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Multi-temporal spectral unmixing to characterise urban change in the Greater Dublin area

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ABSTRACT: Urban growth models are useful tools to assess the impact of alternative public policy scenarios. The calibration of such models requires historical land-use data, which is not always available at frequent time intervals. In this research, information on spatio-temporal change of land-cover gradients is extracted from two multidate Landsat images by linear spectral unmixing. For this purpose, the two images were subjected to a relative radiometrical calibration in order to reduce the impact of sensor drift and differences in illumination and atmospheric conditions. The resulting gradient information can be used to derive spatial metrics, which in turn characterise urban form and morphology and may serve as a proxy to land-use data. Because the sub-pixel proportions do not contain implicit information as to whether a particular pixel belongs to the urban fabric, an urban mask was required to make that distinction. This mask was created by first applying an unsupervised classification based on Kohonen self-organising maps, and subsequently enhanced by applying ad-hoc knowledge-based post-classification rules. The results of this study demonstrate that sub-pixel change maps are useful to identify urban growth patterns. In combination with the urban mask and unsupervised classification, sub-pixel gradients will be used in future research to investigate if they provide useful information on urban structure, and can maybe even be used to infer certain types of land use.

1 INTRODUCTION

The world is urbanising at an increasing pace. Today, more than half of the earth's population lives in cities and the number of urban residents is expected to increase to over 5 billion by 2030 (UN-HABITAT 2006). Despite the many advantages city life offers, uncontrolled urban growth affects both the human and natural environment and calls for effective urban management strategies.
Developing such strategies and monitoring policy effects requires reliable and sufficiently detailed information on the urban environment and its dynamics, including an understanding of urban change processes. For this purpose, analysing changes in urban land use is of great consequence and is facilitated by computer-based models that predict urban development patterns and determine the future impacts of public policy choices. Current and historical land-use maps are required for calibrating urban growth models and given the large effort it takes to create such maps, they are often not available at short intervals. In the European MOLAND project, for instance, urban land use is mapped for four periods: the early 1950s, the late 1960s, the 1980s and the late 1990s (MOLAND 2008). Data from earth observation satellites may provide intermittent information on urban development and could in that way improve the calibration of MOLAND'S growth model. Land use is, however, tied to socio-economic activities. It can therefore not be directly inferred from spectral information as opposed to land cover, which refers to the physical properties of the earth's surface. Previous studies have nevertheless demonstrated a relationship between the spatial struc-

ture of the built-up environment and its functional characteristics (Barr & Barnsley 1997). A rather novel approach in this research area is to describe urban form and structure by means of spatial metrics. Spatial metrics describe various properties of the spatial heterogeneity and configuration of land cover in a given area. They have recently shown considerable potential for structural analysis of urban environments (Herold et al. 2005). Spatial metrics derived from satellite imagery might therefore be the key to complement existing land-use maps and improve the calibration and validation of urban growth models.

Despite the currently available high resolution satellite images, which provide increasingly detailed information about urban surface materials, most of the available historic archive imagery consists of medium resolution data such as from the Landsat or SPOT programmes. Notwithstanding the advantages of medium resolution data in terms of cost, the extensive historic archives and large mapping extents, their relatively low spatial resolution may lead to low mapping accuracies because the sensor's instantaneous field of view (IFOV) often contains different types of land cover, especially in urban areas. Traditional classification algorithms that derive land-cover maps from digital images assign pixels individually to a single class, and will run into difficulties when dealing with such mixed pixels. Spectral mixture analysis addresses this problem by unmixing (deconvolving) each pixel spectrum into fractional abundances of its surface constituents or endmember spectra (van der Meer 1999). It might therefore be a useful technique to extract gradient-based spatial metrics to characterise urban structure and urban change.

In this research, we extracted urban gradient information for the city of Dublin by producing sub-pixel proportions with linear spectral mixture analysis for two dates. Because of the spectral confusion between urban and some none-urban surface types such as bare soil in rural areas, we developed an urban mask to constrain the unmixing to the urban fabric. This mask was created with an unsupervised classifier based on Kohonen self-organising maps (Kohonen 2001) and enhanced with knowledge-based post-classification rules. The produced sub-pixel proportions for each date will be used in the MAMUD project (http://www.mamud.be) together with the unsupervised classification in order to infer information on urban structure and context and, ideally, on land use.

