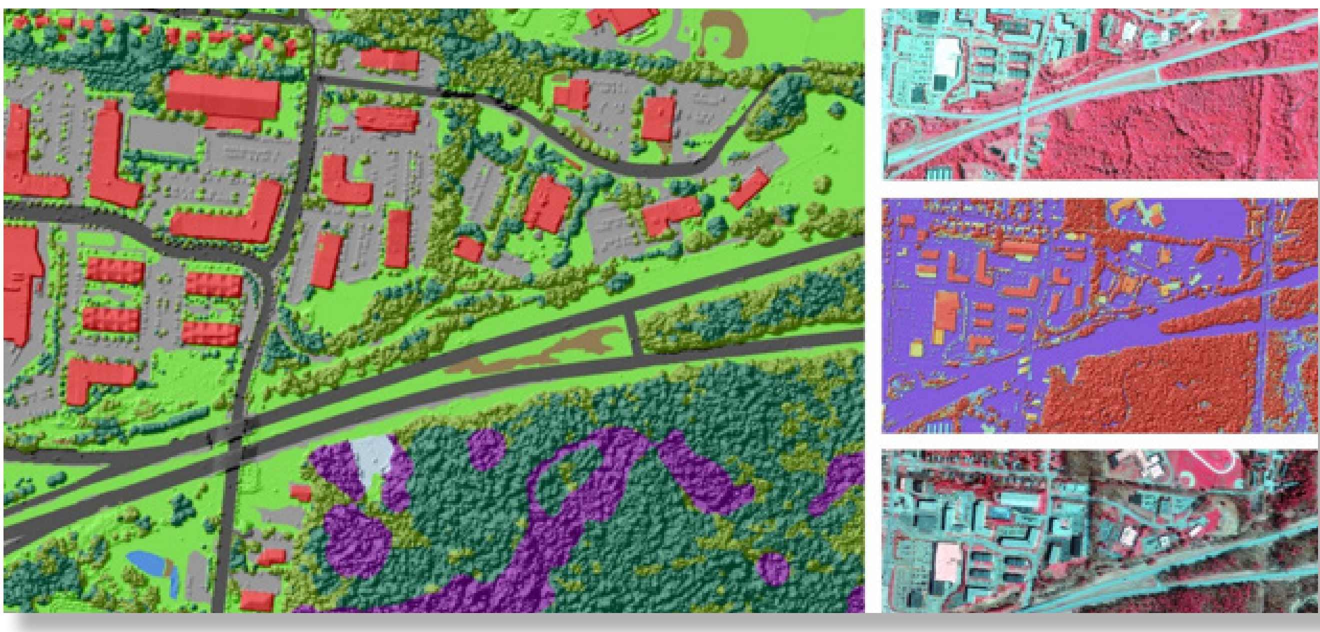
Lake Champlain Basin Program

TECHNICAL REPORT NO. 87

High-Resolution Land Cover Mapping of the Lake Champlain Basin



July 2018

Final Report

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For:
The Lake Champlain Basin Program and
New England Interstate Water Pollution Control Commission

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Executive Summary

This project yielded the most detailed and accurate land-cover dataset ever produced for the United States portion of the Lake Champlain Basin (LCB). It leveraged the considerable investments made by state, regional, and federal organizations in high-resolution imagery and LiDAR for the LCB. Over a year-long period of intensive work, land cover in the Lake Champlain Basin was mapped at a resolution 900-times more detailed than any existing Basin-wide product. This project yielded two principal output datasets. The first is a 1-meter resolution land-cover dataset. The second is a 10-meter land cover layer in which the 1-meter classes were aggregated to the National Land Cover Database (NCLD) classification schema. These related and complementary products ensure that all stakeholders in the LCB have the land-cover data they need to assess landscape status and process, from conservation managers seeking to evaluate riparian buffers to researchers modelling nonpoint source pollution. Land cover was mapped using advanced object-based image analysis techniques using high-performance computing. A detailed accuracy assessment was carried out and the overall accuracy was 91%. All products were documented with compliant metadata. These land cover products will be immediately useful to the Lake Champlain Basin Program and its collaborators and will serve as crucial input data for efforts seeking to address the issues raised in the Lake Champlain Opportunities for Action Management Plan.

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1 Project Introduction

Accurate, high-resolution land-cover maps are essential to a wide range of landscape-analysis and –monitoring efforts, including tree-canopy change detection (O'Neil-Dunne et al. 2014a), nonpoint-source pollution modeling (Cadenasso et al. 2008), carbon stock estimation (Johnson et al. 2015), spatial epidemiology (Lovasi et al. 2013), and urban planning (Troy et al. 2012). These maps provide the quantitative evidence that decision-makers and researchers need to understand and materially affect positive solutions to climate change, environmental degradation, and socioeconomic inequality. When produced with high cartographic realism, they are also very effective tools for highlighting and simplifying complex inter-relationships among environmental and social phenomena. The *Lake Champlain Opportunities for Action Management Plan* lists a multitude of natural resources issues facing Lake Champlain, and all of them would benefit from accurate, high-resolution land-cover data, directly or indirectly.

While sometimes combined in thematic maps, land use and land cover (collectively termed LULC) refer to distinct conceptual entities. Land cover represents actual features on the earth's surface while land use refers to anthropogenic landscape influences. Recent mapping efforts have attempted to differentiate these products. The most prominent example of this trend is the National Land Cover Database (NLCD). When first released in 1992, NLCD was a LULC product that mixed land-use classes (e.g. "low intensity residential") with land-cover classes (e.g. deciduous forest). The NLCD 1992 classification was found to be highly subjective, with overall accuracies as low at 46% for some parts of New England (Stehman et al. 2003). Now in its fourth iteration, NLCD is a pure land-cover product; classes in NLCD 2011 represent strict land-cover features (e.g. "open water") or concentrations of features (e.g. "developed land use"). Other programs such as the NOAA Coastal Change Analysis Program (C-CAP) and the USDA Forest Service's Urban Tree Canopy (UTC) Assessment have similarly moved to land cover-based mapping protocols. At the same time, many municipalities have begun attributing their parcel data with land-use information. Thus, land cover and land use are now commonly derived in distinct mapping efforts, with land cover features extracted from remotely-sensed data and land-use information attributed to parcel databases. To maintain consistency with the NLCD 2011 class definitions that were required in the RFP, we refer to the products generated for this project as "land cover" rather than "land use/land cover."

