CITY OF SAMMAMISH LAND AND CANOPY COVER ANALYSIS: METHODS AND RESULTS

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Contents

Purpose

This is a companion document to the land cover class GeoTIFFs for Sammamish: 270_LC_6class.tif; 000_LC_6class.tif; and 090_LC_6class.tif.

This document describes the background, methodology, and results of the foundational 2015 canopy/land cover analysis completed for the City of Sammamish by researchers at University of Washington between September 2017 and February 2018.

Background

The City of Sammamish is currently writing its first Urban Forest Management Plan (UFMP). City of Sammamish staff recognized the need for a current map of canopy cover to measure how much of Sammamish is forested and where those forests are located to support creation of the UFMP.

Canopy cover over a large area can be determined using land cover analysis. Land cover analyses use multi-band[1] orthoimagery, combined with additional data, to delineate areas of canopy cover, impervious surface, and other land cover types. Various software tools are used to classify this imagery into the different land covers, including Harris Corp.'s ENVI, Trimble eCognition, and Orfeo Toolbox. These analyses provide an accurate, comprehensive measure of canopy extent on both public and private land. Analyses using the same methods with multiple years of data can be used to determine land cover change.

The comprehensive land cover analysis produced for the City of Sammamish serves as a baseline for the City to calculate canopy coverage for specific areas/parcels, monitor land cover change, and provide other relevant information for the UFMP and long-term forest management. Orthoimagery of the City of Sammamish is classified into 5 key land cover categories: water, impervious surface, tree canopy (conifer and deciduous canopy), and low vegetation (shrubs, grasses, and emergent vegetation). The analysis was completed using open, reproducible methods that are fully documented here.

Methods

The methods for this land cover analysis are based on documentation provided by Orfeo ToolBox[2] and SERVIR Global[3]. Orfeo ToolBox is an open source toolkit for processing remote sensing images. SERVIR Global is a partnership between NASA and USAID that develops tools and training programs to help developing countries use satellite geospatial data.

We chose these resources because they are open source—allowing anyone to use them—and the SERVIR documentation provides sufficient detail to allow competent practitioners and members of the public to learn the basics of how to perform a land cover analysis. The following information on our data sources and methods, combined with documentation provided by Orfeo and SERVIR, should allow others to recreate our analysis.

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[1] Multi-band data includes the visible color spectrum—red, green, and blue—along with at least one band of infrared data. See Orthoimagery for more information.

[2] Online at https://www.orfeo-toolbox.org/.

[3] Online at https://www.servirglobal.net/Global/Articles/Article/2549/forest-cover-change-detection-training.

Software Used

QGIS: QGIS is a free and open source geographic information system; it is the open source equivalent of ESRI's ArcMap. Orfeo ToolBox is available as a plugin for QGIS, which provides GUI functionality for ease of use. QGIS version 2.18.14 was used in this analysis.

R: R is an open source statistical programming language[4]. Key R scripts for this analysis have been written as plugins for QGIS. Microsoft Open R version 3.3.3 was used, in the RStudio IDE, version 1.0.153.

Area of Analysis

Our area of analysis comprises the Sammamish area of interest as well as adjacent areas with both orthoimagery and LiDAR data coverage. Impervious data coverage is limited to the Sammamish area of interest; thus predictive capabilities are highest here (Figure 1).

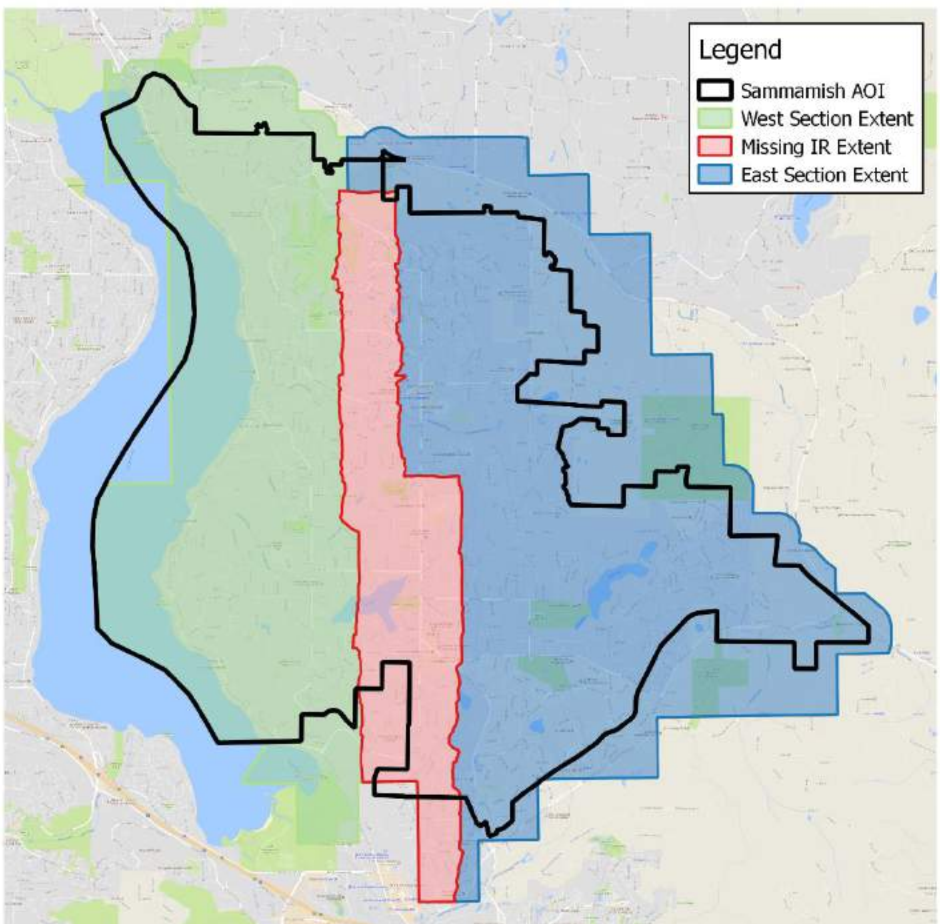

Figure 1: Area of analysis for canopy and land cover classification.

[4] R Core Team (2017). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/.

Data Sources Used in Analysis

Orthoimagery

Two sources of orthoimagery from 2015 were used in this analysis: aerial imagery from the 2015 Regional Aerials (City Consortium) Project and imagery from the National Agriculture Imagery Program (NAIP).

Orthoimagery or orthophotos are aerial photographs that have been ‘orthorectified’. ‘Regular’ orthophotos use a digital elevation model to correct differences in terrain relief[5]. Objects projecting from the ground are still displaced. ‘True’ orthorectification, which uses a digital surface model (see LiDAR Data for additional discussion on DEM vs DSM), is particularly critical for analyses of urban areas, as residual obliquity of buildings and tall trees will otherwise obscure ground objects. With this method, each pixel and object in an orthoimage will appear as though the observer is directly above it (Figure 2).

