

DRCOG High Resolution Land Use/Land Cover Pilot Project

Contents

1. Summary
2. Project Overview
3. Class Definitions
4. Classification Methodology
5. Accuracy Assessment

Summary

The DRCOG HRLULC pilot project is part of an initiative by the Babbitt Center for Land and Water Policy (Lincoln Institute of Land Policy) to further the Lincoln Institute's efforts to geospatially map areas within the Colorado River Basin. This pilot project is a partnership between the Babbitt Center, the Chesapeake Conservancy's Conservation Innovation Center (CIC), and the Denver Regional Council of Governments (DRCOG). The partnership also included help and input from seven local partner organizations. The timeline for this project was rapid, from imagery and supplemental data delivery by DRCOG and its vendors to the CIC in January 2019, to the final product delivery back to DRCOG in June 2019. This meant some quick turnaround times for this pilot project. The CIC was able to bring some of its previous experience with HRLULC generation, but also experienced new challenges in this different geography. The methodology used was able to combine disparate datasets from different vintages, but challenges related to the data and rapid timeline meant some obstacles when aiming for a higher accuracy. Moving forward, the CIC will work with DRCOG and the Babbitt Center to formulate a plan for scaling up the DRCOG HRLULC pilot project to the rest of the greater Denver region.

Project Overview

In January 2019, DRCOG and its aerial imagery vendor delivered the following datasets to the CIC:

1. Very high resolution, leaf-off aerial orthoimagery captured in March 2018. 6-inch resolution everywhere except the mountainous regions to the west, which came in 1-foot resolution.
2. Lidar data collected in 2013, which had coverage everywhere except some border areas in the very western portions of the pilot region.
3. High resolution planimetric datasets reflecting ground conditions in 2016 (see blue coverage area in Figure1 map below). These datasets were composed of different impervious features, including Building footprints, Driveways and sidewalks, Edge of pavement (included most roads), Parking lots

