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Technical note / Note technique

Object-based approaches to change analysis and thematic map update: challenges and limitations

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Abstract. Bitemporal change analysis strategies performed in an object-based environment are prone to the generation of *sliver objects*: small, spurious polygons created by the inconsistent delineation of persistent change features appearing in consecutive coregistered images. The issue represents a serious methodological challenge that can limit the visual and structural quality of the finished map product if not adequately addressed. A critical analysis of annual land cover maps generated by updating and backdating object-based reference maps in a western Alberta study area revealed that sliver objects made up between 3% and 12% of the total area of change, and between 63% and 72% of the total number of change objects, despite high thematic accuracies. The results highlight the emerging need for a methodological framework designed to handle the spatial challenges posed by change analysis in an object-based environment.

Résumé. Les stratégies d'analyse bitemporelles des changements utilisées dans un environnement orienté objet sont sujettes à la génération d'objets ayant la forme d'un ruban (« sliver objects ») : des petits polygones parasites créés par la délimitation irrégulière des caractéristiques persistantes du changement apparaissant dans les images consécutives superposées. Cette problématique représente un défi méthodologique sérieux qui peut limiter la qualité visuelle et structurale du produit cartographique fini si elle n'est pas résolue correctement. Une analyse critique des cartes annuelles du couvert générées au moyen de la mise à jour et l'antidatation des cartes de référence obtenues par la méthode orientée objet dans une zone d'étude située dans l'ouest de l'Alberta ont révélé que les objets non désirés sous forme de ruban constituaient entre 3 % et 12 % de la surface totale du changement et entre 63 % et 72 % du nombre total d'objets de changement identifiés par la routine, en dépit des précisions thématiques élevées. Les résultats démontrent la nécessité de mettre au point un cadre méthodologique conçu pour traiter les défis spatiaux posés par l'analyse du changement dans un environnement orienté objet.
[Traduit par la Rédaction]

Introduction

Multitemporal change analysis of coregistered imagery has emerged as an effective strategy for maintaining the relevancy of thematic maps and other spatial information products, and ranks among the remote sensing discipline's most important and widely adopted family of techniques. Although specific algorithms may vary (Radke et al., 2005), many approaches are designed to identify and delineate *change features* that are well suited for updating and backdating existing map layers in a timely and effective manner. As a result, these methods commonly play key roles in a variety of mapping and monitoring programs (e.g., Kolar, 2001; Hamandawana et al., 2005; Duro et al., 2007), where their competent performance is widely relied upon.

The basic strategy for updating an existing thematic map ($\text{Map}_{\text{date1}}$) for the purpose of creating a new map layer ($\text{Map}_{\text{date2}}$) through the overlay of change features acquired with bitemporal change detection ($\text{Change}_{\text{date2–date1}}$) can be expressed in the following general form:

$$\text{Map}_{\text{date2}} = \text{Map}_{\text{date1}} + \text{Change}_{\text{date2–date1}} \quad (1)$$

This style of map production differs from independent generation of classification products, and has the advantage of limiting efforts in date2 to only those areas undergoing change. However, the quality of the new map product ($\text{Map}_{\text{date2}}$) is largely a function of two factors: (*i*) the effectiveness of the change-detection algorithm in the task of accurately identifying and labeling change features, and (*ii*) the suitability of these

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change features for integration with the original reference map (Map_{date1}). As a result, effective change-analysis procedures require high standards of both spatial and thematic fidelity. Previous studies have demonstrated that image registration errors can limit the performance of bitemporal change-detection algorithms (Townshend et al., 1992; Sundaresan et al., 2007), but the impact of these errors on products generated in a raster environment are easily overlooked, since they tend to be masked by the overall *pixelly* appearance of the image. However, the same basic approach to change analysis in an object-based environment is substantially less forgiving. In addition to the long-standing spatial registration errors noted above, new issues related to the consistent delineation of persistent change objects in coregistered raster layers must also be addressed. The problem of error propagation in vector overlay operations is widely known in the geographic information system (GIS) literature (Zhang and Goodchild, 2002) but is one that receives scant attention in the remote sensing community. The issue has become particularly relevant, however, given the recent proliferation of vector map products generated through object-based classification techniques. Although previous research (e.g., Walter, 2004; Desclee et al., 2006) has investigated the use of object-based approaches for *identifying and labeling* change features, the challenges and issues associated with *updating* object-based map products have remained largely unaddressed (but see Blaschke, 2005).