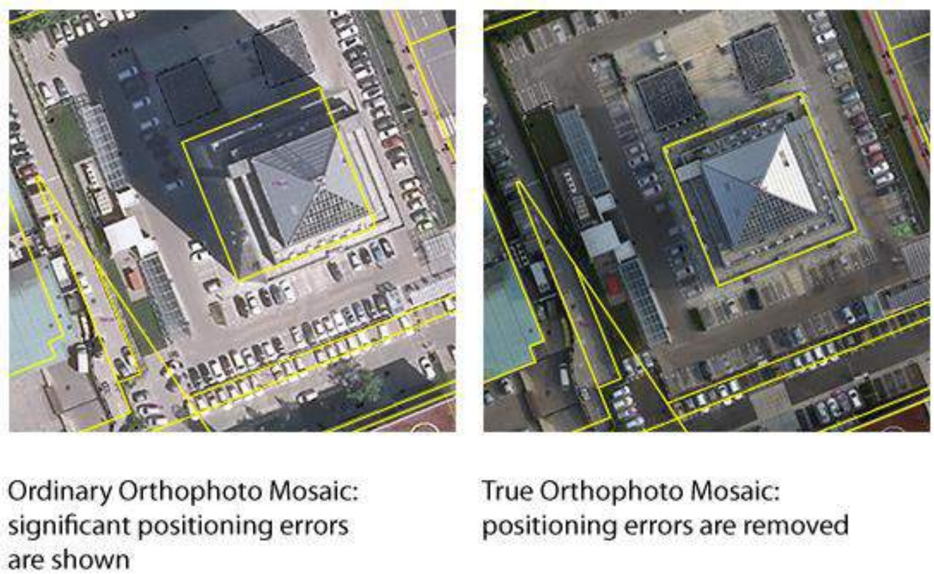

Figure 2: Difference between ordinary and true orthophotographs. Note that ground objects are obscured in the ordinary orthophoto example. Photo courtesy Geavis.

2015 Regional Aerials (City Consortium) Project: This orthoimagery is the primary dataset for this land cover analysis and is referred to as ‘orthoimagery’ or ‘2015 Regional Aerials’ here. These images are orthorectified using a digital elevation model only.

In 2015, an 88-member consortium of cities and counties commissioned aerial four band imagery at 0.25’ to 1’ resolution. Data for the City of Sammamish is available at 0.25’ (3”) resolution. Due to the license agreement with the data provider, this dataset is the only one not publicly available. It must be

[5] The USGS provides a good explaination of different aerial imagery types and their uses: https://pubs.usgs.gov/gip/AerialPhotos_SatImages/aerial.html.

obtained either from the City of Sammamish or King County. The data is available in 3000 x 3000-foot grid tiles. We resampled this dataset to 1’ resolution to improve processing times[6].

This dataset has quality concerns. The lack of ‘true’ orthorectification means that trees and buildings located above the terrain display obliquity and are not displayed true to life—they are instead too large and tilted away from the camera. We use LiDAR data in our model to help correct this issue, however because ‘true’ orthorectification was not done by the data provider, we cannot recover ground image information that is obscured by tree and building obliquity (Appendix A). Obliquity issues are compounded as data was taken with a wider field of view and less image overlap than we have encountered in other, similar datasets.

A 6.97 square mile (18.05 square kilometer) section of the near-infrared data is missing in the City of Sammamish due to equipment failure by the data provider. The broken instrument was replaced with a new instrument, so there are three separate sections of IR data for Sammamish (old instrument data to the west, missing IR data in the center, new instrument data to the east, Figure 3). Note the color differences between west, center, and east sections of Figure 3. Additionally, there is more variation in hue in the west section of the city than the east. Replacing the instrument also led to seasonal differences moving west to east over the city—images from the western portion were take significantly earlier than those in the eastern section, leading to differences in leaf-out (Appendix A).

To analyze the three sections, we created three groups of tiles. Based on the border of the missing IR data, some tiles appear in two groups. In these cases, the tiles were processed twice and trimmed accordingly.

[6] Robert J. Hijmans (2016). raster: Geographic Data Analysis and Modeling. R package version 2.5-8. https://CRAN.R-project.org/package=raster.

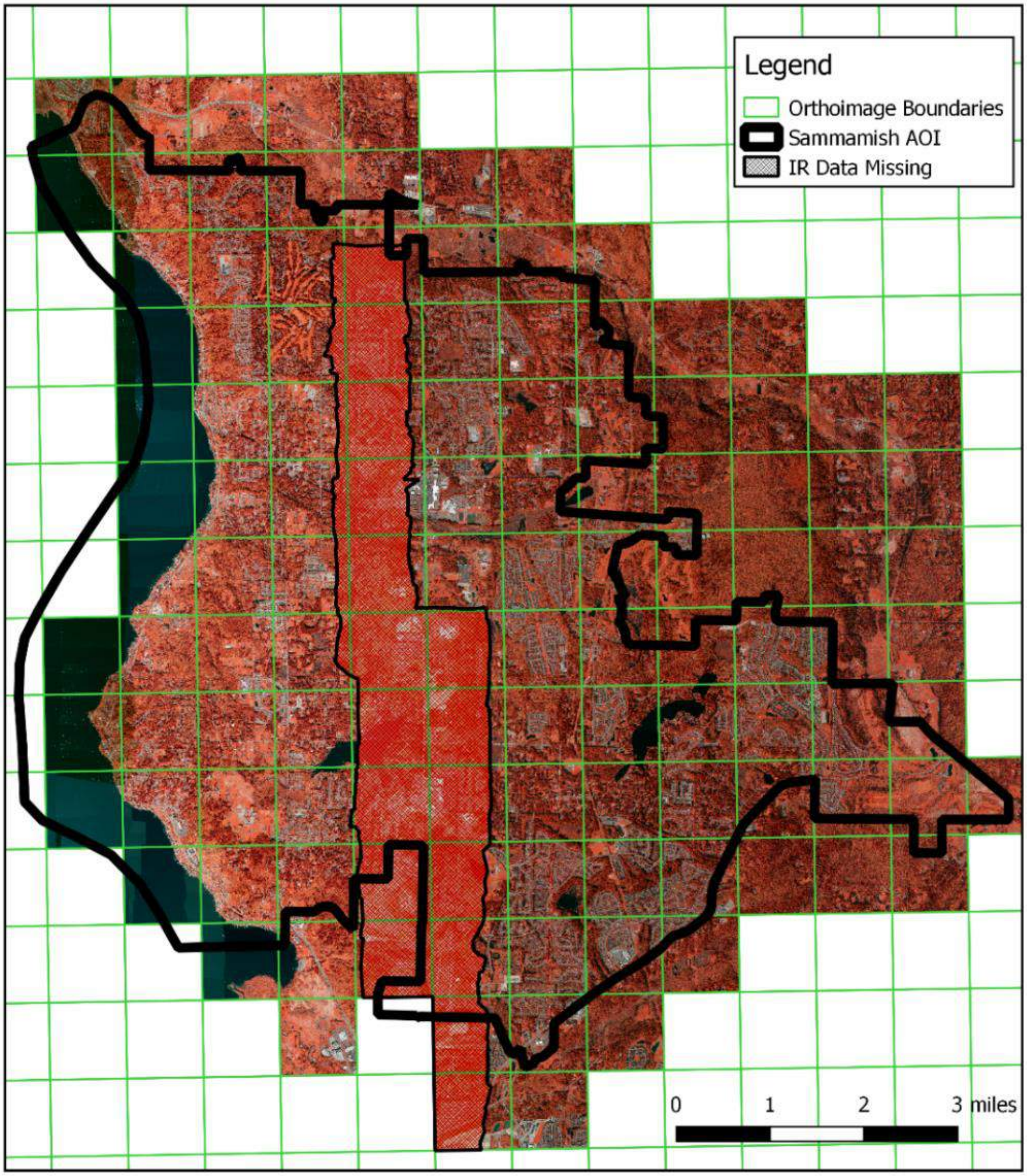

Figure 3: Map of the missing IR data in relation to the City of Sammamish area of interest boundary and orthoimagery tile boundaries. East, center (missing), and west sections of the city were analyzed separately. Orthoimagery shown in false color (IR band is red) to highlight missing data—IR values in this section are the maximum possible so the section appears red.

