Sub-pixel mapping: A comparison of techniques

Koen C. Mertens, Lieven P.C. Verbeke & Robert R. De Wulf
Laboratory of Forest Management and Spatial Information Techniques, Ghent University, 9000 Gent, Belgium
tel +3292646091 - fax +3292646042
koen.mertens@ugent.be, lieven.verbeke@ugent.be, robert.dewulf@ugent.be

Keywords: sub-pixel mapping, soft classification, accuracy assessment, comparison, algorithms

ABSTRACT: Remotely sensed images often contain a combination of both pure and mixed pixels. Hard classification techniques assign mixed pixels to the class with the highest proportion of coverage or probability. Loss of information is inevitable during this process. Soft classification techniques were introduced to correct for this loss: they assign pixel fractions to the land cover classes corresponding to the represented area inside a pixel. The assignment of fractions to the different classes however, renders no information about the location of these fractions inside the pixel. Atkinson (1997) stated that it is possible to assign the fractions spatially to so called 'sub-pixels'. Every pixel is thus divided into a predefined number of sub-pixels, allowing a more spatially detailed representation of the lower resolution pixels. Sub-pixel mapping algorithms have been applied in a variety of forms and on fraction images of varying spatial resolutions, but all algorithms share one common property: accuracy assessment of sub-pixel mapping algorithms is impossible because of missing high resolution ground truth imagery. Therefore, high resolution reference classifications are degraded to yield artificial fraction images. When these artificial fraction images are used as input to the sub-pixel mapping process, the original reference image can serve as ground truth. This way, accuracy assessment of sub-pixel mapping algorithms is facilitated. The aim of this work is to use identical reference images for different sub-pixel mapping techniques, allowing for comparison of the performance of different techniques.

1 INTRODUCTION

Remotely sensed images display a combination of pure and mixed pixels. Crisp or hard classification assigns the mixed pixels to the dominant classes. Soft classification results in fraction images describing the proportions of membership for a pixel to each class. Hence a pixel can belong to different classes. A soft classification has the advantage of containing more information when compared to a hard classification. A crisp classification however is easier to display and interpret for the users. Therefore soft classifications are sometimes transformed into hard classifications. This process is called hardening and disposes of useful information. Sub-pixel mapping attempts to overcome this problem, representing high information content in an easily interpretable manner.

Atkinson (1997) stated that it is possible to assign the fractions spatially to so called sub-pixels. Sub-pixels are a finer resolution representation of a parent pixel. The information from a soft classification is dispersed into the subdivided pixels. A pixel is separated into several pure sub-pixels. The amount of sub-pixels belonging to each class corresponds to the fractions provided by the soft classification. A sub-pixel mapping drawback is the introduction of uncertainty as there is no information about the spatial location of the sub-pixels. This is compensated by the assumption of spatial dependence. An overview of the sub-pixel mapping process is shown in Figure 1. A

