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Interpreting Pleistocene glacial features from SPOT HRV data using fuzzy techniques

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Abstract

The ability to correctly identify landform features from remotely sensed imagery is largely determined by pixel size. This spatial scale element is a particularly important consideration for glacial geomorphological feature identification when remote sensing data are used for mapping and palaeoenvironmental reconstruction in mountain environments. It is important to be able to clearly delineate the boundaries of glacial landforms. However, in common with other phenomena, such features often possess indeterminate boundaries and many geomorphometric changes occur over short distances. Thus, the use of conventional hard classification techniques may not always be appropriate in glacial terrain mapping where investigators are concerned with individual feature identification. In such situations the ability to examine sub-pixel scale information by using soft classifiers is potentially more useful. This paper examines the value of sub-pixel data interpretation derived from supervised and unsupervised fuzzy modelling techniques for the mapping and interpretation of glacial terrains for the wider purposes of glacial reconstruction in the Pindus Mountains of Northwest Greece. This work is part of a larger study involving field-based investigation of the glacial sediments and landforms. Emphasis has been given to the effective delineation of features from 20 m resolution SPOT HRV imagery.

Keywords: Glacial geomorphology; Greece; Mountain environments; SPOT; Fuzzy image analysis

1. Introduction

In recent years many glacial geomorphological investigations have benefited considerably from the availability of airborne and satellite remote sensing data (e.g. Aber et al., 1993; Boulton and Clark, 1990; Punkari, 1993). In the analysis of formerly glaciated terrains, the nature of the data sets used is largely determined by the extent and scale of the landforms of interest, and two main approaches can be identified. First, investigations of individual cirques and glaciated valleys, for example, commonly employ large-scale aerial photography with pixel resolutions approaching a few metres (Lowe and Walker, 1984; Gray and Coxon, 1991). Second, studies of the dynamics of former ice sheets and gla-

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ciated terrains at both regional- and continental-scales have utilised medium and coarse resolution satellite imagery; Boulton and Clark (1990) used Landsat data with 80 m pixels in their study of the Laurentide palaeo-ice sheet. The latter approach has been the focus of recent glacial geomorphological remote sensing research and has allowed geomorphologists to consider the evolution and behaviour of former ice sheets (Aber et al., 1993; Clark, 1993; Clark and Knight, 1994; Punkari, 1993). Such strategies are not designed to account for the complexity within individual mountain catchments because of the limited spatial detail provided by such imagery. Conversely, Landsat TM data (with 30 m pixels) are too detailed for palaeo-ice sheet investigations over continental scales, and in these instances spatial resolutions approaching a few kilometres may be more appropriate (Punkari, 1982).

The study of individual palaeoglaciers and the examination of local landform assemblages has received much less attention in satellite remote sensing investigations. It is only very recently that researchers have begun to explore the potential for analysing smaller scale glacial terrain characteristics and to map individual features and suites of landforms from high spatial resolution satellite remote sensing data (with pixel sizes 30 m or less) such as provided by SPOT HRV and Landsat TM (e.g. Klein and Isacks, 1996). Such studies have the potential to yield important data on the extent and style of glaciation in mountain environments beyond the margins of the major Pleistocene ice sheets. The geomorphology of these mountain environments may include moraine complexes and other glacial landforms that are important for understanding the nature of climate–landscape interactions, but are typically limited in extent and therefore not readily observed from coarse spatial resolution satellite sensor imagery such as from the Landsat MSS. The Mediterranean region is one such area where detailed mapping has not been widely conducted yet the development of valley glaciers during cold stages is known to have exerted an important influence on river behaviour and the archaeological record in upland environments (cf. Woodward et al., 1995).

This paper is concerned with the detection of individual glacial geomorphological features and suites of landforms within the Pindus Mountains of Northwest Greece. We explore the potential for improving glacial landform feature characterisation and increasing the accuracy of mapping from satellite imagery using fuzzy image classification to identify the geomorphometric character and spectral properties of the glacial landforms present at sub-pixel (< 20 m) levels. These contrasts can be important as they may represent age-dependent features that indicate different phases of glaciation.

2. Remote sensing of palaeoglacial environments

Clark (1997) has reviewed the current status of remote sensing in palaeoglaciology. Satellite remote sensing, with its synoptic coverage and spectral capabilities, has been successfully applied to a range of glacial geomorphological investigations. Some of the earliest applications took advantage of the wide areal coverage available for reconnaissance mapping purposes to complement or substitute more time-consuming and expensive fieldwork activities. The increased accessibility provided by satellite sensor imagery has allowed the observation of many previously undocumented areas, including high mountain terrains such as the Himalayas (Bishop et al., 1995) and the High Andes (Llorens and Leiva, 1995).

The issue of scale in remote sensing is of particular significance to glacial geomorphological research (Fig. 1) and Boulton and Clark (1990) have used Landsat MSS images to identify former glacial processes operating at different scales within the Canadian Shield. Remote sensing applications have not been limited to the use of optical sensor systems. Over the last five years, an increasing number of researchers have used Synthetic Aperture Radar (SAR), utilising its capacity to detect surface texture and morphological variation (Clark and Knight, 1994). Optical remote sensing methods are more commonly employed in palaeoglacial investigations because of greater image availability, reduced cost and ease of interpretation (Clark, 1997).

Glacial geomorphological investigations have also benefited from multispectral remote sensing, which has allowed the identification of glacial landforms and deposits through the use of composite spectral signatures. Further, multispectral satellite sensor data have been used in combination with digital elevation models (DEMs) (Clark, 1997; Butler and Walsh, 1998) and this approach has been successful in the detection and mapping of geomorphological landforms.

More recent developments have involved new image processing tools — including neurofuzzy techniques — and these have the potential to increase the accuracy of glacial geomorphological information from existing satellite remote sensing data. The next generation of sensors with increased spatial and spectral resolution (Aplin et al., 1997) will provide this field with valuable new data sets over the next decade.