In this note, we illustrate the challenges and limitations posed by change analysis in an object-based environment, and issue a call for a methodological framework for performing and assessing change detection and thematic map update with image objects derived from remote sensing. Specific issues related to the generation of spatial-delineation errors are revealed, and suggestions for their prevention or removal are presented.

Methods

Study area

The study area for this work is located in the west-central portion of Alberta, Canada, along the eastern slopes of the Rocky Mountains (**Figure 1**). The region is subject to a wide variety of natural and anthropogenic disturbance processes, including forestry, oil and gas extraction, mining, road construction, forest fires, and mountain pine beetle activity, and typifies the kind of fast-changing environment in which change detection – map update strategies play a key role in ongoing monitoring initiatives. Within the larger study area, we selected three 13 km × 13 km case-study areas designed to aid our analysis of the extent and implications of spatial delineation errors on map products updated in an object-based environment. The level of change in the three areas varied from low in area 1 (16 disturbance objects covering 231 ha) to medium in area 2 (74 disturbance objects covering 2019 ha) and high in area 3 (149 disturbance objects covering 2576 ha).

Change detection and map update

A series of Landsat Thematic Mapper and Enhanced Thematic Mapper Plus (SLC On) images were acquired to track annual

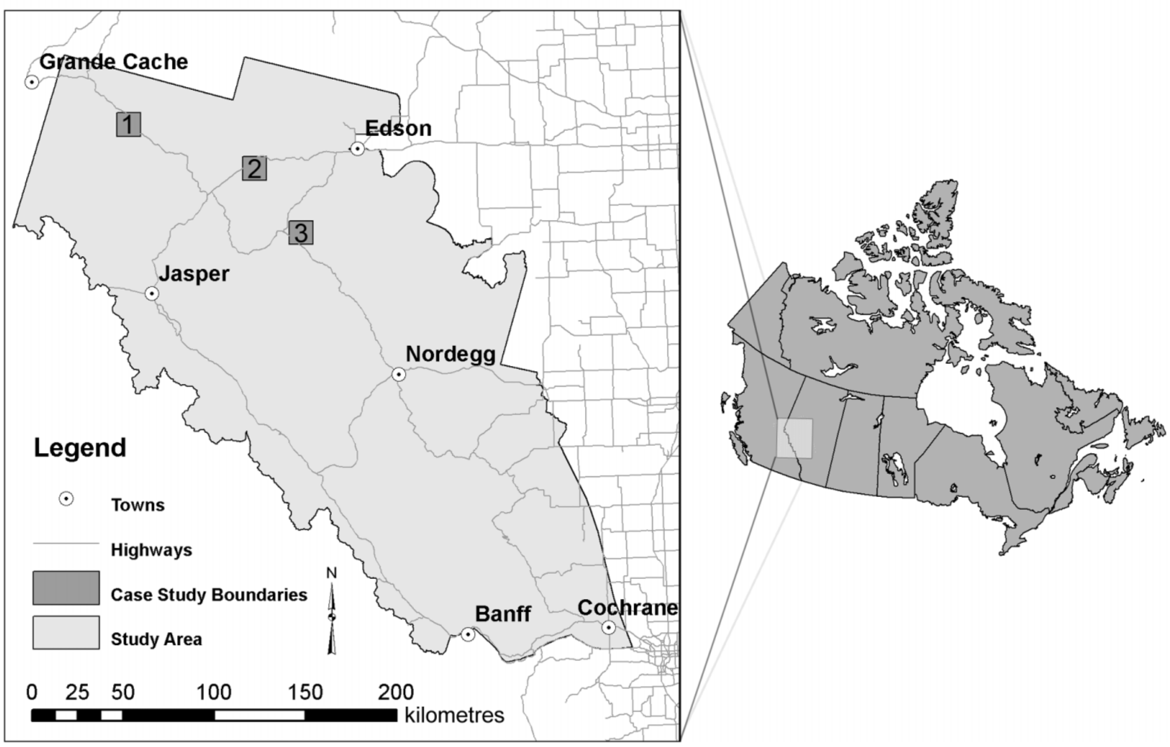

Figure 1. Location of the study area in west-central Alberta, Canada, showing the position of the three case study areas.