Finally, an 80 acre (.12 sq mi) section has been severely compromised (Figures 4 and 5). **It is not possible to make an accurate land cover classification from this data.** The area is located within the central missing IR data section.

Figure 4: The severely compromised section, outlined with a dashed orange line.

Figure 5: Closeup of the northwest corner of the severely compromised section. Note how a neighborhood has been superimposed on the 'correct' golf course and residential area.

NAIP Imagery: NAIP imagery is acquired during the agricultural growing season ("leaf-on"). In King County, four bands of imagery are available at a 1m resolution: red, green, blue, and near-infrared. Horizontal accuracy is within 6m. The most recent data for Washington is from summer 2015 (used in this analysis) and the next update will occur in 2018. The data can be downloaded from The National Map[7].

We paired this leaf-on data with the 2015 Regional Aerials to enhance detection of deciduous trees (Figure 6). Leaf-off data like is particularly useful when a clear view of the ground is important, including development appraisal and assessing the condition of streets and sidewalks. Leaf-on data is critical for accurately estimating deciduous leaf area and canopy cover[8].

Figure 6: Difference in deciduous canopy cover detection between leaf-off (2015 Regional Aerials, .25' resolution) and leaf-on (NAIP, 3' resolution) data. The photos show a contiguous area in west Sammamish.

[7] Online at https://viewer.nationalmap.gov/. Information: https://www.fsa.usda.gov/programs-and-services/aerial-photography/imagery-programs/naip-imagery/index and https://thor-f5.er.usgs.gov/ngtoc/metadata/waf/orthoimagery/naip/wa_2015/.

[8] See https://go.nearmap.com/blog/recent-aerial-imagery-leaf-off-game-on for a good summary of leaf-on vs. leaf-off data.

LiDAR Data

Light Detection and Ranging (LiDAR) data helps with vegetation discrimination, particularly between tree canopy and ground-level vegetation, and correcting obliquity found in the 2015 Regional Aerials.

We used 2016 LiDAR data available via the Washington State Department of Natural Resources Washington LiDAR Portal[9]. The data was collected by Quantum Spatial (QSI) at the behest of and with the assistance of the Puget Sound LiDAR Consortium (PSLC) and the Kitsap County Department of Emergency Management. The City of Sammamish is covered by the King County Delivery 3, flown in March of 2016.

There are two datasets derived from the LiDAR data. Digital terrain models (DTM) consist solely of bare earth surface, or ground points. Digital surface models (DSM) include information about all surfaces, including impervious or manmade surfaces and vegetation. Both are at a 3 foot pixel resolution[10].

Vector Data

Waterbodies: We used the King County waterbody layer (wtrbdy.shp[11]) to help train the image classification. It is current as of 2015 and is an accurate representation of water in Sammamish. The Sammamish GIS waterbody layer generally overstates the size of retention ponds and open water, and was found to be too inaccurate for model inclusion.

Impervious Surface: We used vector files from City of Sammamish representing multiple impervious surface[12], including building outlines (bldgRooflines.shp), sidewalks (walkways_sidewalks.shp), streets (roadway_edgeOfPavement.shp), patios (patios_concretePads.shp), parking lots (parkingLots.shp), decks (decks.shp), and driveways (driveways.shp). Invalid geometries, including open loops, rings, and duplicate features, were fixed manually in QGIS prior to analysis. Additionally, we identified buildings and other infrastructure that had been demolished between creation of the impervious surface layer and the 2015 Regional Aerials. Note that the impervious surface layers are available for most, though not all, of the research extent

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[9] Available online at http://lidarportal.dnr.wa.gov/#47.60243:-122.01068:16.

[10] Documentation available online at http://www5.kingcounty.gov/sdc/addl_doc/King_County_LiDAR_Cumulative_Technical_Data_Report.pdf.

[11] Available online at http://www5.kingcounty.gov/sdc/Metadata.aspx?Layer=wtrbdy; metadata: http://www5.kingcounty.gov/sdc/FGDCDocs/WTRBDY_faq.htm.

[12] Available from the City of Sammamish, online at: https://www.sammamish.us/government/departments/public-works/maps-and-gis-data/.

Derived Data Used in Analysis

All Impervious: All impervious surface layers were merged using the 'Merge Vector Layers' tool in QGIS.

Normalized Difference Vegetation Index (NDVI): NDVI[13] is a calculated index based on near-infrared and red wavelengths. This index is useful for identifying vegetation and vegetation density. It is calculated using the following formula:

$$\mathrm{NDVI} = \frac{NIR - Red}{NIR + Red}$$

We calculated this index for the NAIP data and the 2015 Regional Aerial data.

Normalized Difference Water Index (NDWI): NDWI[14] is a calculated index based on near-infrared and green wavelengths. The index is useful for distinguishing between open water and terrestrial vegetation. It is calculated using the following formula:

$$\mathrm{NDWI} = \frac{Green - NIR}{Green + NIR}$$

We calculated this index for the NAIP data and the 2015 Regional Aerial data.

Emergent Vegetation: Emergent vegetation (vegetation rooted in water where part of the plant is in the air) has a spectral signature between pavement and vegetation that makes it difficult for the image classifier to distinguish. The bogs and wetlands files from Sammamish include substantial portions of forested wetland and overlaps with roads; using these files in the training creates confusion between emergent vegetation and forest and emergent vegetation and pavement. We created a new polygon shapefile by hand in QGIS with areas of emergent vegetation delineated. Boundaries were chosen based on visual inspection of infrared data, NDWI, and the RGB visual spectrum.

Regions of Interest (ROI): Regions of interest are hand-drawn polygons or points used to train the image classification algorithm. For this analysis, we drew approximately 6300 polygons combined for the seven classes using QGIS (Figure 7). Each polygon is labeled with the land cover (e.g. grass, conifer) using both a text field and an integer field. The SERVIR training documentation provides a good overview of ROI and their use in land cover image classification[15]. ROI locations were identified using a random point generator and manually to ensure diverse representation within land cover classes.

[13] A good introduction to NDVI can be found at Wikipedia or from NASA: https://earthobservatory.nasa.gov/Features/MeasuringVegetation/measuring_vegetation_2.php.

[14] See USGS for a good overview: https://deltas.usgs.gov/fm/data/data_ndwi.aspx.

[15] Specifically this training lesson: https://www.servirglobal.net/Portals/0/Documents/Articles/ChangeDetectionTraining/Module3_LC_Classification_Accuracy_Assessment.pdf

Figure 7: Example of the Regions of Interest used to train the land cover model.

The seven classes used in classification were defined as follows:

1. Water: open water.
2. Bare Ground: dirt, mulch, and other bare pervious surface.
3. Impervious: roads, buildings, and other impervious surfaces.
4. Grass: lawns and pasture.
5. Understory: forest and decorative shrubs < 15' tall, emergent vegetation.
6. Conifer cover: conifer evergreen trees.
7. Deciduous cover: deciduous trees.

Note that ROI and the associated training land cover classes are refined using trial and error. We iterated by creating ROI, using them to perform a test classification, examining the results, and altering the ROI and land cover class groupings as needed to improve accuracy. We iterated both on a 5-tile test strip and then on the full tile set. For example, we started by considering 'lawn grass' and 'pasture' separately and found that we did not have sufficient infrared spectral coverage to differentiate between them (especially infrared > 1.4µ). We used the ROI Explorer[16] plugin in QGIS to help maximize differentiation between ROI classes.

Texture Analysis: Measures of ground 'texture' helps the image classifier differentiate between land cover types (particularly between vegetation types) by providing information about each individual pixel's surroundings to group them together into areas of related value. That is, by knowing more about how a pixel relates to the pixels around it, the image classifier can better differentiate between e.g.

