INCORPORATING CONTEXTUAL INFORMATION INTO OBJECT-BASED IMAGE ANALYSIS WORKFLOWS

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ABSTRACT

Object-based approaches to image analysis have achieved considerable prominence in the last decade and are now widely considered superior to pixel-based approaches, particularly when extracting features from high-resolution remotely sensed data. The oft-cited advantage of the object-based approach is the ability to simultaneously incorporate spectral, geometric, textural, and contextual information into the classification process. However, context has been ignored in many applications of object-based techniques, despite its importance to human cognition and the current technical capacity to accommodate it. We attribute this oversight to reliance on linear approaches to image analysis and argue that iterative approaches, while more complex, can produce more stable classifications and lead to improved accuracy. We provide examples from four recent land-cover mapping projects that show how context - the relative position of individual objects to neighbor objects - was used to improve feature discrimination in heterogeneous landscapes. We also show how this key factor in pattern recognition was combined with data fusion techniques to maximize object discrimination and to exploit existing investments in remote-sensing data (e.g., imagery, LiDAR, and vector GIS datasets). Although inclusion of contextual information in object-based image analysis presents both analytical and processing challenges, we found that the benefits of improved accuracy and landscape representation far outweigh potential costs.

KEYWORDS: Object-Based Image Analysis, OBIA, GEOBIA, Context

INTRODUCTION

The way that human analysts extract information from remotely-sensed data was outlined more than five decades ago by Olson (1960). These principles, now commonly known as the "elements of image interpretation" (EII), include: shape, size, tone, shadow, pattern, texture, size, association, and resolution. Of these EII, three (shadow, pattern, and association) can be considered contextual in nature; they provide clues to the identification of individual features by revealing the composition and distribution of neighboring features. The importance of EII in general and contextual elements in particular have been widely acknowledged; EII have been included in many remote sensing manuals, guides, and operating procedures (e.g., Estes 1977; Nefedow et al. 1969; Philipson and Baker 1997; Tiwari 1974; and Watson et al. 1980). Furthermore, numerous studies from the cognitive science and computer vision fields have confirmed the unique role that context plays in human vision (Bai and Ullman 1996; Balkenius 2003; Biederman 1982; De Graef et al. 1990; Metzger an Antes 1983; Hunderson 1992; Olivia and Torralba 2007; Wolf and Bileschi 2006).

Given the practical reliance on contextual information in traditional photointerpretation workflows, it is perplexing that little emphasis was placed on context when the remote-sensing community moved toward automated classification techniques in the 1970s. Notable exceptions include Moller-Jensen (1990) and Wharton (1982), both of whom developed methods for incorporating context into Landsat-based land-use and land-cover mapping. While these studies were cutting-edge for their time, recent work from the field of computer vision has better demonstrated the benefit of direct recognition and analytical use of context (e.g., Bruzzone and Carlin 2006; Divvala et al. 2009; Murphy et al. 2006; Tu 2008). However, incorporating contextual information into automated workflows, first identified by Barnsley (1997), remains a fundamental challenge to effective use of high-resolution remotely-sensed data.

The most obvious explanation for the limited use of context (along with geometric and textural information) in automated classification approaches has been the traditional reliance on pixel-based approaches, which were largely limited to analysis of an image's spectral properties. Object-Based Image Analysis (OBIA) techniques, introduced more than a decade ago, have eliminated this narrow focus. In OBIA, segmentation algorithms group pixels into functional units called image objects; in addition to spectral information, these units have inherent geometric and textural attributes, with contextual attributes added through iterative processing. The ability to incorporate context is one of the key strengths of OBIA (Hay and Castilla 2006), and numerous studies have shown that OBIA approaches are superior to pixel-based approaches for extracting information from high-resolution imagery (see Blaschke 2010).

Interestingly, many studies that employ OBIA techniques cite context as one of the key advantages of the approach but never actually use it to classify image objects (e.g., Cleve et al. 2008; Kamagata et al. 2008; Mallinis et al. 2008). Numerous other studies make use of context, but in a limited way, through the use of image object hierarchies in which the relative properties of super- and sub-objects are specified in the classification process (e.g., Bruzzone and Carlin 2006; Campos et al. 2010; Durieux et al. 2008; Laliberte et al. 2007; Tullis et al. 2003). Other studies have concluded that context should play an important role in future work (Campos et al. 2008; Hodeson et al. 2003), but do not provide specific guidance on how such an approach would work.

