A Conceptual Model for Multi-Temporal Landscape Monitoring in an Object-Based Environment

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***Abstract*—Remote sensing plays a critical role in contemporary monitoring programs, but our strategies for processing these data using automated procedures are not always reliable. In particular, the task of separating *real* from *spurious* changes remains problematic, especially in an object-based environment where differential errors in classification quality, spatial registration, scene illumination, resolution, and object delineation have forced some operators to adopt labor-intensive visual-interpretation strategies, or employ manual interaction on an object-by-object basis. In this paper, we present an updated summary of our new disturbance-inventory approach to land-cover monitoring that combines object-based classification and change-detection strategies with boundary-conditioning routines designed to maximize the spatial and thematic integrity of the finished products. With this approach, the final maps are only altered in regions of confirmed change, and spurious gaps, slivers, stretches, and encroachments are avoided. The approach constitutes an innovative, efficient, and transparent framework that can handle all the basic landscape dynamics, including feature appearance, disappearance, succession, expansion, and shrinkage, without the need for manual editing.**

***Index Terms*—Geographic information systems, image classification, object detection, remote sensing.**

I. Introduction

REMOTE sensing plays a key role in contemporary monitoring programs designed to track changes in land use and land cover through time, and in this manner supports a large number of regional [1]–[3], national [4]–[6], and international [7]–[9] efforts aimed at assessing the impacts of human activities and environmental change. In particular, object-based strategies for classification [10] and change detection [11]–[13] comprise a promising set of analytical techniques designed to generate geographic information system (GIS)-ready information layers that integrate easily with existing data sets [14]. However, previous studies have highlighted issues related to the influence of spatial [15], [16] and thematic [17], [18] inconsistencies on multi-temporal change analysis, particularly when performed in an object-based environment [19], [20]. As a result, many operational monitoring programs have opted for more reliable but labor-intensive manual interpretation strategies [21]–[23] which are designed to maximize consistency, though often at the expense of spatial or temporal coverage. There is a strong need for the development and articulation of automated or semi-automated change-detection procedures that reduce labor costs while maintaining the required spatial and thematic integrity.

Landscape monitoring entails the analysis of landscape conditions across two or more time periods in an effort to reveal changes occurring on the surface of the Earth. These changes are generally summarized through landscape pattern analysis (LPA), wherein various metrics are used to calculate transitions in the structural composition (e.g. area of given cover types, diversity of cover types) and configuration (e.g. edge density, interspersion) of land cover through time. The actual measurements are commonly extracted from classified land-cover data, derived from remotely sensed images and stored in a GIS; with—unfortunately—little attention directed towards the effects of map misclassifications [18], [24]. Classification errors in such products may stem from various sources, including radiometric and geometric calibrations, data handling, and analysis procedures [25]–[27]. However, the distribution of errors is not random. Many errors are spatially autocorrelated around the boundaries of map entities, and are largely attributable to data misregistration and/or mixed pixels [28]. It is precisely in fragmented landscapes, with many edges existing between cover classes, where interest in conducting a LPA is highest, therefore causing pronounced concern about the associated errors in these studies [29].

Early research on the impact of uncertainty on LPA, performed on single-date classifications with varying simulated classification errors, demonstrated that landscape metric errors were no greater than the misclassifications themselves, and therefore metrics did not appear to amplify the uncertainty inherent in the underlying base maps [30]. When viewed from a monitoring perspective, however, more recent investigations have shown that the comparison of multi-date land cover maps tends to compound any errors present in the initial classifications, and can therefore yield large amounts of *spurious change* [31] (Fig. 1). For example, Linke *et al.* [20] documented the impact of spurious changes in a LPA of a fragmented landscape in west-central Alberta, Canada undergoing rapid forest conversion from industrial development. In that study, spatial inconsistencies led to serious distortions in the observed trajectory of edge density, mean patch size, number of patches, and