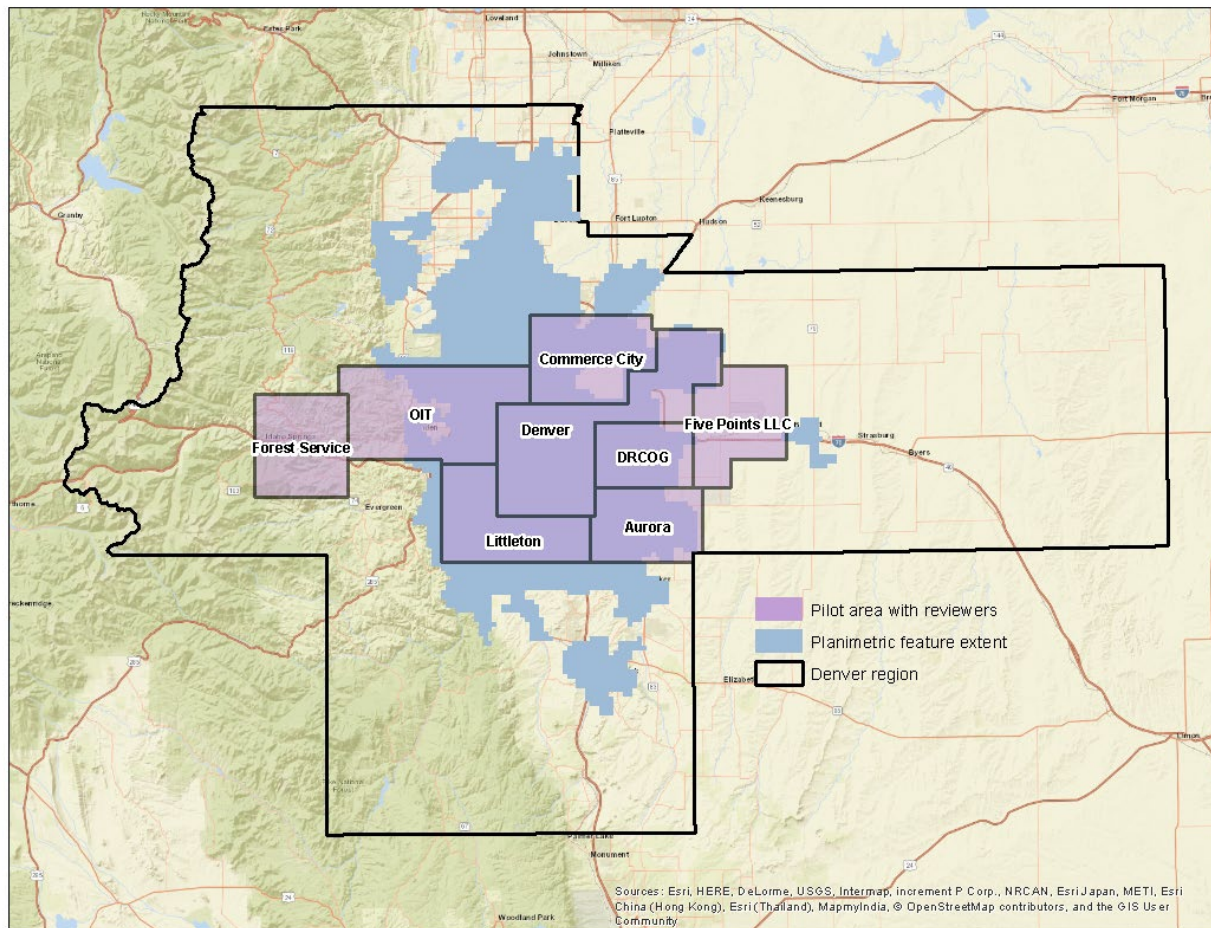


Figure1: Map provided by DRCOG of the pilot project area in purple. The pilot area has a mix of various terrain types ranging from flat open prairie and agricultural lands to the east, through the dense urban and suburban developments that make up the city of Denver, and on to the forested mountains to the west. The 1,000 square mile pilot area was split among seven local partners who agreed to help with the Quality Assurance/Quality Control (QAQC) effort.

After discussion with DRCOG and interested local partners, seven core classes were agreed on for the pilot project, which would be mapped at a 1-meter resolution: Buildings, Impervious surfaces, Water, Prairie/Grassland, Tree Canopy/Shrubs, Irrigated lands/Turf, Barren land, Cropland

During initial testing, the CIC quickly concluded that the 2018 orthoimagery taken during leaf-off winter conditions would not be sufficient to map all the classes desired. Luckily the USDA's National Agriculture Imagery Program (NAIP) 2017 aerial imagery was available for the region, and could supplement the orthoimagery as it was collected during the summer growing season with leaf-on conditions. The methodology developed for this project combined all of these disparate datasets of different vintages and attempted to extract a combined result that could best reflect conditions on the ground for 2017/2018. Because most of the vegetation was in a dormant state in the winter orthoimagery, the decision was made to primarily base the classification on ground conditions seen in the 2017 NAIP imagery. The water class, barren class, and all vegetation classes, including tree canopy/shrub, turf/irrigated lands, and grassland/prairie/natural ground cover were classified with the NAIP imagery. The height values derived from the 2013 lidar data was used to supplement the classification algorithm to extract tall features such as trees and buildings, but due to its older collection date, this produced mixed results in some areas. The 2016 planimetric datasets were very helpful for supplementing the impervious surfaces mapped by the classification algorithm. After all the classes were mapped, a "cookie-cutter" classification algorithm was applied to extract new developments that were constructed in the 2018 orthoimagery after the 2017 NAIP imagery was collected.

Once the seven core classes were classified for the entire pilot region, CIC staff “patched” or corrected large errors. Due to the tight timeframe, only some egregious errors were able to be identified sufficiently.

