L., and ANDRIENKO, N. V., 1999, Interactive maps for visual data exploration. *International Journal of Geographical Information Science*, **13**, 355–374.
- BASTIN, L., FISHER, P., and WOOD, J., 2002, Visualizing uncertainty in multi-spectral remotely sensed imagery. *Computers & Geosciences*, **28**, 337–350.
- BERTIN, J., 1967, *Semiologie Graphique: Les Diagrammes, Les Reseaux, Les Cartes*, Mouton and Gauthiers-Villars (Paris: Mouton).
- BEZDEK, J., 1981, *Pattern Recognition with Fuzzy Objective Function Algorithms* (New York: Plenum Press).

- BLENKINSOP, S., FISHER, P., BASTIN, L., and WOOD, J., 2000, Evaluating the perception of uncertainty in alternative visualization strategies. *Cartographica*, **37**, 1–13.
- BURROUGH, P., and MCDONNELL, R., 1998, *Principles of Geographical Information Systems. Spatial Information Systems and Geostatistics* (Oxford: Oxford University Press).
- DYKES, J., 1997, Exploring spatial data representation with dynamic graphics. *Computers & Geosciences*, **23**, 345–370.
- EHLSCHLAEGER, C. R., SHORTRIDGE, A. M., and GOODCHILD, M. F., 1997, Visualizing spatial data uncertainty using animation. *Computers & Geosciences*, **23**, 387–395.
- EVANS, I. S., 1977, The selection of class intervals. *Transactions of the Institute of British Geographers (new series)*, **2**, 98–124.
- FISHER, P., 1994, Visualization of the reliability in classified remotely sensed images. *Photogrammetric Engineering and Remote Sensing*, **60**, 905–910.
- FISHER, P., 1999, Models of uncertainty in spatial data. In *Geographical Information Systems, Vol. 1 Principles and Technical Issues, Vol. 2 Management Issues and Applications*, 2nd edition (New York: Wiley), pp. 191–205.
- FOODY, G. M., 1996, Approaches for the production and evaluation of fuzzy land cover classifications from remotely sensed data. *International Journal of Remote Sensing*, **17**, 1317–1340.
- FOODY, G. M., and ATKINSON, P. M., 2002, *Uncertainty in GIS and Remote Sensing* (New York: Chichester, UK).
- HARROWER, M., MACEACHREN, M. A., and GRIFFIN, A., 2000, Developing a geographic visualization tool to support Earth science learning. *Cartography and Geographic Information Science*, **27**, 279–294.
- HOOTSMANS, R., 1996, Fuzzy Sets and Series Analysis for Visual Decision Support in Spatial Data Exploration. Ph.D. Thesis, Utrecht University.
- INSELBERG, A., 1985, The plane with parallel coordinates. *The Visual Computer*, **1**, 69–91.
- INSELBERG, A., 1998, Multidimensional detective. In *IEEE Proceedings of Information Visualization '97*, pp. 100–107. IEEE.
- KESSLER, F. C., 2000, Focus groups as a means of qualitatively assessing the U-boat narrative. *Cartographica*, **37**, 33–60.
- KRAAK, M. J., and MACEACHREN, A. M., 1999, Visualization for exploration of spatial data. Guest editorial of a special issue. *International Journal of Geographical Information Science*, **13**, 285–287.
- LEDERMANN, F., 2002, Parvis parallel coordinates visualisation. <http://home.subnet.at/flo/mv/parvis/>
- LUCIEER, A., KOSTER, E., DE JONG, S., and JETTEN, V., 2000, The DAIS La Peyne experiment: Using the optical and thermal DAIS bands to survey and model the surface temperature. In *International Archives of Photogrammetry and Remote Sensing. Vol. XXXIII, Part B4*, Amsterdam. GITC.
- MACEACHREN, A., 1992, Visualizing uncertain information. *Cartographic Perspectives*, **13**, 10–19.
- MACEACHREN, A. M., and TAYLOR, D. R. F., 1994, *Visualization in Modern Cartography* (Oxford: Pergamon).
- MACEACHREN, A. M., and KRAAK, M., 2001, Research challenges in geovisualization. *Cartography and Geographic Information Systems*, **28**, 3–12.
- MACEACHREN, A. M., WACHOWICZ, M., EDSALL, R., HAUG, D., and MASTERS, R., 1999, Constructing knowledge from multivariate spatiotemporal data: integrating geographical visualization with knowledge discovery in database methods. *International Journal of Geographical Information Science*, **13**, 311–334.
- MONMONIER, M., 1989, Geographic brushing: Enhancing exploratory analysis of the scatterplot matrix. *Geographical Analysis*, **21**, 81–84.
- MORGAN, D. L., 1998, *The Focus Group Guidebook—Focus Group Kit 1* (Newbury Park, CA: Sage).
- SLUITER, R., 2001, Homepage Raymond Sluiter—modelling ecological processes using high-resolution hyperspectral remote sensing images, <http://sluiter.geog.uu.nl>
- Sun Microsystems Inc. 2002, The source for Java(TM) technology, <http://java.sun.com>

- VAN DER WEL, F., 2000, Assessment and Visualisation of Uncertainty in Remote Sensing Land Cover Classifications. Ph.D. Thesis, Utrecht University.
- VAN DER WEL, F., VAN DER GAAG, L., and GORTE, B., 1997, Visual exploration of uncertainty in remote sensing classification. *Computers & Geosciences*, **24**, 335–343.
- WANG, F., 1990, Improving remote sensing image analysis through fuzzy information representation. *Photogrammetric Engineering and Remote Sensing*, **56**, 1163–1169.
- ZADEH, L., 1965, Fuzzy sets. *Information and Control*, **8**, 338–353.
- ZHANG, J., and FOODY, G. M., 2001, Fully-fuzzy supervised classification of sub-urban land cover from remotely sensed imagery: statistical and artificial neural network approaches. *International Journal of Remote Sensing*, **22**, 615–628.