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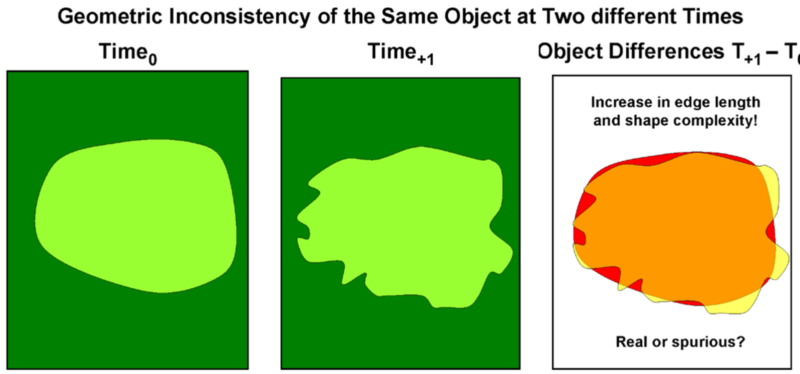


Fig. 1. A hypothetical example of geometric inconsistencies observed between two independent delineations of the same object at two different times. The object at time T_{+1} appears to have increased in edge length and shape complexity in relation to that at time T_0, raising the question as to whether this change is real or due to differences in classification, segmentation, or image registration.

mean shape index through time; a result that supported Langford *et al.*'s [32] assertion that undocumented map errors could undermine the findings of nearly every LPA ever published.

To summarize, effective landscape monitoring requires the use of land-cover maps with high standards of thematic and geometric consistency, so that differences between map dates accurately reflect real changes occurring on the ground. With little doubt, this goal is best achieved through the use of manual procedures performed by skilled photo-interpreters, since the human eye is well-equipped to detect the relatively rare, localized, and spectrally ambiguous events that typically characterize change events [21]. For example, the United States Geological Survey's Land Cover Trends project used manual interpretation strategies to derive "back and forward classifications" from an edited version of the 1992 North American Landscape Characterization for five-year intervals between 1973 and 2000 [22], [33]. However, the labor-intensive nature of such procedures places practical limitations on the scope of the underlying monitoring effort—the Land Cover Trends project was limited to 20-by-20 km sample blocks, for instance—and automated or semi-automated approaches to monitoring that reduce labor costs while maintaining accuracy and consistency remain "the Holy Grail of change detection" [22].

