Ecological Indicators 71 (2016) 660–668

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Across the grain: Multi-scale map comparison and land change assessment

Bruce A. Pond

Wildlife Research and Monitoring Section, Ontario Ministry of Natural Resources and Forestry, 2140 East Bank Drive, Peterborough, ON K9J 0G2, Canada

ARTICLE INFO

Article history:
Received 17 February 2016
Received in revised form 28 June 2016
Accepted 29 June 2016
Available online 9 August 2016

Keywords:
Landcover change detection
Post-classification change detection
Map comparison
Land use planning
Monitoring
Multi-scale

ABSTRACT

Changes in the spatial distribution of land cover and land use can have significant impacts on ecological processes at multiple scales; estimating these changes provides critical data for both monitoring and understanding land-use effects on these processes. One approach to mapping landcover changes, particularly useful over longer periods of time, is comparison of existing landcover maps, (post-classification change analysis). The accuracy of these maps is often unknown and varies depending on data sources and interpretation techniques; therefore, separating change on the ground from differences attributable to sensors and methods is both critical and problematic. Through a novel map comparison method applying major axis regression at multiple spatial grains of analysis, this study partitioned accuracy into components of bias and precision in comparing maps, which aided selection of an optimal analytical grain size. Comparisons between contemporaneous maps showed the magnitude and distribution of error alone, while between-period analyses indicated both cumulative map error and change on the ground. These methods enable exploration of the nature of error and identification of differences between maps, while accounting for the imprecision and bias inherent in the source documents. Mapping landcover change delineates landscapes under recent disturbance pressure, and these measures are more effective as performance indicators for broad-scale evaluation of natural heritage policies and habitat restoration initiatives when error in the data is identified and accounted for.

1. Introduction

Estimating changes in the area and the geographic distribution of land cover are two primary objectives of land cover change studies (Stehman, 2005). Measuring these changes provides critical data for monitoring and understanding broad-scale environmental trends (Lautenbach et al., 2011; Lawler et al., 2014; Lawley et al., 2016; Rugani and Rocchini, 2016). Trends in land cover change are key indicators for land policy evaluation and for understanding both land use dynamics and ecological trajectories. These trends are particularly important indicators of environmental change in landscapes affected by human activity. They have a role in monitoring processes, which include urban expansion, deforestation, afforestation and old field succession; in assessing policy influences on these processes; and in understanding ecological effects of these disturbance processes. Remotely sensed data are commonly used for efficient measurement of land cover change over large geographic extents at fine spatial, temporal and classification resolutions. In addition, existing historic large-scale maps e.g. topographic series, are useful in providing geographically extensive, spatially continuous land cover data that pre-date the development of satellite-based mapping technologies and thus offer a longer time series of change estimation than is possible from satellite-based mapping alone (Bürgi et al., 2015; Kaim et al., 2016; Lancaster et al., 2008).

Methods for processing remotely sensed images to detect changes in landcover and to extract change maps have been widely reviewed (Alqurashi and Kumar, 2013; Coppin et al., 2004; Lu et al., 2004; Mas, 1999; Singh, 1989). These methods may be grouped into two broad categories: 1) multi-date image change classification, in which digital images from multiple dates are analyzed simultaneously to identify areas of change based on classification of spectral characteristics and 2) post-classification change detection, in which two independently developed maps of landcover are compared. The historic land cover maps, regardless of the sources of data, are eminently suited for analysis by the latter method; although typically, these maps have not been subject to accuracy assessments.

This research focussed on post-classification change detection and the nature and spatial distribution of error. Post-classification change detection, which is intuitively appealing and easily under-

E-mail address: Bruce.Pond@Ontario.CA

http://dx.doi.org/10.1016/j.ecolind.2016.06.056
1470-160X/

stood, involves overlaying two maps from two time periods, tabulating land areas for the spatial intersection of cover classes in an agreement matrix and mapping the differences between the maps. There are a number of advantages of this approach over multi-date image change classification approaches: 1) accurate map co-registration is easier to achieve (Singh, 1989); 2) sensor calibrations and correction for sun angle, atmospheric conditions and soil moisture are undertaken separately and optimized for each map date (Coppin et al., 2004; Serra et al., 2003; Singh, 1989); 3) maps from various sources and methodologies can be used, e.g. maps derived from satellite images of differing spatial and spectral resolutions (Gardner et al., 2008; Luong et al., 2015; Petit and Lambin, 2001) or historic topographic maps derived from various data sources (Bürgi et al., 2015; Kaim et al., 2016).