Land cover datasets, such as NLCD were produced from moderate resolution imagery, specifically 30-meter Landsat data. Thanks to investments made by federal and state agencies there exists both high-resolution imagery and LiDAR for the US portion of LCB. The availability of these data made it possible to increase the mapping resolution from the 30-meters used for prior projects, to 1-meter.

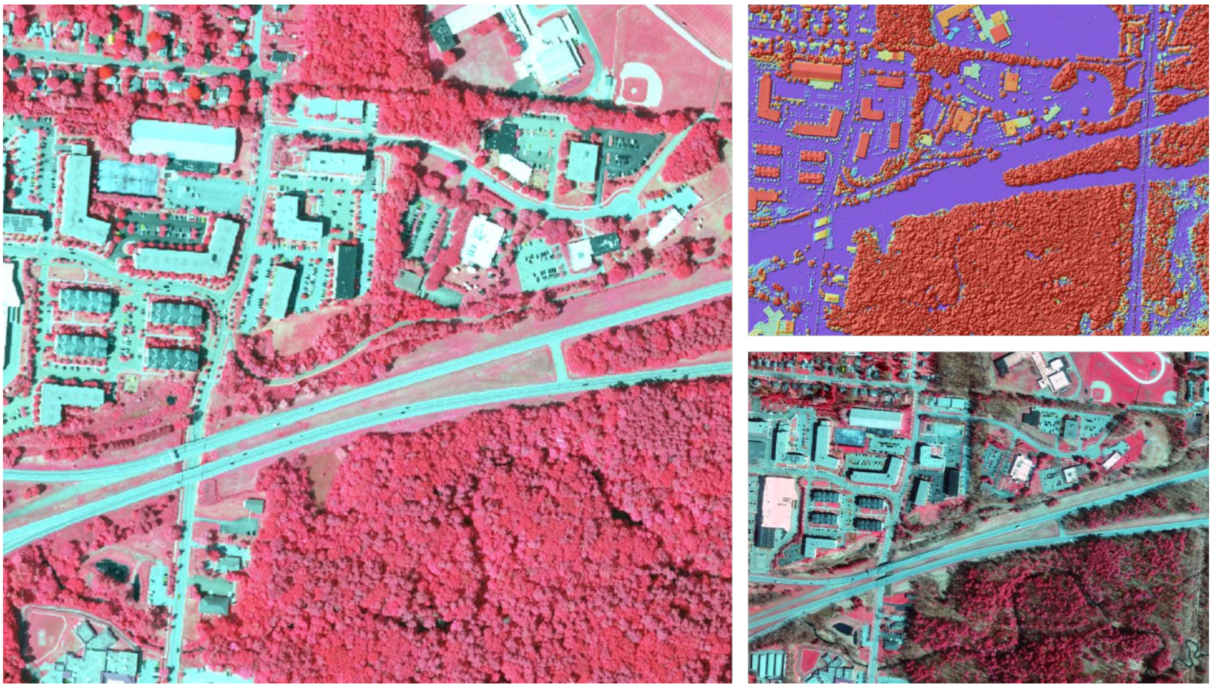

Figure 1. Example of some of the high-resolution data that exists for the Lake Champlain Basin. Leaf-on imagery (left), leaf-off LiDAR (top-right), and leaf-off imagery (bottom-right).

Land-cover mapping for large areas such as the LCB poses great challenges. Foremost is the sheer volume of input data. Transitioning from a 30-meter mapping unit (e.g., NLCD) to a 1-meter mapping unit represents a 900-fold increase in the size of the output land-cover dataset. The data inputs required for high-resolution land cover are exponentially larger than the outputs, necessitating use of high-performance computing environments. Within the Basin there are sixteen unique combinations of LiDAR and imagery. These datasets vary with respect to season they were acquired in, year they were acquired in, specifications, and overall quality. These variations made it impossible to apply a single automated routine for extracting land cover to all the datasets.

High-resolution land-cover mapping also requires very different techniques than those used for moderate-resolution mapping. The 30-meter NLCD products are derived from moderate resolution Landsat imagery. For NLCD, the pixel is the fundamental unit of analysis, and its spectral properties provide the key to determining land cover. In contrast, high-resolution mapping relies on data that have less spectral information but vastly more spatial information. This difference requires approaches that can accommodate the geometric characteristics of a feature and its context in the broader landscape. For example, shrubs in a transitional agricultural field may have spectral characteristics that are similar to shrubs in a wetland complex, but the landscape features that surround them will be the determining factor for the final land cover class designation.

This project employed object-based imagery analysis (OBIA) techniques, which are the most accepted approach for high-resolution land-cover mapping. OBIA focuses on groups of pixels that form meaningful landscape objects (Benz et al. 2004), effectively mimicking the way humans interpret landscape features by incorporating contextual cues such as contrast and adjacency. It is especially important for improving classification of objects whose pixel characteristics alone may not provide enough information to discriminate them from other features (O'Neil-Dunne et al. 2011). Furthermore, OBIA facilitates the fusion of imagery, LiDAR, and thematic data (e.g. road centerlines) into a single, comprehensive land-cover classification workflow. Because the unit of analysis is the object rather than the pixel, OBIA approaches can integrate raster data of varying resolutions and are less sensitive to misalignments that are typical when LiDAR and imagery are jointly used in a feature-extraction workflow.

This project was carried out by the University of Vermont Spatial Analysis Laboratory (SAL), an internationally recognized leader in the development of high-resolution land-cover datasets using OBIA techniques. The SAL has completed some of the largest and most challenging land-cover products in the United States, routinely generating 1-meter or finer land-cover products for expansive landscapes (e.g., MacFaden et al. 2012, O'Neil-Dunne et al. 2014a, O'Neil-Dunne et al. 2014b). Examples include the Lake Tahoe Basin, the Chicago metropolitan region, the Chesapeake Bay Watershed, the Delaware River Basin, San Diego County (CA), the City of New York Watersheds, the Northern Kentucky region, and Los Angeles County (CA). The SAL has a proven track record of generating quality, high-resolution land cover from complex and disparate geospatial datasets, uniquely combining the best of automated feature extraction, high-performance computing, and a team of technicians dedicated to comprehensive quality control.

