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An object-based approach to delineate wetlands across landscapes of varied disturbance with high spatial resolution satellite imagery

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Research Highlights:

- GEOBIA and high spatial resolution imagery can detect wetlands with an accuracy over 80%.
- The multi-scale GEOBIA approach is particularly effective for wetland detection.
- Addition of texture, elevation, and NDVI data improves segmentation.
- A higher landscape heterogeneity may negatively affect wetland classification.

Abstract

Mapping wetlands across both natural and human-altered landscapes is important for the management of these ecosystems. Though they are considered important landscape elements providing both ecological and socioeconomic benefits, accurate wetland inventories do not exist in many areas. In this study, a multi-scale geographic object-based image analysis (GEOBIA) approach was employed to segment three high spatial resolution images acquired over landscapes of varying heterogeneity due to human-disturbance to determine the robustness of this method to changing scene variability. Multispectral layers, a digital elevation layer, normalised-difference vegetation index (NDVI) layer, and a first-order texture layer were used to segment images across three segmentation scales with a focus on accurate delineation of wetland boundaries and wetland components. Each ancillary input layer contributed to improving segmentation at different scales. Wetlands were classified using a nearest neighbour approach across a relatively undisturbed park site and an agricultural site using GeoEye1 imagery, and an urban site using WorldView2 data. Successful wetland classification was achieved across all study sites with an accuracy above 80%, though results suggest that overall a higher degree of landscape heterogeneity may negatively affect both segmentation and classification. The agricultural site suffered from the greatest amount of over and under segmentation, and lowest map accuracy (kappa: 0.78) which was partially attributed to confusion among a greater proportion of mixed vegetated classes from both wetlands and uplands. Accuracy of individual wetland classes based on the Canadian Wetland Classification system varied between each site, with kappa values ranging from 0.64 for the swamp class and 0.89 for the marsh class. This research developed a unique approach to mapping wetlands of various degrees of disturbance using GEOBIA, which can be applied to study other wetlands of similar settings.

Keywords: GEOBIA, wetlands, landscape heterogeneity, multi-scale segmentation, high spatial resolution imagery

Introduction

Mapping wetlands across natural and human-altered landscapes is important for understanding their responses to natural and anthropogenic activities, for developing strategies to conserve wetland biodiversity, and to prioritise areas for restoration or protection. While public perception of the conservation value of wetlands has increased over the past century (Brock et al., 1999), wetland loss appears to continue with little abatement and this change requires ongoing monitoring.

The ability to delineate wetlands and monitor changes in a semi-automated, and ongoing manner is important to the management of these ecosystems. A viable approach is the use of satellite remote sensing data, which provides advantages of large area coverage, ongoing data collection, and improved spatial resolution for wetland detection. While a variety of methods to delineate wetlands have been used with varying success (Davranche et al., 2010; Hirano et al., 2003; Schmidt & Skidmore, 2003; Shanmugam et al., 2006), less attention has been given to the applicability of such methods across different landscapes. Urban and rural landscapes represent uplands subjected to disturbance related to increased surface heterogeneity, changes to hydrologic regime, and land cover composition which may affect wetland detection accuracy.

Previous research has demonstrated that wetlands can be detected within upland surroundings, yet a unified approach to mapping wetlands across landscapes of varying complexity has not been identified. Further, fewer studies have included the detection of small and ephemeral wetlands even though pools as small as 0.2 ha represent important, often critical habitat (Semlitsch & Bodie, 1998). In some areas such as the glaciated prairie pothole region of central Canada, almost 88% of wetlands are less than 0.4 ha in area (Halabisky, 2011). Coarser 30 m data such as those from the Landsat constellation require a minimum of 9 pure pixels (0.9 ha) to consistently identify a feature (Ozesmi & Bauer, 2002), resulting in many mixed pixels and small wetlands below this threshold being missed (Klemas, 2011; Powers et al. 2011). At the local scale, protection of small wetlands is vital, particularly for the maintenance of biodiversity (Gibbs, 1993; Semlitsch & Bodie, 1998), and many wetlands in altered landscapes are significantly reduced in size from their former coverage.

While the current cost associated with obtaining high spatial resolution satellite data can be high, the cost is still significantly lower than field surveying or aerial photographs (see Wei & Chow-Fraser, 2007 for a cost breakdown) and provides the advantage of repeat coverage for monitoring over time and the addition of data outside of the optical range (e.g., in the near infrared region). Current work with high spatial resolution sensors has been used to successfully monitor the change in aquatic vegetation in coastal marshes (Wei & Chow-Fraser, 2007), to discriminate between submerged and emergent wetland vegetation (Davranche et al., 2010), and to estimate marshland composition and biomass in riparian marshes (Dillabaugh & King, 2008).

High resolution data provides the needed spatial resolution to capture smaller wetlands, but it also results in greater within-class spectral variance, making separation of mixed and similar land cover classes more difficult than with coarser-resolution imagery (Klemas, 2011; Hu & Weng, 2011). To address this increased variance an appropriate classification method must be employed. In recent decades object based image analysis (OBIA), or geographic object based image analysis (GEOBIA), has gained much attention as an alternative to traditional pixel-based methods. The packaging of pixels into discrete objects minimizes the variance (noise) experienced by high spatial resolution images, allowing the objects, rather than individual pixels to be classified. Past work has found that the object-based approach is preferred over the pixel-based approach for classifying urban areas (Myint et al., 2011; Hu & Weng, 2011), mapping land cover (Whiteside & Ahmad, 2005; Yan et al., 2006), and land cover change (Dingle-Robertson & King, 2011). The object-based approach has also been successfully used in wetland research for classifying macrophyte communities in coastal marsh habitat (Midwood & Chow-Fraser, 2010; Rokitnicki-Wojcik et al, 2011), evaluating the structure of patterned peatlands (Dissanska, Bernier, & Payette, 2009), and mapping multiple classes of wetlands according to the Canadian Wetland Inventory (Grenier et al., 2007). Fournier et al. (2007) reviewed wetland mapping methods to be applied to the Canadian Wetlands Inventory program and identified the object-based approach as most appropriate due to its flexibility and ability to address the spatial heterogeneity of wetlands. Despite past successes in mapping wetland classes and vegetative communities, the majority of previous research has focussed on wetlands by masking out the surrounding upland matrix in order to concentrate on methods of within wetland classification. Yet the ability to delineate wetlands from regions where a previous wetland inventory does not exist, is important for monitoring trends and mitigating further wetland losses.

Approaches to classification have ranged from traditional unsupervised (Sawaya et al., 2003; Jensen et al., 1995) and supervised algorithms (Wang et al., 2004; Yu et al., 2006) including fuzzy methods (Benz et al., 2004; Townsend & Walsh, 2001) and object-based approaches (Blaschke, 2010; Blaschke et al. 2014) to more complex machine learning algorithms such as classification tree methods (Midwood & Chow-Fraser, 2010; Wright & Gallant, 2007) including random forest classification (Corcoran et al., 2013) with some complex models drawing from numerous data layers to discriminate among wetland types (Wright & Gallant, 2007). As a result, it is not surprising that many studies have been devoted entirely to comparing the utility of these different methods (Dingle-Robertson & King, 2011; Duro et al., 2012; Harken & Sugumaran, 2005; Shanmugam et al., 2006) with no general consensus reached on a universal methodology. Similarly, the use of ancillary data in improving wetland mapping accuracy has been demonstrated by the inclusion of LIDAR (Hopkinson et al., 2005) and RADAR data (Grenier et al., 2007) to characterize vegetation height, time series image data for wetland boundary and change detection (Davranche et al., 2010; Johnston & Barson, 1993), and passive microwave data to map flooded areas (Prigent et al., 2001). Understandably, the process of mapping complex and variable ecosystems such as wetlands have led to equally complex approaches.

This paper focusses instead on the variability in landscapes where wetlands are found and applies a parsimonious approach to mapping these features across each variable scene using high spatial resolution 4-band multispectral imagery from WorldView2 and GeoEye1. Here, we employ a constant GEOBIA supervised-classification approach to wetland landcover mapping across three landscapes varying in disturbance from human activity representing a semi-natural park, agricultural, and urban landscape, to determine the robustness of this method across scenes of varying heterogeneity and composition.

Study Area

Three study sites were selected and categorized as natural, agricultural, and urban. As most natural areas have undergone some level of alteration or disturbance, we define the natural landscape and cover types based on criteria adapted from Fahrig et al. (2011) as areas where (1) most primary production is not consumed by humans, either directly or indirectly, (2) the main species of the cover type has an evolutionary or long-term association with that area, and (3) the frequency and intensity of anthropogenic disturbances are low relative to those in agricultural and urban regions. Study sites were further categorized based on population density with an urban area defined as an area of over 400 people/km^2, a rural-agricultural area of less than 400 people/km^2, and a natural site with no permanent human population which was represented by a relatively undisturbed landscape (http://www.statcan.gc.ca/subjects-sujets/standard-norme/sgc-cgt/notice-avis/sgc-cgt-06-eng.htm).

The natural study site is located in the northeast corner of Algonquin Provincial Park (Ontario, Canada), hereafter referred to as the park site, which represents a protected and relatively undisturbed landscape (Figure 1a). The park was established in 1893 and encompasses 7,630 km^2 which includes approximately 340 ha of wetlands of all classes as defined by the Canadian Wetlands Classification System (NWWG, 1997). Logging activity occurs in the study area as well as recreational use by park visitors, though the study site is located in a less heavily visited section. The agricultural site is in the County of Brant (Ontario, Canada) which sits within the Grand River watershed and is located approximately 130 km west of Toronto, supporting a population of 35,000 people (Figure 1b). Provincial and private roads bisect the agriculturally dominated landscape and surround the Oakland Swamp, an 890 ha wetland of provincial significance. Several smaller wetlands of variable size and shape are also distributed throughout the study area. The urban study site encompasses the eastern portion of Toronto and the adjacent city of Pickering (Figure 1c). Toronto is the largest city in Canada and supports a population of 2.79 million people, and a greater Toronto area (GTA) population of 5.5 million. The study site includes the Rouge Urban National Park, a federally-governed urban recreation area covering roughly 6300 ha and bounded along its western and eastern border by dense urban development including roadways that cross over and through the park interior. A dense pocket of wetlands can be found in the southernmost portion of the park near the Lake, and several smaller wetlands are also scattered within the northern portion of the park and in the adjacent urban and rural regions, including several recently restored wetlands. This urban park receives thousands of visitors annually and its interior is bisected with pedestrian and bike pathways.

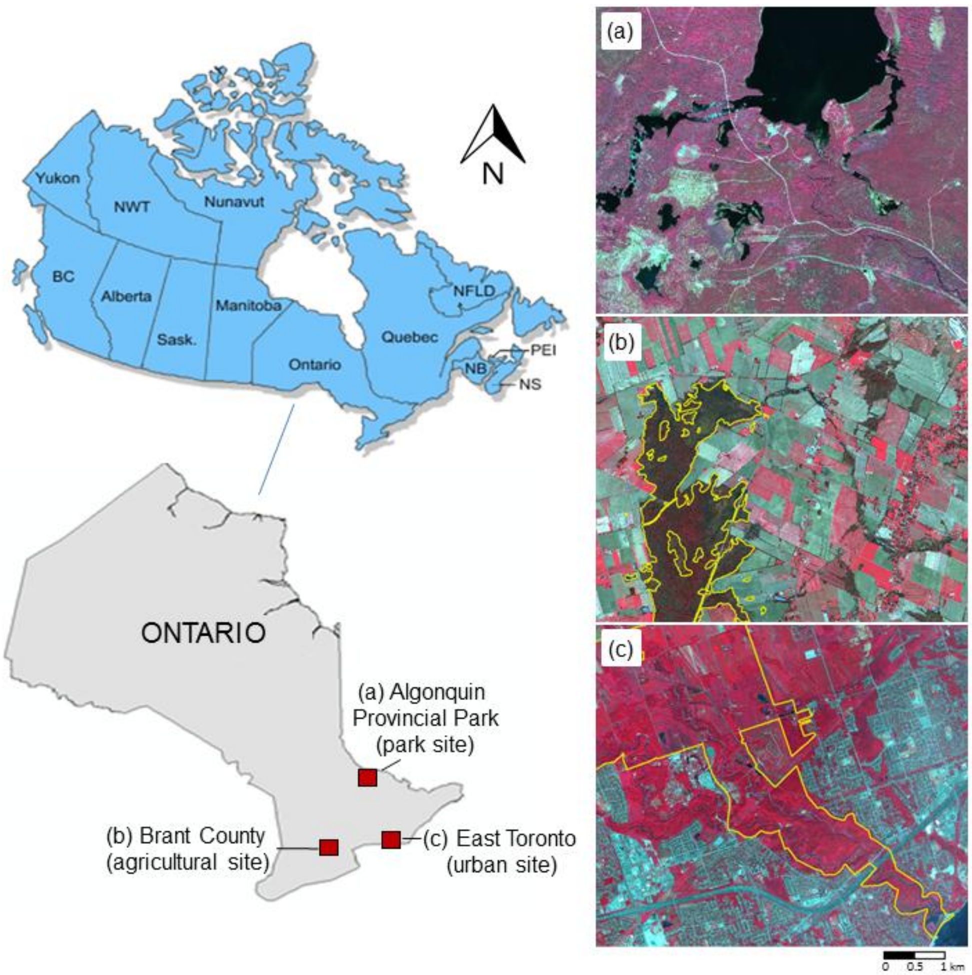

Figure 1. Study areas across southern Ontario, Canada in (a) Algonquin Provincial park site, (b) Brant County agricultural site, and (c) east Toronto urban site (satellite images from GeoEye1 [a,b], and WorldView2 [c] shown in false colour RGB=NIR-red-green). Yellow polygons indicate the provincially significant Oakland swamp [b], and the boundaries of the Rouge Urban National Park [c].

Data and Methods

We employed a multi-scale GEOBIA approach to segment images, which were then classified using a supervised nearest neighbour method (Figure 2). Multiple input layers were utilised during image segmentation with both qualitative and quantitative measures used to select and evaluate the resulting image objects.