[16] Online documentation: https://github.com/beeoda/roi_plugin.

smooth grass and rougher deciduous cover. We used the 'SFS Texture Extraction' tool[17] to extract texture from the NDWI layer calculated from the 2015 Regional Aerials[18]. The NDWI layer was chosen due to high information content. The tool calculates six different measures of Structural Feature Set textures, including SFS Length, SFS Width, SFS PSI, SFS ω-Mean, SFS Ratio and SFS SD [19], and takes approximately 7 minutes per tile.

Infrared Data Recovery: IR data is important for differentiating between pavement and vegetation and between different types of vegetation. As an accurate estimation of canopy cover was the primary goal of this analysis, we created a beta regression model to predict IR values based on intact sections of data and used this model to reconstruct the missing IR data.

We implemented the IR data recovery using a custom R script[20]. The missing IR data was imputed in R via beta regression by developing a global model from intact 2015 Regional Aerial images surrounding the bad data. Tiles neighboring the damaged areas were systematically sampled, with 50,000 samples per image.

The beta regression model contains the following predictor variables: Red, Green, Blue bands from the damaged tile, IR data from NAIP imagery acquired later in the year, NDVI and NDWI derived from NAIP data, binary (0/1) rasterized layers derived from vector data for wetlands, impervious surfaces (roads, parking lots, etc), structures, and open water, along with an edge-weighted, "smoothed" version of the RGB data (to capture neighborhood effects). While creating the model was reasonably fast, imputing the missing IR data and creating the output rasters took approximately 12 hours of computing time.

Shadow Detection and Removal: The orthoimagery was flown on sunny days in early spring, with the sun at a low angle. The shadows cast by buildings and trees were therefore very large and interfered with the image classification, frequently classifying shadows as conifer tree cover (Appendix A). Shadow detection identifies shaded pixels, while shadow removal focuses on recovering the information contained in those pixels[21].

To detect and remove the shadows, we implemented a custom R script based on Singh et al (2012)[22]. We first converted the RGB bands to HSI (hue, saturation, and intensity) and then performed shadow segmentation by applying Otsu thresholding[23] to a normalized difference index ((S-I)/(S+I)). We

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[17] Online documentation: https://www.orfeo-toolbox.org/CookBook/Applications/app_SFSTextureExtraction.html.
[18] With spectral width = 0.05; default tool settings otherwise.
[19] Huang, X., Zhang, L. and Li, P., 2007. Classification and extraction of spatial features in urban areas using high-resolution multispectral imagery. IEEE Geoscience and Remote Sensing Letters, 4(2), pp.260-264. Online at: ieeexplore.ieee.org/document/4156157/.
[20] Francisco Cribari-Neto, Achim Zeileis (2010). Beta Regression in R. Journal of Statistical Software 34(2), 1-24. http://www.jstatsoft.org/v34/i02/.
[21] Zhou, W., Huang, G., Troy, A. & Cadenasso, M. L. Object-based land cover classification of shaded areas in high spatial resolution imagery of urban areas: A comparison study. Remote Sens. Environ. 113, 1769–1777 (2009).
[22] Singh, K. K., Pal, K. & Nigam, M. J. Shadow Detection and Removal from Remote Sensing Images using NDI and Morphological Operators. Int. J. Comput. Appl. 42, 37–40 (2012).
[23]Gregoire Pau, Florian Fuchs, Oleg Sklyar, Michael Boutros, and Wolfgang Huber (2010): EBImage - an R package for image processing with applications to cellular phenotypes. Bioinformatics, 26(7), pp. 979-981, 10.1093/bioinformatics/btq046

performed shadow recovery by applying a modification formula to the red, green, and blue values of each pixel within the shadowed area.

Object Height: Object height is a calculated estimate of the difference between the elevation of the ground (DTM) and the elevation of all surfaces (DSM). It was calculated using the following formula:

$$Object\ Height = DSM - DTM$$

Image Classification

Differences in the quality of the orthoimagery across the city caused by the IR equipment failure required us to perform three separate image classifications (Figure 3). For each of the three sections we first created a raster 'stack' of all pertinent data, then used the 'Image Classification—random forest' tool in the Orfeo ToolBox to create a classification model, then finally used that model to classify each individual pixel into one of the 7 land cover classes. We provide details on each of these steps below.

However, the image classification step is not a straightforward process. Multiple iterations of ROI creation/editing, creating the raster stacks, and performing both image classification steps are required. The results of image classification provide critical information about the quality of your ROI and raster stacks. If the boundaries of your ROI overlap between land covers, you will train the model incorrectly. Likewise, if you include inaccurate or conflicting data in your raster stack - as with the wetlands vector overlapping conifer forest and impervious surface - you will train the model incorrectly. The specifications of the random forest also impact the quality of results, different classifications will result from different tree depth and forest size. Iteration is critical to catching these errors and adjusting to achieve the most accurate result. The validation results (discussed below) and the ROI Explorer tool are particularly important for identifying where and why land covers are inaccurate. This is a very time intensive process; only processing time for the final run is included here.

Raster 'stack'

Creating a raster stack involves merging all pertinent data into one raster, rather like creating a stack of papers out of individual sheets. We used a custom R script with the raster package to create a unique stack for each tile from the 2015 Regional Aerials. The 21 layers included are:

- Shadow corrected red, green, and blue orthoimagery bands (3),
- Original IR or recovered IR bands as applicable (1),
- NDVI values (1),
- NDWI values (1),
- NAIP imagery (4),
- NAIP derived NDVI (1),
- NAIP derived NDWI (1),
- Texture bands based on NDWI (6),
- Waterbodies vector (as raster binary; 1),
- All impervious surfaces vector (as raster binary; 1),
- Emergent vegetation vector (as raster binary; 1), and
- Object height (1).

The NAIP imagery and object height LiDAR layers were resampled to 1' resolution (raster::resample()[24]) and bilinear interpolation. Creating the raster stacks took approximately 12 hours for each of the three sections.

[24] Documentation online at: https://www.rdocumentation.org/packages/raster/versions/2.6-7/topics/resample.

Image Classification Model Creation

We used the 'Image Classification—random forest' tool[25] in the Orfeo ToolBox to create a classification model for each of the three sections[26]. As input, this tool requires the hand-drawn ROI identifying typical examples of each land cover class and the raster stacks generated in the previous step.

This tool first samples pixels from the input ROI classes (water, impervious, etc) to create a pool of pixels known to belong to each class. We used a sample size of 70,000 points per class, with a 1:1 proportion used for training and validation. The tool uses the training pixels to generate a 'forest' of classification and regression trees (CART). Each CART splits the pool of pixel data repeatedly into two maximally different groups of variable size based on the raster layers (e.g. NDVI > or < .5) until some stopping condition is reached. Here we used a maximum tree depth of 15 or a minimum group size of 10 pixels. The resulting CART resembles a branching pathway or tree with each node having exactly two outgoing branches (Figure 8). This process is repeated to generate the forest[27]; we generated 200 trees for each of the three sections.

