Mapping land use in NE Scotland with neural networks from remote sensing imagery

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Abstract:

Landsat TM imagery can be used to classify different land cover types based on reflectance characteristics in seven wavelength bands. Various methods, including NDVI and other simple mathematical transformations, can be used to show strong variations in band reflectance ratios from different surfaces. However, a neural network trained with the backpropagation method should be able to improve on these simple mathematical calculations by developing complex functions which allow recognition of different land cover or land use types. Landsat imagery of Aberdeen and the surrounding area is used to develop a land use map highlighting areas of residential, commercial and industrial land use, along with various natural and semi-natural land cover classes. Appropriate selection of training sites and categorisation of land cover classes are two aspects highlighted as important to the successful development of a neural network land use mapping system.

Keywords

Land cover; remote sensing; neural networks; North-East Scotland; Landsat TM

Introduction

Much research has been carried out into the automation of land cover mapping from remotely sensed information. Various methods exist of distinguishing land cover type in imagery, ranging from simple image analysis measurements to more sophisticated structural definitions. In many cases it is not known what a particular land cover type looks like, and it is often difficult with multispectral information to determine the importance of one band's reflectance over another. A method which automatically determines what each particular land cover type looks like, and can apply this information to a large image rapidly and accurately, is obviously useful.

One method which show great potential in this area is that of neural networks. Neural networks can take image information in many forms. For example, Aria *et al.* (2003) used backpropagation neural networks to identify land cover type, while Dutra *et al.* (1998) used texture as an input for neural network (NN) identification of land cover classes from remote sensing data on Amazonia. Nepomuceno *et al.* (2003) applied neural networks to filtered radar data in an attempt to assess land cover in Amazonia.

Neural networks also work well when applied in parallel with other techniques, or as a first step in image classification. Katartzis *et al.* (2004) developed a method of detecting limits of minefields using a suite of image analysis techniques, including neural networks. Schwaiger *et al.* (1996) adopted an evolutionary approach to land cover classification with neural networks, optimising their network's topology and dynamics to provide the best performance, while Swinnen *et al.* (2001) succeeded in using NNs for measuring sub-pixel proportions of land cover types in imagery from SPOT-VEGETATION. Here, a relatively simple neural network technique is applied with constraints to provide a land cover map for the Aberdeen area that may be of interest to urban planners, rural development agencies and other organisations.

Methods and Results

The imagery from which the map was derived is a Landsat TM image of Scotland taken on 26th June 1995, with seven reflectance bands at wavelengths 0.45-0.52, 0.52-0.60, 0.63-0.69, 0.76-0.90, 1.55-1.75, 10.40-12.50 and 2.08-2.35 microns. Ground resolution on the image is 25m pixels, except for band 6 which has a resolution of approximately 120m. Top left co-ordinates are 368000, 815000 and bottom right co-ordinates are 397975, 785025. The image size is 1200x1200 pixels, or 900 square kilometres.

The neural network used is trained using the backpropagation method, a commonly used error-minimisation technique. The network topology is 14:15:15:N, where N is the number of output nodes (the number of land cover categories used), and the network is trained for 50000 training steps. Each network is fully connected to the one following it. For a detailed description of the backpropagation neural network training method, see Aitkenhead *et al.* (2003).

Training data for the neural network was obtained by examining the Ordnance Survey 1:50000 map of the Aberdeen area and identifying locations where the land cover was known. This required a degree of local knowledge, with 80 training pixels being identified for each land cover type (5 locations, each 4x4 pixels). For each training pixel, the seven Landsat band reflectance values were used (0-255), with the values normalised on a range [0,1]. There was also the problem of identifying a colour scheme for the map that allowed visual examination and interpretation of the image. This was solved using a trial and error process.

An additional seven values were derived for each pixel, these being the proportional reflectance of each band, relative to the summed reflectance over all bands for that pixel. These values were obtained due to a concern that variations in shading over the image could cause different reflectance values for two areas with identical land cover type, when the relative albedo for each band was the same between the two areas.

