# Metro Denver Urban Forest Assessment

Final report, March 28, 2013

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# TABLE OF CONTENTS

## LIST OF ABBREVIATIONS

| | |
|---|---|
| **Agri** | Agriculture land use |
| **ASTER** | Advanced Spaceborne Thermal Emission and Reflection Radiometer |
| **BLD** | Building |
| **bNDVI** | "blue" NDVI, calculated as (NIR-Blue)/(NIR+Blue) |
| **BR** | Brightness |
| **BSDV** | Bare-soil and dry vegetation land cover |
| **CDOT** | Colorado Department of Transportation |
| **CoAgMet** | Colorado Agricultural Meteorological network |
| **Comm** | Commercial land use |
| **DarkIMP** | Dark impervious surface |
| **DarkVeg** | Dark vegetation |
| **DN** | digital number |
| **DOQQs** | digital ortho quarter quad tiles |
| **DRCOG** | Denver Regional Council of Government |
| **GIS** | Geographic Information System |
| **GRatio** | Green ratio, calculated as G/sum(R, G, B) |
| **hmBR** | homogeneity of brightness |
| **Imp** | Impervious land cover |
| **IMP** | Other impervious surfaces that are not in the building or road class |
| **Ind** | Industrial land use |
| **LDR** | Low Density Residential |
| **LiDAR** | Light Detection And Ranging |
| **LST** | Land Surface Temperature |
| **LSTG** | land surface temperature index gradient |
| **MHM** | The Mile High Million tree initiative |
| **Mixed** | Mixed Uses land |
| **MODIS** | Moderate Resolution Imaging Spectroradiometer |
| **MTFCC** | MAF/TIGER feature class code |
| **MultiFam** | Multi-Family residential land use |
| **NAIP** | National Agricultural Imagery Program |
| **NDVI** | Normalized Difference Vegetation Index |
| **NGOs** | non-governmental organizations |
| **NHD** | National Hydrography Dataset |
| **OBIA** | object-based image analysis |
| **OpenSpace** | Open Space |
| **PQP** | Public/Quasi-Public land |
| **PTPS** | Potential tree planting sites |
| **PUTC** | potential UTC, potential urban tree cover |
| **QC** | Quality Control |
| **RS** | Remote Sensing |

| | |
|---|---|
| **SingleFam** | Single Family residential land use |
| **SSI** | Spectral Shape Index |
| **UFORE** | Urban Forest Effects Model |
| **UHI** | The urban heat island |
| **UTC** | Urban tree canopy |
| **varBR** | variance of brightness |
| **Veg** | Vegetation |
| **VOC** | volatile organic compound emissions |

# EXECUTIVE SUMMARY

The eight-county Metropolitan Denver area is home to 2.8 million people. Because it is such an attractive place to live, work and play it is experiencing rapid growth, especially in outlying areas, which is accelerating air pollution, water, and energy demand problems. More sustainable infill growth is placing higher concentrations of people in multi-use urban environments, where green space is critical to quality of life. Finding adequate space for trees in these densely engineered developments is a challenge. These problems urgently need solutions. Urban forestry is integral to land use planning, mitigating water shortages, conserving energy, improving air quality, enhancing public health programs, increasing land values and local tax bases, providing job training and employment opportunities, reducing costs of city services, and increasing public safety. Expanding the urban forest through judicious tree planting and stewardship activities can insure long term environmental and economic health benefits to local communities and maximum return on investment in planning and management.

In July, 2006 then Denver Mayor John Hickenlooper launched Greenprint Denver, an ambitious agenda for sustainable development in the City and County of Denver. The Mile High Million (MHM) tree initiative was one component of Greenprint Denver, with the goal of planting one million trees by 2025 in Metro Denver . During the six years since the MHM program began over 250,000 trees have been planted. Just as important, through partnerships with sponsors, NGOs such as The Park People and Colorado Tree Coalition, cities and agencies, the MHM has reached an unprecedented number of residents with its stewardship message. Now that program participation and visibility are at an all-time high, it is time to reaffirm the relevance of Metro Denver's urban forest and to plan for its future.

This study provides up-to-date information on the extent and potential of the Metro Denver urban forest. It quantifies the distribution of current tree canopy cover, maps locations of potential tree planting sites and identifies where tree plantings can best mitigate urban heat islands. Also, the study estimates the dollar value of ecosystem services provided by the current and future urban forest.

Urban tree canopy (UTC), defined as the percentage of a site covered by the canopies of trees and shrubs, is the metric used to quantify the extent, function and value of the Metro Denver urban forest. To calculate benefits of the Metro Denver urban forest canopy, field survey data from Golden, Boulder and Fort Collins were combined with UTC mapped across the area from satellite remote sensing. The value of ecosystem services was calculated on a per tree basis with numerical models developed by the US Forest Service. These values were converted to units per area of UTC. Benefits per unit UTC were applied to the measured UTC to calculate benefits for existing and additional UTC (runoff reduction, air quality, carbon dioxide removal, and building cooling energy use savings).

The Metro Denver urban forest is extensive, covering 15.7 percent of the 721 square mile region. Urban tree canopy (UTC) for the 29 cities ranged from 5 to 37 percent. Impervious surfaces, such as roads, buildings and parking lots, accounted for 34 percent of the land area, while irrigated grass, bare soil and dry vegetation covered 48 percent. The accuracy assessment found that UTC was classified with 91.5 percent accuracy, above the 90 percent standard set for the study.

Hot spots, areas with surface temperatures elevated more than 1.25$^{o}$F above the mean, occupied 21 percent of the region. Not surprisingly, the mean UTC was only 4.5 percent for these areas. These urban heat islands are associated with higher summer air conditioning demand, increased ozone concentrations and greater risk of illness and death to residents, especially to vulnerable populations.

There are approximately 10.7 million trees in the Metro Denver urban forest, assuming an average crown diameter of 19-ft per tree. The mean tree density of 23.2 per acre compares favorably with values reported for other large cities such as Chicago (24), Philadelphia (25) and New York City (26). The average number of trees per capita is 4.8, comparable to 5.2 reported for California cities (McPherson and Simpson, 2003).

The Metro Denver urban forest produces ecosystem services valued at $551 million annually. The largest benefit, $436.6 million, is for property value increases and other intangible benefits gained from the region’s 72,272 acres of existing canopy. The second largest benefit, $91 million, is reduced stormwater runoff management costs from 21,141 acre feet (6.9 billion gals) of rainfall intercepted by the existing canopy. Air temperature reductions from evapotranspirational cooling reduce residential air conditioning demand by 182,000 MWh, saving $21.8 million in cooling costs each year. If carbon dioxide sequestered and emissions avoided from cooling savings by the existing trees (172,270 tons) were sold at $10 per ton, the revenue would be $1.72 million. The Metro Denver urban forest filters 1,400 lbs of air pollutants from the air at an estimated annual value of $7,465.

The Denver Metro urban forest contains approximately 10 million vacant planting sites. This number assumes plantable space for a 30-ft crown diameter and that about 30 percent of the vacant sites are not plantable because of physical limitations such as utilities. Seventy percent of these plantable vacant sites are in single family residential and mixed land uses, while 16 percent are in public and institutional land uses. Potential tree planting sites (PTPS) are nearly evenly distributed between lawn areas already irrigated (56%) and unirrigated grass and bare soil (44%). Approximately 1.5 million vacant sites are located in hot spots. Shading parking lots, arterial streets, dark roofs and other sites where people work outdoors and recreate can provide significant health benefits from reduced heat stress and improved air quality.

Setting realistic targets for additional UTC is not straightforward because each city has a different land use mix, as well as different existing UTC and potential UTC (PUTC) that reflects historical patterns of development and tree stewardship. After discussion with partners it was decided to fill 50 percent of the calculated PTPS in non-agricultural land use zones. Setting a target for each city of filling 50 percent of its PTPS acknowledged that cities with the most vacant planting sites will achieve the greatest relative increase in UTC, whereas those with higher stocking levels will gain less UTC. Also, each city can do its "fair share" by filling 50 percent of its available tree planting sites, thus contributing to the common regionwide goal.

Filling 50 percent of the plantable vacant sites region wide will require planting 4.25 million more tree sites. This will result in about 14 million planted sites and is projected to increase UTC from 16 to 31 percent. There is adequate space in irrigated lawn areas to achieve the target. The gradual conversion of agricultural land to urban land uses will provide additional opportunities for planting. The assumption here is that current UTC remains stable and program tree sites remain fully stocked with 30-ft crown diameter trees. Because some program trees will die and need to be replaced, more than 4.25 million trees will be needed to keep this number of additional sites fully stocked. It will take 20 to 30 years to achieve the projected level of canopy cover after planting.

Achieving the targeted 15 percent UTC increase will pay dividends. The value of annual ecosystem services will nearly double, increasing by $449.7 million, from $551 million to $1.0 billion. The value of increased annual property values and other intangible services is projected to be $351.7 million. The annual savings for reduced stormwater management costs from additional 20,180 acre feet of rainfall interception (6.6 billion gals) is projected to be $86.9 million. Reduced demand for 86,370 MWh of electricity for air conditioning is expected to save another $10.4 million in cooling costs. Trees in the additional sites will reduce atmospheric carbon dioxide by 81,922 tons, valued at $819,843 annually. The additional UTC will reduce another 1,332 lbs of pollutants from the air.

Expansion of the UTC from 16% to 31% is projected to result in provisioning of ecosystem services valued at over $1.0 billion annually from approximately 14 million trees. The average annual value of $67 per tree is comparable to results for the same services reported for street and park trees in Boulder and Fort Collins, CO (McPherson et al. 2001, 2003). This is a very conservative estimate of service value, as it does not fully capture all benefits associated with increased UTC, such as job creation, improved human health and fitness, wildlife habitat and biodiversity.

The values for ecosystem services have been expressed in annual terms, but trees provide value across generations. Also, the benefits trees provide are becoming increasingly scarce and more valuable with time. The annual flows of realized benefits from trees were converted into an estimate of asset value. This enables tree planting and stewardship to be seen as a capital investment that provides an annual flow of benefits. The asset value was calculated as the net present value, which is a discounted sum of annual future benefits. Discount rates were 4.125 percent, which is applied by the US Corps of Engineers for large projects, and 0 percent over 100 years for Existing UTC, Additional UTC and Existing plus Additional UTC. Some economists argue that natural capital has a lower discount rate because the benefit stream is more certain over longer periods of time. The asset value of Metro Denver's existing urban forest is $13 billion, calculated at a 4.125 percent discount rate for the next 100 years. At zero discount rate, the urban forest's asset value is estimated at $55 billion. If UTC is increased to 30 percent over the next 30 years, the urban forest's asset value increases to $26.1 billion and $93.6 billion, assuming 4.125 and zero percent discount rates, respectively. Hence, the ecosystem services produced by the Metro Denver urban forest provide a stream of benefits over time the way a freeway or other capital infrastructure does. Quantifying the asset value of this "green infrastructure" can help guide advancement towards a sustainable green economy by shifting investments towards the enhancement of natural capital.

Results from this study can be used to:

- Communicate the ecological and economic value of the existing urban forest
- Establish tree planting and UTC targets for communities
- Describe the level of benefits obtained by reaching these targets
- Track changes in UTC that reflect progress made reaching targets
- Link changes in UTC to causal drivers such as levels of community tree planting, drought, pests, storms and vandalism

Metro Denver is a vibrant region that has invested in its urban forest as it has grown. The task ahead is to better integrate the green infrastructure with the gray infrastructure by targeting tree planting and stewardship activities to maximize their environmental and human health impacts. This study provides information that can be used to plan, prioritize and implement new urban forestry programs. In so doing, Metro Denver's urban forest will become larger, more resilient and better able to meet the challenges that loom ahead.

# INTRODUCTION

Metropolitan Denver is home to 2.8 million people. Because it is such an attractive place to live, work and play, the region's population is growing. Urban growth has increased impervious surfaces and the flow of contaminants into water bodies, air pollution from commuting traffic, and energy required to support new development. The urban forest works to mitigate these adverse effects associated with the built environment.

- Impervious surfaces increase runoff during storm events. Urban trees retain rainfall on their leaf surfaces and reduce storm water runoff.
- The built environment absorbs and stores solar radiation, causing urban heat islands that accelerate ozone formation and increase the need for air conditioning. Urban tree canopy cover can play a significant role by reducing the heat island effect through shading and evapotranspirational cooling of the air.
- City trees absorb air pollutants and sequester atmospheric carbon dioxide. By shading parked cars and asphalt concrete streets, trees reduce the release of evaporative hydrocarbons that are involved in ozone formation.
- Tree shade and air temperature reductions reduce the rate that street surfaces deteriorate and decrease repaving costs.
- Additionally, urban trees increase property values.

Although the benefit of any single tree may be small, the sum of benefits is significant when it comes to mitigating the environmental impacts that result from converting pervious land cover into built environments.

The eight-county Metro Denver region is experiencing rapid growth, especially in outlying areas, which is accelerating air pollution, water, and energy demand problems. More sustainable infill growth is placing higher concentrations of people in multi-use urban environments, where greenspace is critical to quality of life. Finding adequate space for trees in these densely engineered developments is a challenge. These problems urgently need solutions. Urban forestry is integral to land use planning, mitigating water shortages, conserving energy, improving air quality, enhancing public health programs, increasing land values and local tax bases, providing job training and employment opportunities, reducing costs of city services, and increasing public safety. Expanding the Metro Denver urban forest through judicious tree planting and stewardship activities can insure long term environmental and economic health benefits to local communities and maximum return on investment in planning and management.

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Urban tree canopy (UTC), defined as the percentage of a site covered by the canopies of trees and shrubs, is the metric used to quantify the extent, function and value of Metro Denver's urban forest. UTC is relatively easy to measure with remote sensing technology and it is an easy-to-understand concept that is useful in communicating to the public. It is comparable across a city and among cities because the size of the area measured does not matter. Success meeting UTC targets can be measured across time as well as space. Though many UTC assessments have been conducted in the US, to our knowledge none have matched the size and scope of this study.

To calculate benefits of the Metro Denver urban forest, field survey data from Golden, Boulder and Fort Collins were combined with UTC mapped across the area from satellite remote sensing. The value of ecosystem services was calculated on a per tree basis with numerical models developed by the US Forest Service. These values were converted to units per area of UTC and applied to the measured UTC to calculate benefits for existing and additional UTC (runoff reduction, air quality, carbon dioxide removal, property values and building cooling energy use savings).

Results from this study can be used to:

- Communicate the ecological and economic value of the existing urban forest
- Establish tree planting and UTC targets for communities
- Describe the level of benefits obtained by reaching these targets
- Track changes in UTC that reflect progress made reaching targets

- Link changes in UTC to causal drivers such as levels of community tree planting, drought, pests, storms and vandalism

This study provides information that is critical to planning and managing Metro Denver's urban forest to maximize production of ecosystem services and meet future challenges.

# METHODOLOGY

## STUDY SITE

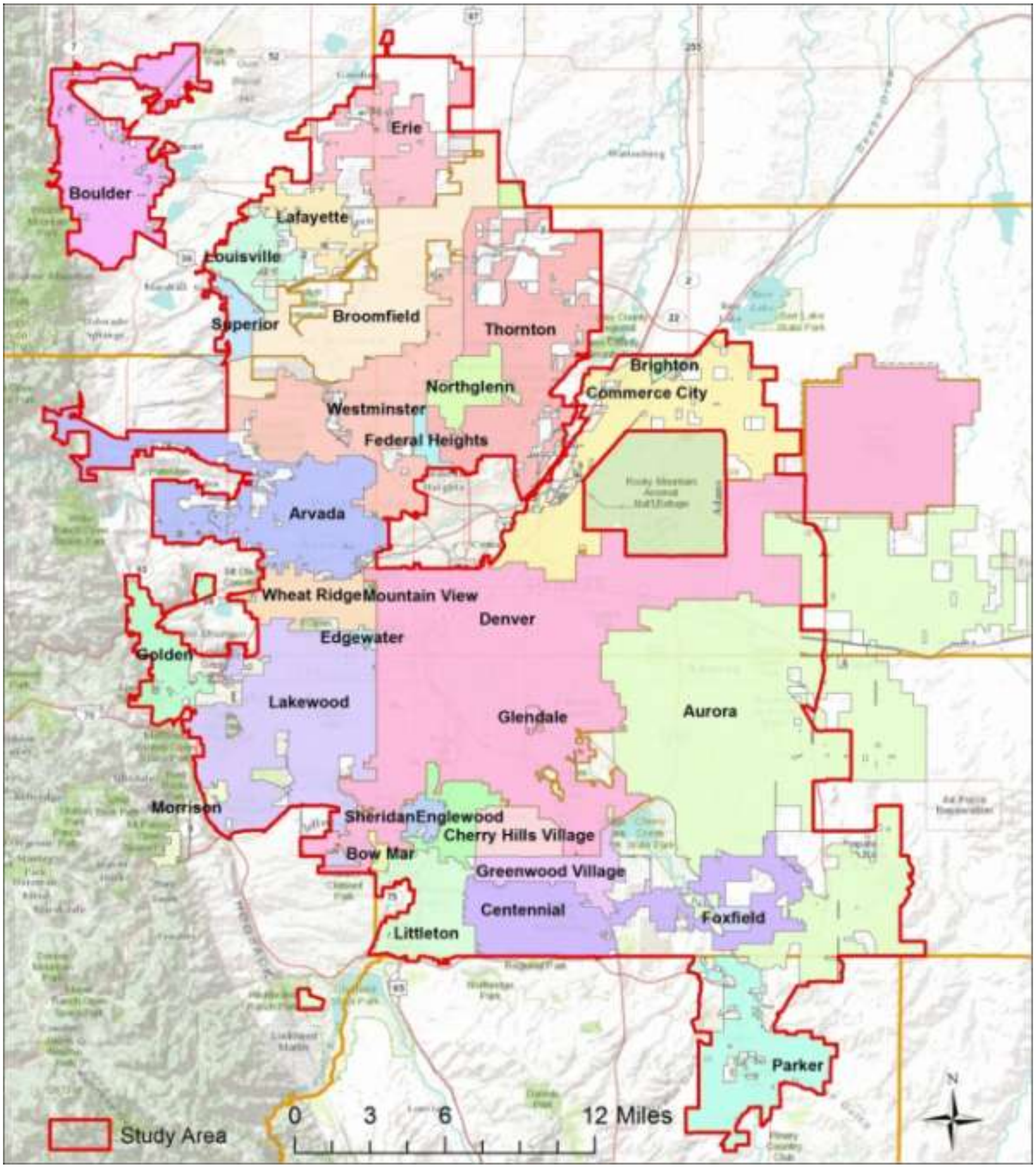



**Figure 1 Study Area**

The study site covers 721 square miles (1,867 square kilometers) of land located at the foot of the Rocky Mountains (Figure 1). It has a semi-arid, continental climate with four distinct seasons. Annual rainfall averages about 18 inches and occurs throughout the year. This part of the High Plains region has an elevation of about 5,000 feet. The study area covers most of Metropolitan Denver and includes all or portions of 33 cities and 8 counties (Table 1). The three largest cities in terms of population and area are: Denver, Aurora, and Lakewood. The smallest communities are Mountain View, Foxfield and Bow Mar. There are over 2 million inhabitants in the study area, and they account for 40% of Colorado's total population (5,029,196, as of April, 2010).

The study area boundary was delineated based on 2010 Census Block boundary data. In some cases, the boundaries of the study area and jurisdictions do not exactly overlap. Large, nonurban areas on the periphery of jurisdictions were excluded because the study's focus was mapping urban tree canopy.

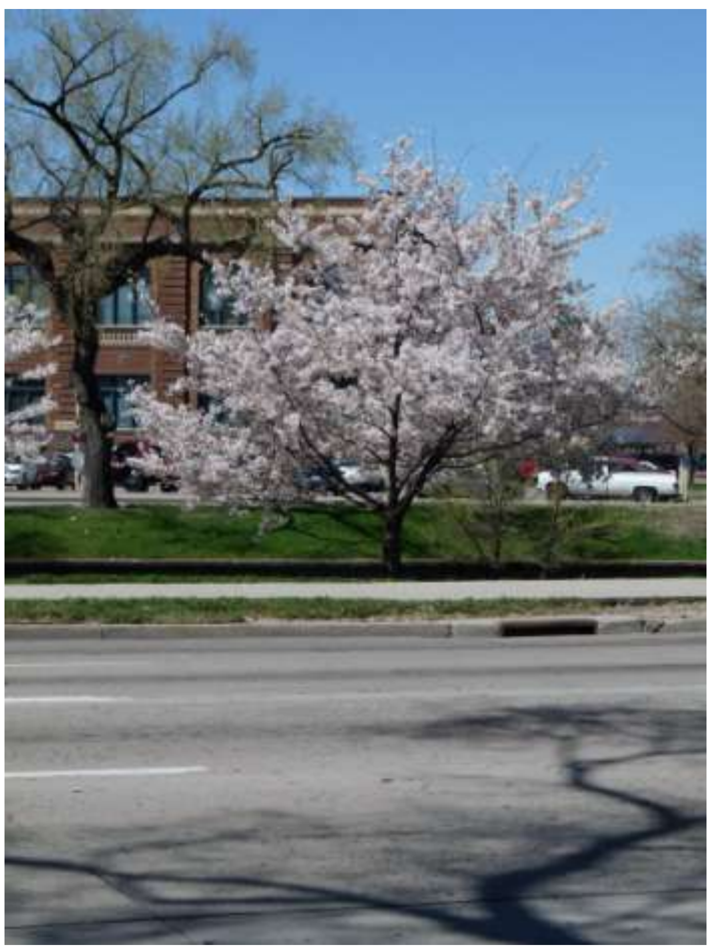


**Table 1 Jurisdictions within the Study Area**

| City Name | County | Total Population (2010 census) | Total Area (ac) | Area inside Study Area (ac) |
|---|---|---|---|---|
| **Arvada** | Jefferson; Adams | 106,433 | 22,776 | 22,606 |
| **Aurora** | Arapahoe; Adams; Douglas | 323,242 | 98,325 | 64,518 |
| **Boulder** | Boulder | 97,385 | 16,272 | 16,149 |
| **Bow Mar** | Arapahoe; Jefferson | 866 | 508 | 508 |
| **Broomfield** | Broomfield | 55,889 | 21,459 | 21,455 |
| **Centennial** | Arapahoe | 100,377 | 18,423 | 18,423 |
| **Cherry Hills Village** | Arapahoe | 5,987 | 4,021 | 4,021 |
| **Commerce City** | Adams | 45,913 | 22,124 | 21,806 |
| **Denver** | Denver | 600,158 | 98,741 | 76,321 |
| **Edgewater** | Jefferson | 5,170 | 442 | 442 |
| **Englewood** | Arapahoe | 30,255 | 4,249 | 4,249 |
| **Erie** | Boulder; Weld | 18,135 | 11,034 | 11,017 |
| **Federal Heights** | Adams | 11,467 | 1,143 | 1,142 |
| **Foxfield** | Arapahoe | 685 | 833 | 833 |
| **Glendale** | Arapahoe | 4,184 | 352 | 352 |
| **Golden** | Jefferson | 18,867 | 6,195 | 6,054 |
| **Greenwood Village** | Arapahoe | 13,925 | 5,309 | 5,309 |
| **Lafayette** | Boulder | 24,453 | 5,974 | 5,944 |
| **Lakewood** | Jefferson | 142,980 | 28,192 | 28,079 |
| **Littleton** | Arapahoe; Jefferson; Douglas | 41,469 | 8,775 | 8,708 |
| **Louisville** | Boulder | 18,376 | 5,086 | 5,049 |
| **Mountain View** | Jefferson | 507 | 59 | 59 |
| **Northglenn** | Adams; Weld | 35,789 | 4,754 | 4,754 |
| **Parker** | Douglas | 45,297 | 13,175 | 13,160 |
| **Sheridan** | Arapahoe | 5,664 | 1,461 | 1,461 |
| **Superior** | Boulder; Jefferson | 12,483 | 2,686 | 2,386 |
| **Thornton** | Adams; Weld | 118,772 | 22,989 | 22,968 |
| **Westminster** | Adams; Jefferson | 106,114 | 21,547 | 21,534 |
| **Wheat Ridge** | Jefferson | 30,166 | 6,134 | 6,118 |
| **Total** | | **2,021,008** | 453,037 | 395,423 |

## DATA AND SOFTWARE

The following computer hardware, software, imagery and GIS data layers were used for Phase I.

- Hardware

Four computer workstations (Dell XPS 8300 Desktop) equipped with eCognition and ENVI image processing software and ESRI ArcGIS.

- Software

  - Image processing system ENVI (Environment for Visualizing Images, Research Systems; Lafayette, Colorado),
  - eCognition (Trimble GeoSpatial, Westminster, Colorado), and
  - ArcGIS (Environmental Systems Research Institute, Inc. (ESRI), Redlands, CA).