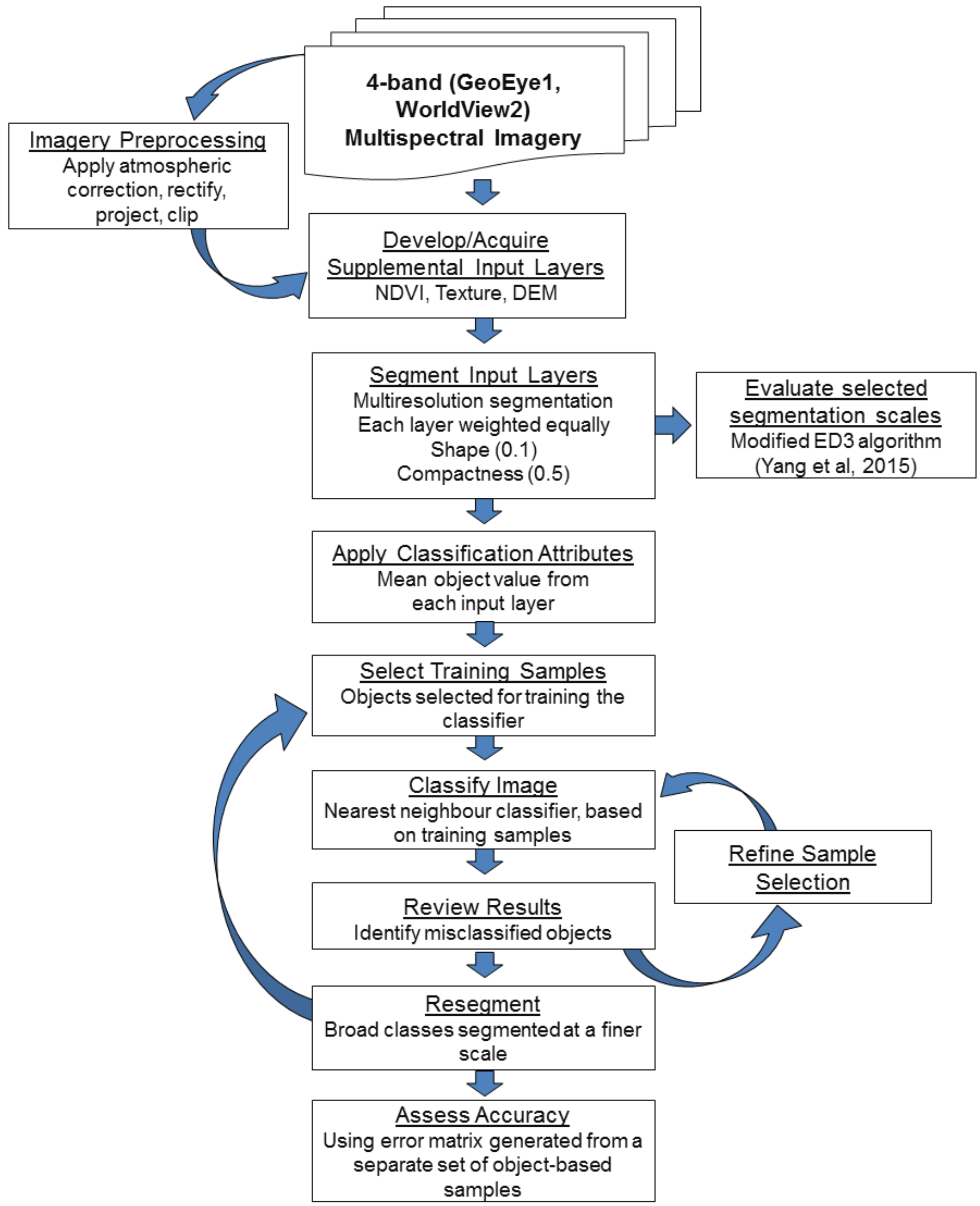

Figure 2. Process framework for segmentation and classification of wetland landscapes

Satellite imagery and preprocessing

High spatial resolution data from WorldView2 and GeoEye1 sensors were acquired over each study site (Table 1). Each scene covered 40 km^2 and contained natural segments (unmanaged forests, wetlands, open water), built segments (paved roads, commercial, residential and urban structures), and altered natural components (agricultural crops, dirt roads) in varying proportions. All three study areas were located in southern Ontario (44^{o}00’N 80^{o}00’W) which covers a core area of 126,819 km^2. Full deciduous leaf-on conditions are typically reached by the end of the month of May or beginning of June. Leaf-off conditions generally occur by late October or early November. All effort was made to acquire imagery from the same sensor over all study sites, however coverage with high resolution satellites is rarely complete and data from a single sensor did not cover all three study areas.

Table 1. Satellite Image data information

Sites	**Rouge Park (urban site)**	**Algonquin Park (natural site)**	**Brant County (rural site)**
Acquisition date	25 July 2012	25 May 2013	9 April 2012
Sensor	WorldView2	GeoEye1	
Spatial Resolution (m)	2 m multispectral		
Spectral Resolution	Blue (450-510nm) Green (510-580nm) Red (630-690nm) Near infrared (770-895nm)	Blue (450-510 nm) Green (510-580nm) Red (655-690nm) Near infrared (780-920nm)	
Radiometric Resolution	16 bits		

All images were radiometrically normalized using the ATCOR module implemented through PCI Geomatica (PCI Geomatica, 2014), and projected to the Universal Transverse Mercator projection datum (NAD83, UTM Zone 17). The scenes were georeferenced to a root mean squared error of less than 2 pixels using a 1^{st} order polynomial transformation and nearest neighbour resampling method, and clipped to the same extent using ArcGIS version 10.2 (Environmental Systems Research Institute, Redlands, CA, USA). The panchromatic layer was not used, as it increased processing time to unrealistic lengths.

Feature development

Seven features (or input layers) were used for image segmentation including four multispectral layers (blue, green, red, and near infrared), a DEM layer, an NDVI (normalized difference vegetation index) layer, and a standard deviation texture layer.

A 10-m digital elevation model (DEM) was acquired from the Ontario Ministry of Natural Resources (Figure 3a) which was interpolated from an DTM (digital terrain model), a contour map, spot height data, and a water virtual flow map to a ±10 m vertical precision. The DEM for each image scene was resampled to 2 m to match the resolution of the other input layers. Resampling the DEM did not provide any additional information but ensured continuity in pixel size across all input layers and avoided a coarser resolution affecting the boundaries of image objects. Elevation was included as an input layer because wetlands and water bodies are known to sit topographically low in the landscape due to their close association with ground water and surface run-off (Mitsch & Gosselink, 2000). Other elevation-related input layers such as slope and aspect were originally included, but were discarded as they did not contribute any additional information.

Texture information refers to the spatial variation in the spectral brightness of a digital image, and has a high potential for revealing differences between classes in remotely sensed imagery (Berberoğlu et al., 2007). Texture measure can also be derived directly from satellite imagery, and do not require the acquisition of additional data. For this study we created a first-order texture layer (Figure 3b) based on the standard deviation within a 3 pixel by 3 pixel moving window. A 3 by 3 window was selected as they most likely to cross spatial resolutions with the least areal effects (Ryherd & Woodcock, 1996).

NDVI is a well-established indicator of live green vegetation (Rouse et al, 1974). An NDVI layer was thus created from the red and near infrared bands of the multispectral data to separate water from dry land, and delineating wetland boundaries (Ozesmi & Bauer, 2002) (Figure 3c). Other input layers such as slope and aspect were originally included, but were discarded as they did not contribute any additional information. All final image layers were weighted equally in the segmentation process.

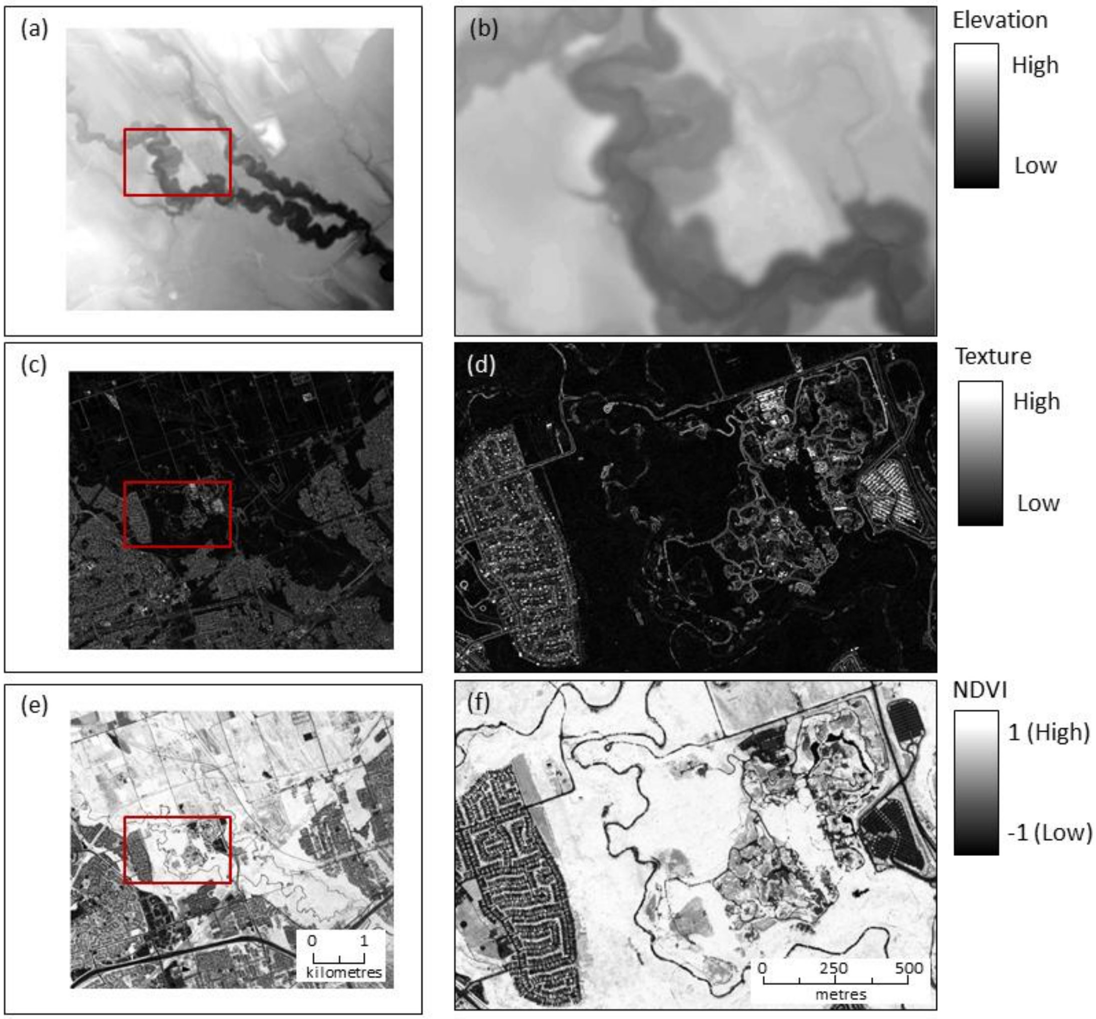

Figure 3. Subset of input layers from the urban site of eastern Toronto showing (a) a digital elevation model layer, (b) a standard deviation texture layer, and (c) an NDVI layer

Image segmentation

Segmentation is a key aspect of GEOBIA relating to the ultimate quality of the final classification (Baatz et al., 2008) and its optimal result is a scene segmented into objects that reflect real-world features of interest. This study employed a multiresolution segmentation algorithm based on the fractal net evolution approach (FNEA; Baatz & Schape, 2000) implemented in Definiens Developer 7.0 (Munich, Germany; Definiens, 2008, formerly eCognition).

Three key segmentation parameters - shape (S_{sh}), compactness (s_{cm}), and scale (S_{sc}) - control the size, shape and spectral variation of segmented image objects. Shape parameters were set to 0.1 to place greater emphasis on pixel values of input layers rather than shape, and compactness was set to 0.5 to balance both compactness and smoothness of object boundaries equally. The most critical step is the selection of the scale parameter which controls the size of the image objects. The scale parameter sets a threshold of homogeneity which determines how many neighbouring pixels can be merged together to form an image object (Benz et al., 2004).

In this paper, we applied a multi-scaled segmentation approach that utilized three levels of scale parameterization to capture different landcover classes (Figure 4). Dominant landcover classes that covered the majority of the scene were segmented at the coarse level, while remaining classes were delineated at the medium level. Entire wetlands were segmented and defined as objects at the mid-range scale, and further segmented at the finest scale level to delineate components within wetlands and classify these as marsh, swamp, fen or bog. These smaller (child) objects retain links to their larger (parent) class which employs a true multi-scale approach through applying vertical constraints in segmentation and classification. Classification for specific landcover classes was thus completed at each scale level, with remaining unclassified objects undergoing further segmentation, followed by classification. A thematic road network layer was available for each scene and was used in the segmentation process.

We first employed a qualitative visual approach to select the scale parameter at each level (coarse, medium, and fine). At the medium and fine segmentation level this ensured that the optimal scale parameter for wetlands was selected by drawing upon knowledge of the study areas, and based on the premise that the human eye is best capable of interpreting and recognizing complex patterns in conjunction with neighbourhood context (Benz et al., 2004; Myint et al., 2011). This approach is especially fitting for wetlands that can be highly variable in both size and shape. Scale values ranging from 5 to 250 with an interval of 5 were evaluated for each image and final scale selection was guided by field knowledge, thematic maps and aerial imagery.

