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Generating land cover boundaries from remotely sensed data using object-based image analysis: overview and epidemiological application

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Abstract

Satellite imagery and aerial photography represent a vast resource to significantly enhance environmental mapping and modeling applications for use in understanding spatio-temporal relationships between environment and health. Deriving boundaries of land cover objects, such as trees, buildings, and crop fields, from image data has traditionally been performed manually using a very time consuming process of hand digitizing. Boundary detection algorithms are increasingly being applied using object-based image analysis (OBIA) technology to automate the process. The purpose of this paper is to present an overview and demonstrate the application of OBIA for delineating land cover features at multiple scales using a high resolution aerial photograph (1 m) and a medium resolution Landsat image (30 m) time series in the context of a pesticide spray drift exposure application.

Keywords

image segmentation; Landsat; aerial photograph; pesticide exposure

1. Introduction

Satellite imagery and aerial photographs represent a vast resource to significantly enhance environmental mapping and modeling applications for use in understanding spatio-temporal relationships between environment and health. Deriving land cover information from high resolution data has been primarily performed using a manual approach where boundaries are first hand digitized around individual land cover features and then assigned a class label (Jensen, 2007). However, hand digitizing boundaries is very labor intensive, time-consuming, and impractical for studies spanning large geographical regions. Object-based image analysis (OBIA) technology has emerged over the last decade that provides the potential to automate the process of land cover boundary detection (Blaschke, 2010).

The goal of this paper is to give the reader an overview of OBIA technology focusing specifically on the detection of land cover boundaries. A case study is presented to demonstrate the process used in OBIA to delineate land cover object boundaries at multiple scales from remotely sensed imagery in the context of a pesticide spray drift exposure application in California. A high resolution aerial photograph (1 m) and an intra-annual time

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series of 13 medium resolution Landsat images (30 m) are integrated and processed using Definiens eCognition 8.0 software (Definiens AG, 2009).

2. Object-Based Image Analysis (OBIA) using Definiens eCognition

A key objective of OBIA is to develop systems that replicate manual interpretation of remotely sensed images using automated or semi-automated methods (Hay and Castilla 2006). An increasing number of studies have reported promising results using OBIA technology applied to high resolution images (Al-Khudhairy et al., 2005; Hay et al., 2005; Laliberte et al., 2007; Walker and Briggs 2007; Platt and Rapoza, 2008) and medium resolution images such as Landsat (Budreski et al., 2007; Carvalho et al., 2001; Flanders et al., 2003; Maxwell et al., 2008). OBIA consists of basically two processes: segmentation and classification. OBIA begins by the analyst first segmenting the image to generate boundaries around groups of pixels based on their spectral similarity. Boundaries are typically generated for landscape features at different scales so that attributes such as texture, shape, and association can be used during the classification process. Examples of small objects include individual houses and trees, and examples of large-scale objects include crop fields, cities, and forests. Early research identified the advantages of segmenting and classifying images based on homogeneous regions as opposed to individual pixels (Haralick et al., 1973; Kittle and Langrebe, 1976), yet the process has not been operationally feasible until recently due to hardware and software constraints (Blaschke, 2010). Only within the last decade has OBIA technology become commercially available (e.g., Definiens eCognition, ERDAS Imagine Objective, ENVI Feature Extraction Module).

2.1 Development of a segmentation strategy using Definiens eCognition software

Developing a segmentation strategy requires careful consideration of the approach and parameter settings. The optimum solution will depend on several factors such as image spatial resolution, spectral bands available, objects of interest, and environmental conditions at the time of image acquisition (Al Khudhairy et al., 2005; Budreski et al., 2007; Dobrowski et al., 2008). The multiresolution segmentation algorithm used in eCognition is a bottom-up region-merging approach referred to as the fractal net evolution approach (Benz et al., 2004). The segmentation process begins by initially recognizing each individual pixel in the image as one segment. These single-pixel segments are then successively merged into larger segments using a pair-wise clustering process. The algorithm uses three parameters: scale, shape weighting, and compactness weighting. The scale parameter determines the areal size of the segments generated whereas the shape and compactness weighting values are used to determine the shape of the segments. A small scale value (e.g., 10) produces small segments and a large scale value (e.g., 300) produces large segments. The shape and compactness parameter values range from 0 to 1. A low shape value (e.g., 0.1) places a high emphasis on color which is normally the most important for creating meaningful objects (Definiens AG, 2009). Higher compactness weightings (e.g., 0.9) result in more compact object boundaries, such as is typical with crop fields or buildings.