This project leveraged prior work. The SAL developed the improved LCB moderate-resolution LULC data for use in phosphorus-loading modeling (Troy et al., 2007) and more recently produced a high-resolution impervious surfaces map (O'Neil-Dunne, 2013). With funding from AmericaView, the SAL developed processes for high-resolution land-cover mapping for select Vermont portions of the LCB. For this project AmericaView funds contributed to funding undergraduate student employees on this project. All work for this project was performed in the State of Vermont by faculty, staff, and students at the University of Vermont.

The approach to land-cover mapping for this project focused on leveraging the considerable investments that have been made in remotely-sensed data acquisition by state and federal organizations, using a combination of LiDAR and multispectral imagery. The combination of these two datasets increased the mapping accuracy, allowing for features that may be spectrally and geometrically similar (e.g., buildings and parking lots) or texturally similar (e.g. trees and shrubs) to be distinguished (O'Neil-Dunne et al. 2013). LCB-wide LiDAR was not yet available for most of the LCB when the SAL produced the most recent impervious surfaces map, and only became available for all areas halfway through this project. High-resolution leaf-on and leaf-off imagery are already were available for the entirety of the LCB, but some of the leaf-on data in NY was actually acquired under partial leaf-off conditions in the fall. The base mapping dates for this project were set using the most current NAIP data (leaf-on imagery), which was 2015 for NY and 2016 for VT.

As 1-meter raster land cover for the entirety of the LCB is an extremely large dataset and challenging to use for some modeling applications, an aggregated 10-meter land cover was generated. This product adhered to the NLCD classification schema (Figure 2). The land cover information was also summarized at various geographical units of analyses, ranging from town to watershed.

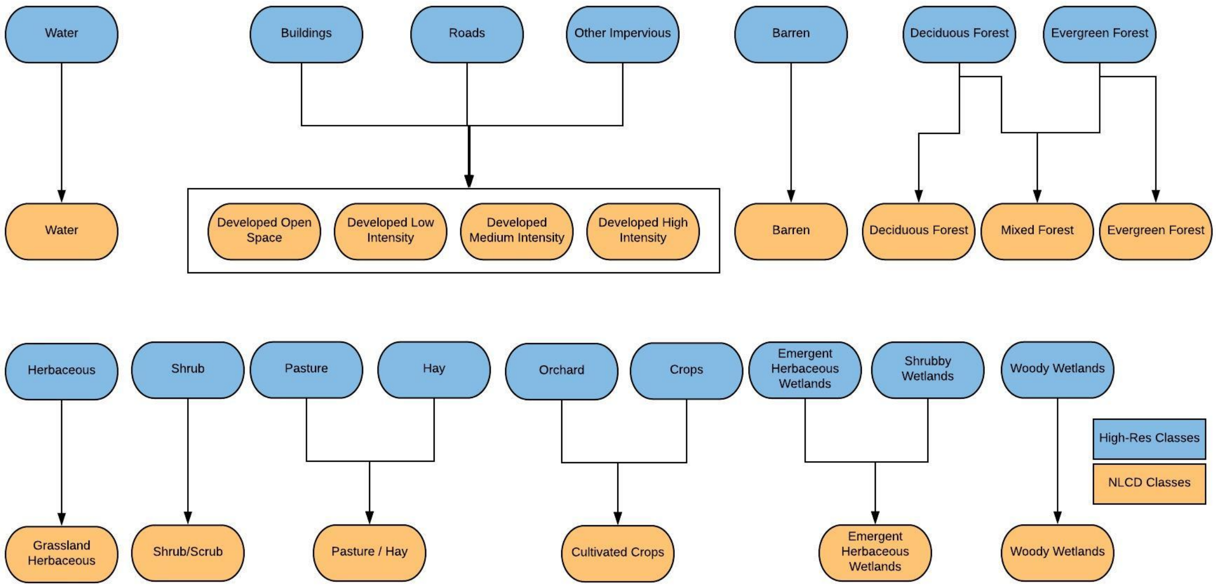

Figure 2. Classification crosswalk.

2 Tasks Completed

The overarching objectives of this project were to produce the most detailed and accurate land-cover dataset in existence for the LCB and to make these products available online through via the Lake Champlain Basin Atlas.

Our workflow, excluding the development of the QAPP and work plan, is presented in Figure 3. It consisted of nine specific tasks: 1) project initiation; 2) data preparation; 3) automated feature extraction; 4) manual corrections; 5) quality evaluation and accuracy assessment; 6) land-cover aggregation; 7) ancillary product generation; and 8) documentation and reporting.

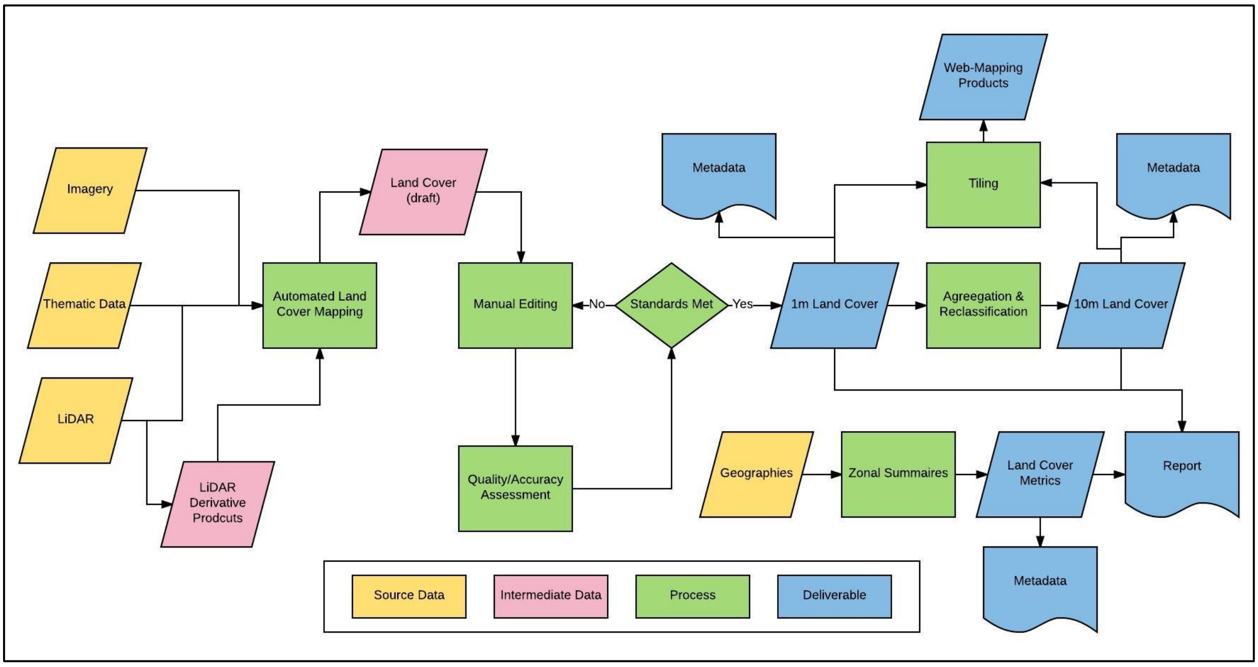

Figure 3. Project workflow. Note that the project initiation tasks (QAPP and work plan) have been excluded from this diagram.