- Remote sensing data

- *NAIP imagery*

2011 multispectral National Agricultural Imagery Program (NAIP) imagery was purchased from USDA (http://www.fsa.usda.gov/FSA/). The spectral resolution of NAIP imagery is four bands: Red, Green, Blue, and Near Infrared, while spatial resolution is 1 meter. We obtained NAIP imagery as digital ortho quarter quad tiles (DOQQs): each tile covered a 3.75 x 3.75 minute quarter quadrangle plus a 300 meter buffer on all four sides. The metadata indicated that the images were acquired in July, 2011.

- *USGS LiDAR data*

USGS LiDAR data for March, 2008 were collected, which covered most of Metro Denver (Figure 2). However, LiDAR data were not used in the land cover classification because of partial coverage (Figure 2) and the three year time gap between acquisition of the NAIP and LiDAR data sets.

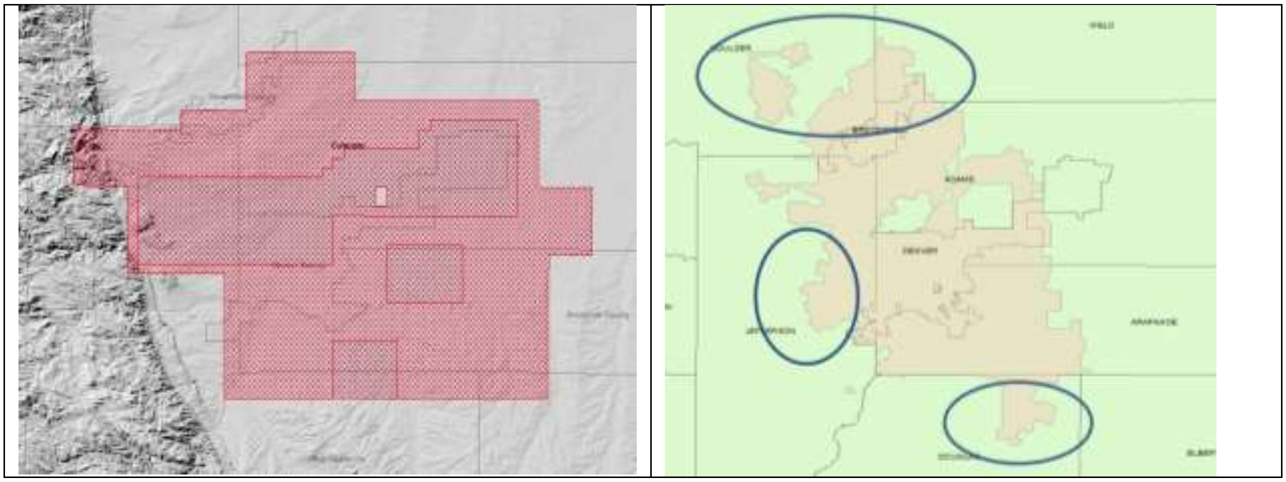
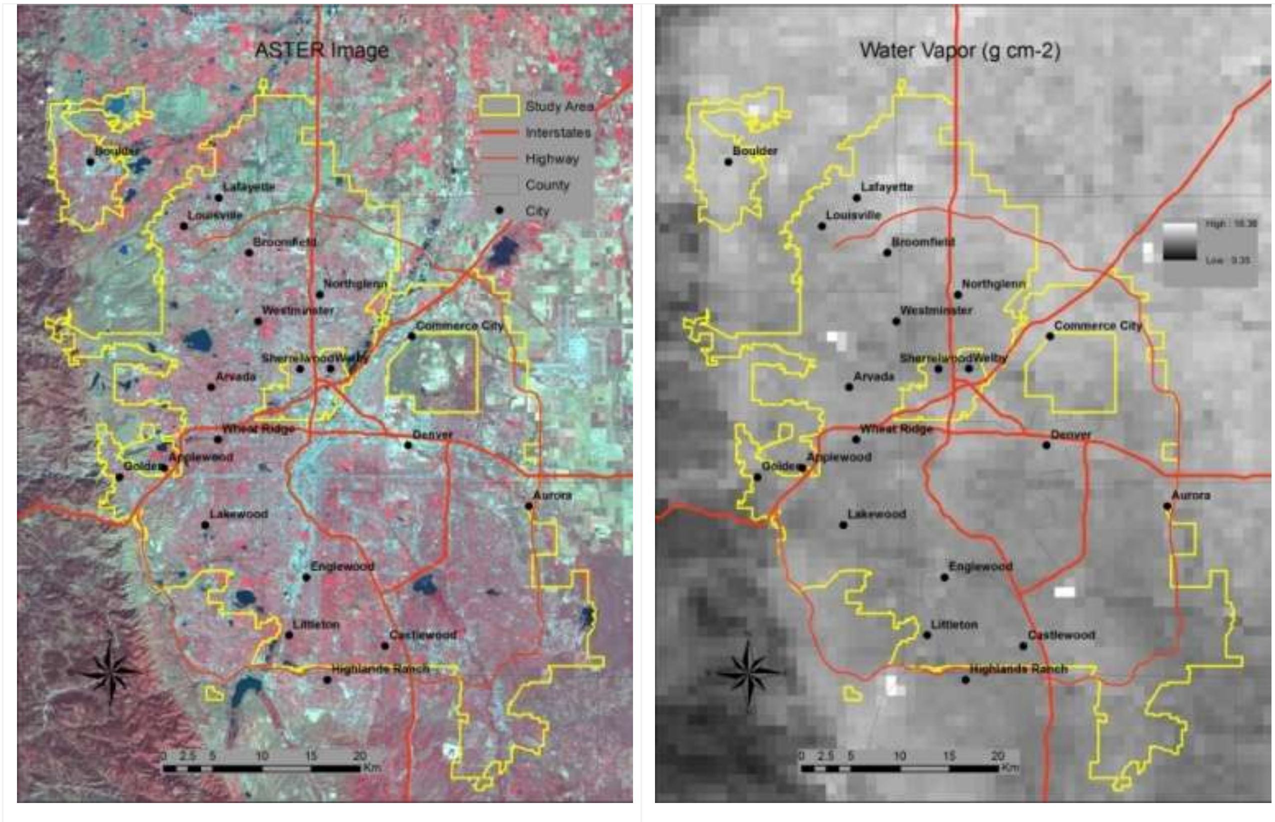


**Figure 2. LiDAR data coverage. The left image shows the LiDAR data coverage. The right image shows the study boundary and circled areas without LiDAR data**

- *ASTER and MODIS data*

ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) and MODIS (Moderate Resolution Imaging Spectro radiometer) data were collected for mapping the Urban Heat Island.

Two ASTER data sets (*image ID: AST_L1B_00307152010180049 and AST_L1B_00309252007180102*)(Figure 3a) and the water vapor data from the MODIS data (*image ID: MOD05_L2.A2007268.1800.005.2007271072941*) (Figure 3b) from September 25, 2007 were downloaded from the Land Processes Distributed Active Archive Center (*https://lpdaac.usgs.gov/*). The ASTER data has 15m spatial resolution for visible and near infrared bands and 90m spatial resolution for thermal bands. The water vapor data were generated at the 1-km spatial resolution of the MODIS instrument using the near-infrared algorithm during the day by the MODIS Atmosphere Team as part of their atmospheric products (*http://modis-atmos.gsfc.nasa.gov/index.html*). These remotely sensed data were used to retrieve Land Surface Temperature (LST). Air temperature and other hourly meteorological data were collected from CoAgMet (Colorado Agricultural Meteorological network) (*http://ccc.atmos.colostate.edu/~coagmet/*). The air temperature data were used to calibrate the LST. ASTER and MODIS data were resampled to 15m spatial scale and were geo-referenced using road network GIS data from the Colorado Department of Transportation (*http://dtdapps.coloradodot.info/Otis/catalog*). The resampling and geo-referencing processes reduced data shift problems between the relatively low spatial resolution of the ASTER thermal data and high resolution NAIP imagery.




**a. ASTER image** **b. Water vapor**

**Figure 3 ASTER image and water vapor image**

- <u>GIS data</u>

- *<u>2010 Census data</u>*

2010 census block, block group, and road data were collected and used in land cover mapping (Table 2).

**Table 2 2010 Census datasets used in the study**

| 2010 Census Data | Feature type | Data Source |
|---|---|---|
| Census blocks | polygon | ftp://ftp2.census.gov/geo/tiger/TIGER2010/TABBLOCK/2010/tl_2010_08_tabblock10.zip |
| Census block groups | polygon | ftp://ftp2.census.gov/geo/tiger/TIGER2010/BG/2010/tl_2010_08_bg10.zip |
| Census blocks with population attributes (Region2 & Region 3) | polygon | http://www.colorado.gov/cs/Satellite?c=Page&childpagename=DOLA-Main%2FCBONLayout&cid=1251595720266&pagename=CBONWrapper |
| Road segments | polyline | ftp://ftp2.census.gov/geo/tiger/TIGER2010/ROADS/ |

- *Hydrologic data*

Data on water bodies were collected from two sources: 1) 2010 census and the 2) National Hydrography Dataset (NHD). Both datasets were overlaid on the 2010 NAIP imagery and found to be incomplete and inaccurate.

***2010 Census data areawater:***

Area water data downloaded from ftp://ftp2.census.gov/geo/pvs/tiger2010st/08_Colorado/

tl_2010_08001_areawater.zip4/ 6/ 2012 4:37 PCompressed (zipp... 545 KB
tl_2010_08005_areawater.zip4/ 6/ 2012 4:37 PCompressed (zipp... 329 KB
tl_2010_08013_areawater.zip4/ 6/ 2012 4:37 PCompressed (zipp... 452 KB
tl_2010_08035_areawater.zip4/ 6/ 2012 4:37 PCompressed (zipp...80 KB
tl_2010_08059_areawater.zip4/ 6/ 2012 4:38 PCompressed (zipp... 375 KB
tl_2010_08123_areawater.zip4/ 6/ 2012 4:38 PCompressed (zipp... 222 KB

***NHD data for CO state:***

Download NHD data for Corolado state from ftp://nhdftp.usgs.gov/DataSets/Staged/States/
ftp://nhdftp.usgs.gov/DataSets/Staged/States/FileGDB/HighResolution/

| Name | Size | Last Modified | |
|---|---|---|---|
| File:NHDH_CO_92v200.zip | 578718 KB | 10/14/2011 | 12:00:00 AM |
| File:NHDH_CO_931v210.zip | 630427 KB | 5/17/2012 | 8:16:00 PM |

About the NHD (http://nhd.usgs.gov/userguide.html)

The National Hydrography Dataset (NHD) is the surface water component of *The National Map*. The NHD is a digital vector dataset used by geographic information systems (GIS). It contains features such as lakes, ponds, streams, rivers, canals, dams and stream gauges. These data are designed to be used in general mapping and in the analysis of surface-water systems.

These two datasets were carefully fused together and the resulting water layer was not accurate. It over-estimated water in one area and missed water bodies in another area. However, the omission and commission of water bodies from the combined water data appeared to be offsetting. The processed water data set, in addition to spectral features, was used as to classify water bodies.

- *Other GIS data:*

Other GIS data layers used in this study included zoning and municipal boundary layers. Zoning data were acquired from the DRCOG (Denver Regional Council of Governments, 1290 Broadway, Suite 700, Denver, CO 80203). The original GIS zoning data were organized by city and by county and included 50 separate GIS layers with 202 unique zoning classes. The data were first mosaicked as one single GIS layer and the overlap between GIS layers was excluded. For example, the county's zoning layer for Boulder was a single polygon, while the City of Boulder's data contained multiple zoning classes. After the data layers were mosaicked, the zoning classes were cross-walked into 8 classes (Table 3). For areas without zoning information, a zoning class was assigned by visually interpreting 2011 NAIP imagery. A large portion of study area (over 40%) was zoned for residential use, while land zoned for mixed use occupied 23% of study area.

**Table 3 General definitions for the 8 zoning classes used in this study**

| Zoning Class | Definition | Distribution within Study Area | |
|---|---|---|---|
| | | Total Area (ac) | % |
| Agriculture (Agri) | agricultural land, including nurseries and orchards | 38,516 | 8.3 |
| Commercial (Comm) | small, large, and mixed commercial | 24,350 | 5.3 |
| Industrial (Ind) | light, heavy, and mixed industrial | 30,828 | 6.7 |
| Mixed Uses (Mixed) | multiple land uses | 105,847 | 22.9 |
| Multi-Family Residential (MultiFam) | medium, high, and mixed density residential | 13,124 | 2.8 |
| Open Space (OpenSpace) | open space, excluding parks | 17,881 | 3.9 |
| Public-Quasi Public (PQP) | roads/highways, water ways, schools, sports fields and golf courses, cemeteries, airports, parks, etc. | 47,391 | 10.3 |
| Single Family Residential (SingleFam) | low density residential | 183,498 | 39.8 |

All GIS data were projected to NAD83_UTM_zone_13N to match NAIP imagery for land-cover analysis. 2010 census block group data and jurisdictional boundary data were used to summarize and report land cover classification results.

- Definitions

  - Minimum mapping unit: 4 $m^2$.
  - GIS Mapping unit: census block group
  - Reporting units: municipalities/counties/unincorporated areas and census block groups

**URBAN HEAT ISLAND MAPPING**

The urban heat island (UHI) is an urban area that is significantly warmer than the surrounding rural area (American Meteorological Society, 2000). Modification of the land surface is one of the main factors that cause UHIs. During urban development, vegetation is removed to make space for buildings, streets, parking lots, parks and other uses. Reducing vegetation cover reduces evapotranspiration from plants, a driving force behind urban heat flux. Replacing vegetation with materials that effectively retain heat results in warmer temperatures, especially evening temperatures. UHIs are associated with decreased air quality and increased energy consumption for cooling. Increasing urban tree canopy is a Best Management Practice to mitigate the UHI effect. Accurately mapping urban hot spots makes it possible to locate tree planting sites that will maximize the UHI mitigation benefit they can provide. The objective of this urban hot spots mapping task was to create a GIS data layer that spatially locates areas where air temperatures are highest.

Land Surface Temperature (LST) has been used to quantify the UHI (Liu and Zhang, 2011; Mao et al., 2005) and it is an important parameter governing the surface energy balance. ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) and MODIS (Moderate Resolution Imaging Spectro radiometer) are satellite data widely used to record LST because of their high spatial and spectral resolution. ASTER and MODIS data were collected with the same satellite (i.e., the Terra mission) for September 25, 2007. ASTER data has five thermal bands with 90 m spatial resolution. MODIS includes three water vapor bands (i.e., band 17, 18, 19) with a spatial resolution 1,000 m. Algorithms for retrieving LST from ASTER data have been well documented (Zhou et al., 2008; Coll et al., 2007; Pu et al., 2006; Gustafson et al., 2006; Qin et al., 2006; Mao et al.,2005; Schmugge et al., 2002).

A split-window algorithm was used to retrieve LST (Mao et al., 2005). Generally speaking, only two essential parameters (atmospheric transmittance and ground emissivity) must be known using split window algorithms. Major steps for retrieving LST from ASTER data are briefly described below.

1. Convert the ASTER's digital number (DN) into spectral radiance

   $L_{13} = 0.005693 Qdn - 0.005693$

   $L_{14} = 0.005225\ Qdn - 0.005225$

   where $L_{13}$ and $L_{14}$ is the at-sensor spectral radiance ($MW\ cm^{-2}\ sr^{-1}\ \mu m^{-1}$) of ASTER 13, 14 and *Qdn* represents the DN value of pixel.

2. Convert the spectral radiance into at-sensor brightness temperature

   $T_i = C_2/\{\lambda_i \ln[1+C_1/(\lambda_i^5 L_i)]\}$

   $C_1 = 1.19104356 \times 10^{-16}\ W\ m^2$

   $C_2 = 1.4387685 \times 10^4\ \mu m\ k$

   $\lambda_{13} = 10.657\ \mu m$

   $\lambda_{14} = 11.318\ \mu m$

where $T_i$ is the at-sensor brightness temperature (K); and $L_i$ represents the at-sensor spectral radiance. i represent ASTER thermal bands 13 and 14.

3. Estimate ground emissivity

The ground emissivity can be calculated from NDVI. The relationship between NDVI and emissivity is listed in Table 4 (Van de Griend and Owe, 2003).

**Table 4 Estimation of emissivity using NDVI**

| NDVI | Land surface emissivity ($\varepsilon_i$) |
|---|---|
| NDVI < −0.185 | 0.995 |
| −0.185 ≤ NDVI < 0.157 | 0.97 |
| 0.157 ≤ NDVI ≤ 0.727 | 1.009 4 + 0.047ln(NDVI) |
| NDVI > 0.727 | 0.99 |

4. Estimate atmospheric transmittance

Atmospheric transmittance is a function of water vapor content in the atmosphere. The relationship between transmittance and water vapor content in the atmosphere is listed in Table 5 (Qin et al., 2006).

**Table 5 Relationship between transmittance and water vapor content in the atmosphere**

| Water vapor content (*w*) (g cm-2) | Estimation equations |
|---|---|
| 0.4-2.0 | $\tau_{13} = 0.979160 - 0.062918\omega$<br>$\tau_{14} = 0.968144 - 0.098942\omega$ |
| 2.0-4.0 | $\tau_{13} = 1.035378 - 0.097514\omega$<br>$\tau_{14} = 1.026468 - 0.135133\omega$ |
| 4.0-6.0 | $\tau_{13} = 1.098068 - 0.118847\omega$<br>$\tau_{14} = 1.034865 - 0.139598\omega$ |

5. Retrieve LST using following equations.

$$LST = \{[C_{14}(D_{13} + B_{13})]-[C_{13}(D_{14} + B_{14})]\}/(C_{14}A_{13} - C_{13}A_{14})$$
$$A_{13} = 0.145236 \times \varepsilon_{13} \times \tau_{13}$$
$$B_{13} = 0.145236 \times T_{13} + 33.685 \times \varepsilon_{13} \times \tau_{13} - 33.685$$
$$C_{13} = (1 - \tau_{13}) \times [1 + (1 - \varepsilon_{13}) \times \tau_{13}] \times 0.145236$$
$$D_{13} = (1 - \tau_{13}) \times [1 + (1 - \varepsilon_{13}) \times \tau_{13}] \times 33.685$$
$$A_{14} = 0.13266 \times \varepsilon_{14} \times \tau_{14}$$
$$B_{14} = 0.13266 \times T_{14} + 30.273 \times \varepsilon_{14} \times \tau_{14} - 30.273$$
$$C_{14} = (1 - \tau_{14}) \times [1 + (1 - \varepsilon_{14}) \times \tau_{14}] \times 0.13266$$
$$D_{14} = (1 - \tau_{14}) \times [1 + (1 - \varepsilon_{14}) \times \tau_{14}] \times 30.273$$

6. Calculate mean atmospheric temperature

The mean atmospheric temperature ($T_a$) was calculated using equations developed for mid-latitude summer (Qin et al., 2001).

$T_a = 16.0110 + 0.92621 \times T_0$
where $T_0$ is the near-surface air temperature.

An UHI temperature index was created by binning the LSTs into four temperature groups: cool, cool/warm, warm/hot, and hot. The regional LST average value was calculated for the study area. This temperature was used as the threshold value for cool areas. LSTs above the regional average by amounts of 0.75°F, 1.25°F, and more than 1.25°F were used to index the cool/warm, warm/hot, and hot groups, respectively.

**LAND COVER MAPPING**

Urban land cover for the Metro area was mapped at 1-meter spatial resolution using Colorado's 2011 multispectral NAIP imagery with a minimum mapping unit of 4 $m^2$. Eight land cover classes were classified (Table 6). The land cover classes were: trees/shrubs, irrigated non-woody vegetation, dry vegetation and bare soil, buildings, roads, other impervious surfaces, and water. Note that tree and shrub cover are combined and subsequently referred to as Urban Tree Canopy (UTC). The two were combined because it is very difficult to extract shrub cover from tree cover using the spectral and spatial analysis tools at our disposal. Given the limited resources for this study, it was not practical to attempt to do this. Another alternative is to adjust the classified tree/shrub cover based on results from field surveys that measure the extent of shrub cover extending beyond tree cover. These data were not available from the Golden UFORE data set. As a result, our tree/shrub data reflect a slight overestimation of actual tree cover. For example, in Sacramento the field survey found that tree/shrub cover was 21.2 percent and tree cover was 18.2 percent once adjusted for 3 percent shrub cover extending beyond tree cover (McPherson et al., submitted).

**Table 6 Land-cover classes and definitions**

| Level 1 | Level II | Definition | Plantable | Denoted as |
|---|---|---|---|---|
| Built-up land/impervious | Building | Any 3-dimensional permanent structure | No | BLD |
| | Roads or paths | Linear/long, concrete or asphalt, with vehicular or pedestrian (through) traffic | No | Road |
| | Water bodies | Lakes/ponds/river | No | Water |
| | Other Impervious | Other impervious not in the building, or road class such as sidewalks, driveways, parking lots, patios etc | No | IMP |
| Vegetation/Pervious | Trees/shrubs | Woody plant | No | Tree |
| | Irrigated non-woody plant | irrigated grass/herbaceous | Yes | Grass |
| | Non-irrigated non-woody plant and bare soil | Non-irrigated grass/herbaceous and pervious surface (soil, gravel, pavers, etc) | Yes | BSDV |

- <u>Preparing for mapping</u>

A series of preprocessing steps were conducted to prepare the NAIP imagery, road data, hydrology data, and census data for land cover mapping.

- *<u>NAIP imagery quality control</u>*

NAIP images were examined for potential quality issues before land cover mapping. Two major spectral differences were identified within the NAIP images (Figure 4). Tiles were grouped into two clusters based on these observed spectral differences (Figure 5). Further investigation found that the observed differences were not due to differences in the time of image collection. These differences in image quality can cause significant differences in NAIP derived features, especially Normalized Vegetation Index (NDVI), a key index used to extract vegetation. The primary consequence of image quality differences was the need to develop two sets of land cover mapping rules, one for each image cluster.

**Figure 4 NAIP image quality differences are seen in the two scenes as lighter and darker areas**

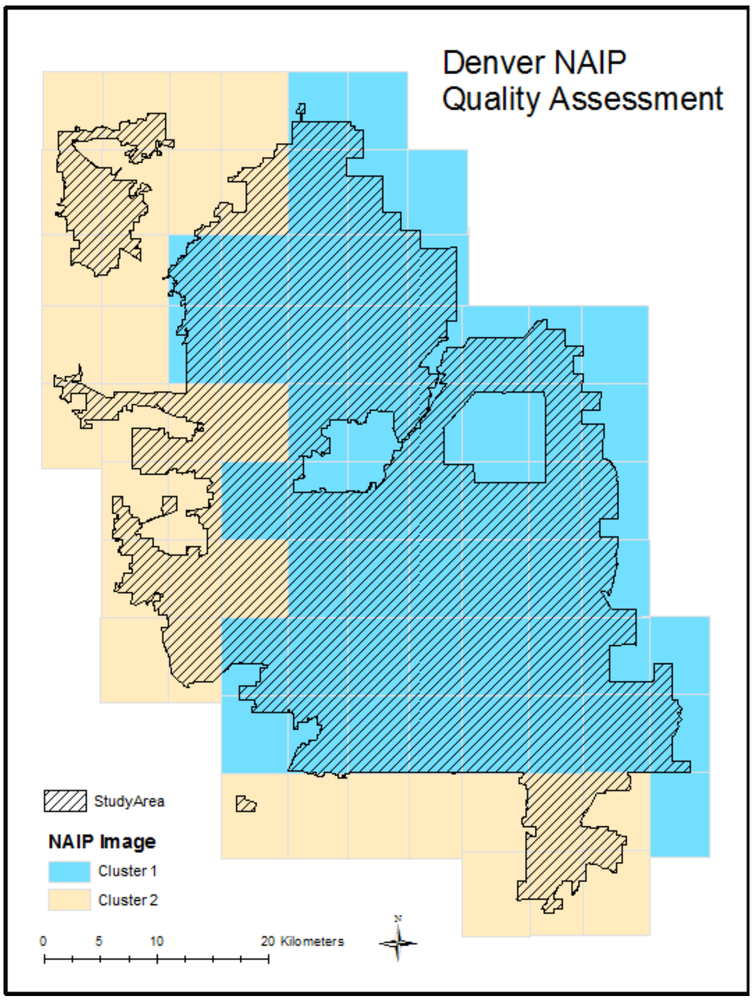



**Figure 5 Two image clusters were created in response to NAIP image quality differences**

- *Features derived from NAIP imagery*

In addition to the original spectral bands from NAIP images (Red, Green, Blue, and Near Infrared (NIR), several features derived from NAIP's spectral bands were helpful in characterizing land cover objects. These features included: Normalized Vegetation Index (NDVI), Brightness (BR), Green ratio (GRatio), Spectral Shape Index (SSI), bNDVI (a "blue" NDVI, (Dinis et al. 2010) and two co-occurrence measurements (variance and homogeneity) of BR (varBR and hmBR).

