SPATIALLY CONSISTENT LANDCOVER MAPS FOR RELIABLE LANDSCAPE MONITORING: AN OBJECT-BASED DISTURBANCE-INVENTORY APPROACH

Julia Linke, PhD Candidate, and Gregory J. McDermid, PhD

Foothills Facility for Remote Sensing and GIScience, Department of Geography,
University of Calgary, Calgary, AB, T2N 1N4, Canada
E-mail: jlinke@ucalgary.ca, mcdermid@ucalgary.ca

ABSTRACT

Landscape monitoring studies often employ metrics to quantify changes in landscape composition (e.g. proportional forest area) and pattern (e.g. edge density, mean patch size), through the analysis of land cover maps arranged in a time series. Remote sensing plays a key role in such studies; however, the approaches for generating multi-temporal time series are not yet fully developed. For example, spurious differences can arise from errors in classification, image registration, scene illumination, resolution, and segmentation; and can substantially impact the monitoring of trends. While much progress has been made in refining classification and change detection in an object-based environment, separating *real* from *spurious* changes is still a complex task, and one that is often performed manually. In this paper, we present a summary of our new disturbance-inventory approach to creating spatially consistent landcover maps through the automated updating and backdating of an existing object-based reference map. With this approach, the final maps are only altered in confirmed regions of change, i.e. detected dynamic objects, and spatial consistency is enforced through boundary-conditioning rules. This approach constitutes an innovative, efficient and transparent framework that is able to produce spatially consistent time series with landscape dynamics ranging from feature appearance, disappearance, succession, expansions and shrinkage, without the need for manual editing.

INTRODUCTION

Landscape monitoring studies often employ metrics to quantify changes in landscape composition (e.g. proportional forest area) and pattern (e.g. edge density, mean patch size), through the analysis of land cover maps arranged in a time series. Remote sensing plays a key role in such studies by providing the data layers and processing strategies from which land cover maps are derived; however, our handling of these data in a multi-temporal time series is not yet fully developed. When analyzing a time series, special emphasis should be placed on land cover maps that are *spatially consistent* through time, so that changes between maps only reflect real changes on the ground. Unfortunately, spurious differences can arise from differential errors in classification, image registration, scene illumination, resolution, and segmentation of the maps from the different instances in time (Yuan and Elvidge 1998; Brown *et al.* 2000, Roy 2000) (Figure 1). If left unchecked, these differences can create *spurious change features* that have a serious impact on landscape metrics (Linke et al. 2009a) and limit our ability to conduct reliable monitoring programs (Shao and Wu 2008; Linke et al. 2009a). While much progress has been made in refining our approaches to classification and change detection in an object-based environment (Walter 2004; Desclée *et al.* 2006), separating *real* from *spurious* changes is still a complex task, and one that is often performed manually (e.g. Blaschke 2005, Gamanya *et al.* 2009) on an object-by-object basis. These very labour-intensive GIS approaches may yield highly precise spatio-temporal databases, but, their accuracy remains challenged by operator inconsistencies, classification differences, and the combined effects of mixed pixels, image mis-registration, and the positional accuracy of the interpretations (Käyhkö and Skånes, 2006, Jansen *et al*. 2006, 2008). We require an efficient approach to creating spatially explicit time series of maps that can represent basic landscape dynamics