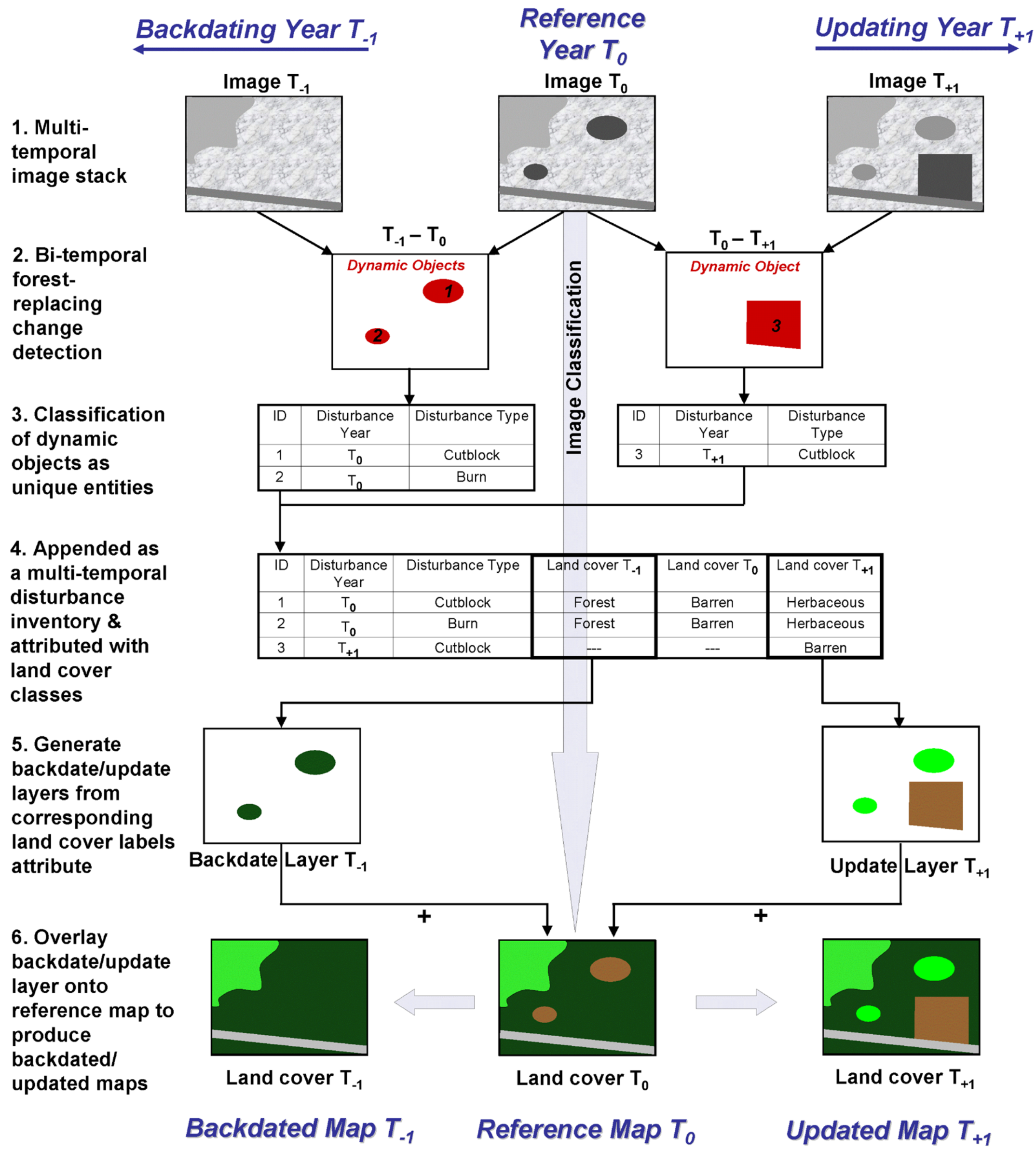
While a great deal of progress has been made in object-based classification and change detection procedures (e.g. [11], [13], [34]), the task of separating *real* from *spurious* changes in operational monitoring programs using automated strategies geared towards wall-to-wall mapping remains problematic. For example, Feranec *et al.* [23] used computer-aided visual interpretation of Landsat imagery to delineate change objects manually across 29 European countries (4.5 million square kilometers) between 1990 and 2000 as part of the IMAGE and CORINE Land Cover 2000 project. The methods were deemed necessary because of the challenges associated with identifying real changes consistently using automated techniques. Faced with similar issues, Gamanya *et al.* [35] relied on manual interaction by skilled operators to deal with spatial inconsistencies in a post-classification analysis of object-based maps used to document changes in the city of Harare, Zimbabwe between 1989 and 2002.

Our research [19], [20], [36] has focused on the development of an automated approach to landscape monitoring that involves creating time series of reliable, spatially consistent land cover maps using object-based processing strategies. Applied correctly, our methods permit the application of LPA and change analysis techniques in a manner that avoids the labor-intensive manual intervention methods documented above. This approach revolves around the identification, boundary conditioning, and integration of thematically classified change objects stored in a GIS vector database: a so-called *disturbance inventory* [36]. In its basic form, the disturbance-inventory framework to multi-temporal landscape monitoring consists of (i) identifying *dynamic features* that occur over the extent of the monitoring horizon (i.e. objects that appear, disappear, and/or change thematically), and (ii) overlaying these features onto a previously classified *reference map* in a manner that represents changes occurring on the ground. The framework can handle all the basic landscape dynamics as represented by the vector (object-based) data model, including *feature appearance*, *feature disappearance*, *feature shrinkage*, *feature expansion*, *feature persistence*, and *feature succession*. Spatial consistency across the time series is achieved by maintaining the constant delineation of *static features* (i.e. objects that do not change over the monitoring horizon), and performing boundary-conditioning routines on dynamic features to ensure their proper integration into the reference map.