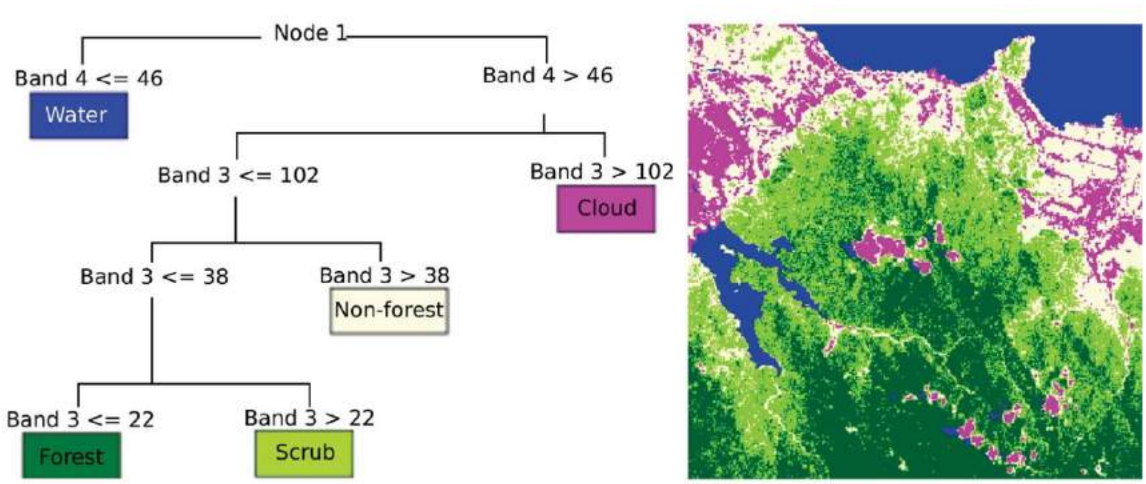

Figure 8: Example of CART model used to classify land cover. From www.ee.co.za/article/image-classification-generation-continuous-field-data-sets.html.

The tool then generates a validation matrix by using the newly created model to classify each of the reserved validation pixels into one of the land cover classes. The tool then compares this output with the land cover class identified in the ROI (the 'true' class) and determines if they match. This validation step provides feedback for iterative model specification[28]. Final processing for this step took approximately 10 hours per section.

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[25] A specific form of the 'TrainImagesClassifier' tool; documentation online at: https://www.orfeo-toolbox.org/CookBook/Applications/app_TrainImagesClassifier.html.

[26] Note that we found object-based methods performed poorly with the 2015 Regional Aerial data; they were much slower than CART based random forests and did not provide better classification outcomes. Dimension reduction methods also performed poorly.

[27] Similar to the 'ensemble' models used for weather or hurricane path predictions.

[28] The resource found at www.ee.co.za/article/image-classification-generation-continuous-field-data-sets.html provides a good overview of using CART and random forests for land cover classification.

Classify Image into Land Cover Classes

Once the model is created, it is used to classify each pixel in each orthoimage. This is accomplished by taking the information from all layers in the raster stack for the pixel and feeding this information into the random forest CART model using the ImageClassifier[29] tool in Orfeo Toolbox. Though conceptually straightforward, the process is very computationally intensive. It takes approximately 24 hours to process each of the sections. This creates a classification image where each pixel is assigned an integer value corresponding to one of the land cover classes.

The completed classification image is then subjected to visual inspection, where the classified image is compared with the original ROI and the original RGB-IR orthoimagery. Any areas where classification is particularly inaccurate are noted, and the inputs for the image classifier tool adjusted accordingly.

Clipping and Post-Processing

Following land cover classification, we clipped each of the three sections based on the area of analysis and boundaries of the missing IR section.

We then compared the land cover classification output and the 2015 Regional Aerials and LiDAR data to identify areas of model confusion. Post-processing required the use of vector layers used in the classification as well as the creation of three additional vector layers:

1. **Buildings**
2. **Driveways**
3. **Sidewalks and Walkways**
4. **Roadway edge of Pavement**
5. **Waterbodies**
6. **Emergent Vegetation**
7. **Severely Damaged area**: The 80 acre seriously damaged area (2015 Regional Aerials (City Consortium) Project) was delineated. Due to the extent of the damage, the entire area was re-classified as 'no-data.' Land cover classification data is not available for this area.
8. **New Construction:** 20 new developments were started in the time that passed between the 2015 Regional Aerial and NAIP imagery data collection, and that number again between the NAIP imagery and LiDAR data collection. This created model confusion as these developments were different land covers between the two image and LiDAR datasets. We manually digitized the proper land cover for each new development based on the 2015 Regional Aerial data to create a consistent land cover map for use as a baseline by Davey Resource Group and the City of Sammamish. Detecting new developments by observing differences between layers and digitizing each land cover area by hand was time consuming and took approximately 20 hours.
9. **Sport Courts:** Artificial turf grass and the red/green impervious surface of sport courts can cause model confusion (impervious sometimes identified as bare or grass) particularly in the IR damaged section. We created this layer by manually digitizing sport fields and sport

[29] Documentation online at: https://www.orfeo-toolbox.org/CookBook/Applications/app_ImageClassifier.html.

courts, including high school tracks, football and baseball fields with artificial turf, tennis courts, and the smaller half courts in residential backyards.

Each layer was converted to a raster using R (raster::rasterize()[30]).

We also used the Object Height raster described previously. As in the model, the raster was resampled to a 1” resolution using R (raster::resample()) and bilinear interpolation.

We created a series of rules for postprocessing to address these areas and help achieve the specified 90% overall and 94% canopy user’s accuracy. These rules were applied in two phases: corrections based on the rasterized vector layers, and corrections based on Object Height. Rules were applied using the raster::overlay() function and Boolean conditions. Due to differences in the orthoimagery in the three sections, some rules differed between the sections:

West Section:

Vector Layer	Start Class	End Class
Water (wtrbdy)	Impervious Grass Understory	Water Deciduous
Emergent Vegetation	Impervious Bare Ground Grass	Water Understory
Building Rooflines	Understory	Impervious
Roadways	Understory Grass	Deciduous Impervious
Sport Courts	Bare Ground Grass Understory	Impervious

Central Section (missing IR):

Vector Layer	Start Class	End Class
Water (wtrbdy)	Impervious Bare Ground Grass	Water
Emergent Vegetation	Impervious Bare Ground Grass	Understory
Roadways	Understory	Deciduous
Sport Courts	Bare Ground Grass Understory	Impervious
Severe Damage	Any Value	No Data

[30] Documentation online at: https://www.rdocumentation.org/packages/raster/versions/2.6-7/topics/rasterize.

East Section:

Vector Layer	Start Class	End Class
Water (wtrbdy)	Impervious Bare Ground Grass	Water
Emergent Vegetation	Impervious Bare Ground Grass	Water Understory
Walkways and Sidewalks	Bare Ground Grass	Impervious
Building Rooflines	Grass Understory	Impervious
Roadways	Grass Understory	Impervious Deciduous
Sport Courts	Bare Ground Grass Understory	Impervious

Corrections based on Object Height were the same for all sections:

Start Class	Height Rule	Vector Rule	End Class
Conifer	< 10’		Understory
Deciduous	< 7’		Understory
Water	> 15’		Deciduous
Understory	> 15’		Deciduous
Grass	> 15’		Deciduous
Understory	< .3’	NOT Emergent Vegetation or Water	Grass
Impervious	> 30’	IS Road	Deciduous
Impervious	> 30’	IS Sidewalk	Deciduous
Impervious	> 30’	IS Driveway	Deciduous

Finally, all sections were updated with the new development values by replacing existing classes with the manually delineated values. Post-processing took approximately 3 hours per section and required multiple iterations.

During post-processing we observed some significant patterns worth noting here. First, grass and understory appearing in classified outputs on areas that should be impervious is caused by obliquity in the 2015 Regional Aerials. The vector based rules assisted with these misclassifications. Second, while the shadow correction helped greatly, low vegetation (grass and understory) was misclassified as conifer due to deep shadows in the 2015 Regional Aerials. The conifer height cutoff (< 10’) helps further reduce the impact of shadows on these areas. Finally, while the height based to Deciduous rules introduced errors due to power lines—that is, high tension lines show up on the radar as > 30’ tall and were reclassified as deciduous tree canopy—the overall improvement was positive.