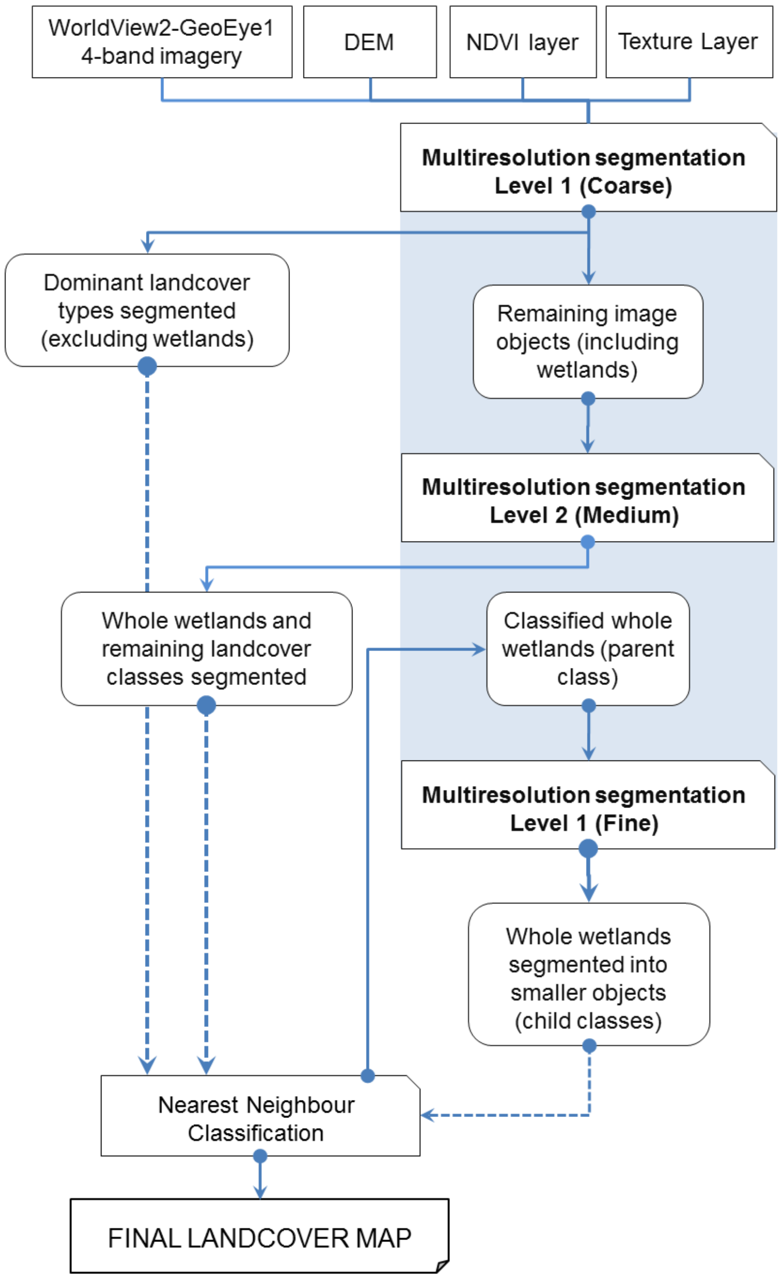

Figure 4. Multi-scale segmentation process used to segment images at three levels, with a hierarchical parent-child relationship developed between wetlands and within wetland components at the medium (level 2) and fine (level 1) scale.

This selection was then quantitatively evaluated using the modified ED3 discrepancy measure of Yang, He, and Weng (2015) based on global geometric and arithmetic relationships (e.g. over-under segmentation) between hand-digitized reference polygons and corresponding segments produced by the multiresolution segmentation algorithm. This multi-band scale parameter evaluation method allows identification of multiple appropriate scale parameters, where a candidate segment will be labelled as the corresponding segment of a reference polygon only when the overlapping area is over 50%. Results are normalized between zero and 0.71, with lower values indicating a higher segmentation quality (Yang et al., 2015). Multiresolution segmentation results between scale values of 5 to 200 (intervals of 5) were compared to a set of manually delineated reference polygons at each scale level (coarse, medium, fine), and for each image. A total of 30 reference polygons per scale level were used in the analysis. There are multiple quantitative and automated approaches to selecting the scale parameter including automated parameterisation using the potential of local variance to detect scale transitions (Drăguţ et al., 2014; Drăguţ et al., 2010), supervised methods that use various indices to describe the discrepancy between reference polygons and corresponding image objects (Clinton et al., 2010; Liu et al., 2012), and a comparison index using both topological and geometric object metrics (Moller et al 2007). However, there is no perfect algorithm that is appropriate for all images (Munoz et al, 2003) and a certain element of trial, error, and repetition is inherent to the overall process of scale selection and evaluation.

Sample selection and classification

Our final classification scheme was based on the land cover and land use classification system developed by Anderson et al. (1976). Specifically, we aimed to classify our study areas into following classes: agricultural land, barren land, forested upland, herbaceous upland, urban matrix, water, and wetland (Table 2). Wetlands were broadly defined as land that is saturated with water for a period of time sufficient to promote wetland or aquatic processes resulting in characteristics such as poorly drained soils, hydrophytic vegetation, and other biological activity adapted to wet environments (NWWG, 1997). According to the Canadian Wetland Classification System (NWWG, 1997) wetlands were further classified as marsh, swamp, bog, or fen (Table 3). All wetland classes were found in the park study site, while only marshes and swamps were found in the agricultural and urban locales.

Table 2. Landcover class descriptions adapted from Anderson et al, (1976) and the Canadian wetland classification system (National Wetlands Working Group, 1997)

Class	Description
Agricultural Land	Land used primarily for production of food and fiber (e.g., Row crops, bare (idle) fields, shaded crops; groves; orchards)
Barren Land	Land of limited ability to support life; less than one-third of the area has vegetation or other cover (e.g., sands, rocks, thin soil)
Forested Upland	Closed canopy deciduous , coniferous, or mixed forests
Herbaceous Upland	Land where vegetation is dominated by a mix of grasses, grass-like plants, forbs, shrubs or bush; either naturally-occurring or modified (e.g. old fields, roadside vegetation, meadows, mixed composition short vegetation upland)
Urban or Built Matrix	Areas of intensive use with much of the land covered by man-made structures (e.g., residential, commercial, industrial, utility, and transportation sites such as those found in cities, towns, rural communities and strip developments)
Water	All areas that are persistently water-covered (e.g., lakes, reservoirs, streams, bays, estuaries)
Wetland	Bog, fen (or wet meadow), swamp, marsh, shallow open water

Table 3. Wetland land cover class descriptions according to the Canadian Wetland Classification System (NWWG, 1997).

Class	Description
Bog	A peat landform, raised or level with the surrounding terrain and isolated from runoff and groundwater, receiving water primarily from precipitation, fog, and snowmelt. Water table sits at or slightly below the bog surface. Treed or treeless, and usually covered with *Sphagnum* spp. and shrubs, or woody remains of shrubs.
Fen	A type of peatland which receives both surface and groundwater flow due to its topographic position which is level with the surface of the fen (+/- a few centimetres). Vegetation can include graminoids, bryophytes, shrubs, and also trees (in drier fens).
Marsh	A shallow water wetland with water levels that can fluctuate daily, annually, or seasonally resulting in highly variable hydrology. Receives water from the surrounding catchment as well as precipitation. Marsh

	vegetation is comprised of emergent aquatic macrophytes such as graminoids (e.g. rushes, reeds, sedges), floating-leaved species (e.g. lilies) and submergent species (e.g. water milfoil). Marsh plant communities are seasonal and dynamic, often shifting with water levels.
Swamp	Forested or wooded wetland, dominated by minerotrophic groundwater and a water table below the ground surface of the swamp for the majority of the year. Vegetation dominated by coniferous or deciduous trees or tall shrubs (generally over 30%).

Sample selection - Training sample objects were selected using aerial photographs, thematic maps and ground truth data collected during field campaigns. A minimum of 50 training sample objects were chosen for each class, with some exceptions for classes which only covered a small proportion of the scene. An advantage of the multi-scale approach is the ability to adequately sample rarer classes such as wetlands by segmenting these landforms into smaller image objects. A random stratified sampling strategy was employed for sample selection with additional samples collected over rare classes as needed. Sample image objects for wetlands were grouped into classes as defined by the Canadian Wetland Classification System. In some cases, a dominant class such as 'marsh' was further separated into emergent marsh and wet meadow in order to capture the spectral and textural variation in these heterogeneous marsh communities. These groups were later merged into one marsh class for comparison across landscapes.

Nearest Neighbour Classifier - A non-parametric nearest neighbour classifier was used to place image objects into defined landcover classes. This iterative process involved selecting training samples, comparing sample attributes, and refining training samples until a satisfactory result was achieved. The nearest neighbour classifier is advantageous when image data are composed of spectrally similar classes that are not well separated using a few features or just one feature (Definiens, 2008) and also when training sample sizes may be uneven (Myint et al., 2011; Yu et al., 2006). The mean feature values of pixels in each object (calculated from the input layers), were used to quantify separation distance between classes. The nearest neighbour, or k-NN approach as it is often called, is a simple yet efficient classification algorithm that has been shown to perform as well as more complicated methods such as support vector machines (SVM) under constant conditions (Im et al., 2008). There are many attributes that can be used to inform the nearest neighbour classifier; however, the contribution of each will vary and constraints such as processing time will dictate the maximum number. We developed a parsimonious model based upon the mean object value for each input layer, in order to maintain a realistic processing time and an efficient model that can be compared across landscapes.

Accuracy assessment

A minimum of 35 independently selected samples were used for accuracy assessment. Sample selection was based upon very high resolution (VHR) aerial photographs over each site, reference thematic maps, and ground truth data collected in June 2011 from each study area. Validation and training samples did not overlap. Accuracy was assessed based on the error matrix and associated statistics, namely overall accuracy, kappa statistic and producer's accuracy (1 - errors of omission) and user's accuracy (1 - errors of commission).

Results

Multi-scale segmentation

Final scale values selected through visual assessment varied between study areas (Table 4). Dominant landcover classes of mixed forest (park site), crop field (agricultural site), and urban matrix (urban site) were most accurately delineated at a scale of 125, 200, and 75 respectively. Boundaries were generally clearly defined with minimal absorption of smaller classes. Similarly, whole wetland boundaries were generally well defined and often included greater spatial detail than reference thematic maps, although specific depiction varied across each landscape. Medium level scale values of 40, 60, and 50 were selected at the park, agricultural, and urban site respectively. Whole wetlands were further segmented at the finest scale level (20 [park], 10 [agricultural], 15 [urban]) to further classify these objects into marsh, swamp, bog, fen, or water. This parent-child relationship maintained a hierarchical constraint which limited classification of the five wetland classes to only those objects defined earlier as wetlands. Scales values of 20 (park), 10 (agricultural) and 15 (urban) were selected at the finest level. Segmentation scales varied across all scenes, and no segmentation scale mirrored those of the other sites at any level.

Table 4. Hierarchical segmentation scale for each study site and corresponding landcover class

Park Landscape		**Agricultural Landscape**		**Urban Landscape**	
Scale	Target Landcover	Scale	Target Landcover	Scale	Target Landcover
125	Forested upland, water	200	Agricultural fields	75	Urban matrix, agricultural fields
40	Wetland, barren land, herbaceous upland	60	Wetlands, water, urban matrix, meadow	50	Wetlands, water, forests, herbaceous upland, barren land
20	Wetland classes	10	wetland classes	15	Wetland classes

Modified ED3 results showed a consistent positive evaluation for all scale parameters selected by visual assessment (Figure 5). ED3 results range from 0 to 0.71 with lower values corresponding to better quality segments that more closely match with reference polygons (Yang et al, 2015). In the corresponding graphs, the selected scales fell within the lowest dip in the data points, which characterises scale parameters with the greater fitness in matching with reference polygons (Yang et al, 2015). Across all scale levels (coarse, medium, fine) and image scenes (park, agricultural, urban), scale values selected through visual assessment fell within this region indicating a robust selection. Interestingly, at the coarse (first) level, results across all three scenes do not demonstrate a pronounced trough but rather a gradual descent in values indicating that several scale values are appropriate at this level.

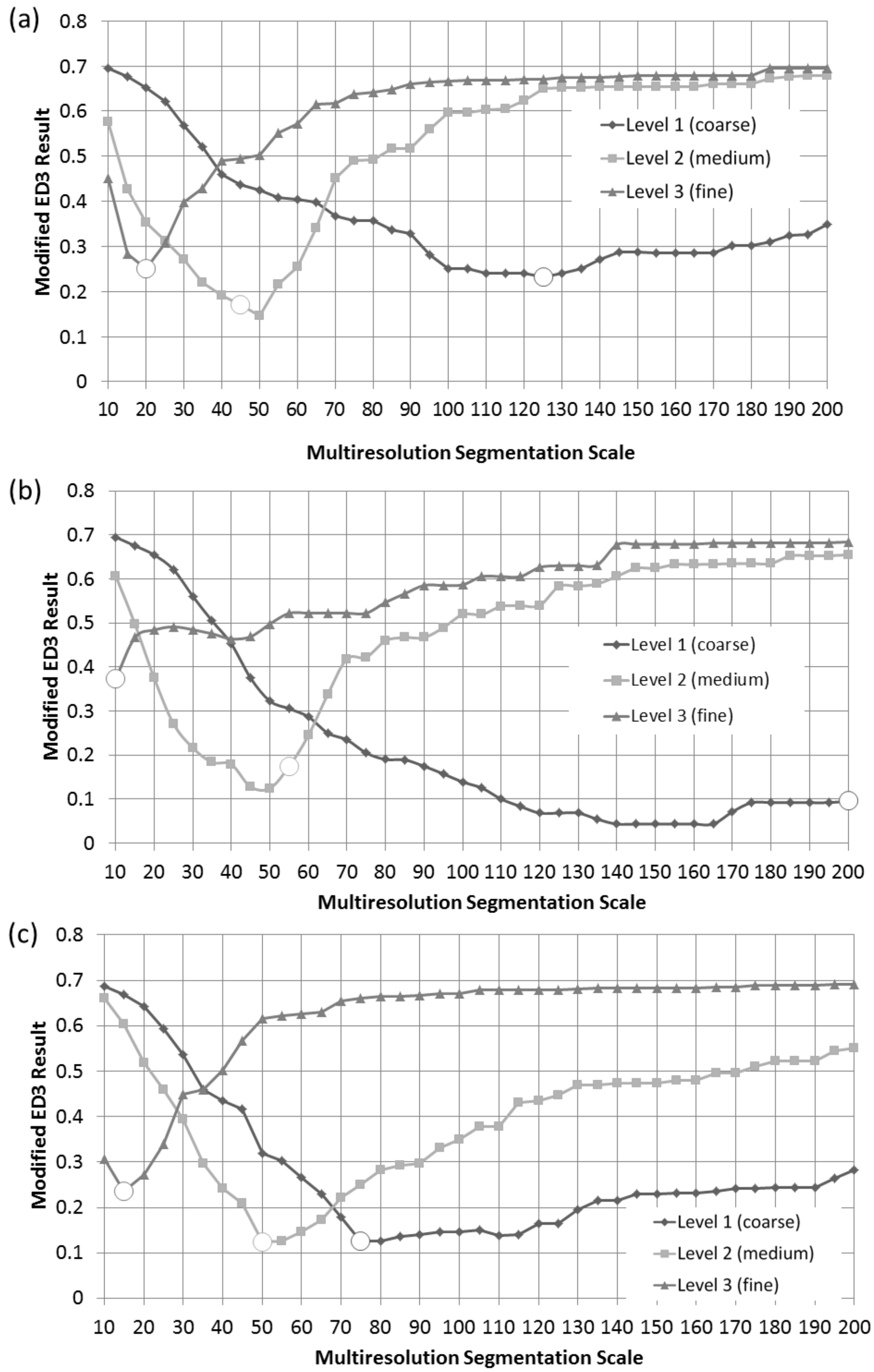

Figure 5. Quantitative evaluation of selected scale parameter with the modified ED3 algorithm at the coarse (diamond), medium (square), and fine (triangle) levels for the (a) Algonquin park site, (b) Brant county agricultural site and (c) east Toronto urban site. Hollow circles denote the scale value selected through visual assessment.