The objective of this short paper is to provide an updated summary of the disturbance-inventory framework to landscape monitoring, and describe its use of object-based classification and change-detection techniques for creating a spatially consistent time series. Our presentation here is largely conceptual; readers interested in a more technical description of the framework and its successful sample application to a 40,000 km^2 study area in west-central Alberta over an eight-year time frame are directed to Linke *et al.* [36].

II. The Disturbance-Inventory Approach to Backdating and Updating Land-Cover Maps

The disturbance-inventory approach to landscape monitoring involves identifying and then modifying an existing object-based *reference map* of land cover. By modifying the reference map in areas of documented change, additional maps that represent time steps over the specified monitoring horizon are thereby constructed (Fig. 2). A prerequisite for



ID	Disturbance Year	Disturbance Type
1	T_0	Cutblock
2	T_0	Burn

ID	Disturbance Year	Disturbance Type
3	T_{+1}	Cutblock

ID	Disturbance Year	Disturbance Type	Land cover T_{-1}	Land cover T_0	Land cover T_{+1}
1	T_0	Cutblock	Forest	Barren	Herbaceous
2	T_0	Burn	Forest	Barren	Herbaceous
3	T_{+1}	Cutblock	---	---	Barren

Fig. 2. A flow chart summarizing the conceptual framework for the disturbance-inventory approach to generating spatially consistent maps through the updating and backdating of a categorical land-cover map (treated as the reference map) at time T_0 over a given monitoring horizon (given here as T_{-1} to T_{+1}).

this approach is that the existing map at the reference year T_0 must foremost meet acceptable spatial and thematic quality standards.

In order to facilitate change detection, a multi-temporal image stack covering the desired time span is prepared, and forms the basis for identifying land cover-conversion disturbances, which are to appear, disappear, and/or change attributes with respect to the reference map (Step 1, Fig. 2). Standard bi-temporal change-detection techniques (e.g. semi-automated image differencing and thresholding strategies) between consecutive images (e.g. $T_1 - T_0$ in Step 2, Fig. 2) are used to create a binary *change/no change layer*, which is then segmented to create discrete entities. These change entities are hereafter referred to as *dynamic objects*. Each dynamic object is stored as a unique record in a spatial database with the following attributes: (i) unique identifier (ID), (ii) time of origin (i.e. disturbance year), and (iii) disturbance type (Fig. 2). The time of origin corresponds to the date of the image where the dynamic object first appears, and is important for tracking its age and appearance (i.e., land cover attribute) over time. The disturbance type may be derived from a combination of spectral, spatial, and contextual information using a decision-tree classification approach [36], though other methods are certainly applicable. This attribute is used to infer the land-cover class that the particular disturbance type can assume over time (e.g. a clearcut is initially *barren*, and will eventually become *forest* after a few decades), and may also imply the spatial overlay order of appearance in areas of overlap (e.g. a new road built *on top of* a previously burned area). After each dynamic object has been classified as a unique entity in this manner, all these vector records are appended to one all-inclusive vector database which constitutes the multi-temporal disturbance inventory (Step 4, Fig. 2). The objects in the disturbance inventory are stored in temporally ascending order (e.g. $T_0, T_{+1}, \ldots$), according to their time of origin and spa-