Reclassification and Regularization

We reclassified conifer and deciduous classes to “Tree Canopy”.

We then regularized the land cover classes using the ‘Classification Map Regularization’ tool[31] to reduce noise caused by classification. We processed isolated pixel only, using a threshold of 3 pixels. This means that land cover classifications with contiguous area < 3 square feet were reclassified as their surrounding majority.

Error Analysis

Error analysis was conducted after all three of these steps were completed and the classification had passed an initial visual inspection. The purpose of the error analysis—also called a confusion matrix[32]—is to quantify two key metrics for each land cover class as well as the overall classification:

1. Given that a pixel is of a land cover class, what is the chance that it was correctly classified as that land cover?
2. Given that a pixel has been classified as a land cover class, what is the chance that it belongs to that land cover class?

There are two pieces of information needed to answer these questions: the ‘true’ land cover class assignment, which is done by a human, and the ‘as classified’ land cover class assignment, which is output by the model. As with the classification methodology described above, this error analysis was conducted separately for each of the three sections (West/old instrument, Central/broken instrument, East/new instrument).

To calculate the ‘true’ land cover classes, we took a random sample of 9500 points[33] for each of the three sections using the “Random points inside polygons (fixed)” algorithm in QGIS. We then manually checked each of these randomly selected pixels to determine the ‘true’ land cover class to which it belongs. The obliquity of the orthoimagery was the main challenge in assigning a ‘true’ land cover class. To address this issue, we used the LiDAR data in conjunction with 2015 Regional Aerials and NAIP data to assign the ‘true’ class—the LiDAR data helps correct for obliquity in the land cover classification model, and NAIP data is orthorectified. We also considered the bounds of deciduous tree canopy based on summer leaf-out.

We then tabulated the ‘true’ and ‘as classified’ land cover class assignments to create the confusion matrix using the Orfeo “Compute Confusion Matrix” algorithm. The process for all three sections took approximately 150 hours.

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[31] Documentation online at: https://www.orfeo-toolbox.org/CookBook/Applications/app_ClassificationMapRegularization.html.

[32] See http://spatial-analyst.net/ILWIS/htm/ilwismen/confusion_matrix.htm for a more in-depth discussion.

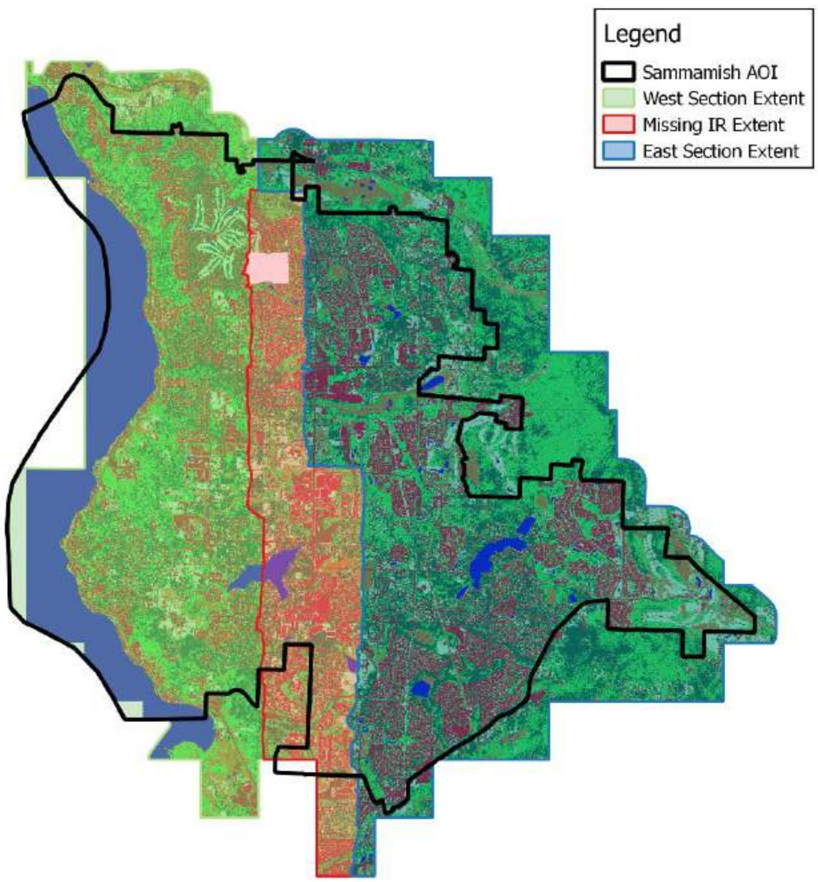
[33] Our goals used in calculating sample size were: overall alpha = 0.95, beta = 0.95; with a 1% minimum detectible difference and a target accuracy of 94%. This gives us 9423 points needed, which we rounded up to 9500 points per region. This also gives us a resulting power close to 1. Sample size calculation equation from: Foody, G. M. Sample size determination for image classification accuracy assessment and comparison. Proc. 8th Int. Symp. Spat. Accuracy Assess. Nat. Resour. Environ. Sci. 30, 154–162 (2008).

Results

Classification Results

Classification results are contained in the three GeoTIFFs which accompany this document:

1. 270_LC_6class.tif: Western section of Sammamish.
2. 000_LC_6class.tif: Central (no IR) section of Sammamish
3. 090_LC_6class.tif: Eastern section of Sammamish
4. 6classLandCoverStyle.qml: 6 class style for all land cover geotiffs.



The six land classes in these GeoTIFFs are: [1] Bare Ground; [2] Impervious Surface; [5] Grass; [6] Understory; [7] Tree Canopy; [9] Water.

Cover Class Area Estimates

These estimates are for within the Sammamish area of interest, less the data gaps. These estimates are for illustration purposes only; Davey Resource Group will produce more detailed statistics.

	West Sammamish		Central Sammamish		East Sammamish		Overall	
All								
	Proportion	**Acres**	**Proportion**	**Area**	**Proportion**	**Area**	**Proportion**	**Area**
Bare Ground	0.9%	60.4	2.4%	58.1	1.9%	134.9	**1.6%**	**253.4**
Impervious	15.1%	997.1	25.9%	625.4	24.5%	1697.4	**20.8%**	**3319.9**
Grass	7.7%	509.4	12.5%	302.6	12.8%	885.2	**10.6%**	**1697.2**
Understory	9.2%	610.3	9.4%	228.1	12.8%	887.1	**10.8%**	**1725.5**
Tree Canopy	40.4%	2671.5	46.8%	1130.5	45.8%	3167.8	**43.7%**	**6969.8**
Water	26.7%	1762.6	2.9%	71.2	2.1%	145.1	**12.4%**	**1979.0**
Total	100.0%	6611.3	100.0%	2415.9	100.0%	6917.6	**100.0%**	**15944.7**
Excluding Water								
	Proportion	**Area**	**Proportion**	**Area**	**Proportion**	**Area**	**Proportion**	**Area**
Bare Ground	1.2%	60.4	2.5%	58.1	2.0%	134.9	**1.8%**	**253.4**
Impervious	20.6%	997.1	26.7%	625.4	25.1%	1697.4	**23.8%**	**3319.9**
Grass	10.5%	509.4	12.9%	302.6	13.1%	885.2	**12.2%**	**1697.2**
Understory	12.6%	610.3	9.7%	228.1	13.1%	887.1	**12.4%**	**1725.5**
Tree Canopy	55.1%	2671.5	48.2%	1130.5	46.8%	3167.8	**49.9%**	**6969.8**
Total	100.0%	4848.6	100.0%	2344.7	100.0%	6772.5	**100.0%**	**13965.8**

Error Analysis Results

Here we present the error analysis confusion matrixes for each of the three sections. Overall, all three sections perform well. Importantly, there is little confusion between non-vegetation and vegetation land covers (dark grey shading), though error between the vegetation classes is higher (light grey shading). Post-processing improved model outputs by 3-5% overall accuracy. Cohen's kappa[34] is also reported.