We attribute the limited use of contextual information in OBIA to reliance on linear approaches. In a linear work flow, segmentation algorithms are used to create image objects, which are then classified according to their attributes. Linear approaches to OBIA are appealing, particularly because they permit application of brute-force approaches to image-object classification such as Classification And Regression Trees (CART). However, the contextual EII, particularly association and pattern, can only be obtained through an iterative process in which the identity of some features is used to inform classification of others. In their study of spatial context, Bar and Ullman (1996) supported this iterative approach by concluding that objects, for which the class assignment was known, improved the ability to identify nearby objects for which the classification was unknown. Indeed, the case for an iterative approach to incorporating context is not new in the OBIA community. The oft-cited work from Benz et al. (2004), which provided much of the applied foundation for the OBIA field, supported an iterative approach, as did a subsequent paper from Baatz et al. (2008). Nonetheless, few OBIA studies have successfully incorporated context into iterative work flows (e.g., Oostdjijk et al. 2008), but they generally focus on small study areas.

OBJECTIVES AND STUDY SITES

In presenting practical examples, our objective is to demonstrate the value of incorporating contextual information into OBIA work flows through an iterative approach. While the examples are selective, they come from actual projects that collectively produced more than 100 billion pixels worth of land-cover information. All land-cover products were subjected to detailed quality-assurance/quality-control measures and are now being used by our collaborators to support a wide range of decision making tasks. We do not attempt to quantify the impact of incorporating context on the accuracy of resulting land-cover data, nor do we feel that such an assessment is currently feasible. Rather, we accept the premise that context is vital to successful image interpretation and demonstrate how it can be used to identify features that would be difficult, if not impossible, to isolate accurately using a linear approach.

The four recent projects we cite here are from the Mid-Atlantic region of the United States: The Abingtons region in Pennsylvania, Jefferson County in West Virginia, Lancaster County in Pennsylvania, and New York City. The overall goal in each case was development of a 7-class land-cover map as part of a tree canopy assessment using the USDA Forest Services Tree Canopy Assessment Protocols (http://nrs.fs.fed.us/urban/utc/). To reduce costs and maximize return on existing investments, all projects relied solely on readily-available imagery, LiDAR, and vector GIS data; no new data were acquired. As such, many of the datasets could be considered less than ideal for the task. For example, some imagery contained limited or inconsistent spectral information depending on the time of year it was acquired. Also, the imagery and LiDAR datasets were acquired on different dates and did not always align correctly. Finally, the vector datasets were typically dated and incomplete. Table 1 presents a summary of study site characteristics, pertinent remotely sensed data, and the size of resulting land-cover products.

Table 1. Study sites, source data sets, and size of resulting land cover rasters.

Study Site	Imagery	LiDAR	Vector	Land Cover
Abingtons	Leaf-off, RGB, 0.16m	Leaf-off, 1m	Building footprints, road polygons	716,266,710 pixels
Jefferson County	Leaf-on, NRGB, 1m	Leaf-off, 1m	Building approximations, road centerlines	1,326,091,408 pixels
Lancaster County	Leaf-on, NRGB, 1m	Leaf-off, 1.5m	Building footprints, road polygons	4,776,150,722 pixels
New York City	Mix of leaf-on/off, NRGB, 0.15m	Leaf-off, 0.3m	Building footprints, road polygons	97,528,707,488 pixels

EXAMPLES OF CONTEXT-BASED CLASSIFICATION

The example projects were coordinated by three analysts who collectively have more than 13 years of experience developing OBIA systems. In our approach, the goal was to translate human perception of landscape complexity into a set of rules that segmented the available datasets into functional image objects and then classified them into pre-determined land-cover categories. This rule-based expert system was developed using the Cognition Network Language (CNL), which is available in the commercial OBIA software package eCognition ® (formerly Definiens). CNL was selected because it: 1) provides access to a broad range of segmentation, classification, image processing, and morphological algorithms; 2) relies on a graphical user interface that allows non-programmers to construct rule-based expert systems; 3) permits development of customized features that describe context; and 4) facilitates efficient processing of massive data sets using eCognition Server, which supports parallel processing and grid computing.