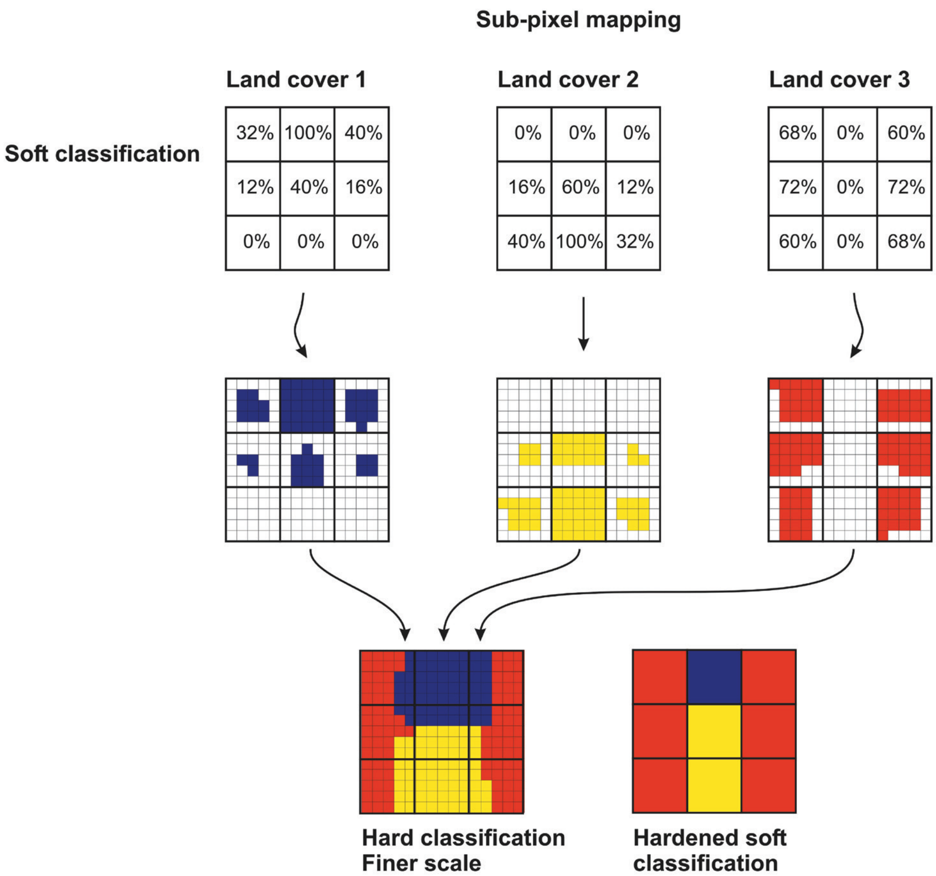

Figure 1. An overview of the sub-pixel mapping process. The amount of sub-pixels is calculated for each class, before they are spatially allocated.

variety of techniques have been proposed e.g. by Schneider (1993); Gavin and Jennison (1997); Gross and Schott (1998); Foody (1998); Aplin and Atkinson (2001); Tatem et al. (2001, 2002); Verhoeye and De Wulf (2002) and Pinilla and Ariza (2002). The techniques that will be applied in this paper are described in Mertens *et al.* (2003, 2004a and 2004b).

2 MATERIALS AND METHODS

2.1 *Synthetic imagery*

Sub-pixel mapping algorithms have been applied in a variety of forms and on fraction images of varying spatial resolutions, but all algorithms share one common property: accuracy assessment of sub-pixel mapping algorithms is impossible because of missing high resolution ground truth imagery. If this was present, there would be no need for sub-pixel mapping algorithms. High resolution reference classifications are therefore degraded to yield artificial fraction images. The degradation process consists of splitting up the hard classification into binary images (0 or 1 for membership or not) for each class, and applying an averaging filter. The degradation process is illustrated in Figure 2. When these artificial fraction images are used as input to the sub-pixel mapping process, the original reference image can serve as ground truth, facilitating accuracy assessment of sub-pixel mapping algorithms. This approach excludes errors due to coregistration and poor soft classification, focusing solely on errors introduced by the sub-pixel mapping process. Reference source imagery can either be real or artificial.

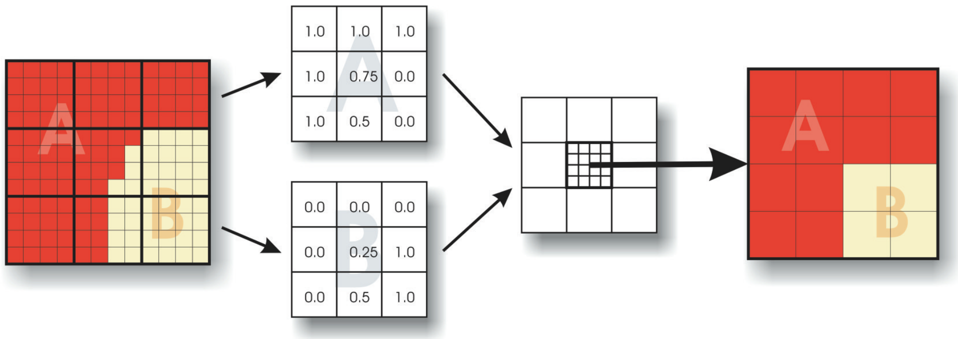

Figure 2. Degradation of a reference image with classes A and B to fraction images before sub-pixel mapping of the centre pixel.