Table 1. The impact of slivers on the three 13 × 13 km case study areas, as expressed by the proportion and number of reference change features occupied by slivers.

	Total observed change features		Total reference change features		Total sliver features		Sliver proportion (%)	
Case study area	Area (ha)	No. of features	Area (ha)	No. of features	Area (ha)	No. of features	Based on area	Based on no.
Backdating (2003–1998)								
1. Low change	203	47	231	16	28	31	12.1	66.0
2. Moderate change	1369	147	1415	53	46	94	3.3	63.9
3. High change	1585	296	1667	109	82	187	4.9	63.2
Updating (2003–2005)								
1. Low change	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
2. Moderate change	586	76	604	21	18	55	3.0	72.4
3. High change	853	122	909	40	56	82	6.1	67.2

Note: No change was detected in case study area 1 in the update direction.

change patterns across the study area from 1998 to 2005. Binary change masks were created by manual, analyst-selected thresholding of coregistered tasseled cap (Kauth and Thomas, 1976; Crist and Cicone, 1984) wetness difference images following the enhanced wetness difference index method of Franklin et al. (2001): a strategy that has proven effective for detecting a variety of disturbance agents in similar forested settings (e.g., Skakun et al., 2003; Jin and Sader, 2005). Spectral and topographic values from within the *change* areas were imported to Definiens Professional 5.0 (Definiens AG, 2006) and segmented for further processing. A series of logical decision rules were used to classify the change objects into one of four disturbance categories: cut blocks, mines, burns, and well sites. Disturbance objects were then exported from Definiens Professional to ArcMap 9.2 (ESRI, 2005), transformed to land-cover classes using additional decision rules (e.g., well site = barren; cut block = barren, herbaceous, or shrub, depending on age of disturbance), and spatially mosaicked to create annual update layers. Annual update layers were overlaid on the coregistered 2003 base land-cover map to generate updated land-cover maps for each year of interest. Dates prior to 2003 were said to be *backdated*; those after 2003 were *updated*.

The thematic accuracy of the change features were assessed at two levels: (*i*) change identification and (*ii*) change labeling. Change identification assessed the ability of the algorithm to accurately separate *change* areas from *no change*, using 178 test points evaluated through manual interpretation of temporally coincident, high spatial resolution ortho photos. Change labeling accuracy was assessed with an additional 256 test points distributed in a stratified random sample, allocated proportionally using Hawth's Analysis Tools for ArcGIS (available at http://www.spatialecology.com/htools).

To quantify the geometric nature of the backdated and updated map layers, we compared the finished products with *spatial reference maps* generated within each of the three case-study areas (low change, medium change, and high change). The reference maps were created by removing spurious change objects through manual editing, by way of reference to the relevant Landsat scenes. Differences were noted with simple summary statistics.

Results

Although the results of the accuracy assessment suggested efficient *thematic* performance of the procedure, both in the identification (100% overall accuracy; Kappa = 1.0) and labeling (93% overall accuracy; Kappa = 0.889) of change objects, significant spatial errors were encountered that limited the visual and structural qualities of the final map products. The challenges were caused by spatial differences in the boundary delineation of ground features occurring in both the *base* and *change* layers. Virtually undetectable throughout the entire processing phase, these differences were revealed as *slivers* in the final map overlay, and were present in each of the finished map products. The areal proportion of slivers observed in the three case-study areas ranged from 3% to over 12% of the total reference change areas, representing more than 100 ha of spurious sliver polygons in a single 13 × 13 km case-study area (**Table 1**). The sliver proportion, based on the number of sliver objects, ranged from 63% to 72% of the total reference change objects.