3. Research aims and available data sets

The main aim of this research was to improve our ability to identify palaeoglacial landforms within the Pindus Mountains at fine spatial resolutions (examining terrain characteristics at sub-pixel level ≤20 m) from SPOT HRV imagery to determine their spatial extent. The nature of the available data sets necessitated the development of novel strategies, and the use of advanced image processing methods to alleviate the constraints imposed by the 20 m pixel size and spectral resolution to identify those landforms smaller than the effective spatial resolution of the satellite sensor. To examine the potential for determining sub-pixel change in a glaciated mountain environment using SPOT HRV data, thereby maximising the image data potential, fuzzy classification methods have been used. This approach has been taken because there is some debate over the suitability of satellite sensor data for palaeoglacial mapping (because of coarse pixel size and scale constraints), and sub-pixel scale information is often required to characterise landforms and determine the true complexity of the former glacial system. Thus, this paper explores whether fuzzy classifiers can cope with the complex terrains present within formerly glaciated mountain environments and discusses whether fuzzy output is a good representation of reality.

4. Study area

The glaciated mountain headwaters of the Voidomatis River basin in Northwest Greece formed the study area for this project. The mountains are formed in Palaeocene-Eocene limestone and several peaks exceed 2400 m (Fig. 2A). The area is characterised by numerous cirques, several large glacial troughs, and distinctive moraine complexes (Bailey et al., 1990, 1997; Lewin et al., 1991). The glaciated terrain is partly influenced by geological structure, with glacial valleys closely following fault lines. Well-preserved glacial sediments and landforms are found throughout the area and some of these probably result from Late Pleistocene glaciation, although a detailed field mapping and radiometric dating programme is still in progress (Bailey et al., 1990; Lewin et al., 1991; Woodward et al., 1995; Boenzi and Palmentola, 1997). The glacial sediments and landforms are mainly derived from the hard limestone bedrock and include ice-scoured bedrock surfaces and boulder strewn moraines. Flysch bedrock is present at lower elevations beyond the limits of glacial activity although some limited outcrops are evident within the limestone uplands (Fig. 2A).

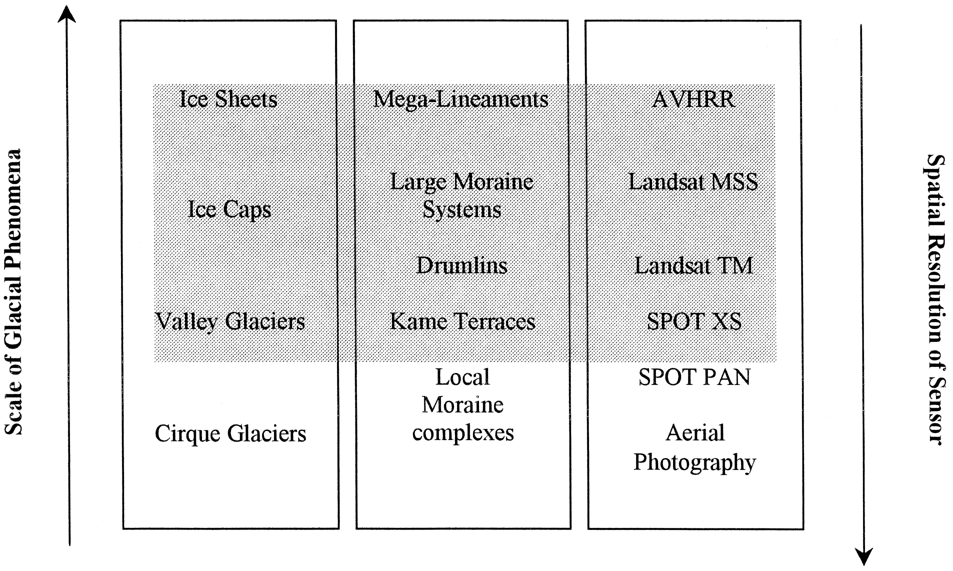

Fig. 1. Scale of glacial geomorphological phenomena and sensor resolution requirements Grey shaded area highlights current applications which have employed different satellite sensors in study of glacial landforms at range of scales.