- NDVI: NDVI = (NIR-Red)/(NIR+Red)
- BR: BR=sum(R,G,B, NIR)/4
- GRatio: GRatio=G/sum(R, G, B)
- varBR, hmBR
- bNDVI: bNDVI= (NIR-Blue)/(NIR+Blue)
- SSI: SSI=abs(R+B-2*G)

- *Partitioning study area into processing units*

The study area was partitioned into 15,000 ft X 10,000 ft processing units (tiles).These tiles were grouped into three processing groups based on their relationship to the NAIP imagery: 1) Group 100: contained images from NAIP Cluster 1; 2) Group 200: contained images from NAIP Cluster 2; and 3) Group 888: contained images from NAIP Cluster 1 and Cluster 2 (Figure 6). Different land cover mapping rule sets were developed and applied to each processing group in this sequence: Group 100, Group 200, and then Group 888. Processing scripts were developed using IDL and ENVI to batch process the calculation of NAIP derived features for each processing unit.

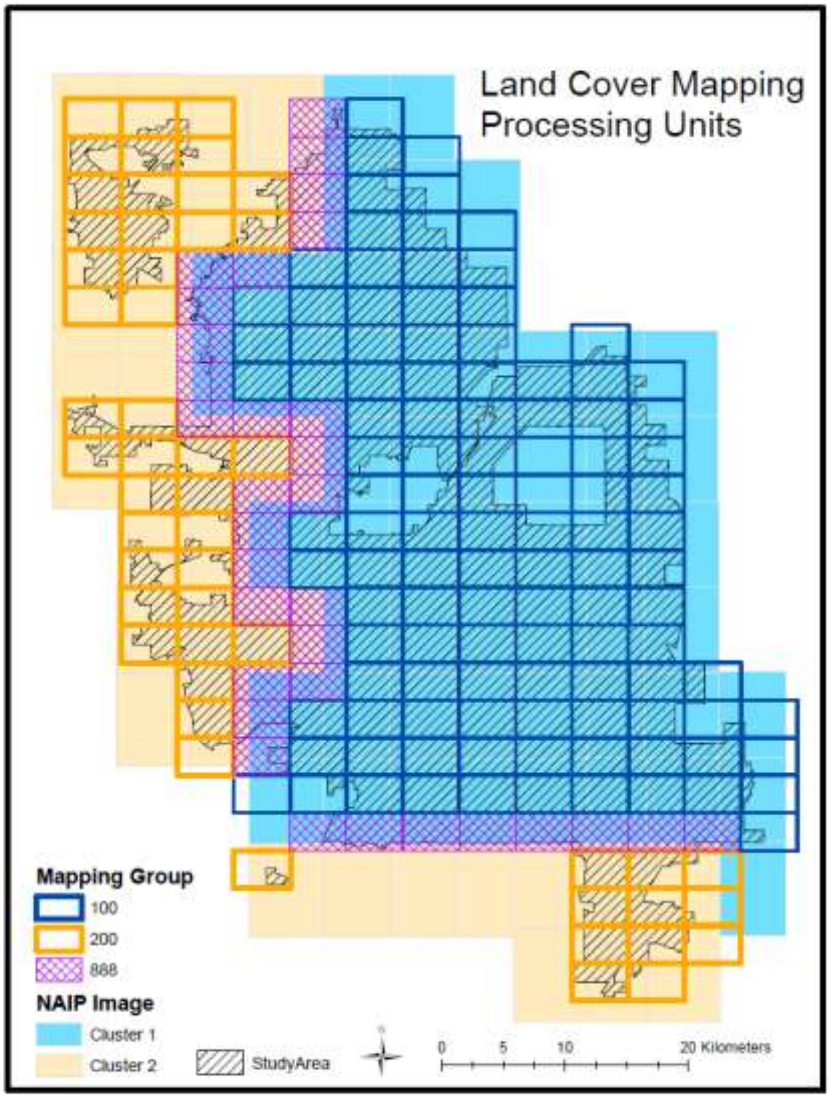



**Figure 6 NAIP image clusters and land cover mapping processing groups**

- *Thematic data preprocessing*

Major preprocessing conducted on thematic data involved combining census tab block and road data to generate a street surface data layer. Road data for the 8 counties within the study area were downloaded from 2010 Census data website and processed to create one single road dataset. Each road segment was buffered to a certain width to generate road surface polygon based on the attribute “MTFCC”. MTFCC is MAF/TIGER feature class code, defining feature class types (*https://www.census.gov/geo/www/tiger/tgrshp2010/TGRSHP10SF1AF.pdf*): e.g. MTFCC = “S1100” means primary road, “S1200” means secondary road, and “S1780” means parking lot road. Road width usually varies from county to county and varies with the time period when the road was built. According to CDOT Roadway Design Guide 2005 (*http://www.coloradodot.info/business/designsupport/bulletins_manuals/roadway-design-guide*), 36-inch width was suggested for streets in single family residential (32’ paved width plus 2-2’ gutter pans) and 44-inch width for multi-family residential streets.

When the 2010 census road data were overlaid with NAIP imagery, road features did not always align with the street centerlines. Road surface data were acquired to improve the accuracy of building and road segmentation. Three major road types were used to generate road surfaces: 49 ft*2 for primary and secondary Road; 22 ft*2 for local neighborhood road, rural road, City Street; and 10 ft*2 for parking lot road and private driveway. Census block data boundaries aligned with street center lines. Census block boundaries were used to supplement road data in areas where road data were missing.

- <u>Land cover mapping workflow</u>

This project used a four-stage land cover mapping strategy (Figure 7). Stage I is the development of basic classification rules. Stage II is refining classification rules based on review and evaluation, called Quality Control (QC) feedback. Stage III is streamlining the land cover classification and QC process. Stage IV includes post-classification processing, accuracy assessment, and finalizing/summarizing land cover.

Although Figure 7 shows accuracy assessment as a single task in Phase IV, it was an important part of Stage II and Stage III as well. Accuracy assessment in Stage II and Stage III involved quality control checks by the developer and independent fresh-eye reviews.

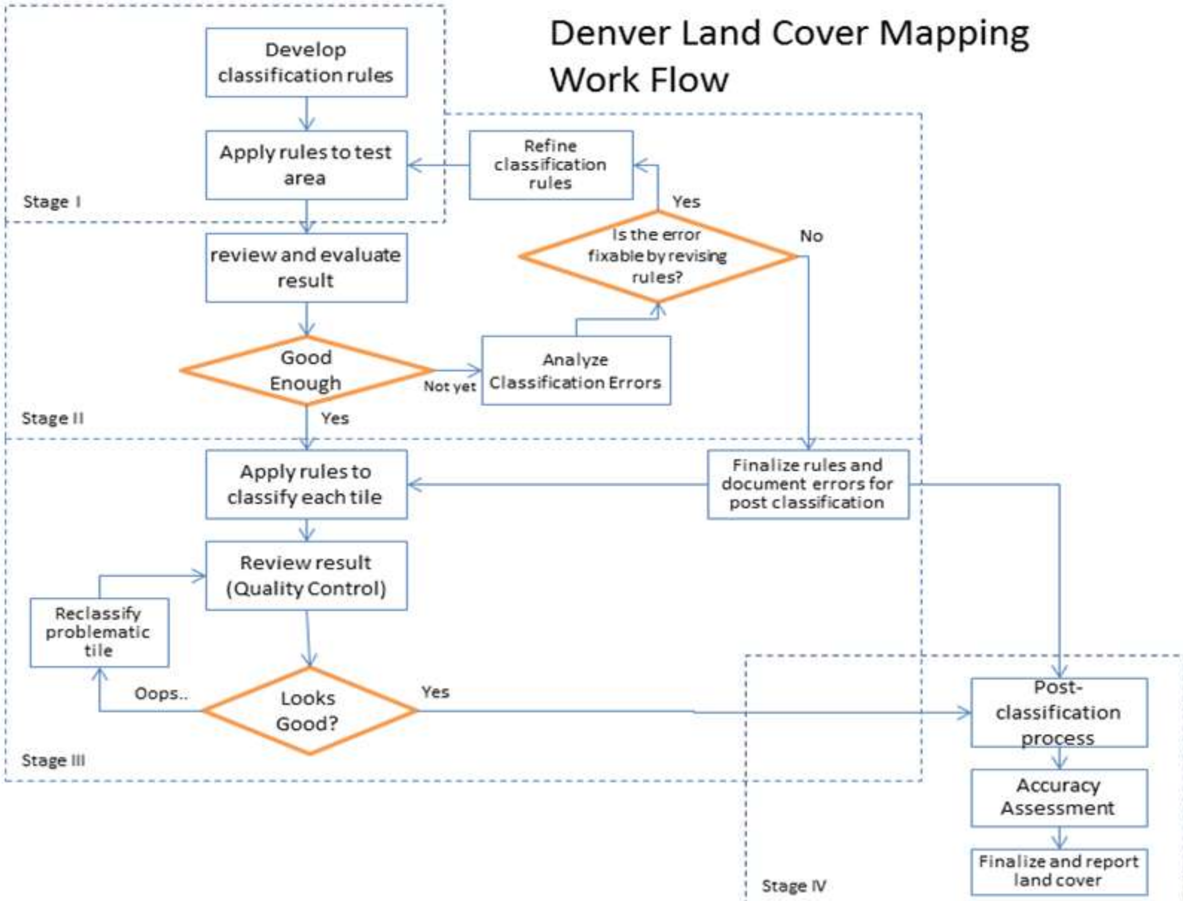



**Figure 7 Land cover mapping workflow**

- <u>Quality control of land cover mapping</u>

- *<u>Developer's review</u>*

The developer's review of classification results occurred during the development of classification rules (in Stage I and Stage II) and the deployment of classification rules to each processing unit (in Stage III). To ensure a high level of classification accuracy, classification results were constantly reviewed and evaluated by the developer throughout the rule set development process. The developer's reviews led to changes in the classification rule set (e.g., to test out segmentation algorithms and classification methods). After a significant amount of trial-and-error testing and rule refinement, the classification results were accepted as accurate by the developer, at which point they were subjected to an independent fresh-eye review.

- *Fresh-eye review*

Multiple fresh-eye reviews were performed, including general exploring (in Stage II) and systematic reviewing (in Stage II and Stage III). By browsing classification results over the NAIP imagery, the first fresh-eye review identified obvious classification errors (or problems) and reported these back to the developer. The developer analyzed the fresh-eye results and addressed each issue accordingly: some errors were corrected by refining classification rules, some were documented and left for post-classification processing. The updated classification results were then exported for a second fresh-eye review that checked each processed unit systematically. To facilitate this review, a quality control grid file that partitioned each processing tile into 100 grids was created. Five grids were randomly selected to check the classification accuracy. Errors were once again recorded and reported back to the developer for further rule development.

Before starting post-classification editing, the post-classification team also checked if processed tiles needed to be re-processed. This can be considered a third type of fresh-eye review.

- ## Object-based land cover classification

An object-based image analysis (OBIA) approach was used in mapping the land cover within the study area. OBIA overcomes the limitation of traditional pixel-based methods that purely describe spectral characteristics of pixels. OBIA gives users more flexibility in characterizing image objects using both spectral and spatial information (Liu, Li et al. 2006; Matinfar et al. 2007; Myint, Gober et al. 2011).

- *Key challenges*

Urban land cover classification from remote sensing images remains challenging due to the complexity and heterogeneity of urban landscapes. This study found the following tasks to be especially challenging in our land cover mapping: 1) segmentation of objects, 2) classification of shaded area, and 3) classification of BSDV. Each task was carefully addressed.

High resolution imagery allows users to identify small objects in urban settings, and mixing of spectrum still occurs within the pixels along object boundaries. Depending on the segmentation algorithms used in delineating the objects, the boundary pixels can be classified into any of the adjacent land cover classes. Optimizing segmentation parameters depends on the scale and nature of features to be detected (Hay 2005; Bo S. and Han 2010), and remains a hot research topic in OBIA (Hay, Niemann et al. 1997; Hay, Marceau et al. 2001; Hay, Dube et al. 2002; Hay, Blaschke et al. 2003; Hay 2005; Castilla, Hay et al. 2008; Hay and Blaschke 2010). Urban areas are very heterogeneous. Even areas with the same type of land cover have a variety of objects with different sizes. For example, the sizes and arrangement of building (BLD) objects differ among single family residential, multi-family residential and commercial /industrial land uses. Therefore, a segmentation algorithm that works well in one area may cause problems in another area.

Instead of developing an optimal classification method for the entire study area, this study applied a localized segmentation strategy: applying certain segmentation methods in one area for one type of object, and combining a series of algorithms together to extract certain features. This method was applied and improved through trial-and-error testing: different segmentation methods and parameters were tested with different landscape combinations; and each result was evaluated to determine whether it should be adopted or abandoned.

Approximately 2 percent of the study area was shaded area. Shaded area usually has a very weak spectral signal, which makes it difficult to detect the underlying land cover. Shaded area is often confused with wetland and water bodies due to spectral similarities. Considerable effort has been put into using a variety of classification approaches (Dare 2005; Chen, Wen et al. 2007; Arevalo, Gonzalez et al. 2008; Zhou, Huang et al. 2009; Lu, Hetrick et al. 2011). A few studies (Dare 2005; Chen, Wen et al. 2007; Chen, Su et al. 2009; Zhou, Huang et al. 2009) suggested extracting dark objects based on spectral signals and further classifying dark objects into water using a Spectral Shape Index (SSI)(Chen, Wen et al. 2007). Some studies classified land cover under shadow by integrating other non-shadow images (Dare 2005; Chen, Wen et al. 2007; Zhou, Huang et al. 2009). Tests conducted for this study found that while SSI worked in some parts of the study area to separate water from shaded area, it failed in other areas. Although integrating images from other sources can help recover information for shaded areas, the fusion of two images can further complicate the problem. Additionally, the view angle and time difference between two images can often cause false indications of shaded land cover. In this study, shaded areas were classified using both contextual information and spectral signals. Also, shadows were used to help separate Trees from Grass.

BSDV was often confused with the impervious land cover class due to spectral similarity. Semi-supervised classification was used to extract BSDV from impervious: e.g. a set of features including BR, NDVI, SSI, and bNDVI were used to describe BSDV and impervious; selected BSDV training samples were used to extract the value range of each feature, and image objects were classified according to their similarity with the training samples.

- *Land Cover Classification*

Land cover classification was carried out in four steps (Figure 8).

1. Classify the image at the pixel level into four primary types of objects: Dark Imp (dark impervious), Dark Veg (dark vegetation), Imp (normal impervious), and Veg (normal vegetation).

2. Extract Road, Water, and BLD impervious objects

3. Extract Grass objects (extract relatively smooth grass land, from large areas to small areas), extract trees with shadows (adjacent to Dark Veg objects), and extract other trees and grass.

4. Extract BSDV from objects that have not been assigned a land cover class.

The entire classification rule set included over 800 algorithms. Presenting a detailed description for the algorithms is beyond the scope of this report. Major features used to extract each type of land cover object can be found in

Table 7. The eCognition rule set file is available upon request.

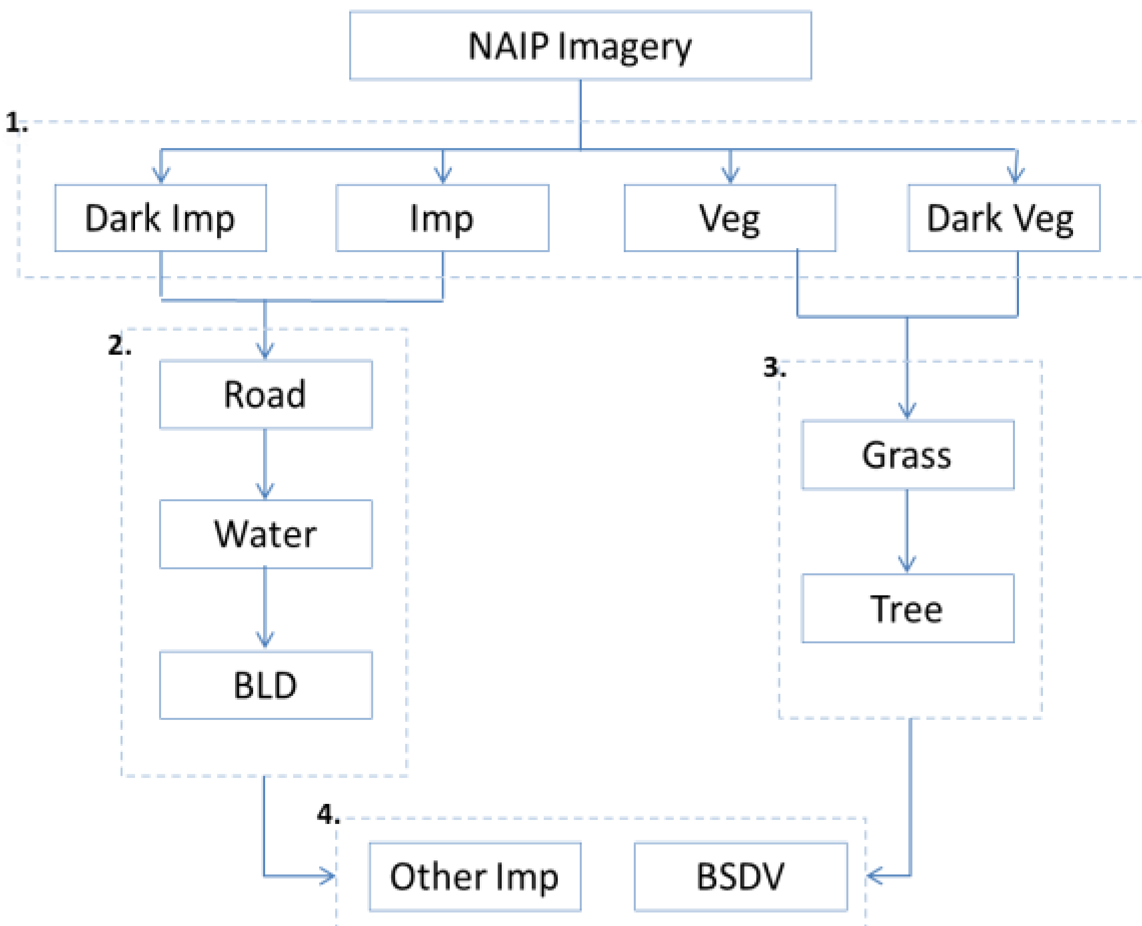



**Figure 8 Major steps for extracting land cover objects from NAIP image**

**Table 7 Features used to describe land cover objects**

| Land Cover Classes | Features used to descript land cover objects | | |
|---|---|---|---|
| | **Spectral** | **Thematic** | **Other *** |
| **DarkIMP** | BR, NDVI, bNDVI | | |
| **DarkVeg** | BR, NDVI | | |
| **Imp** | NDVI | | |
| **Veg** | NDVI, Gratio, bNDVI | | |
| **Road** | NDVI | Street Center Line; Road surface polygons | size, shape |
| **Water** | B, BR, hmBR, SSI, | Census block; Hydrologic data | size |
| **BLD** | BR, NDVI, varBR | Census blocks | size, shape, Border index, Compactness, Shape index ; Rel. border to road |
| **Grass** | NDVI, BR, bNDVI, varBR | | size, |
| **Tree** | NDVI, varBR, BR, | | size, shape, Rel. border to DarkVeg, Compactness |
| **BSDV** | bNDVI, NDVI, BR, hmBR | Census blocks | size, Rel. border to Grass, |
| **other IMP** | NDVI | | |

Other*: other features, e.g. Geometry, relation to neighbor objects

- <u>Post classification</u>

Post-classification is the manual correction of land cover classification results exported from eCognition. To facilitate post-classification editing, classification results were exported as individual object polygons, so that misclassified objects were easily assigned to their correct class without segmenting or digitizing new polygons. Because Tree, Grass, and BSDV were the main emphasis of this project, post-classification efforts focused on these important classes. The post-classification protocol is in the Appendix.

- <u>Accuracy assessment of land-cover classification</u>

Assessing the quality of information derived from remotely sensed data is a complex subject and remains challenging. Although it is agreed that accuracy assessment is important to qualify the results of image classification, there are still debates on the evaluation of the classification results from remote sensing data (Foody, 2002). A common approach is to select a sample of locations and determine the reference land cover present using field observations or using the land cover that was derived from fine resolution images. The discrepancies between the land cover map and the reference data can be presented as an error matrix ( or confusion matrix), from which various measures can be derived to report classification accuracy, including errors of omission and commission, producer's and user's accuracies and the Kappa coefficient (Congalton and Green, 2009).

This study used a point-based accuracy assessment approach to evaluate the quality of the land cover classification. Visual interpretations from NAIP images were compared to classifications on sample points randomly drawn across the study area; and the results were then summarized as error matrices.

- *Sampling*

To build a statistically valid error matrix, a sufficient sample of points needs to be collected. Congalton (1988) recommended a minimum of 50 samples for each map class for maps of less than 1 million acres in size and fewer than 12 classes. The percentage of "Water" class in our study area was calculated using the mashed water data set that combined 2010 census water data and NHD data as

$$\frac{\text{A\_water}}{\text{A\_studyarea}} = \frac{\text{the area of mashed water data}}{\text{the area of project site}} = \frac{48.14 \text{ sq km}}{1837.78 \text{ sq km}} = 2.57\%$$

The relationship between study site area and sample size is:

$$\frac{\text{Ai}}{\text{A}} = \frac{\text{Ni}}{\text{N}}$$

Ai -- the total area of land cover class i; Ni – the number of samples for land cover class i;

A – the total area of project site; N – the total number of samples within study site

To assure a minimum of 50 samples for the smallest land cover class (water), the total number of random samples needed for the entire study area was

$\frac{50}{\text{N}} = 2.57\%$ ➔ N = 1,946

Therefore, 2,000 random sample points were generated across the entire study area. If the combined water data set underrepresented the water features within the study area (which is very unlikely according to our observation on NAIP imagery over the study area), the total number of samples for "Water" land cover class may be less than 50. However, as "Water" land cover type is not the focus of this study, the sample size of 2,000 is still valid and practical for accuracy assessment.

- *Reference data*

The land cover type for each of the 2,000 sample points was visually interpreted from the NAIP imagery and referred to as the reference data. The visual interpretation of certain types of sample points was especially challenging: 1) points that fell on object boundaries, 2) points on objects less than 4 pixels, and 3) points under shadows. Up to three land cover types were recorded for each of these confusing points: primary, secondary, and tertiary land cover classes (see Appendix II for Reference Land Cover Data Protocol). An independent review of these confusing points was conducted to reduce uncertainty. If the classification result for these points matched the reference land cover class, the classification was considered accurate. An error matrix was generated by comparing post-classification results to referenced data for the entire 2,000 sample points.

**NUMBER OF EXISTING TREES**

The number of existing trees was estimated assuming an average tree crown diameter of 19 ft. (5.9 m), based on results from the Golden UFORE study (Bertuglia et al. 2008). In the Golden study, 120 plots were generated for Golden in a random grid system: the city was divided into grids, and plots were randomly located within each grid. Each plot was 1/10 acre size and field visited to collect land cover, land use, and tree data (more details about field data collection can be found in Bertuglia et al. 2008). The field data were preprocessed and sent to the US Forest Service Research Station in Syracuse, New York, where UFORE was run and outputs generated. The UFORE outputs included urban forest structure, volatile organic compound emissions (VOC), air pollutant removal ($O_3$, $SO_2$, $NO_2$, CO, $PM_{10}$ and $CO_2$), effects of trees on building energy use and $CO_2$ emissions, total carbon stored and net annual carbon sequestration. Details about UFORE model can be found in (Nowak et al. 2003). Findings of the Golden UFORE study can be found in the final report (Bertuglia et al. 2008). A total of 196 trees were sampled in the 120 plots located throughout the city.

**POTENTIAL TREE PLANTING SITES (PTPS)**

Potential urban tree cover (PUTC) is the percentage of area on the ground without UTC that could be covered by additional tree canopy. Traditionally, PUTC is the amount of residual pervious surface, including all grass and bare soil. Impervious surfaces such as parking lots and sidewalks in commercial areas are another type of PUTC. However, these types of PTPS are not included in this analysis because of the difficulty identifying them accurately with remote sensing and the expense of planting. In this study, PUTC focused on pervious surfaces.