2.1 Task 1: Project Initiation

A Quality Assurance Project Plan (QAPP) was developed and approved by the Basin Program and the U.S. EPA.

2.2 Task 2: Data Preparation

All required source datasets were obtained. Pre-processing, including normalization and classification of LiDAR point clouds, derivation of raster surface models, development of imagery mosaics, compilation of thematic vector data, and re-projection of datasets to a common coordinate system were performed.

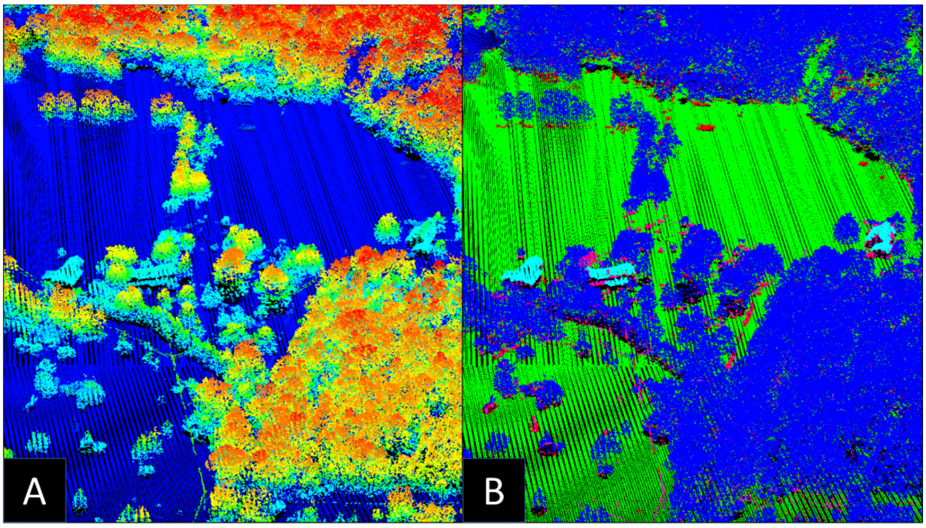

Figure 4. Preprocessing of LiDAR data. Original point cloud (A) and classified point cloud (B).

2.3 Task 3: Automated Feature Extraction

We designed, developed, and deployed an OBIA framework that automatically extracted 14 land-cover classes (Figure 2) from the source datasets using a rule-based expert system.

2.4 Task 4: Manual Corrections

The 1-meter resolution land-cover product were manually reviewed and edited at a scale of 1:5,000.

2.5 Task 5: Quality Evaluation & Accuracy Assessment

The accuracy of the 1-meter product was assessed using a stratified random sampling approach. Although the accuracy assessment threshold set for the project was achieved, the accuracy of certain classes was a cause for concern and thus additional manual corrections were carried out.

2.6 Task 6. Land Cover Aggregation

The final 1-meter land-cover dataset was aggregated to a 10-meter product.

2.7 Task 7: Ancillary Product Generation

The 1-meter land cover product was processed into cached imagery tiles for use online with the Lake Champlain Basin Atlas. Land cover was summarized by pertinent geographical units.

2.8 Task 8: Reporting and Documentation.

Status reports were submitted every quarter and this document consists of the final report. Metadata was generated for all geospatial deliverables.

3 Methodology

We designed, developed, and deployed an OBIA framework that automatically extracted 14 land-cover classes (Figure 2) from the source datasets using a rule-based expert system. The expert system made use of segmentation, classification, and morphology algorithms to group pixels into objects, classify the objects based on the properties of the source datasets, and then refined the objects to enhance the aesthetics and to improve the visual realism (Figure 5). Our approach to land-cover mapping for this project mirrored what we have published peer-reviewed journal articles (MacFaden et al. 2012, O'Neil-Dunne et al. 2014a, O'Neil-Dunne et al. 2014b, O'Neil-Dunne et al. 2013).

Tree canopy class (Tree Canopy-Deciduous, Tree Canopy-Coniferous) delineation was based on methods previously used by the SAL in many projects throughout the United States and Canada (O'Neil-Dunne et al. 2014a, MacFaden et al. 2012). This method directly extracts information LiDAR point clouds, permitting effective discrimination of trees from buildings and other aboveground anthropogenic features. Coniferous trees were distinguished from deciduous trees using spectral indices and LiDAR point cloud properties. The LiDAR was also used to discriminate trees from shrubs and other low-growing vegetation (Shrub\Scrub, Grassland\Herbaceous).

Wetlands mapping followed methods described by Rampi et al. (2014) and recently used by the SAL to map primary wetland types in several New York watersheds (Houston et al. 2015). These methods rely on a LiDAR-derived cartographic topographic index (CTI) that combined slope and flow potential, identifying topographies where water could theoretically collect; these sites were highly textured in CTI layers. Leaf-off orthoimagery assisted with the classification of sites with high CTI textures, especially the near infrared band (water strongly absorbs this band, producing low imagery values). After potential wetlands were identified, they were further classified into primary types (Wetlands-Emergent, Wetlands-Scrub\Shrub, Wetlands-Forested) using LiDAR-derived vegetation height.

The agricultural classes (Agriculture-Pasture, Agriculture-Hay, Agriculture-Crops, Orchards) similarly incorporated vegetation height and spectral differences, and they also included object texture and landscape context. In leaf-on orthoimagery such as NAIP datasets, crops had a rougher texture than hayfields and pastures, and they occurred in rural or semi-rural areas at low elevation and slope. Textural and spectral characteristics were employed to discriminate heavily-grazed pastures from hayfields.