Our approach to building rule sets focused on trying to replicate human cognition to the fullest extent possible. In a rule-based expert system, this involves the iterative application of segmentation and classification algorithms until the desired end state (i.e., accurate land-cover objects) is achieved. With iterative processing, the amount of contextual information increases with each successive step in the rule set, progressively quantifying the relationship between an individual image object and its neighboring objects. As more objects are classified, more landscape context is available to classify other, less easily defined objects. Early in processing, we use relatively simple rules to classify the objects in order to divide the scenes into broad categories, often based on thresholds (e.g., spectral thresholds for imagery and height thresholds for LiDAR-derived digital surface models). These initial rules create a series of temporary classifications that presage, but do not necessarily match, the final seven land-cover classes, including “bright” vs. “dark” or “short” vs. “tall.” Later, rules generally become complicated, often combining multiple contextual variables from multiple preliminary classes. Although the final rule set permits automated feature extraction, its development is entirely manual; each algorithm is added to the processing sequence if it approximates a human’s ability to discern pattern among heterogeneous objects. Accordingly, a rule set is conceptually similar to a photointerpretation key; each moves sequentially through a series of decision points that assign features to specific land-cover categories.

Like photointerpretation keys, rule sets can be unavoidably complex. To derive enough contextual information for effective land-cover classification, our rule sets included 362 to 512 separate algorithms and specified 36 to 78 temporary classes. Although the rule sets were generally similar in flow and composition, each was unique to the data sets for which it was designed, and each had to be iteratively tested and refined on small representative subsets. When each rule set was ultimately applied to the full extent of its corresponding study area, 3-6 iterations were required to incorporate additional refinements.

Abingtons

The chief challenge in the Abingtons project was extracting tree canopy from remotely sensed data that were less than ideal for the task. Both the imagery and the LiDAR were acquired in the same year, but at separate times and under leaf-off conditions. Furthermore, the imagery, which consisted of 8-bit, natural color digital orthophotos, contained relatively little spectral information. Nevertheless, we found that experienced image analysts were able to manually delineate tree canopy using a combination of the orthophotos and the LiDAR with at a level of accuracy that exceeded the project specifications.

In assessing the visual cues used in the manual interpretation process we determined that LiDAR was particularly useful in extracting tree canopy, and that contextual information played a key role in distinguishing patches of deciduous tree canopy. Coniferous species and isolated deciduous trees tended to be readily recognizable in the LiDAR due to branching patterns and, in the case of the coniferous species, the presence of needles (Figure 2b). Tree canopy from these classes could be largely be extracted using object attributes obtained directly from the LiDAR such as Z deviation, slope, and height above ground In contrast, deciduous forested patches had no distinct object attributes. The leaf-off and point density characteristics of the LiDAR created a situation in which dense, closed canopy deciduous forest patches appeared in the LiDAR as a sparse collection of trees. We were able to successfully extract these patches though an iterative process.

Figure 1 shows a portion of the CNL rule set that was developed to initially classify these deciduous forested patches (further refinement of the patches occurred later in the rule set, which is not depicted in Figure 1). Although an in-depth explanation of the rule set is not possible within the confines of this paper, there are four general phases that warrant mention. In the first phase, image objects are created through the application of a multiresolution segmentation algorithm. In the second phase the "urban area" was incorporated. The "urban area" was generated early on in the rule set through an iterative process that examined proximity of objects to buildings and roads obtained from the vector layers. This type of a priori contextual information was particularly valuable as deciduous tree canopy patches tended to exist outside of this area. However, some deciduous tree patches did fall within the urban area, but they always bordered tree patches outside of the urban area. The third phase incorporated this knowledge, first identifying tree patches outside of the urban area and then growing those tree canopy patches into neighboring image objects within the urban area using fuzzy logic. In the final phase, image-object hierarchies, proximity analyses, and object comparisons to continually refine the tree patch class. The final classification, shown in Figure 2, demonstrates that a variety of tree canopy types were extracted despite the limited amount of spectral information and widely varying characteristics of the LiDAR data.

