UNIVERSITAT DE LLEIDA
Escola Tècnica Superior d'Enginyeria Agrària
Departament de Medi Ambient i Ciències del Sòl

Suelo-Paisaje-Erosión. Erosión por cárcavas y barrancos en el Alt Penedès – Anoia (Cataluña).

Un enfoque de estudio mediante tecnologías de la información espacial: Bases de Datos, Sistemas de Información Geográfica y Teledetección.

Soil-Landscape-Erosion. Gully erosion in the Alt Penedès – Anoia (Catalonia).

A spatial information technology approach: Spatial databases, Geographical Information Systems and Remote Sensing

Memoria presentada por:

José Antonio Martínez Casasnovas

Para optar al grado de Doctor

Director: Prof. Dr. Jaume Porta i Casanellas

El director de la tesis,

El doctorando,

Lleida, septiembre de 1998

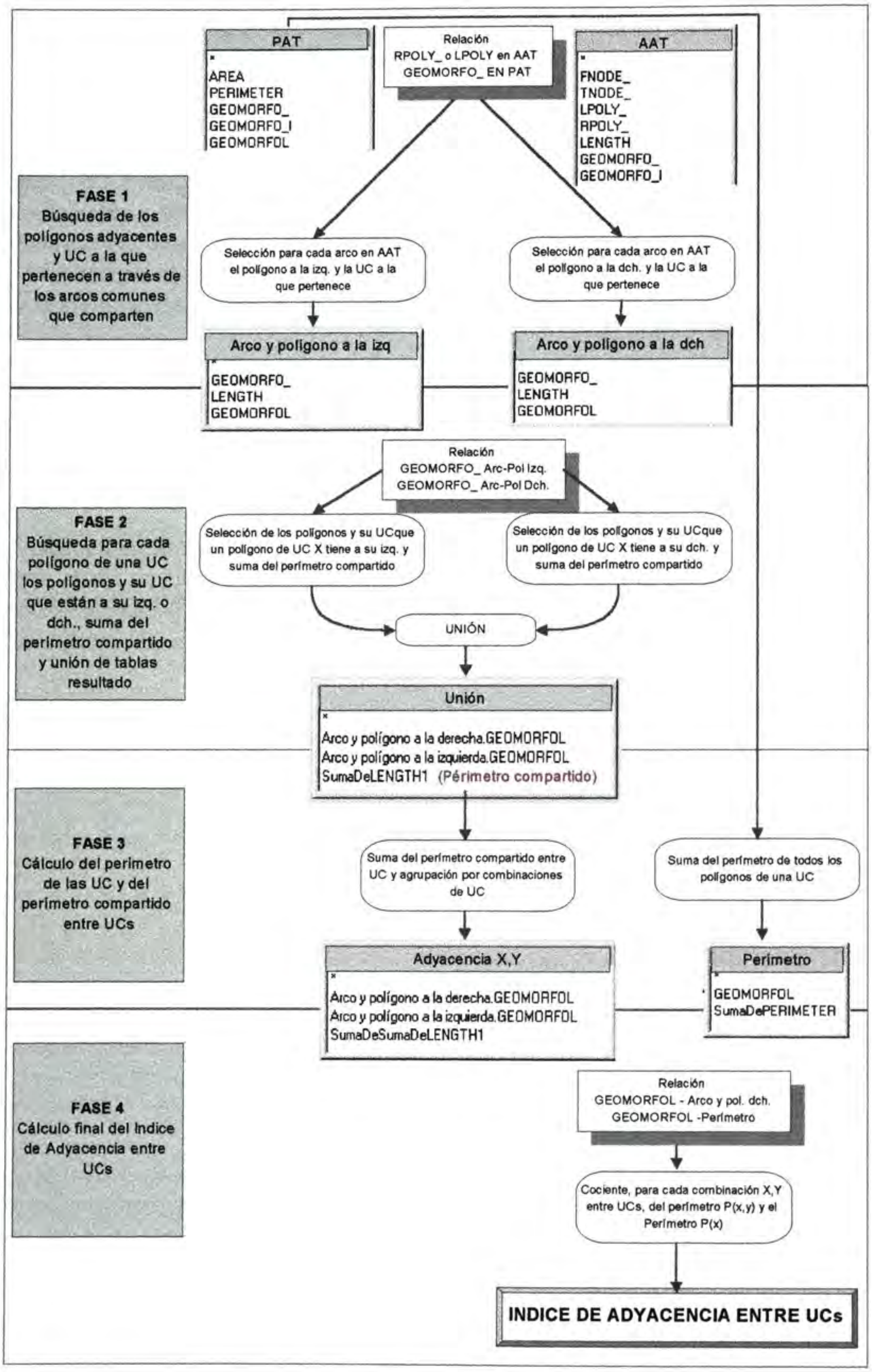


Figura 5.1.7. Diagrama de flujo con el procedimiento utilizado para el cálculo del índice de adyacencia a partir de las tablas de atributos del mapa vectorial de unidades cartográficas.

Tabla 5.1.5. Consultas SQL para la obtención del índice de adyacencia entre unidades del mapa vectorial de Paisaje/Relieve.

FASE 1	
Consulta Arco y Polígono a la Derecha SELECT DISTINCTROW AAT.GEOMORFO_, AAT.LENGTH, PAT.GEOMORFOL FROM PAT INNER JOIN AAT ON PAT.GEOMORFO_ = AAT.RPOLY_;	**Consulta Arco y Polígono a la Izquierda** SELECT DISTINCTROW AAT.GEOMORFO_, AAT.LENGTH, PAT.GEOMORFOL FROM PAT INNER JOIN AAT ON PAT.GEOMORFO_ = AAT.LPOLY_;
FASE 2	
Consulta de unión de tablas de adyacencia derecha-izquierda e izquierda-derecha SELECT DISTINCTROW [Arco y polígono a la derecha].GEOMORFOL, [Arco y polígono a la izquierda].GEOMORFOL, Sum([Arco y polígono a la izquierda].LENGTH) AS SumaDeLENGTH1 FROM [Arco y polígono a la derecha] INNER JOIN [Arco y polígono a la izquierda] ON [Arco y polígono a la derecha].GEOMORFO_ = [Arco y polígono a la izquierda].GEOMORFO_ GROUP BY [Arco y polígono a la derecha].GEOMORFOL, [Arco y polígono a la izquierda].GEOMORFOL; UNION SELECT DISTINCTROW [Arco y polígono a la izquierda].GEOMORFOL, [Arco y polígono a la derecha].GEOMORFOL, Sum([Arco y polígono a la izquierda].LENGTH) AS SumaDeLENGTH FROM [Arco y polígono a la izquierda] INNER JOIN [Arco y polígono a la derecha] ON [Arco y polígono a la izquierda].GEOMORFO_ = [Arco y polígono a la derecha].GEOMORFO_ GROUP BY [Arco y polígono a la izquierda].GEOMORFOL, [Arco y polígono a la derecha].GEOMORFOL;	
FASE 3	
Consulta de obtención de las Relaciones Adyacencia Pol X Pol Y SELECT DISTINCTROW Unión.[Arco y polígono a la derecha].GEOMORFOL, Unión.[Arco y polígono a la izquierda].GEOMORFOL, Sum(Unión.SumaDeLENGTH1) AS SumaDeSumaDeLENGTH1 FROM Unión GROUP BY Unión.[Arco y polígono a la derecha].GEOMORFOL, Unión.[Arco y polígono a la izquierda].GEOMORFOL;	**Cálculo del perímetro** SELECT DISTINCTROW PAT.GEOMORFOL, Sum(PAT.PERIMETER) AS SumaDePERIMETER FROM PAT GROUP BY PAT.GEOMORFOL;
FASE 4	
Consulta del cálculo del índice de adyacencia final SELECT DISTINCTROW [Relaciones Adyacencia Pol X Pol Y].[Arco y polígono a la derecha].GEOMORFOL, [Relaciones Adyacencia Pol X Pol Y].[Arco y polígono a la izquierda].GEOMORFOL, [Relaciones Adyacencia Pol X Pol Y].SumaDeSumaDeLENGTH1, perimetro.GEOMORFOL, perimetro.SumaDePERIMETER, [Relaciones Adyacencia Pol X Pol Y]![SumaDeSumaDeLENGTH1]*100/[perimetro]![SumaDePERIMETER] AS Expr1 FROM [Relaciones Adyacencia Pol X Pol Y] INNER JOIN perimetro ON [Relaciones Adyacencia Pol X Pol Y].[Arco y polígono a la derecha].GEOMORFOL = perimetro.GEOMORFOL;	
Consulta del cálculo del índice de adyacencia a barrancos o badlands SELECT DISTINCTROW [Indice de adyacencia Final].[Arco y polígono a la derecha].GEOMORFOL, [Indice de adyacencia Final].[Arco y polígono a la izquierda].GEOMORFOL, [Indice de adyacencia Final].Expr1 FROM [Indice de adyacencia Final] WHERE ((([Indice de adyacencia Final].[Arco y polígono a la izquierda].GEOMORFOL)="M2"));	

5.1.3.3. Aplicación al cálculo del IA de las UC del mapa vectorial de Paisaje/Relieve del Alt Penedès-Anoia

El programa desarrollado para el cálculo del IA entre UCs de mapas vectoriales ha sido aplicado al mapa de Paisaje/Relieve del Alt Penedès-Anoia (Figura 5.1.8). En la Tabla 5.1.6 se muestran los resultados del IA entre UCs y áreas de barrancos o badlands.

Tabla 5.1.6. Índice de adyacencia entre unidades cartográfica del mapa de Paisaje/Relieve y las áreas de barrancos o badlands (Alt Penedès-Anoia).