2 STUDY AREA

The city of Dublin was chosen as study area for this research. Dublin is the political, social, economical and cultural capital of Ireland, and is home to over 40% of the country's population. As Ireland's most prominent urban centre, the significant demographic and economic changes that have been taking place in the country since the mid 1980's are especially apparent in the city (Kitchen 2002). Dublin experienced rapid urban expansion in the 1980's and 1990's, fuelled by the building of new roads that drove residential and commercial development rapidly outward into the urban fringe. While the Greater Dublin area as a whole experienced only a moderate population growth of 3.6% between 1986 and 1996, population in the urban periphery increased more rapidly with as much as 9.6% in South Dublin and 21.1% in Fingal, to the north. This has resulted in a hollowing of the central city and a simultaneous growth and movement into Dublin's low density, car-oriented and seemingly unplanned periphery (Bannon 1999).

3 DATA AND PREPROCESSING

Two Landsat image datasets (path 206, row 23) were used to extract sub-pixel gradient information for Dublin: a TM image of 13th June 1988 and an ETM+ image of 24th May 2001. While the 1988 image was nearly cloud free, the 2001 image was partly covered by clouds to the east, mainly above the sea. A cloud mask was used to minimise the impact on the formation of spectral clusters by the unsupervised classification algorithm. The images were geometrically co-registered to the Irish Grid projection system by a first-order polynomial transformation. The RMS error on an independent set of control points was 27.61 m for the 1988 image and 27.62m for the 2001 image, which implies that on the average the geometric shift is less than a 30m Landsat pixel. The raw digital numbers of both images were converted to exoatmospheric reflectance according to the formulas and calibration parameters presented by The Landsat 7 Users Handbook (Irish 2007). While this conversion removes predictable effects caused by differences in solar irradiance and solar angle, it does not take into account the influence of atmospheric condition and sensor drift on the measured radiances. To quantify changes in surface reflectance between the two acquisition dates with spectral mixture analysis, the impact of temporal spectral variability that is not caused by changes in surface reflectance should therefore be minimised. Because no atmospheric data or field measurements of ground reflectance were available, a relative reflectance calibration based on the identification of pseudo-invariant features (Schott 1988) was applied. By visually comparing the 1988 and the 2001 images, nine sites were selected for which the surface reflectance was not expected to have changed in between the two dates. Three were chosen to represent high albedo surfaces: highly reflective roofs of commercial or industrial buildings in the port area. Three low albedo sites were selected on the Liffy River in central Dublin, and three sites with asphalt were selected on the airport runway. Because at-sensor radiances vary linearly with ground reflectances for visible and short wave infrared wavelengths (Conel 1990) and because this relationship can be extended to multidate images (Caselles & Garcia 1989), the pseudoinvariant features of the 2001 image can be linearly transformed to give them the same apparent reflectance as in the 1988 image (Hall et al. 1991). The estimated linear function between the pseudoinvariant sites of the two images can then be applied on the entire 2001 image to reduce temporal spectral variability caused by the combined impact of differences in illumination, sensor drift and atmosphere.

4 METHODS

4.1 *Linear spectral mixture analysis*

Linear spectral mixture analysis (LSMA) is a common approach to sub-pixel classification whereby a pixel's observed reflectance is modelled as a linear combination of spectrally pure "endmember" reflectances. Each endmember contributes proportionally to the overall spectral response according to its relative abundance within the sensor's instantaneous field of view (IFOV). To estimate the fractional cover of each endmember within a given pixel, the following equation has to be solved for all image bands simultaneously, using a least squares approach:

$$R_b = \sum_{i=1}^{n} f_i r_{i,b} + e_b \qquad (1)$$

where R_b is the reflectance of the pixel for band b, f_i is the proportion of endmember i within the pixel, $r_{i,b}$ is the reflectance of endmember i for band b, n is the number of endmembers and e_b the error of fit for band b (van der Meer et al. 1999). Inverting this system of mixing equations to retrieve endmember fractions that best fit the observed mixed reflectances implies determining the optimal location of endmembers in feature space.