2.2 *Sub-pixel mapping accuracy*

Comparison of sub-pixel mapping techniques is only possible when the means to evaluate the performance of the different algorithms are available. Different criteria can be proposed, depending on the intended use, e.g. evaluation of the sub-pixel mapping result, performance speed, user-friendliness, among many others. Evaluation of the sub-pixel mapping result can also be performed using a variety of criteria. Foody (2002) focused on positional accuracy for the refinement of estimates of ground control point location. The opinion of Tatem *et al.* (2002) was that recreating the spatial pattern of land cover can be more important than attempting accurate mapping. In this paper priority is given to the thematic accuracy of the sub-pixel mapping result. Although there is no predefined standard yet for assessing the accuracy of sub-pixel mapping, generally accepted classification accuracy indices like the Kappa coefficient (Cohen, 1960) and the overall accuracy in terms of percent correctly classified (PCC) are often used to evaluate the accuracy of the algorithm's result. Many other measures are often used to assess classification accuracy. The most conventional classification accuracy indices are:

- Error matrix (user and producer accuracies)
- PCC (percent correctly classified)
- Kappa
- Tau
- AEP (area error proportion)
- GT-index
- Closeness
- RMSE (root mean squared error)
- Correlation coefficient
- Visual interpretation

It is assumed that using any other thematic classification accuracy index will lead to similar results as the ones obtained by using the more popular methods. Instead of trying to develop a novel sub-pixel mapping technique, the aim of this work is to use the same reference images for different sub-pixel mapping techniques, allowing comparison of the performance of the different techniques. Developing a database of standard images, the authors wish to assess the qualities of sub-pixel mapping techniques regarding the following characteristics:

- Reconstruction of pattern, texture
- Conservation of fractions
- Conservation of linear features
- Conservation of curvature
- Isotropy/Anisotropy
- Noise dependency
- Border effects

- Scale factor independence
- Ability to handle real data
- Ability to deal with multiple classes
- Computation time

A database was constructed containing 6 sets of fraction images of 36×36 pixels. All images were artificially constructed except for one real classification of the Logone inundation plain in the north of Cameroun. Fraction images were obtained after degradation of a 5184×5184 reference image. The reason for starting the degradation from such a large image, was the amount of different possible values in the fraction images, e.g. degradation with scale factor 2 only yields 5 potential fraction values in an image: 0, 0.25, 0.5, 0.75 and 1. The real classification differs from other images the size of the source reference image (2592×2592) and the number of classes (3 instead of 2). Each set of images contained 5 crisp images at intermediate resolutions, forming the reference imagery for the sub-pixel mapping with different scale factors: S = 2, 3, 4, 8 and 16. The 6 source reference images are shown in Figure 3.

3 RESULTS AND DISCUSSION

The resulting sub-pixel mapping images, the reference image and the hardened soft classification are shown in Figures 4 and 5 for the concentric circles and the real image with scale factor 4. Table 1 shows the percentage correctly classified and Kappa for the sub-pixel mapping results and the hardened soft classification. Visual assessment of Figure 4 suggests the wavelet and neural network technique to outperform the other two, especially towards the centre of the image. All sub-pixel mapping techniques seem to better approximate the reference image than the hardened soft classification. These statements are confirmed by the numbers in Table 1 except for the results of the wavelet technique compared to the other techniques. Although its result is visually more appealing, its numerical accuracy is lower. The same counts for all the sub-pixel mapping results in Figure 5 that appear more favourable than the hardened soft classification, although their accuracy is lower. Again, the wavelet technique forms an exception, providing visual and numerical improvement over the hard classification. This proves that visual assessment may lead to other conclusions than the numerical analysis.