Código Unidad Cartográfica	Índice adyacencia a barrancos (% perímetro)
A	5.6
B11	2.7
B12	21.8
B13	6.8
B2	39.9
B31	52.8
B32	30.2
B33	40.7
B34	14.7
B4	12.6
C1	11.2
C21	50.9
C22	45.4
C23	39.3
C24	22.6
D1	33.4
D21	12.9
D22	57.4
D23	36.8
D24	27.3
D3	4.7
E1	20.5
E2	10.4
E31	10.1
E32	40.5
E33	0

El IA de la Tabla 5.1.6, considerado como un atributo de la entidad UC, se analiza cartográficamente en la Figura 5.1.9. Hay que remarcar que la relación puesta de manifiesto en este mapa es una relación global a nivel de UC.

Estos resultados muestran la utilidad del empleo y automatización del cálculo del IA en estudios de erosión. En este caso, el IA muestra las áreas con mayor perímetro de contacto con zonas que sufren particulares procesos de erosión (desprendimiento de paredes por movimientos en masa o deslizamientos, erosión de paredes por los cauces de los barrancos, etc.), lo cual repercute en las áreas adyacentes y en sus usos.

No obstante, el cálculo del IA en el nivel topológico superior de UC, y no en el intermedio de la delineación, puede enmascarar altos valores de IA en delineaciones con pequeña superficie que pertenecen a UCs con un bajo IA global. En este sentido, el cálculo de la adyacencia a nivel de delineación seguiría las mismas pautas que el proceso indicado en la Figura 5.1.7 hasta la fase 2 (inclusive). Este cálculo ha de considerar como P(x) en la Ecuación 5.1.1 el perímetro de la delineación en la tabla PAT.

El IA a barrancos y badlands no debe tomarse como único indicador del riesgo de erosión en las unidades con un alto valor. Hay que considerar también otros factores como el grado de estabilización de las paredes de los barrancos (Martínez-Casasnovas y Cervera 1996).

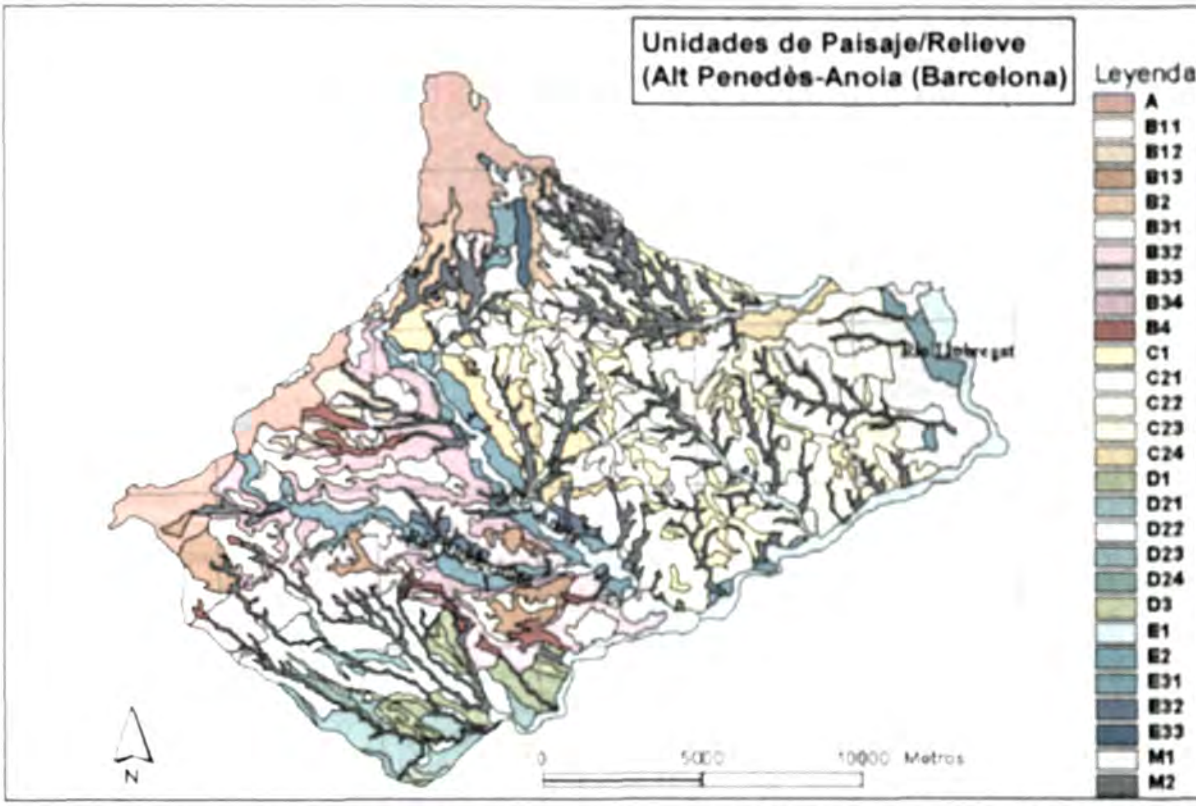


Figura 5.1.8. Unidades de paisaje/relieve (geoformas) del Alt Penedès-Anoia (Barcelona). (Ver descripción de la leyenda en la Tabla 5.1.1).

5.1.4. Conclusiones

Del presente trabajo se desprende que la adecuada manipulación de las relaciones topológicas, que en una estructura vectorial quedan registradas en el nivel inferior de la estructura formal de datos, puede servir para la obtención de relaciones espaciales significativas en el nivel superior, que es en el cual se conciben las relaciones espaciales a nivel del usuario.

Este es el caso de la relación de adyacencia entre unidades cartográficas de mapas vectoriales de áreas. De este tipo es el ejemplo mostrado, relativo a las relaciones de adyacencia entre unidades de un mapa de unidades de paisaje/relieve. En este caso la relación de adyacencia se ha cuantificado y analizado cartográficamente por medio del denominado índice de adyacencia.

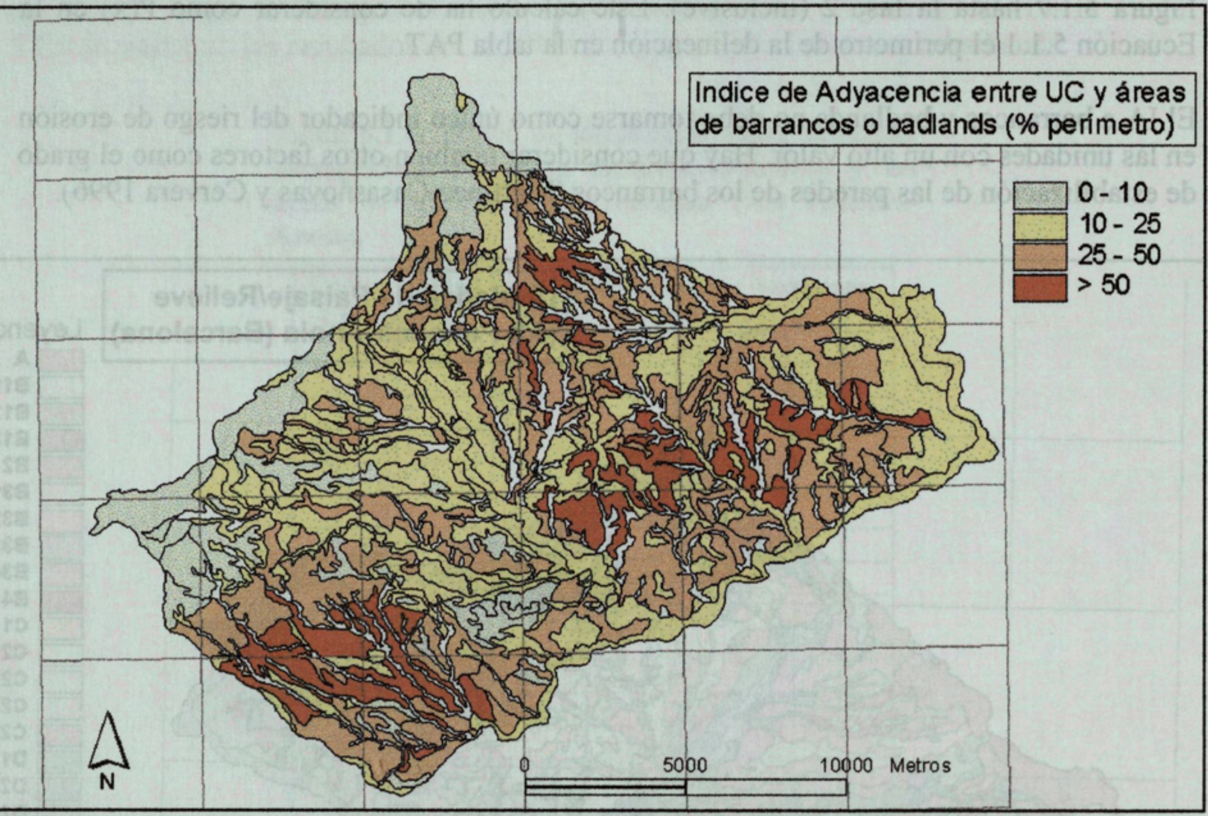


Figura 5.1.9. Indice de Adyacencia entre las unidades cartográficas de paisaje/relieve (geoformas) a las áreas de barrancos o badlands (Alt Penedès-Anoia, Barcelona).

La obtención automática de este índice se ha hecho mediante la manipulación de las tablas de atributos del mapa vectorial (PAT y AAT en ArcInfo) con un gestor de base de datos relacional, utilizando lenguaje de consulta estructurado (SQL).

Este índice no solo puede ser obtenido al nivel de clase de objetos área sino también a nivel de individuos de clase o delineaciones, dependiendo de las necesidades del usuario. El índice de adyacencia a nivel de clase puede ser utilizado como descriptor global de las relaciones entre unidades cartográficas, si bien su representación cartográfica puede enmascarar relaciones parciales con diferencias significativas en el valor del índice.

Los resultados obtenidos del cálculo del índice de adyacencia en el área de estudio han mostrado las unidades con mayor perímetro de contacto con las zonas de barrancos y badlands. Sin embargo, este índice no debe tomarse como único indicador del riesgo de erosión en las unidades geomorfológicas con un alto valor del índice de adyacencia. Esta información puede ser útil en la descripción de las unidades de paisaje/relieve.