Studies where eCognition was used to segment high resolution images (i.e., 1 m) applied a bottom-up multiresolution segmentation strategy. Scale parameter settings of 5 to 100 were used to obtain land regions of varying sizes. Van der Sande et al. (2003) applied four scale parameter settings (5, 10, 30, and 100) to an Ikonos image (1 m) for a flood risk and damage assessment application. Different spectral bands, shape, and compactness parameters were applied depending on the objects of interest. For example, they used all spectral bands for generating boundaries at Scale 5 (shape/compactness = 0.3/0.1) yet only the red visible and near-infrared bands were used for generating the largest features (e.g., agriculture, water). Al-Khudhairy et al. (2005) used an Ikonos image to generate landscape boundaries for an urban structural damage assessment study. Only three scales (10, 20, and 30) were used in

their analysis and they also applied different spectral band combinations for each scale depending on the targeted land cover objects. In contrast, Walker and Briggs (2007) used only one scale (10) with zero shape weighting applied to a 0.61 meter aerial photograph for an urban forest mapping application.

Segmentation parameters applied to Landsat image data (30 m) were similar to the parameters applied to high resolution imagery. Flanders et al. (2003) used a variety of scales (25–200) to delineate boundaries in a Landsat image (bands 1-5 and 7) for forest clear-cut mapping. Lewinski et al., 2006 used only one scale (10) for general land cover mapping. Whereas, Maxwell et al., 2008 found that three scales (10, 15, and 20) with shape/compactness weightings of 0.3/0.5 using three Landsat spectral bands (red visible, near infrared, and middle infrared band) resulted in the best solution for a general purpose land cover characterization application. No studies were found in the literature that incorporated both high resolution and multitemporal medium resolution images to delineate land cover boundaries.

2.2 Deriving true object boundaries

Although the boundaries resulting from the initial segmentation process are referred to as *objects* in this paper, they do not actually represent true objects such as a tree or a building until the classification process is completed. The initial boundaries generated from the image segmentation process are sometimes referred to as “object primitives” or “object candidates” to distinguish them from true objects (Blashke, 2010). An iterative process of segmentation and classification will generally be required to arrive at the final boundaries. In some cases developing a method that is 100% automated may not be achieved and some manual corrections may be required (Dobrowski et al., 2008).

3. Case study: Generation of land cover boundaries to support pesticide spray drift exposure assessment in California

3.1 Background

Epidemiological studies have found associations between agricultural pesticides applied to crop fields near residential locations and adverse health outcomes such as childhood cancers (Daniels et al., 1997; Infante-Rivard and Weichenthal, 2007; Carozza et al., 2009), neural tube defects (Rull et al., 2006), and Parkinson’s disease (Costello et al., 2009). The ability to link pesticide use to a specific crop field is important for improving pesticide exposure estimates in California (Nuckols et al., 2007; Riggs, 2007). The California Pesticide Use Reporting (PUR) database is the primary source of information on where, when, and how pesticides are used in California (CDPR, 2000). Each PUR record contains information on the type of chemical applied, the type of crop the chemical was applied to (e.g., cotton, tomato) and the number of acres planted, among other attributes. While this database is one of the most comprehensive pesticide use reporting database in the world (CDPR, 2000), the data is only recorded at a geographic scale of an approximately 2.6 km² polygon, or “Section” in the U.S. Public Land Survey. The ability to identify which specific crop field the pesticides were applied would provide information at a much finer level of spatial detail potentially improving exposure estimates considerably.

Transport and fate of pesticide chemicals is a complex process which depends on many factors such as weather conditions, vegetation characteristics, soil properties, application method, and chemical persistence (Hursthouse and Kowalczyk; 2009). Identifying landscape features that may affect chemical dispersion are particularly important as relatively small features such as trees or buildings have been shown to significantly impact the flow of chemicals (Figure 1) (Lazzaro et al., 2008; Longley and Sotherton, 1997; Miller et al., 2000;

Richardson et al., 2004). Use of simple measures of proximity to pesticides applied to crop fields can lead to substantial misclassification errors in exposure studies (Brody et al., 2002; Rull and Ritz, 2003). Geographic-based transport and fate models are used to derive more precise estimates of human exposure (Brody et al., 2002; Riggs, 2007; Ward et al., 2006). Detailed land cover information is required to support these models which can be acquired from remotely sensed images. Satellite image data can be used to identify the specific location where chemicals are applied (e.g., crop field) and to identify land cover features that potentially affect chemical movement (e.g., buildings, trees). Aerial photographs and Landsat image data have been particularly useful for agricultural chemical exposure assessment to identify the location of chemical applications (e.g., crop field) and to identify landscape features that affect chemical movement, such as trees and buildings (Brody et al., 2002; O'Leary et al., 2004; Ward et al., 2006).