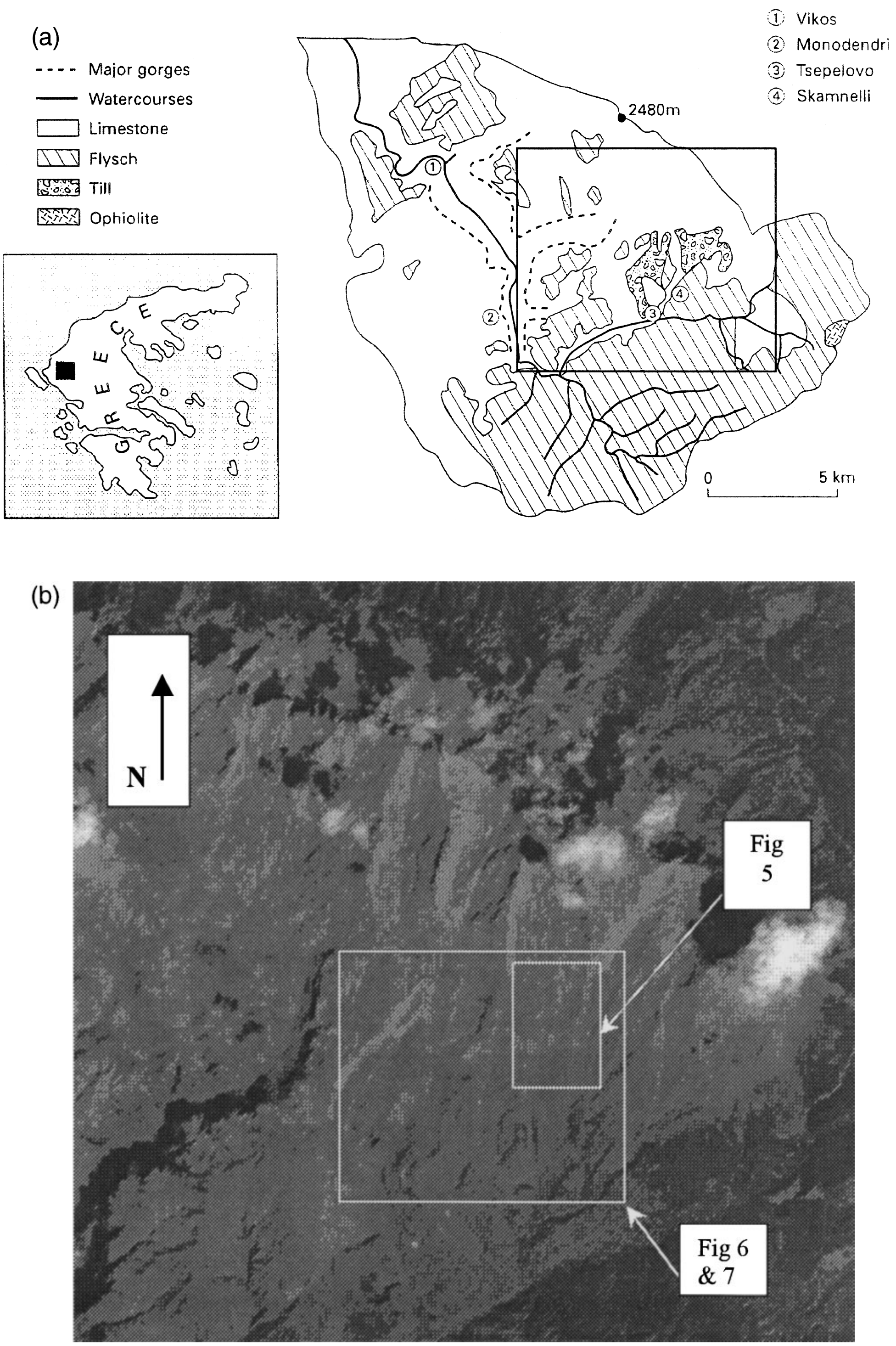

Fig. 2. (A) Simplified geology and drainage map of Voidomatis basin (modified from Woodward et al., 1995); box represents SPOT HRV image areal coverage used in study. (B) SPOT image of part of Pindus Mountains in NW Greece with the location of Figs. 5–7 shown. Scene covers approximately 15 × 15 km.

5. Why employ fuzzy image classifiers to map glaciated terrain?

It is widely accepted that conventional 'one pixel–one class' classification methods cannot account for all landform variation present within an image (Wang, 1990; Fisher and Pathirana, 1990). The fundamental problems of conventional per-pixel based classifiers stem from the inadequacy of the pixel as a unit of observation, and the fact that crisp classification does not account for the mixture of spectral signatures and/or spatial variation present within the confines of a single pixel or image cell (Fisher, 1997; Gopal and Woodcock, 1994; Maselli et al., 1996; Wang, 1990).

In glaciated mountain terrains, landform changes commonly occur at sub-pixel scales or less than 20–30 m in the case of SPOT HRV and Landsat TM imagery (Fig. 1). Sub-pixel terrain variations can be important in glacial geomorphological research where accurate landform feature mapping forms the basis for any palaeoenvironmental reconstruction. While fuzzy classification and remote sensing imagery have been used to study modern periglacial environments (Anto-

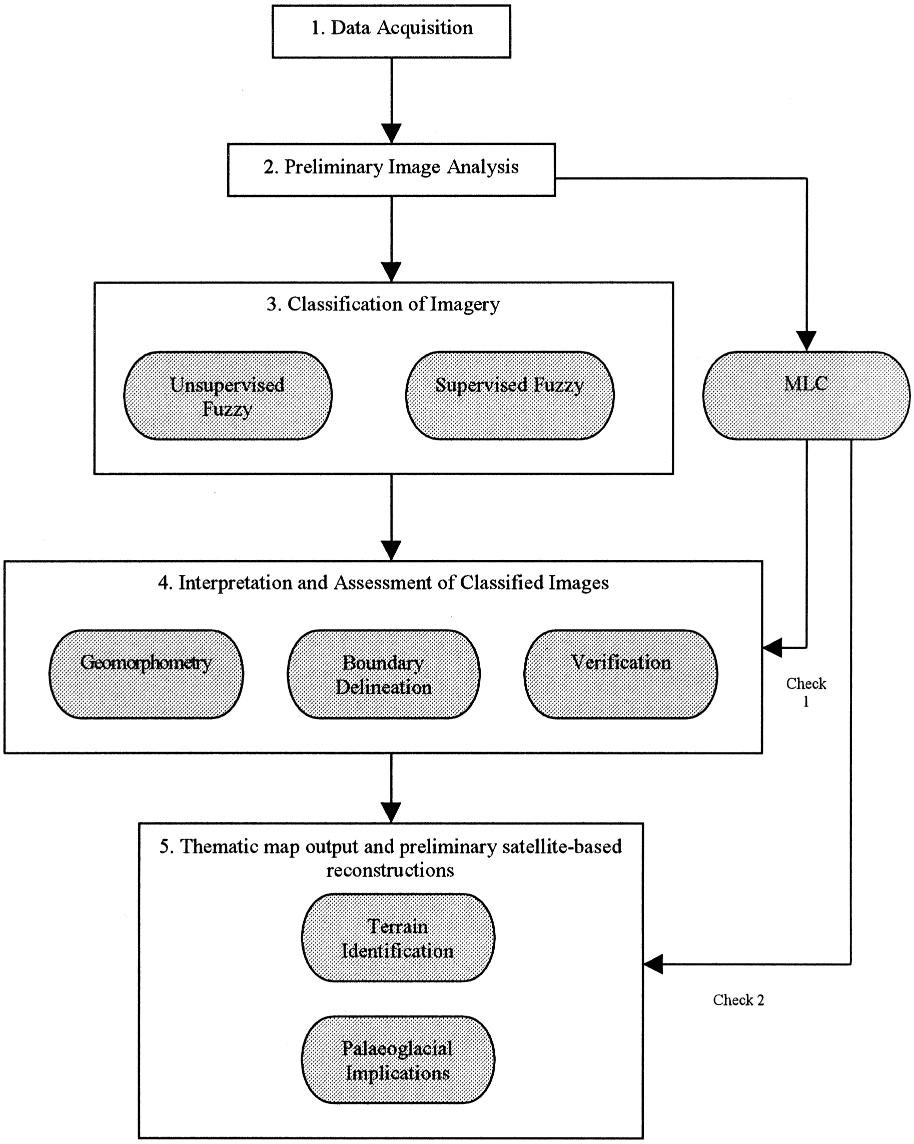

Fig. 3. Flow diagram of fuzzy-based strategy used in this study.

ninetti et al., 1997; Leverington and Duguay, 1997), there has been little work on fuzzy classification approaches in the mapping of small scale glaciated terrains associated with cirque and valley glaciation.