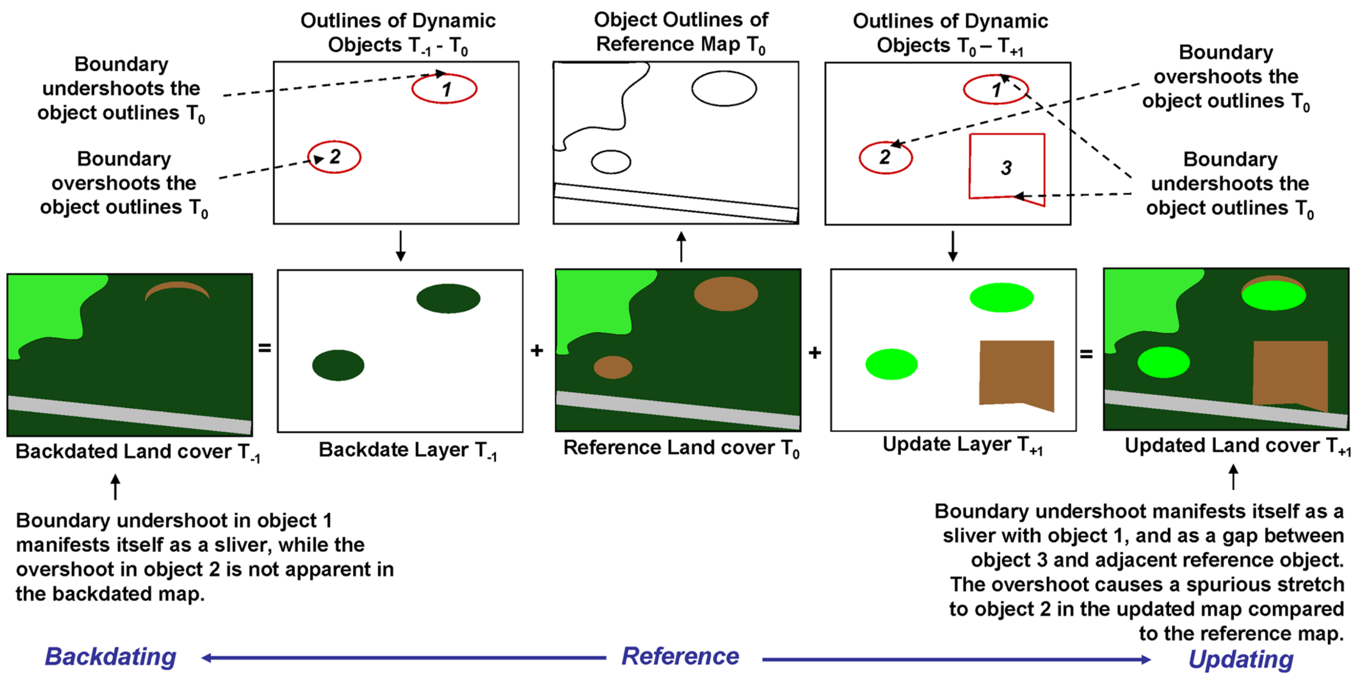


Fig. 3. Boundary-delineation mismatches between the independently derived dynamic objects and the objects in the reference map (T_0) can introduce spurious changes and hence spatial inconsistencies in the final time series. For example, if the dynamic-object boundary falls short (i.e. boundary undershoot) of a coinciding (such as object 1) or an adjacent (such as object 3) reference object, spurious 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.).