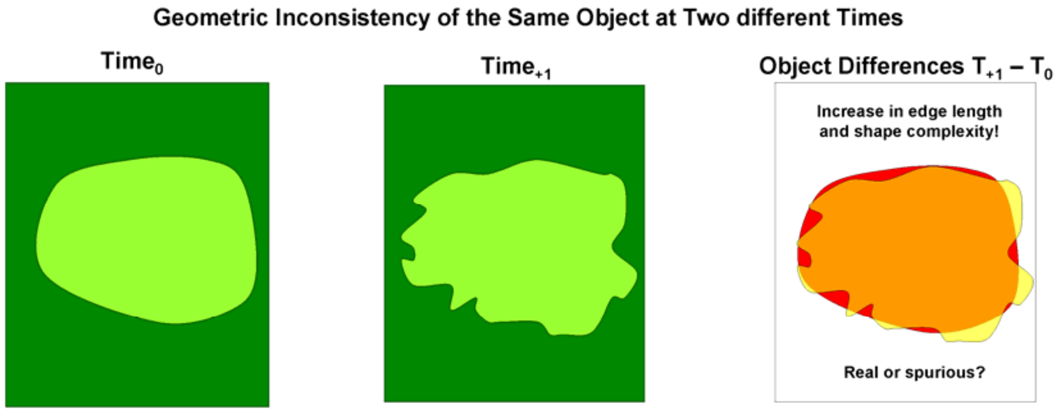

Figure 1. Hypothetical example of geometric inconsistencies observed between two independent classifications of the same object at two different times. The object appears to have increased in edge length and shape complexity, raising the question whether this change is real or whether it is due to differences in classification, segmentation or image registration.

consistently, and provide a reliable foundation for subsequent change analysis.

One strategy for reducing the problem of spurious changes in multi-temporal time series is to avoid classifying each image independently, and proceed instead by updating (project forward in time) or backdating (project backward in time) a single reference map. The strategy is attractive, since it limits analysis to areas where change has been detected, thereby reducing the spatial extent over which spurious changes may be introduced (McDermid *et al.* 2008, Linke *et al.* 2009a). Previous studies employing this updating-backdating approach in an operational monitoring environment have used visual interpretation and manual editing (e.g. Feranec 2000; 2007); a tedious and labour-intensive process. Our research has revolved around the development of an automated approach to creating reliable, spatially consistent land cover map time series through the overlay of thematically classified change objects stored in a GIS vector database: a *disturbance inventory* (Linke *et al.* 2009b). The disturbance-inventory framework to multi-temporal thematic mapping consists of 1) the identification of *dynamic features* over the extent of the multi-temporal study (i.e. objects that appear, disappear, and/or thematically change), and 2) the overlay of these temporally matched dynamic features into a *reference map* (Linke *et al.* 2009b). The basic landscape dynamics that can be represented in the resulting map series are a combination of a) feature appearance, b) feature disappearance, c) feature persistence, and d) feature succession (Linke *et al.* 2009b). Spatial consistency over time is achieved by maintaining the constant positioning of *static features* (i.e. objects that do not change over the monitoring horizon), and performing boundary conditioning routines that ensure the proper delineation and integration of the *dynamic features*. It is the objective of this short paper to provide a summary of how the disturbance-inventory approach is used to update and backdate a categorical landcover map for the purpose of creating a spatially consistent time series (described in full by Linke *et al.* 2009b), and to exemplify how other landscape dynamics, such as feature shrinkage and expansion can be represented using this approach.

THE DISTURBANCE-INVENTORY APPROACH TO BACKDATING AND UPDATING CATEGORICAL MAPS

The disturbance-inventory approach is based on the presence of an existing, object-based landcover map that constitutes the reference for all other derived maps over the specified monitoring time horizon (Figure 2). Therefore, the existing map at the reference year must foremost meet acceptable classification standards. The multi-temporal image stack covering the desired time span forms the basis for detecting forest-replacing disturbances, which are to appear, disappear and/or change in landcover attribute with respect to the reference map. Standard automated bi-temporal change detection techniques (e.g. image differencing and thresholding) between consecutive images (e.g.