The land cover categories originally designated included the following:

1. Low-density residential
2. High-density residential
3. Commercial
4. Low-density industrial
5. High-density industrial
6. Urban greenspace
7. Arable
8. Forest
9. Water
10. Natural

This was the classification used in Figure 1, from which close examination and comparison to maps revealed that (a) in general, good classification was achieved over broad areas of the region covered (b) several small areas were obviously misclassified, for example in the categorisation of large areas of forest and natural land as having dense urban land cover, or where the beaches have been categorised as high-density industry.

Two reasons were identified for this misclassification tendency:
1. Poor selection of training areas, resulting in misclassification of pixels.
2. Poor selection of land cover categories, resulting in correct classification of areas from the point of view of the network, but not from that of the user.

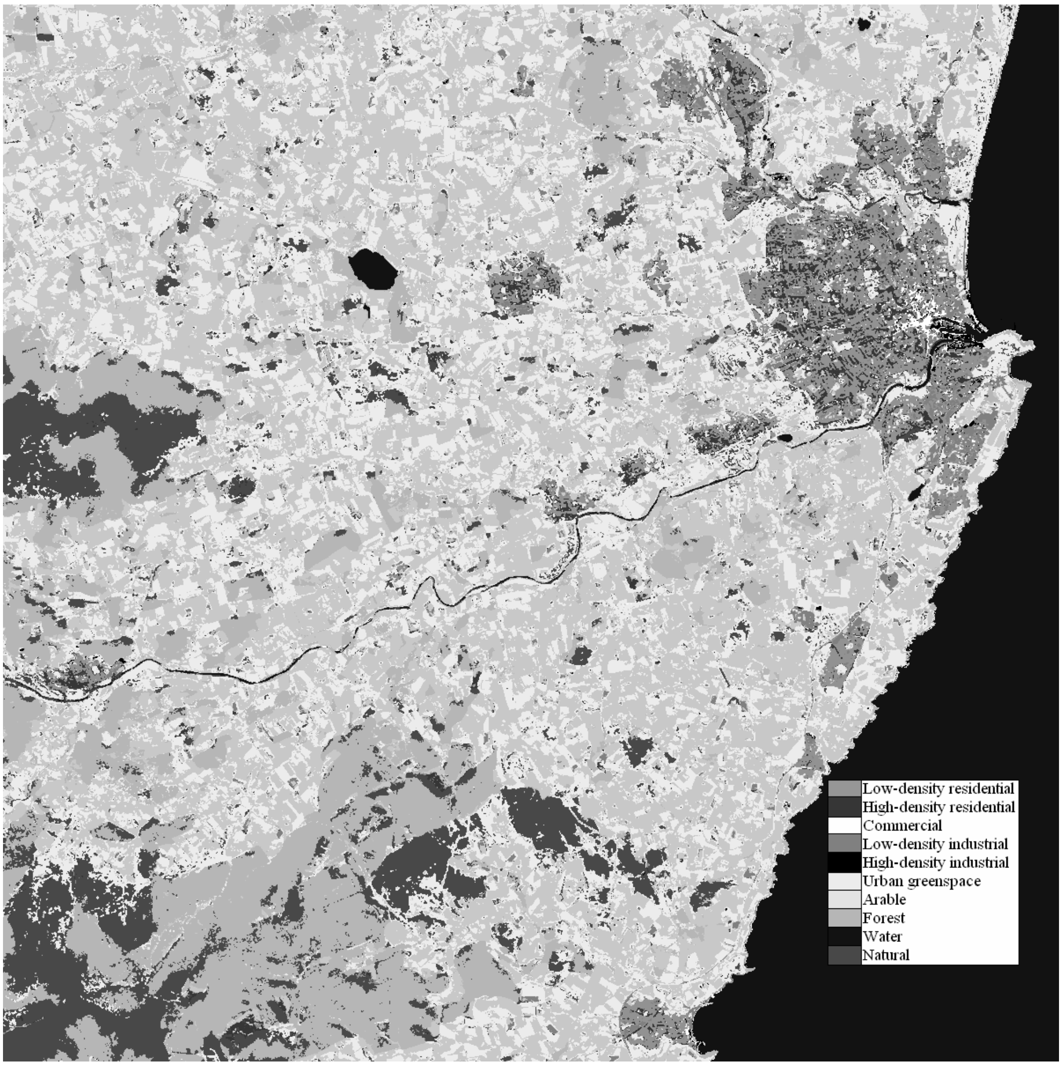

Figure 1. Initial map developed of land cover categories in Aberdeen area

The training sites and land cover categories were reviewed and redefined, with the following land cover definitions being used to generate Figure 2, using new training data:

1. Low-density residential
2. High-density residential
3. Commercial
4. Low-density industrial
5. High-density industrial
6. Grass
7. Crops
8. Forest
9. Water
10. Natural
11. Bare ground

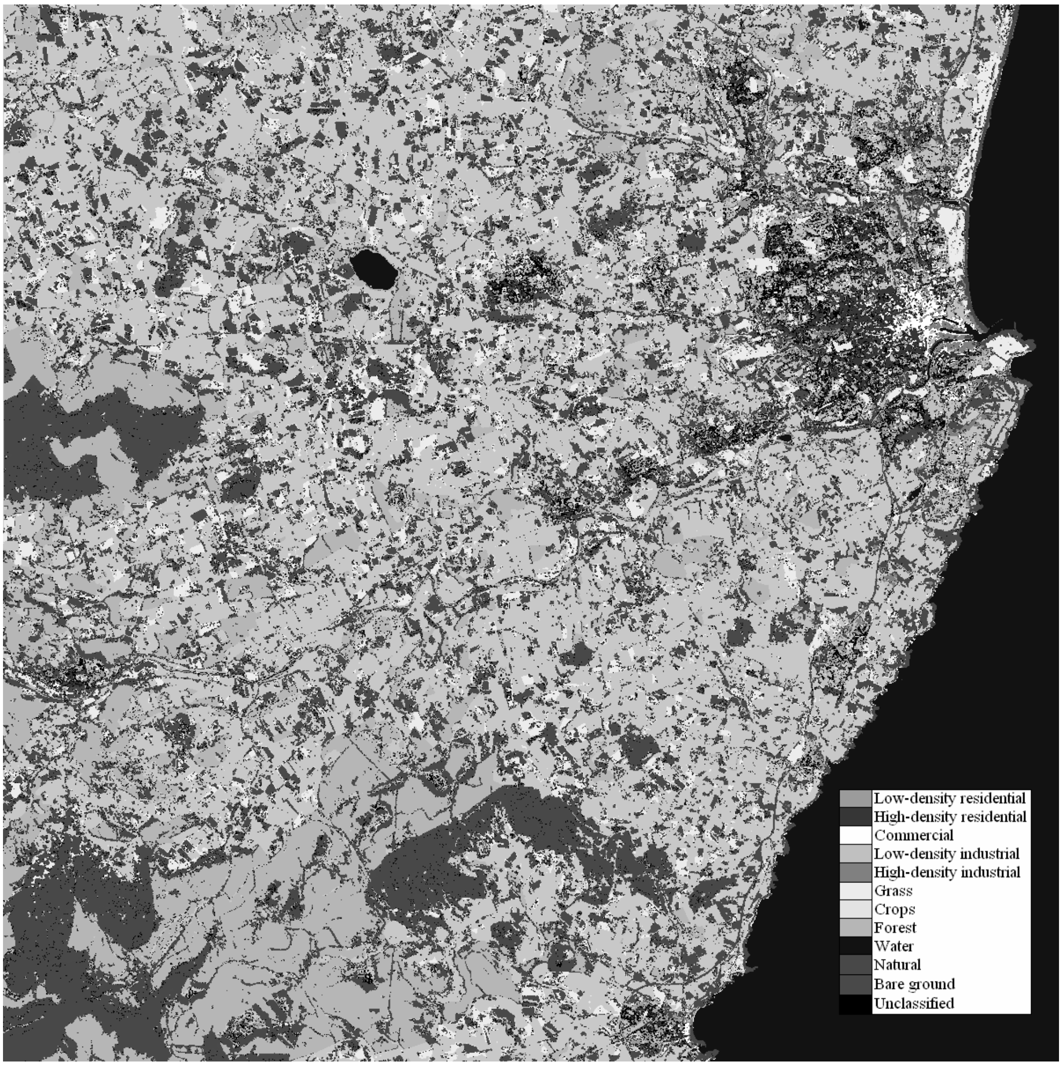

Figure 2. Improved map of land cover categories in Aberdeen area

There are two main differences in the land cover classifications used between Figure 1 and Figure 2. The first was due to a recognition that certain areas of arable land are under grass, which appears similar to urban greenspace. This necessitated a redefinition of arable as crops and grass, with urban greenspace being included in the grass category. The second difference was the inclusion of bare ground, to allow separate classification of sand and bare ploughed fields.

Another difference in Figure 2 is that there are large areas of unclassified ground. This was due to a decision to accept only those pixel classifications by the network in which one category had been a clear and obvious winner, through having an activation value of at least 0.2 more than the second most activated candidate node. This demonstrates that it would be a mistake to adopt a simple winner-takes-all strategy for land cover classification, without realising that because there is a certain proportion of pixels on the image that have reflectance values similar to more than one land cover category.

In Figure 3, these 'problem' pixels have been removed using a comparison with neighbouring pixels. To classify a problem pixel, the most activated candidate was accepted as long as there was another pixel neighbouring this one that was already classified as the same land cover type. In this way, all but 8622 of 73491 problem pixels were eliminated.