5.1.5. Referencias bibliográficas

Martínez-Casasnovas, J.A.,1994, *Hydrographic information abstraction for erosion modelling at regional level. A database perspective in a GIS environment.* MSc Thesis, Wageningen Agricultural University, Wageningen, Holanda.

Martínez-Casasnovas, J.A. y Molenaar, M., 1995. Aggregation hierarchies for multiple scale representations of hydrographic networks in GIS. *Proceedings of the 17th International Cartographic Conference,* 1: 358-362.

Martínez-Casasnovas, J.A. y Cervera, T., 1996, Gully erosion mapping by remote sensing techniques. A case study in the Anoia-Penedès region (NE Spain). *Primer Congreso Europeo sobre el Control de la Erosión,* Sitges (Barcelona).

Molenaar, M, 1989, Single valued vector maps. A concept in GIS. *Geo-Information Systemes,* 2: 18-26.

Molenaar, M., 1993, Object hierarchies and uncertainty in GIS or Why is standarisation so difficult. *Geo-Informations Systemes,* 4:22-28.

Moleaar, M. y Martínez-Casasnovas, J.A., 1996, A formalism for the structural description of vector maps, and its use for multi-scale representations: a hydrographic example. *Cartographica,* 33: 55-63.

Tobler, W.R., 1970, A computer movie simulating urban growth in the Detroit region. Economic *Geography,* 46.

Van Smaalen, J.W.N., 1996, Spatial abstraction based on hierarchical reclassification. *Cartographica,* 33: 64-72.

Van Smaalen, H.W.N. y Molenaar, M., 1993. *Feature level for Arcinfo using the Arcinfo-Oracle interface.* Wageningen Agricultural University, K075-702. Wageningen, Holanda.

Zinck, A. y Valenzuela C.R., 1990, Soil geographic database: structure and application examples. *ITC Journal,*1990-3: 270-294.

Zinck, J.A., 1998, *Physiography and soils.* Soil Survey Courses. Subject matter K6. ITC Lecture Notes SOL-41.

5.2. A cartographic and database approach for land cover/use mapping and generalisation from remotely sensed data.

Martínez-Casasnovas, J.A. A cartographic and database approach for land cover/use mapping and generalisation from remotely sensed data. *International Journal of Remote Sensing*, (submitted February 1998, accepted September 1998).

A cartographic and database approach for land cover/use mapping and generalisation from remotely sensed data.

Abstract
Classification of remotely sensed data involves a set of generalisation processes. Reality is simplified to a set of few classes that are relevant for the application being considered. This article introduces an approach for image classification that uses a class hierarchy structure for mapping unit definition at different generalisation levels. This structure is implemented as an operational relational database and allows querying of more detailed land cover/use information from a higher abstraction level, which is the one viewed by the map user. Elementary mapping units are defined on the basis of an unsupervised classification process, in order to uncover the land cover/use classes registered in the remotely sensed data. Mapping unit composition at different generalisation levels is defined on the basis of membership values of sampled pixels to land cover/use classes. Unlike fuzzy classifications, membership values are presented to the user at a mapping unit level.

5.2.1. Introduction

Classification of remotely sensed data, either by visual interpretation or by digital image processing techniques (supervised or unsupervised), involves a set of generalisation processes. In essence, reality is simplified or reduced to a set of few classes, relevant for the application being considered, and having a spatial representation in a map or in a digital spatial data structure.

The four different processes in information abstraction from reality to a data model are classification, class generalisation, aggregation and association (Egenhofer and Frank 1989, Molenaar 1993, Molenaar and Richardson 1994, Martínez-Casasnovas 1994), of which the first two are undertaken during supervised or unsupervised classification of remote sensing images.

Supervised classifications provide a statistical description of land cover based on a class structure and training data provided by the analyst. The classification process starts with the definition of informational classes, followed by the assignment of these classes to pixels. The most commonly used classification method evaluates the likelihood that each pixel belongs to each class based on their spectral and statistical characteristics. Unsupervised classifications attempt to uncover the land cover classes that exist in the image. The multispectral image is classified into a number of spectral classes, without prior knowledge of what they might be. The analyst provides the number of the output spectral classes and indicates the clustering algorithm. After the clustering process, the analyst also needs to assign information labels to the spectral clusters by means of ground sampling procedures, and to determine which clusters need to be merged or to be further defined to achieve a legend according to the purposes of the user.

Neither supervised nor unsupervised methods provide an immediate solution to the problems that a digital classification implies (Chuvieco 1996). The supervised method is more subjective since the analyst may force the discrimination of classes without a clear spectral meaning (Chuvieco 1996). Also, the supervised method is considered as restrictive, since some existing land cover classes may be unknown by the user prior to the classification process and, therefore, they are not considered in the training data set (Palacio and Luna 1996). Sometimes, the existence of those non-sampled land cover classes may be known and it is a decision of the analyst either to consider them in the classification process or not. In other situations, those classes are known during accuracy assessment, provided that ground truth areas are different from training areas. This represents a loss of spectral information during the image classification process, that some authors have tried to face through fuzzy supervised classification (Wang 1990a, b, Foody 1996) or by In-Process Classification Assessment methods (Eastman 1997).

Unsupervised classifications are sometimes difficult to interpret or to produce results that are related to the user needs. The unsupervised process, however, overcomes some problems related to the knowledge of the spectral response variability of terrain objects. In this respect, the combination of both classification procedures is often advised by using unsupervised classification as an alternative method for spectral signature definition (García and Álvarez 1994, Chuvieco 1996).

From the generalisation process viewpoint, supervised and unsupervised classification procedures involve land cover class and mapping unit definition and generalisation. In supervised classification, the selection of the generalisation level (level of detail) of the informational classes to be sampled is very important and determines the classification results. Several authors have concluded that classification results are often influenced more by previous definition of informational classes than by the criterion and/or the classification algorithm used to discriminate them during the classification process (Story and Campbell 1986, Gong and Howarth 1990, Chuvieco 1996, Palacio and Luna 1996). The statistical and compositional variability of informational classes should be taken into account by sampling elementary field training classes, and then merging or generalising them at a higher level (or superclass level) in the class hierarchy (class generalisation). A very good knowledge of the area and of terrain object spectral response is required for an accurate supervised classification.

Unsupervised classification usually produces a wider range of spectral classes. An appropriate sampling strategy is required for cluster definition. A particular land cover class may be represented in more than one spectral class, and conversely, one spectral class may represent more than one land cover class. Thus, the analyst may merge clusters according to their composition in terms of informational classes and class similarity, or may try to further split clusters when they include more than one land cover class, always depending on the target legend.

A fact being noticed in image classification maps is the lack of references to the user regarding the class generalisation process and aggregation or disaggregation of spectral classes that has taken place. Informational classes are defined at the level of detail that can be recognised at pixel or sub-pixel level (elementary informational classes), e.g. bare agricultural soil or bare industrial soil. Those classes may compose a super class (class at a higher hierarchical level in the classification system), e.g. bare soil, that may be presented in the final map legend because either the convenience of the user or the impossibility to produce distinct spectral signatures for each elementary class. Also, the lack of references in maps to mapping unit composition in terms of membership values to land cover classes (super classes as well as elementary informational classes) is observed. Information about the composition of super classes and their distribution in the mapping units should be reported so that users will be aware of the purity of the map units (Janssen and van der Wel 1994).

Present methods to assess classification accuracy such as error or confusion matrices can be used to calculate measures such as the proportion of pixels correctly classified, errors of omission and commission, user's and producer's accuracy, coefficients of agreement and hypothesis testing. These indices report on the accuracy of final informational classes but not on the presence of elementary classes and their spatial distribution in the case that final informational classes are super classes. These measures of accuracy, however, have been recognised as valuable tools in judging the fitness of the resulting map for a particular application (Aronoff 1982, Aronoff 1989, Story and Congalton 1986, Janssen and van der Wel 1994, Lark 1995).

In view of these issues, the objective of the present paper is to introduce a conceptual framework for spectral signature class definition and map generalisation. It is based upon definition of elementary informational classes by stratified random sampling of clusters produced by unsupervised classifications. Once defined, clusters and informational classes are generalised according to a hierarchical structure. Clusters are viewed as 'cartographic or mapping units' and may be composed of one or more informational classes. A database model is designed and implemented in a Relational Database Management System (RDBMS) to support the generalisation in a hierarchical structure. This framework allows users to know class and mapping unit composition in terms of elementary informational classes at any level of the generalisation hierarchy. Also, queries about the most probable location of elementary informational classes not represented in the legend at a higher generalisation level can be answered.

5.2.2. Test site and data

An area located in the Alt Penedès-Anoia region (Catalonia, NE Spain) was selected to test the proposed methodology (Figure 5.2.1). This region is mainly dedicated to the cropping of vineyards for wine and sparkling wine ('cava') production. In this area, modern practices have replaced traditional management practices. Old small size parcels are being transformed into bigger parcels, an operation that involves huge soil movements. Residential and industrial areas have grown during the last three decades, due to the nearness to the Barcelona metropolitan area. This region suffers serious problems of erosion, which have been reported by Ramos *et al.* (1991), Porta *et al.* (1994) and Martínez-Casasnovas and Cervera (1996). In addition to sheet erosion, a dense and deep gully network has developed in the area. To locate more stable and higher erosion risk areas, the mapping of vegetation cover on gully walls from remotely sensed data has been explored by Martínez-Casasnovas and Cervera (1996).