Developed feature (Buildings, Roads, Other Impervious Surfaces) were mapped from a combination of all data inputs. As with tree canopy, buildings were based primarily on direct manipulation of LiDAR point clouds, but spectral indices assisted in differentiation the buildings from vegetated features. For roads and other surface features such as parking lots, the existing impervious surfaces layer for the LCB was augmented with LiDAR intensity values, which often provided a sharp contrast between anthropogenic and natural surfaces. Available thematic GIS datasets such as road centerlines and building locations were used to error check the initial classification for these features.

Bare soil and other barren areas (Barren Lands) were distinguished from agriculture and impervious surfaces using a combination of spectral criteria, texture, and landscape context. Cliffs and bedrock-exposed peaks proved to be isolated features surrounded by tree canopy, while beaches and rocky shorelines were classified using rules that focused on identifying low-NDVI objects occurring adjacent to water. Building sites with exposed soil most often had bright imagery values in leaf-on imagery and occur near roads and other impervious surfaces.

The Water class was based on combination of available thematic datasets, principally the 1: 5,000 National Hydrography Dataset, along with the low near-infrared reflectance and high Normalized Difference Vegetation Index (NDWI) values.

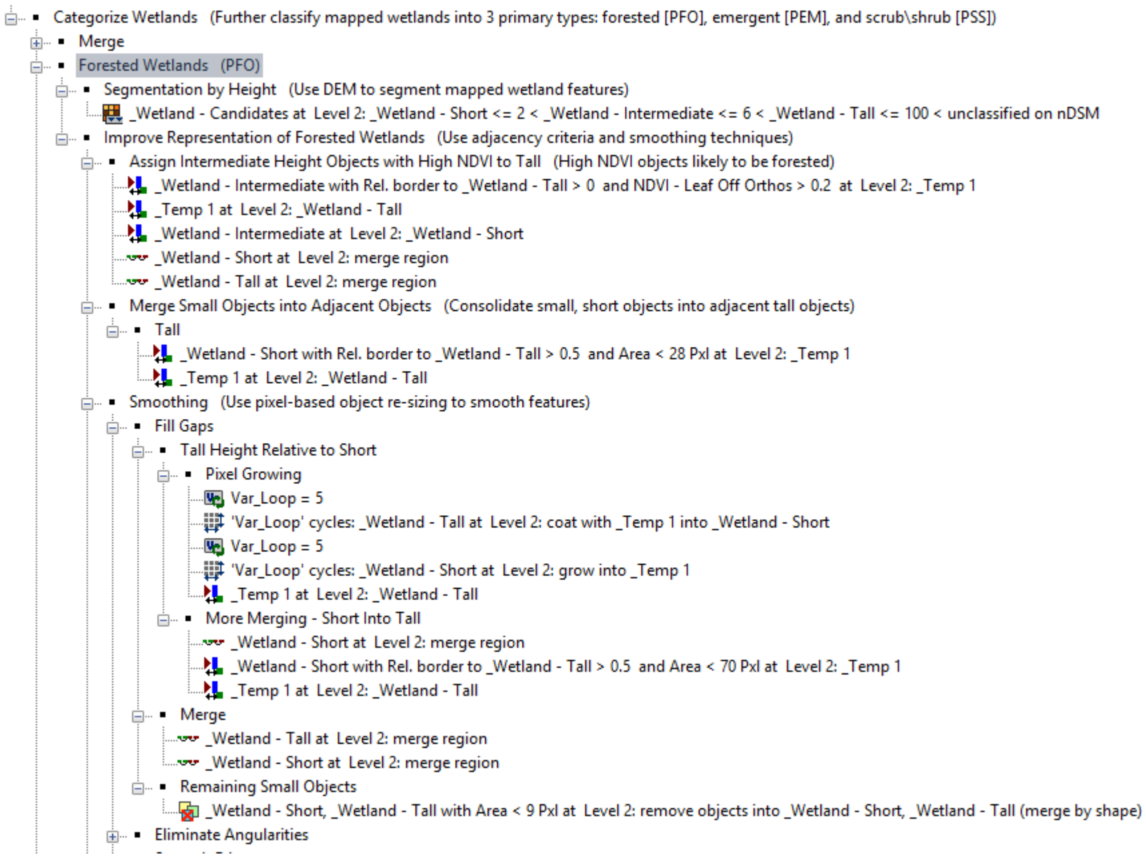

Figure 5. Portion of the rule-based expert system used to map the forested wetland class.

The 1-meter resolution land-cover product were manually reviewed and edited at a scale of 1:5,000 using desktop GIS software. In general, the manual edited focused on non-systematic errors and inconsistencies that could not be remedied by additional refinement to the OBIA system. The technicians involved in the editing process were trained using a standard set of image interpretation keys. All visible errors were corrected using the source imagery and LiDAR data as reference datasets. Edits made by technicians were reviewed by a team leader to ensure quality and consistency.

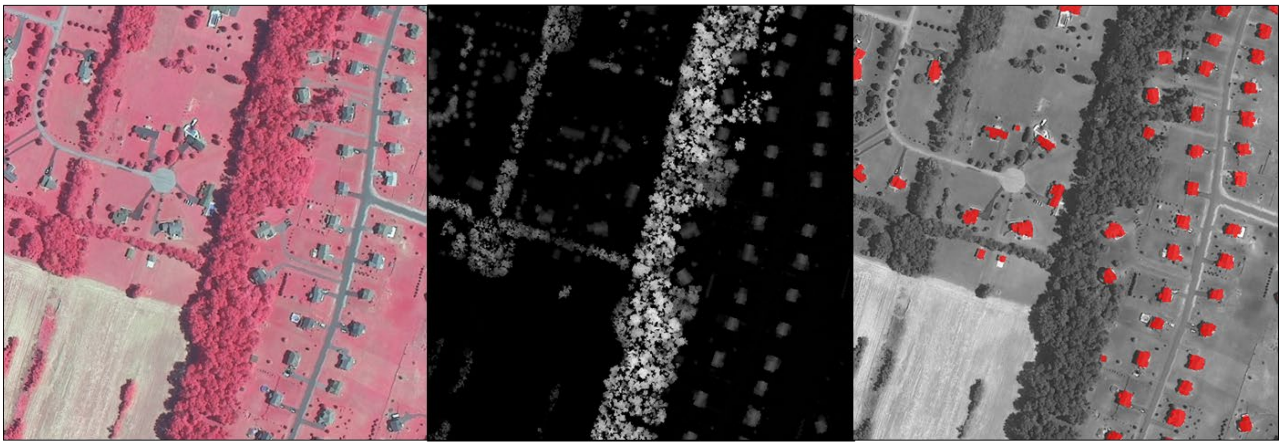

Figure 6. Leaf-on imagery (left), LiDAR surface model (center), and buildings (right).