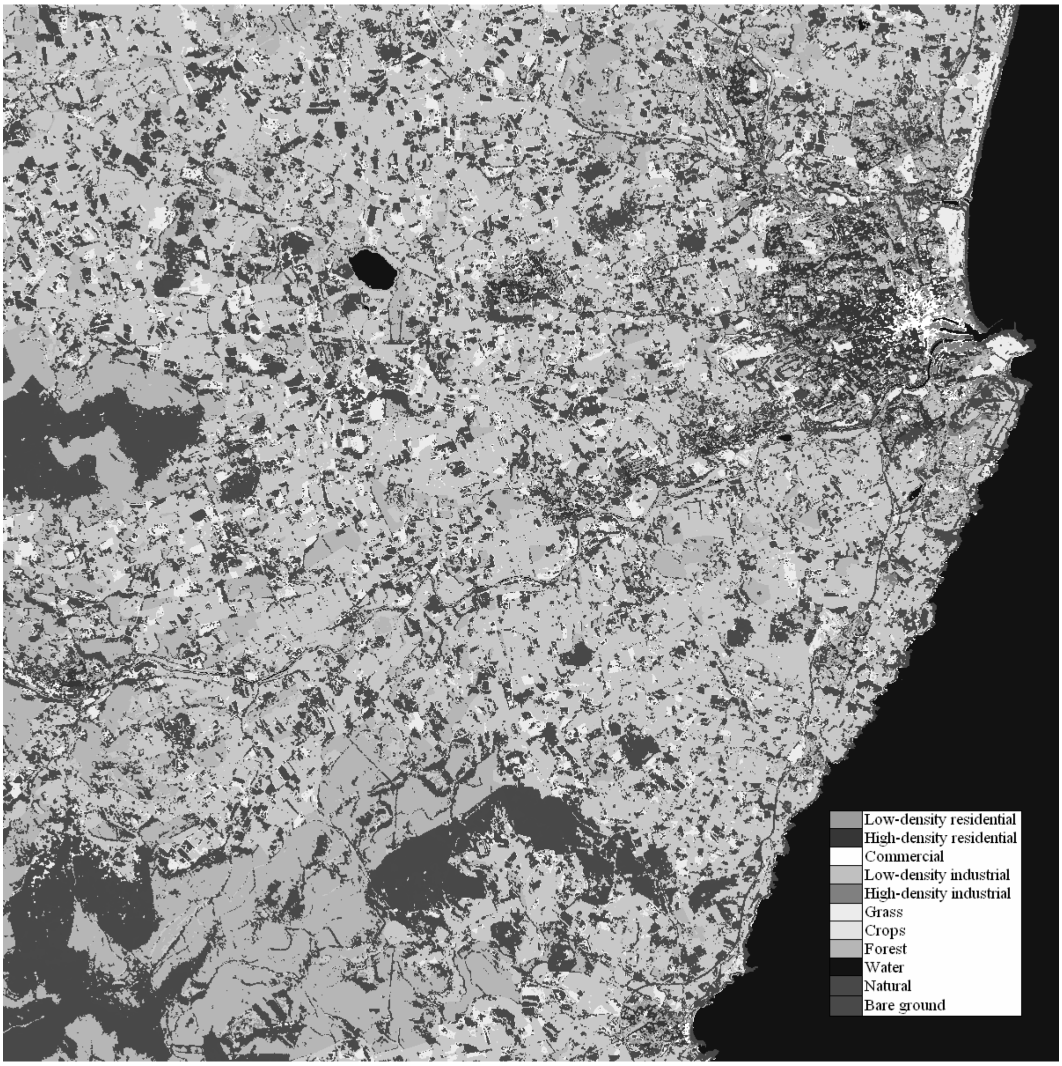

Figure 3. Improved land cover map with problem pixels eliminated

Examination of Figure 3 showed that good classification appeared to have been achieved, except for the separation of low-density and high-density urban land cover classes. As can be seen from Figure 2, a large proportion of the pixels classified as high-density urban land cover were originally problem pixels, meaning that their classification had not been certain in the first place. The network was therefore retrained with a different topology of 14:30:30:11, for a total of 500000 training steps rather than the 50000 originally used, and with a slower and more accurate error minimisation rate. This more comprehensive training resulted in the much more satisfying Figure 4, in which only 46782 problem pixels were encountered.

Map validation was necessary to get an idea of just how good the map really was. In order to do this, the map was sampled randomly to provide 20 pixels for each of the land cover types, or a total of 220 points. Determination of the land cover type (according to the categories used here) was then made using a combination of maps, local knowledge and field excursions. Table 1 shows the accuracy of the network for each of the land cover types predicted.