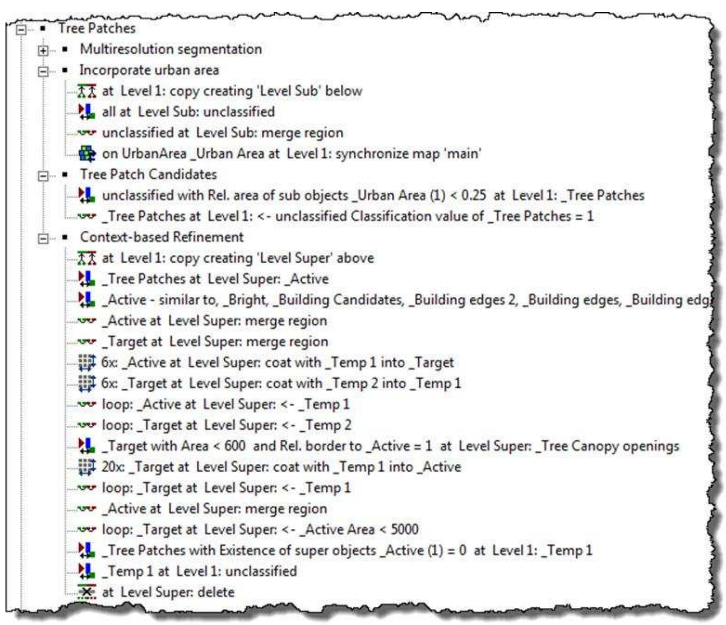

Figure 1. Portion of the rule set for the Abingtons region used to identify deciduous patches of tree canopy through the use of context-based rules.

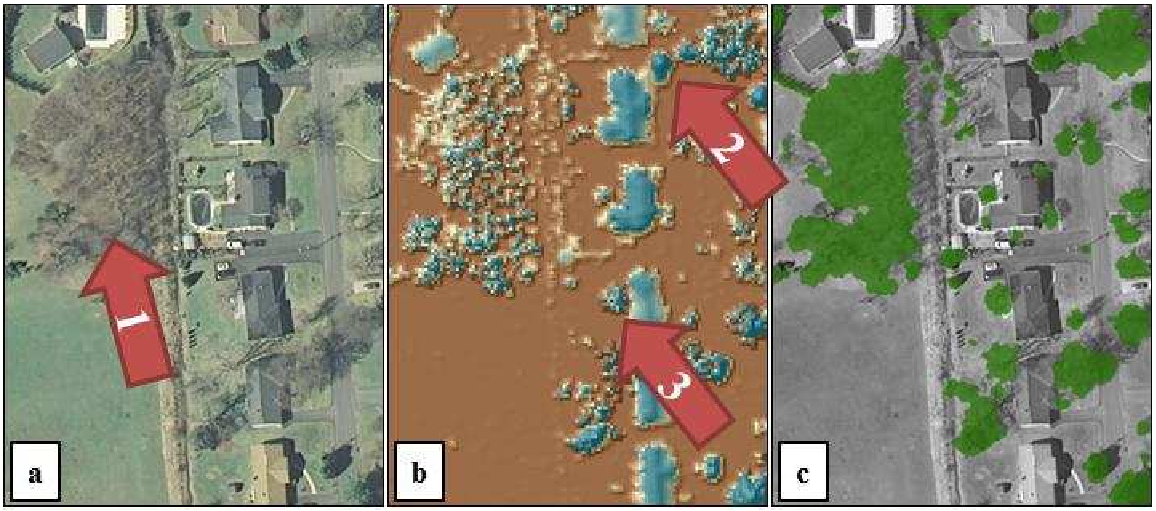

Figure 2. Source imagery (a), LIDAR (b), and resulting tree canopy classification (c) for the Abingtons region. Tree canopy was accurately classified for deciduous patches (1), coniferous trees (2), and isolated deciduous trees (3) using a combination of direct object attributes along with customized iterative context-based processes.

Jefferson County

An iterative approach to OBIA allows contextual information to be used to improve the quality of image objects derived from segmentation algorithms. For the Jefferson County project we developed a technique called "meaningful objects." The underlying rationale for the meaningful objects approach is that segmentation algorithms are inherently flawed, and that the resulting objects rarely resemble the polygons that an experienced imagery analyst would generate through heads-up digitizing. We surmised that this is because humans are simultaneously classifying and segmenting in a single process. By developing a workflow that iteratively combined multiple passes of segmentation and classification routines we were able to generate objects that closely resembled heads-up digitizing, thereby simplifying the subsequent classification of those objects.