The contribution of supporting input layers (DEM, NDVI, texture) improved overall segmentation results across all scenes. At the coarse level, we found the inclusion of the NDVI layer improved delineation of vegetated boundaries. For example in the agricultural scene, NDVI data improved crop field segments such that object boundaries more closely followed the outer edges of each field (Figure 6). At the medium level, elevation data from the DEM resulted in improved segmentation of wetland boundaries (Figure 7). Texture information was useful at the finest scale level for segmenting medium scale wetland objects (Figure 8). The inclusion of this layer resulted in larger image objects more representative of distinct vegetation communities.

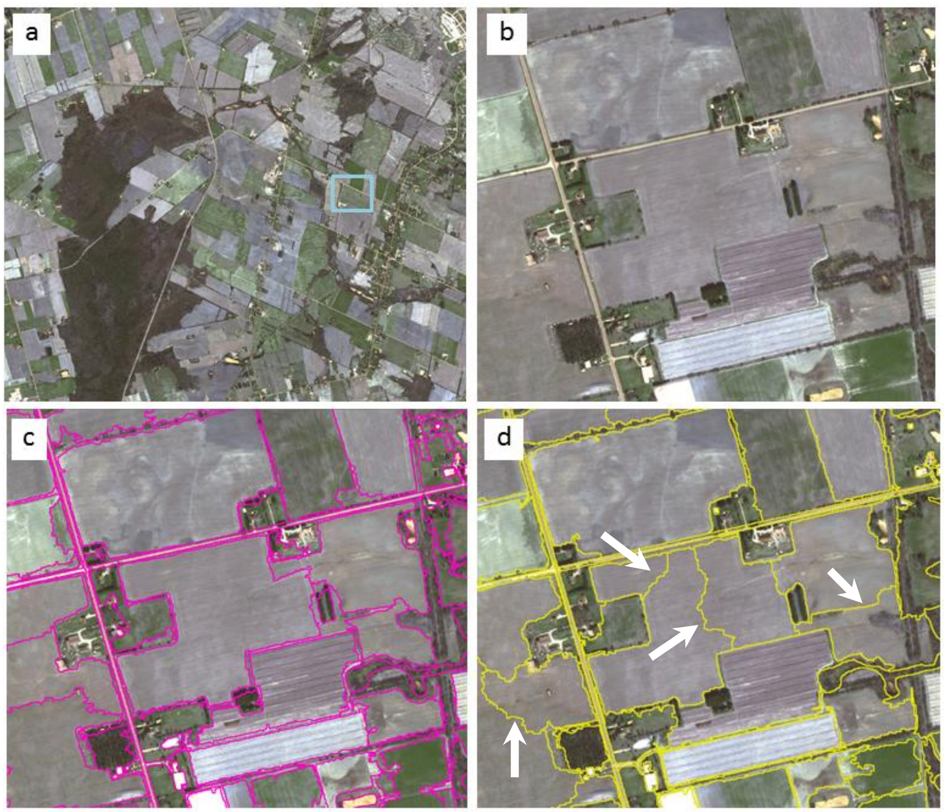

Figure 6. Comparison of coarse level segmentation results over the Brant County agricultural scene and subset (a, b), at scale 200 using all seven input layers (c), and at the same scale 200 with the NDVI layer excluded (d). White arrows in (d) show locations of over-segmentation that do not correspond with crop field boundaries.

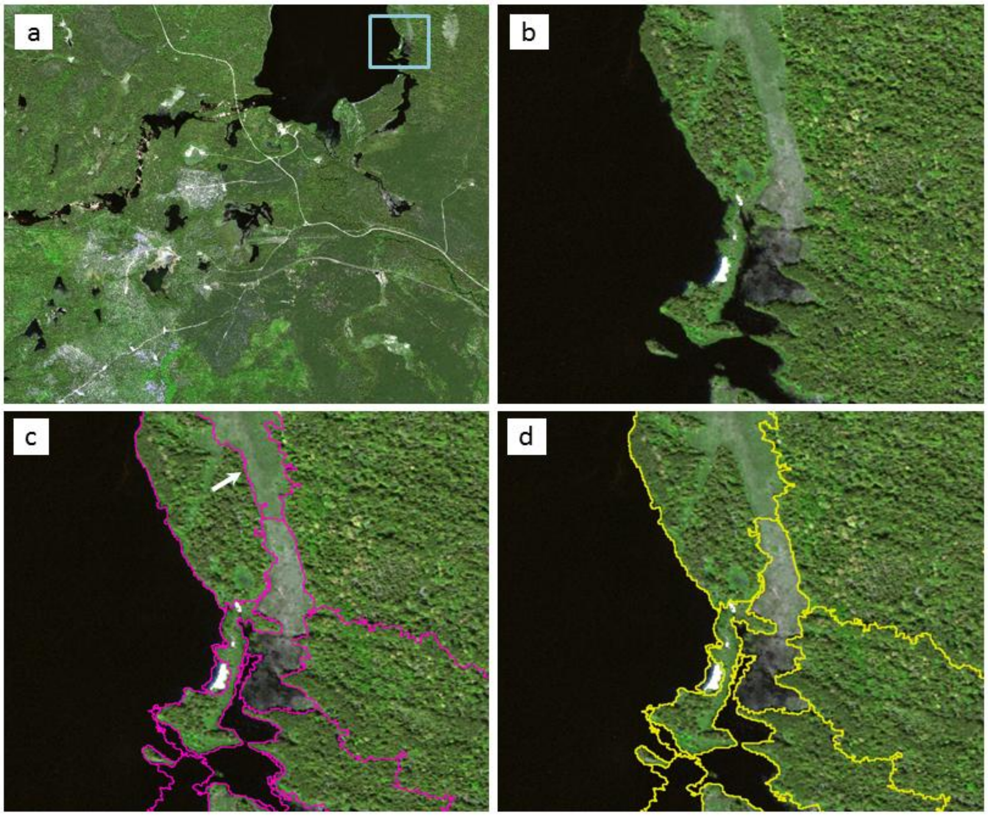

Figure 7. Comparison of medium level segmentation results over the Algonquin park scene (a) and subset of a marsh, fen, bog complex (b) at scale 40 using all seven input layers (c), and at the same scale 40 with the DEM layer excluded. White arrow shows improved segmentation of a wetland boundary (to the right of the indicated line) with the inclusion of the DEM layer.

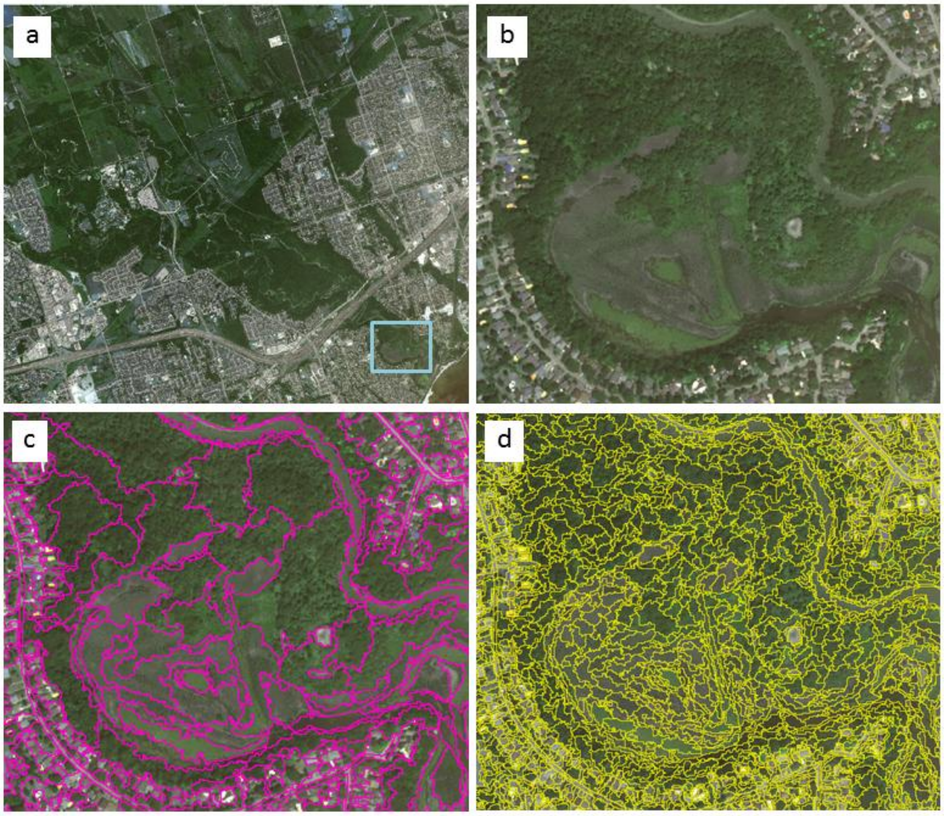

Figure 8. Comparison of fine level segmentation results over the east Toronto urban scene (a) and subset of a marsh complex (b) showing scale 15 using all seven input layers (c), and at the same scale 15 with the texture layer excluded. Note the significant over-segmentation of the texture-excluded image.

A comparison with reference thematic maps indicated that the segmentation captured a greater level of variation in wetland components such as floating vegetation, islands, and water (Figure 9 a,b,c), yet suffered from a varying degree of over and under segmentation when the swamp class was present (Figure 9 d,e,f). Multispectral data from the shorter visible and near infrared wavelengths did not capture information from the mid infrared water-absorbing regions, therefore if standing water was not evident at the time of image acquisition, swamps could be easily confused with upland forests. In both the rural and agricultural study areas, some wetlands were identified that were missing from provincial reference datasets indicating that our approach is not only able to capture additional wetlands, but also able to provide a greater level of detail concerning within wetland variation.

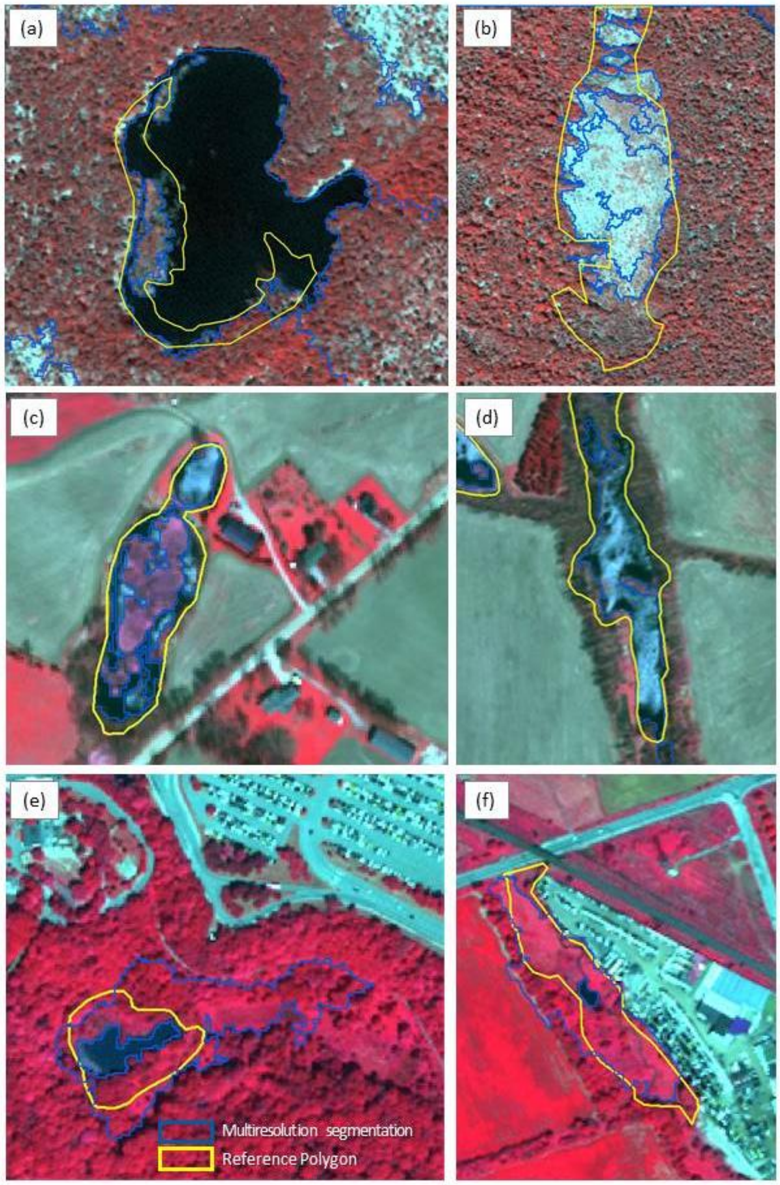

Figure 9. Sample view of wetlands enclosed by object boundaries created by the FNEA multi-scale segmentation algorithm (blue), and its corresponding reference boundary (yellow) in the natural site (a,b), rural-agricultural site (c,d) and the urban site (e,f).

Segmentation of non-wetland classes varied across sites. The acquisition of early spring imagery resulted in better overall segmentation of dominant crop land in the agricultural scene likely due to the fact that the majority of fields were bare, and borders were clearly visible. However, some smaller features such as hedgerows and isolated irrigation ponds suffered from absorption into these larger agricultural fields. This is attributed to variation in land-use patterns and a greater proportion of mixed vegetation classes adjacent to managed agricultural fields (see final classification maps, Figure 11). In contrast, the urban scene which also included agricultural fields suffered from a greater over and under-segmentation of crop fields, as boundaries were not as distinct in this landscape. There were no agricultural fields, or isolated ponds in the natural Algonquin Park study area and the dominant forest class was segmented with a high accuracy. While forest cover was relatively continuous across most of the scene in the natural landscape, forested uplands in the urban and rural sites were highly fragmented resulting in comparatively lower segmentation accuracy.