6. A fuzzy-based strategy

A strategy employing fuzzy classifiers is used here (Fig. 3) and the data sets and algorithms are described below. Unsupervised and supervised fuzzy classification techniques have both been used to determine their effectiveness in obtaining useful palaeoglacial data at sub-pixel scales from the SPOT HRV image. The results of the fuzzy classifications are shown by probability of membership and the level of mixed pixels present is used as an indicator of geomorphometric variation and change in landform type (or the boundary transition of glacial features). The image processing results are also compared with the Maximum Likelihood Classifier. Two proprietary Digital Image Processing software systems were used, PCI EASI PACE™ and IDRISI for Windows™, both of which offer a range of soft classification algorithms.

6.1. Data sources

We have used SPOT HRV satellite data with 20 m pixels that were acquired during September 1986. A combination of band 2 (0.61–0.68 μm), band 3 (0.79–0.89 μm) and band 1 (0.50–0.59 μm) was used in visual analysis and image classification. Panchromatic aerial photography (1: 30,000) was used for qualitative comparison and accuracy assessment. Field observations also provided additional ground verification.

6.2. Unsupervised fuzzy classification

The unsupervised fuzzy clustering algorithm available with EASI-PACE™ was used. This is a modification of the optimal fuzzy clustering method developed by Gath and Geva (1989):

$$J_q(U, V) = \sum_{j=1}^{N} \sum_{i=1}^{K} (u_{ij})^q d^2(X_j, V_i); \quad K \leq N \tag{1}$$

where U is the fuzzy K-partition of the data set and V a set of K prototypes. The degree of membership of X_j is given by u_{ij} and K is the number of clusters employed in the classification procedure (Gath and Geva, 1989).

Clusters were created from the input image using Maximum Likelihood Estimation (MLE) methods and for each of the clusters the membership grade is shown by pixel intensity (EASI PACE, 1997). This algorithm was particularly attractive to this project because it allows the creation of fuzzy cluster composite maps and it allows the user to create composite images of any three of the fuzzy clusters created. These are useful image interpretation tools and can optimise user assessment of changes in degree of pixel membership between different fuzzy clusters shown by changes in image pixel intensity. The unsupervised approach was also chosen to highlight any natural spectral groupings within the image that could be related to subtle geomorphometric changes not previously noted, either in the field or from preliminary visual interpretation of the image.

6.3. Supervised fuzzy classification

The supervised fuzzy classification procedure was performed using FUZCLASS, one of the soft classifiers available in IDRISI for Windows™ image processing software. Training data chosen for each informational class can possess both pure and fuzzy signatures. The classification allows different levels of pixel membership (0.00–1.00) and this is shown by pixel intensity:

$$\mu = \cos 2\alpha \tag{2}$$

where μ is the sigmoidal membership function, α is defined as (x - point a)/(point b - point a) $*$ pi/2. When x > point b, $\mu = 1$ (IDRISI, 1997).

6.4. Maximum Likelihood Classification

The Maximum Likelihood Classifier (MLC) was also used for control purposes to allow comparison with the fuzzy classification results. This procedure uses probability values to classify each image pixel. Although this procedure does not provide sub-pixel information from the SPOT scene, it does emphasise broad-scale changes in the nature of the glaciated terrain. The results of the MLC were compared with fuzzy outputs at two stages: check 1 at the interpretation and verification stage, and check 2 during thematic map output and satellite-based reconstruction (Fig. 3).

7. Digital image processing: image classification and results

Visual image and air photograph analyses were used to identify and select classes from the SPOT HRV data to be used in the fuzzy and MLC supervised classifications. The geology of the glaciated area is dominated by resistant limestone with small outcrops