The driving challenge for this approach was the spectral similarities between exposed soil in agricultural fields and impervious surfaces. Prior to incorporating the meaningful objects routine we had already been able to classify buildings and tree canopy using a combination of the LiDAR surface models, imagery, and existing vector layers. Thus, the starting point for the meaningful objects routine was all of objects that remained unclassified. The rule set is depicted in Figure 3. The process began with a standard multiresolution segmentation at a fine scale based on only the LiDAR intensity data. Objects were then merged based on the similarity of their mean values in the LiDAR intensity layer and the three imagery bands using a spectral difference algorithm. Next, an iterative routine, starting with the largest object in the scene, would consume neighboring objects based on their spectral and contextual properties. The context-based fuzzy logic used to evaluate the objects for grouping is shown in Figure 4. A comparison of the output from the meaningful objects approach to the output of both a "fine" and "coarse" scale standard multiresolution segmentation is shown in Figure 5.

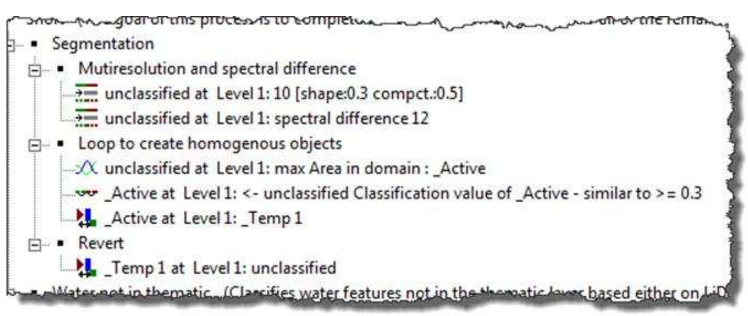

Figure 3. Meaningful objects portion of the rule set form the Jefferson County project.

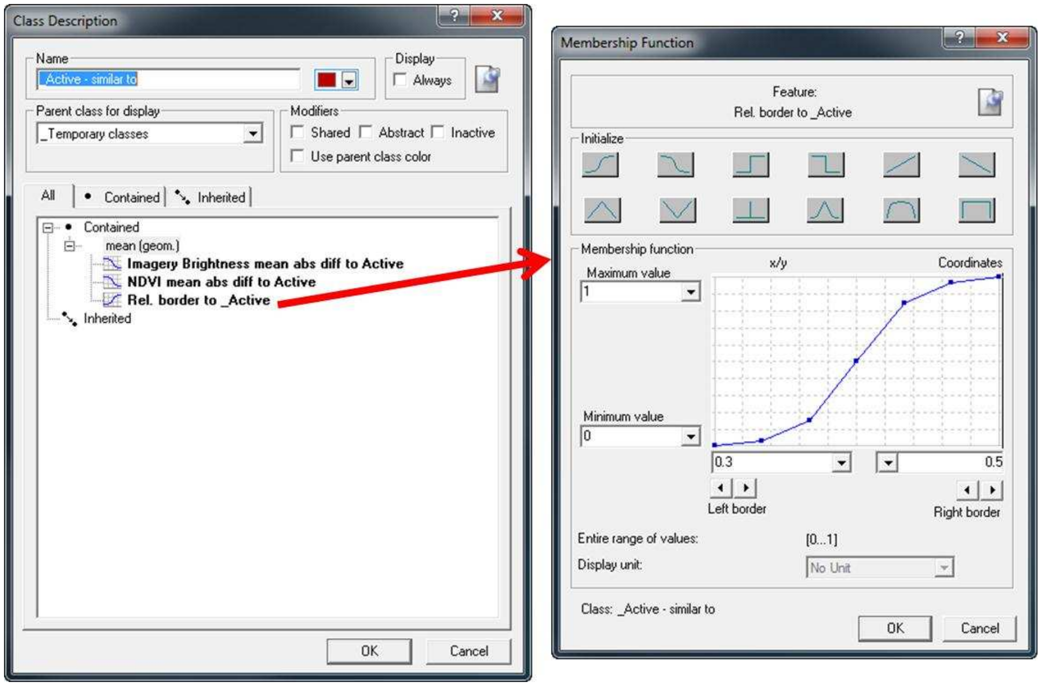

Figure 4. Context-based fuzzy logic used to evaluate image object fusion as part of the "meaningful objects" routine in the Jefferson County rule set. The geometric mean of the mean absolution difference of the brightness and NDVI derived from the imagery, along with the relative border to the active image object were computed. Only those objects whose values met the cutoff threshold were consumed by the "active" image object.