Classification

GeoeEye1 and WorldView2 data were classified initially into 8 classes for the park and urban sites, and 7 classes for the agricultural site. Overall classification accuracy was the highest (kappa 0.88) over the natural Algonquin Park landscape, followed by the urban east Toronto landscape (kappa, 0.84) and lowest over the agricultural Brant County landscape (kappa 0.78). Final error matrix statistics are shown in Table 5 and final classification maps are shown in Figure 11. A different number and proportion of wetland classes (bog, fen, swamp, and marsh) were found in each landscape, and class kappa accuracy values ranged from 0.89 for the marsh class over the natural site to 0.64 for the swamp class over the rural site. Overall, forested wetlands achieved the lowest accuracy (0.66 – 0.74 across all sites). For all study sites, water received the highest classification accuracy, followed by forests (in the natural site), agricultural fields (in the rural site), and the built/urban matrix (in the urban and rural sites).

Table 5. Error matrix statistics for landcover classes in each study site (PA = producer's accuracy, UA = user's accuracy)

	***Park Site* (Algonquin Park)**		***Agricultural Site* (Brant County)**		***Urban Site* (East Toronto)**	
Land cover Class	**PA**	**UA**	**PA**	**UA**	**PA**	**UA**
Marsh	0.91	0.94	0.81	0.93	0.81	0.90
Swamp	0.83	0.81	0.69	0.65	0.67	0.95
Fen	0.89	0.83	-	-	-	-
Bog	0.87	0.84	-	-	-	-
Water	0.97	0.94	0.98	0.96	0.97	0.88
Forested Upland	0.94	0.91	0.74	0.66	0.89	0.96
Herbaceous Upland	0.80	0.82	0.57	0.50	0.84	0.74
Agricultural Land	-	-	0.81	0.79	0.91	0.83
Built/Urban Matrix	-	-	0.95	0.95	1.0	0.89
Barren Land	0.92	0.95	-	-	0.85	0.85
Overall (kappa)	**0.90 (0.88)**		**0.81 (0.78)**		**0.86 (0.84)**	

Wetland-Upland Classification **–** Individual classes were merged into wetland (marsh, fen, bog, swamp), upland (forest, meadow, agricultural field, built, barren), and water categories in order to compare wetland accuracy amongst non-wetland classes (Table 6). Accuracy for the merged classification map was the highest for the park study site (overall accuracy 0.90, kappa 0.86), followed by the urban site (overall accuracy 0.86, kappa 0.81) with the agricultural landscape receiving the lowest accuracy (overall accuracy 0.76, kappa 0.71). Producer's accuracy was high across all study sites (> 80%) with the exception of uplands in the agricultural landscape. Map user accuracies were generally high (> 80%) with the exception of wetlands, and water classes in the agricultural and urban landscape (66-77%). Across the merged classification map of the park site, only minimal errors occurred between wetland and upland classes while greater errors were found in the agricultural and urban merged maps. Focussing on wetlands, there was a high error of commission of uplands into the wetland class, and a slightly lower omission of wetland objects into the water class in the agricultural landscape. Over the urban study area wetland objects were erroneously classified as both water and upland, while only minimal errors of commission occurred.

Table 6. Error matrix statistics for merged wetland, upland, water classes over each study site (PA = producer's accuracy, UA = user's accuracy).

	***Park Site* (Algonquin Park)**		***Agricultural Site* (Brant County)**		***Urban Site* (East Toronto)**	
Land cover Class	**PA**	**UA**	**PA**	**UA**	**PA**	**UA**
Wetland	0.86	0.95	0.80	0.71	0.85	0.74
Upland	0.92	0.90	0.64	0.91	0.97	0.84
Water	0.95	0.97	1.00	0.66	0.98	0.77
Overall (kappa)	**0.90 (0.86)**		**0.76 (0.71)**		**0.86 (0.81)**	

Comparison of Sample Attribute Separation Between Classes – Since the nearest neighbour classifier selects the most suitable attributes to classify a land cover class, we further investigated the most suitable attributes used for class separation by examining overlap values between classified polygons. We found that the mean object values of the red band, near infrared band and NDVI provided the greatest separation between wetlands and all other classes (Figure 10). The mean object value from the NDVI layer was used most frequently in discriminating wetland classes from other land cover groups over the urban east Toronto site. The near-infrared layer was used most frequently to separate between wetland and upland classes over the natural Algonquin Park and rural Brant County sites. Texture was used to separate wetlands from built areas in the rural site disproportionately more than in the natural and urban landscapes.

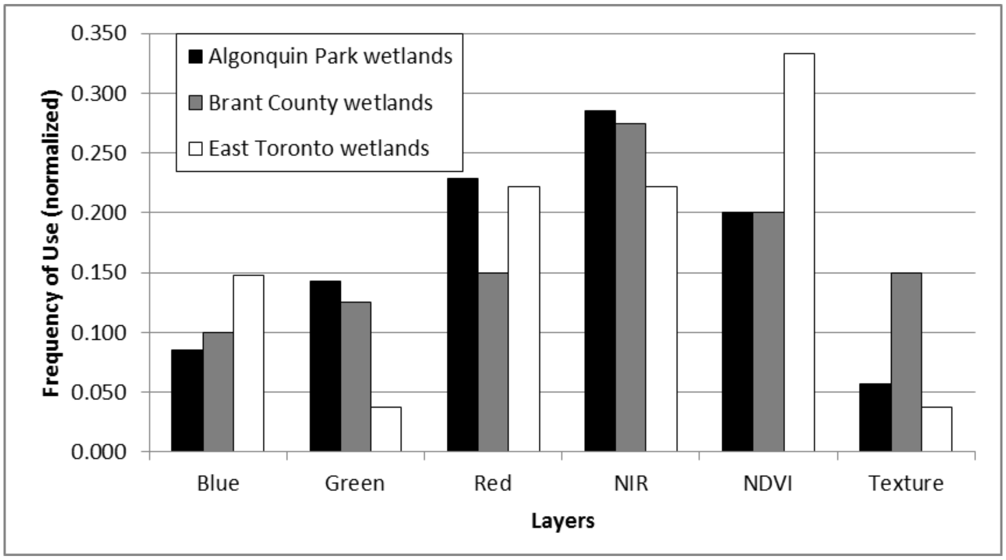

Figure 10. Comparison of mean object layer values providing the best separation between wetland classes and all other landcover classes at each study site. Y-axis is showing the number of times a layer provided the best separation distance between classes, normalized out of 1. Average values are standardized across total number of landcover classes at each site.

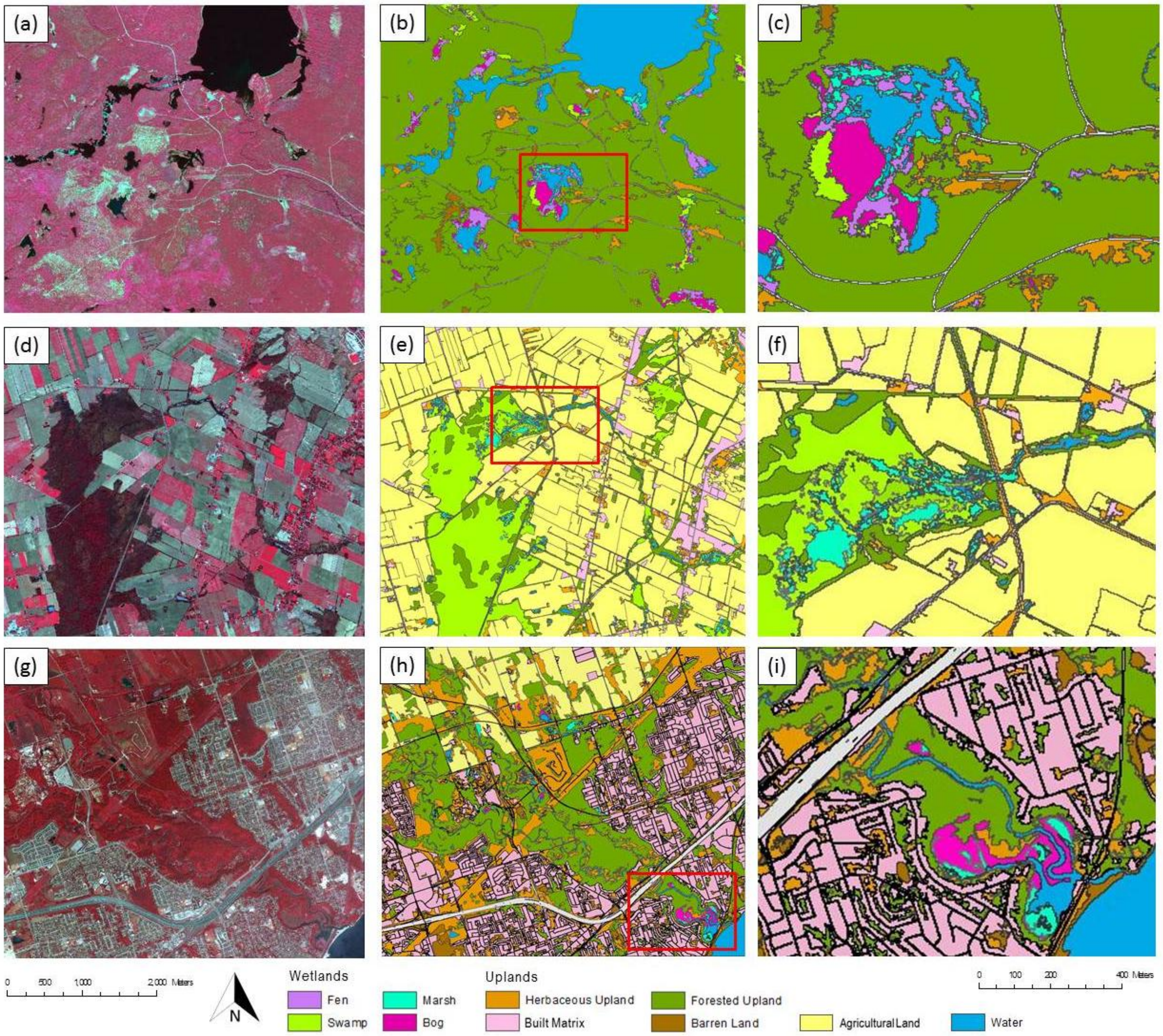

Figure 11. Classification results showing original satellite image (RBG: 432), final classified map, and subset of classified map over the Algonquin Park natural site (a, b, c), the Brant county rural-agricultural site (d, e, f), and the east Toronto urban site (g, h, i).

Discussion

In this study we examined the accuracy of a multi-scale GEOBIA approach in correctly classifying wetlands across three different landscapes. Despite the variability in study areas, overall wetland class accuracy across scenes was greater than 80% indicating that this methodological approach is robust across scenes of varying heterogeneity due to human-disturbance.

Segmentation and the GEOBIA approach

The multi-scale object-based approach provided an effective method of partitioning wetlands, and other landcover classes. The class accuracy of wetlands (marsh, swamp, bog, fen) was higher than grouped upland-wetland accuracy across all sites, which we attribute in part, to the use of the hierarchical parent-child segmentation approach. The segmentation of whole wetland objects into smaller objects for within wetland classification allowed this process to be constrained to its parent class which minimizes the potential for misclassification with other groups. Repeatedly modifying training objects to achieve the best classification also contributed to improving final map results. Specifically, a sample of incorrectly classified objects should be iteratively selected as training samples to retrain the classifier so that subsequent classifications can target areas of demonstrated spectral overlap or confusion. The visual approach to selecting the scale parameter proved to be a robust method drawing upon the inherent ability of the human eye to distinguish between landscape elements and neighbourhood context. The use of the modified ED3 algorithm to evaluate the scale parameter provided important quantitative support for scale selection, as well as further information on the range of appropriate scale values. Thus, the combination of both quantitative and qualitative measures are recommended as each is important for selecting the scale parameter.

At the coarse segmentation level, the addition of the NDVI layers resulted in a general improvement in delineating boundaries of classes which were comprised of, or adjacent to vegetation such as crop fields bordered by hedgerows, or mixed herbaceous vegetation. Multispectral indices have been shown to improve models of wetland discrimination (Bradley & Fleishman, 2008) due to their sensitivity to vegetation surface roughness and phenological stage (Davranche et al., 2010). Elevation information improved segmentation of whole wetland boundaries at the medium scale, and particularly in palustrine (inland) wetlands as opposed to lacustrine (lake-associated) wetlands. This is likely a result of a greater difference in elevation between inland wetlands and the terrestrial uplands which completely surround them. The NDVI layer contributed more to the segmentation of lacustrine wetlands, which were present in small proportions in the park and urban scenes.

Texture contributed most to segmentation at the finest scale where the spatial information improved delineation of wetland vegetation communities. Resultant image objects were larger than those segmented without textural information, and also resulted in objects that more accurately captured edges where macrophyte communities transitioned. Previous work has shown that texture analysis can improve classification accuracy by reducing the confusion between permanent crops and perennial meadows (Peña-Barragán et al., 2011). For future work, we recommend the exploration of higher order texture measures such as those derived from the grey-level co-occurrence matrix (Haralick et al.,1973), which has shown success in discriminating between deciduous and evergreen tree species (Kim et al, 2009) and may improve classification accuracy between treed uplands and swamps (treed wetlands).

It should also be noted that the identified scale at each level cannot be interpreted as a universal value that can be applied to any image of similar composition or resolution (spectral, spatial, and radiometric). The size and shape of image objects is greatly affected by the extent, composition, spectral heterogeneity and type of segmentation algorithm used. For example in preliminary segmentation tests, it was found that a subset of a larger image segmented at a scale value of 100, would create very different image objects than those created by segmenting the entire image at the same scale of 100. Here, the extent alone alters the resultant objects relative to the scale value which remains constant. Nevertheless, the scale values reported here are for the purpose of comparison of targeted land cover classes within the study sites, and not as a recommendation for optimal scale values to use for other images composed of similar elements as ours.

Classification accuracy

Wetlands in landscapes of varying heterogeneity were classified with an accuracy between 81% (kappa 0.78) and 90% (kappa 0.88) with the least disturbed site achieving the highest accuracy. While what is considered acceptable for mapping accuracy may vary, the recommended target of 85% overall accuracy (Foody, 2002; Thomlinson et al., 1999) was achieved by two of the three classification maps. Not unexpectedly, differences in upland complexity resulted in varied outcomes with regard to both segmentation and classification accuracy. When comparing overall classification accuracy, there is a small but consistently poorer performance in the agricultural site across all accuracy measures and grouping of classes, including wetlands.