tial overlay order. This ensures that dynamic objects, overlapping each other in space and time, can behave in a logically consistent manner. Finally, each dynamic object is assigned a land-cover class for each time step in the series, consistent with the cover class used in the reference map. For example, a *cut-block* that originated in the reference year and hence also existed in the reference map (T_0), would need to be backdated to a *forest* class for the previous year (T_{-1}), and could transition to a *herbaceous* category in the year following (T_{+1}) (object 1 in Step 4, Fig. 2). Any disturbance objects that originate after the reference year require dynamic land-cover labels in the *update* direction only (object 3 in Step 4, Fig. 2). Ideally, these labels should be derived through multi-spectral classification of the images from the respective year, in correspondence with GIS rules that prevent successionally illogical sequences (e.g. classification errors that suggest a dynamic object progresses from *barren* to *forest*, then back to *herbaceous* in three subsequent years). Using the land-cover attributes in the disturbance inventory as legend categories, a backdated or updated map can easily be generated by overlaying the relevant dynamic objects on to the reference map in a GIS (Steps 5 and 6, Fig. 2). Performed properly, the strategy helps maintain the spatial and thematic consistency of the new map (relative to the reference map) by altering only those areas that have undergone change. All other areas of the map (i.e. *static objects*) remain unchanged. In addition, since the dynamic objects are only delineated once, their spatial positioning is maintained consistently across the monitoring horizon. In this manner, dynamic changes in the final map series can arise only through the alteration of land-cover attributes, thereby ensuring spatial consistency throughout.

A. Boundary Conditioning to Ensure the Seamless Integration of Dynamic Objects

While the basic framework outlined above ensures the spatial consistency of all static and dynamic entities over the course of the monitoring horizon, the final time series is not inherently free of spurious changes. The quality of the final map series depends naturally on the accuracy of the detected dynamic features, since both errors of omission and commission will affect the representation of change within the time series. In addition, spatial consistency requires that the boundary delineation of the dynamic features respects those of objects already existing in the reference map [19], [20], [36]. This is a key point that largely determines the spatial integrity of the overall map series. It is practically impossible to delineate objects consistently in images from two or more time periods, even if the corresponding feature has remained perfectly stable on the ground. Subtle differences in illumination conditions, sensor geometry, registration, and segmentation routines conspire to frustrate any attempt to overlay image objects delineated from one scene (e.g. the dynamic objects from one of the binary change/no change layers) onto objects in an existing layer (e.g. the reference map) without creating spatial inconsistencies. The issue arises when the boundaries of dynamic objects undershoot or overshoot those of objects in the reference map—hereafter referred to as a *reference object* (Fig. 3). During the integration of the dynamic objects into the reference map, these boundary mismatches create *intersect objects* that manifest themselves as slivers, spurious gaps, stretches, or encroachments [36]. These map-overlay byproducts are known to cause serious problems in spatial datasets and ought to be suppressed [37].

In order to ensure the seamless integration of dynamic object features, our approach employs the following boundary-conditioning rules:

1) Object boundaries in the reference map are assumed to be correct and must be adhered to [18], and
2) All intersect objects that are narrower than the minimum mapping width (MMW) will be assumed to originate from boundary mismatches and deemed as spurious.

The MMW refers to the minimum width that dynamic objects must achieve in order to be included in the disturbance inventory. The size of the MMW can be determined through visual inspection of a randomly stratified sample of dynamic objects in relation to spatially coincident reference objects and the underlying imagery. Specifically, the analyst overlays the outline of a randomly sampled collection of dynamic objects onto their spatially coincident reference objects (e.g. objects 1 and 2 in Fig. 3). The potential boundary mismatches can be visually evaluated with respect to the two relevant remote-sensing images: one from the time of origin of the dynamic object, and the other from the reference year. If, in the judgment of the analyst, the feature of interest remained unaltered between the two image dates—i.e., no change occurred—then the boundary mismatch in question would constitute spurious change in the final time series. However, if the feature in question has in fact expanded or shrunk between the two time steps, then this boundary mismatch would be indicative of real changes on the ground. By inspecting a number of dynamic objects sampled throughout the monitoring horizon, it is anticipated that the analyst will arrive at a MMW threshold that balances the omission of small disturbance features (larger MMW) against the commission of spurious change slivers (smaller MMW), based on the specific conditions encountered. Once the MMW is set, the spurious boundary mismatches can be corrected in an automated manner by *intersecting* the dynamic objects with the reference objects in a GIS, and subsequently trimming or expanding the dynamic objects by the spurious intersect objects using proximity and respective width constraints [20], [36].