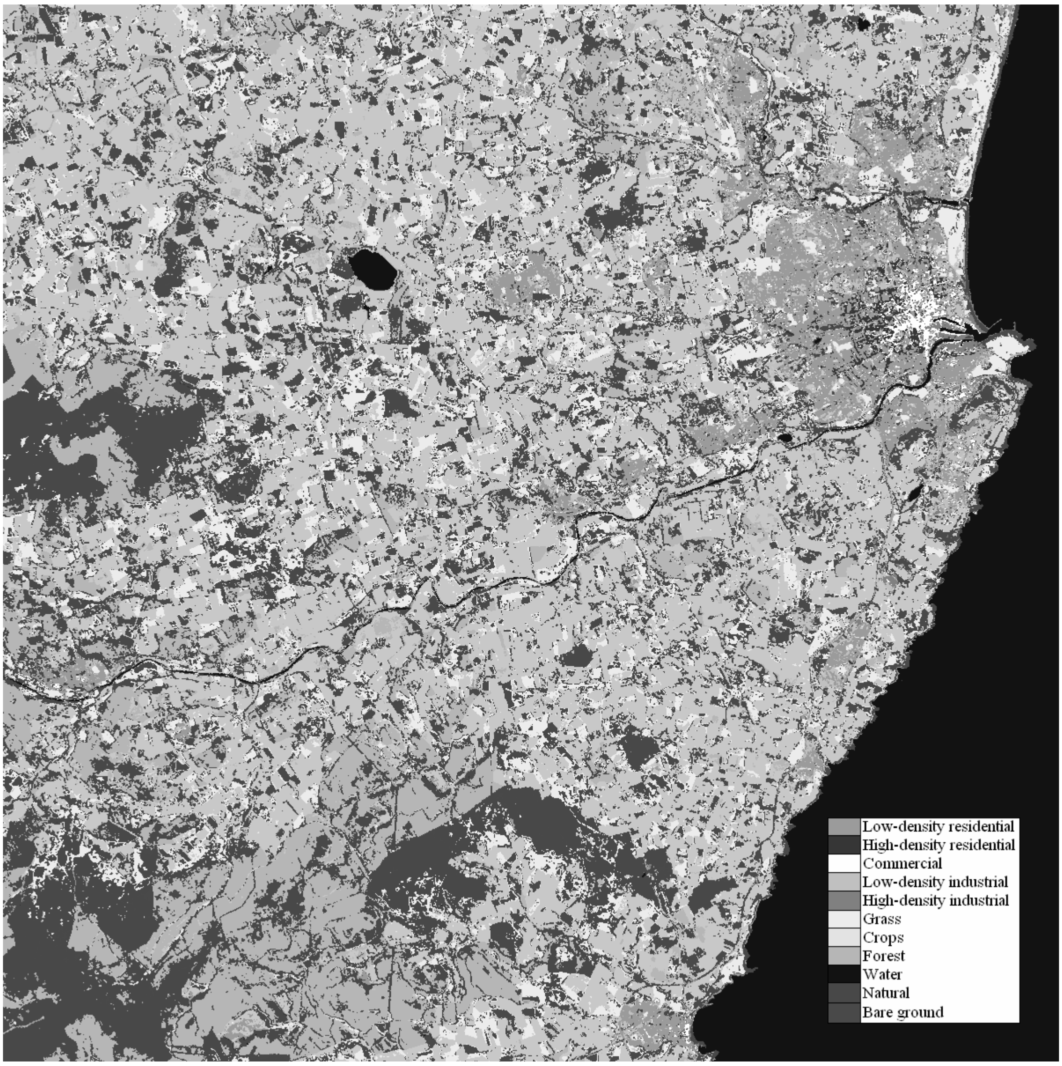

Figure 4. Final land cover map of Aberdeen obtained using neural network

Table 1. Accuracy of predictions for land cover map

Land cover type	Accuracy (%)	Mistaken for
Low-density residential	75	High-density residential
High-density residential	75	Low-density residential, commercial, low-density industrial
Commercial	60	High-density residential, low-density industrial
Low-density industrial	80	Commercial, high-density industrial
High-density industrial	70	Low-density industrial
Grass	85	Low-density residential, natural
Crops	95	Grass
Forest	100	n/a
Water	100	n/a
Natural	90	Grass
Bare ground	90	Natural

The images as they are presented here, in greyscale, are not as easy to interpret as the originals, which are in colour. The original images can be obtained from the contact author at the email address given.

Discussion

The use of neural networks in classifying land cover from remote sensing imagery, while not a novel concept, definitely has scope for improvement as shown here. Requirements for a successful system include (a) optimal selection of training data, and (b) determination of land cover classes that can be distinguished using the pixel reflectance values. An additional consideration is the level of faith placed in the trained network, in other words how great a distinction has to be made by the network between the winning land cover candidate and that in second place, before the user is satisfied that the network has made a correct identification. An example used here in which relatively large certainty was required of the network still managed to result in a high proportion of the image being classified, but this was after a adjustment of the initial training data set and land cover 'legend'. In short, neural networks should not be trusted too implicitly to give good land cover maps without a certain level of expertise having gone into the determination of what they are looking for on the ground. Having said that, the land cover map eventually obtained here once the method had been refined had a high level of accuracy with the subjective land cover classes used.

Improvement of the basic neural network method would require the addition of an extra technique, as it is felt that NNs by themselves cannot improve much beyond what is available here. Civco *et al.* (2002) carried out a comparison of several methods of land cover and land cover change detection, and concluded that no single method can be used to solve all of the problems involved, while Tadesse *et al.* (2003) showed that an object-recognition approach often worked better than a pixel-by-pixel approach for land cover class recognition. Structural measurements carried out in parallel to analysis of reflectance information may prove useful for identifying problem pixels which resist more simple forms of identification. Moriyama *et al.* (2004) discussed a method of estimating terrain, or land cover, from Synthetic Aperture Radar (SAR). The scattering effects of SAR from different surfaces would prove useful in determining land cover type, as an adjunct to visual and infrared reflectance. Shah and Gandhi (2004) discuss the use of textural information in improving accuracy of neural network mapping methods. Textural descriptions contain information about the structure of the location being examined, and can assist methods that use simple greyscale as input.

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