Class Definitions

In the designated pilot area, CIC classified the landscape into these eight classes:

1. Structures - Human-constructed objects made of impervious materials that are greater than approximately 2 meters in height. Houses, malls, and electrical towers are examples of structures. MMU = 9 square meters.
2. Impervious Surfaces - Human-constructed surfaces through which water cannot penetrate, and that are below approximately 2 meters in height. This includes asphalt, concrete, gravel, pavement, treated lumber (e.g. docks and decks), and dirt roads/hard-packed dirt lots, etc. MMU = 9 square meters, minimum 2 meters wide for linear features.
3. Water - All areas of open water, generally with less than 25% cover of vegetation/land cover. This includes water-filled backyard pools, ponds, lakes, rivers, natural tidal pools in wetland areas, and boats that are not attached to docks. MMU = 9 square meters.
4. Grassland/Prairie/Natural ground cover - Large open semi-arid areas composed of perennial grasses, herbaceous vegetation, and shrubs. These lands are often used for ranching and grazing but are not managed beyond these activities. This class also includes unmanaged natural ground cover that is less than a meter tall, such as wetland areas. MMU = 9 square meters.
5. Tree Canopy - Deciduous and evergreen woody vegetation of either natural succession or human planting that is over approximately 5 meters in height. Stand-alone individuals, discrete clumps, and interlocking individuals are included. MMU = 9 square meters. Includes individual large shrubs.
6. Turf/Irrigated Lands - Turf grass and areas of land that are actively managed and watered that do not fall in the cropland class. Examples of turf: lawns, cemeteries, golf courses, sports fields. MMU = 9 square meters.
7. Barren/Rock - Areas void of vegetation consisting of natural earthen material regardless of how it has been cleared. This includes beaches, mud flats, bedrock, xeriscaped lawns, and bare ground in construction sites (hard-packed paths/roads in construction sites would be better suited for the impervious class). MMU = 25 square meters.
8. Cropland - Large fields, generally found in non-urban areas used for the production of various annual crops. These lands can be in active or inactive use, but must show visual signs of recent usage from the 2017 NAIP imagery, such as tilled fields or tire tracks. The USDA Farm Service Agency 2008 Common Land Unit (CLU) boundaries were used to guide the visual interpretation of the landscape. Irrigated fields that were not in relative proximity to the CLU boundaries and were well within the Census Urban Area boundary were not included in the cropland class.

Classification Methodology



Figure 2. Methodology for the Esri classification workflow.

1. Setup

The first step to the classification process was to set up the geoprocessing environments in ArcPro. Depending on the type of data, the map document output coordinate system was either set to “NAD_1983_UTM_Zone_13N” for the NAIP imagery, or “NAD_1983_2011_StatePlane_Colorado_Central_FIPS_0502_Ft_US” for the orthoimagery. This ensured all of the outputs of each tool were set to the same coordinate system, which helped avoid projection errors throughout the methodology.

2. Preprocessing

Lidar data was preprocessed, and a normalized difference surface model (nDSM) and intensity layer were created. Both layers were clipped and projected to match the imagery datasets.

A normalized difference vegetation index (NDVI) layer was created for both the NAIP imagery and the orthoimagery, using the scientific output “NDVI” dynamic raster function in ArcPro. A “composite bands” tool was run to combine the source imagery with the derived bands. Once those were created, the preprocessing section was complete. The following methodology was applied to both the orthoimagery and NAIP imagery, unless otherwise noted.

3. Classification

The first step of the classification methodology is to segment the stacked imagery into “objects” based on similarities found within the input imagery bands. It was important to experiment with different variables until a result that split up the image into clean, concise, and separate segments was found. The Segment Mean Shift geoprocessing tool requires spectral detail, spatial detail, and a minimum segment size in on which to segment the image. Depending on the underlying geography, different input bands and segmentation variables were needed in each group of mosaicked tiles. An example SMS result can be seen in Figure 3. The SMS raster was then converted to polygon segments to make it easier to select samples for the classification training process (Figure 4).