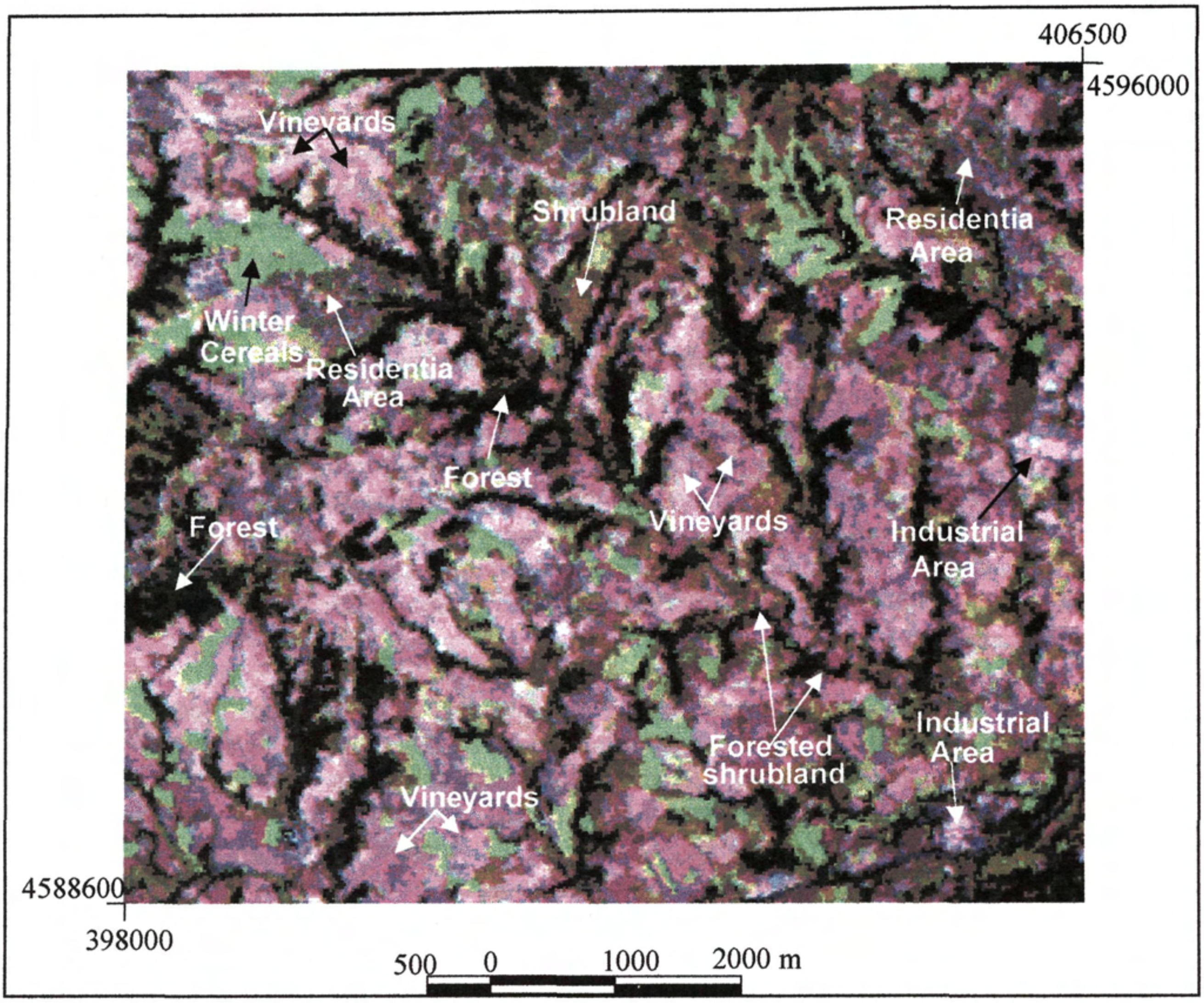


Figure 5.2.1. Landsat TM image of the Alt Penedès-Anoia region (Catalonia, NE Spain). False colour composite red-green-blue 543. March 1993.

A Landsat TM subscene (March 1993), covering an area of 62.9 km^2 in the study area, was used to test the application of the general procedure. The atmospheric scattering effect was corrected by applying the improved dark-object subtraction technique (Chavez 1988). A quadratic mapping function based on 14 control points and a nearest neighbour resampling were applied for geometric correction. Pixel size was slightly decreased to 25x25 m, in order to match the resolution of a digital elevation model. An overall root-mean-square error less than one pixel was achieved. The image classification results and the digital elevation model were later combined to map vegetation cover on gully walls.

A 1:25 000 scale true colour orthophoto of July 1993, produced by the Cartographic Institute of Catalonia, was used to support fieldwork for ground truth data collection.

5.2.3. Methodology

5.2.3.1. General procedure

A first step in building a hierarchy to support generalisation of image classification results was the definition of basic or elementary terrain object classes. In this article, elementary classes should be interpreted as land cover/use types that can be recognised at the pixel or sub-pixel resolution level. For example, if medium resolution remote sensing data is used (e.g. 20 m resolution SPOT data or 30 m resolution Landsat TM data), a pixel may be described by a unique class (e.g. bare agricultural soil) or may be mixed (e.g. bare agricultural soil and shrubland, in the border area of these classes).

For the definition of the basic information level of the hierarchy an unsupervised classification process was applied. This revealed the existing land cover/use information. The unsupervised process was seeded from a colour composite image, selected from the three-band combinations with the largest Optimum Index Factor (Chavez *et al.* 1982). This index is based on the variance and the correlation among the different bands. The three-band combination having the largest index value is usually selected for colour composition because it should display the most spectral information of the whole set of bands (six spectral bands for the Landsat TM sensor) with the least amount of duplication.

A random sampling procedure, stratified per cluster class, was performed. Each cluster was pixel-sampled, as proposed by Janssen and van der Wel (1994). These authors support that individual pixels are the most appropriate sampling units if a per-pixel classification is performed. They also consider that stratified sampling based on distinguished classes is preferable above other sampling strategies (e.g. random or systematic distribution). A minimum sample of 50 pixels per cluster was used to achieve an accurate estimation of cluster composition (Hay 1979, Congalton 1991, Chuvieco 1996).

The result of this process was the basic mapping generalisation level at the image resolution. This was a many-to-many relationship between clusters and informational classes (land cover/use classes). Clusters should be understood as elementary level cartographic or mapping units. One or more land cover/use classes are represented in a mapping unit and a specific land cover/use class can be included in different mapping units. Mapping units and land cover/use classes are different concepts but both can be organised in a hierarchical way as it is proposed in Figure 5.2.2.

The class generalisation hierarchy structure of Figure 5.2.2 was translated to a database model (figure 3). This model focuses on structuring of data and determination of relationships among data elements according to a relational database approach (Chen 1976). The Relational Database Management Systems Access (Microsoft™) was used to implement the database structure of Figure 5.2.3 in an internal operating model. Finally, Structured Query Language (SQL) was used to analyse elementary terrain information for mapping unit definition and to move up and down through the information generalisation hierarchy.

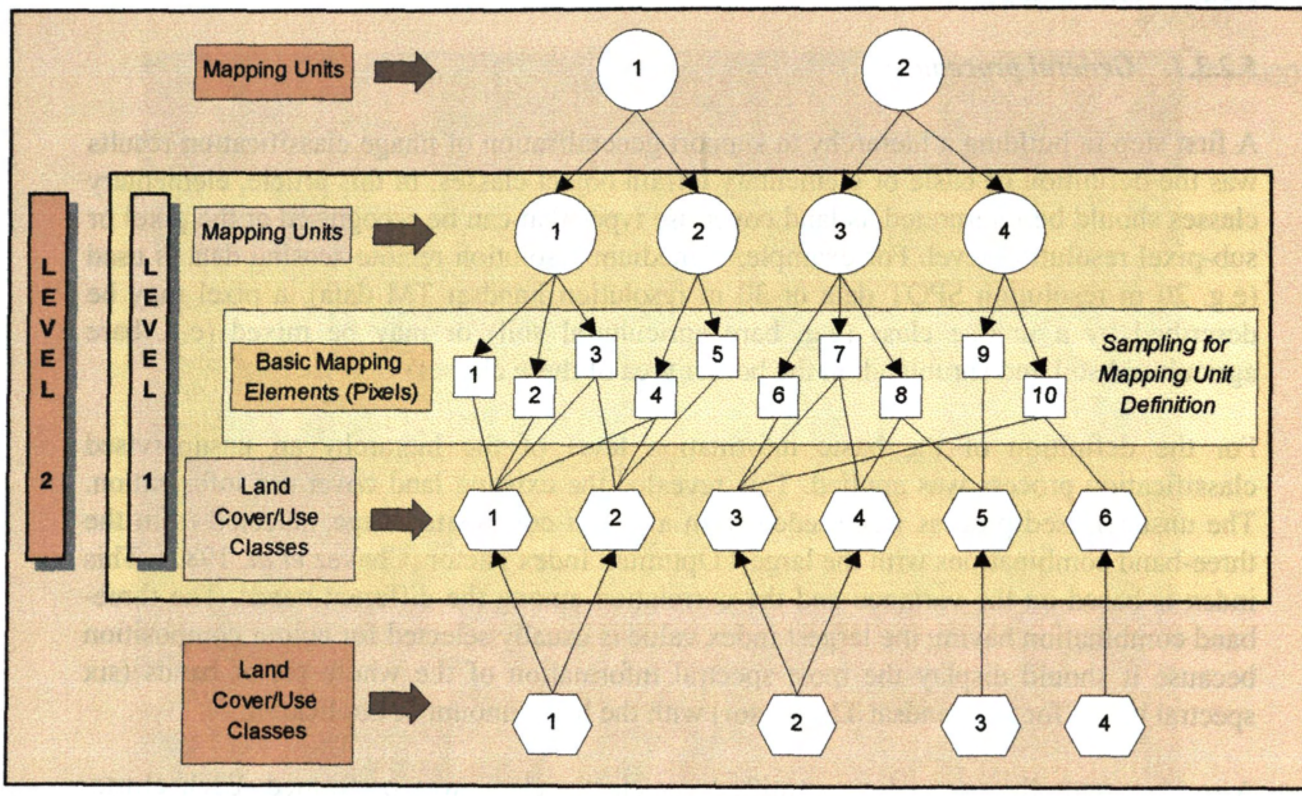


Figure 5.2.2. Generalisation hierarchy structure for land cover/use mapping from remotely sensed data. Level 1 represents the basic level of spatial information (more detailed), that is defined by membership of pixels of spectral classes to elementary land cover/use classes. Level 2 represents a higher level in the generalisation hierarchy (less detailed), that is created by class generalisation and aggregation of mapping units of level 1.