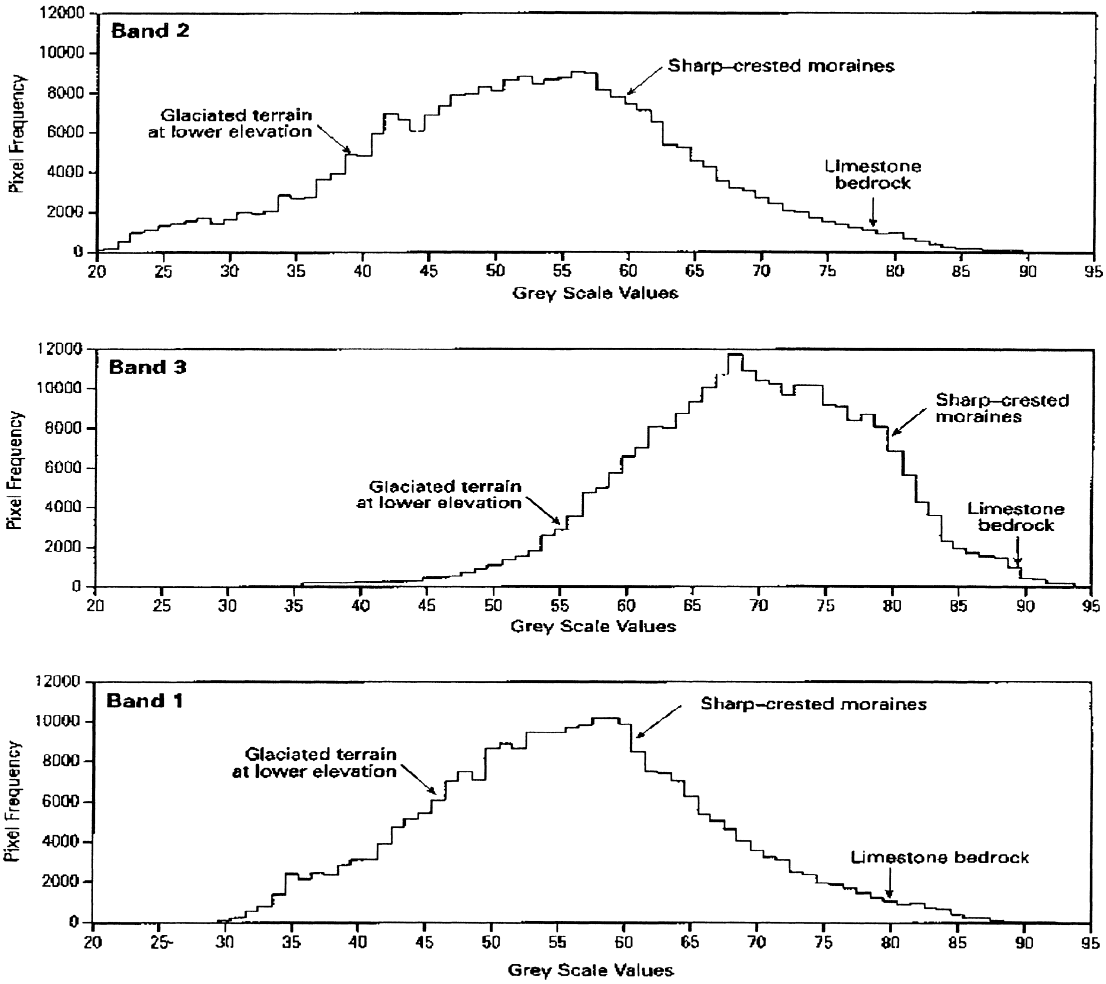

Fig. 4. Histograms showing DN range for all SPOT bands (radiance value mid ranges associated with particular features are marked approximately). Band 2 (0.61–0.68 μm), band 3 (0.79–0.89 μm), and band 1 (0.50–0.59 μm) are shown.

of flysch (IGME, 1970). Limited lithological variation made it difficult to isolate spectral signatures (overlapping spectral signatures were present) for the various landforms identified from analysis of the aerial photographs and field observations. Fig. 4 shows the histograms for the radiance values of each SPOT HRV band (annotated with markers for each of the landform and feature types). The raw image allowed discrimination, albeit rather limited, between the glacial depositional landforms present above about 1600 m and below 1400 m elevation. Five terrain classes were selected for supervised classification (Table 1). These

Table 1
Thematic classes used in supervised classification procedures (fuzzy and MLC)

Category	Associated geomorphological process
Scree and bare rock surfaces	Subject to frost action and ice abrasion
Fresher glacial landforms and deposits	Glacial erosion and deposition
Glacial landforms and deposits at lower elevations	Glacial erosion and deposition
Sparse vegetation cover	
Forest cover	

classes were judged to represent the major terrain variability within the study area. For comparative purposes the maximum possible number of clusters for the unsupervised fuzzy operation was set to five to account for the dominant landscape features. The classes comprised:

1. Scree and bare rock (coarse limestone screes and glacially-scoured limestone bedrock surfaces). This class was characterised by very high spectral response in all three SPOT HRV bands.
2. High relief glaciated terrain and deposits on the upper slopes, including well preserved sharp crested moraines. These were characterised by greater morphological complexity and limited vegetation cover (Fig. 5), and similarly high spectral reflectances (there has been minimal soil development on these moraines).
3. Glaciated terrain at lower elevations with lower local relief, which includes some flatter moraines with weathered surfaces resulting in a distinctive spectral pattern. These landforms were also characterised by lower complexity and the smoother topography of the moraines.
4. Sparsely vegetated areas and non-glaciated surfaces.
5. Tree and shrub cover. This included nearly all land below 1000 m above sea level and some of the moraines which reach down to these lower altitudes.

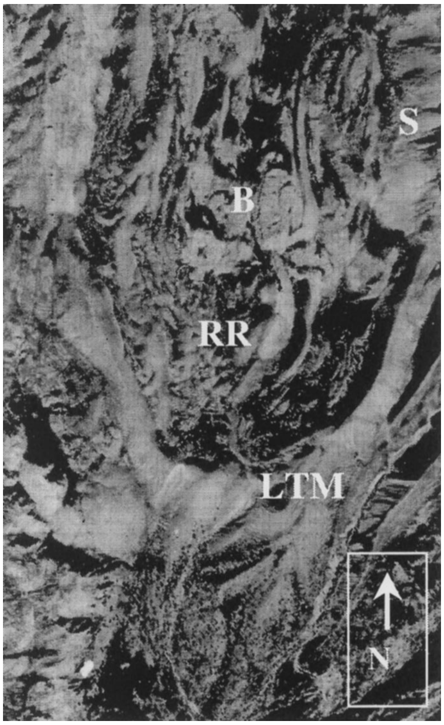

Fig. 5. Aerial photograph showing latero-terminal moraine complex above ca. 1600 m. Photo is 1: 30,000 scale and covers approximately 3 × 2 km, LTM — large terminal moraine; RR — Recessional/Readvance moraines; B — Ice scoured limestone bedrock; S — scree deposits. See Fig. 2B

7.1. Results

Figs. 6 and 7 show the results of the unsupervised and supervised fuzzy classification procedures. The unsupervised fuzzy classification identified three spectral groupings out of a possible five (five clusters were set as a maximum). The clusters identified from the procedure closely related to first, the forest cover; second, areas of glacial deposition and vegetation cover, which also included the moraines on the lower slopes and intra-moraine areas; and third, bare-rock and scree formations as well as the sharp-crested moraines on the upper slopes (Fig. 5).

Fig. 6A shows the fuzzy cluster image that closely approximates the high local relief moraines on the upper slopes and many of the scree deposits and ice scoured bedrock surfaces. The similar high pixel intensity values for these features demonstrate the common reflectance properties of these particular landscape features. A composite image was then created (Fig. 6B) which allowed all the major landforms within the upper glaciated areas to be detected. The fact that the large arcuate terminal moraine shown in Fig. 5 and the associated smaller moraine systems proximal to it were clearly identifiable was of particular interest. This can be seen in Fig. 6B by the marked changes in pixel intensity in the upper right portion of the classified image. Indeed, the cluster composites successfully highlighted landform character and the unsupervised fuzzy classification was the only classifier that clearly identified this distinctive glaciated terrain.

The supervised fuzzy classification also produced a clearly interpretable glacial geomorphological map. Figs. 7A and B show the results of the attempt to classify the high local relief moraines above ca. 1600 m (Fig. 7A) and the well vegetated low relief moraines below ca. 1400 m (Fig. 7B). In particular, the supervised approach provides effective discrimination of the lower glacial terrain (moraines) class (3); changes in pixel membership are shown by pixel intensity. The crests of several landforms can be defined clearly, and their boundaries coincide with a tailing-off of pixel membership.