4 CONCLUSIONS AND FUTURE RESEARCH

Sub-pixel mapping is a useful technique combining both advantages from hard and soft classifications. Yet this coincides with the introduction of uncertainty. Accuracy assessment of sub-pixel mapping algorithms is very difficult and is often related to the intended use. Thematic accuracy of the resulting map appears to be the most obvious choice to assess the performance of the sub-pixel mapping result. Visual assessment of the results may lead to different conclusions than those drawn from the numerical analysis.

ACKNOWLEDGEMENTS

The Belgian Science Policy is gratefully acknowledged for funding this work (project SR02). Thanks are due to Jan Verhoeye and our colleagues for their support.

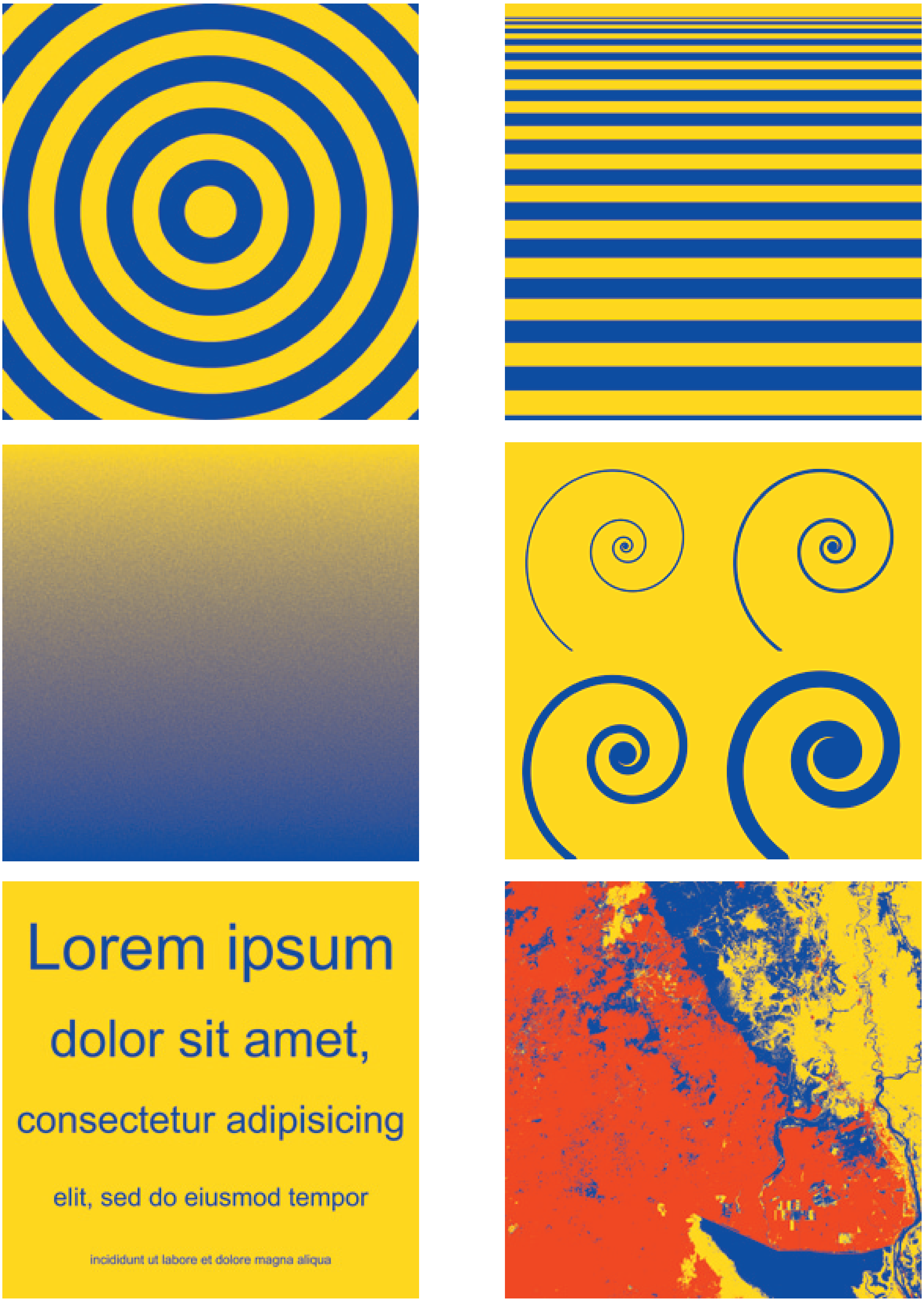

Figure 3. The source reference images in the database.