A dominant contributor to mapping error was the confusion between the forested upland and swamp class. The high proportion of swamp areas present in the agricultural landscape likely contributed to the lower classification error. Here, the lower accuracy results were partly attributed to the presence of facultative tree species such as Red maple (*Acer rubrum*) which can grow in both saturated wetland soils and dry upland soils and would show spectral and textural similarity if above ground reflectance does not reveal the hydrologic state beneath (Sader et al, 1995). Confusion between agricultural land and herbaceous upland further reduced accuracy. Notably, all confused classes belonged to groups containing an abundance of vegetation, indicating the need for better measures to separate these similar classes. Similarly, the urban land cover map demonstrated reduced accuracy with the swamp class, despite (or partly as a result of) the low proportion of swamps in this scene. The use of advanced texture measures such as the grey level co-occurrence matrix, multi-date MS imagery or data from active sensors would likely help to improve accuracy over this class and should be investigated further.

Overall, it is generally accepted that mapping error on less frequent classes like wetlands will be higher than error on dominant classes (Cunningham, 2006). The relative rarity of wetlands at each site likely contributed to the over/under classification and to spectral confusion of wetlands classes. Wright & Gallant (2007) documented a similar error for palustrine wetland mapping in Yellowstone National Park for which wetlands comprised less than 6% of the total cover.

The use of temporal imagery has been shown to improve wetland detection, and utilises a major advantage of Earth-observing satellite data. Dechka et al. (2002) classified prairie wetland habitats in southern Saskatchewan using two IKONOS images acquired 24 May 2000 and 29 July 2000 to maximize seasonal variation in vegetation growth from minimal spring conditions to mid-summer growth. The multi-temporal combination of May and July imagery produced the highest accuracy (95.9%), although compared to results using the only the July image (84.4%) authors concluded that the increase in accuracy may not be enough to justify the high cost of additional multi-temporal image acquisitions. Interestingly, in this study the earlier season (May) image produced the lower classification accuracy (50.5%), while others found that spring imagery was most optimal for wetland discrimination (Ozesmi & Bauer, 2002; Gilmer et al., 1980). Dingle-Robertson (2014) examine Ontario wetland classification according to the Ontario Wetland Evaluation System across three seasons using WorldView2, Landsat5, and Radarsat2 data and found that high spatial resolution WorldView2 data from spring or summer acquisitions produced the highest accuracies. Other multi-temporal work has found improvement in the identification of wetland plant species using a combination of field spectral data, LiDAR top of canopy data, and multi-date Quickbird imagery (Gilmore et al., 2002), as well as improved accuracy in mapping seasonally flooded forested wetlands using multi-date RADARSAT data (Townsend, 2001). In this study, multi-date imagery was only available for two of the three sites (the urban east Toronto site only had high spatial resolution data available in July) therefore a multi-date evaluation was not possible. However, future work requiring higher classification accuracy, for example in wetland change detection studies, should consider employing a multi-temporal approach.

Other factors may have influenced final classification accuracy such as the difference in timing of image acquisitions across study areas, and the difference in sensors. The Brant County agricultural site and the Algonquin park site were both acquired in the spring from the GeoEye1 sensor (25 May 2013, and 9 April 2012 respectively), albeit in different years, whereas the east Toronto urban site was acquired in the summer (25 July 2012) from the WorldView2 sensor. From an operational standpoint, acquiring satellite imagery that perfectly matches the required timing and conditions mandated by the study, can present one of the greatest challenges in remote sensing research. Shifting priorities in commercial tasking orders, limited availability of archived imagery, presence of cloud cover, and high cost, can collectively contribute to mismatches in sensor and temporal continuity. Thus results from the urban scene may not be directly comparable to results from the agricultural and park scenes, as the presence of vegetation further along in development and growth, as well as the slightly narrower bandwidth of the red channel (630-390 nm WorldView2 compared to 655-690 nm GeoEye1), and the near infrared channel (770-895 nm WorldView2 compared to 780-920 nm GeoEye1) may have influenced final results. Yet, these differences can also have a positive effect if identifying potential benefits or disadvantages of one sensor configuration in comparison with the other. For example, it is interesting that for the landscapes represented by GeoEye1 imagery (park and agricultural), which operates with a wider NIR bandwidth, the contribution of this band to classification is greater than the NDVI layer. Conversely, for the urban site based on the narrower NIR band of WorldView2, the opposite is true. This raises the possibility that different sensors may utilise spectral layers differently in the classification process as a result of their bandwidth, and is a topic warrants further investigation. However, despite this discontinuity in sensor and image acquisition timing, accuracy results over the urban site were neither higher nor lower than the accuracy over the other two sites with matching sensors and dates. While this uncertainty should be recognized, I do not believe it negates the results provided in this study, and our results further demonstrate that wetland detection can be successfully achieved across landscapes of varying heterogeneity without the use of extensive ancillary data.

Landscape heterogeneity

A primary objective of this study was to examine if this methodological approach was robust to variability in scene heterogeneity caused by human-disturbance. Overall, with wetland accuracy results above 80% across all scenes, we concluded that this method was indeed well-suited to classifying wetlands from landscapes of varied heterogeneity, but there was a slight pattern of decreased accuracy with increasing scene complexity. Fahrig et al. (2011) made an important distinction between compositional heterogeneity (a landscape with a greater variation of land cover types) and configurational heterogeneity (a more complex spatial patterning of land cover types) with which to describe a landscape. Although, it should be noted that there is no universally accepted description of ecological heterogeneity (Cadenasso et al. 2007) which makes it difficult to identify those regions for which special considerations should be taken.

In terms of land cover heterogeneity, Smith et al. (2002) quantified both landcover patch size and heterogeneity over a large portion of the eastern US and demonstrated an almost continuous decrease in accuracy as heterogeneity increased, suggesting that landscape characteristics should be afforded the same consideration in accuracy assessments as those conducted on landcover classes. We noticed a similar relationship between landcover heterogeneity and map accuracy among our study sites with the natural site achieving the best results, and more disturbed sites performing worse. The decreased accuracy over the agricultural site was not anticipated since built features were considered more complex than agricultural fields, and coverage of built areas was considerably higher in the urban region. Yet, the relative ease of segmentation and classification of residential parcels in both disturbed landscapes indicated that this class may not contribute as much to classification confusion as originally thought. Upon further examination of results, urban-built features have greater spectral and textural distinction which separate them more easily from spectrally and texturally similar vegetated land cover classes. A careful review of misclassified objects indicated that the wide range of upland vegetation classes of both human and natural origin, may be responsible for the lower map accuracy in the rural site. This was especially true along transitional areas where one dominant class transitioned into another. Cingolani et al. (2004) experienced a similar challenge in mapping heterogeneous rangeland ecosystems where the influence of grazed lands combined with natural environmental gradients to create complex vegetated patterns that were difficult to separate.

Conclusions

A simple yet efficient methodology procedure for mapping wetlands across landscapes of varied heterogeneity was presented in this paper. High spatial resolution satellite data and the GEOBIA approach can be combined to provide a sound methodology for characterizing whole wetlands and individual wetland classes. The GEOBIA approach specifically, was very appropriate for wetland detection as it allowed for a nested multi-scale approach to constrain classification of wetland components to within defined wetland boundaries. In regards to landscape variations, a more heterogeneous landscape may negatively affect accurate wetland classification due to increased spatial and compositional complexity. Specifically, rural landscapes presented special challenges due to the large proportion of vegetated upland classes of both anthropogenic and natural origin that reduced segmentation accuracy and resulted in greater spectral overlap during the classification.

Future work in wetland mapping of treed swamp wetlands should include SAR data which can capture the presence of standing water underneath tree canopies. In all cases, image acquisition during early spring leaf-off conditions are recommended to aid in discriminating between confounding vegetation classes, though from an operational standpoint reliance on archived imagery often means that this is not possible.

Overall, the trend of reduced wetland coverage with increasing landscape complexity due to human disturbance creates ongoing challenges for accurate wetland delineation. Wetlands are important ecosystems contributing an estimated 40% of the value of global ecosystem services (Zedler, 2003) and a better recognition of their value should be demonstrated through stricter legislation for wetland protection, particularly where new developments are concerned. In many areas a previous wetland inventory may not exist, making identification, evaluation and monitoring of wetlands a challenge. This study demonstrated a robust approach to delineating wetlands across variable landscapes which can provide starting information for better management of these ecosystems. The multi-temporal aspect of satellite sensors can be exploited to provide repeat coverage allowing for change detection and evaluation of wetland health over time. However, the greater issue at hand is the ongoing loss and degradation of wetlands worldwide, which will have serious consequences for global climate as well as the maintenance of biodiversity.

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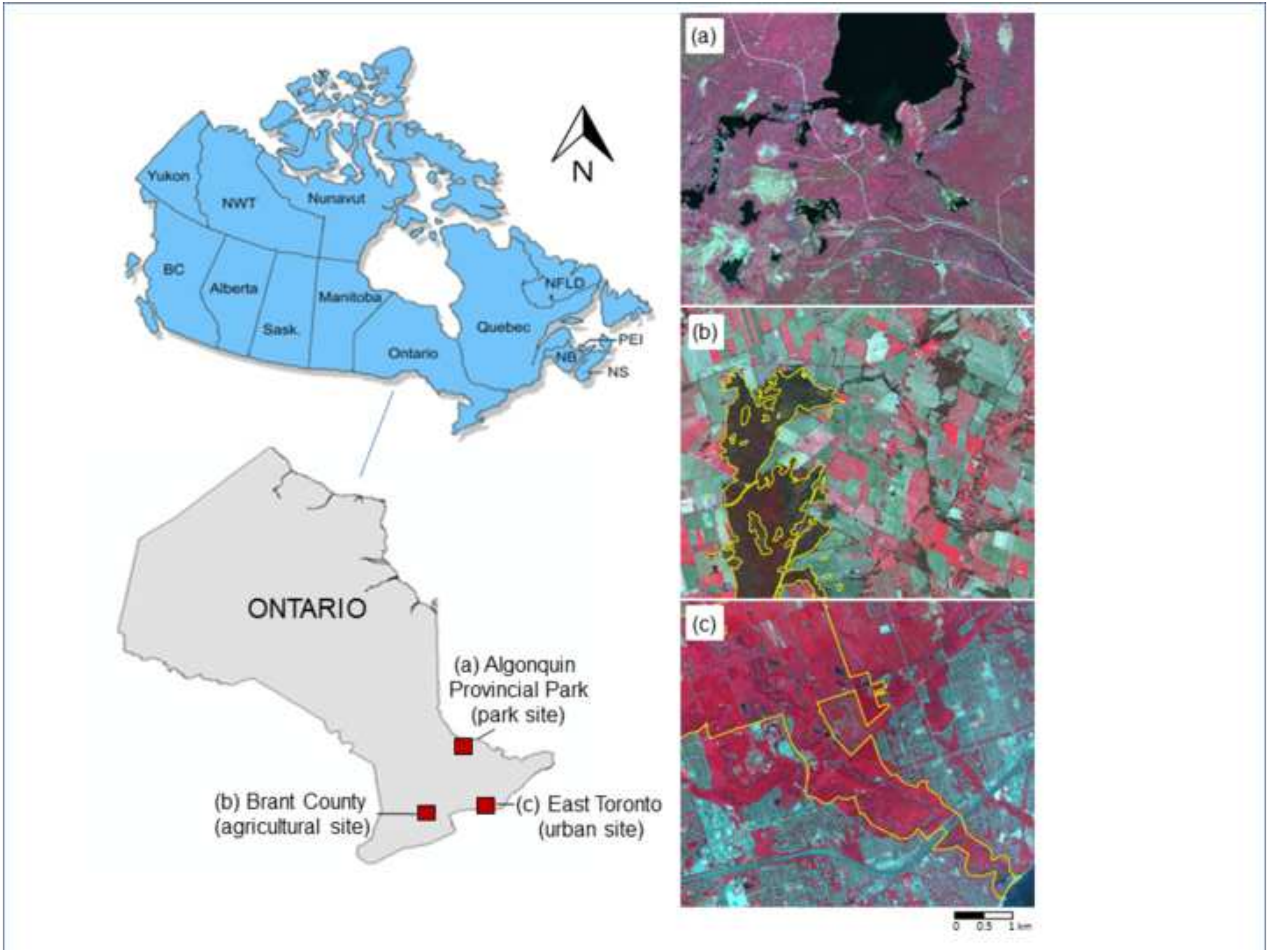