Potential tree plantings sites (PTPS) were calculated for two types of pervious areas, irrigated grass and bare soil/dry vegetation (BSDV). The number of PTPS was calculated separately for each cover type because trees planted in irrigated grass do not require additional materials and water to support establishment. Trees planted in areas without irrigation will require more resources to support water delivery during the establishment period than trees planted in areas already receiving irrigation.

The goal was to calculate the approximate number of planting sites. Locating the exact X-Y coordinates of each site was not a goal because this is better accomplished during site visits, when the full range of factors influencing site suitability are assessed.

A PTPS was defined as the size of a medium-sized tree; 30-ft. crown diameter (9.1 m), 700 $ft^2$ crown projection area (65 $m^2$). The number of PTPS was calculated on an area basis for all polygons classified as grass or bare soil/dry grass. The gross number of PTPS was reduced by adjustment factors to account for physical limitations to tree planting such as power lines, sports fields or vegetable gardens. Adjustment factors of 0.83 for irrigated grass and 0.64 for bare soil/dry grass were based on field data collected from 211 PTPS in San Jose, CA (McPherson et al., 2012). The field assessment involved noting the number and type of physical limitations to tree planting on field maps (NAIP images with 1 m resolution) that showed each PTPS drawn in the lab. We found that existing trees, other vegetation and grey infrastructure (mainly sidewalks and buildings) were the most common physical limitations. Adjustment factors were calculated as the fraction of PTPS determined not plantable due to physical limitations. Net PTPS were calculated as the product of adjustment factors and gross PTPS (2 and 3).

$$\# \text{PTPS} = \text{polygon area } (m^2) \,/\, 65\ (m^2) \tag{1}$$

$$\# \text{PTPS adjusted for physical limitations } (\text{PTPS}_{PL}) \text{ Grass} = \text{PTPS}_{GL} * 0.83 \tag{2}$$

$$\# \text{PTPS adjusted for physical limitations } (\text{PTPS}_{PL}) \text{ BSDV} = \text{PTPS}_{GL} * 0.64 \tag{3}$$

- PTPS Accuracy Assessment

To assess the accuracy of estimates of PTPS, 15 polygons were randomly located across the study area (34 acres). Circles representing 30-ft diameter tree crowns were drawn manually on plantable areas identified with the NAIP imagery. The number of PTPS drawn were counted by polygon and served as the reference data set. A total of 350 PTPS were drawn as reference data, and 396 PTPS were estimated to exist using the decision-rules employed over the entire study area (Table 8). Results indicate that the method overestimates the number of gross PTPS by about 12 percent. To an unknown extent, this overestimation is offset by PTPS in impervious surfaces that were not included in the analysis.

**Table 8 Accuracy of PTPS Estimates**

| ID | Area (ac) | PTPS | Reference PTPS | Diff |
|---|---|---|---|---|
| 39034 | 1.8 | 7 | 6 | 1 |
| 45259 | 5.8 | 32 | 13 | 19 |
| 45391 | 0.8 | 18 | 16 | 2 |
| 46754 | 0.1 | 1 | 1 | 0 |
| 77723 | 1.3 | 1 | 1 | 0 |
| 103872 | 0.1 | 1 | 0 | 1 |
| 105136 | 0.1 | 1 | 1 | 0 |
| 106026 | 0.3 | 1 | 0 | 1 |
| 140134 | 6.6 | 238 | 241 | -3 |
| 183692 | 0.2 | 3 | 0 | 3 |
| 192046 | 0.3 | 14 | 17 | -3 |
| 212904 | 1.2 | 12 | 6 | 6 |
| 249858 | 0.1 | 1 | 1 | 0 |
| 258731 | 15.1 | 63 | 43 | 20 |
| 259390 | 0.2 | 3 | 4 | -1 |
| Total | 34.0 | 396 | 350 | 46 |

## URBAN TREE CANOPY TARGETS

Communities set UTC targets as measurable goals that inform policies, ordinances, and specifications for land development, tree planting, and preservation. Targets should respond to the regional climate and local land use patterns. Cities in regions where the amount of rainfall favors tree growth tend to have the most UTC. Within a city, land use patterns affect the amount of space available for vegetation: for example, residential land tends to have higher capacity than commercial/industrial land for potential tree planting (Sanders 1984, McPherson et al., 2008).

McPherson (1993) differentiated between two other terms related to UTC, technical potential and market potential: technical potential is the total amount of planting space—existing UTC plus pervious surfaces that could have trees—whereas market potential is the amount of UTC plus the amount of PUTC that is plantable given physical or preferential barriers that preclude planting. Physical barriers include conflicts between trees and other higher priority existing or future uses, such as sports fields, vegetable gardens, and development. Another type of market barrier is personal preference to keep certain locations free of UTC. Whereas technical potential is easily measured, market potential is a complex sociocultural phenomenon that has not been well studied. Setting UTC targets requires collaboration between local planners, policy makers, and urban forestry professionals and usually will be linked to planting certain percentages of potential tree planting sites. Additional UTC is the amount of UTC that is needed to add to existing UTC to achieve the target UTC.

In this study, UTC targets were designed to fill 50 percent of the calculated net PTPS in land use zones not designated as agricultural. The goal of filling 50 percent of all net PTPS acknowledged that:

- Each city and county is unique because it has a different land use mix, as well as different existing UTC and PUTC that reflects historical patterns of development and tree stewardship.
- Each city and county can do its “fair share” by filling 50 percent of its available tree planting sites, thus contributing to a shared Metro Denver goal. This aspect of the approach is attractive because it addresses issues of equity and environmental justice across Metro Denver.
- Cities and counties with the most empty planting sites will achieve the greatest relative increase in UTC, whereas those with higher stocking levels will obtain less enhancement.

This approach meets four important criteria for UTC target setting. It is easily applied in a systematic manner across a diverse group of cities with readily available data. It is easily communicated and readily understood by a variety of stakeholders, such as elected officials, planners, business community, non-profit tree groups and interested residents. Progress towards reaching the UTC targets can be repeatedly measured in a standardized fashion over time. The UTC targets are set at a scale that is locally relevant (i.e., city) and logistically feasible.

**ECOSYSTEM SERVICE BENEFITS ASSESSMENT**

Urban trees provide ecosystem services by providing food and water, regulating climate and conserving building energy use, filtering pollutants from air and water, reducing soil erosion and creating habitat for plants and animals. The natural beauty of trees plays an important role making communities attractive places to work and play. Urban forests produce shaded streets and trails that promote fitness from walking and biking. Planting and maintaining trees creates jobs and provides environmental education opportunities for youth.

This study evaluated ecosystem services values including energy, carbon, air quality, storm runoff and property value effects for existing UTC and additional UTC. Benefits of carbon storage, carbon sequestration and air quality were calculated based on transfer functions calculated from the UFORE study in Golden, CO (Bertuglia et al. 2008); while the remaining services were estimated based on transfer functions derived from research conducted in Fort Collins (McPherson et al. 2003) and Boulder, CO (McPherson et al. 2005).

Transfer function is a term used to describe the transfer of data for a particular “study site” to a “policy site” for which little or no data exist (Brookshire & Neill, 1992; Downing & Ozuna, 1996). In this study, transfer functions are defined as field plot-based measures of a service (e.g., gallons of rainfall intercepted) per acre UTC (kWh ac-1 UTC) that are aggregated and applied to a region by land use class. We express ecosystem services in terms of UTC because previous research found that this approach provided higher accuracy, greater precision and improved spatial detail compared to services derived by land use class alone and applied as density values (e.g., gallons $ac^{-1}$ residential land) (Strohbach & Haase, 2012).

Different transfer function values reflect different stand structures and dynamics that influence the provision of ecosystem services. For instance, the C storage transfer function for an acre of UTC in an old residential neighborhood will be relatively high when the stand consists of closely spaced, mature oaks (*Quercus sp*.) and a lush understory. In contrast, the transfer function for an acre of UTC in a new residential area will be lower when the stand is characterized by juvenile pear (*Pyrus sp*.) trees with a sparse understory. Hence, the value of a transfer function reflects species composition and attributes of stand structure, such as tree and basal area densities. Species is important because of its influence on the tree’s biomass and partitioning into roots, bole, branches, stems and foliage. Stand attributes, such as the vertical layering of biomass in strata, tree density and bole size also influence the amount of woody and foliar biomass per acre UTC and the resulting value of a transfer function.

The transfer function for each land use class is transferred to the UTC delineated for the corresponding land use. Using GIS capabilities, services are mapped and values are summed based on the amount of UTC in each land use class. These maps provide spatially explicit information on the distribution of ecosystem services for planning and management purposes.

- <u>Energy Savings</u>

The effects of trees on building energy use  has been studied using varying approaches (Carver et al. 2004; McPherson et al. 2005; McPherson & Simpson 2003; Jo & McPherson 2001). Because this study has focused on UTC, we have estimated the effects of existing and additional UTC on summer air temperatures and annual air conditioning energy use by residential structures.

The first step was determining the number of 1-unit structures by vintage for each census block group. Vintage refers to construction type, which differs by age built. Vintages match buildings constructed pre-1950, 1950-80, and post-1980 because of differences in average floor area, floor type, glazed area, insulation (R value), and number of stories. Because these parameters affect the energy use of a building, analyses and results are separated by vintage class. More information on each vintage and the energy modeling is in (McPherson et al. 2003).

The number of 1-unit structures by vintage was obtained from 2010 American Community Survey data (Table B25024 - UNITS IN STRUCTURE and Table B25034 - YEAR STRUCTURE BUILT) retrieved from the US Census website. The 5-year estimates were used. The number of 1-unit structures by vintage varied at the block group level. The number of 1-unit structures was calculated for each vintage and census block group by multiplying the percentage of units in each vintage by the total number of 1-unit structures in each census block group. Table 9 shows an example of the estimated number of residential units by vintage and census block group. A detailed table can be found in the digital files submitted with this report.

**Table 9. Example of the number of 1-unit structures in each building vintage by census block group**

| Census block group | Number of 1-unit structures | | |
|---|---|---|---|
| | pre-1950 | 1950-80 | post-1980 |
| 080010078011 | 14 | 90 | 42 |
| 080010078012 | 31 | 202 | 28 |
| 080010078021 | 14 | 171 | 4 |
| 080010078022 | 4 | 38 | 7 |
| 080010078023 | 20 | 100 | 0 |
| 080010079001 | 31 | 438 | 38 |
| 080010079002 | 0 | 11 | 1 |
| 080010079003 | 67 | 227 | 21 |
| 080010079004 | 17 | 277 | 25 |
| 080010080001 | 10 | 222 | 4 |
| 080010080002 | 21 | 192 | 5 |
| …. | …. | …. | …. |

Relations between the percentage UTC, air temperature depression and kWh saved for air conditioning were derived from previous building energy performance simulations using typical meteorological data for Denver, CO (McPherson et al. 2003). The simulations used only air conditioning savings from a tree (*Fraxinus americana*) at 9 dbh size classes that was always located too far from each vintage to cast shade on the building, and assumed that each 1 percent increase in UTC was associated with a 0.2°F air temperature depression (Anyanwu and Kanu 2006). Table 10 shows the regression equations that resulted for each vintage class.

**Table 10 Relations between percentage of UTC and kWh saved**

| Vintage Class | Relations between percentage of UTC (x) and kWh saved (y) | Coefficients (Ki) |
|---|---|---|
| pre-1950 | y= 1586.1 x | K1 = 1586.1 |
| 1950-80 | y= 1167.1 x | K2 = 1167.1 |
| post 1980 | y = 1274.9 x | K3 = 1274.9 |

Given census block group "n", with percentage of UTC as UTC (n) and the number of 1-unit structures for each vintage class i as Di, the total energy savings E(n) can be calculated as:

$$\mathrm{E(n)} = \sum_{i=1}^{3} \mathrm{Ki} * \mathrm{UTC}\left(\mathrm{n}\right) * \mathrm{Di}$$

Electricity was priced at $0.12 per kWh, the typical summer rate in the Denver Metropolitan Service Area (Public Service Company of Colorado, personal communication, Customer Service Center, Dec 12, 2012). Avoided $CO_2$ emissions at power plants generating electricity resulted from air conditioning savings from UTC. Based on Public Service Company of Colorado's fuel mix that was 70 percent coal and 30 percent natural gas, an emission factor of 1,897 lbs $CO_2$ per MWh was used to calculate avoided emissions.

- <u>Rainfall interception</u>

Urban trees can reduce the amount of runoff and pollutant loading in receiving waters by intercepting and storing rainfall on leaves and branch surfaces. Root growth and decomposition can also increase the capacity and rate of soil infiltration by rainfall and reduce overland flow. Studies of urban forest impacts on stormwater reported an annual runoff reduction of 2-7% (Xiao et al. 1998).

This study quantified rainfall interception using findings from the municipal forest resource assessment conducted in Boulder, CO (McPherson et al. 2005). Approximately 473 acres of UTC were estimated to intercept 60,305 CCF (100 cubic ft) of rainfall annually. That equates with 95,306 gallons of interception by each acre of UTC.

Interception was priced based on stormwater management costs for retention/detention basins. Boulder has constructed a number of detention ponds for stormwater retention/detention. Data on the construction and maintenance for nine ponds were analyzed to derive average costs citywide. For a typical 6.5 acre basin, land costs totaled $1.78 million ($274,000/acre) and construction costs were $1.6 million ($253,000/acre) (McPherson et al.

2005). The annual cost for operation and maintenance was about $3,000. Assuming a 20-year life before dredging and reconstruction, the total life-cycle cost was $3.46 million. Assuming the pond adds one foot of depth due to runoff seven times a year, it will store 45 ac-ft of runoff annually over the course of a year. The current annual cost of storage in the holding pond is $0.0132/gal. This price is comparable to the average price for stormwater runoff reduction ($0.01/gallon) reported in similar studies (McPherson and Xiao 2004).

- <u>Property value</u>

Many benefits attributed to urban trees are difficult to translate into economic terms. Beautification, privacy, wildlife habitat, shade that increases human comfort, sense of place, and well-being are services that are difficult to price. However, the value of some of these benefits may be captured in the property values of the land on which trees stand. To estimate the value of these "other" benefits, we applied results of research that compared differences in sales prices of houses to statistically quantify the difference associated with trees. All else being equal, the difference in sales price reflects the willingness of buyers to pay for the benefits and costs associated with trees. This approach has the virtue of capturing in the sales price both the benefits and costs of trees as perceived by the buyers. Limitations to this approach include difficulty determining the value of individual trees on a property, the need to extrapolate results from studies done years ago in the East and South to this region, and the need to extrapolate results from front-yard trees on residential properties to trees in other locations (e.g., back yards, streets, parks, and non-residential land) and UTC.

Anderson and Cordell (1988) surveyed 844 single-family residences in Athens, GA, and found that each large front-yard tree was associated with a 0.88% increase in the average home sales price. This percentage of sales price was utilized as an indicator of the additional value a resident in the Metro Denver region would gain from selling a home with a large tree. The sales price of residential properties varied widely by location within Metro Denver, but on average was $233,004 (http://www.divisionofhousing.com/2012/02/median-home-prices-up-in-metro-denver.html). Therefore, the value of a large tree that added 0.88% to the sales price of such a home was $2,055. To estimate annual benefits, the total added value was divided by the leaf surface area of a 30-year-old shade tree (*Fraxinus pennsylvanica*) ($2,055/5,382 $ft^2$) to yield the base value of $0.38/$ft^2$ of leaf surface area. This value was converted to units of UTC by multiplying by the Leaf Area Index of 4 (one-side of leaf). To annualize this value, the mature tree value ($1.77 $ft^{-2}$ UTC) was multiplied by the amount of leaf surface area added to the tree during 1 year of growth ($0.187 $ft^{-2}$ UTC). As a result, a base value of $0.33 $ft^{-2}$ UTC was calculated for an annual increase in sales price per unit UTC for a mature tree.

To adapt and apply the base value to the Metro Denver urban forest a land use reduction factor was applied because the value of trees located in back yards and nonresidential property will have less impact on sales price and other intangible benefits compared-to front-yard trees (Richards et al. 1984). Lacking specific research findings and wanting to be conservative, it was assumed that single family residential UTC had 50 percent of the impact of a front-yard tree. Reduction factors for other UTC on other land uses were multi-family residential: 40 percent, commercial: 20 percent and other: 10 percent. The transfer function for each land use was calculated as the product of the base value and land use reduction factor. For example, the calculation for single family residential land use was:

\$0.165 $ft^{-2}$ UTC = \$0.33 $ft^{-2}$ UTC X 50%

- <u>Other ecosystem services</u>

Other ecosystem services benefits, including carbon dioxide storage, carbon dioxide sequestration and air pollution removal were estimated using transfer functions derived from the Golden UFORE study (Bataglia et al. 2008). Transfer functions for $CO_2$ storage and sequestration varied across land uses. Because the land use categories in this study are different from the ones in the Golden UFORE study, we cross-walked the land uses to derive meaningful transfer functions for the Denver study (Table 11). It was assumed that “Mixed” land uses in the Denver study were comprised of the same mix and proportion of land uses as found for non-mixed land use, except “Agri” land use was excluded. The “PQP” land use in Denver was assumed to contain both institutional and park land uses found in the Golden UFORE study. The PQP transfer functions were derived assuming that these two land uses had the same distribution in Metro Denver as they had in Golden. Ecosystem services provided by existing UTC in Agricultural land were estimated using the same transfer functions that we used for Open Space. Air quality services applied the same transfer functions across land use classes because they were location independent.

**Table 11 Transfer functions derived from the Golden UFORE study.**

| Denver Study Land Use | Golden UFORE study land use | $CO_2$ storage (lb/ac) | $CO_2$ SEQ (lb/ac) | Air quality (pollution removal) CO (lb/ac) | $NO_2$ (lb/ac) | $O_3$ (lb/ac) | $PM_{10}$ (lb/ac) | $SO_2$ (lb/ac) |
|---|---|---|---|---|---|---|---|---|
| Agri | | 76.22 | 1.51 | | | | | |
| Comm | Commercial | 52.56 | 2.61 | | | | | |
| Ind | Industrial | 55.72 | 1.78 | | | | | |
| Mixed | | 40.46 | 1.79 | | | | | |
| MultiFam | Residential | 40.28 | 1.87 | 0.0005 | 0.0028 | 0.0083 | 0.0075 | 0.0008 |
| OpenSpace | Vacant/Open Space | 76.22 | 1.51 | | | | | |
| PQP | Institutional, Park | 42.47 | 1.61 | | | | | |
| SingleFam | Residential | 40.28 | 1.87 | | | | | |

The value of ecosystem services  for air quality were monetized using models that calculated the marginal cost of controlling different pollutants to meet air quality standards (Wang and Santini 1995). Emission concentrations were obtained from U.S. EPA (2004) and a regional population estimate of 2.79 million was used. The monetary value of sequestered and avoided $CO_2$ was $0.005/lb based on average high and low estimates for emerging carbon trading markets. All air pollutant prices are shown in Table 12.

**Table 12 Prices for ecosystem services.**

| | **Energy saving** | **$CO_2$ SEQ** | **Heat/Cool $CO_2$ avoided** | **$NO_2$** | **$O_3$** | **$PM_{10}$** | **$SO_2$** | **Rainfall interception** |
|---|---|---|---|---|---|---|---|---|
| | $/MWh | $/lb | $/lb | $/lb | $/lb | $/lb | $/lb | $/1000 gals |
| **Service value** | 120.00 | 0.005 | 0.005 | 3.34 | 3.34 | 8.61 | 2.47 | 13.21 |

# RESULTS AND DISCUSSION

## ACCURACY OF LAND COVER CLASSIFICATION

Based on the analysis of 2,000 random sample points, overall classification accuracy was 89 percent for the post-classified map that combined impervious surfaces (i.e., buildings, roads, water and other impervious) into a single cover type (Table 13). Urban tree canopy (UTC) was classified with 91.5 percent accuracy. Not surprisingly, BLD was found most often confused with other impervious and had the lowest success rate (65.7%). The absence of building GIS data and wall-to-wall LiDAR data contributed to the low accuracy for BLD extraction. Factors that affected mapping accuracy were the treatment of the shadowed areas and vague boundaries between Grass and BSDV cover types. Nevertheless, urban tree canopy (UTC) classification exceeded the 90 percent accuracy target for this study.

The UTC estimation error, calculated as the difference between the classification and reference data divided by the total reference area, indicates the extent to which UTC is overestimated or underestimated. Based on a random sample of 2,000 points, UTC was overestimated by 0.8%, a relatively small amount.

**Table 13 Accuracy of land cover classification**

| | Tree | Grass | BSDV | BLD | IMP | Road | Water | Grand Total | User's Accuracy |
|---|---|---|---|---|---|---|---|---|---|
| **Tree** | 260 | 34 | 1 | | 5 | | | 300 | 86.7% |
| **Grass** | 20 | 435 | 21 | | 2 | | 1 | 479 | 90.8% |
| **BSDV** | 1 | 2 | 466 | | 3 | | | 472 | 98.7% |
| **BLD** | | | | 109 | 25 | 1 | 1 | 136 | 80.1% |
| **IMP** | 3 | 2 | 3 | 54 | 297 | 12 | | 371 | 80.1% |
| **Road** | | | 2 | 3 | 24 | 156 | | 185 | 84.3% |
| **Water** | | | | | | | 57 | 57 | 100.0% |
| **Grand Total** | 284 | 473 | 493 | 166 | 356 | 169 | 59 | 2000 | |
| **Producer's Accuracy** | 91.5% | 92.0% | 94.5% | 65.7% | 83.4% | 92.3% | 96.6% | | 89.0% |

## ACCURACY BY LAND USE/ VINTAGES

The accuracy assessment of UTC was extended to determine how it varied by land use (Table 14) and building age of construction, or vintage (Table 15). Overall, UTC was slightly overestimated. At the land use level, UTC was overestimated for PQP and Mixed land uses, and underestimated for Comm and Agri land uses, The overall land cover mapping accuracies were above 90 percent for both Agri and PQP land use.

**Table 14 UTC mapping accuracy by land use**

| Land Use | Overall | Reference | RS Mapping | Reference matched with RS Mapping | User's Accuracy | Estimation error |
|---|---|---|---|---|---|---|
| Agri | 96% | 6 | 5 | 5 | 100% | -0.05% |
| Comm | 83% | 10 | 8 | 7 | 88% | -0.10% |
| Ind | 91% | 11 | 12 | 10 | 83% | 0.05% |
| Mixed | 88% | 40 | 49 | 39 | 80% | 0.45% |
| MultiFam | 89% | 14 | 14 | 13 | 93% | 0% |
| OpenSpace | 95% | 7 | 7 | 6 | 86% | 0% |
| PQP | 94% | 17 | 21 | 16 | 76% | 0.2% |
| SingleFam | 87% | 179 | 184 | 164 | 89% | 0.25% |
| Total | 89% | 284 | 300 | 260 | 87% | 0.80% |
| STD | 0.04 | | | | 0.08 | 0.002 |

At the building vintage level, UTC was overestimated by 0.64% (STD: 0.002) for areas developed during 1990 – 2000, 1970-1980, 1950-1960, and 1960-1970. Urban tree canopy was underestimated for areas developed during 1980-1990 and after year 2000. Most trees are planted at the time of development. In the most recently developed areas the trees may be small and isolated, making their canopy more difficult to detect than in older areas, where tree crowns are mature and growing together.

**Table 15 Urban tree cover mapping accuracy for LDR land use by vintage**

| Vintage | Overall | Reference | RS Mapping | Reference matched with RS Mapping | User's Accuracy | Estimation error |
|---|---|---|---|---|---|---|
| 1940 | 97% | 14 | 14 | 14 | 100% | 0% |
| 1940-1950 | 92% | 6 | 6 | 6 | 100% | 0% |
| 1950-1960 | 82% | 39 | 41 | 35 | 85% | 0.25% |
| 1960-1970 | 85% | 34 | 35 | 32 | 91% | 0.13% |
| 1970-1980 | 84% | 35 | 38 | 31 | 82% | 0.38% |
| 1980-1990 | 89% | 23 | 21 | 20 | 95% | -0.25% |
| 1990-2000 | 84% | 16 | 18 | 15 | 83% | 0.25% |
| 2000-2010 | 90% | 12 | 11 | 11 | 100% | -0.13% |
| Grand Total | 87% | 179 | 184 | 164 | 89% | 0.64% |
| STD | 0.06 | | | | 0.08 | 0.002 |

## URBAN HEAT ISLAND

The land surface temperatures of the study area for September 25, 2007 varied from 49.3°F to 75.4°F (Mean: 74°F and STD: 1.27°F) (Figure 9). A four level land surface temperature index gradient (LSTG) map (Figure 10) shows the spatial distribution of the hottest areas. Most of these hot spots are composed of impervious surfaces such as buildings, parking lots, and roads.