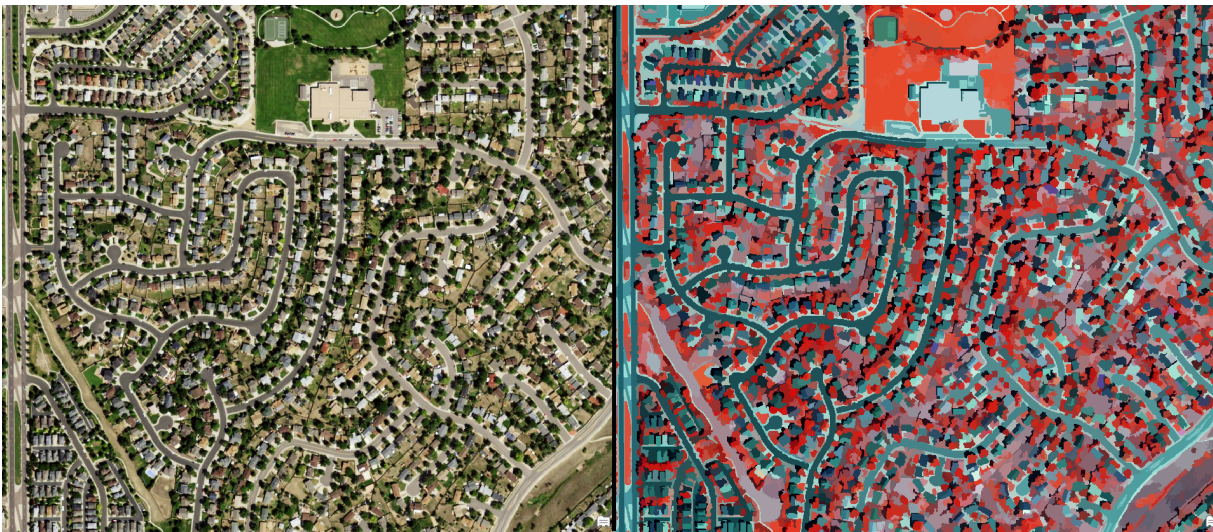


Figure 3. Close-up of imagery next to SMS results (respectively).



Figure 4. Segments created from the SMS raster. Training was performed on these segments.

To perform the classification training, the “selection” options were changed to “add to current selection (Shift + Click).” This allowed for an easy and quick training process and eliminated the potential for an analyst to accidentally reset the selection when adding a new segment. Training for each class was done by selecting segments that contain the class in question based on a visual inspection and editing a field labeled “LC” to match the class definition. Various symbology changes were made to make the process easier to understand and follow (ex: transparency and color).

The classified polygon file was imported into the “training sample manager.” The resulting training sample dataset was saved as a new polygon file to be used in the classification process.

Using the training sample polygon layer, segmented raster, and the original stacked image, an Esri classifier definition (ECD) file was created using a classifier tool. The last step to the classification methodology was using the “classify raster” tool with inputs of the SMS raster, ECD file, and the stacked imagery.

4. Quality Assurance Quality Control

Once several iterations of classification results were complete, underlying mistakes were fixed by applying filters and performing a manual QA/QC analysis. The manual corrections process could be very time-intensive, and was ideally performed by a team trained to work with raster and vector formats and have experience with visual interpretation skills. Depending on the geography, the types of errors found, supplemental datasets, and experience of the QA/QC staff, the QA/QC portion of the project could be substantial. After the QA/QC was complete, the individual mosaics were joined together to create a single large dataset covering the study area.

In addition to the base classification, ancillary datasets in raster or vector form could be incorporated as “patches” to assist with the classification, and inform additional classes. Doing so could add value, but also could introduce additional sources of error that come with ancillary datasets.

Accuracy Assessment

The CIC performed an accuracy assessment for a 100 square mile area selected by DRCOG, covering a wide variety of land use and land cover types representative of the region (Figure5).