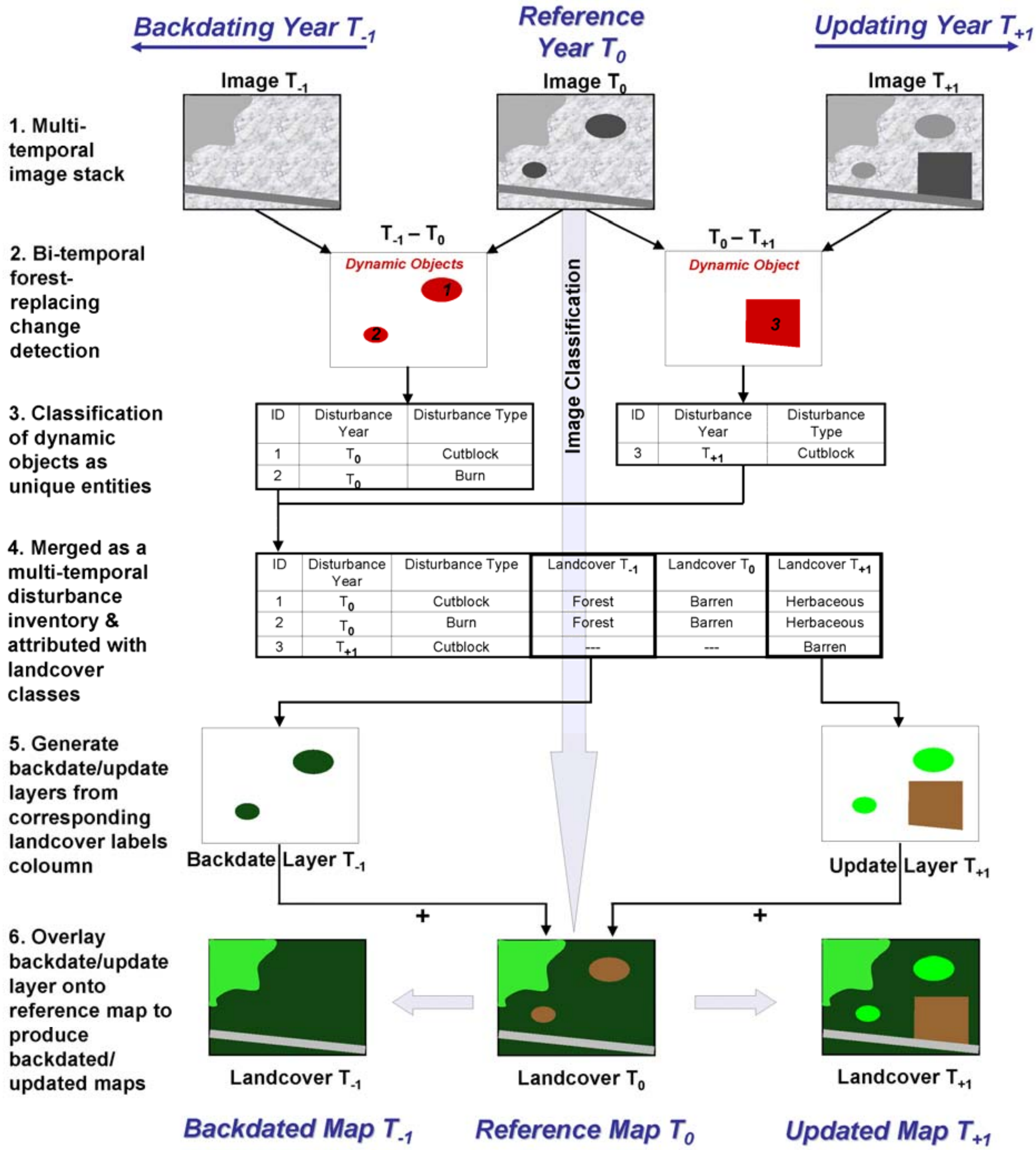

Figure 2. Conceptual framework for the disturbance-inventory approach to generating spatially consistent maps through the updating and backdating of a categorical landcover map (treated as the reference map) at time T_0 over a given monitoring horizon (here T_{-1} to T_{+1}).