5.2.3.2. Image processing

An unsupervised classification was performed using the ISOCLUST algorithm, implemented in the Idrisi for Windows package (Clark University). This algorithm is an iterative self-organising unsupervised classifier based on a concept similar to the ISODATA routine (Ball and Hall 1965 quoted by Eastman 1997) and cluster routines such as the H-means and K-means procedures (Eastman 1997).

A red-green-blue 543 colour composite was used to seed the clusters for the unsupervised classification. This band combination was preferred to TM bands 4, 5 and 7, which had the highest Optimum Index Factor (26.8) because it also produced a high Optimum Index Factor (25.3), it was more sensitive to vegetation cover variability (Gilabert 1990) and it covered the basic image dimensions of greenness, brightness and moisture content (Eastman 1997).

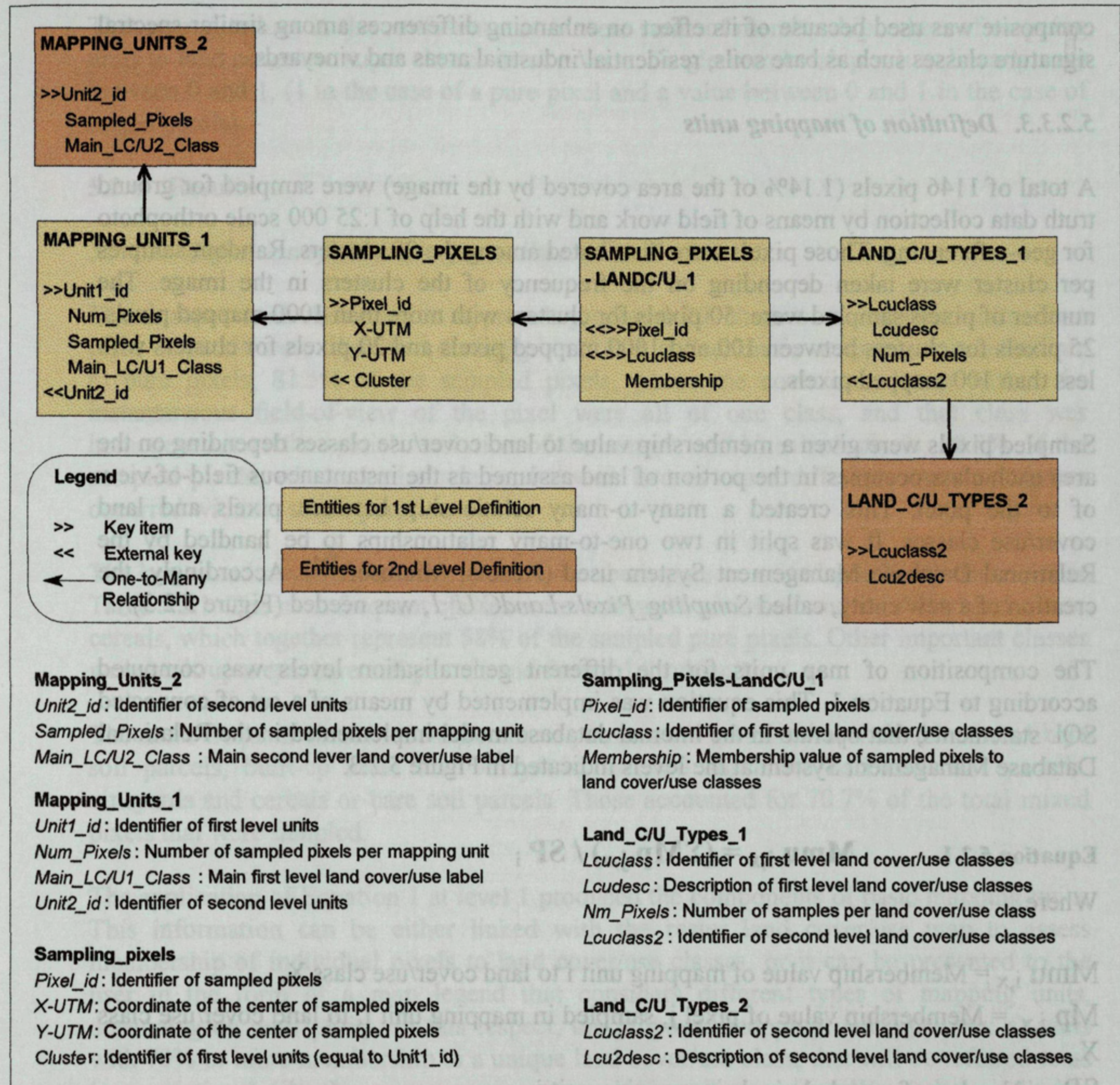


Figure 5.2.3. Relational database model for definition of mapping units at different generalisation levels according to the proposed hierarchy structure of Figure 5.2.2.

The ISOCLUST classifier produced first a histogram that expressed the frequency with which the clusters occurred in the seed image. After examining the histogram, a number of 29 clusters (of a total of 41) was specified as the output of the unsupervised classification. The selected clusters accounted for 99.9 % of the total number of pixels in the seed image. These clusters were used in an iterative maximum likelihood procedure using bands 4, 5, 7, NDVI and principal component analysis (PCA) 1, 2 and 3 as a colour composite. Three iterations were performed before no significant change in output was produced. Bands 4, 5 and 7 were selected because it was the three-band composition with the highest Optimum Index Factor among the 20 possible combinations (band 6 excluded). NDVI was introduced to distinguish vegetated from non-vegetated areas and the PCA colour composite was used because of its effect on enhancing differences among similar spectral signature classes such as bare soils, residential/industrial areas and vineyards.

5.2.3.3. Definition of mapping units

A total of 1146 pixels (1.14% of the area covered by the image) were sampled for ground truth data collection by means of field work and with the help of 1:25 000 scale orthophoto for geo-referencing. Those pixels were distributed among the 29 clusters. Random samples per cluster were taken depending on the frequency of the clusters in the image. The number of pixels sampled were: 50 pixels for clusters with more than 1000 mapped pixels, 25 pixels for clusters between 100 and 1000 mapped pixels and 20 pixels for clusters with less than 100 mapped pixels.

Sampled pixels were given a membership value to land cover/use classes depending on the area each class occupies in the portion of land assumed as the instantaneous field-of-view of to the pixel. This created a many-to-many relationship between pixels and land cover/use classes. It was split in two one-to-many relationships to be handled by the Relational Database Management System used (Access, Microsoft™). Accordingly, the creation of a new entity, called *Sampling_Pixels-LandC/U_1*, was needed (Figure 5.2.3).

The composition of map units for the different generalisation levels was computed according to Equation 1. This equation was implemented by means of a set of connected SQL statements, that operate in the internal database model implemented in the Relational Database Management System at the levels indicated in Figure 5.2.3.

Equation 5.2.1 $$\mathbf{Mmu_{i,x} = (\Sigma Mp_{j,x}) / SP_i}$$

Where,

$Mmu_{i,x}$ = Membership value of mapping unit i to land cover/use class X.

$Mp_{j,x}$ = Membership value of pixel j, sampled in mapping unit i, to land cover/use class X.

SP_i = Number of sampled pixels in mapping unit i.

The definition of both the land cover/use class and the mapping unit hierarchies was needed prior to definition of mapping units at higher generalisation levels. The decision about land cover/use classes making up land cover/use super classes was based on class similarity according to the map purpose: assessment of erosion risk. The decision to define the mapping unit hierarchy was based on the target map legend and composition of basic mapping units.

The legend of the final land cover/use map was presented from a user's point of view, with an indication of membership of mapping units to land cover/use super classes. A classification accuracy assessment was also performed using a confusion matrix. The accuracy assessment not only considered one land cover/use super class per mapping unit in the cases of associations but the land cover/use super classes forming the association.

That means, values in the confusion matrix were sums of membership values of mapping units to land cover/use super classes or vice versa. Single membership values linearly vary between 0 and 1, (1 in the case of a pure pixel and a value between 0 and 1 in the case of mixed pixels).

5.2.4. Results

5.2.4.1. Definition of the basic generalisation level

The unsupervised classification approach produced 29 clusters or mapping units. Two types of pixels were identified during ground data collection for mapping unit definition: a) pure pixels, 81.5% of the sampled pixels, where the cover/use classes within the instantaneous field-of-view of the pixel were all of one class, and that class was homogeneous at the spatial resolution of the sensor; and b) mixed pixels, 18.5% of the sampled pixels, where the boundaries between two or more different cover/use classes occurred within a single pixel.

The basic land cover/use classes identified in both pure or mixed pixels are described in Table 5.2.1. The most frequent classes were vineyards, grassland and shrubland and winter cereals, which together represent 58% of the sampled pure pixels. Other important classes were built-up areas, bare soil parcels and forested shrubland.

The most frequent combinations in mixed pixels were grassland and shrubland and bare soil parcels, built-up areas and vineyards, forested shrubland and bare soil parcels, vineyards and cereals or bare soil parcels. Those accounted for 70.7% of the total mixed pixels that were sampled.

The application of Equation 1 at level 1 produced the components of basic mapping units. This information can be either linked with the raster land cover/use map to assess membership of individual pixels to land cover/use classes, or it can be presented to the user in the form of a map legend that considers different types of mapping units, depending on their purity. In this respect, the proposed mapping unit types are: a) units with 70% or more membership to a unique land cover/use class, that will be referred to as 'consociations', like the most pure mapping units in soil maps (van Wambeke and Forbes 1985); b) units with two main land cover/use classes covering 70% or more of the unit, that will be referred to as 'associations'; and c) units with more than two representative land cover/use classes, that will be referred to as 'complexes'.