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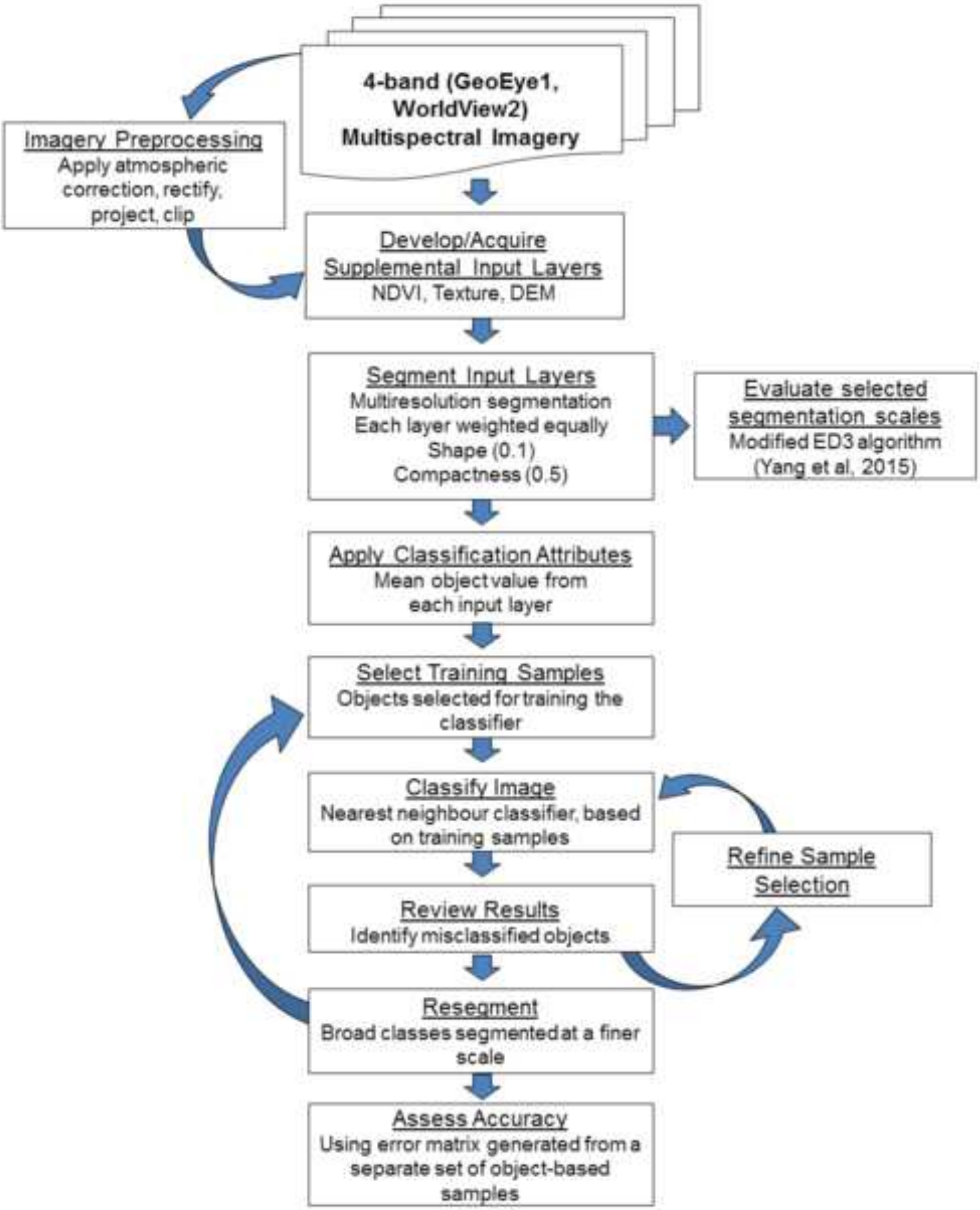

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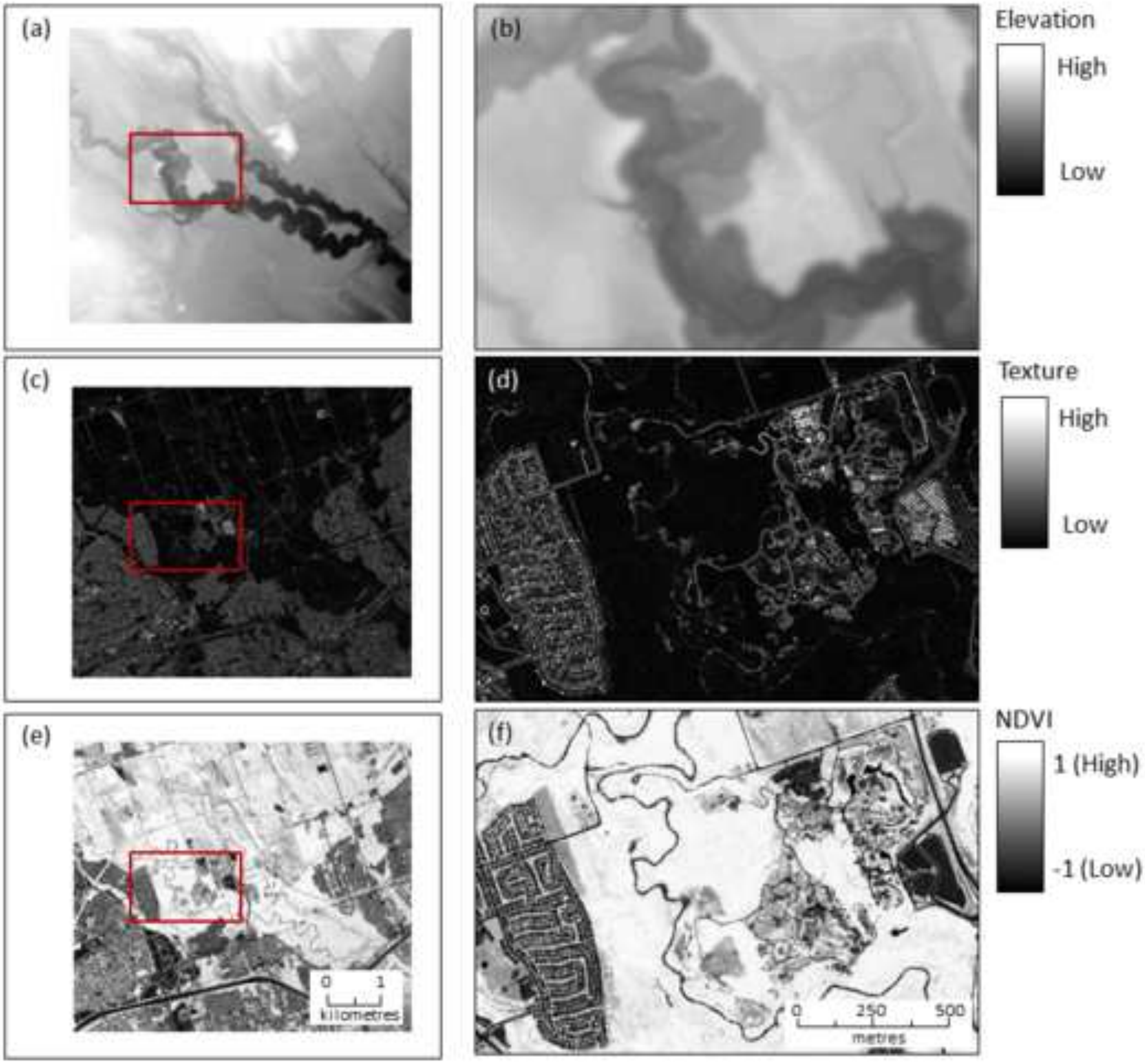

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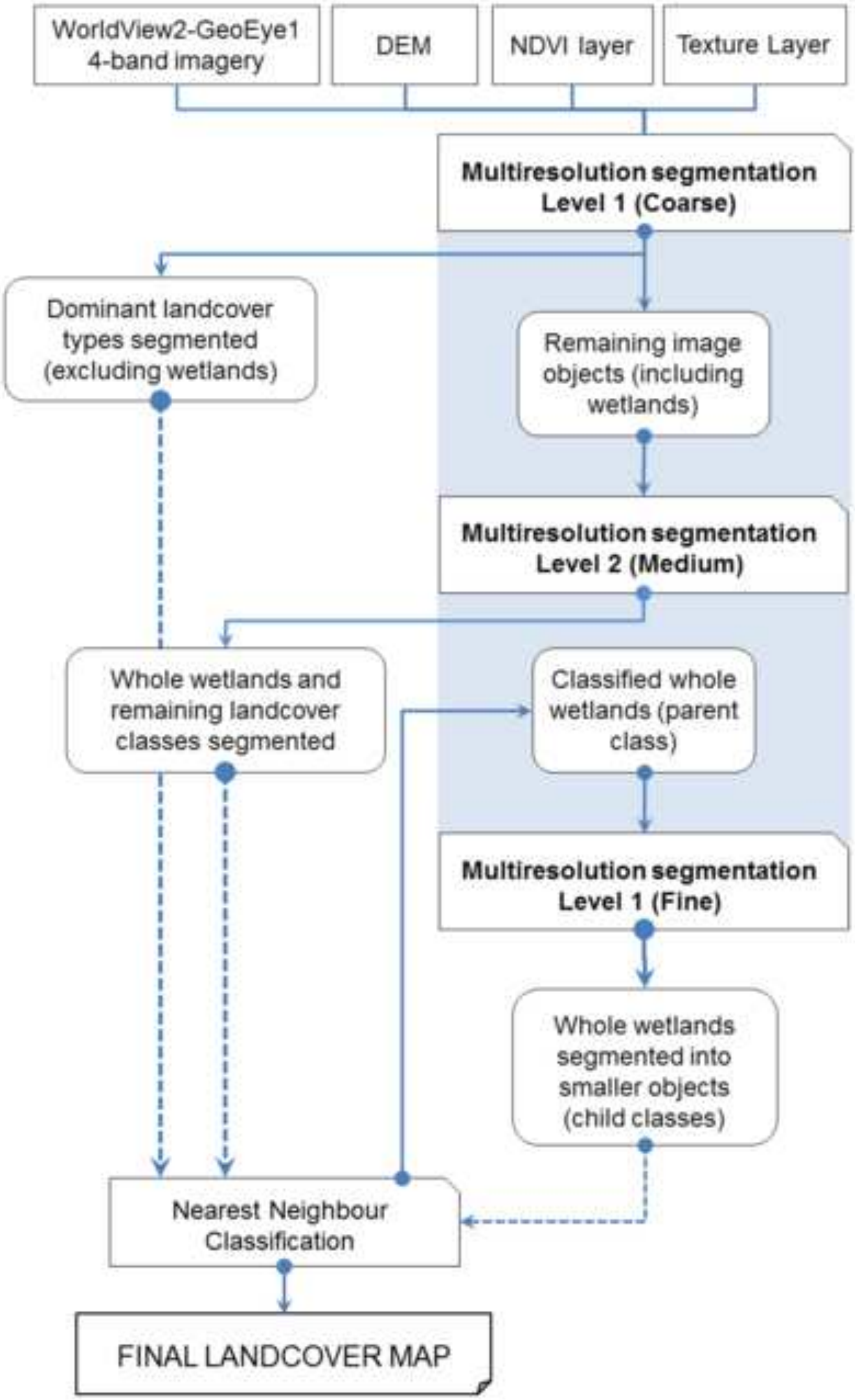

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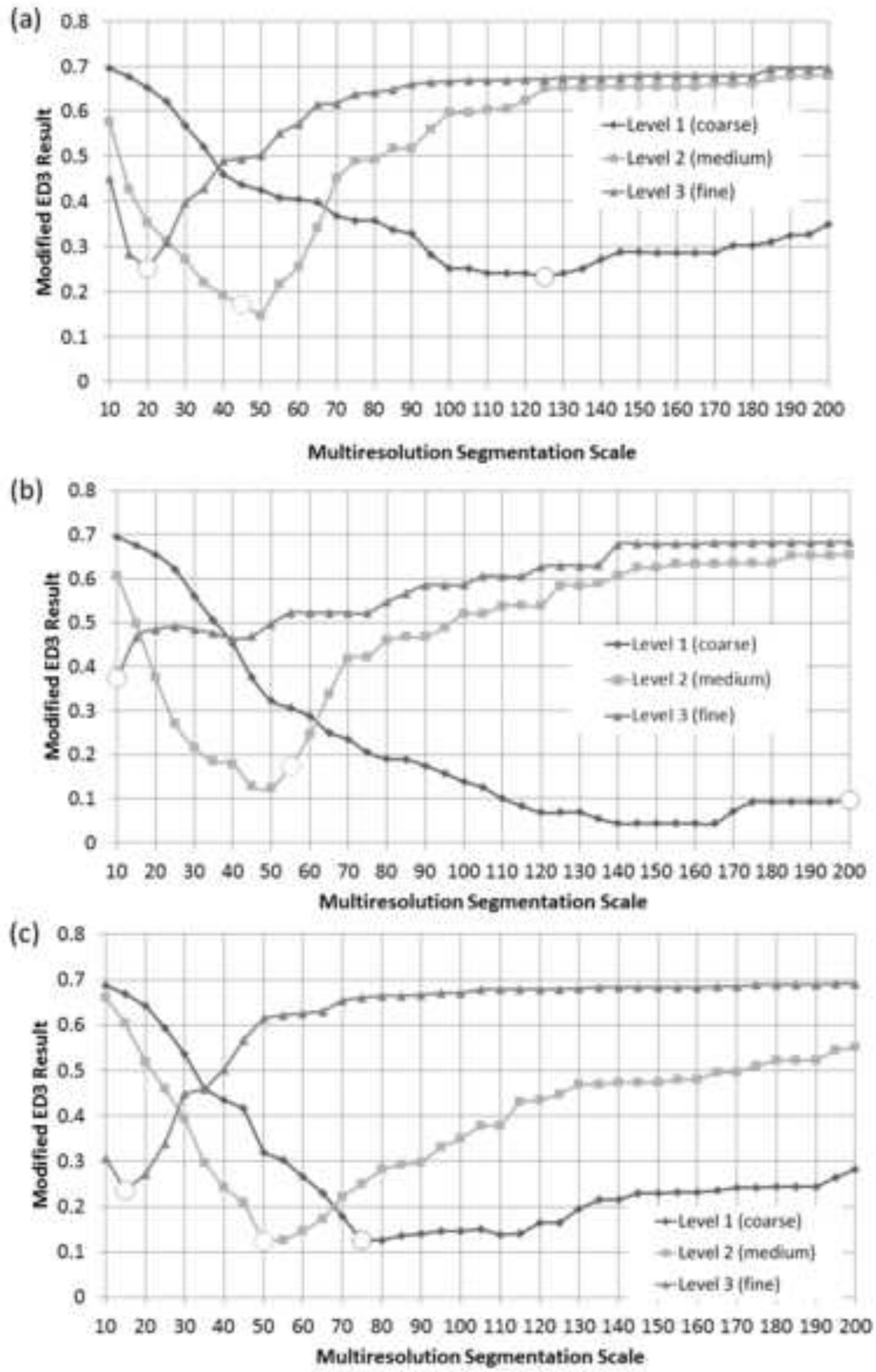