To assess the accuracy of the 1-meter product we performed a quantitative accuracy assessment using stratified sampling methods described by Congalton (1991). 200 random points were generated for each of the 14 land-cover classes. The actual land cover at each point were manually determined by examining available reference imagery and LiDAR data. These points were then intersected with the 1-meter land-cover map, yielding an error matrix provided the user's and producer's accuracies for each class as well as an overall accuracy.

The final 1-meter land-cover dataset was aggregated to a 10-meter product consistent with the current NLCD class definitions using the crosswalk presented in Figure 2. Functionally, this step was performed by overlaying a 10-meter grid on the 1-meter land-cover map and applying a set of aggregation rules to each 10-meter cell that assigns the appropriate NLCD class. The Buildings, Roads, and Other Impervious Surfaces classes from the 1-meter land cover were consolidated into developed classes that indicated relative land-use intensity: Developed-Open Space (NLCD code 21), Developed-Low Intensity (22), Developed-Medium Intensity (23), and Developed-High Intensity (24). Land-use intensity was estimated by first calculating the proportion of each cell in the 10-meter grid that is occupied by developed features in the 1-meter layer and then assigning each cell according to NLCD thresholds (Developed-Open Space, >0<20%; Developed-Low Intensity, 20-49%; Developed-Medium Intensity, 50-79%; Developed-High Intensity, >79%).

Similarly, the Tree Canopy-Deciduous and Tree Canopy-Coniferous classes were re-assigned to the three NLCD categories using proportional representation between the 10-meter and 1-meter layers: Deciduous Forest (>20% tree cover, >75% deciduous), Evergreen Forest (>20% tree cover, >75% coniferous), and Mixed Forest (>20% tree cover, <75% deciduous or coniferous). The Agriculture-Pasture and Agriculture-Hay classes were simply combined into a single NLCD class (Pasture/Hay). The Water, Barren Land, Shrub/Scrub, Grassland/Herbaceous, and Agriculture-Cultivated Crops classes in the 10-meter LULC already match the NLCD classification scheme and thus required no further modification.

4 Quality Assurance Tasks Completed

The tasks and QAPP tasks for this project correspond to tasks 2 through 8 listed above.

5 Deliverables Completed

1. Work plan
2. QAPP
3. Composite LiDAR DEMs for the New York and Vermont LCB lands.
4. Composite 1-meter land cover dataset in raster format with metadata
5. Tree canopy vector product developed as part of the 1-meter land cover with metadata
6. Building vector product developed as part of the 1-meter land cover with metadata
7. 10-meter land cover dataset in raster format with metadata
8. Tiled 1-meter and 10-meter resolution maps for use in the Lake Champlain Atlas
9. Land cover metrics for various geographies with metadata
10. Quarterly reports
11. Final report

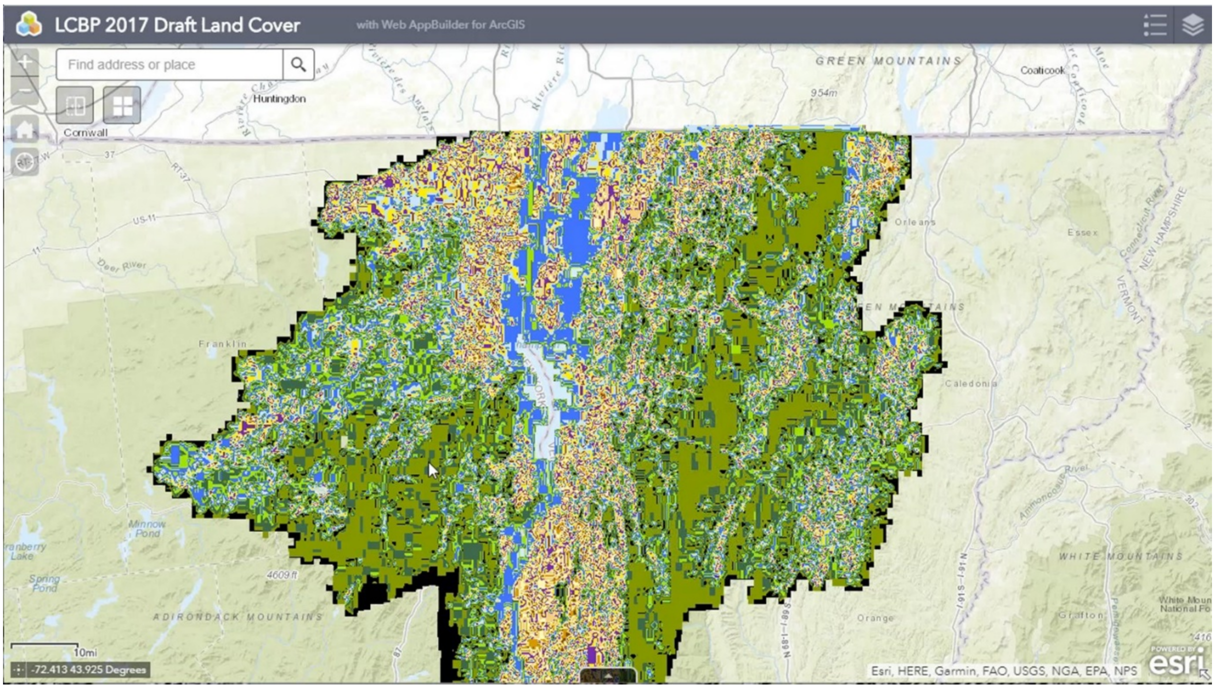

Figure 7. Web-based viewer.

6 Conclusions

This project succeeded in generating the highest-resolution, highest-accuracy land cover product in existence for the Lake Champlain Basin. The improvement in quality compared to NLCD is clearly evident (Figure 8). The 900-fold improvement over 30-meter mapping means that fine-scale features such as forested riparian buffers, street trees, buildings, and bare soil in athletic fields are visible (Figure 8 and Figure 9). This improvement in spatial resolution enables land cover to be examined at the full range of scales from Basin-wide to the property parcel.

One of the drawbacks of the classification schema used for this project is that certain features are resolved at different scales and overlap. Both orchards and forested wetlands represent aggregates of multiple other features and thus have an inherent conflict with the scale at which tree canopy was mapped. To overcome this situation, additional products, such as a separate tree canopy (Figure 10) and building datasets were produced.