According to this adopted criterion, Table 5.2.2 shows the legend of the land cover/use map of the Alt Penedès-Anoia region for the basic generalisation level. Percentages in Table 5.2.2 indicate membership of mapping units to land cover/use classes, which was different from membership of individual pixels to land cover/use classes. This way of mapping unit definition allows the map producer to know purity of units and to determine the ones to be merged in order to make a higher level unit.

Table 5.2.1. Land cover/use classes identified at pixel or sub-pixel resolution in the Alt Penedès-Anoia region.

Class	Land cover/use class	Description
1	Bare gully walls and badlands	Gully walls and badlands without vegetation cover
2	Semivegetated gully walls and badlands	Gully walls and badlands, less than 30% vegetation cover (shrubland): *Brachipodium rhamosum, Ulex parviflorus, Genista sp., Juniperus oxicedrus, Rosmarinus officinalis, Thymus vulgaris, Quercus coccifera, Pinus halepensis*
3	Grassland and shrubland	Grassland and shrubland, 30-60% vegetation cover, typically southern oriented areas: *Brachypodium rhamosum, Ulex parviflorus, Genista sp., Rosmarinus officinalis, Thymus vulgaris, Spartium junceum, Lepidium graminifolium,Quercus coccifera*
4	Shrubland	Shrubland, 50-75% vegetation cover, typically north and eastern oriented areas: *Brachipodium phoenicooides, Vicia sp., Spartium junceum, Diplotaxis erucoides, Shorgum halepense, Genista sp., Rosmarinus officinalis, Quercus coccifera, Quercus ilex*
5	Riparian shrubland	Riparian shrubland, 65-80% vegetation cover, typically bottom gully valleys: *Rubus ulmifolius, coriaria myrtifolia, Arundo donax, Populus sp.*
6	Forested shrubland	Forested shrubland, 65-80% vegetation cover, typically north and northwestern oriented areas: *Brachipodium phoenicoides, Coriaria myrthifolia, Vicia sp., Spartium junceum, Genista sp., Pistacia lentiscus, Rosmarinus officinalis, Quercus ilex, Pinus halepensis, Pinus pinea*
7	Forested areas	Forested areas, 65-80% vegetation cover, typically northern oriented areas: *Pinus halepensis, Pinus pinea, Quercus ilex, Quercus coccifera*
8	Vineyards	Old traditional or modern vineyard plantations, without vegetation cover at the date of the image
9	Vineyards (parcels with weeds)	Old traditional or modern vineyard plantations, with weeds cover between vine rows
10	Vineyards (new plantations in level parcels)	Recent modern vineyard plantations in level parcels
11	Almond tree plantations	Almond tree plantations
12	Peach tree plantations	Peach tree plantations
13	Winter cereals	Well-developed winter cereals: wheat or barley
14	Winter cereals (under-developed)	Under-developed winter cereals: wheat or barley
15	Bare soil parcels	Bare soil parcels and recent level parcels
16	Bare soil parcels with scarce weed cover	Bare soil parcels and recent level parcels with scarce weed cover
17	Residential or industrial built-up areas	Residential (urban and recreational) or industrial built-up areas
18	Industrial or urban areas (bare soil)	Bare industrial or urban parcels
19	Roads	
20	Road banks	

Table 5.2.2. Legend of the Land cover/use map of the Alt Penedès-Anoia region (generalisation level 1).

Mapping unit	% Area (*)	Land cover/use class description (**)	Main inclusions (**)
1	9.5	Grassland and shrubland (70%)	Bare-semivegetated gully walls and badlands (9.2%), Residential and industrial built-up areas (8%)
2	12.0	Association of Forested shrubland (60%) and Forested areas (40%)	
3	13.1	Vineyards (98%)	
4	4.5	Grassland and shrubland (77.8%)	Vineyards (6%) and Residential and industrial built-up areas (4%)
5	7.2	Complex of Residential and industrial built-up areas (32%), Bare soil parcels (29.6%) and Grassland and shrubland (15.6%)	Vineyards (9%) and Almond tree plantations (5.8%)
6	2.8	Vineyards (70%)	Bare soil parcels (17%) and Grassland and shrubland (4%)
7	7.6	Grassland and shrubland (80.4%)	Forested shrubland (8%) and Bare gully walls and badlands (6%)
8	6.7	Vineyards (98%)	
9	3.8	Complex of Residential or industrial built-up areas (59%), Bare soil parcels (11.8%) and Grassland and shrubland (10%)	Roads (6%)
10	5.0	Association of Forested shrubland (54.8%) and Shrubland (22%)	Grassland and shrubland (8%) and Forested areas (4%)
11	5.8	Vineyards (81%)	Residential and industrial built-up areas (12%)
12	3.4	Vineyards (70%)	Bare soil parcels (29%)
13	2.3	Grassland and shrubland (74%)	Winter cereals (under-developed) (12%) and Riparian shrubland (8%)
14	0.8	Association of Winter cereals (61.2%) and Grassland and shrubland (16.4%)	Bare soil parcels (6%), Residential and industrial built-up areas (6%) (6%)
15	1.2	Association of Winter cereals (57.5%) and Grassland and shrubland (18.7%)	Forested shrubland (8.3%), Vineyards (6.25%) and Bare soil parcels (6.25%)
16	2.0	Grassland and shrubland (81%)	Vineyards (5.1%)
17	1.7	Winter cereals (100%)	
18	0.6	Winter cereals (100%)	
19	0.6	Winter cereals (100%)	
20	1.8	Association of Residential and industrial built-up areas (66%) and Bare soil parcels (12%)	Vineyards (12%)
21	0.9	Bare soil parcels (72%)	Residential-industrial built-up areas and roads (16%), Vineyards (6%)
22	1.3	Association of Bare soil parcels (44%) and Vineyards (44%)	Almond tree plantations (4%)
23	0.4	Winter cereals (100%)	
24	0.5	Association of Winter cereals (37.5%) and Vineyards (27.5%)	Grassland and shrubland (17%)
25	1.0	Complex of Residential and industrial built-up areas (42%), Grassland and shrubland (22.5%), Bare soil parcles (16.7%) and Forested shrubland (14.6%)	
26	0.4	Association of Residential and industrial built-up areas (60%) and Bare soil parcels (14.6%)	Semivegetated gully walls and badlands (6.7%)
27	1.4	Complex of Bare soil parcels (31.8%), Grassland and shrubland (30.6%) and Vineyards (21.5%)	Forested shubland (10.2%)
28	0.7	Complex of Bare soil parcels (30%), Grassland and shrubland (26.5%) and Vineyards (12.5%)	Roads (5%)
29	0.7	Bare soil parcels (72%)	Industrial-urban (bare soil parcels) (24%)

(*) % of the area of the mapping unit over the total study area.

(**) Percentages are referred to the total area of the mapping unit.

5.2.4.2. Definition of the second generalisation level and classification accuracy assessment

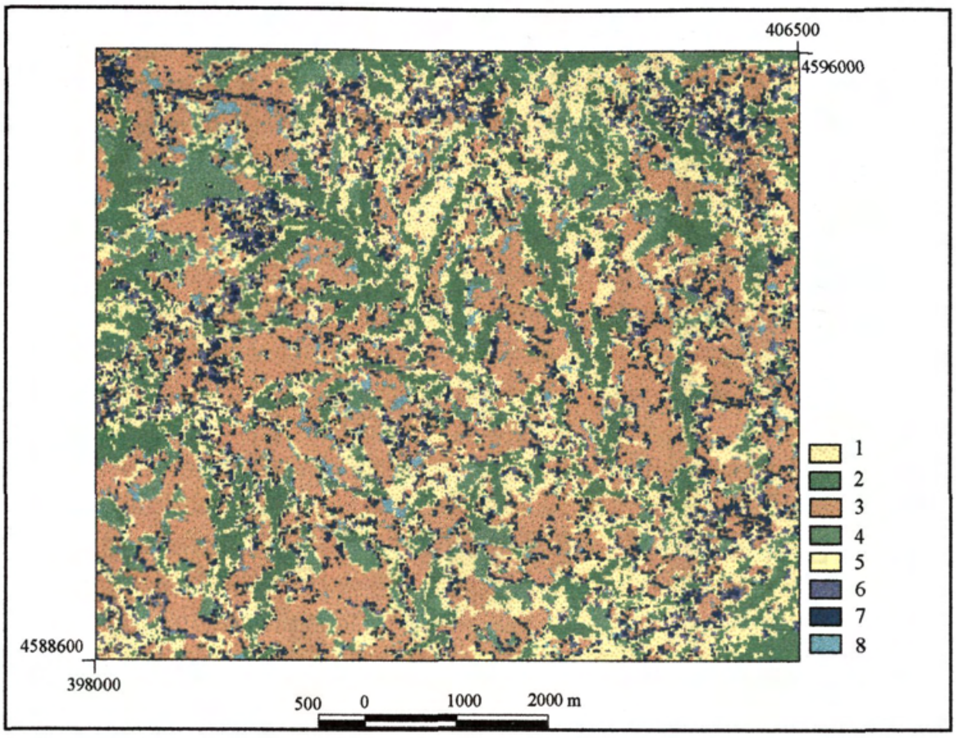
A more simplified legend than the one of Table 5.2.2 is usually presented to the user. This requires previous determination of basic mapping units that have to be merged, and it is guided by the target map legend to achieve. In the present case study, nine land cover/use super classes were identified as relevant for the application and used to define the class hierarchy to support mapping unit generalisation (Table 5.2.3).

Table 5.2.3. Land cover/use class hierarchy considered for the Alt Penedès-Anoia case study.