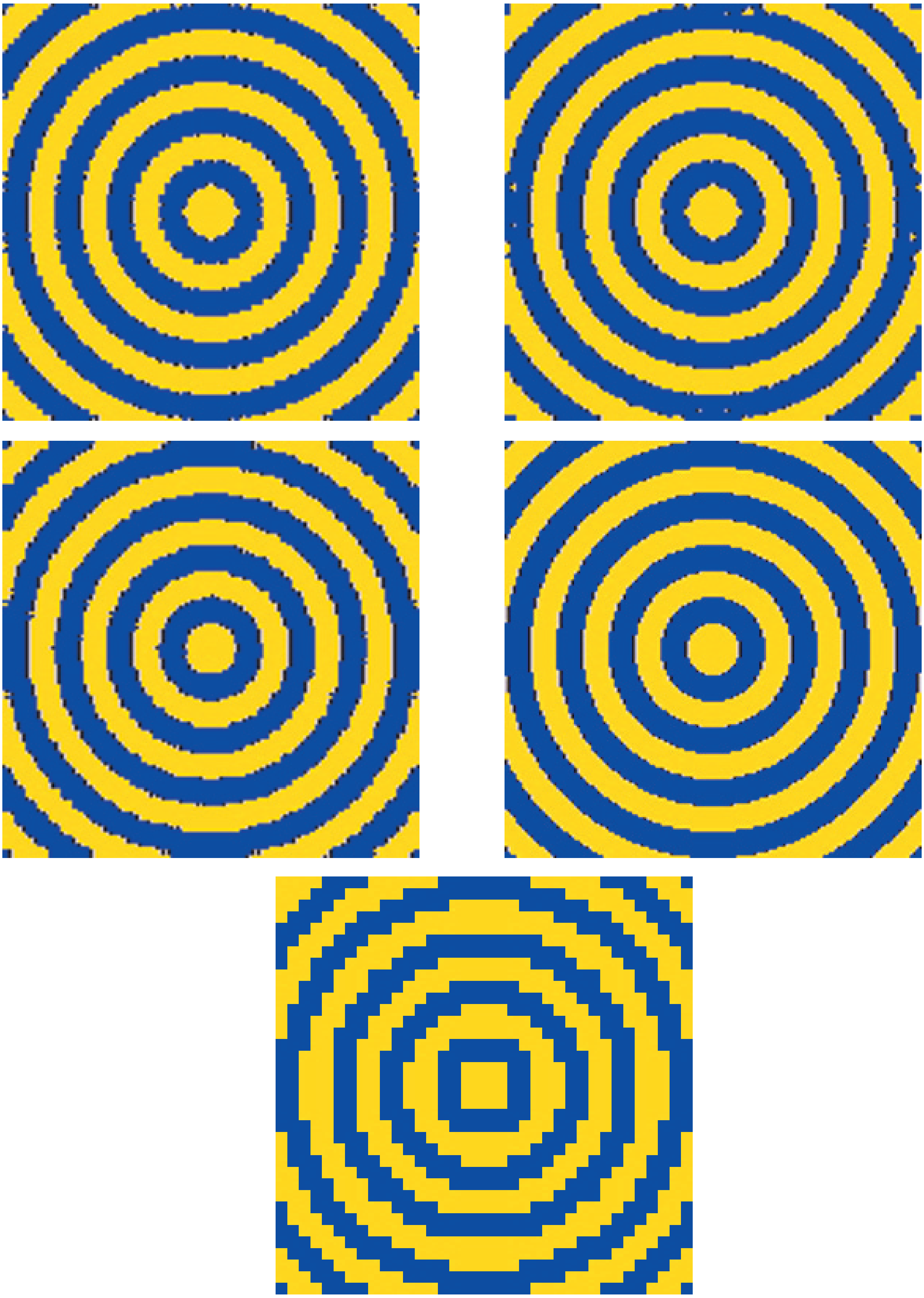

Figure 4. Sub-pixel mapping results of the concentric circles with the different techniques: (a) attraction (b) genetic algorithms (c) wavelets (d) the reference image and (e) the hardened soft classification.