3.2 Image Data

Both high resolution (e.g., 1 m) and medium resolution (e.g., 30 m) multitemporal image data were used to identify the land cover features of interest for the case study (Figure 2). Relatively small features, such as buildings and trees, are readily identifiable from high resolution images (Figure 2, Plates A and C), however these images are generally only collected once during a given year, limiting the capability to determine individual crop fields or the type of crop grown (e.g., cotton, tomato). In Figure 2, both crop field A and crop field B are bare soil at the time the image was acquired (Summer 2005). Images collected multiple times over the crop growing season were required to improve field boundary delineation as well as to assist in the identification of the specific type of crop grown on the field. Landsat images are collected every 8–16 days providing information on inter-annual crop vegetation dynamics. Small features such as individual trees and buildings are not distinguishable in Landsat images due to the lower spatial resolution (Figure 2, Plates B and D). Merging a Landsat image time series with higher resolution image data provides the optimum solution for identifying the required land cover features (Figure 2, Plate E).

A high resolution (1 m) natural color digital orthophoto quad (DOQ) acquired during the summer of 2005 was used in this study. The DOQ photograph was collected as part of the National Agriculture Imagery Program (NAIP) and subsequently scanned, corrected for camera orientation and terrain effects (i.e., orthorectified), and georeferenced to 1 meter spatial resolution. The DOQ was obtained from the California geospatial clearinghouse (DOQQ: Riverdale: 36119d7sw, accessed from <http://www.atlas.ca.gov/quads/> March 2010).

Thirteen Landsat 5 Thematic Mapper images (30 m) for Path 42 Row 35 acquired during 2005 were downloaded from the U.S. Geological Survey Global Visualization Viewer (GloVis) website (<http://glovis.usgs.gov/>). Landsat image dates for 2005 included: Apr 12, May 14, May 30, Jun 15, Jul 1, Jul 17, Aug 2, Aug 18, Sep 3, Sep 19, Oct 5, Oct 21, and Nov 22. The Landsat images were reprojected to match the DOQ projection (UTM 11, NAD83, WRS80) and then radiometrically corrected to at-sensor reflectance to correct for seasonal reflectance variances caused by sun angle and distance (Chander et al., 2009). Each image was then converted to the Normalized Difference Vegetation Index (NDVI) ((near infrared band – red visible band)/(near infrared band + red visible band)) and clipped to the same extent as the DOQ study area. The NDVI is correlated with biophysical parameters such as green biomass and leaf area index and used as a measure of photosynthetic 'greenness' (Gamon et al., 1995).

3.3 Image segmentation

Figure 3 shows the results of various segmentation parameter settings applied to generate boundaries of 1) small objects in an urban area (Figure 3, Plates A and B) using only the DOQ and 2) large objects in an agricultural region using the combined DOQ and 13-date NDVI Landsat images (Figure 3, Plates C and D). Small objects such as residential buildings, road segments, and individual trees in an urban area were delineated with a scale value of 20 (shape/compactness = 0.1/0.9) (Figure 3, Plate A). Applying a second level using scale set at 100 and shape/compactness as 0.3/0.9 resulted in larger objects delineated, such as the row of trees and crop field on the right side. At this larger scale several objects such as residential homes, lawns, and trees were merged into one object.

An example where both the DOQ and multitemporal Landsat NDVI images were used in delineating objects is shown in Figure 3, Plates C and D. A three-level segmentation procedure was applied where the first level was created using a scale of 30 (shape/compactness = 0.1/0.9) applied to only the DOQ image bands. The second level was generated using a large scale of 200 applied using both the DOQ and Landsat image data with a heavy weighting applied to the DOQ image bands (all bands weight = 50). The final level shown in Figure 3(C and D) was generated using a spectral difference function of 10 applied to only the Landsat NDVI images. Most of the field boundaries were delineated in their entirety yet some fields remained only partially delineated.