Land cover/use super class (level 2)	Land cover/use super class description	Land cover/use class (level 1)
1	Bare or semivegetated gully sidewall and badlands	1, 2
2	Grassland and shrubland	3
3	Forested shrubland and shrubland	4, 5
4	Forested shrubland and forested areas	6, 7
5	Vineyards	8, 9, 10
6	Almond and peach plantations	11, 12
7	Winter cereals	13, 14
8	Bare soil parcels (agricultural or industrial/urban)	15, 16, 18
9	Industrial and residential built-up areas	17, 19, 20

According to the target map legend of Table 5.2.3 and looking at the basic mapping units composition of Table 5.2.2, eight mapping units were considered for the second level of generalisation. The decision on what basic mapping units had to compose a higher level mapping unit was not automated at this stage. The analyst was the one driving the process by looking at both the target map legend and the composition of the basic mapping units. Consociations were preferred above associations or complexes, since the former represent the most pure mapping units from the map user's point of view. Figure 5.2.4 shows the final land cover/use map and the associated legend. Information on basic mapping units making up second level units has been included.

The legend of figure 4 shows the composition of the mapping units of the land cover/use map and user's accuracy in a more comprehensible way for the map user than a confusion matrix. Information on commission errors or map producer's accuracy is not given in the map user's legend. Land cover/use super classes that appeared only as minor components in mapping units had the highest omission errors (Figure 5.2.4), and were explicitly detailed in Table 5.2.4.



Legend

Mapping unit (level 2)	% Area (*)	Land cover/use class description (**)	Main inclusions (**)	Mapping units (level 1)
1	25.8	Grassland and shrubland (76.6%)	Bare or semivegetated gully sidewalls and badlands (4.9%) and Vineyards (4.2%)	1, 4, 7, 13, 16
2	17.0	Forested shrubland and forested areas (79.4%)	Forested shrubland and shrubland (16%) and Grassland and shrubland (4%)	2, 10
3	31.8	Vineyards (83.2%)	Bare soil parcels (agricultural and industrial/urban) (11.4%)	3, 6, 8, 11, 12
4	6.0	Winter cereals (83.3%)	Grassland and shrubland (5.1%) and Vineyards (4.4%)	14, 15, 17, 18, 19, 23, 24
5	1.6	Bare soil parcels (agricultural and industrial/urban) (84%)	Industrial and residential built-up areas (8%) and Vineyards (5%)	21, 29
6	6.1	Association of Indutrial and residential built-up areas (64.8%) and Bare soil parcels (agricultural and industrial/urban) (15.6%)	Vineyards (6.9%) and Grassland and shrubland (5.2%)	9, 20, 26
7	7.7	Complex of Industrial and residential built-up areas (35.3%), Bare soil parcels (agricultural and industrial/urban) (25.4%) and Grassland and shrubland (17.8%)	Vineyards (7.4%) and Forested shrubland and forested areas (6.1%)	5, 25
8	3.4	Complex of Bare soil parcels (agricultural and industrial/urban) (37.7%),. Vineyards (31.6%) and Grassland and shrubland (16.5%)	Forested shrubland and forested areas (6.1%)	22, 27, 28

(*) % of the area of the mapping unit over the total study area.
(**) Percentages are referred to the total area of the mapping unit.

Figure 5.2.4. Land cover/use mapping units of the Alt Penedès-Anoia region, (second generalisation level).

Table 5.2.4. Accuracy assessment of the Land cover/use map of the Alt Penedès-Anoia region, (generalisation level 2).

	REFERENCE DATA (Land cover/use super classes) (*)											
CLASSIFIED DATA (Mapping units level 2) (**)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Sum**	**User's accuracy**	**Error of Commission**
1	12.2	190.8	6.5	7.3	10.5	1.0	7.5	5.5	7.7	249.0	76.6	23.4
2	0.6	4.0	16.0	79.4						100.0	79.4	20.6
3		3.2			208.0	2.0		28.5	8.3	250.0	83.2	16.8
4	1.2	10.0		5.0	8.5		161.7	4.0	3.6	194.0	83.4	16.6
5	1.0	0.5			2.5			42.0	4.0	50.0	84.0	16.0
6	3.0	6.0	1.0	1.0	8.0	2.6		18.9	74.5	115.0	81.2	18.8
7	1.5	13.2	1.5	4.5	5.5	2.9		18.8	26.1	74.0	78.5	21.5
8	1.0	18.8	1.0	7.0	36.0	2.0	0.5	45.0	2.7	114.0	87.5	12.5
Sum	20.5	146.5	26.0	104.2	279.0	10.5	169.7	162.7	126.9	1146.0		
Producer's accuracy	0.0	0.0	76.6	76.2	0.0	90.4	79.3	87.5	95.3			
Error of Omission	100.0	100.0	23.4	23.8	100.0	9.6	20.7	12.5	4.7			

Proportion of pixels correctly classified (shaded cells): 81.4%
Overall error of commission: 18.3%
Overall error of omission: 43.9%

(*) The reference data represents the land cover/use super classes described in Table 5.2.3.
(**) The classified data represent the mapping units, whose components described in the legend of Figure 5.2.4.

The confusion matrix shows an overall accuracy of 81.4%, according to the adopted map legend. Omission errors were higher than commission errors, since some representative land cover/use super classes were considered as mapping unit inclusions (minor components).

5.2.5. Discussion

The proposed method for a mapping hierarchy using remote sensing imagery as input improves the user's knowledge on main and minor unit components, and may be used to produce new maps at different aggregation levels.

An unsupervised classification method was used. The bands and the unsupervised algorithm used to obtain the basic mapping units (units of level 1) could be arguable. The quality of the classification would not probably be very different by simply using the original non-thermal bands. From the mapping unit definition viewpoint, what is more important is the use of the unsupervised method above the supervised one since it attempts to uncover the land cover classes that are registered in the spectral data.

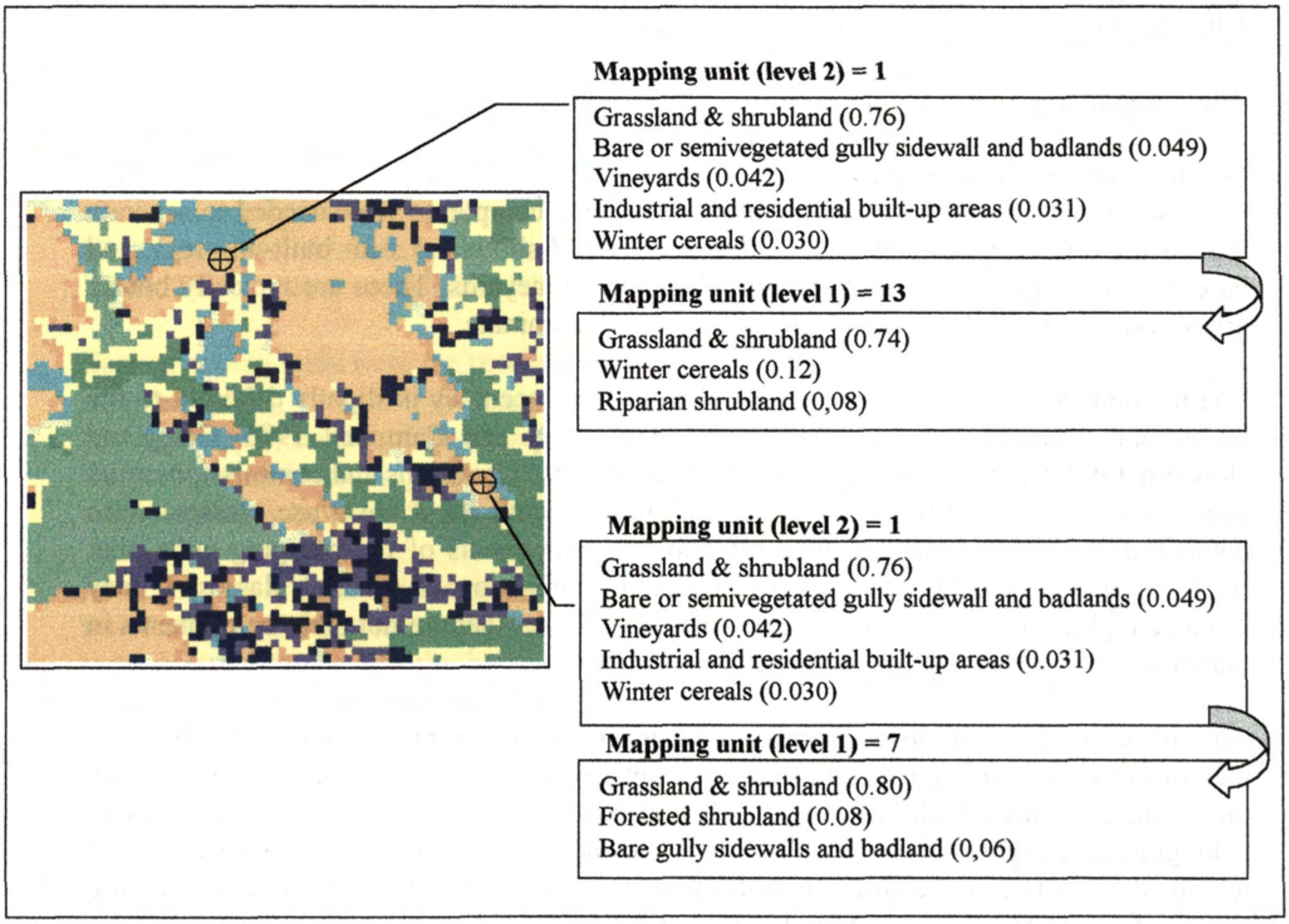


Figure 5.2.5. Example of querying from the second to the first generalisation level.

The use of consociations, associations and complexes as mapping units is not a new approach. It relates to other research fields, particularly to soil mapping (Wambeke and Forbes 1985). This approach is useful to structure the type of mapping units that result from unsupervised classifications. Consociations are the most pure mapping units. Associations are usually the result of the aggregation of spectral classes that correspond with distinct land cover/use classes, and which are merged because of a decision of the analyst or of the map user. Complexes are usually units that group land cover/use classes which are difficult to discriminate from the spectral data used.