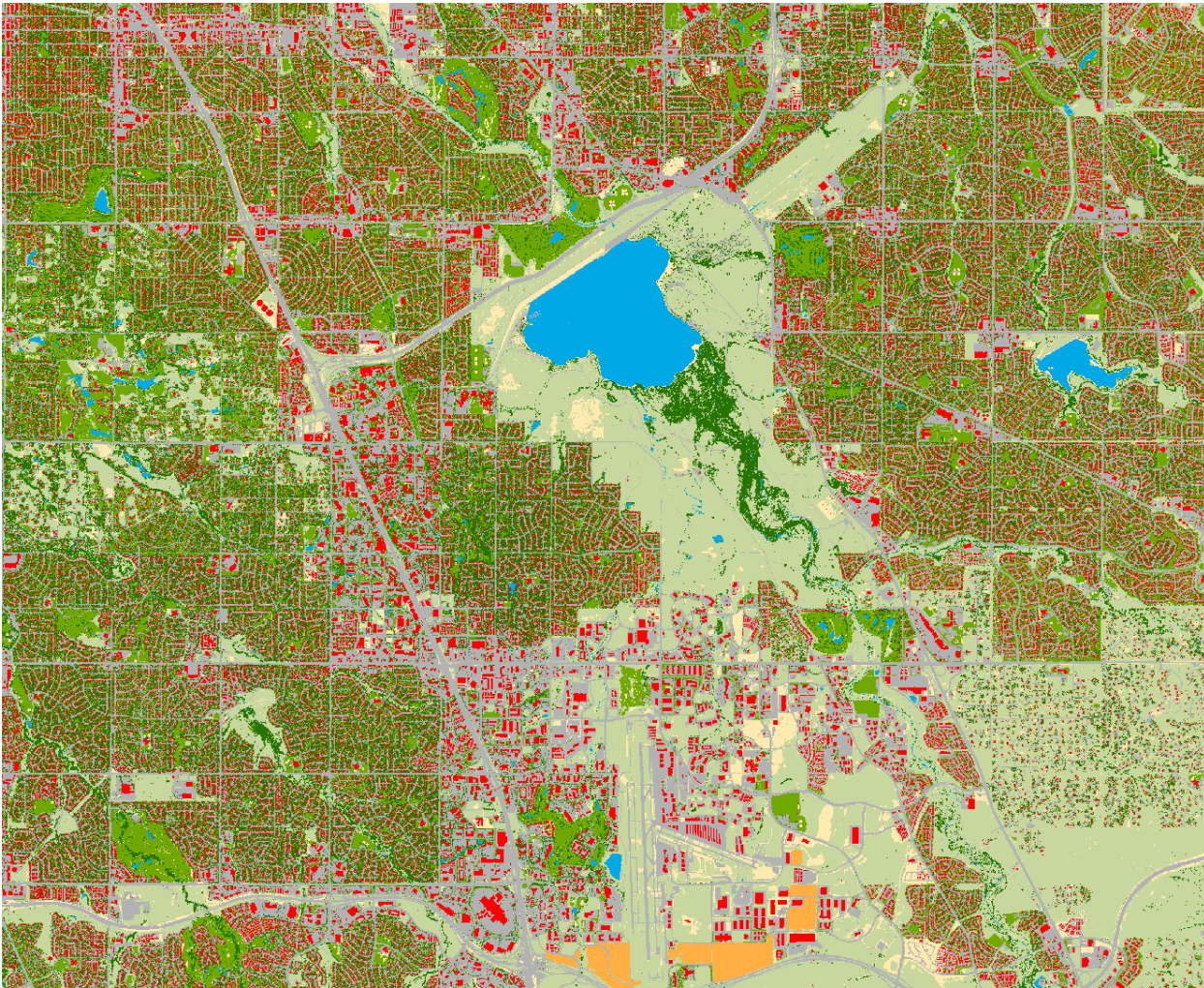


Figure5: High Resolution Land Use/Land Cover for the accuracy assessment area

The accuracy assessment methodology utilized for the Chesapeake Bay HRLC project was adapted to the DRCOG project, with the adjustment for different classes in this region (please refer to the accompanying Chesapeake Bay Land Cover Accuracy Assessment Methodology document).