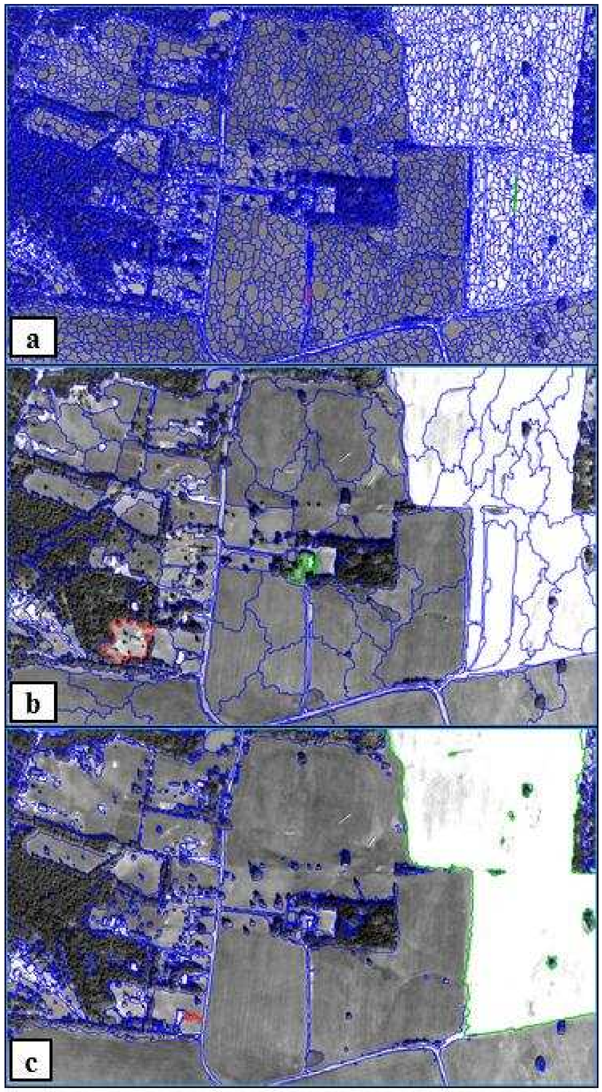

Figure 5. Comparison of objects generated through the application of the multiresolution algorithm available in eCognition to the iterative approach used in this project to generate "meaningful objects" through a combination of segmentation and classification routines. A fine scale segmentation (a) results in the red (driveway) and green (agricultural field) objects having nearly identical spectral and geometric properties, making classification difficult. A coarse scale segmentation (b) yields objects that contain multiple features. The "meaningful objects" routine (c) yields objects that better represent the land cover features, making it easier to classify the objects based on their spectral and geometric properties.

Lancaster County

Bare soils and agricultural fields can be easily misclassified as impervious surfaces because they often share spectral similarities with driveways, sidewalks, concrete bunkers, and other developed features. To avoid this problem in Lancaster County, PA, we used the relative location of buildings and roads as a contextual filter for discriminating bare soils and fields from actual impervious surfaces. Detailed planimetric layers representing buildings and roads were first used to classify these features, then for creating a layer representing the Euclidian distance from buildings and roads to all other features. Initial classification was based on spectral criteria; non-vegetated features were identified using a normalized difference vegetation index (NDVI) threshold (NDVI < 0) and a fuzzy range of imagery brightness (mean of the visible bands ranging from 100 to 185). Subsequent classification was contextual; non-vegetated features that are unlikely to be impervious surfaces (e.g., bare soil or sparsely-vegetated fields) were reclassified to the vegetated class. Specifically, non-vegetated features bordering buildings were retained in the original class (Figure 6b) while non-vegetated features distant from roads (>18.3 m) and buildings (>22.9m) and with a building density >5 were re-assigned to the vegetated class (Figure 6c). This contextual logic is not foolproof; some impervious features may be located far from buildings and roads. However, it is a reasonable assumption for an agricultural area like Lancaster County where a proportion of farm fields will have exposed soil or thin cover.