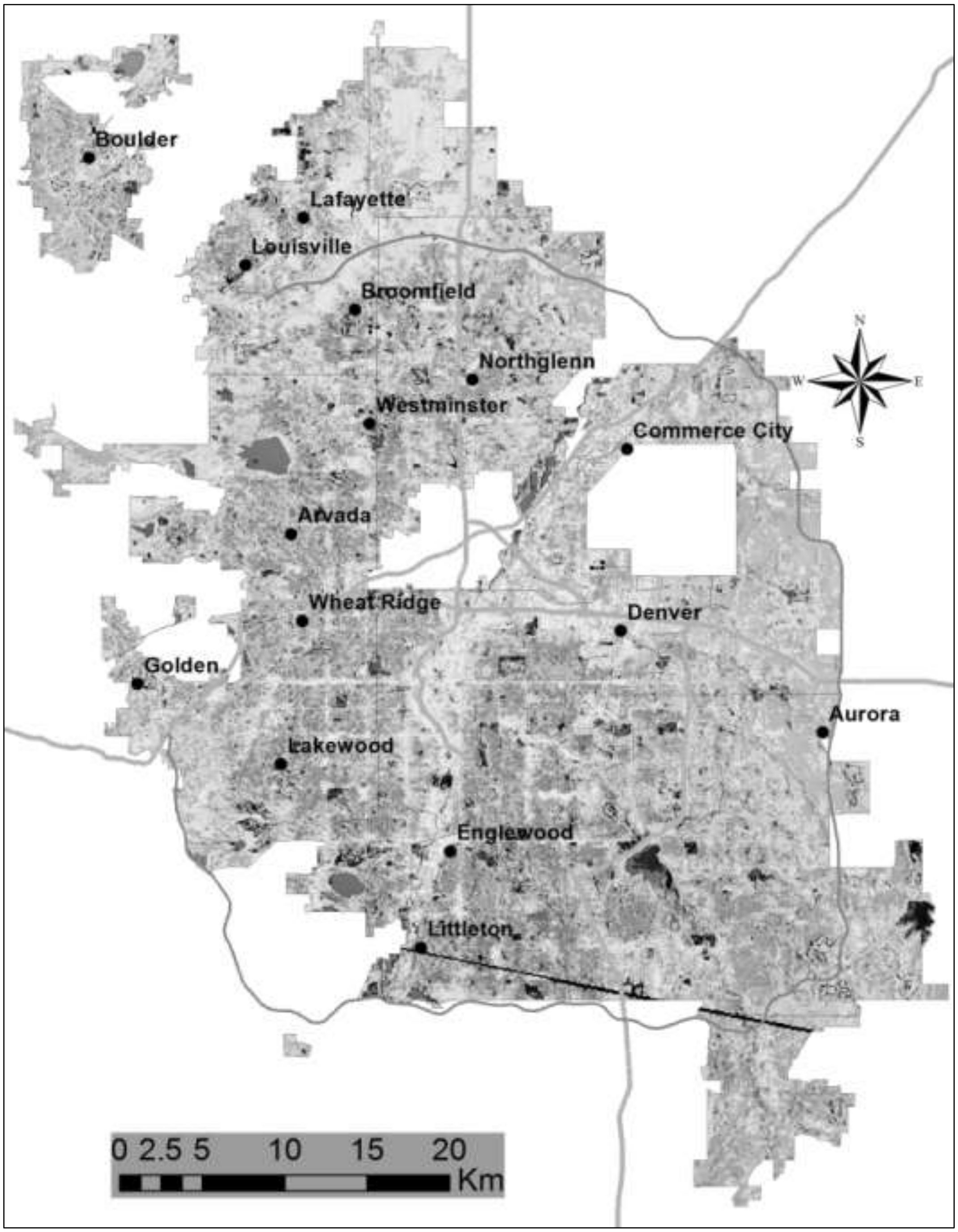



**Figure 9 Surface temperatures of the study area. The higher brightness corresponds to the higher temperature.**

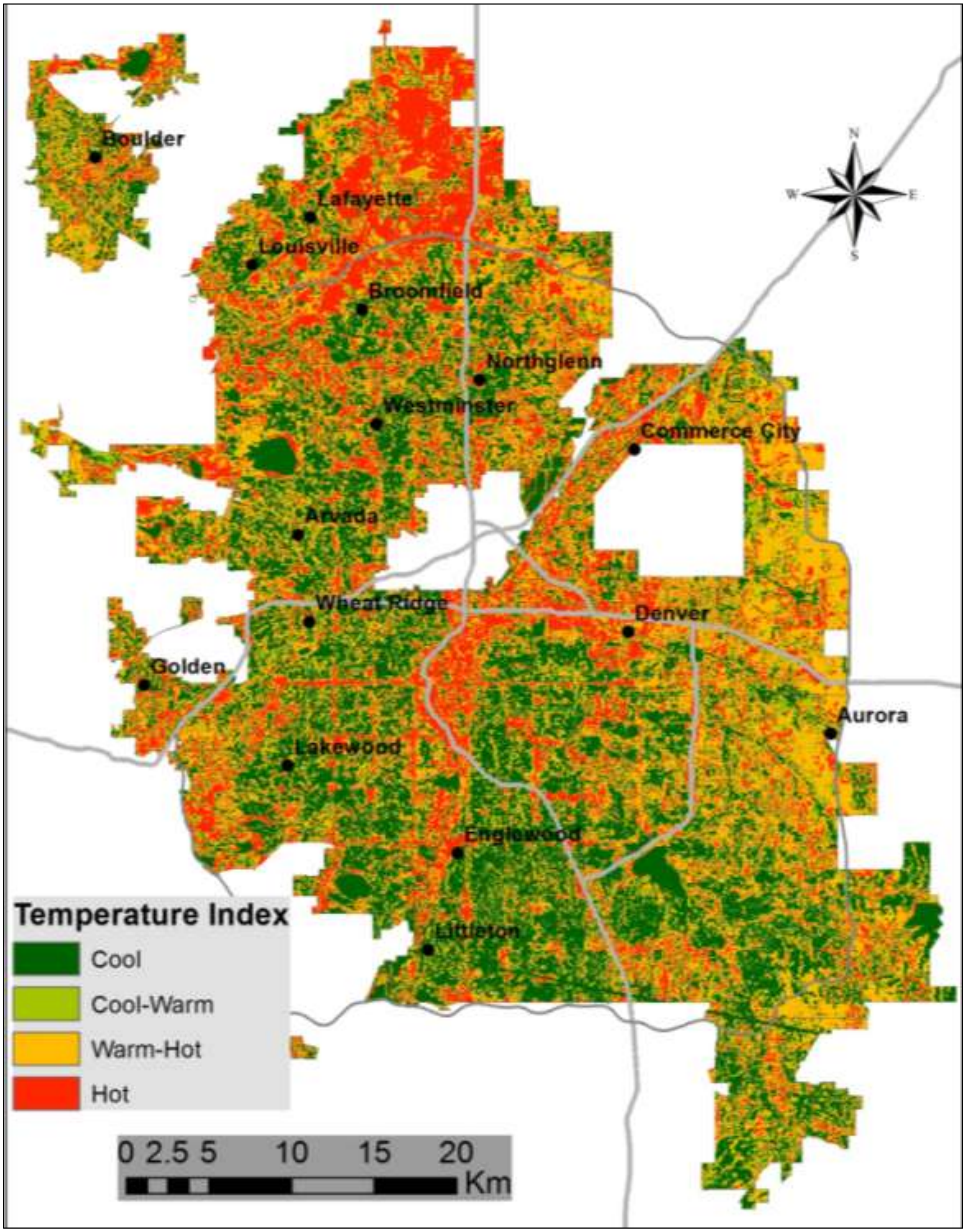
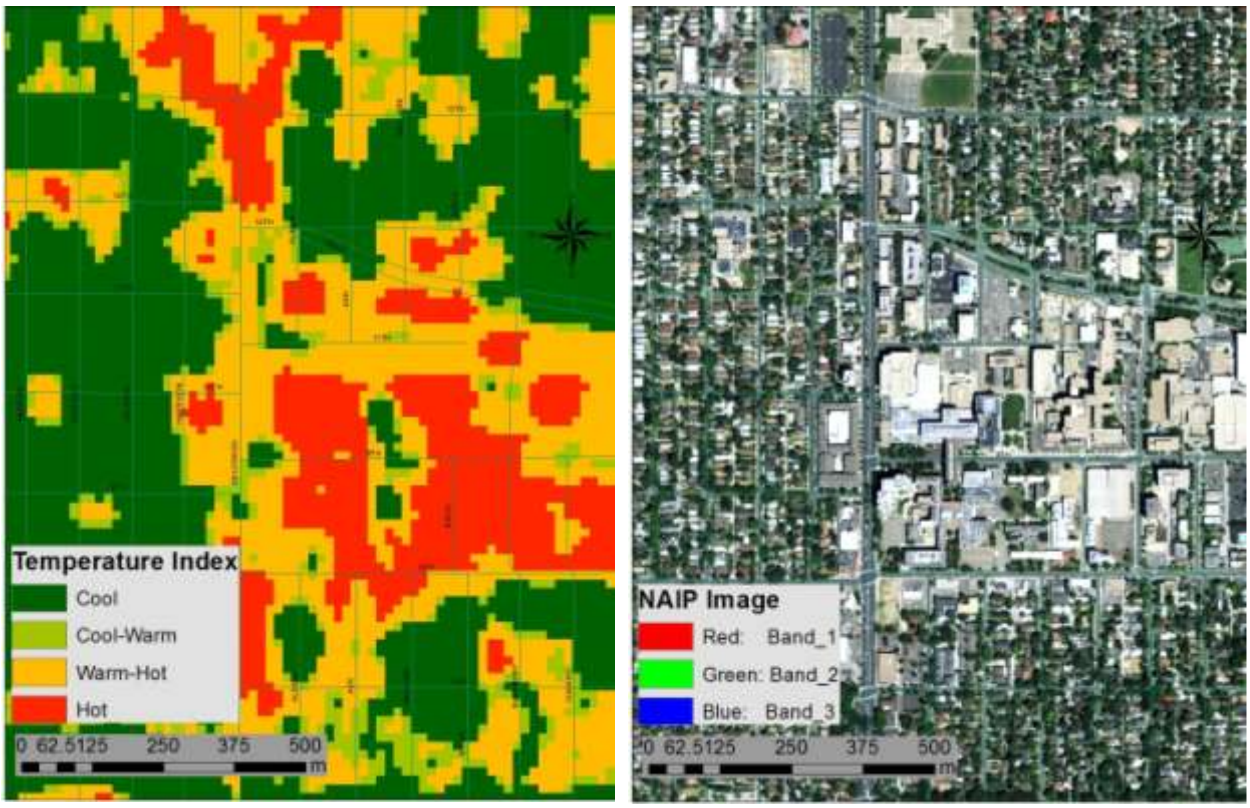



**Figure 10. A four level Land Surface Temperature Gradient (LSTG) map shows the spatial distribution of hot areas.**

This LST and LSTG data layers are registered image files that can be over-laid with other GIS data. Figure 11 shows LSTG and high resolution NAIP aerial imagery for the same area. There is a strong correlation between impervious surfaces (i.e., buildings, parking lot, and roads) and hot areas. Further quantitative analysis of relations among urban LSTG, vegetation index, and impervious index could help explain how urban tree planting can be best targeted to mitigate UHIs.




**a. LSTG map. The LSTG data has 15m spatial resolution.**

**b. True color NAIP image. The NAIP image has spatial resolution of 1 meter**

**Figure 11 Comparison of the LSTG map with NAIP image**

## LAND COVER

Land cover was classified at each processing unit level and summarized for reporting at study area, city, and census block group levels. For the 721 square miles of land within the study area, UTC was 15.7 percent; grass or non-woody irrigated surface was 22.7 percent and bare soil and dry vegetation was 25 percent (Table 16). Impervious and water surfaces accounted for the remaining 36.6 percent of the study area.

- ## Land cover by land use

Within the eight types of land use, single family and multi-family residential had the highest tree canopy cover rates of 25.5 and 19.4 percent, respectively (Table 16). The highest Grass (33.9%) and BSDV cover rates (48.9%) were found in Agricultural land. BSDV was the most abundant cover type for Open Space (39.3%) and Public/Quasi-Public (PQP) land (34.9%). Land cover was also analyzed by land use for each city and results are found in the digital data files submitted with this report.

**Table 16 Land cover percentages by land use (includes unincorporated areas)**

| Land Use | Tree (%) | Grass (%) | BSDV (%) | BLD (%) | IMP (%) | Road (%) | Water (%) |
|---|---|---|---|---|---|---|---|
| Agri | 6.4 | 33.9 | 48.9 | 1.3 | 4.7 | 2.5 | 2.3 |
| Comm | 8.5 | 15.6 | 20.2 | 9.8 | 34.0 | 10.7 | 1.3 |
| Ind | 5.6 | 15.4 | 23.1 | 12.5 | 33.0 | 9.4 | 1.0 |
| Mixed | 9.8 | 23.5 | 29.3 | 6.2 | 20.0 | 9.9 | 1.2 |
| MultiFam Resid. | 19.4 | 18.1 | 9.2 | 10.8 | 29.2 | 13.0 | 0.4 |
| OpenSpace | 7.5 | 27.9 | 39.3 | 0.8 | 6.8 | 2.5 | 15.3 |
| PQP | 10.4 | 25.7 | 34.9 | 1.7 | 8.8 | 10.2 | 8.3 |
| SingleFam Resid. | 25.5 | 21.2 | 15.6 | 7.8 | 18.7 | 10.2 | 0.9 |
| **Grand Total** | **15.7** | **22.7** | **25.0** | **6.5** | **18.4** | **9.3** | **2.4** |

- ## Land cover by cities

The percent of each land cover class is presented by city in Table 17. Cities with the most urban tree canopy (UTC) were: Cherry Hills Village (37.4%), Bow Mar (29.7%) and Greenwood Village (28.9%). The cities of Erie (4.5%) and Commerce City (4.7%) had the least UTC. Figure 12 shows the percentage UTC for each city. Denver’s regional results (15.7% UTC) in Table 16 differ from the grand total for cities (16.4% UTC) in Table 17 because the former includes unincorporated land outside city limits.

This study’s findings of 15.7 percent UTC for the Metro Denver region and 19.7 percent UTC for the City of Denver (Table 17) are relatively high compared to the median value of 10.8 percent reported by NCDC (2006) using QuickBird imagery from 2005 and 2006. Shrub cover is included in this study’s UTC estimates, and probably accounts for 3 to 5 percent of the UTC. It is not clear if shrub cover was included in the UTC values reported by NCDC. This analysis used more recent imagery (2011 vs. 2005-06) that was higher resolution (1 m vs. 2.4 m), and likely to be more accurate. Also, it used eCognition imagery analysis software, which is a sophisticated imagery analysis software specialized in object-based imagery segmentation and classification. These contemporary techniques are considered more advanced and improved compared to those used 6 years ago in the NCDC study. The accuracy assessment by NCDC indicated an underestimate of UTC, while this accuracy assessment indicated a slight overestimate of UTC. A portion of the difference in UTC estimates may be due to differences in study area boundaries, as well as growth in UTC from recent tree planting efforts and natural expansion of existing tree crowns.

**Table 17 Percentages of land cover for each city (excludes unincorporated areas)**

| Cities | Tree (%) | Grass (%) | BSDV (%) | BLD (%) | IMP (%) | Road (%) | Water (%) |
|---|---|---|---|---|---|---|---|
| Arvada | 19.4 | 16.0 | 26.6 | 8.5 | 19.1 | 8.6 | 1.8 |
| Aurora | 11.9 | 21.0 | 31.6 | 6.3 | 17.6 | 9.9 | 1.7 |
| Boulder | 27.4 | 9.6 | 20.9 | 8.0 | 20.6 | 9.7 | 3.9 |
| Bow Mar | 29.7 | 29.1 | 3.1 | 3.7 | 11.7 | 4.2 | 18.6 |
| Broomfield | 8.2 | 32.2 | 32.8 | 4.3 | 13.5 | 7.5 | 1.6 |
| Centennial | 24.6 | 21.4 | 12.9 | 7.2 | 21.4 | 12.3 | 0.1 |
| Cherry Hills Village | 37.4 | 33.1 | 5.4 | 3.5 | 14.1 | 5.2 | 1.2 |
| Commerce City | 4.7 | 24.7 | 40.8 | 4.3 | 16.5 | 7.3 | 1.6 |
| Denver | 19.7 | 20.2 | 10.6 | 9.3 | 25.5 | 12.8 | 1.9 |
| Edgewater | 21.8 | 22.2 | 1.5 | 13.2 | 29.0 | 12.3 | - |
| Englewood | 24.0 | 15.8 | 2.6 | 12.0 | 29.8 | 14.6 | 1.2 |
| Erie | 4.5 | 26.1 | 51.9 | 3.0 | 9.2 | 4.6 | 0.8 |
| Federal Heights | 14.0 | 29.0 | 4.8 | 11.4 | 28.2 | 12.2 | 0.3 |
| Foxfield | 12.1 | 20.9 | 48.5 | 2.0 | 10.6 | 5.9 | - |
| Glendale | 12.4 | 9.6 | 0.9 | 12.0 | 51.3 | 12.9 | 0.8 |
| Golden | 21.9 | 4.6 | 35.6 | 9.5 | 19.5 | 7.9 | 1.0 |
| Greenwood Village | 28.9 | 24.1 | 7.0 | 6.3 | 23.3 | 9.9 | 0.4 |
| Lafayette | 16.6 | 25.3 | 23.5 | 7.6 | 14.3 | 10.5 | 2.2 |
| Lakewood | 20.0 | 17.3 | 21.4 | 7.5 | 21.7 | 9.6 | 2.5 |
| Littleton | 24.5 | 24.3 | 6.2 | 6.6 | 20.7 | 9.9 | 7.9 |
| Louisville | 16.6 | 33.1 | 15.9 | 5.9 | 17.9 | 9.5 | 1.1 |
| Mountain View | 26.8 | 16.9 | 2.3 | 11.1 | 30.3 | 12.5 | - |
| Northglenn | 20.5 | 24.7 | 7.3 | 8.7 | 21.9 | 12.9 | 3.9 |
| Parker | 11.4 | 14.4 | 45.1 | 6.1 | 17.7 | 5.2 | 0.2 |
| Sheridan | 12.2 | 25.5 | 6.5 | 9.8 | 32.2 | 11.5 | 2.2 |
| Superior | 11.7 | 27.7 | 27.9 | 4.3 | 16.6 | 10.4 | 1.5 |
| Thornton | 11.4 | 29.7 | 21.9 | 5.7 | 15.3 | 11.0 | 5.1 |
| Westminster | 14.4 | 29.8 | 14.6 | 6.1 | 18.7 | 9.5 | 6.8 |
| Wheat Ridge | 25.1 | 22.3 | 6.0 | 8.7 | 24.5 | 11.0 | 2.4 |
| **Grand Total** | **16.4** | **21.9** | **22.6** | **7.0** | **19.7** | **10.0** | **2.4** |

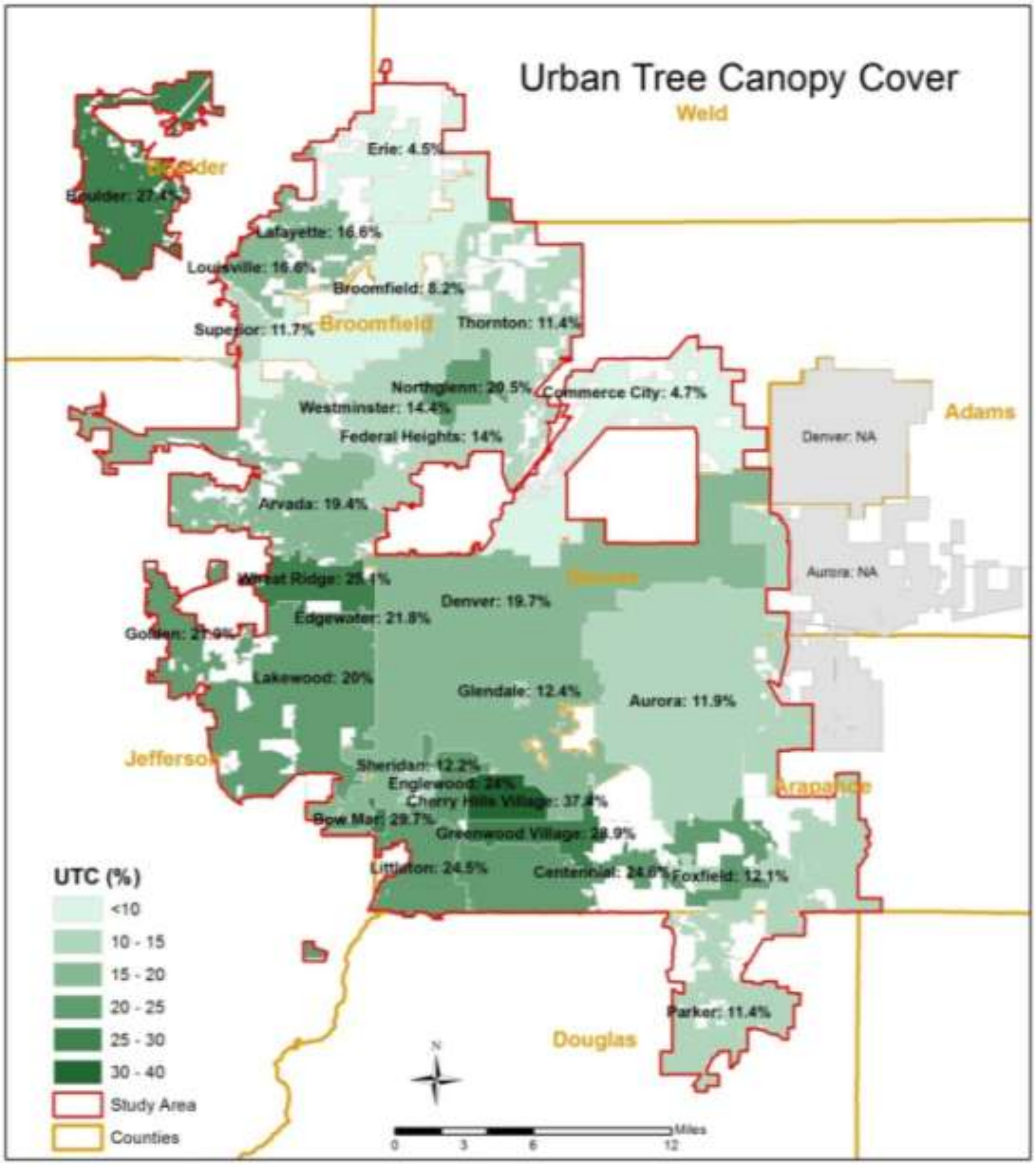



**Figure 12 Urban tree canopy cover percentages for each city**

The land cover classification results were similar to the findings from the accuracy assessment, which involved random sampling of 2,000 points across the study area (Table 18).

**Table 18 Land cover estimates (%) from classification and from random sampling with 2,000 points**

| | Tree | Grass | BSDV | BLD | IMP | Road | Water |
|---|---|---|---|---|---|---|---|
| **Classification** | 15.7 | 22.7 | 25.0 | 6.5 | 18.4 | 9.3 | 2.4 |
| **Sampling** | 14.2 | 23.7 | 24.7 | 8.3 | 17.8 | 8.5 | 3.0 |

- Land cover by census block groups

According to 2010 census block group metadata (*http://www.census.gov/geo/www/tiger/tgrshp2010/usernotes.html*), 2010 census block groups were identified by "GEOID10", which is a concatenation of 2010 Census state FIPS code, county FIPS code, census tract code, and block group number. The land cover classification results were calculated and reported for each of the 1,628 census block groups in the study area. These data are not shown here, but included in the digital data files submitted with this report.

**NUMBER OF EXISTING TREES**

Cities within the Metro Denver study area were estimated to contain 9.6 million trees, assuming an average tree crown diameter of 19 feet (Table 19). Cities with the largest numbers of trees were Denver (2.2 million), Aurora (1.1 million) and Lakewood (833,522). The average ratio of trees per capita was 4.8 for all cities in the study area. Cities with the highest number of trees per capita were Cherry Hills Village (37.3), Bow Mar (25.8) and Foxfield (21.8).

The average tree density for cities in the study area was 24 trees per acre. Cities with the highest tree density were Cherry Hills Village, Bow Mar, Greenwood Village, and Boulder, all with tree densities greater than 40. It should be noted that tree density reported in Table 19 is based on city area within the Metro Denver study area. Denver airport and other non-urban areas were excluded from the study area. The estimated number of existing trees, trees per capita and tree density were reported by census block group and included in the digital file submitted with this report.