LSMA has recently received quite some attention in studies that aim to characterise urban environments (e.g. Rashed et al. 2005, Small 2003). For this purpose, the VIS model is a useful conceptualisation of the urban environment because it allows representing any urban area by three physical components: vegetation (V), impervious surfaces (I) and soil (S), in addition to water (Ridd 1995). If these components could be unambiguously represented as endmembers in feature space, fractions derived from unmixing an urban area would allow to position urban pixels in the VIS triangle. This in turn would make it possible to analyze urban morphology, form and function starting from medium resolution satellite imagery. However, not all pure vegetation, impervious surfaces or bare soil pixels occupy extreme positions in feature space and can, as such, not be directly used as endmembers for unmixing. Instead, the apexes of the typical triangular shaped feature space correspond to true biophysical endmembers representing high albedo substrate (S), bright vegetation (V) and dark surfaces (D) (Small 2004). Any pixel falling inside the convex hull circumscribing the apexes can be considered as a mixture of these three components, and not of V-I-S. One reason for this is that endmembers are spectrally variable because of brightness differences (Wu 2004). In mixture space, pure vegetation pixels are mostly located on the vegetation – dark axis, indicating binary mixing between these two endmembers. Darker vegetation types such as trees are located closer to the dark endmember, while brighter vegetation types such as grass or crops are typically found closer to the vegetation endmember. Binary mixing on the "grey axis" between the dark and substrate endmembers represents different types of urban surfaces, e.g. asphalt versus concrete, while binary mixing on the vegetation – high albedo substrate axis is extremely rare (Small 2004). This complicates the direct use of the VIS ternary as an appropriate model for unmixing. Although bare soil was indeed present as a separate endmember in some studies carried out on other areas (e.g. Phinn et al. 2002), man-made impervious surfaces and exposed soils may indeed be spectrally very similar, depending on the soil type and characteristics on broadband image data. For instance, Van de Voorde *et al.* (2007) reported high levels of spectral confusion between exposed soils near Brussels and red-clay roof tiles, very common in the city. This will further complicate the unmixing process and will lead to some degree of confusion between these two land-cover types if they are chosen to represent endmembers of a VIS unmixing model.

Because bare soil could not be used as an endmember in the Dublin study area, the SVD unmixing model was applied. The substrate (S) and dark (D) endmembers for each image were chosen to be identical to the bright and dark pseudo-invariant features that were used for the radiometric calibration. The vegetation endmembers were selected from the extreme pixels on the vegetation axis in a feature space visualisation of each image by means of high-order principal components.

4.2 *Creating urban masks with self-organising maps and knowledge-based post-classification*

In order to characterise urban structure with spatial metrics based on sub-pixel proportions of SVD endmembers, it is necessary to distinguish urban from non-urban fabric. An urban mask is required because pixels consisting of rural bare soil or urban surface types may exhibit a similar substrate-dark mixture, and will therefore also share the same metric signature. To create this mask, we applied a non-parametric unsupervised classification approach and enhanced the resulting thematic map with knowledge-based post-classification rules.

The unsupervised classification approach was based on Kohonen self-organising maps (SOM) (Kohonen 2001). A SOM is a type of artificial neural network that was originally developed to visualise topologies and hierarchical structures of multi-dimensional data by transforming the input space into an ordered two dimensional map. The SOM architecture consists of two network layers: an input layer, which is fully connected to a typically two dimensional array of nodes called Kohonen layer or codebook vector map. The SOM is trained by passing an input vector (i.e. a pixel's spectral values) to the network, and by choosing a winning node based on its distance from that input vector. Then, the weights of the winning node and its neighbours are adjusted in order to reduce the node's distance to the input vector. After each image pixel or a representative set of image pixels is passed to the SOM during training, the built model can be applied to any part of the image and even to other images when atmospheric or other calibration constraints are taken into account. Because the trained SOM network assigns each pixel to a particular node in the codebook vector, each such node can be considered to represent a certain information category. This is similar to other unsupervised classification approaches, except that nodes or classes that are closer to each other on the codebook vector are also more spectrally similar. In this research, we applied a SOM with a 3 by 5 Kohonen layer, which divides the image into 15 spectral classes.