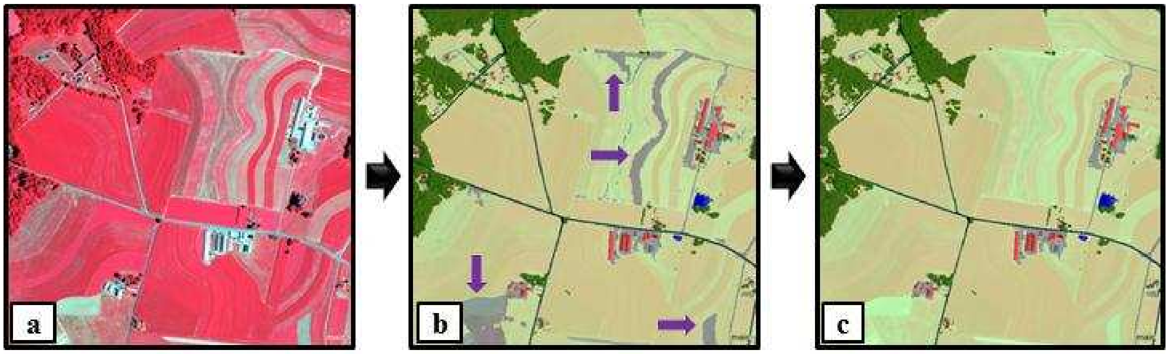

Figure 6. Classification of impervious features from digital orthophotography (a) using spectra resulted in misclassification of agricultural fields as impervious features (b). Contextual information based on the distance of impervious features from buildings and roads, density of buildings, and impervious features neighboring buildings and/or roads reduced misclassification of agricultural fields and bare soils as impervious features (c).

New York City

Landscape context can also be used to identify and eliminate erroneous tree-canopy objects in dense urban settings. For New York City, we used a 0.30-m LiDAR-derived surface model to map canopy vegetation to the scale of individual trees. Like many cities, however, New York contains various above-ground features that can be confused with trees, including lampposts, doorway awnings, and the margins of elevated roadways. If multi-spectral imagery is available, it can be used to develop vegetation indices (e.g., NDVI) that help discriminate these impervious-surface objects from actual tree canopy, but the color-infrared orthophotography (0.15 m) available for New York City was acquired during a series of spring dates that encompassed both leaf-off and leaf-on canopy conditions. Consequently, NDVI could not serve as a reliable city-wide indicator of tree canopy vegetation.

We addressed this problem by examining the location of small tree-canopy objects relative to buildings, roads, and other impervious surfaces. For example, initial classification steps incorrectly identified potential tree canopy adjacent to or above elevated roadways (Figure 7a). A good thematic layer exists for roads in New York City, but elevated roads are not coded separately. Also, we could not simply eliminate all tree canopy objects occurring within the thematic roads layer because we intended to map actual tree canopy when it overhangs roads and other structures. Alternatively, we first isolated roadway surfaces higher than 9.1 m (30 ft) aboveground by comparing roads to a normalized digital surface model (nDSM) derived from LiDAR. We next identified all tree-canopy objects that partly overhang these elevated roads and divided them by the thematic road boundary (Figure 7b). Using size and adjacency criteria, we then eliminated all small canopy objects that directly border the selected roads. Subsequent cleanup steps also eliminated any remaining tree-canopy "islands" occurring on the elevated roads. The final tree-canopy map effectively discriminates actual trees from false objects that are unavoidable artifacts of LiDAR-based feature extraction in complex urban environments (Figure 7c).