**Table 19 Estimated numbers of existing trees, trees per capita, and tree density (trees per acre) by city (excludes unincorporated areas)**

| Cities | Existing Trees | Trees/Capita | Tree density (trees/ac) |
|---|---|---|---|
| Arvada | 649,066 | 6.1 | 28.7 |
| Aurora | 1,137,523 | 3.5 | 17.6 |
| Boulder | 656,486 | 6.7 | 40.7 |
| Bow Mar | 22,356 | 25.8 | 44.0 |
| Broomfield | 259,590 | 4.6 | 12.1 |
| Centennial | 672,751 | 6.7 | 36.5 |
| Cherry Hills Village | 223,022 | 37.3 | 55.5 |
| Commerce City | 152,596 | 3.3 | 7.0 |
| Denver | 2,225,124 | 3.7 | 29.2 |
| Edgewater | 14,318 | 2.8 | 32.4 |
| Englewood | 151,022 | 5.0 | 35.5 |
| Erie | 73,481 | 4.1 | 6.7 |
| Federal Heights | 23,695 | 2.1 | 20.8 |
| Foxfield | 14,939 | 21.8 | 17.9 |
| Glendale | 6,489 | 1.6 | 18.4 |
| Golden | 196,797 | 10.4 | 32.5 |
| Greenwood Village | 227,629 | 16.3 | 42.9 |
| Lafayette | 146,556 | 6.0 | 24.7 |
| Lakewood | 833,522 | 5.8 | 29.7 |
| Littleton | 316,113 | 7.6 | 36.3 |
| Louisville | 123,894 | 6.7 | 24.5 |
| Mountain View | 2,339 | 4.6 | 39.8 |
| Northglenn | 144,744 | 4.0 | 30.4 |
| Parker | 222,433 | 4.9 | 16.9 |
| Sheridan | 26,455 | 4.7 | 18.1 |
| Superior | 41,219 | 3.3 | 17.3 |
| Thornton | 388,460 | 3.3 | 16.9 |
| Westminster | 460,324 | 4.3 | 21.4 |
| Wheat Ridge | 227,921 | 7.6 | 37.3 |
| **Grand Total** | **9,640,864** | **4.8** | **24.4** |

To put Metro Denver's urban forest stocking levels in perspective they are compared with data for other US cities obtained from UTC and UFORE studies (Table 20). When results for cities and unincorporated areas in Metro Denver are added, the number of existing trees is 10.7 million, with 5.0 trees per capita and 23.2 trees per acre.

**Table 20 Comparison of results from the Denver metro area with other cities. Denver data includes unincorporated areas.**

| City | Population | Study Area (sq mi) | Tree Cover (%) | Trees | Trees/capita | Tree density (trees/ac) |
|---|---|---|---|---|---|---|
| Metro Denver, CO | 2,700,000 | 721 | 15.7 | 10,713,292 | 4.0 | 23.2 |
| Los Angeles, CA | 3,800,000 | 471 | 11.1 | 6,000,000 | 1.6 | 19.9 |
| Sacramento Metro, CA | 2,500,000 | 505 | 17.0 | 6,889,000 | 2.8 | 21.3 |
| Casper, WY | 55,316 | 21 | 8.9 | 123,000 | 2.2 | 9.1 |
| Jersey City, NJ | 248,000 | 15 | 11.5 | 136,000 | 0.6 | 14.4 |
| Chicago, IL | 2,700,000 | 231 | 17.2 | 3,585,000 | 1.3 | 24.3 |
| Minneapolis, MN | 382,000 | 58 | 26.4 | 979,000 | 2.6 | 26.2 |
| New York, NY | 19,465,000 | 308 | 20.9 | 5,212,000 | 0.3 | 26.4 |
| Philadelphia, PA | 1,526,000 | 132 | 15.7 | 2,113,000 | 1.4 | 25.1 |

Metro Denver's urban forest has a surprisingly high UTC (15.7%) and trees per capita (4.0) given its location in a semi-arid environment where trees seldom thrive without significant levels of stewardship (Table 20). The UTC and trees per capita values are nearly twice those reported for Casper, WY, the most comparable city to Denver in terms of climate (Nowak et al. 2006a). Similarly, UTC, trees per capita and tree density for Metro Denver are substantially greater than reported for Jersey City, NJ, which has a more salubrious climate for tree growth (Nowak and Crane 2002). Denver's UTC is the same as Philadelphia's, but the number of trees per capita is over three times greater (Nowak et al. 2007b). This result may reflect, in part, Metro Denver's lower population density. Average tree density for the Metro Denver urban forest (23.2) is comparable to values reported for large cities in the Northeast (New York, Philadelphia) and Midwest (Chicago and Minneapolis) (Nowak et al. 2006b, 2007a, 2010). The Metro Denver's UTC and tree density compare favorably with values for Sacramento and Los Angeles, where summer drought can limit natural regeneration (McPherson et al. submitted).

## POTENTIAL TREE PLANTING SITES

There are approximately 8 million PTPS in municipalities throughout the Metro Denver study area once the gross count is adjusted to account for physical limitations to planting (Table 21). This number increases to 10 million when PTPS in unincorporated areas are included (Table 22). About 56 percent of the vacant sites are in irrigated turf, and the rest are in bare soil/dry grass. Aurora (1.5 million) and Denver (1.1 million) have the most vacant planting sites. Potential planting sites in impervious surfaces, such as parking lots and wide sidewalks, were not included in these totals. Potential tree planting sites were reported by census block groups and can be found in the digital file submitted with this report.

**Table 21 PTPS for cities within the study area (unincorporated areas excluded)**

| Cities | Gross PTPS in Grass | Gross PTPS in BSDV | Net PTPS in Grass | Net PTPS in BSDV | Total Net PTPS |
|---|---|---|---|---|---|
| Arvada | 225,496 | 374,621 | 187,162 | 239,758 | 426,920 |
| Aurora | 843,718 | 1,270,170 | 700,286 | 812,909 | 1,513,195 |
| Boulder | 96,157 | 209,879 | 79,810 | 134,322 | 214,132 |
| Bow Mar | 9,187 | 984 | 7,626 | 630 | 8,255 |
| Broomfield | 429,825 | 437,986 | 356,755 | 280,311 | 637,065 |
| Centennial | 245,760 | 148,287 | 203,981 | 94,904 | 298,884 |
| Cherry Hills Village | 82,835 | 13,603 | 68,753 | 8,706 | 77,459 |
| Commerce City | 335,007 | 554,511 | 278,055 | 354,887 | 632,942 |
| Denver | 960,511 | 502,345 | 797,224 | 321,501 | 1,118,725 |
| Edgewater | 6,106 | 409 | 5,068 | 262 | 5,330 |
| Englewood | 41,839 | 6,942 | 34,727 | 4,443 | 39,170 |
| Erie | 179,312 | 355,977 | 148,829 | 227,825 | 376,654 |
| Federal Heights | 20,616 | 3,384 | 17,111 | 2,166 | 19,277 |
| Foxfield | 10,835 | 25,135 | 8,993 | 16,086 | 25,080 |
| Glendale | 2,094 | 204 | 1,738 | 131 | 1,869 |
| Golden | 17,383 | 134,234 | 14,428 | 85,910 | 100,338 |
| Greenwood Village | 79,730 | 23,260 | 66,176 | 14,887 | 81,062 |
| Lafayette | 93,462 | 86,873 | 77,573 | 55,598 | 133,172 |
| Lakewood | 302,492 | 373,633 | 251,069 | 239,125 | 490,194 |
| Littleton | 131,800 | 33,826 | 109,394 | 21,649 | 131,042 |
| Louisville | 104,088 | 49,977 | 86,393 | 31,986 | 118,379 |
| Mountain View | 618 | 83 | 513 | 53 | 566 |
| Northglenn | 73,257 | 21,740 | 60,803 | 13,914 | 74,717 |
| Parker | 117,611 | 369,627 | 97,617 | 236,561 | 334,178 |
| Sheridan | 23,232 | 5,924 | 19,282 | 3,791 | 23,074 |
| Superior | 41,186 | 41,460 | 34,185 | 26,534 | 60,719 |
| Thornton | 424,369 | 312,492 | 352,226 | 199,995 | 552,221 |
| Westminster | 400,090 | 195,628 | 332,075 | 125,202 | 457,276 |
| Wheat Ridge | 85,077 | 22,753 | 70,614 | 14,562 | 85,176 |
| **Grand Total** | **5,383,694** | **5,575,946** | **4,468,466** | **3,568,606** | **8,037,072** |

The numbers of existing trees and potential tree planting sties for cities and unincorporated lands were summarized by land use types (Table 22). Single family residential land uses had the highest capacity for planting with 3.2 million PTPS. Although agricultural land had space for 1.4 million PTPS, in reality many of these may not be plantable unless land development occurs.

**Table 22 Existing trees and potential tree planting sites by land use (unincorporated lands included)**

| Land Use | Existing Trees | Tree density (trees/ac) | Gross PTPS in Grass | Gross PTPS in BSDV | Net PTPS in Grass | Net PTPS in BSDV | Total Net PTPS |
|---|---|---|---|---|---|---|---|
| Agri | 363,388 | 9.4 | 813,750 | 1,171,284 | 675,413 | 749,622 | 1,425,034 |
| Comm | 305,082 | 12.5 | 235,702 | 306,043 | 195,633 | 195,868 | 391,500 |
| Ind | 256,091 | 8.3 | 295,448 | 442,778 | 245,222 | 283,378 | 528,600 |
| Mixed | 1,537,108 | 14.5 | 1,546,813 | 1,933,350 | 1,283,855 | 1,237,344 | 2,521,199 |
| MultiFam | 377,617 | 28.8 | 147,719 | 74,904 | 122,607 | 47,939 | 170,545 |
| OpenSpace | 197,618 | 11.1 | 310,225 | 437,838 | 257,487 | 280,216 | 537,703 |
| PQP | 732,637 | 15.5 | 756,841 | 1,030,498 | 628,178 | 659,519 | 1,287,697 |
| SingleFam | 6,928,076 | 37.8 | 2,421,372 | 1,786,516 | 2,009,739 | 1,143,370 | 3,153,109 |
| **Grand Total** | **10,697,617** | **23.2** | **6,527,870** | **7,183,211** | **5,418,132** | **4,597,255** | **10,015,387** |

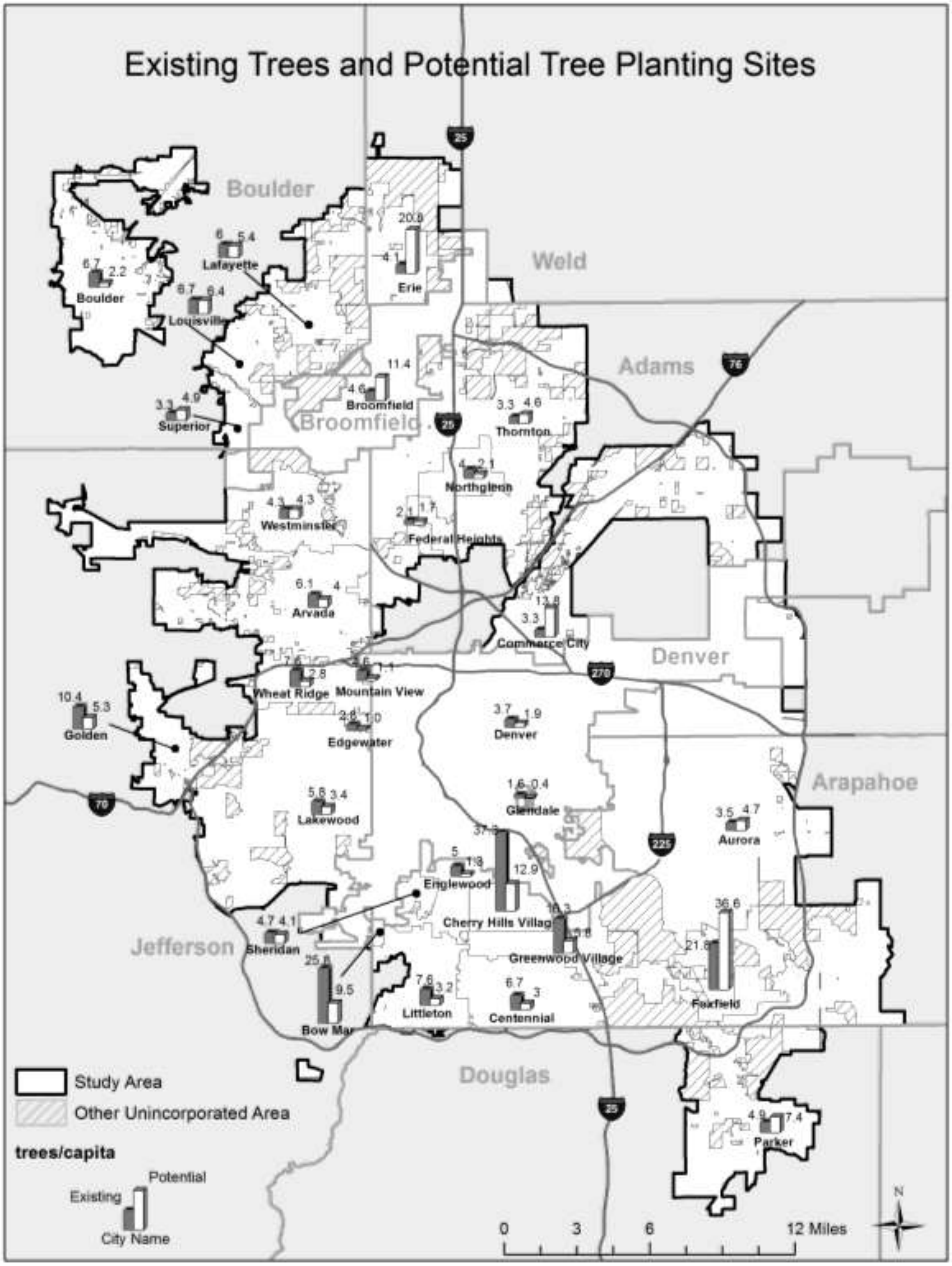



**Figure 13 Existing trees and PTPS (trees/capita) for each city**

- <u>PTPS by hot spots by city/county</u>

Hot spots were further analyzed for land cover composition and potential tree planting capacity. According to the urban heat island analysis, approximately 21 percent of the study area consists of hot spots (95,620 ac) (Table 23 ). The top three cities with the highest percentage of hot spots are Glendale (55.2%), Erie (49.5%), and Broomfield (40.3%). More than half of the city of Glendale was identified as a hot spot area. Also, more than half of the unincorporated areas in Broomfield County and Weld County were identified as hot spots.

Not surprisingly, the dominant land covers in hot spot areas are Bare Soil/Dry Vegetation and impervious surfaces (i.e., Road, Building and Other Impervious); these land cover classes account for approximately 80% of the hot spot area. As expected, tree canopy cover rates are low within the hot spot areas. Urban tree canopy ranges from 0.6% to 11.9% with an average UTC percentage of 4.5%. After excluding PTPS in Agricultural land and assuming a UTC target of 50 percent net PTPS, there are approximately 763,859 potential planting sites (Table 23).

**Table 23 Hot spots and PTPS by city/county**

| | Total Area | Hot Spots Area | | Hot spots land cover composition | | | Net PTPS | | | | Additional PTPS | | | | Future UTC |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | UTC | Grass | IMP & BSDV | Grass | BSDV | Total | PTPs per ac | Grass | BSDV | Net PTPS | PTPs per ac | |
| | ac | ac | % | % | % | % | ------- Number ------- | | | #/ac | ------- Number ------- | | | #/ac | % |
| **Cities** | **395,606** | **79,920** | **20.2** | **4.9** | **12.8** | **82.3** | **524,018** | **986,090** | **1,510,108** | **18.9** | **242,083** | **448,588** | **690,671** | **8.6** | **19.0** |
| Arvada | 22,606 | 3,785.8 | 16.7 | 4.2 | 6.0 | 89.8 | 11,636 | 60,955 | 72,591 | 19.2 | 5,674 | 30,113 | 35,787 | 9.5 | 19.6 |
| Aurora | 64,518 | 8,935.6 | 13.8 | 5.1 | 10.7 | 84.2 | 48,977 | 96,688 | 145,665 | 16.3 | 24,348 | 47,969 | 72,317 | 8.1 | 18.2 |
| Boulder | 16,149 | 2,895.7 | 17.9 | 9.3 | 4.7 | 86.0 | 7,024 | 39,067 | 46,091 | 15.9 | 2,899 | 15,766 | 18,665 | 6.4 | 19.7 |
| Bow Mar | 508 | 8.6 | 1.7 | 11.2 | 16.3 | 72.4 | 72 | 14 | 86 | 10.0 | 36 | 7 | 43 | 5.0 | 19.3 |
| Broomfield | 21,455 | 8,646.4 | 40.3 | 2.4 | 22.2 | 75.4 | 98,308 | 182,279 | 280,587 | 32.5 | 38,905 | 71,054 | 109,959 | 12.7 | 23.0 |
| Centennial | 18,423 | 1,474.1 | 8.0 | 5.5 | 8.4 | 86.0 | 6,361 | 8,035 | 14,396 | 9.8 | 3,152 | 3,957 | 7,109 | 4.8 | 13.4 |
| Cherry Hills Village | 4,020 | 125.5 | 3.1 | 11.9 | 25.8 | 62.3 | 1,657 | 1,132 | 2,789 | 22.2 | 828 | 566 | 1,394 | 11.1 | 29.9 |
| Commerce City | 21,806 | 5,947.1 | 27.3 | 2.6 | 14.4 | 82.9 | 43,915 | 95,456 | 139,371 | 23.4 | 19,264 | 42,955 | 62,219 | 10.5 | 19.6 |
| Denver | 76,503 | 16,617.2 | 21.7 | 6.5 | 8.8 | 84.7 | 74,474 | 66,106 | 140,580 | 8.5 | 36,615 | 31,701 | 68,316 | 4.1 | 13.2 |
| Edgewater | 442 | 57.4 | 13.0 | 6.9 | 8.1 | 85.0 | 237 | 11 | 248 | 4.3 | 119 | 6 | 125 | 2.2 | 10.5 |
| Englewood | 4,249 | 921.6 | 21.7 | 6.3 | 6.8 | 86.9 | 3,183 | 1,220 | 4,403 | 4.8 | 1,592 | 610 | 2,202 | 2.4 | 10.2 |
| Erie | 11,017 | 5,454.1 | 49.5 | 1.1 | 17.9 | 81.0 | 49,948 | 146,222 | 196,170 | 36.0 | 24,520 | 70,685 | 95,205 | 17.5 | 29.4 |
| Federal Heights | 1,142 | 344.7 | 30.2 | 8.6 | 17.7 | 73.7 | 3,118 | 622 | 3,740 | 10.8 | 1,559 | 311 | 1,870 | 5.4 | 17.4 |
| Fox field | 833 | 17.7 | 2.1 | 2.0 | 7.6 | 90.3 | 69 | 249 | 318 | 18.0 | 34 | 124 | 158 | 8.9 | 16.5 |
| Glendale | 352 | 194.4 | 55.2 | 7.2 | 4.8 | 88.0 | 476 | 43 | 519 | 2.7 | 238 | 21 | 259 | 1.3 | 9.3 |
| Golden | 6,054 | 1,543.3 | 25.5 | 10.5 | 1.3 | 88.2 | 1,016 | 24,305 | 25,321 | 16.4 | 483 | 11,871 | 12,354 | 8.0 | 23.5 |
| Green wood Village | 5,309 | 563.5 | 10.6 | 6.4 | 11.8 | 81.8 | 3,394 | 2,945 | 6,339 | 11.3 | 1,671 | 1,472 | 3,143 | 5.6 | 15.5 |
| Lafayette | 5,944 | 1,547.2 | 26.0 | 3.6 | 17.1 | 79.3 | 13,502 | 28,092 | 41,594 | 26.9 | 4,051 | 7,028 | 11,079 | 7.2 | 15.2 |
| Lakewood | 28,079 | 5,299.7 | 18.9 | 5.5 | 7.0 | 87.5 | 19,078 | 71,308 | 90,386 | 17.1 | 9,413 | 35,574 | 44,987 | 8.5 | 19.3 |
| Littleton | 8,708 | 1,268.1 | 14.6 | 8.5 | 14.6 | 77.0 | 9,466 | 4,961 | 14,427 | 11.4 | 4,733 | 2,458 | 7,191 | 5.7 | 17.7 |
| Louisville | 5,049 | 1,104.3 | 21.9 | 3.2 | 24.5 | 72.3 | 13,838 | 16,103 | 29,941 | 27.1 | 6,884 | 8,033 | 14,917 | 13.5 | 25.2 |
| Mountain View | 59 | 8.2 | 13.9 | 5.8 | 5.1 | 89.1 | 21 | 8 | 29 | 3.5 | 11 | 4 | 15 | 1.8 | 8.8 |
| Northglenn | 4,754 | 737.0 | 15.5 | 7.7 | 13.9 | 78.4 | 5,240 | 3,310 | 8,550 | 11.6 | 1,824 | 601 | 2,425 | 3.3 | 13.1 |
| Parker | 13,160 | 1,293.3 | 9.8 | 4.1 | 7.0 | 88.8 | 4,658 | 16,522 | 21,180 | 16.4 | 2,270 | 7,876 | 10,146 | 7.8 | 16.8 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sheridan | 1,461 | 495.7 | 33.9 | 5.2 | 11.6 | 83.2 | 2,928 | 1,499 | 4,427 | 8.9 | 1,464 | 749 | 2,213 | 4.5 | 12.4 |
| Superior | 2,386 | 778.6 | 32.6 | 2.7 | 16.9 | 80.3 | 6,746 | 15,941 | 22,687 | 29.1 | 3,223 | 7,515 | 10,738 | 13.8 | 25.1 |
| Thornton | 22,968 | 5,224.3 | 22.7 | 5.3 | 19.8 | 74.9 | 52,878 | 59,624 | 112,502 | 21.5 | 25,402 | 27,943 | 53,345 | 10.2 | 21.9 |
| Westminster | 21,534 | 3,788.9 | 17.6 | 4.6 | 19.6 | 75.7 | 38,071 | 39,038 | 77,109 | 20.4 | 19,024 | 19,515 | 38,539 | 10.2 | 21.1 |
| Wheat Ridge | 6,118 | 842.6 | 13.8 | 5.9 | 8.6 | 85.4 | 3,727 | 4,335 | 8,062 | 9.6 | 1,847 | 2,104 | 3,951 | 4.7 | 13.5 |
| **Other unincorporated area** | **65,829** | **15,699.1** | **23.8** | **2.5** | **18.3** | **79.2** | **146,954** | **357,056** | **504,010** | **32.1** | **24,691** | **48,497** | **73,188** | **4.7** | **10.1** |
| Adams County | 14,081 | 3,200.8 | 22.7 | 3.5 | 27.0 | 69.5 | 44,241 | 55,026 | 99,267 | 31.0 | 13,150 | 11,422 | 24,572 | 7.7 | 16.0 |
| Arapahoe County | 18,745 | 2,094.2 | 11.2 | 3.7 | 9.9 | 86.4 | 10,560 | 23,618 | 34,178 | 16.3 | 3,971 | 7,915 | 11,886 | 5.7 | 12.9 |
| Boulder County | 11,165 | 4,499.8 | 40.3 | 1.4 | 18.1 | 80.5 | 41,646 | 130,103 | 171,749 | 38.2 | 2,164 | 6,249 | 8,413 | 1.9 | 4.5 |
| Broomfield County | 180 | 104.7 | 58.1 | 0.6 | 19.2 | 80.2 | 1,026 | 2,914 | 3,940 | 37.6 | 113 | 261 | 374 | 3.6 | 6.4 |
| Douglas County | 4,546 | 268.1 | 5.9 | 4.4 | 14.8 | 80.8 | 2,028 | 3,985 | 6,013 | 22.4 | 404 | 1,516 | 1,920 | 7.2 | 16.1 |
| Jefferson County | 11,536 | 2,393.6 | 20.7 | 3.6 | 8.3 | 88.1 | 10,192 | 54,383 | 64,575 | 27.0 | 3,194 | 18,814 | 22,008 | 9.2 | 18.5 |
| Weld County | 5,575 | 3,137.8 | 56.3 | 1.4 | 23.2 | 75.4 | 37,261 | 87,027 | 124,288 | 39.6 | 1,695 | 2,320 | 4,015 | 1.3 | 3.5 |
| **Grand Total** | **461,434** | **95,620** | **20.7** | **4.5** | **13.7** | **81.7** | **670,972** | **1,343,146** | **2,014,118** | **21.1** | **266,774** | **497,085** | **763,859** | **8.0** | **17.5** |

## URBAN TREE CANOPY TARGET

By filling 50% of net PTPS that are not in Agricultural land, a 15% UTC increase can be achieved, thereby increasing future UTC to 31% (Table 24 and Table 25). This 15% UTC increase corresponds to planting an additional 4.25 million tree sites.