Although Kohonen SOM is a rather advanced approach to unsupervised classification, spectral confusion between certain surface types is still likely to occur and will cause errors in the urban mask. To enhance the classification output with respect to the intended purpose, i.e. distinguishing urban from non-urban areas, a rule-based post-classification approach was adopted (Van de Voorde et al. 2007). This method uses post-classification rules that operate on clumps or groups of adjacent pixels of the same class. If certain user defined criteria are met, a clump's original class label (O) is changed to a target class (T). For the purpose of developing an urban mask in this paper, the target class is always a neighbour's class label. Each rule uses two criteria: area (A) and adjacency (Ad). The area criterion constrains a rule's operation to clumps of a certain maximum size, expressed as number of pixels within the group. Adjacency constrains a rule to pixel groups that are next to clumps of a given type. The value of the adjacency criterion represents the fraction of the clump's border that is shared with the target class. For example: a rule might be developed to assign small bare soil groups (O = bare soil, A < 20 pixels) that share more than half of their border with urban clumps (Ad > 0.5) to the urban class (T). The values of O, T, Ad and A are determined from a visual inspection of the unsupervised classification, keeping in mind the intended use of the post-classification. For the purpose of developing an urban mask, it is especially important that confusion between rural bare soil and urban fabric is resolved, and that each class from the unsupervised classification is unambiguously assigned to either urban or non urban. In addition to the knowledge-based rules, all single pixel groups were removed from the map before and after post-classification to reduce the amount of noise. This was done by applying a majority filter on a 3 by 3 window centred on groups that consisted of only one pixel.

5 RESULTS AND DISCUSSION

The 15 classes of the land-cover maps produced by the SOM classifier were recoded into 6 meaningful information classes (figures 1a and 1c). Both the 1988 and the 2001 maps show a high level of spectral confusion between urban and bare soil, which makes it impossible to directly use the classification output as an urban mask. In the 2001 classification, clearly even more confusion occurs between urban and bare soil surface types compared to the 1988 map. This is partly caused by the presence of many construction sites, but also by a higher level of spectral confusion in the 2001 SOM. To enhance the unsupervised classification output, three knowledge-based post-classification rules (table 1) were developed and applied in combination with a filter to remove individual, isolated pixels.

Table 1. Overview of the knowledge-based post-classification rules and their parameters

Rule nr.	Original class (O)	Target class (C)	Area (A)	Adjacency (Ad)
1	Bare Soil	Urban	Unlimited	0.75
2	Peat bog / mixed urban-vegetation	Urban	< 200	Unlimited
3	Shadow	Urban	< 1000	0.75

The first rule was intended to re-assign erroneous bare soil clumps within the urban fabric to neighbouring urban type clumps. The adjacency threshold was set to a relatively high 0.75, meaning that bare soil clumps that shared at least 75% of their border with an urban clump had their class changed to urban. Because actual fallow fields do not share a large part of their border with urban surfaces, setting an area threshold was not necessary. This rule effectively cleaned up most of the bare soil/urban confusion in the city centre for both time steps. In the 1988 map, part of the ring road remains classified as bare soil probably because it was still under construction at the time.

The higher degree of confusion in the 2001 classification produced some larger misclassified areas near the western part of the city, which the post-classification was not able to resolve fully. A few large misclassified clumps were therefore manually corrected after visual inspection. A second post-classification rule was developed to operate on parts of low density urban areas that were classified into the same class as *peat and bog*, a type of vegetation cover that is common in the Wicklow Mountains (coloured yellow on figures 1a and 1c). Because all misclassified clumps of this type within the city are relatively small compared to actual *peat and bog* regions, an area threshold was sufficient to improve the classification. A third and final rule was applied to remove small groups of shadow pixels in the city. To avoid confusion with shadows near vegetation, an adjacency threshold was used together with the area threshold. After post-classification, the two land-cover maps clearly improved (figures 1b and 1d), and could be used to derive an urban mask.