West Section:

	Bare	Impervious	Grass	Understory	Tree Canopy	Water	TOTAL (reference)	Producer's Accuracy
Bare	75	65	3	18	3	0	164	45.7%
Impervious	14	1249	0	2	7	1	1273	98.1%
Grass	4	4	646	199	17	0	870	74.3%
Understory	16	8	78	733	27	5	867	84.5%
Tree Canopy	1	5	4	12	3773	0	3795	99.4%
Water	1	5	0	4	3	2518	2531	99.5%
TOTAL (produced)	111	1336	731	968	3830	2524	9500	
User's Accuracy	67.6%	93.5%	88.4%	75.7%	98.5%	99.8%		94.7%

Kappa index: 0.927313

[34] See e.g. https://en.wikipedia.org/wiki/Cohen%27s_kappa.

Central (no IR) section:

	Bare	Impervious	Grass	Understory	Tree Canopy	Water	TOTAL (reference)	Producer's Accuracy
Bare	231	79	31	30	2	1	374	61.8%
Impervious	98	2316	28	31	23	3	2499	92.7%
Grass	20	16	1013	155	32	2	1238	81.8%
Understory	9	31	95	613	112	6	866	70.8%
Tree Canopy	0	52	11	40	4180	0	4283	97.6%
Water	0	1	3	7	3	227	241	94.2%
TOTAL (produced)	358	2495	1181	876	4352	239	9501	
User's Accuracy	64.5%	92.8%	85.8%	70.0%	96.0%	95.0%		90.3%

Kappa index: 0.861065

East Section:

	Bare	Impervious	Grass	Understory	Tree Canopy	Water	TOTAL (reference)	Producer's Accuracy
Bare	110	46	6	19	0	1	182	60.4%
Impervious	25	1590	5	14	8	1	1643	96.8%
Grass	9	7	970	131	13	2	1132	85.7%
Understory	27	11	94	927	28	1	1088	85.2%
Tree Canopy	0	5	9	25	5251	0	5290	99.3%
Water	0	3	0	20	0	142	165	86.1%
TOTAL (produced)	171	1662	1084	1136	5300	147	9500	
User's Accuracy	64.3%	95.7%	89.5%	81.6%	99.1%	96.6%		94.6%

Kappa index: 0.914946

Suggestions for Future Analyses

Better quality data: Future analyses would be greatly improved with better quality orthoimagery. Requiring tighter aerial image collection specifications from vendors, including enforcing minimum image overlaps (forward and lateral) and reduced camera field-of-view will reduce image distortion and data loss due to ground occlusion by buildings and trees. Ideally, all images should be flown in one day. Requiring 'true' orthorectification would also greatly improve data quality. The USDA has best practices for NAIP image collection[35], which provide a good starting point.

Collect IR in addition to NIR: Additional bands of infrared data—particularly shortwave infrared >1.4µm—are useful for distinguishing between different types of vegetation, including deciduous and conifer canopy cover and between deciduous trees, grass, and understory cover. These last three are particularly difficult to distinguish using only near-infrared but more differentiated at the longer infrared wavelengths (Figure 9).

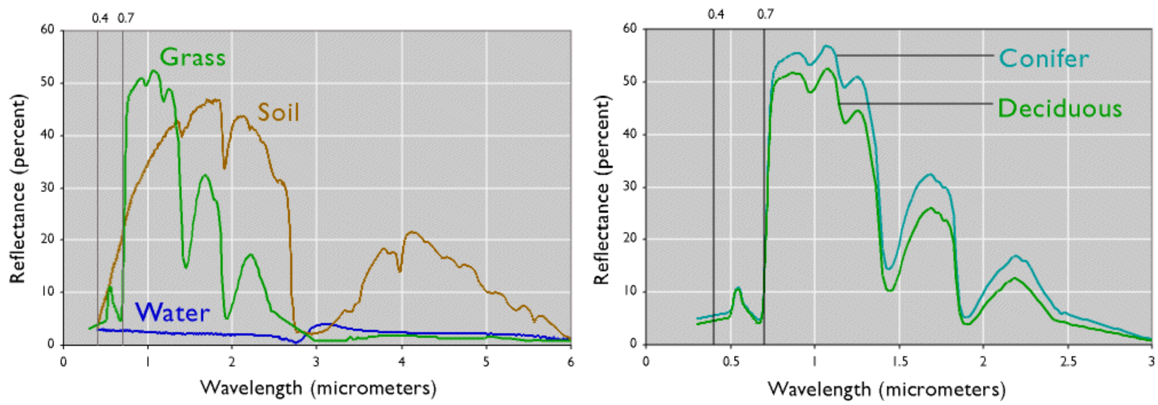


Figure 9: Spectral response pattern of Grass, Soil, Water, Conifer trees, and Deciduous trees. Differences between conifer and deciduous trees are greatest at approx. 1.7µm. Note that wavelength scales are different. From Adapted from https://www.e-education.psu.edu/natureofgeoinfo/c8_p5.html.

Additional IR bands would also allow better delineation of wetlands, including forested wetlands.

Alter data collection timing: Collecting orthoimagery in the summer will greatly help with deciduous canopy cover detection and analysis. For this analysis, we had to supplement the 'leaf-off' spring orthoimages with the 'leaf-on' NAIP data to improve identification of deciduous trees (see Orthoimagery and Figure 6). Using both datasets created confusion for the model. The NAIP data is available with larger (1m) pixels, reducing resolution. Also, due to the rapid pace of development in Sammamish, there were land cover mismatches between the two images that necessitated additional post-processing. Collecting 'leaf-on' high-resolution orthoimagery data eliminates the need to use NAIP data and will result in a more accurate estimation of deciduous canopy cover and canopy cover in general.

[35] Bunis, L., & Mootz, J. (2007). Aerial Photography Field Office—National Agriculture Imagery Program (NAIP) Suggested Best Practices–Final Report. Available online at https://www.fsa.usda.gov/Internet/FSA_File/naip_best_practice.pdf.

Synchronous collection of LiDAR: Collecting LiDAR data with aerial imagery would improve future orthoimagery and land cover analyses. Most importantly, synchronous collection allows contemporaneous digital surface models to be used for 'true' orthorectification[36] (Figure 10).

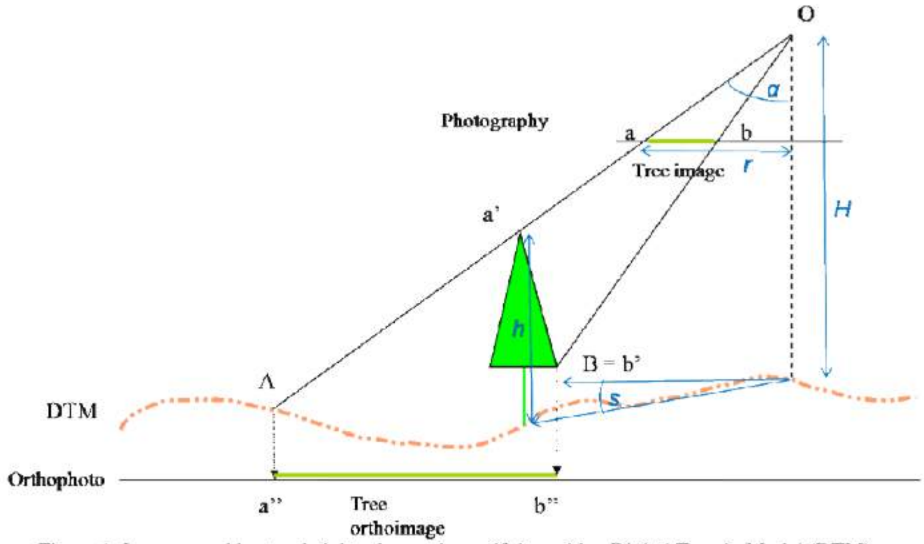


Figure 1: Lean caused by tree height when orthorectifying with a Digital Terrain Model (DTM).