The overall accuracy for the 1-meter land cover product was 91%, exceeding the project's standard of 85% (Table 1). For individual classes the story is more complicated (Table 2). User's accuracy is the most pertinent measure of accuracy as it provides an indication of the probability that a feature, when viewed in a map, is assigned to the correct class. The user's accuracy for certain classes, such as the buildings, water, and tree canopy classes were exceptionally high. On the other hand, the user's accuracy for the pasture, hay, and crops classes was quite low. The vast majority of the source of error for each of these classes was from other agricultural classes. Thus, while the mapping of agricultural land cover in general was accurate, the distinction between classes was far less accurate. Some of this error is undoubtedly due to the ever-changing agricultural land use patterns combined with the fact that the imagery used in the project was not always acquired at a consistent or ideal time for agricultural mapping.

This project was only possible due to the sizable investments made in remotely sensed data for the Basin. With a base high-resolution land cover product now complete it will be much more cost effective to update the data going forward, but such an endeavor will only be possible if new high-resolution imagery and LiDAR are collected. Deciding when and where to update the land cover could be done based on "tip-off" analysis, in which moderate resolution satellite imagery (e.g. Sentinel and Landsat) provide indicators of change, and/or as new high-resolution datasets become available.

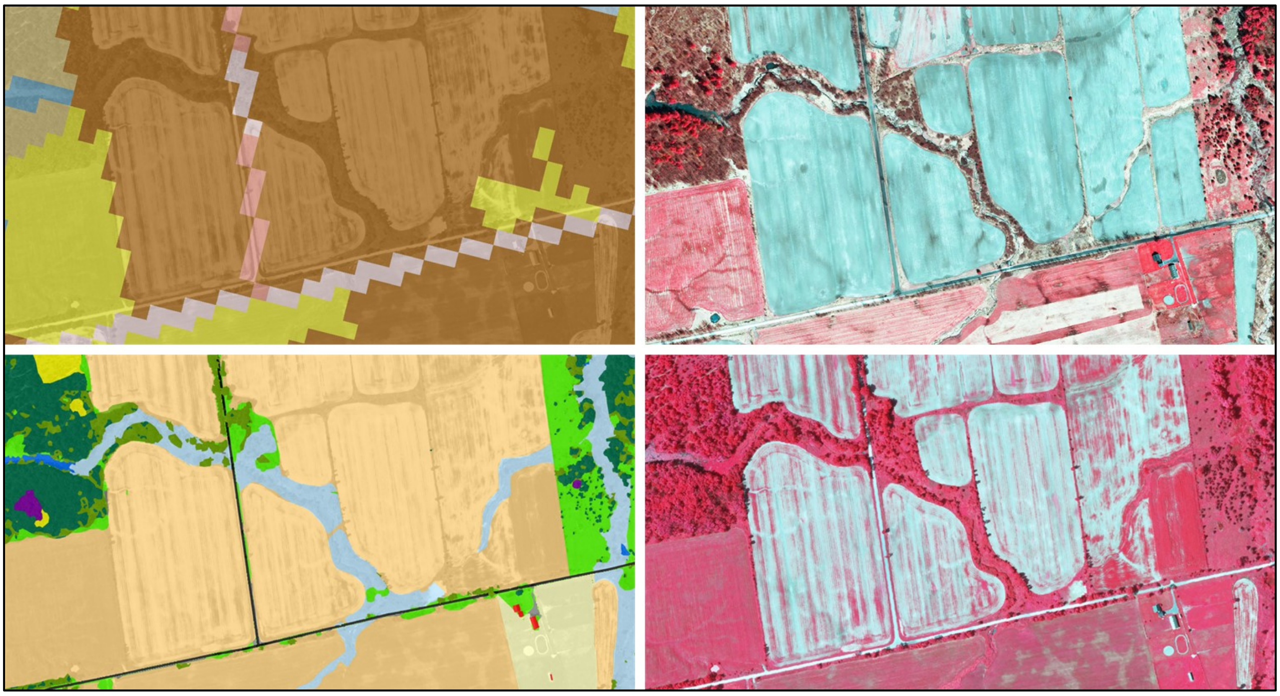

Figure 8. Comparison of 30-meter NLCD 2011 land cover product (top-left) to the 1-meter product generated through this project (bottom-left). Leaf-off (top-right) and leaf-on (bottom-right) are provided for reference.