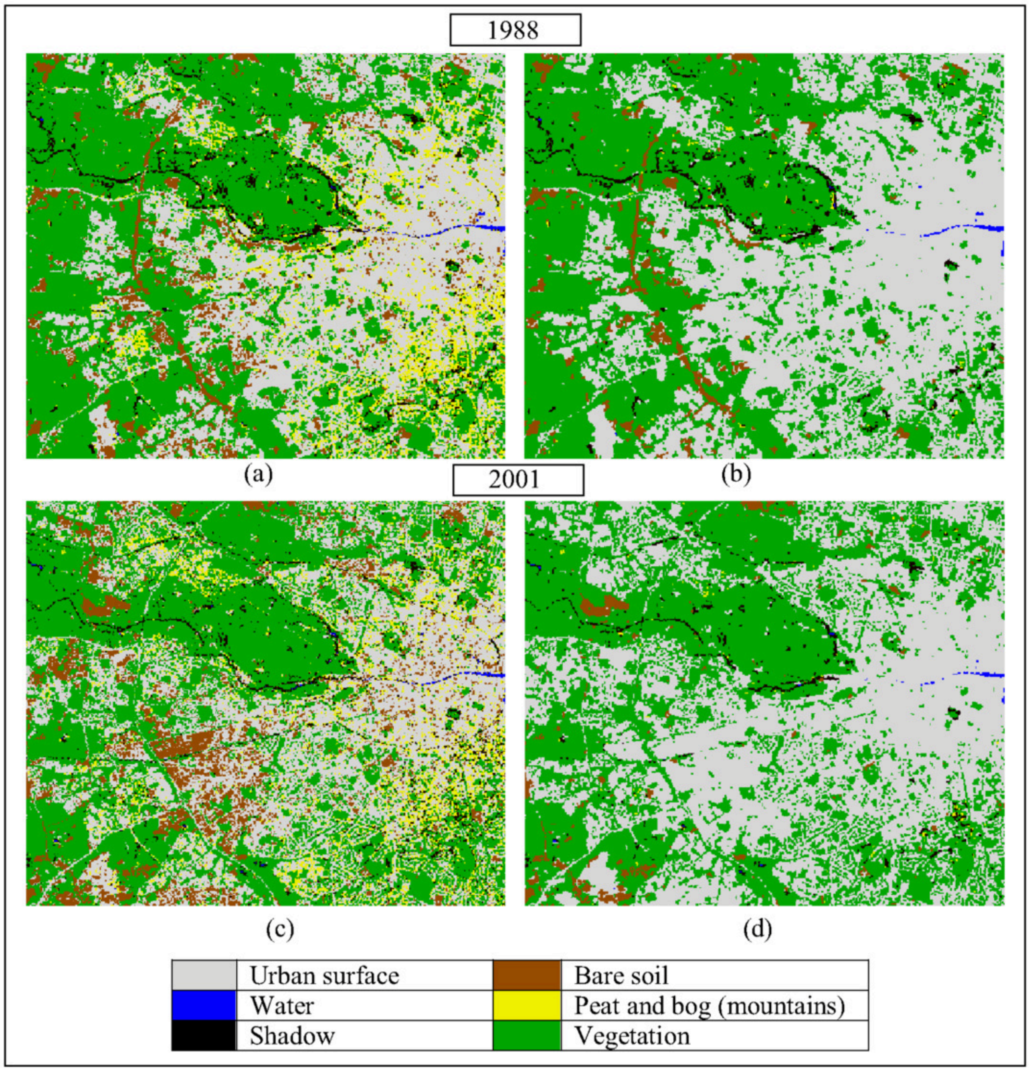

Figure 1. Land-cover classifications for 1988 and 2001 created by self-organising map (left) and enhancement by knowledge-based post-classification (right)

The proportion maps for the three end-members (figure 2) prove useful to visually detect changes in the urban fabric of Dublin. Especially the high albedo substrate and vegetation maps indicate urban expansion to the west of the city centre. The substrate map also shows the expansion of an industrial or commercial area to the southwest, which has a bright appearance because most structures in that area have roofs made of metal or other highly reflective materials. The ring road under construction is also clearly present in the 1988 substrate map, while the asphalt of the finished ring road is no longer detectable in the 2001 substrate map. Interpretation near the city's outer edge is, on the other hand, complicated by the presence of fallow land in 2001 that was covered by crops in 1988. This demonstrates the necessity of using an urban mask. The dark endmember proportion maps appear to be somewhat less useful for visual change detection, but may prove useful for quantitative structural gradient analysis because the amount of shadow, for instance, may provide information on the size and type of urban structures.