In comparison, the MLC results were much less informative (Smith et al., 1998). The two main glaciated valleys can be identified but the detection of glacial landforms is more difficult. In the portion of higher elevation glaciated terrain shown in Fig. 5, it does pick out one of the long lateral moraines, although it does not cope well with the spatial com-

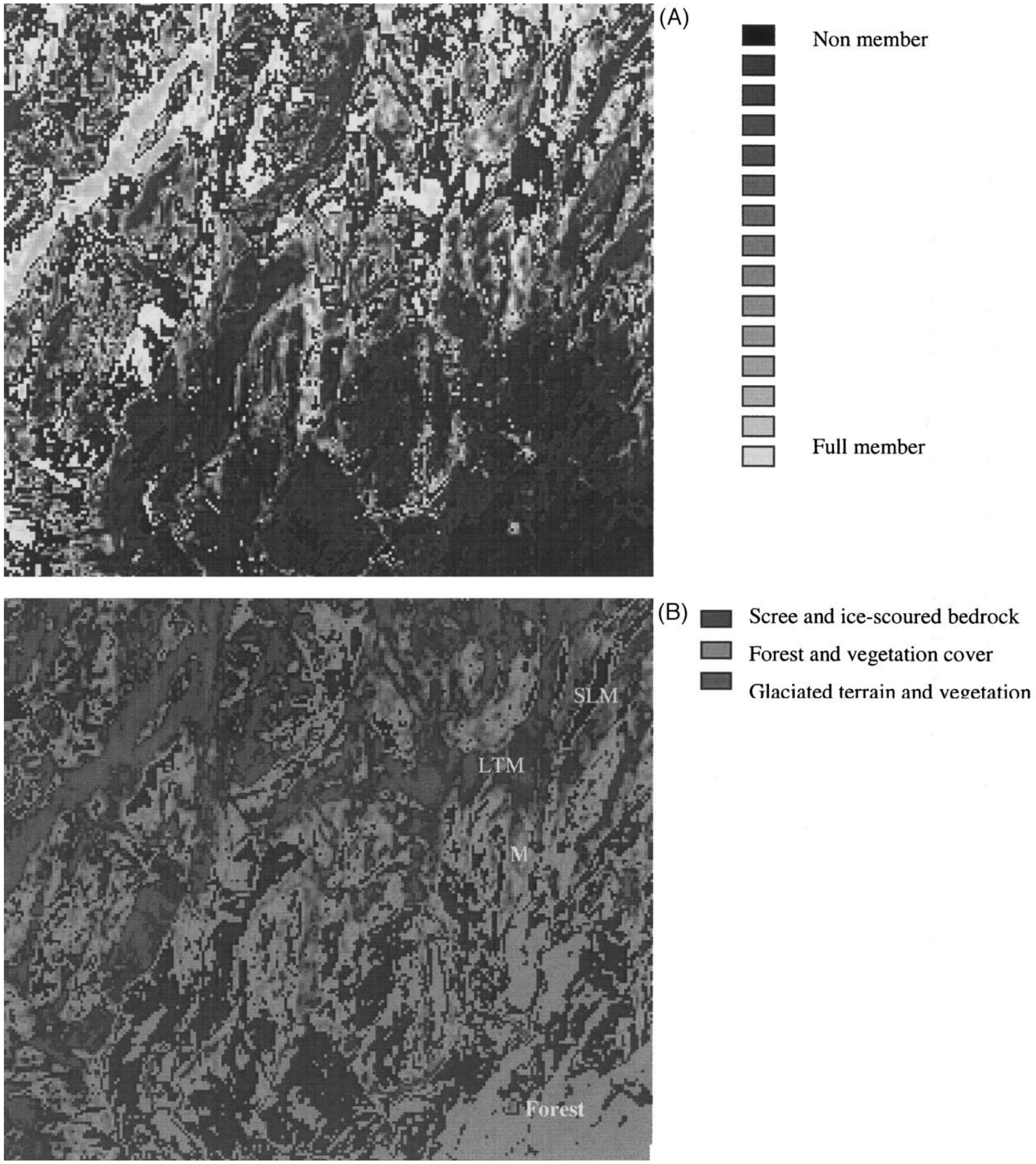

Fig. 6. (A) Unsupervised fuzzy classification cluster 1. North is at top of figure. This cluster mainly shows high local relief moraines on upper slopes and ice scoured bedrock surfaces, with their similar reflectance characteristics (shown by high pixel intensity values). Image covers approximately 6 × 5 km. See Fig. 2B. (B) Unsupervised fuzzy classification composite image. This has been created from three clusters resulting from unsupervised procedure. North is at top of figure. LTM — large terminal moraine; M — termino-lateral moraines; SLM — sharp crested long lateral moraines above Skamnelli. Image covers approximately 6 × 5 km. See Fig. 2B.