T_1 –T_0) yield these regions of change, which are subsequently delineated to create unique entities (i.e. dynamic objects) that can be stored in a GIS database and classified by year of origin (e.g. objects 1 and 2 in T_0) and disturbance type (e.g. objects 1 as clearcut and object 2 as burn) (Figure 2). Starting at the beginning of the time series, the following records are appended to the database to create a multi-temporal disturbance inventory (Figure 2). The disturbance inventory must be compiled according to a spatial overlay order so that dynamic objects overlapping each other (e.g. a new road built through a previously burned area) can behave in a logically consistent manner. Each dynamic object in the inventory is then assigned a landcover class for each year in the time series, consistent with the labels in the reference year. For example, a cutblock that originated in the reference year and hence existed in the reference map (T_0), would need to be backdated with a forest label for the previous year (T_{-1}), and updated with a herbaceous label for the year following (T_{+1}) (object 1, Figure 2). Any dynamic object that originated after the reference year requires dynamic landcover labels in the update direction only (object 3, Figure2). Ideally, these labels should be derived through classification of the images at the respective year, in correspondence with GIS rules that prevent successionally illogical decisions (i.e. classification errors that suggest a dynamic object progresses from barren to forest and back to herbaceous in three subsequent years). Using the landcover labels of the disturbance-inventory as attributes, a *backdate* or *update layer* can be generated which coincides spatially with all the dynamic features relevant for the given year. This backdate/update layer then is integrated with the reference map through GIS overlay routines, thereby altering the existing map only under the regions of change, and hence maintaining the positioning and landcover labelling of all other regions (i.e. all static objects). Since the dynamic objects are only delineated once, they maintain their spatial positioning consistently across the monitoring horizon. Dynamic elements in the final map series can arise only through the alteration of landcover attributes, thereby ensuring spatial consistency throughout.

Boundary conditioning to ensure the seamless integration of dynamic objects

While the basic framework ensures spatial consistency of all static and dynamic objects over the course of the monitoring time span, the final time series is not inherently free of spurious changes. The quality of the map series depends naturally on the accuracy of the detected dynamic features, since both errors of omission and commission will affect the estimates of change between the time series maps. In addition, spatial consistency requires the boundary delineation of the dynamic features to respect those of objects already existing in the reference map (McDermid *et al.* 2008, Linke *et al.* 2009a,b). Since the same factors that affect the post-classification change analysis (e.g. image differences in illumination, classification, registration) also affect the independent delineation of dynamic objects from the consecutive image pairs, it is basically impossible for the delineations of these objects to exactly match their coinciding or adjacent counterparts in the reference map. Spatial inconsistencies can appear when the boundaries of the dynamic features either undershoot or overshoot those of objects in the reference map (Figure 3). These mismatches manifest themselves as slivers, spurious gaps or stretches (Figure 3), or encroachments (Linke *et al.* 2009b).

In order to ensure the seamless integration of dynamic objects, it is thus necessary to define the following boundary conditioning rules: 1) boundaries of the reference objects are correct and must be adhered to, and 2) a minimum mapping width must to be specified to define the maximum allowable deviance below which mismatches will be deemed spurious (McDermid *et al.* 2008, Linke *et al.* 2009a). This threshold value can be determined through visual inspection of the mismatched dynamic objects and objects in the reference map, with reference to the underlying imagery. Once this threshold is set, boundary mismatches can be corrected in an automated way by intersecting the dynamic objects with the reference objects in a GIS, and subsequently trimming or expanding the dynamic objects by the small intersect pieces belonging to boundary undershoots, using proximity and size constraints (Linke *et al.* 2009a,b, Linke and McDermid 2009).

Landscape dynamics in the backdated and updated map series

The basic landscape dynamics that can be represented by the disturbance-inventory approach to backdating and updating are feature appearance (object 3 at T_{+1}, Figure 2), feature disappearance (objects 1 and 2 at T_{-1}, Figure 2), feature persistence (an object which does not change thematically over a time step), and feature succession (objects 1 and 2 at T_{+1}, Figure 2). In each of these cases, the same dynamic object is overlaid onto the reference map, and the object's attribute is the only element that changes. However, there are other dynamics which can be observed on the real ground which can affect the location and shape of a feature. For example a clearcut-harvested area can be *expanded* if an adjacent strip of trees falls down during a windstorm. Alternatively, the very same area could *shrink* in size, if the area was partially planted with trees, thereby reducing the size of the area devoid of trees. As previously described, all dynamic features maintain their geometry and positioning throughout the entire monitoring horizon. Changes in any of these dimensions may be achieved indirectly through the overlay of new dynamic features adjacent to (i.e. feature expansion) or inside (i.e. feature shrinkage) existing reference or dynamic objects (Figure 4). With this overlay approach, all landscape dynamics that originate from a forest-replacing disturbance