However, post-classification change detection has limitations. Co-registration remains a crucial process for accurate change detection, and can be a significant source of error. Classification errors in the original mapping are compounded in post-classification change assessment. Overall accuracy in a map of change, ignoring errors due to misregistration, is, at best, the product of the classification or thematic accuracies of the two source maps (Coppin et al., 2004; Serra et al., 2003; Singh, 1989). Classification errors can be exacerbated by inconsistent map category definitions; for example one map may define Christmas tree farms as plantations and therefore consider them woodland, while a second map might identify these areas as agricultural cropland. Some of this error can be reduced through careful cross-map thematic class matching and class aggregation (Herold et al., 2008; Petit and Lambin, 2001), but some must be accepted as bias when comparing one map to another. Finally, even with consistent class definitions and accurate classification, map differences will result from independent interpretation of different data sources (e.g. multispectral satellite images, film negative aerial photographs), different interpretation standards (e.g., varying minimum mapping unit size) and different interpretation methods (e.g. visual human interpretation, automated supervised classifications). Any of these differences may result in errors of bias in which one map, when compared to another, consistently over- or under-estimates a cover class area, or, if differences are randomly distributed, may simply introduce noise or imprecision to the resulting maps of change.

A number of strategies have been developed to account for or to control the impact of post-classification change detection errors on estimating and mapping landcover change. Petit and Lambin (2001) explored the effect of two of the error sources identified above. First, they harmonized map legends by aggregating classes to more general, but more equivalent and consistent classes. Aggregation of classes, in general, improves the accuracy of a map classification (Lunetta et al., 1991; Maxie et al., 2010); however, it is done at the cost of classification resolution: fewer classes convey less information. Second, Petit and Lambin (2001) reduced mapping resolution by spatially aggregating landcover data from 1 m pixels through to 101 m pixels using a majority rule to assign land class to the aggregated pixels. Aggregation of pixels spatially smooths out some of the error arising from misregistration (Petit and Lambin, 2001; Pond et al., 2014; Pontius et al., 2008), but with a loss of spatial precision.

Conventional map accuracy assessment uses error matrices, which are crosstabulations of landcover classes observed at a set of reference locations, commonly called "ground-truth," with the landcover classes on the map at those locations (Congalton and Green, 2008; Foody, 2010). Recent research has exploited this error information to improve the accuracy of the change measures and to provide statistical statements of the significance of changes over time (McRoberts, 2013; Olofsson et al., 2014, 2013; Sannier et al., 2014). Accuracy assessments have become a required part of contemporary land cover map production (Stehman and Wickham, 2011). However, older map products often lack this information, which is particularly crucial for estimating and mapping land cover change.

This research addressed two issues identified above: the absence of accuracy assessments, particularly common for historic mapping, and the impact of spatial aggregation on accuracy measures. In the absence of accuracy assessments, the consistency or congruence of maps of the same phenomenon at the same time period should prove a useful surrogate for map accuracy. Exploring the response of these consistency measures to changing the degree of spatial aggregation, that is, the grain of analysis in the sense of Dungan et al. (2002) and Scheiner et al. (2000), provides a tool for choosing an optimal mapping resolution and for selecting the best maps to use for change mapping. Examination of map data and their associated error characteristics over a range of spatial grains provides a means of selecting appropriate data grain for the grain of ecological processes of interest.

The model system I used as a case study to examine this methodology was wooded area in a temperate North American urbanizing agricultural landscape. Woodland area is one of the key natural heritage features of biodiversity concern in these settled landscapes. The distribution of woodland is altered by both agricultural and urban development activities. Urban expansion, generally, causes loss of forest cover; agriculture may remove woodland through field expansion due to increased demand for agricultural products, e.g. corn for ethanol production. Conversely forest cover may regenerate from idle fields or through afforestation initiatives. Forest cover is valued as a component of biodiversity and ecological integrity (Lawler et al., 2014; Pereira et al., 2013; Skidmore et al., 2015). For example, it serves as wildlife habitat, protects ground water recharge processes, and offers aesthetic, recreational and economic benefits to local residents (Farber et al., 2006; Troy and Bagstad, 2009; Wilson, 2008). Assessing both the amount of forest cover change and where the changes are occurring are important elements of state of resource reporting, biodiversity monitoring and assessment (Hansen et al., 2013; Ontario Biodiversity Council, 2015; Taylor et al., 2014) and for land use policy performance assessment. Post-classification change detection is an intuitively appealing methodology which offers the possibility of using existing historic maps of land cover to assess long term forest cover change.

My objective in this research was to compare contemporaneous maps of wooded cover over a range of grains of analysis to understand the nature, magnitude and distribution of error in these map comparisons. That understanding of bias, precision and their responses to changing spatial grain, as well as the degree of correspondence between two time periods identified an optimal map pair and spatial grain to assess and to map change in wooded cover over time.

2. Methods

2.1. Study area

The area used as a model region for this study surrounds, but does not include the City of Toronto, Ontario, Canada (≈690 000 ha) (Fig. 1). Ecoregionally, it is situated in the Mixedwood Plains ecozone, a temperate, agricultural urbanizing landscape (Taylor et al., 2014). In 1991, the first time period for this study, the region had about 2.2 million residents; by 2001 this had risen by 39.9% to 2.8 million people. In 2001, the region plus the City of Toronto had a population of 5.1 million and had experienced a population growth rate from 1991 of 9.5%.