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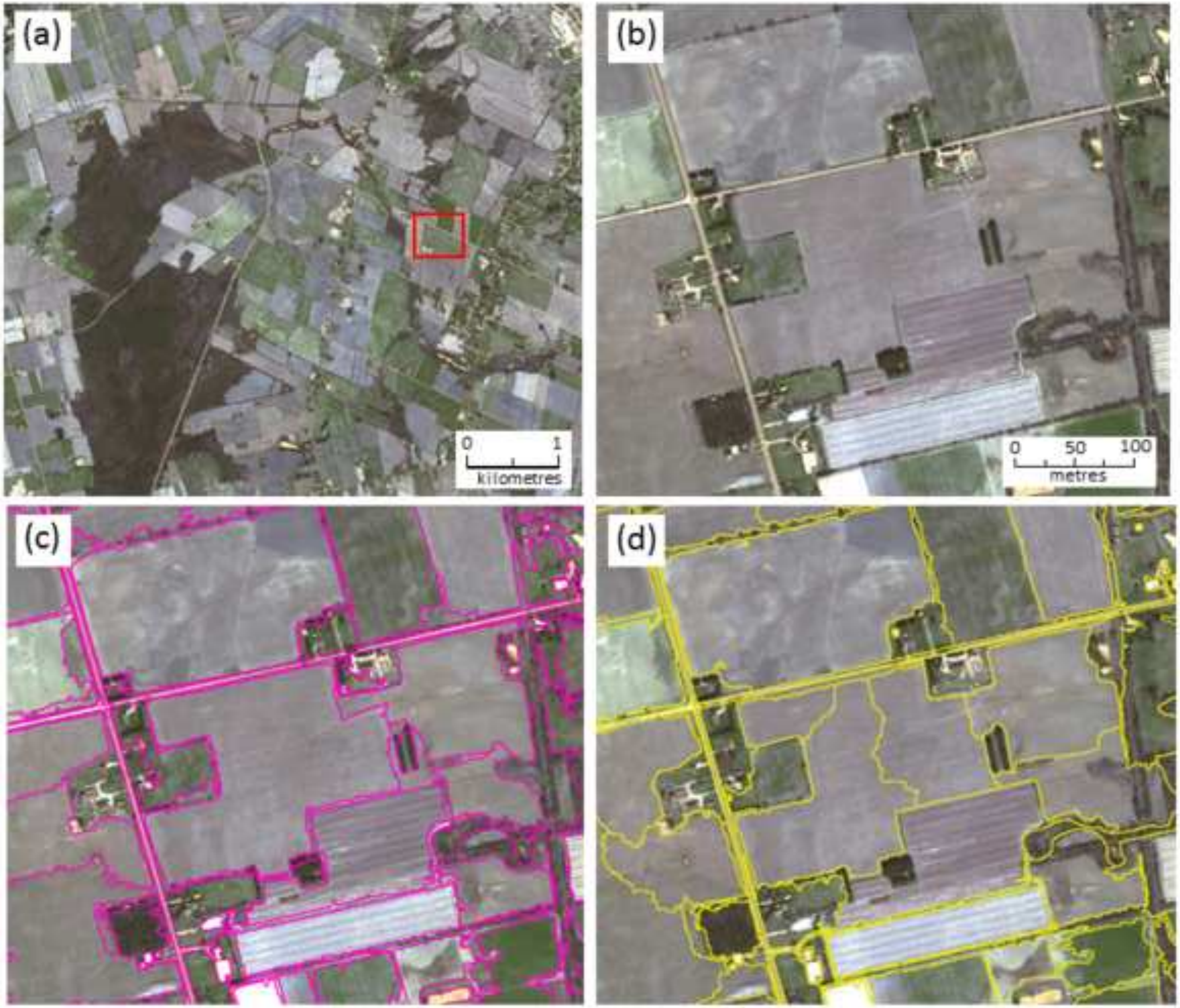

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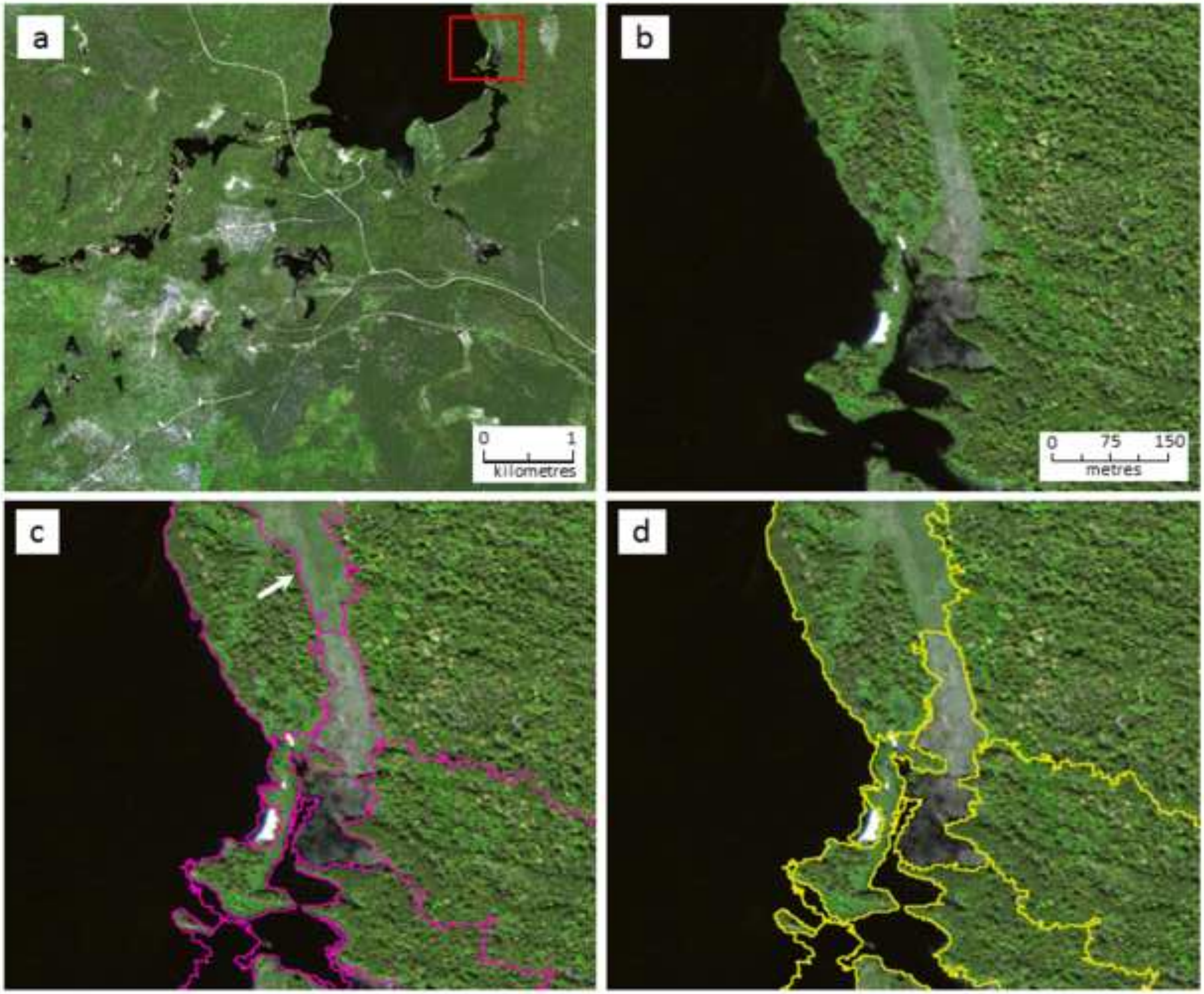

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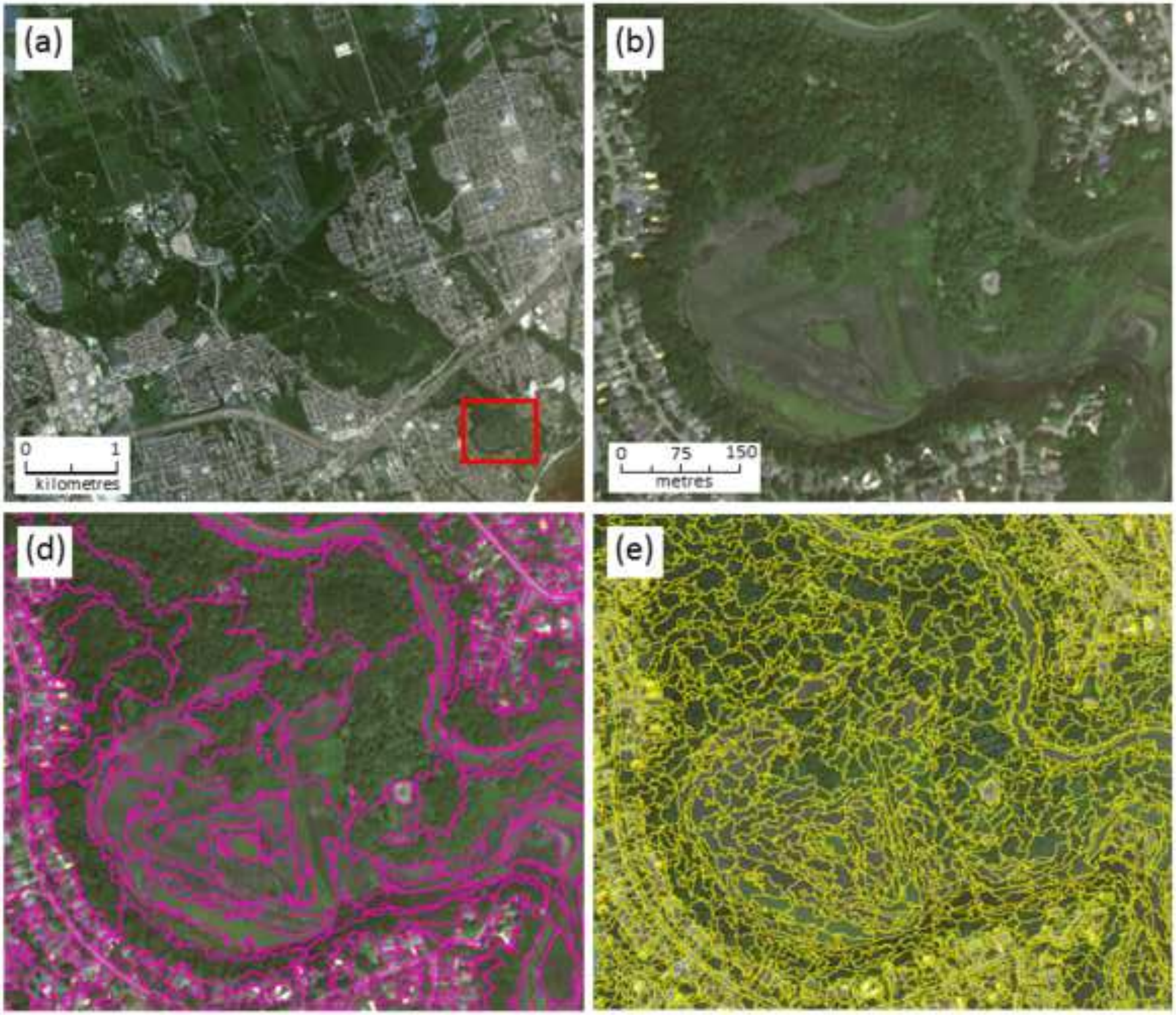

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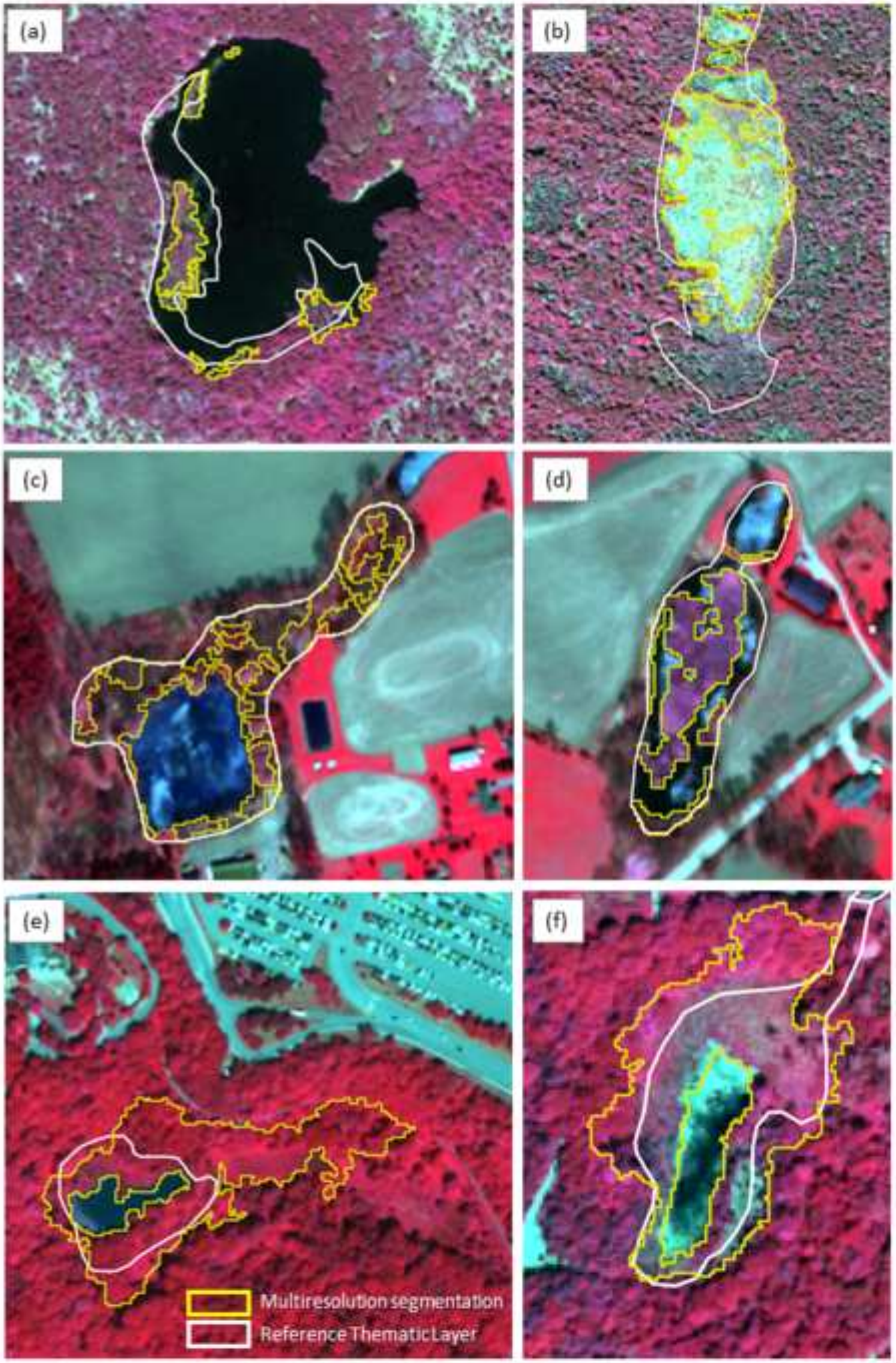
(a)
(b)
(c)
(d)
(e)
(f)
Multiresolution segmentation
Reference Thematic Layer

Figure 11

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