While these boundary-conditioning rules ensure the production of a spatially and temporally consistent time series of land cover maps, they—by definition—also preclude the inclusion of dynamic objects narrower than the MMW. However, if registration errors are kept to a minimum, the MMW should remain within an acceptable range. In an operational application using 30 m-resolution Landsat Thematic Mapper imagery, the MMW is anticipated to not exceed two to four pixels [36], which is comparable to other published photo-interpretation guidelines [22].

It should be emphasized that the time series of maps generated by the disturbance-inventory approach to landscape monitoring is still subject to any spatial or thematic errors that were present in the initial reference map. As a result, it is important to apply this framework to suitable (i.e. accurate) reference maps. If the reference map is of sub-standard quality, it may be necessary to manually correct the thematic and spatial attributes of those reference objects underlying the regions of change, as outlined by the disturbance inventory, before any boundary-conditioning rules are applied. Any errors in the reference map that exist outside the regions of change will not seriously affect the change analysis performed on the generated time series, since they will remain unaltered throughout the framework application. These static errors may lead to a systematic under- or over-estimation of certain land-cover classes or patterns, but should not become compounded across the monitoring horizon. Linke *et al.* [20] explored the propagation of map errors on multi-temporal LPA; interested readers are referred to that work for more information on this important topic.

Since our approach to landscape monitoring assumes that the original base map is correct, any retroactive improvements to that map—the acquisition of new high-spatial-resolution imagery designed to improve the original boundary delineations, for example—would require the creation of a new base map and the subsequent re-construction of the entire time series. In all cases, we encourage the use and reporting of standard accuracy-assessment strategies and statistics [38].

B. Landscape Dynamics in the Backdated and Updated Map Series

A full range of landscape dynamics can be represented using the disturbance-inventory approach outlined above, including (i) *feature appearance* (object 3 at T_{+1}, Fig. 2), (ii) *feature disappearance* (objects 1 and 2 at T_{-1}, Fig. 2), (iii) *feature persistence* (an object which does not change thematically over a time step), and (iv) *feature succession* (objects 1 and 2 at T_{+1}, Fig. 2). In each of these cases, the same dynamic objects (boundary-conditioned) have been used throughout the time series; only the object's land-cover attribute has been allowed to change. However, there are disturbances or succession events that can affect the location and shape of a feature. For example, the boundary of 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. Human activities related to crop production, urban development, and forest harvesting have been documented to simplify the shape of land cover patches, by smoothing and flattening their boundaries [39], and to fragment the forest landscape, causing increases in edge density and decreases in patch size and shape complexity [40]. It could be mistakenly assumed that the boundary-conditioning rules used by the disturbance-inventory approach could preclude the detection of such subtle landscape changes. However, these two additional categories of landscape dynamics—(v) *feature shrinkage* and (vi) *feature expansion*—are accommodated indirectly through the overlay of new dynamic features on top of or adjacent to existing ones (Fig. 4). As a result, any landscape dynamic involving the thematic transition from one land cover class to another can be represented in the final map series, so long as they exceed the MMW.

III. Conclusion

A spatially consistent, temporally dynamic time series of land-cover 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