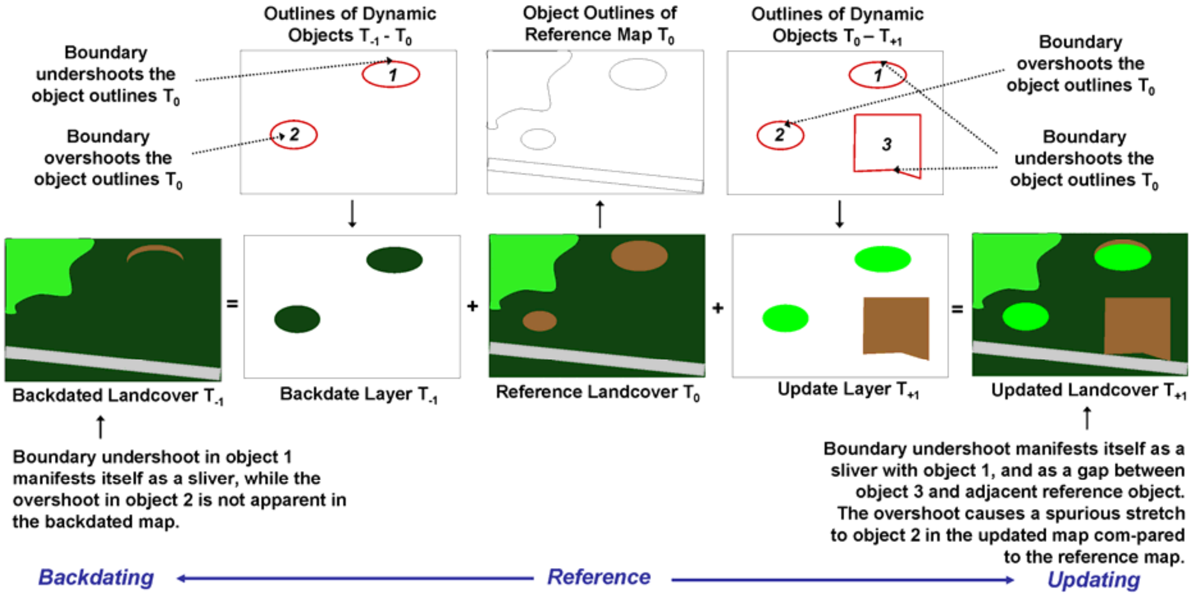

Figure 3. Boundary-delineation mismatches between the independently derived dynamic objects and the objects in the existing reference map (T_0) can introduce spurious changes and hence spatial inconsistencies in the final time series. For example, if the dynamic-object boundary falls short (i.e. boundary undershoot) of coinciding (such as object 1) or adjacent (such as object 3) reference-object, slivers or gaps will appear. If the dynamic-object boundary extends slightly beyond an existing object in the reference map (i.e. boundary overshoot), the object will appear stretched in size compared to the reference map (object 2). (Please note that an overshoot can also create a stretch in the backdate direction if the attribute contrasts with the ones of the adjacent/ or surrounding objects.)

during the monitoring horizon can be represented in the final map series, as long as they exceed the minimum mapping width. Any disturbances that are narrower than the minimum mapping width will be ignored due to the boundary-conditioning needs.

SUMMARY AND CONCLUSIONS

A spatially consistent, temporally dynamic time series of categorical landcover maps can be created by adopting an object-based disturbance-inventory approach to backdating and updating an existing reference map. Spatial consistency is achieved by maintaining stable geometry and positioning of all dynamic objects, and by respecting the reference map boundaries outside the identified areas of change. Temporal dynamics can be manipulated efficiently throughout the entire monitoring horizon by storing disturbance features and attributes in a multi-temporal GIS database. All major landscape dynamics, including feature appearance, disappearance, persistence, succession, shrinkage and expansion can be represented by this approach. The quality of the final product is subject to the accurate detection and classification of dynamic objects, and the adherence of boundary-conditioning rules. Since these rules are based on standard GIS procedures, no manual manipulations are required. This framework can be implemented in an efficient and semi-automated way, and therefore constitutes an innovation to multi-temporal remote sensing map generation.