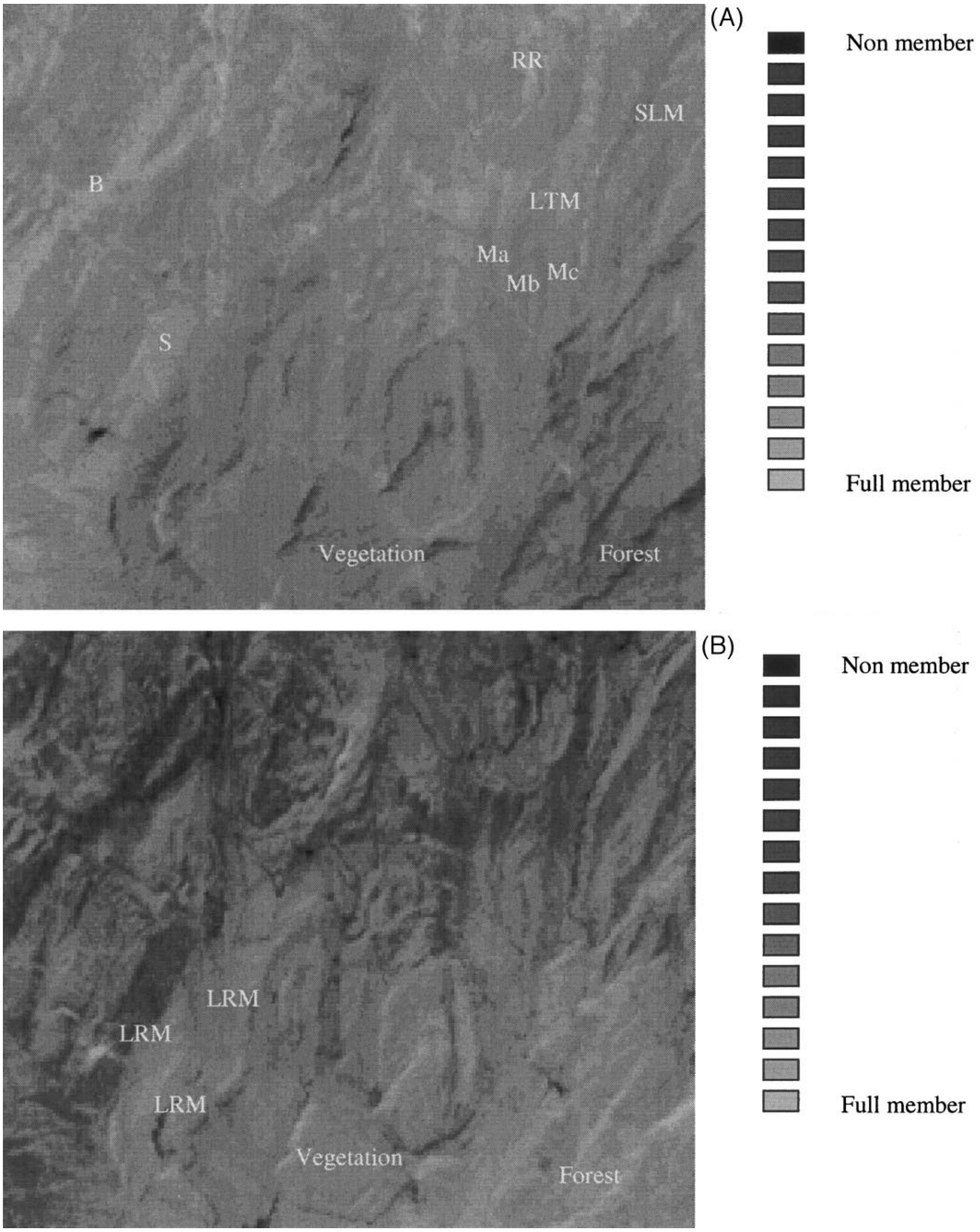

Fig. 7. (A) Supervised fuzzy classification of high local relief moraines on upper slopes above 1600 m. North is at top of figure. LTM — large terminal moraine; Ma-Mc — termino-lateral moraines; SLM — sharp crested long lateral moraines above Skamnelli; RR — recessional/readvance moraines; B — ice scoured limestone bedrock; S — scree deposits. Image covers approximately 6 × 5 km. See Fig. 2B. (B) Supervised fuzzy classification of well-vegetated low relief moraines below 1400 m. North is at top of figure. LRM — low relief moraines at lower elevations. Image covers approximately 6 × 5 km. See Fig. 2B.

plexity shown by this moraine system. As for the glacial terrain on the lower slopes (below ca. 1400 m), it only depicts a large scar in one of the latero-terminal moraines.

The following section interprets the results and describes how the membership probabilities were used as a morphological indicator. All satellite-derived interpretations have been compared with fieldwork observations and panchromatic aerial photography, and the fuzzy results are in turn compared to the MLC output.

8. Interpretation of fuzzy imagery

The fuzzy (supervised and unsupervised) and MLC classified images have been assessed in terms of their glacial geomorphological content. Conventional accuracy assessments have not been used because of the problems associated with determining quantitative measures of accuracy for unsupervised fuzzy classification results. The fuzzy output has been compared with the MLC data, examining system complexity, landform (moraine) geomorphometry and differentiating between different glacial phases and their associated landforms. All classified images have been examined in conjunction with aerial photographs and field data to determine the accuracy of glacial geomorphological content. The results from the image classification indicate that both supervised and unsupervised fuzzy clustering methods can deal effectively with the landform complexity within the study area (Figs. 6 and 7). The nature of the high relief moraines on the upper slopes above Skamnelli was of particular interest and the terrain variability here (sharp crested moraines in close proximity) was represented most effectively by the unsupervised fuzzy classification. The classification strongly highlighted sub-pixel changes associated with this complex topography, as shown by the large percentage of mixed pixels covering that portion of the image. The glaciated terrain at lower elevations possessed less complexity as the moraine surfaces were weathered, flatter and rounded in shape. This reduction in spatial complexity resulted in less fuzziness within the resultant classified image (Fig. 6).

The supervised fuzzy classification allowed better landform discrimination than the raw SPOT HRV satellite data. Changes in pixel intensity closely followed the boundaries of many of the glacial landforms (Fig. 7). These improvements in boundary delineation suggest that supervised fuzzy classification can be successfully applied to glacial feature detection and identification from satellite imagery. Both types of fuzzy classification were capable of dealing with the complex terrain of a formerly glaciated mountain karst environment. This was not the case with the MLC output, which, in the present case, did not provide a reliable basis for a detailed glacial geomorphological interpretation and reconstruction. The poor performance of the conventional classifier resulted from the terrain complexity and low spectral variability within much of the study area (Smith et al., 1998)

9. Discussion of fuzzy-based strategy and its wider implications

This paper has demonstrated the potential for using fuzzy image classification methods for improving glacial geomorphological feature detection and interpretation from SPOT HRV data. The fuzzy classifiers provided sub-pixel scale information concerning spatial geomorphometric changes, which are associated with glacial landform type and age. Interestingly, it has shown that the level of fuzziness represented within an image of this glaciated area is related to the type and age of landforms. The most recent moraines, which were sharp and in close proximity to each other, were highly fuzzy on the classified image. In contrast, the older glaciated terrain contains moraines that were flatter and less complex and possessed less image fuzziness.

The work presented here is still in progress and it is expected that the interpretation of the glacial landforms within the study area will be refined, particularly with further modification of the fuzzy classifiers used here and completion of the field mapping and dating programme. The authors are currently working with Landsat TM data to examine whether greater *spectral* resolution will improve the accuracy of terrain mapping and the interpretation of the glacial landforms, and whether the spectral range of the data is more important than spatial resolution in such investigations.

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References

Aber, J.S., Spellman, E.E., Webster, M.P., Landsat remote sensing of glaciated terrain. In: Aber, J.S. (Ed.), Glaciotectonics and Mapping Glacial Deposits. Proceedings of the INQUA Commission on Formation and Properties of Glacial Deposits, 1993, pp. 215–225.