4. Discussion and conclusion

Remotely sensed data can provide important information to support epidemiological studies (Herbreteau et al, 2007; Maxwell et al., 2010). Studies, such as the agricultural chemical exposure assessment application described in this paper, require that the satellite image data first be converted to digital land cover maps before integrating with other geospatial data in an exposure model. The majority of digital land cover maps generated from Landsat satellite data are produced using pixel-based classification methods where individual pixels in the image are assigned a land cover class based primarily on the spectral properties of the pixel. Ancillary data, such as population density and elevation, may also be included in the classification to improved separation of some spectrally similar cover types. Image pixels are typically labeled as general land cover or land use types, such as urban, grassland, forest, and agriculture. Pixels labeled as grassland include a variety of land types such as urban lawns, golf courses, and natural grassland, because the vegetation, and hence spectral characteristics, are generally very similar. An epidemiological study evaluating the relationship between chemicals used on golf courses and health outcomes require spatial maps depicting the location of golf courses which is not provided in typical land cover maps. One of the strengths of OBIA is that it provides the potential to identify features, such as golf courses, from satellite data based the spatial and contextual relationship of land cover objects, as well as their spectral properties, similar to human visual interpretation. For example, golf courses are generally near urban areas and have long, narrow grassland areas as compared to natural grasslands which are large landscape regions in rural areas.

In the pesticide exposure assessment example presented in this paper, a map locating specific crop fields was required. Use of a pixel-based approach allows for the identification of the crop type only at the pixel-level. Pixels are treated as independent units in pixel-based classification models where no consideration is made to neighboring pixels. Maps derived from this approach typically result in pixels containing labels of different crop types within the same crop field. For example, pixels labeled as corn and pixels labeled as soybeans occurring within the same crop field. This occurs because pixels within the corn field may look spectrally similar to pixels within a soybean field due to variations in factors such as soil, topography, and moisture. This can have a substantial impact on epidemiological

studies that do not consider this factor. OBIA technology facilitates analysis of images at the crop field level which allows for a more complete representation and characterization of crop fields to support agricultural chemical exposure assessment.

Although OBIA technology has the potential to improve land cover characterization for epidemiological applications, the technology is still fairly new. The example above demonstrated that there are several factors to consider in determining the segmentation parameter values. The subjective nature of this process supports the findings of other studies (Flanders et al., 2003; Budreski et al., 2007). Results of the segmentation process presented in the case study above display only a few of the many parameter setting variations that were explored. More research is needed to determine if alternative parameter values would improve the results, especially when considering multiresolution imagery. Benz et al., (2004) suggest that there is no one optimum parameter setting that will result in boundaries delineating both small and large objects and one must consider the particular data set and project objectives to determine suitable parameters. Deriving true object boundaries, such as for a crop field, will require an iterative process of segmentation and classification and in some cases developing a method that is 100% automated may not be achieved (Dobrowski et al., 2008).

This paper presented an overview of OBIA and presented an example of how the technology is applied to derive land cover boundaries from satellite imagery for an epidemiological study. Focus was placed on the image segmentation process which is the first step in generating land cover object boundaries. The demonstration was performed using Definiens eCognition OBIA software which is only one of several packages that are currently available. Although OBIA technology shows promise, the ability to accurately characterize land cover boundaries will depend on many factors including image spatial resolution, spectral bands available, image quality, segmentation approach, and classification method, to name a few.

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Fig. 1. Digital aerial photograph (1 m spatial resolution) of residential homes near crop fields. Residences outlined in yellow have less exposure to agricultural chemicals sprayed on crop fields A and B as compared to residences outlined in red due to trees on the east side and buildings on the south side.

Fig. 2.

Comparison of natural color digital orthophoto quad (DOQ, 1m) and multitemporal Landsat image color composite (30m). Residential buildings and trees are identifiable from the DOQ (A and C). Individual crop fields are more distinctive in the multitemporal Landsat data (B and D). Merging the high resolution DOQ and multitemporal Landsat images allows for both small (e.g., residential homes, trees) and large (e.g., crop fields) features to be identified. The Landsat color composite is developed using three NDVI images (July 1 as red, September 3 as green, and September 19 as blue).

Fig. 3.

Comparison of boundaries (yellow lines) generated using various segmentation parameter settings and image data sets. Plates A and B show boundaries generated using small scale values (A:scale=20; B:scale=100) applied to a 1 meter natural color digital orthophoto quad (DOQ). Plates C and D depict boundaries generated using a combined DOQ and Landsat NDVI time series with a relatively large scale setting (scale = 200) to delineate urban areas and crop fields. Plates C and D are displayed with a color combination of the DOQ and three 2005 Landsat NDVI dates (July 1 as red, September 3 as green, and September 19 as blue).