Cities with the greatest UTC percentage gains are Erie (26.5%), Foxfield (24.2%), and Commerce City (21.2%). Although the additional UTC increase for Cherry Hills Village is not the highest, its future UTC will be above 50% due to its high percentage of existing UTC (37.4%). Other cities with target UTC levels that exceed 40 percent are Bow Mar (42.7%) and Greenwood Village (41.0%).

Figure 14 shows existing, additional and target TCC for each city in percentages. Figure 15 shows the number of existing and additional trees for each city.

**Table 24 Summary of UTC and tree number estimates for entire study area**

| | Existing | Potential | Tech Potential | Additional | Target |
|---|---|---|---|---|---|
| Urban Tree Canopy (%) | 15.7 | 34.9 | 50.5 | 15.0 | 30.7 |
| Tree Numbers | 10,697,617 | 10,015,387 | 20,713,005 | 4,251,403 | 14,949,021 |

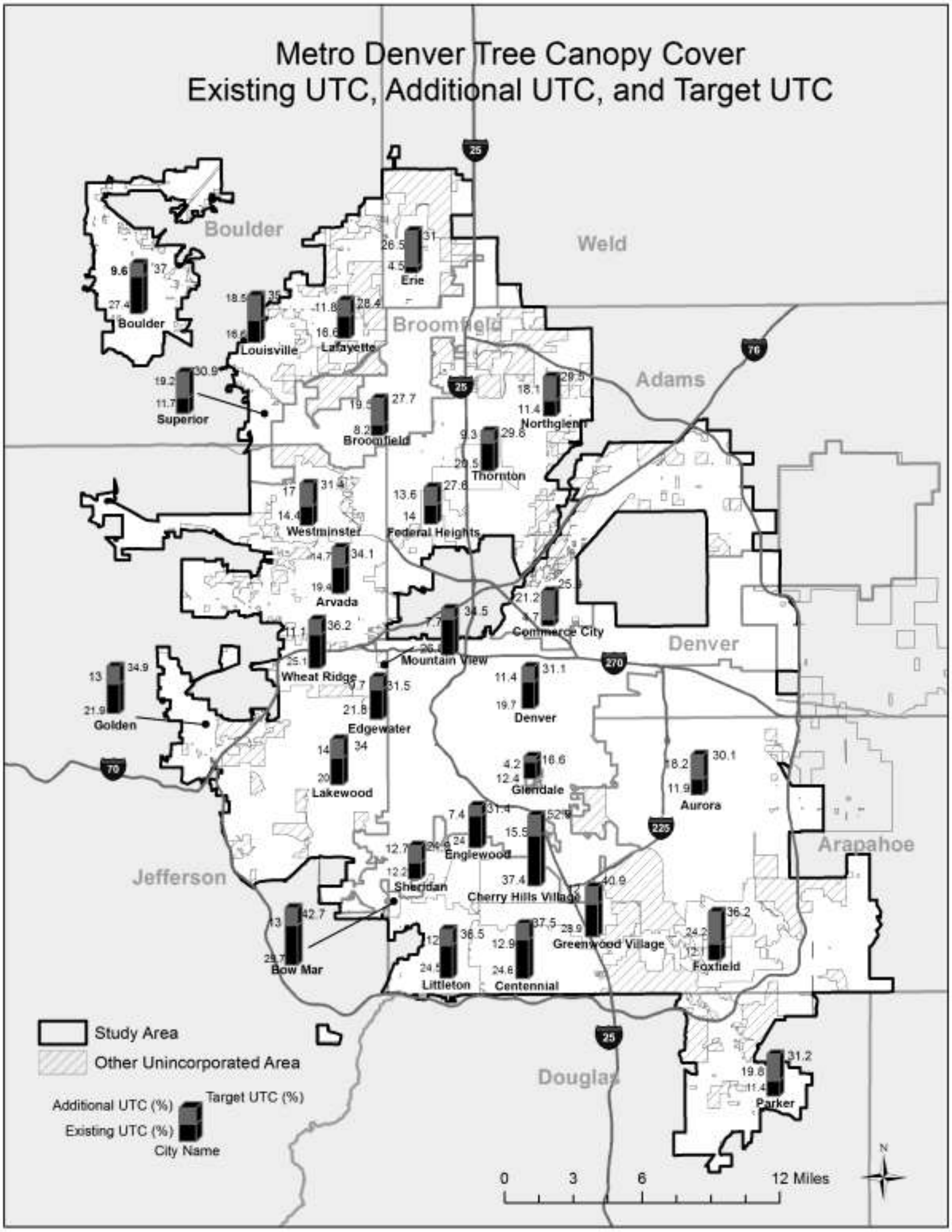



Figure 14 Existing, Additional, and Target UTC by City

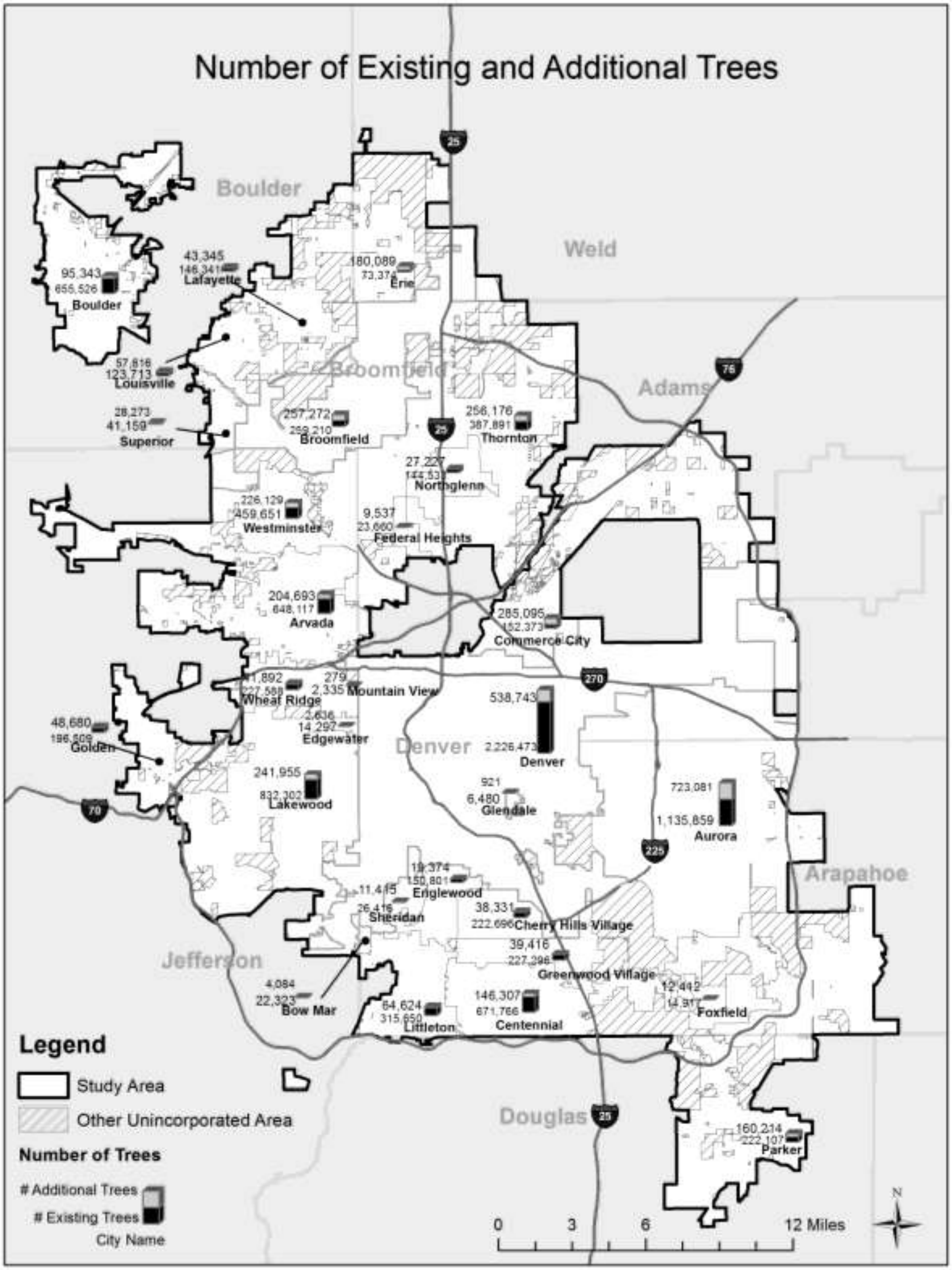



**Figure 15 Approximate number of existing and additional trees**

**Table 25 Existing, potential, additional and target tree canopy cover (UTC) by city/county ("Number" refers to tree sites)**

| Name | Area | Existing UTC | | | Net Potential Trees | | | Potential UTC | | Additional UTC* | | | Target UTC | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Irrigated Grass | BS/DV | Total | | | | | | | |
| | acres | acres | % | Number | -------------- | Number | ------------ | acres | % | acres | Number | % | Number | % |
| **Cities** | **395,606** | **65,068** | **16.4** | **9,631,364** | **4,469,950** | **3,569,184** | **8,039,134** | **129,123.2** | **32.6** | **61,097.9** | **3,765,156** | **15.4** | **13,396,520** | **31.9** |
| Arvada | 22,606 | 4,379 | 19.4 | 648,117 | 187,130 | 239,733 | 426,863 | 6,856.2 | 30.3 | 3,321.6 | 204,693 | 14.7 | 852,810 | 34.1 |
| Aurora | 64,518 | 7,674 | 11.9 | 1,135,859 | 700,191 | 812,840 | 1,513,032 | 24,302.0 | 37.7 | 11,733.6 | 723,081 | 18.2 | 1,858,940 | 30.1 |
| Boulder | 16,149 | 4,429 | 27.4 | 655,526 | 79,788 | 134,301 | 214,089 | 3,438.7 | 21.3 | 1,547.2 | 95,343 | 9.6 | 750,869 | 37.0 |
| Bow Mar | 508 | 151 | 29.7 | 22,323 | 7,623 | 628 | 8,251 | 132.5 | 26.1 | 66.3 | 4,084 | 13.0 | 26,406 | 42.7 |
| Broomfield | 21,455 | 1,751 | 8.2 | 259,210 | 356,711 | 280,280 | 636,991 | 10,231.2 | 47.7 | 4,174.8 | 257,272 | 19.5 | 516,482 | 27.6 |
| Centennial | 18,423 | 4,538 | 24.6 | 671,766 | 203,945 | 94,879 | 298,824 | 4,799.7 | 26.1 | 2,374.2 | 146,307 | 12.9 | 818,074 | 37.5 |
| Cherry Hills Village | 4,020 | 1,505 | 37.4 | 222,696 | 68,747 | 8,703 | 77,451 | 1,244.0 | 30.9 | 622.0 | 38,331 | 15.5 | 261,027 | 52.9 |
| Commerce City | 21,806 | 1,029 | 4.7 | 152,373 | 278,018 | 354,858 | 632,877 | 10,165.2 | 46.6 | 4,626.3 | 285,095 | 21.2 | 437,468 | 25.9 |
| Denver | 76,503 | 15,042 | 19.7 | 2,226,473 | 799,315 | 322,523 | 1,121,838 | 18,018.8 | 23.6 | 8,742.3 | 538,743 | 11.4 | 2,765,217 | 31.1 |
| Edgewater | 442 | 97 | 21.8 | 14,297 | 5,066 | 260 | 5,327 | 85.6 | 19.3 | 42.8 | 2,636 | 9.7 | 16,933 | 31.5 |
| Englewood | 4,249 | 1,019 | 24.0 | 150,801 | 34,713 | 4,433 | 39,146 | 628.8 | 14.8 | 314.4 | 19,374 | 7.4 | 170,174 | 31.4 |
| Erie | 11,017 | 496 | 4.5 | 73,374 | 148,801 | 227,805 | 376,606 | 6,049.0 | 54.9 | 2,922.3 | 180,089 | 26.5 | 253,463 | 31.0 |
| Federal Heights | 1,142 | 160 | 14.0 | 23,660 | 17,106 | 2,163 | 19,270 | 309.5 | 27.1 | 154.8 | 9,537 | 13.6 | 33,197 | 27.6 |
| Foxfield | 833 | 101 | 12.1 | 14,917 | 8,993 | 16,086 | 25,079 | 402.8 | 48.4 | 201.4 | 12,412 | 24.2 | 27,329 | 36.3 |
| Glendale | 352 | 44 | 12.4 | 6,480 | 1,731 | 129 | 1,861 | 29.9 | 8.5 | 14.9 | 921 | 4.2 | 7,400 | 16.7 |
| Golden | 6,054 | 1,328 | 21.9 | 196,509 | 14,415 | 85,899 | 100,314 | 1,611.2 | 26.6 | 789.9 | 48,680 | 13.0 | 245,189 | 35.0 |
| Greenwood Village | 5,309 | 1,536 | 28.9 | 227,296 | 66,156 | 14,874 | 81,030 | 1,301.5 | 24.5 | 639.6 | 39,416 | 12.0 | 266,712 | 41.0 |
| Lafayette | 5,944 | 989 | 16.6 | 146,341 | 77,554 | 55,583 | 133,137 | 2,138.4 | 36.0 | 703.4 | 43,345 | 11.8 | 189,686 | 28.5 |
| Lakewood | 28,079 | 5,623 | 20.0 | 832,302 | 251,024 | 239,094 | 490,117 | 7,872.2 | 28.0 | 3,926.2 | 241,955 | 14.0 | 1,074,257 | 34.0 |
| Littleton | 8,708 | 2,132 | 24.5 | 315,650 | 109,370 | 21,635 | 131,004 | 2,104.2 | 24.2 | 1,048.7 | 64,624 | 12.0 | 380,274 | 36.5 |
| Louisville | 5,049 | 836 | 16.6 | 123,713 | 86,388 | 31,981 | 118,369 | 1,901.2 | 37.7 | 934.9 | 57,616 | 18.5 | 181,329 | 35.1 |
| Mountain View | 59 | 16 | 26.8 | 2,335 | 511 | 52 | 564 | 9.1 | 15.4 | 4.5 | 279 | 7.7 | 2,614 | 34.5 |
| Northglenn | 4,754 | 976 | 20.5 | 144,533 | 60,792 | 13,905 | 74,697 | 1,199.8 | 25.2 | 441.8 | 27,227 | 9.3 | 171,759 | 29.8 |
| Parker | 13,160 | 1,501 | 11.4 | 222,107 | 97,591 | 236,541 | 334,132 | 5,366.8 | 40.8 | 2,599.8 | 160,214 | 19.8 | 382,321 | 31.2 |
| Sheridan | 1,461 | 178 | 12.2 | 26,416 | 19,278 | 3,787 | 23,064 | 370.5 | 25.4 | 185.2 | 11,415 | 12.7 | 37,831 | 24.9 |
| Superior | 2,386 | 278 | 11.7 | 41,159 | 34,177 | 26,529 | 60,706 | 975.0 | 40.9 | 458.8 | 28,273 | 19.2 | 69,432 | 30.9 |
| Thornton | 22,968 | 2,621 | 11.4 | 387,891 | 352,184 | 199,958 | 552,142 | 8,868.4 | 38.6 | 4,157.0 | 256,176 | 18.1 | 644,067 | 29.5 |

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Westminster | 21,534 | 3,105 | 14.4 | 459,651 | 332,031 | 125,171 | 457,201 | 7,343.5 | 34.1 | 3,669.4 | 226,129 | 17.0 | 685,780 | 31.5 |
| Wheat Ridge | 6,118 | 1,538 | 25.1 | 227,588 | 70,601 | 14,552 | 85,153 | 1,367.7 | 22.4 | 679.8 | 41,892 | 11.1 | 269,480 | 36.2 |
| **Other unincorporated Area in Counties** | **65,829** | **7,203** | **10.9** | **1,066,254** | **948,182** | **1,028,071** | **1,976,253** | **31,742.2** | **48.2** | **7,890.4** | **486,247** | **12.0** | **1,552,501** | **22.9** |
| Adams County | 14,081 | 1,150 | 8.2 | 170,289 | 274,154 | 198,908 | 473,062 | 7,598.2 | 54.0 | 2,054.1 | 126,587 | 14.6 | 296,875 | 22.8 |
| Arapahoe County | 18,745 | 2,243 | 12.0 | 331,963 | 220,021 | 242,146 | 462,166 | 7,423.2 | 39.6 | 3,094.9 | 190,723 | 16.5 | 522,686 | 28.5 |
| Boulder County | 11,165 | 1,043 | 9.3 | 154,330 | 190,711 | 210,730 | 401,441 | 6,447.9 | 57.7 | 494.5 | 30,470 | 4.4 | 184,800 | 13.8 |
| Broomfield County | 180 | 4 | 2.0 | 546 | 2,859 | 4,081 | 6,939 | 111.5 | 61.9 | 10.7 | 660 | 5.9 | 1,206 | 8.0 |
| Douglas County | 4,546 | 733 | 16.1 | 108,485 | 39,686 | 76,305 | 115,990 | 1,863.0 | 41.0 | 715.7 | 44,106 | 15.7 | 152,590 | 31.9 |
| Jefferson County | 11,536 | 1,813 | 15.7 | 268,430 | 129,609 | 167,116 | 296,725 | 4,765.9 | 41.3 | 1,294.1 | 79,749 | 11.2 | 348,179 | 26.9 |
| Weld County | 5,575 | 218 | 3.9 | 32,212 | 91,144 | 128,785 | 219,929 | 3,532.5 | 63.4 | 226.4 | 13,953 | 4.1 | 46,164 | 8.0 |
| **Grand Total** | **461,434** | **72,272** | **15.7** | **10,697,617** | **5,418,132** | **4,597,255** | **10,015,387** | **160,865.4** | **34.9** | **68,988.4** | **4,251,403** | **15.0** | **14,949,021** | **30.6** |

* Additional Urban Tree Cover (UTC) is 50% of potential UTC and excludes potential UTC in Agricultural land.

**BENEFITS**

- <u>Benefits of Existing UTC</u>

The annual value of ecosystem services provided by existing UTC is $551 million (Table 26, Figure 16). UTC was estimated to increase property values and provide other intangible benefits valued at $436.5 million annually. Rainfall interception and cooling energy savings accounted for $90.9 million and $21.8 million, respectively. The total annual value of ecosystem services provided by UTC in the City of Denver alone is $122 million.  These are very conservative estimates of service value because they do not fully capture all benefits associated with increased UTC, such as job creation, improved human health and fitness, wildlife habitat and biodiversity.

**Table 26 Existing UTC benefits by city/county**

| Name | UTC | Energy saved (Cooling) | | CO2 storage | CO2 Seq (per year) | | Cooling CO2 avoid | | Total CO2 | | Air Quality (pollutant removed per year) | | Rain fall Interception | | Property values | Total Benefit |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | % | MWhs | $ | ton | ton | $ | Ton | $ | ton | $ | lb | $ | 1000 gals | M$ | M$ | M$ |
| **Cities** | **16.4** | **171,711** | **20,605,339** | **1,374.4** | **60.1** | **601.3** | **162,868** | **1,628,680** | **162,928** | **1,629,282** | **1,257** | **6,721** | **6,201,636** | **81.9** | **402.61** | **506.8** |
| Arvada | 19.4 | 10,269 | 1,232,244 | 92.1 | 4.1 | 40.9 | 9,740 | 97,399 | 9,744 | 97,440 | 84.6 | 452 | 417,322 | 5.51 | 28.80 | 35.6 |
| Aurora | 11.9 | 21,611 | 2,593,305 | 164.6 | 7.2 | 71.7 | 20,498 | 204,979 | 20,505 | 205,051 | 148.2 | 793 | 731,380 | 9.66 | 49.92 | 62.4 |
| Boulder | 27.4 | 12,472 | 1,496,692 | 92.9 | 4.1 | 40.5 | 11,830 | 118,301 | 11,834 | 118,342 | 85.6 | 457 | 422,093 | 5.58 | 25.95 | 33.1 |
| Bow Mar | 29.7 | 297 | 35,617 | 3.0 | 0.1 | 1.4 | 282 | 2,815 | 282 | 2,817 | 2.9 | 16 | 14,374 | 0.19 | 1.08 | 1.3 |
| Broomfield | 8.2 | 3,391 | 406,966 | 38.3 | 1.6 | 16.0 | 3,217 | 32,167 | 3,218 | 32,183 | 33.8 | 181 | 166,905 | 2.20 | 10.69 | 13.3 |
| Centennial | 24.6 | 11,543 | 1,385,188 | 95.7 | 4.2 | 41.5 | 10,949 | 109,488 | 10,953 | 109,529 | 87.7 | 469 | 432,551 | 5.71 | 28.45 | 35.7 |
| Cherry Hills Village | 37.4 | 1,035 | 124,184 | 30.4 | 1.4 | 13.9 | 982 | 9,816 | 983 | 9,830 | 29.1 | 155 | 143,394 | 1.89 | 10.21 | 12.2 |
| Commerce City | 4.7 | 1,487 | 178,430 | 23.6 | 0.9 | 9.3 | 1,410 | 14,103 | 1,411 | 14,113 | 19.9 | 106 | 98,113 | 1.30 | 5.37 | 6.9 |
| Denver | 19.7 | 56,471 | 6,776,570 | 310.6 | 14.0 | 140.2 | 53,563 | 535,631 | 53,577 | 535,772 | 290.6 | 1,554 | 1,433,626 | 18.94 | 95.73 | 122.0 |
| Edgewater | 21.8 | 470 | 56,419 | 1.9 | 0.1 | 0.9 | 446 | 4,459 | 446 | 4,460 | 1.9 | 10 | 9,206 | 0.12 | 0.69 | 0.9 |
| Englewood | 24.0 | 3,339 | 400,661 | 21.1 | 0.9 | 9.4 | 3,167 | 31,669 | 3,168 | 31,678 | 19.7 | 105 | 97,101 | 1.28 | 6.50 | 8.2 |
| Erie | 4.5 | 530 | 63,565 | 10.3 | 0.4 | 4.5 | 502 | 5,024 | 503 | 5,029 | 9.6 | 51 | 47,245 | 0.62 | 2.91 | 3.6 |
| Federal Heights | 14.0 | 161 | 19,295 | 3.3 | 0.1 | 1.4 | 153 | 1,525 | 153 | 1,527 | 3.1 | 17 | 15,235 | 0.20 | 0.94 | 1.2 |
| Foxfield | 12.1 | 39 | 4,682 | 2.1 | 0.1 | 0.8 | 37 | 370 | 37 | 371 | 1.9 | 10 | 9,605 | 0.13 | 0.14 | 0.3 |
| Glendale | 12.4 | 23 | 2,709 | 1.1 | 0.1 | 0.6 | 21 | 214 | 21 | 215 | 0.8 | 5 | 4,172 | 0.06 | 0.13 | 0.2 |
| Golden | 21.9 | 2,136 | 256,282 | 28.3 | 1.3 | 13.0 | 2,026 | 20,257 | 2,027 | 20,270 | 25.6 | 137 | 126,532 | 1.67 | 8.14 | 10.1 |
| Greenwood Village | 28.9 | 1,524 | 182,889 | 32.4 | 1.4 | 14.0 | 1,446 | 14,456 | 1,447 | 14,470 | 29.7 | 159 | 146,356 | 1.93 | 9.35 | 11.5 |
| Lafayette | 16.6 | 1,744 | 209,291 | 21.1 | 0.9 | 9.0 | 1,654 | 16,543 | 1,655 | 16,552 | 19.1 | 102 | 94,229 | 1.24 | 5.92 | 7.4 |
| Lakewood | 20.0 | 11,856 | 1,422,712 | 115.5 | 5.1 | 51.3 | 11,245 | 112,454 | 11,250 | 112,505 | 108.6 | 581 | 535,919 | 7.08 | 32.94 | 41.6 |
| Littleton | 24.5 | 4,854 | 582,490 | 45.4 | 2.0 | 20.3 | 4,604 | 46,041 | 4,606 | 46,061 | 41.2 | 220 | 203,247 | 2.68 | 13.44 | 16.8 |

| | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Louisville | 16.6 | 1,759 | 211,054 | 17.0 | 0.7 | 7.5 | 1,668 | 16,682 | 1,669 | 16,689 | 16.1 | 86 | 79,659 | 1.05 | 5.17 | 6.4 |
| Mountain View | 26.8 | 107 | 12,858 | 0.3 | 0.0 | 0.1 | 102 | 1,016 | 102 | 1,016 | 0.3 | 2 | 1,504 | 0.02 | 0.09 | 0.1 |
| Northglenn | 20.5 | 2,964 | 355,650 | 21.5 | 0.9 | 9.0 | 2,811 | 28,111 | 2,812 | 28,120 | 18.9 | 101 | 93,065 | 1.23 | 6.24 | 7.9 |
| Parker | 11.4 | 2,897 | 347,692 | 37.5 | 1.3 | 13.3 | 2,748 | 27,482 | 2,750 | 27,495 | 29.0 | 155 | 143,015 | 1.89 | 7.06 | 9.3 |
| Sheridan | 12.2 | 321 | 38,482 | 3.9 | 0.2 | 1.7 | 304 | 3,042 | 304 | 3,043 | 3.4 | 18 | 17,009 | 0.22 | 0.84 | 1.1 |
| Superior | 11.7 | 508 | 60,950 | 5.8 | 0.2 | 2.5 | 482 | 4,818 | 482 | 4,820 | 5.4 | 29 | 26,502 | 0.35 | 1.69 | 2.1 |
| Thornton | 11.4 | 6,635 | 796,240 | 55.8 | 2.4 | 24.1 | 6,294 | 62,936 | 6,296 | 62,960 | 50.6 | 271 | 249,763 | 3.30 | 15.51 | 19.7 |
| Westminster | 14.4 | 7,538 | 904,616 | 66.6 | 2.8 | 27.8 | 7,150 | 71,502 | 7,153 | 71,530 | 60.0 | 321 | 295,969 | 3.91 | 18.50 | 23.4 |
| Wheat Ridge | 25.1 | 3,730 | 447,607 | 32.2 | 1.5 | 14.7 | 3,538 | 35,380 | 3,539 | 35,394 | 29.7 | 159 | 146,544 | 1.94 | 10.20 | 12.6 |
| **Other Unincorporated areas** | **10.9** | **9,844** | **1,181,338** | **181.7** | **6.3** | **62.6** | **9,337** | **93,375** | **9,344** | **93,438** | **139.2** | **744** | **686,561** | **9.07** | **33.86** | **44.2** |
| Adams County | 8.2 | 1,209 | 145,045 | 28.1 | 1.0 | 10.2 | 1,146 | 11,465 | 1,147 | 11,475 | 22.2 | 119 | 109,649 | 1.45 | 6.13 | 7.7 |
| Arapahoe County | 12.0 | 4,153 | 498,321 | 50.0 | 2.0 | 19.7 | 3,939 | 39,388 | 3,941 | 39,408 | 43.3 | 232 | 213,751 | 2.82 | 10.75 | 14.1 |
| Boulder County | 9.3 | 1,278 | 153,316 | 29.5 | 0.9 | 8.8 | 1,212 | 12,118 | 1,213 | 12,127 | 20.1 | 108 | 99,373 | 1.31 | 4.05 | 5.5 |
| Broomfield County | 2.0 | 0 | 0 | 0.1 | 0.0 | 0.0 | - | - | 0 | 0 | 0.1 | 0 | 352 | 0.00 | 0.01 | 0.0 |
| Douglas County | 16.1 | 1,088 | 130,591 | 16.8 | 0.7 | 6.5 | 1,032 | 10,322 | 1,033 | 10,329 | 14.2 | 76 | 69,853 | 0.92 | 4.31 | 5.4 |
| Jefferson County | 15.7 | 2,085 | 250,191 | 49.7 | 1.6 | 15.7 | 1,978 | 19,776 | 1,979 | 19,791 | 35.0 | 187 | 172,842 | 2.28 | 8.11 | 10.7 |
| Weld County | 3.9 | 32 | 3,874 | 7.5 | 0.2 | 1.7 | 31 | 306 | 31 | 308 | 4.2 | 22 | 20,741 | 0.27 | 0.50 | 0.8 |
| **Grand Total** | **15.7** | **181,556** | **21,786,677** | **1,556** | **66.4** | **663.9** | **172,206** | **1,722,055** | **172,272** | **1,722,719** | **1,396** | **7,465** | **6,888,197** | **90.98** | **436.5** | **551.0** |