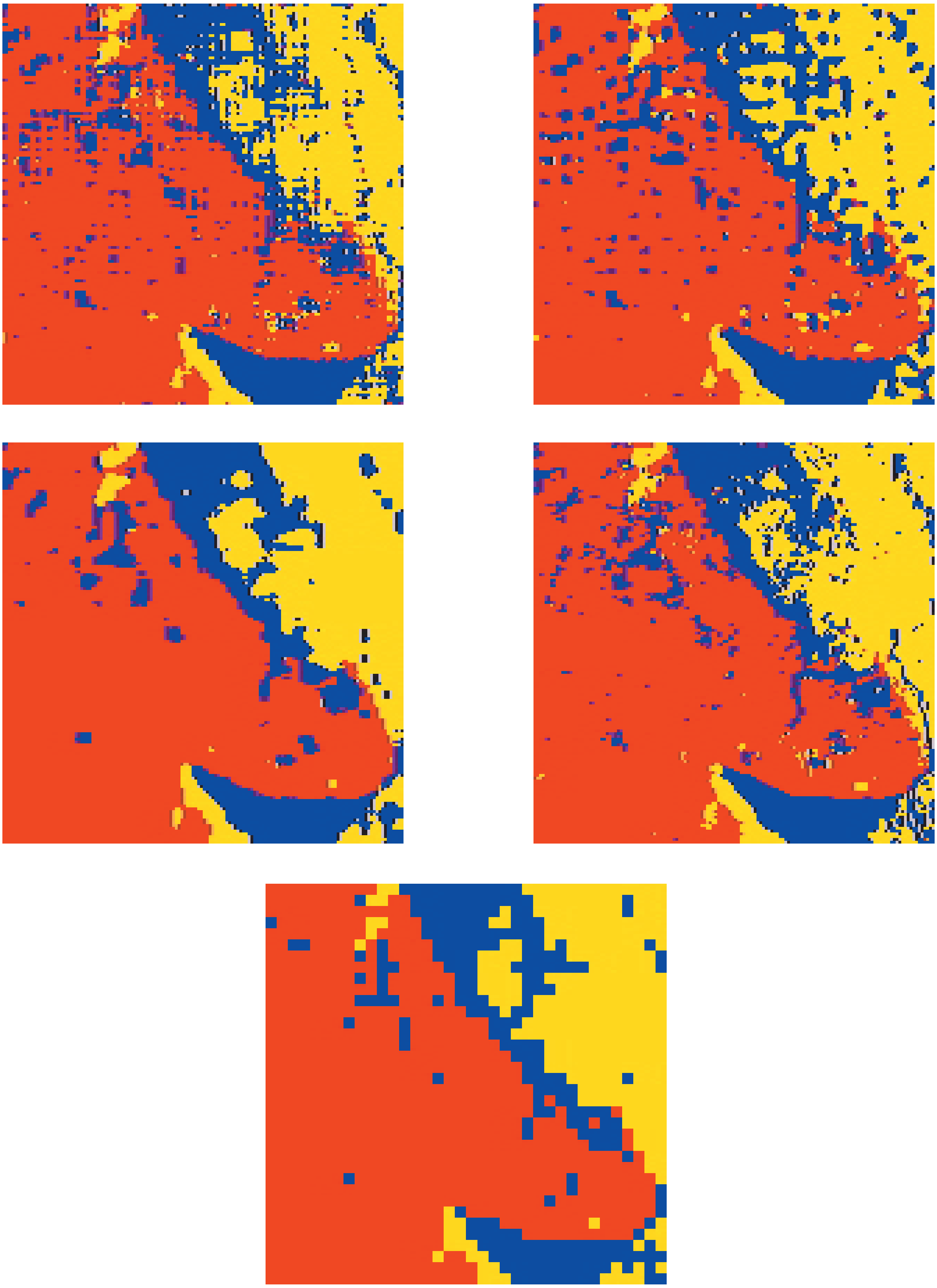

Figure 5. Sub-pixel mapping results of the real classification with the different techniques: (a) attraction (b) genetic algorithms (c) wavelets (d) the reference image and (e) the hardened soft classification.