Antoninetti, M., Balduzzi, A., Binaghi, E., Guglielmin, M., Rampini, A., 1997. Use of thematic maps derived from a digital elevation model for permafrost classification in high mountain areas. In: Proceedings of the 4th International symposium on High Mountain Remote Sensing Cartography, Karlstad, Sweden, August 19–29, 1996, 1–16.

Aplin, P., Atkinson, P.M., Curran, P.J., 1997. High spatial resolution satellite sensors for the next decade. International Journal of Remote Sensing 18, 3873–3881.

Bailey, G.N., Lewin, J., Macklin, M.G., Woodward, J.C., 1990. The 'Older Fill' of the Voidomatis Valley Northwest Greece and its relationship to the Palaeolithic Archaeology and Glacial History of the Region. Journal of Archaeological Science 17, 145–150.

Bailey, G.N., Turner, C., Woodward, J.C., Macklin, M.G., Lewin, J., 1997. The Voidomatis basin: an introduction. In: Bailey, G.N. (Ed.), Klithi: Palaeolithic Settlement and Quaternary Landscapes in Northwest Greece, vol. 2. McDonald Institute, Cambridge, UK, pp. 321–345.

Bishop, M.P., Schroder, J.F., Ward, J.L., 1995. SPOT multispectral analysis for producing supraglacial debris-load estimates for Batura Glacier, Pakistan. Geocarto International 10 (4), 81–90.

Boenzi, F., Palmentola, G., 1997. Glacial features and snowline trend during the last glacial age in the Southern Apennines (Italy) and on Albanian and Greek mountains. Zeitschrift für Geomorphologie 41 (1), 21–29.

Boulton, G.S., Clark, C.D., 1990. A highly mobile Laurentide ice sheet revealed by satellite images of glacial lineations. Nature 346, 813–817.

Butler, D.R., Walsh, S.J., 1998. The application of remote sensing and geographic information systems in the study of geomorphology: an introduction. Geomorphology 21 (3/4), 179–181.

Clark, C.D., 1993. Mega-scale glacial lineations and cross-cutting ice-flow landforms. Earth Surface Processes and Landforms 18, 1–29.

Clark, C.D., 1997. Reconstructing the evolutionary dynamics of former ice sheets using multi-temporal evidence, remote sensing and GIS. Quaternary Science Reviews 16, 1067–1092.

Clark, C.D., Knight, J.K., 1994. ERS SAR data as a tool for landform and lineament identification in previously glaciated areas. In: Proceedings of the First ERS-1 Pilot Project Workshop, Toledo, Spain, 22–24.

EASI PACE, 1997. Help system (online) and user manuals for EASI PACE 6.1 Image Processing Software, PCI, Richmond Hill, Ontario. Canada.

Fisher, P., 1997. The pixel: a snare and a delusion. International Journal of Remote Sensing 18 (3), 679–685.

Fisher, P.F., Pathirana, S., 1990. The evaluation of fuzzy membership of land cover classes in the suburban zone. Remote Sensing of Environment 34, 121–132.

Gath, I., Geva, A., 1989. Unsupervised optimal fuzzy clustering. IEEE Transactions PAMI II (7), 773–789.

Gopal, S., Woodcock, C., 1994. Theory and methods for accuracy assessment of thematic maps using fuzzy sets. Photogrammetric Engineering and Remote Sensing 60, 181–188.

Gray, J.M., Coxon, P., 1991. The Loch Lomond Stadial glaciation in Britain and Ireland. In: Ehlers, J., Gibbard, P.L., Rose, J. (Eds.), Glacial Deposits in Great Britain and Ireland, Balkema, Rotterdam pp. 89–105.

IDRISI, 1997. Help system (online) and users manuals for IDRISI for Windows 2 Image Processing Software, Clark Labs, Worcester, MA.

IGME, 1970. Tsepelovon 1: 50,000 Geology map sheet, IGME, Greece.

Klein, A.G., Isacks, B.L., 1996. Glaciers-tracking change in the Central Andes Mountains. GIS World 9 (10), 48–53.

Leverington, D.W., Duguay, C.R., 1997. A neural network method to determine the presence or absence of permafrost near Mayo, Yukon Territory, Canada. Permafrost and Periglacial Processes 8 (2), 207–217.

Lewin, J., Macklin, M.G., Woodward, J.C., 1991. Late Quaternary fluvial sedimentation in the Voidomatis basin, Epirus, northwest Greece. Quaternary Research 35, 103–115.

Llorens, R.E., Leiva, J.C., 1995. Glaciological studies in the High Central Andes using digital processing of satellite images. Mountain Research and Development 15 (4), 323–330.

Lowe, J.J., Walker, M.J.C., 1994. Reconstructing Quaternary Environments. Longman, London.

Maselli, F., Rodolfi, A., Conese, C., 1996. Fuzzy classification of spatially degraded thematic mapper data for the estimation of sub-pixel components. International Journal of Remote Sensing 17 (3), 537–551.

Punkari, M., 1982. Glacial geomorphology and dynamics in the eastern parts of the Baltic Shield interpreted using Landsat imagery. Photogrammetric Journal of Finland 9, 77–93.

Punkari, M. 1993. Modelling of the dynamics of the Scandinavian ice sheet using remote sensing and GIS methods. In: Aber, J.S. (Ed.), Glaciotectonics and Mapping Glacial Deposits, Proceedings of the INQUA Commission on Formation and Properties of Glacial Deposits, pp. 232–250.

Smith, G.R., Woodward, J.C., Heywood, D.I., Gibbard, P.L., 1998. Mapping glaciated karst terrain in Mediterranean mountain environments using SPOT and TM data. In: Proceedings of the 24th Annual Conference of the Remote Sensing Society, 9–11 September 1999, Greenwich, 457–463.

Wang, F., 1990. Fuzzy supervised classification of remote sensing images. IEEE Transactions on Geoscience and Remote Sensing 28, 194–201.

Woodward, J.C., Lewin, J., Macklin, M.G 1995. Glaciation, river behaviour and Palaeolithic settlement in upland northwest Greece. In: Lewin, J., Macklin, M.G., Woodward, J.C. (Eds.), Mediterranean Quaternary River Environments. A.A. Balkema, Rotterdam, pp. 115–130.