The approach proposed in the present paper to define mapping units is different from the use of primary and secondary labels (Woodcock *et al.* 1996, Ludin and Harrison 1997). In the scheme proposed by these authors, secondary labels are evaluated from a set of polygons defined from a segmentation of a classified image or from a classified image segmented by land parcel boundaries. The mapping units are not inherent to the spectral data that the image contains and the image is used to attach information to spatial units defined by other means. In the proposed approach main components of mapping units are similar to primary labels and minor components or inclusions are similar to secondary labels, but primary and secondary labels are different from super classes and elementary land use classes, which have to do with the class generalisation level being considered.

The important cover/use classes were clearly distinguished in the present case study despite using data when the vines had not yet sprouted (Figure 5.2.4). Confusion existed in the classification of built-up areas, bare soil parcels and young vineyard plantations. These units, where confusion existed, form complexes. Two complexes were needed to separate typical mixtures: bare soil parcels and grassland and shrubland with built-up areas, and bare soil parcels and grassland and shrubland with vineyards. These are typically border areas between these classes and were difficult to discriminate.

The method that was used to assess the classification accuracy is slightly different to the traditional error or confusion matrix approach (Story and Campbell 1986, Gong and Howarth 1990, Chuvieco 1996, Palacio and Luna 1996). Omissions and commission errors were measured on a different basis since reference data (land cover/use classes) were compared to classified data as they refer to the components of the mapping units, that result from the unsupervised classification and aggregation of spectral classes. It may produce high errors of omission in land cover/use classes that are not main components in mapping units and only appear as minor components.

An advantage of the proposed mapping unit generalisation hierarchy, above conventional methods of presenting image classification results, was the possibility for the user to query the basic thematic level, to identify elementary class membership of a given pixel belonging to a higher level unit. The ability to undertake queries was the result of the relationships between the different information levels in the defined hierarchy (Figure 5.2.2 and Figure 5.2.3), as illustrated in Figure 5.2.5.

Like all labelling methods, the proposed one is not exempt from subjectivity. Map production was guided by the map purpose and the analyst or map user must to decide about the level of class hierarchy and mapping unit hierarchy to implement. Variations on the basic land cover/use classes or mapping units to merge change the output map and legend. This can be viewed as an advantage, since the basic information registered in the raster map and in the database can be used to produce different purpose maps. The assessment of classification accuracy or those different maps is possible because of the inheritance of the class membership information available from a lover level to a higher level of the generalisation hierarchy structure.

5.2.6. Conclusions

An approach for image classification that considers information abstraction structures such as class generalisation hierarchies, in order to guide mapping unit definition from data collection to information presentation, has been presented.

Several aspects of the proposed method might be viewed as advantageous. From the user's point of view, the map legend reports a more detailed mapping unit composition than usual legends, which only present the main land cover/use classes as labels. Although confusion matrices also carry information about mapping unit components, only generalised main components can be expressed. Information to the user is not also as explicit as in the proposed method. Here the user can decide the level of detail to query. The generalisation hierarchy allows transparency of information from one level to another. The user can obtain knowledge of basic mapping unit components from queries at a higher level. It also allows querying for location of land cover/use classes that are not main mapping unit labels. The output is accompanied by the corresponding unit membership value.

Basic mapping units were the product of an unsupervised classification. Each decision that is taken during the clustering process will vary the output (e.g. input bands, seeding, classifier type), but the date of the image will significantly influence the land cover/use classes that can be distinguished. In the case study presented, the use of multitemporal data would probably have produced a more accurate land cover/use map.

Some aspects related to the proposed method remain unexplored. Perhaps, one of the most interesting would be the complete automation of the generalisation hierarchy after ground truth data collection. On the basis of membership values of basic mapping units to land cover/use classes, the system would compute the combinations of related or similar mapping units in terms of cover/use class components (according to the classification system) that produce a minimum overall classification error. The user would only supervise the land cover/use class hierarchy, since this information can vary depending on the cover/use classes existing in different areas.

Acknowledgements

This research was supported by the Spanish Dirección General de Ciencia y Tecnología, and was carried out in the Departament de Medi Ambient i Ciències del Sòl de la Universitat de Lleida, in the context of the project: 'Rainfall kinetic energy and erosivity in vineyard areas in the Mediterranean basin (Anoia – Penedès): Modelling of erosive processes by gullies'. The author also acknowledges the anonymous referees for their useful comments and corrections which improved the paper.

References

ARONOFF, S., 1982, Classification accuracy: A user approach. *Photogrammetric Engineering and Remote Sensing*, **48**, 1299-1307.

ARONOFF, S., 1989, *Geographic Information Systems: A management perspective*, (Otawa: WDL Publications).

CHAVEZ, P.S., BERLIN, G.L. Jr. and SOWERS, L.B., 1982, Statistical methods for selecting Landsat-MSS ratios. *Journal of Applied Photogrammetric Engineering*, **8**, 23-30.

CHAVEZ, P.S., 1988, An improved dark-object substraction technique for atmospheric scattering correction of multispectral data. *Remote Sensing of Environment*, **24**, 459-479.

CHEN, P.P., 1976, The entity-relationship medel – Toward a unified view of data. *ACM Transactions on Database Systems*, **1**, 9-36.

CHUVIECO, E., 1996, *Fundamentos de teledetección espacial*, 3a Edición (Madrid: Rialp).

CONGALTON, R.G., 1991, A review of assessing the accuracy of classifications of remote sensing data. *Remote Sensing of Environment*, **37**, 35-46.

EASTMAN, J.R., 1997, *Idrisi for Windows User's Guide. Version 2.0*, (Worcester: Clark University).

EGENHOFER, M.J. and FRANK, A.V., 1989, Object-oriented modelling in GIS: Inheritance and propagation. *Auto-Carto*, **9**, 588-598.

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.

GARCÍA, M.C. and ÁLVAREZ, R., 1994, TM digital processing of a tropical forest region in south-eastern Mexico. *International Journal of Remote Sensing*, **15**, 1611-1632.

GILABERT, M.A., 1990, *Caracterización radiométrica, en el intervalo espectral solar, de cultivos cítricos. Modelo geométrico de reflectividad de aplicación en teledetección*, PhD Dissertation, (Valencia: University of Valencia).

GONG, P. and HOWARTH, P.J., 1990, An assessment of some factors influencing multispectral land-cover classification. *Photogrammetric Engineering and Remote Sensing*, **56**, 597-603.

HAY, A.M., 1979, Sampling designs to test land-use map accuracy. *Photogrammetric Engineering and Remote Sensing*, **45**, 529-533.

JANSSEN, L.L.F. and VAN DER WEL, F.J.M., 1994, Accuracy assessment of satellite derived land-cover data: A review. *Photogrammetric Engineering and Remote Sensing*, **60**, 419-426.

LARK, R.M., 1995, Components of accuracy of maps with special reference to discriminant analysis on remote sensor data. *International Journal of Remote Sensing*, **16**, 1461-1480.

LUDIN, A.N.M. and HARRISON, A.R., 1997, An assessment of primary and secondary labels in land use maps derived from remotely sensed data. In *Observations & Interactions.* 23rd Annual Conference and Exhibition of the Remote Sensing Society, Reading, UK, 2-4 September 1997, (Reading: Remote Sensing Society), pp. 316-321.

MARTÍNEZ-CASASNOVAS, J.A., 1994, *Hydrographic information abstraction for erosion modelling at regional level. A database perspective in a GIS environment.* MSc. Thesis, (Wageningen: Wageningen Agricultural University).

MARTÍNEZ-CASASNOVAS, J.A. and CERVERA, T., 1996, Gully erosion mapping by remote sensing techniques. A case study in the Penedès-Anoia region (NE Spain). *I European Congress on Erosion Control, Sitges, Spain, 29-31 May 1996.*

MOLENAAR, M., 1993, Object hierarchies and uncertainty in GIS or why is standardisation so difficult? *Geo-Informationssysteme,* **4**, 22-28.

MOLENAAR, M. and RICHARDSON, D.E., 1994, Object hierarchies for linking aggregation levels in GIS. *Proceedings of ISPRS Commission IV, Athens, US, May-June 1994. International Archives of Photogrammetry and Remote Sensing,* **30**, 610-617.

PALACIO, J.L. and LUNA, L., 1996, Improving spectral results in a GIS context. *International Journal of Remote Sensing*, **17**, 2201-2209.

PORTA, J., RAMOS, C. and BOIXADERA, J., 1994, Mechanical measures for runoff management and erosion control in vineyards of NE Spain. In *Conserving soil resources. European perspectives*, Edited by R.J. Rickson, (Wallingford: CAB International), pp. 369-378.

RAMOS, C., PORTA, J. and BOIXADERA, J., 1991, Rainfall characteristics and soil lossess in vineyards in the NE Spain. *ESSC Seminar on Combating Erosion in Vineyards*, Trier, Germany, 22-25 May 1991.

STORY, M.H. and CAMPBELL, J.B., 1986. The effect of training data on classification accuracy. *ACSM-ASPRS Annual Convention, Washington, D.C., US, 16-21 March. Technical Papers*, **4**, 370-379.

STORY, M.H. and CONGALTON, R.G., 1986, Accuracy assessment: A user's perspective. *Photogrammetric Engineering and Remote Sensing*, **52**, 397-399.

WAMBEKE, A. VAN and FORBES, T., 1985, *Guidelines for using Soil Taxonomy in the names of soil map units*. S.M.S.S. Technical Monograph N. 10. (Washington, D.C.: USDA).

WANG, F., 1990a, Fuzzy supervised classification of remote sensing images. *IEEE Transactions on Geoscience and Remote Sensing*, **28**, 194-201.

WANG, F., 1990b, Improving remote sensing image analysis through fuzzy classification representation. *Photogrammetric Engineering and Remote Sensing*, **56**, 1163-1169.

WOODCOCK, C.E., GOPAL, S. and ALBERT, W., 1996, Evaluation of the potential for providing secondary labels in vegetation maps. *Photogrammetric Engineering and Remote Sensing*, **62**, 393-399.