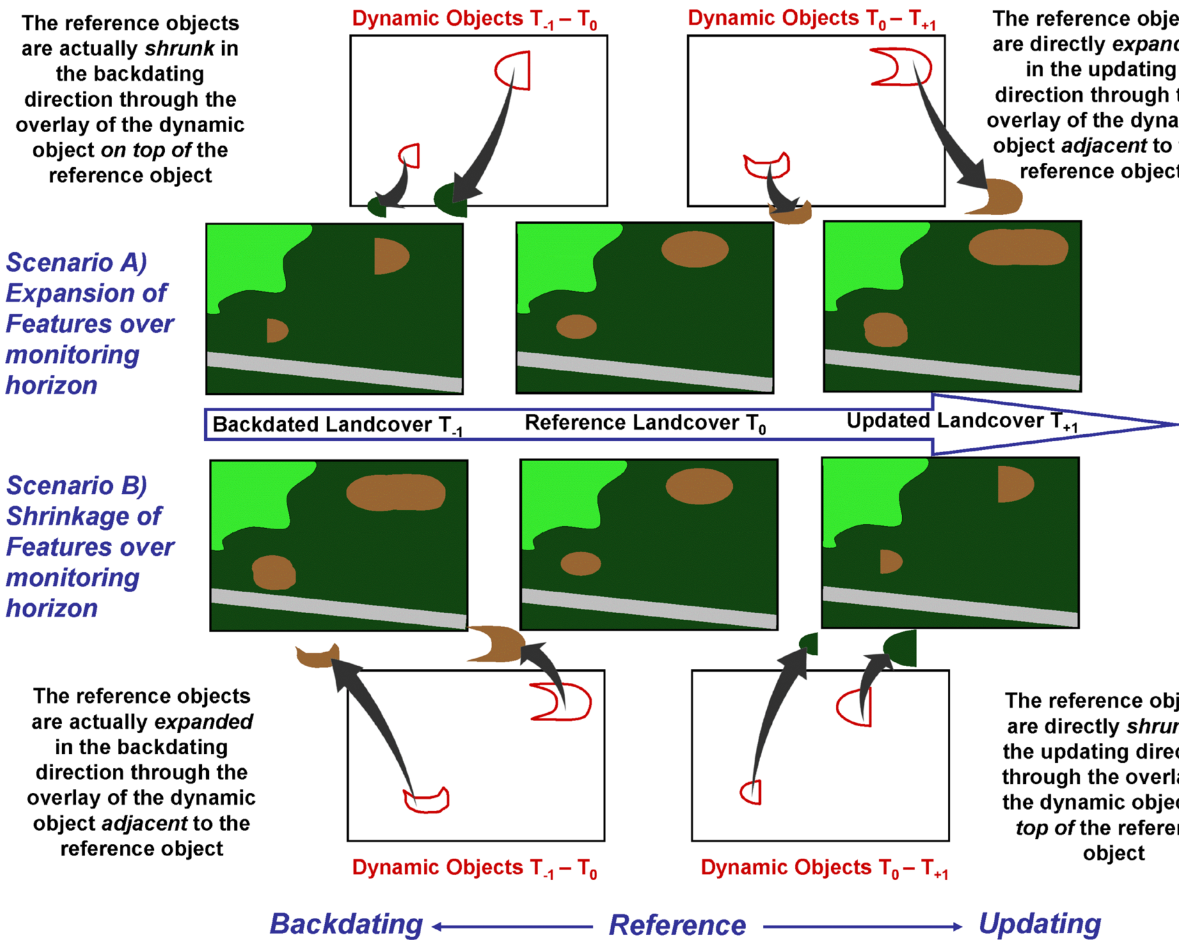


Fig. 4. Subtle landscape dynamics such as feature expansions and shrinkages over the monitoring time horizon are achieved by overlaying thematically classified dynamic objects either on top of or adjacent to objects delineated in the reference map.

captured efficiently across the entire monitoring horizon by storing disturbance features and their respective multi-temporal attributes in a GIS database. All major landscape dynamics, including feature appearance, disappearance, persistence, succession, shrinkage, and expansion can be handled with this approach. The quality of the final multi-temporal product is a function of (i) the accuracy of the reference map; (ii) the efficiency with which dynamic objects are detected, delineated, and classified; and (iii) the degree to which boundary-conditioning rules are adhered to, including the selection of an appropriate MMW. 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 manner, and therefore constitutes an innovation to landscape monitoring and multi-temporal map generation.

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