Discussion and recommendations

Our experience and results suggest that bitemporal change analysis and map-update strategies pose substantial challenges when performed in an object-based vector environment, primarily due to spatial errors caused by boundary-delineation mismatches in image objects that appear in both the *change* and *reference* image layers. "Sliver objects" are spurious polygons generated within the overlap zone of slightly different delineations of the same entity, and are a common by-product of polygon-overlay operations (Zhang and Goodchild, 2002). In this application, polygon overlays occur when change objects delineated through bitemporal change detection are overlaid on the reference map to insert (updating case) or remove (backdating case) change features from the base reference map (**Figure 2**). If the delineation of persistent objects in both the reference and change maps are consistent, then no slivers will appear (**Figure 2A**); if persistent objects are mismatched, then slivers will be generated (**Figure 2B**).

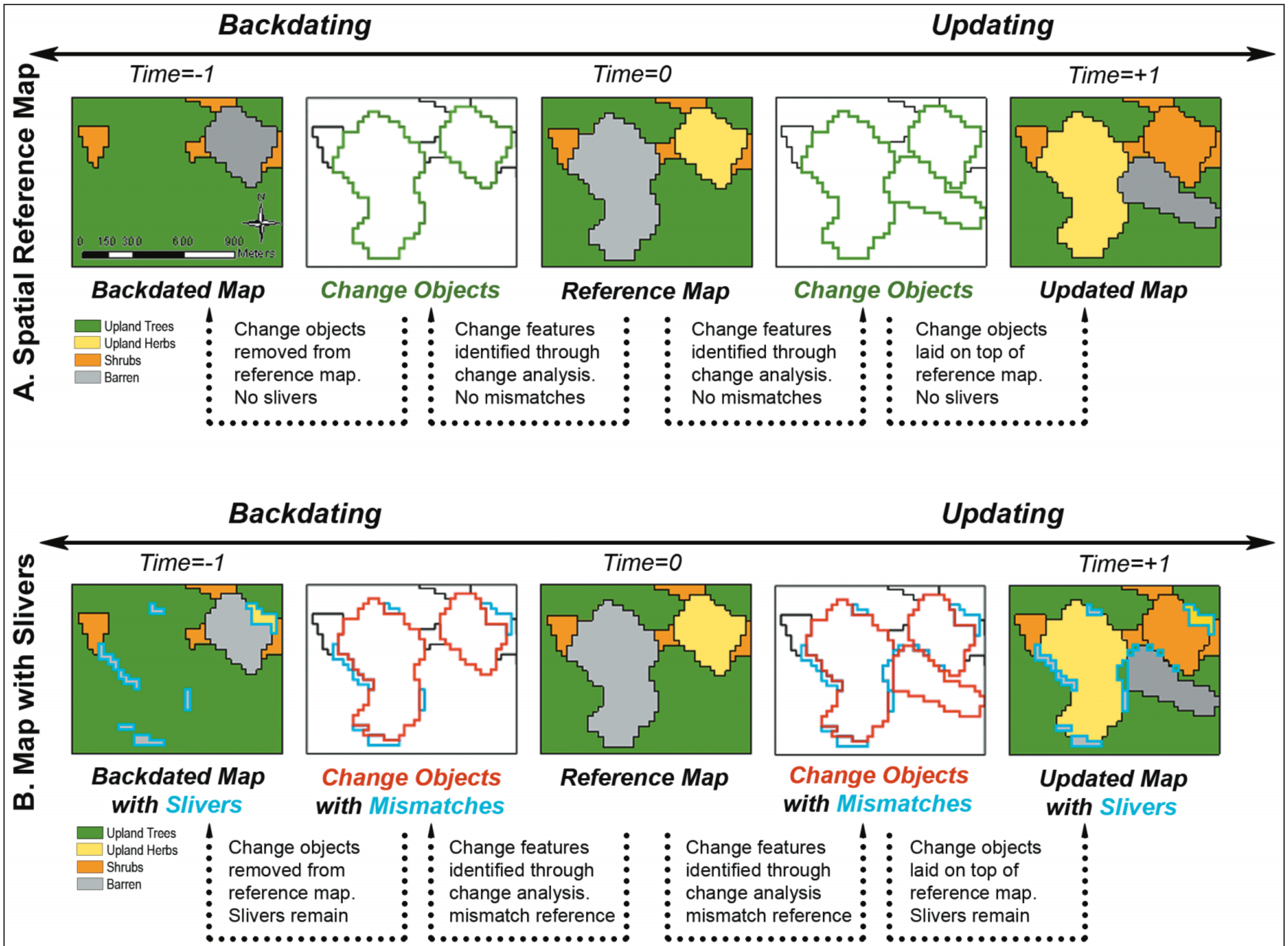

Figure 2. Backdating and updating strategies in an object-based environment. Change objects that do not spatially match their counterparts in the reference map have the potential to generate layers with slivers (B) when compared with spatial reference products (A).

Spatial-delineation mismatches are extensions of familiar segmentation issues commonly experienced in object-based classification analysis, and resemble similar challenges faced by human photointerpreters performing manual polygon delineation (Edwards and Lowell, 1996). Fuzzy boundary transitions are always difficult to characterize with hard polylines, but the problem is compounded by the need to maintain spatial consistency between change objects appearing in more than one image date. For example, if a cut block existing in the reference map at time $T = 0$ appeared as a change object between $T = 0$ and $T = -1$, then any delineation mismatches between the two objects would create slivers in the backdated land-cover map (left side of **Figure 2B**); in other words, little pieces of the cut block that were not properly erased. Slivers also manifest themselves in the update direction in cases where the thematic label of the change object disagrees with the land-cover label of the base map, or where small gaps are introduced between a change object and an existing object in the reference map (right side of **Figure 2B**). Although the results reported here focus on sliver objects generated by 30 m Landsat imagery, we contend that the issue of fuzzy-boundary delineation is not limited to medium-spatial-resolution sensors. Although sliver objects generated by finer-resolution sensors might be proportionally smaller, we would expect the number and overall impact of slivers to remain similar.