Table 1. PCC and kappa for the sub-pixel mapping results compared to the hardened soft classification.

Accuracy assessment	Concentric circles			Real image		
	GA	attraction	wave	GA	attraction	wave
PCC	0.98	0.98	0.97	0.86	0.87	0.91
Kappa	0.97	0.95	0.93	0.76	0.78	0.85
PCC hard	0.89	0.89	0.89	0.90	0.90	0.90
Kappa hard	0.79	0.79	0.79	0.82	0.82	0.82

REFERENCES

Aplin, P. & Atkinson, P. M. 2001, Sub-pixel land cover mapping for per-field classification. *International Journal of Remote Sensing* 22 2853–2858.

Atkinson, P. M. 1997, Innovations in GIS 4 chap. 12 (Taylor & Francis, London, U.K.), pp. 166–180.

Cohen, J. 1960, A coefficient of agreement for nominal scales. *Educational and Psychological Measurement* 20 37–46.

Foody, G. M. 1998, Sharpening fuzzy classification output to refine the representation of sub-pixel land cover distribution. *International Journal of Remote Sensing* 19 2593–2599.

Foody, G. M. 2002, The role of soft classification techniques in the refinement of estimates of ground control point location. *Photogrammetric Engineering and Remote Sensing* 68(9) pp. 897–903.

Gavin, J. & Jennison, C. 1997, A subpixel image restoration algorithm. *Journal of Computational and Graphical Statistics* 6 182–201.

Gross, H. N. & Schott, J. R. 1998, Application of spectral mixture analysis and image fusion techniques for image sharpening. *Remote Sensing of Environment* 63 85–94.

Mertens, K. C., Verbeke, L. P. C., Ducheyne, E. I. & De Wulf, R. R. 2003, Using genetic algorithms in sub-pixel mapping. *International Journal of Remote Sensing* 24 4241–4247.

Mertens, K. C., Verbeke, L. P. C., De Baets, B. & De Wulf, R. R. 2004a, Direct Sub-pixel Mapping Exploiting Spatial Dependence. *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium*, IGARSS 2004, September 20-24, Alaska, USA, pp. 3016–3049.

Mertens, K. C., Verbeke, L. P. C., Westra, T. & De Wulf, R. R. 2004b, Sub-pixel mapping and sharpening using neural network predicted wavelet coefficients. *Remote Sensing of Environment* 91 225–236.

Pinilla, C. R. & Ariza, F. J. L. 2002, Restoring SPOT images using PSF-derived deconvolution filters. *International Journal of Remote Sensing* 23 2379–2391.

Schneider, W. 1993, Land use mapping with subpixel accuracy from Landsat TM image data. In *Proceedings of 25th International Symposium, Remote Sensing and Global Environmental Change*, vol. II (Environmental Research Institute of Michigan (ERIM), Graz, Austria), pp. 155–161.

Tatem, A. J., Lewis, H. G., Atkinson, P. M. & Nixon, M. S. 2001, Super-resolution mapping of urban scenes from IKONOS imagery using a Hopfield neural network. *In Proceedings of the International Geoscience and Remote Sensing Symposium* (IEEE, Sydney, Australia) pp. 3200–3202.

Tatem, A. J., Lewis, H. G., Atkinson, P. M. & Nixon, M. S. 2002, Super-resolution land cover pattern prediction using a Hopfield neural network. *Remote Sensing of Environment* 79 1–14.

Verhoeye, J. & De Wulf, R. 2002, Land cover mapping at sub-pixel scales using linear optimization techniques. *Remote Sensing of Environment* 79 96–104.