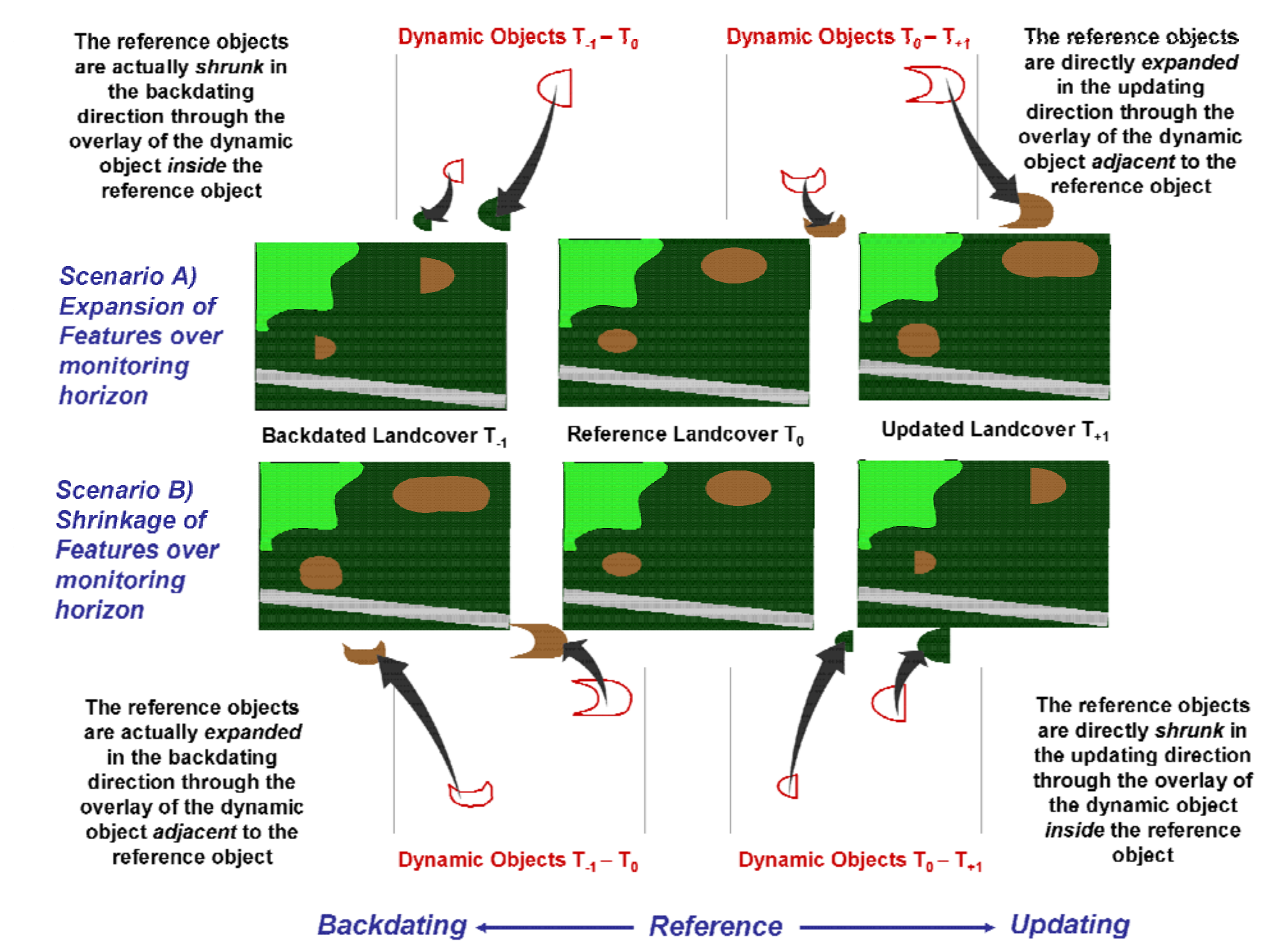

Figure 4. Landscape dynamics such as feature expansions and shrinkages over the monitoring time horizon are achieved by overlaying thematically classified dynamic objects either inside or adjacent to objects delineated in the reference map.

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