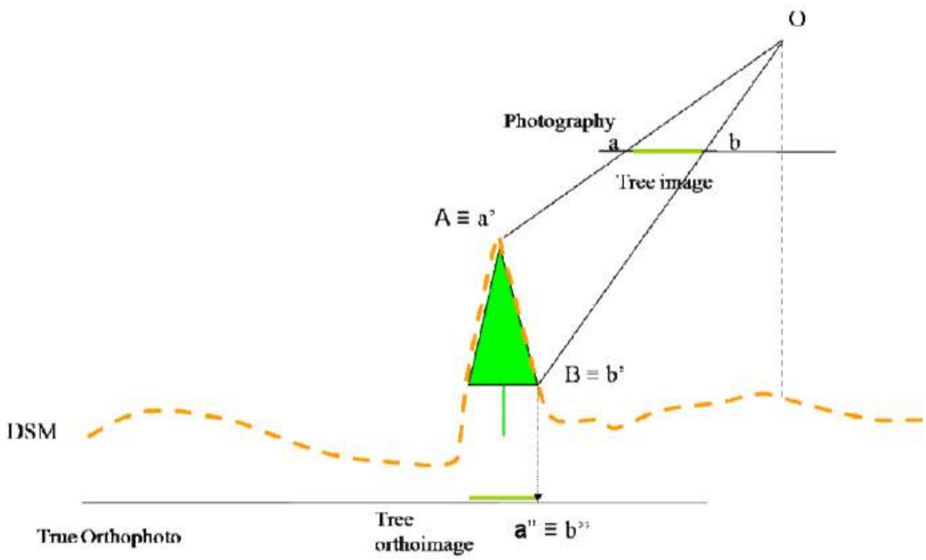


Figure 4: Lean correction by using a Digital Surface Model (DSM) in the orthorectification process.

Figure 10: Top: 'Regular' orthophoto using DTM. Bottom: 'True' orthophoto using DSM. Note the difference between a" and b" in the two images. Diagrams from Valbuena et al 2008.

[36] Valbuena, R., Fernández de Sevilla, T., Mauro, F., Pascual, C., García-Abril, A., Martín-Fernández, S., & Manzanera, J. A. (2008). Lidar and true-orthorectification of infrared aerial imagery of high Pinus sylvestris forest in mountainous relief. In *Proc. 8th Int. Conf. LiDAR Appl. Forest Assess. Inventory SilviLaser* (pp. 596-605).

Additionally, LiDAR data is valuable in detecting tree tops and distinguishing different types of vegetation in land cover analysis based on height and rugosity[37]. LiDAR for the City of Sammamish was collected in 2016, approximately one year following the 2015 Regional Aerials. The asynchronous data collection resulted in land classification errors due to development and tree removal that occurred between time periods; synchronous collection would eliminate this error.

[37] Yan, W.Y., Shaker, A. and N. El-Ashmawy. 2015. Urban Land Classification using airborne LiDAR data: A review. Remote Sensing of Environment. 158: 295-310.

Appendix A: Data Quality Issues

Data quality issues in the 2015 Regional Aerial Orthophoto dataset were the largest barriers in this analysis. The goal of this Appendix is to illustrate some of the issues encountered that are not already discussed in the text (e.g. missing IR data and corrupted area). Many of these errors could have been avoided with better quality data collection methods and others eliminated with the use of 'true' orthorectification.

As a reference point, here is a good image. Note that the image is sharp and it has low amounts of obliquity or distortion. Colors are consistent across the image.

Image Blur: This image is blurry and out of focus, resulting in reduced resolution and precision. While this is a minor problem for homogeneous forests, it is more concerning in heterogenous urban areas where image blur makes discriminating between adjacent land cover classes more difficult.

Obliquity: This image shows significant obliquity. In a 'true' orthorectified image, the water tower would appear as a circle positioned above its true location in x-y space. Objects and ground cover are obscured by the shifted position of the water tower and as this image data does not exist (not enough image overlap), the land cover cannot be determined accurately. Our analysis leverages LiDAR object height to help correct for obliquity, however there is a significant reduction in accuracy that is unavoidable due to the limits in the aerial imagery.

Poor image stitching: This image is poorly stitched together. This problem is caused by not overlapping aerial photography passes densely enough. Image artefacts like this create significant uncertainty in the model and increase error of the land cover classification.

Color inconsistency: These photos align well, however the adjacent images contain different red/green values which have not been corrected. Increased color variability within land covers makes it more difficult for the model to distinguish between similar classes (e.g. roads and bare dirt).

Deep shadows: Shadows are particularly problematic in urban areas and areas with tall Douglas-fir trees. While shadows in aerial photographs are unavoidable, photos taken in winter early morning and late afternoon create particularly deep shadows that obscure ground land cover and create more RG variability within land covers. The shadow correction algorithm employed in this analysis greatly reduces shadows.

Appendix B: Canopy Cover Analysis FAQ

Q1. What year does the canopy cover assessment represent?

A. Spring 2015, when the 2015 Regional Aerial Orthophotos were collected.

Q2. Why was 2015 data used?

A. 2015 data (2016 for LiDAR) is the most recent data available for Sammamish.

Q3. Why didn't we have more up-to-date data?

A. More up-to-date aerial data has not been commissioned by the City of Sammamish or King County.

Q4. Is there any way to estimate the amount of tree canopy lost to development in the intervening time?

A. Yes and no. We can estimate the tree canopy lost to development between Spring 2015 and Spring 2016 because we had to digitize it for the New Development layer. The total area lost is greater than 5 acres.

However, we cannot estimate tree canopy lost to development between Spring 2015 and today (2018) without additional data or analysis.

Q5. What is the margin of error of the assessment?

A. Overall user's accuracy of the land cover analysis is 94.7% for the west section, 90.3% for the central section, and 94.6% for the east section. User's accuracy for tree canopy is 98.5% for the west section, 96% for the central section, and 99.1% for the east section. Kappa index is 0.927 for the west section, 0.861 for the central section, and 0.915 for the east section.

Q6. What error is typical or acceptable for this type of work?

A. 85% overall accuracy is good. Davey Resource Group requested greater than 90% overall user's accuracy and 94% user's accuracy for tree cover.

Q7. Why wasn't the stressed tree detection and mapping completed?

A. The stressed tree detection and mapping was a speculative analysis to be completed based on data availability. Unfortunately, based on the poor data quality of the 2015 Regional Aerials Orthophotos and limited IR band availability, we determined that creating a model for stressed tree detection would be difficult and likely inaccurate. Additionally, the time and budget limitations resulting from the extra work created by the poor orthophoto quality precluded our ability to attempt this task.

Q8. Why are there holes in the land cover classification output?

A. Comparing the land cover classification output and the Sammamish area of interest shows two holes in the data. In north-central Sammamish, there is a data gap caused by corrupted data from the 2015 Regional Aerials. At the very south end of Sammamish, there is a tile missing from the 2015 Regional Aerials.