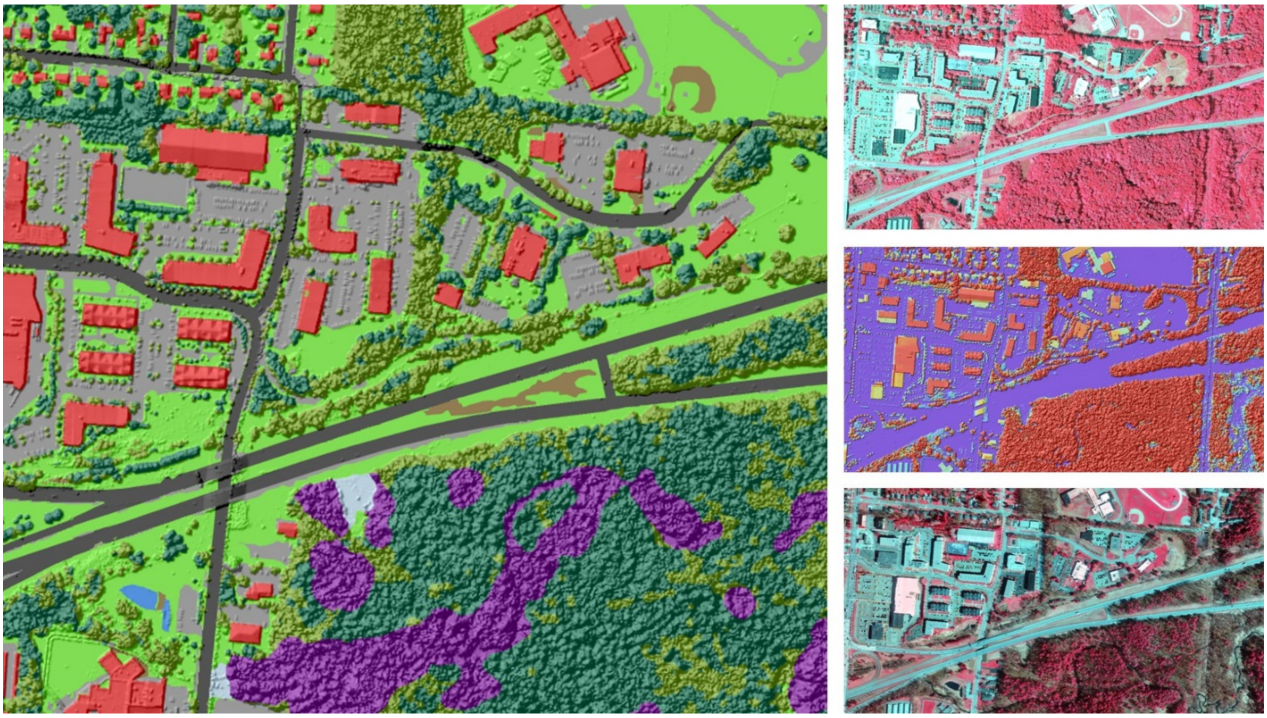

Figure 9. 1-meter land cover product and associated source datasets.

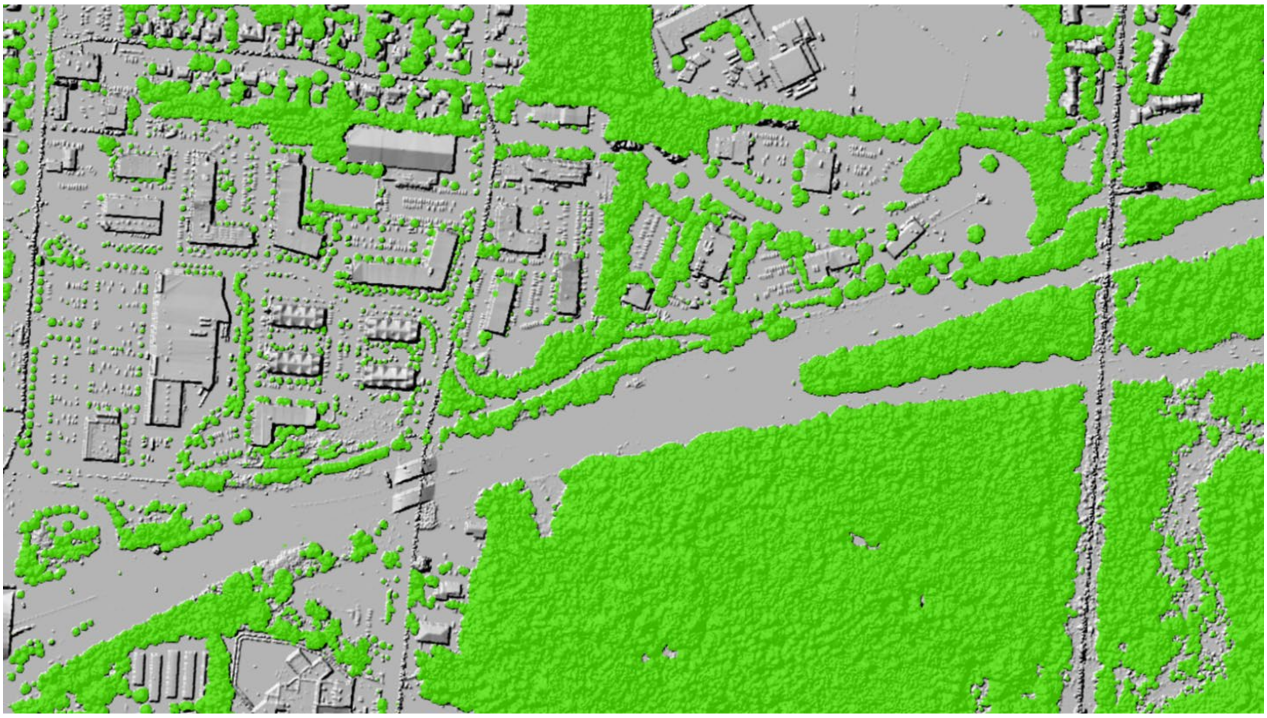

Figure 10. Separate tree canopy product for the same area as shown in Figure 9.

Table 1. Accuracy assessment error matrix for the 1-meter product.

	Reference Data																
	Water	Buildings	Roads	Other Impervious	Barren	Deciduous Tree Canopy	Coniferous Tree Canopy	Herbaceous	Shrub	Pasture	Hay	Orchard	Crops	Emergent Herbaceous Wetlands	Shrubby Wetlands	Woody Wetlands		User's Accuracy
Water	**197**				2					1							200	**99%**
Buildings		**193**		3		5	1										202	**96%**
Roads			**186**	11	3												200	**93%**
Other Impervious	1		5	**186**	7										1		200	**93%**
Barren				9	**171**			6	2	4			8				200	**86%**
Deciduous Tree Canopy		2				**194**	4										200	**97%**
Coniferous Tree Canopy		7				8	**185**										200	**93%**
Herbaceous				2	1			**181**	8		6		1		1		200	**91%**
Shrub								7	**178**	6	5	1			2	1	200	**89%**
Pasture								4		**124**	38		29	5			200	**62%**
Hay								2	2	14	**171**		11				200	**86%**
Orchard						2			3			**195**					200	**98%**
Crops								2		14	35	1	**148**				200	**74%**
Emergent Herbaceous Wetlands														**196**	2	2	200	**98%**
Shrubby Wetlands														3	**197**		200	**99%**
Woody Wetlands															2	**198**	200	**99%**
	198	202	191	211	184	209	190	202	193	163	255	197	197	204	205	201	2900	
Producer's Accuracy	**99%**	**96%**	**97%**	**88%**	**93%**	**93%**	**97%**	**90%**	**92%**	**76%**	**67%**	**99%**	**75%**	**96%**	**96%**	**99%**		**91%**

Table 2. User's and Producer's accuracies from Table 2.

Class	User's Accuracy	Producer's Accuracy
Water	99%	99%
Buildings	96%	96%
Roads	93%	97%
Other Impervious	93%	88%
Barren	86%	93%
Deciduous Tree Canopy	97%	93%
Coniferous Tree Canopy	93%	97%
Herbaceous	91%	90%
Shrub	89%	92%
Pasture	62%	76%
Hay	86%	67%
Orchard	98%	99%
Crops	74%	75%
Emergent Herbaceous Wetlands	98%	96%
Shrubby Wetlands	99%	96%
Woody Wetlands	99%	99%

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Appendices