Spatial-delineation mismatches represent a difficult challenge to resolve, and arise from the lack of hard boundaries in a world of gradual, fuzzy transitions. Just as two photointerpreters are unlikely to agree on the manual delineation of polygons, automated segmentation algorithms working with two different input images are not likely to produce the exact same result. Since neither delineation is *correct*, strategies must be adopted that minimize the effects of the two interpretations. Two basic approaches present themselves: (*i*) processing for the prevention of slivers and (*ii*) post-processing for the elimination of slivers. Processing strategies designed to eliminate the propagation of spatial errors should adopt the premise that the original *reference* objects are correct, and must be adhered to throughout all subsequent processing activities. Ideally, change detection would take place for the sole purpose of identifying objects in the reference maps that have undergone (backdate) or must subsequently undergo (update) change. Segmentation of the *change* image — if it must occur at all — would strictly incorporate the boundaries of the original objects and only allow for internal adjustments. Of course, boundary errors in the base map would propagate through to the finished product, but the introduction of secondary errors from the change image would be limited. If processing approaches designed to prevent slivers are impractical or unsuccessful, then post-processing routines could be designed to eliminate sliver objects from the final product. Since slivers tend to be both small and occur adjacent to identified change features, then size- and context-specific operators could be applied. The limitation of this technique would be the potential for mistaking real change objects for slivers, and eliminating small-but-important entities from the finished map product. However, if post-processing was restricted to entities outside the boundaries of detected change features (as originally acquired before the updating and backdating routine), then small real change objects could be differentiated from sliver objects. This might well present the most efficient strategy.

Although the issue of sliver creation is well known within the GIS community (e.g., Zhang and Goodchild, 2002), the problem remains largely unreported in the remote sensing literature (but see Blaschke, 2005). With an increasing focus on applications employing time series of land-cover maps to characterize changes in landscape structure, spurious sliver objects have the potential to severely alter measured patterns (e.g., mean patch size, patch density; see Linke et al., 2008 for a detailed analysis of this issue). The results of this note highlight the emerging need for a methodological framework designed to handle the spatial challenges posed by change analysis in an object-based environment, and develop strategies for generating spatially consistent map products suitable for reliable landscape monitoring.

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