A stratified random sample of points was generated for the entire accuracy assessment area, with a representative group of samples for each class. An equal sample of 75 points was generated for each class, plus an additional 200 points was distributed proportionately by area for each class within the accuracy assessment boundary, for a total of 800 points. These points came from a much larger pool, which had been filtered to discard any points that overlapped or contained multiple LULC classes.

As detailed in the Chesapeake Bay accuracy assessment document, points were buffered by 3-meters to provide contextual information for the reviewers, and to account for edge effects. After “bad” points were discarded, two reviewers who had not been involved with the DRCOG HRLULC project assessed the points.

Those points that were discarded or where there was disagreement between the two reviewers were subsequently reviewed by a third reviewer, who served as a tie-breaker. Due to the unique nature of HRLULC, “confusable” classes were allowed. Three confusable classes were chosen for this project due to the difficult nature of their classification and/or how they were derived:

1. Barren land vs Impervious
 - a. Only for hard-packed dirt paths/roads and in constructions sites
2. Cropland vs Turf/irrigated land
3. Cropland vs Grassland/prairie/natural ground cover

After the three reviewers had assessed the data, a total of 754 points that had not been discarded were input into a confusion matrix (Figure6).

ClassValue	Structures	Impervious Surfaces	Water	Grassland/Prairie/ Natural ground cover	Tree Canopy/ Shrub	Turf/Irrigated Lands	Barren Land	Cropland	Total	U_Accuracy	Kappa
Structures	91	0	0	0	2	0	0	0	93	0.98	0
Impervious Surfaces	1	116	0	0	2	4	1	0	124	0.94	0
Water	0	0	79	0	0	0	0	0	79	1.00	0
Grassland/Prairie/Natural ground cover	0	2	0	100	5	6	2	0	115	0.87	0
Tree Canopy/Shrub	1	0	0	6	79	14	0	0	100	0.79	0
Turf/Irrigated Lands	0	2	0	7	2	83	0	0	94	0.88	0
Barren Land	0	6	0	25	0	0	43	1	75	0.57	0
Cropland	0	0	0	8	0	0	3	63	74	0.85	0
Total	93	126	79	146	90	107	49	64	754	0	0
P_Accuracy	0.98	0.92	1.00	0.68	0.88	0.78	0.88	0.98	0	0.87	0
Kappa	0	0	0	0	0	0	0	0	0	0	0.847289

Figure 6: Final confusion matrix showing user's and producer's accuracies for each class value.

The accuracy assessment area was mapped with an overall accuracy of 87%. Certain classes did well in both their producer's and user's accuracies, such as structures and water, while other classes struggled due to commission errors (barren land and tree canopy), and omission errors (grassland/prairie/natural ground cover). The disparate datasets utilized from different years produced a unique set of obstacles which the classification algorithms struggled with. The orthoimagery was not very helpful for “natural” classes, as it was taken in winter leaf-off conditions. The NAIP imagery, taken during growing season leaf-on conditions, was more helpful in extracting vegetation conditions, but also could not fully help the classifier differentiate between dry turf lawns with areas of brownish colored grassland/prairie, and even barren land at times mixed with sparse vegetation. Contributions to error were difficult transitional areas between classes, and a product of the ability of the classification to segment features properly. Vague transitional landscape features would occasionally get lumped into one “object” which the classifier would need to place, even if the object had multiple classes within. The tree canopy class had difficulties with commission and omission errors, due to the old lidar data from 2013 not matching up with conditions seen in the 2017/2018 imagery datasets. Ideally, lidar and imagery acquisitions would coincide as much as possible to reduce temporal error.