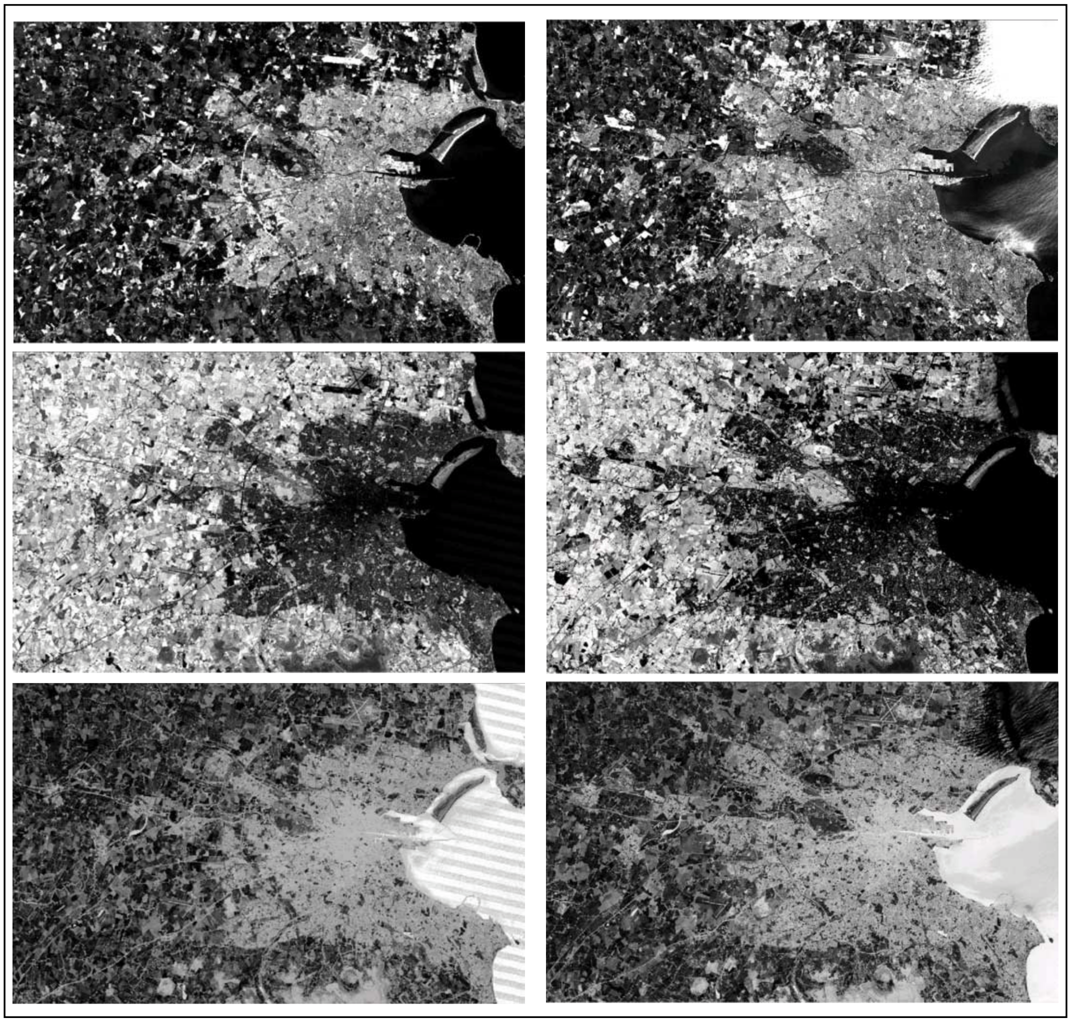

Figure 2. Sub-pixel proportion maps for substrate (top), vegetation (middle) and dark materials (bottom), obtained by unmixing the Landsat images of 1988 (left) and 2001 (right)

6. CONCLUSIONS

The objective of this research was to extract urban gradient information by applying linear spectral unmixing on a set of two multitemporal Landsat images. Spectral confusion between urban surfaces and non-urban land-cover types made it impossible to use VIS endmembers, and required the development of a mask to restrict the unmixing to urban areas. This mask was created with a SOM-based unsupervised classification and was then successfully enhanced with knowledge-based classification rules. The outcome of this study will be used to develop spatial metrics to characterise urban spatial form, which will aid the calibration of urban land-use models.

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