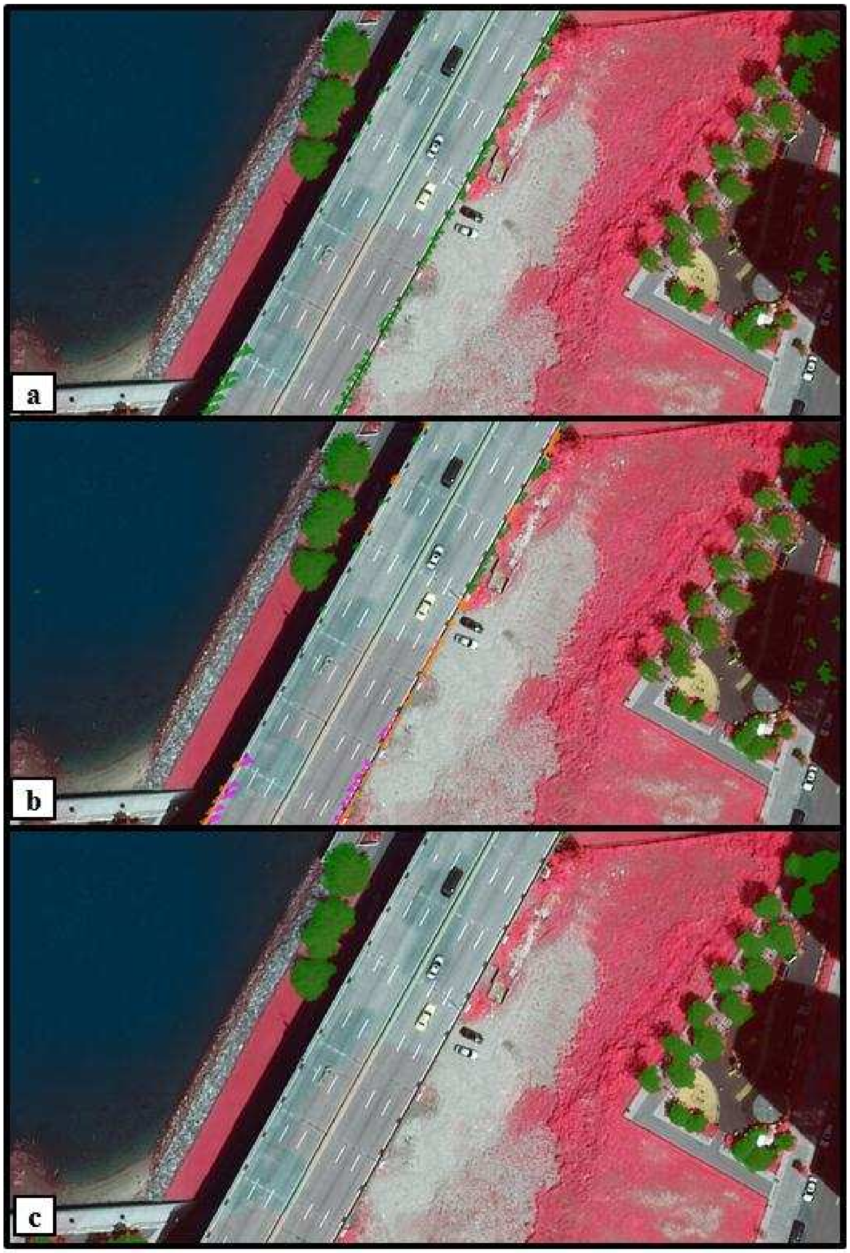

Figure 7. Initial classification of tree canopy on and adjacent to an elevated roadway, New York City (a). Erroneous tree-canopy objects along the road margin must be selected and eliminated while preserving nearby objects that are correctly classified as trees. False tree-canopy objects (orange and magenta) along the margin of an elevated roadway, New York City (b). These objects were identified by size and adjacency criteria. Final tree-canopy classification along the margin of an elevated roadway, New York City (c). All false objects have been removed while preserving nearby objects that correctly represent trees.

CONCLUSIONS

Functionally, context-based processing in OBIA is not altogether dissimilar from traditional statistical classifiers; objects are classified by rules that maximize the probability of correctly distinguishing certain features from surrounding ones. Aside from the focus on objects rather than pixels, the vital distinction is that multiple incremental gains in knowledge derived from earlier processing steps are used to inform subsequent evaluation criteria. Context is thus an emergent property; it is not present in the original source data and must instead be developed from sequential analysis of feature content and relative landscape position.

In our projects, we first classified the features that are easily identified by their own inherent characteristics: spectral value, height, shape, size, vector attribute, etc. If the source datasets were high quality, these initial processing steps generally captured about 70% of individual scenes. However, subsequent processing inevitably became more complex and context-based; objects in the remaining 30% could not be discriminated by their individual characteristics alone, and only through comparison to other objects could they be effectively isolated and classified. This is the same sequence of iterative cognition that humans use in manual photointerpretation. We first focus on features that are immediately familiar to us, such as water bodies, roads, and buildings; these objects anchor our understanding of landscape pattern. For features that are not so readily identifiable, we compare and contrast them with neighboring features, looking for logical connections.

We strongly believe that incorporating contextual information into our OBIA workflows is one of the reasons we have been able to accurately extract information from massive remotely sensed data sets across heterogeneous landscapes. We find it surprising, that despite ample evidence in the peer reviewed literature, few published studies on automated classification approaches in the remote sensing community make use of context. When pixel-based approaches were dominant, this avoidance was understandable as the technology simply was not there. Given the recent advances in OBIA, we theorize that the problem is likely a cultural one, stemming from the slow erosion of imagery tradecraft in favor of linear, statistical approaches. The effective application of OBIA technology will require a workforce that understands the fundamental cognitive processes that allow humans to so effectively extract information from remotely sensed data, not a workforce that simply sees imagery as a set of data points.

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