- <u>Benefits of Additional UTC</u>

Increasing UTC by an additional 15% through planting approximately 4.25 million tree sites (assuming 30-ft mature crown diameter) is projected to increase the annual value of ecosystem services by $449.7 million (Table 27). This assumes that current UTC remains stable and program tree sites remain fully stocked with 30-ft crown diameter trees. Because some program trees will die and need to be replaced, more than 4.25 million trees will need to be planted to keep this number of additional sites fully stocked. It will take 20 to 30 years to achieve the projected level of canopy cover after planting (Table 27).

The approximate annual value of ecosystem services provided per tree is $52 for existing trees and $106 for additional trees (Table 28). The difference can be explained by assumed differences in average tree size: existing trees were assumed to have an average crown diameter of 19 ft (based on Golden study), while additional trees were assumed to have a 30-ft crown diameter. This conclusion was confirmed by calculating values on a per unit UTC basis ($/ac). Values were similar: $7,624 per acre UTC for existing UTC and $6,519 for additional UTC.

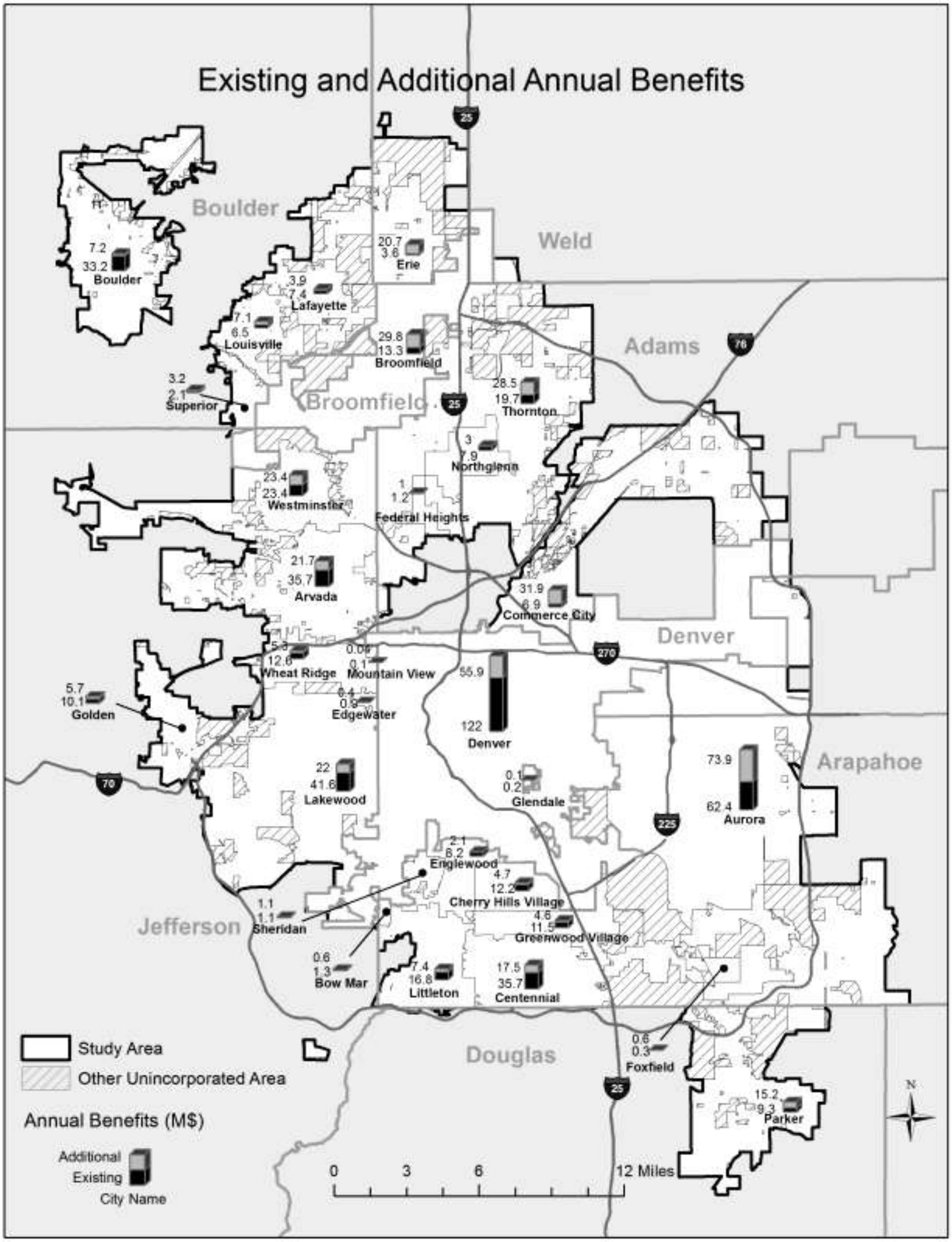



**Figure 16 Total existing and additional benefits by city in millions ($)**

**Table 27 Additional UTC benefits and total future TCC benefit by city/county**

| | Add. UTC | Energy Saving (Cooling) | | CO2 storage | CO2 Seq. (per yr) | Cooling CO2 avoided | | total CO2 | | Air Quality ( pollutant removed per year) | | Rainfall Interception | | Property Values | Add. UTC Total Benefit | Total Future UTC Benefit |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | % | MWhs | $ | ton | ton | ton | $ | Ton | $ | lb | $ | 1000 gals | M$ | M$ | M $ | M $ |
| **Cities** | **15.4** | **77,804** | **9,336,425** | **1,365** | **55.4** | **73,797** | **737,967** | **73,852** | **738,521** | **1,180** | **6,311** | **5,823,245** | **76.92** | **311.14** | **398.1** | **904.9** |
| Arvada | 14.7 | 4,604 | 552,504 | 73.1 | 3.2 | 4,367 | 43,671 | 4,370 | 43,702 | 64.2 | 343 | 316,581 | 4.18 | 16.88 | 21.7 | 57.3 |
| Aurora | 18.2 | 11,038 | 1,324,569 | 287.5 | 10.6 | 10,470 | 104,696 | 10,480 | 104,803 | 226.7 | 1,212 | 1,118,328 | 14.77 | 57.71 | 73.9 | 136.3 |
| Boulder | 9.6 | 2,803 | 336,319 | 34.2 | 1.3 | 2,658 | 26,583 | 2,660 | 26,597 | 29.9 | 160 | 147,459 | 1.95 | 4.85 | 7.2 | 40.3 |
| Bow Mar | 13.0 | 203 | 24,319 | 1.3 | 0.1 | 192 | 1,922 | 192 | 1,923 | 1.3 | 7 | 6,316 | 0.08 | 0.48 | 0.6 | 1.9 |
| Broomfield | 19.5 | 2,940 | 352,757 | 90.0 | 3.8 | 2,788 | 27,882 | 2,792 | 27,921 | 80.6 | 431 | 397,901 | 5.26 | 24.16 | 29.8 | 43.1 |
| Centennial | 12.9 | 4,408 | 528,924 | 52.3 | 2.2 | 4,181 | 41,807 | 4,183 | 41,829 | 45.9 | 245 | 226,281 | 2.99 | 13.91 | 17.5 | 53.1 |
| Cherry Hills Village | 15.5 | 382 | 45,813 | 12.6 | 0.6 | 362 | 3,621 | 363 | 3,627 | 12.0 | 64 | 59,283 | 0.78 | 3.86 | 4.7 | 16.9 |
| Commerce City | 21.2 | 2,661 | 319,278 | 97.1 | 4.1 | 2,524 | 25,236 | 2,528 | 25,278 | 89.4 | 478 | 440,931 | 5.82 | 25.68 | 31.8 | 38.7 |
| Denver | 11.4 | 17,438 | 2,092,534 | 183.9 | 7.9 | 16,540 | 165,397 | 16,548 | 165,476 | 168.9 | 903 | 833,228 | 11.01 | 42.65 | 55.9 | 177.9 |
| Edgewater | 9.7 | 173 | 20,763 | 0.9 | 0.0 | 164 | 1,641 | 164 | 1,642 | 0.8 | 4 | 4,077 | 0.05 | 0.31 | 0.4 | 1.3 |
| Englewood | 7.4 | 833 | 100,004 | 6.8 | 0.3 | 790 | 7,904 | 791 | 7,907 | 6.1 | 32 | 29,964 | 0.40 | 1.55 | 2.1 | 10.3 |
| Erie | 26.5 | 1,093 | 131,189 | 60.8 | 2.7 | 1,037 | 10,369 | 1,040 | 10,396 | 56.5 | 302 | 278,529 | 3.68 | 16.83 | 20.7 | 24.3 |
| Federal Heights | 13.6 | 122 | 14,663 | 3.2 | 0.1 | 116 | 1,159 | 116 | 1,160 | 3.0 | 16 | 14,749 | 0.19 | 0.81 | 1.0 | 2.2 |
| Foxfield | 24.2 | 76 | 9,172 | 4.3 | 0.2 | 72 | 725 | 73 | 727 | 3.9 | 21 | 19,196 | 0.25 | 0.29 | 0.6 | 0.8 |
| Glendale | 4.2 | 5 | 656 | 0.4 | 0.0 | 5 | 52 | 5 | 52 | 0.3 | 2 | 1,424 | 0.02 | 0.04 | 0.1 | 0.2 |
| Golden | 13.0 | 894 | 107,232 | 17.1 | 0.8 | 848 | 8,476 | 848 | 8,484 | 15.3 | 82 | 75,289 | 0.99 | 4.62 | 5.7 | 15.8 |
| Greenwood Village | 12.0 | 477 | 57,252 | 14.3 | 0.6 | 453 | 4,525 | 453 | 4,531 | 12.4 | 66 | 60,961 | 0.81 | 3.74 | 4.6 | 16.1 |
| Lafayette | 11.8 | 879 | 105,430 | 15.4 | 0.6 | 833 | 8,333 | 834 | 8,340 | 13.6 | 73 | 67,037 | 0.89 | 2.88 | 3.9 | 11.3 |
| Lakewood | 14.0 | 5,512 | 661,393 | 82.0 | 3.4 | 5,228 | 52,278 | 5,231 | 52,312 | 75.8 | 406 | 374,210 | 4.94 | 16.31 | 22.0 | 63.5 |
| Littleton | 12.0 | 1,898 | 227,786 | 23.7 | 1.0 | 1,800 | 18,005 | 1,802 | 18,015 | 20.3 | 108 | 99,948 | 1.32 | 5.81 | 7.4 | 24.1 |
| Louisville | 18.5 | 1,160 | 139,241 | 18.9 | 0.8 | 1,101 | 11,006 | 1,101 | 11,014 | 18.1 | 97 | 89,110 | 1.18 | 5.81 | 7.1 | 13.6 |
| Mountain View | 7.7 | 37 | 4,435 | 0.1 | 0.0 | 35 | 351 | 35 | 351 | 0.1 | 0 | 432 | 0.01 | 0.03 | 0.04 | 0.16 |

| | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Northglenn | 9.3 | 1,223 | 146,813 | 11.2 | 0.4 | 1,160 | 11,604 | 1,161 | 11,608 | 8.5 | 46 | 42,109 | 0.56 | 2.27 | 3.0 | 10.8 |
| Parker | 19.8 | 3,644 | 437,336 | 65.2 | 2.3 | 3,457 | 34,568 | 3,459 | 34,591 | 50.2 | 269 | 247,790 | 3.27 | 11.46 | 15.2 | 24.5 |
| Sheridan | 12.7 | 177 | 21,204 | 4.0 | 0.2 | 168 | 1,676 | 168 | 1,678 | 3.6 | 19 | 17,654 | 0.23 | 0.83 | 1.1 | 2.2 |
| Superior | 19.2 | 682 | 81,821 | 10.4 | 0.4 | 647 | 6,467 | 647 | 6,471 | 8.9 | 47 | 43,727 | 0.58 | 2.50 | 3.2 | 5.3 |
| Thornton | 18.1 | 5,634 | 676,022 | 88.5 | 3.9 | 5,343 | 53,434 | 5,347 | 53,473 | 80.3 | 429 | 396,205 | 5.23 | 22.55 | 28.5 | 48.2 |
| Westminster | 17.0 | 5,276 | 633,112 | 90.7 | 3.2 | 5,004 | 50,042 | 5,007 | 50,074 | 70.9 | 379 | 349,734 | 4.62 | 18.10 | 23.4 | 46.8 |
| Wheat Ridge | 11.1 | 1,532 | 183,883 | 14.6 | 0.7 | 1,453 | 14,534 | 1,454 | 14,541 | 13.1 | 70 | 64,790 | 0.86 | 4.21 | 5.3 | 17.9 |
| **Other Unincorporated areas** | **12.0** | **8,566** | **1,027,967** | **167.7** | **7.0** | **8,125** | **81,252** | **8,132** | **81,322** | **152.4** | **815** | **752,037** | **9.93** | **40.52** | **51.6** | **95.8** |
| Adams County | 14.6 | 1,659 | 199,129 | 44.0 | 1.9 | 1,574 | 15,739 | 1,576 | 15,758 | 39.7 | 212 | 195,781 | 2.59 | 12.55 | 15.4 | 23.1 |
| Arapahoe County | 16.5 | 3,293 | 395,102 | 66.6 | 2.7 | 3,123 | 31,229 | 3,126 | 31,256 | 59.8 | 320 | 294,975 | 3.90 | 12.78 | 17.1 | 31.2 |
| Boulder County | 4.4 | 1,129 | 135,452 | 10.3 | 0.5 | 1,071 | 10,706 | 1,071 | 10,711 | 9.6 | 51 | 47,126 | 0.62 | 3.15 | 3.9 | 9.5 |
| Broomfield County | 5.9 | - | - | 0.2 | 0.0 | - | - | 0 | 0 | 0.2 | 1 | 1,021 | 0.01 | 0.04 | 0.1 | 0.1 |
| Douglas County | 15.7 | 1,025 | 122,967 | 14.5 | 0.7 | 972 | 9,719 | 973 | 9,726 | 13.8 | 74 | 68,214 | 0.90 | 4.79 | 5.8 | 11.2 |
| Jefferson County | 11.2 | 1,260 | 151,148 | 27.4 | 1.2 | 1,195 | 11,947 | 1,196 | 11,958 | 25.0 | 134 | 123,341 | 1.63 | 5.89 | 7.7 | 18.3 |
| Weld County | 4.1 | 201 | 24,170 | 4.7 | 0.2 | 191 | 1,910 | 191 | 1,912 | 4.4 | 23 | 21,579 | 0.29 | 1.32 | 1.6 | 2.4 |
| **Grand Total** | **15.0** | **86,370** | **10,364,392** | **1,532.3** | **62.4** | **81,922** | **819,219** | **81,984** | **819,843** | **1,332** | **7,126** | **6,575,282** | **86.9** | **351.66** | **449.7** | **1,000.7** |

**Table 28 Total benefit and per tree benefit of existing, additional, and future UTC by City/County**

| Name | Total Existing UTC Benefit | | Total Additional UTC Benefit | | Total Future UTC Benefit | |
|---|---|---|---|---|---|---|
| | $ | $/tree | $ | $/tree | $ | $/tree |
| **Cities** | **506,764,368** | **52.6** | **398,137,494** | **105.7** | **904,901,861** | **67.5** |
| Arvada | 35,647,224 | 55.0 | 21,654,111 | 105.8 | 57,301,335 | 67.2 |
| Aurora | 62,378,825 | 54.9 | 73,914,787 | 102.2 | 136,293,612 | 73.3 |
| Boulder | 33,145,252 | 50.6 | 7,164,767 | 75.1 | 40,310,020 | 53.7 |
| Bow Mar | 1,312,275 | 58.8 | 585,379 | 143.4 | 1,897,654 | 71.9 |
| Broomfield | 13,335,436 | 51.4 | 29,796,458 | 115.8 | 43,131,895 | 83.5 |
| Centennial | 35,653,673 | 53.1 | 17,472,108 | 119.4 | 53,125,780 | 64.9 |
| Cherry Hills Village | 12,241,066 | 55.0 | 4,688,736 | 122.3 | 16,929,802 | 64.9 |
| Commerce City | 6,858,090 | 45.0 | 31,847,083 | 111.7 | 38,705,173 | 88.5 |
| Denver | 121,981,440 | 54.8 | 55,914,246 | 103.8 | 177,895,686 | 64.3 |
| Edgewater | 876,487 | 61.3 | 383,598 | 145.5 | 1,260,085 | 74.4 |
| Englewood | 8,215,516 | 54.5 | 2,052,726 | 106.0 | 10,268,242 | 60.3 |
| Erie | 3,600,545 | 49.1 | 20,655,326 | 114.7 | 24,255,871 | 95.7 |
| Federal Heights | 1,160,343 | 49.0 | 1,016,624 | 106.6 | 2,176,967 | 65.6 |
| Foxfield | 276,813 | 18.6 | 553,049 | 44.6 | 829,863 | 30.4 |
| Glendale | 185,077 | 28.6 | 62,618 | 68.0 | 247,695 | 33.5 |
| Golden | 10,088,590 | 51.3 | 5,731,605 | 117.7 | 15,820,195 | 64.5 |
| Greenwood Village | 11,484,527 | 50.5 | 4,606,030 | 116.9 | 16,090,557 | 60.3 |
| Lafayette | 7,388,761 | 50.5 | 3,883,879 | 89.6 | 11,272,640 | 59.4 |
| Lakewood | 41,550,879 | 49.9 | 21,964,610 | 90.8 | 63,515,489 | 59.1 |
| Littleton | 16,755,238 | 53.1 | 7,376,670 | 114.1 | 24,131,908 | 63.5 |
| Louisville | 6,448,777 | 52.1 | 7,136,355 | 123.9 | 13,585,132 | 74.9 |
| Mountain View | 120,389 | 51.5 | 36,203 | 129.8 | 156,592 | 59.9 |
| Northglenn | 7,853,756 | 54.3 | 2,983,770 | 109.6 | 10,837,526 | 63.1 |
| Parker | 9,323,048 | 42.0 | 15,209,762 | 94.9 | 24,532,810 | 64.2 |
| Sheridan | 1,101,682 | 41.7 | 1,090,259 | 95.5 | 2,191,941 | 57.9 |
| Superior | 2,106,631 | 51.2 | 3,166,344 | 112.0 | 5,272,975 | 75.9 |
| Thornton | 19,667,089 | 50.7 | 28,516,191 | 111.3 | 48,183,281 | 74.8 |
| Westminster | 23,384,571 | 50.9 | 23,405,548 | 103.5 | 46,790,119 | 68.2 |
| Wheat Ridge | 12,622,365 | 55.5 | 5,268,651 | 125.8 | 17,891,016 | 66.4 |
| **Other unincorporated areas in counties** | **44,201,110** | **41.5** | **51,563,285** | **106.0** | **95,764,395** | **61.7** |
| Adams County | 7,732,669 | 45.4 | 15,351,028 | 121.3 | 23,083,697 | 77.8 |
| Arapahoe County | 14,112,254 | 42.5 | 17,100,630 | 89.7 | 31,212,884 | 59.7 |
| Boulder County | 5,532,119 | 35.8 | 3,921,215 | 128.7 | 9,453,335 | 51.2 |
| Broomfield County | 15,465 | 28.3 | 55,670 | 84.3 | 71,134 | 59.0 |
| Douglas County | 5,370,583 | 49.5 | 5,821,750 | 132.0 | 11,192,333 | 73.3 |
| Jefferson County | 10,661,540 | 39.7 | 7,680,633 | 96.3 | 18,342,173 | 52.7 |
| Weld County | 776,479 | 24.1 | 1,632,360 | 117.0 | 2,408,839 | 52.2 |
| **Grand Total** | **550,965,477** | **51.5** | **449,700,778** | **105.8** | **1,000,666,256** | **66.9** |

- <u>Asset Value of Existing and Additional UTC</u>

The values for ecosystem services have been expressed in annual terms, but trees provide value across generations. Also, the benefits trees provide are becoming increasing scarce and more valuable with time. The annual flows of realized benefits from trees were converted into an estimate of asset value. This enables tree planting and stewardship to be seen as a capital investment that provides an annual flow of benefits. The asset value was calculated as the net present value, which is a discounted sum of annual future benefits. Discount rates of 4.125 percent, which is used by the US Corps of Engineers for large projects, and 0 percent were applied over 100 years for Existing UTC, Additional UTC and Existing plus Additional UTC. Some economists argue that natural capital has a lower discount rate because the benefit stream is more certain over longer periods of time.

The asset value of Metro Denver's existing urban forest is $13 billion, calculated at a 4.125 percent discount rate for the next 100 years (Table 29). At zero discount rate, Metro Denver's urban forest asset value is estimated at $55 billion. If UTC is increased to 31 percent over the next 30 years, the urban forest's asset value increases to $26.1 billion and $93.6 billion, assuming 4.125 and zero percent discount rates, respectively. Hence, the ecosystem services produced by Metro Denver's urban forest provide a stream of benefits over time, just as a freeway or other capital infrastructure does.

Table 29. Asset value of Metro Denver's urban forest projected over 100 years

| | Discount | Rate |
|---|---|---|
| | 0% | 4.125% |
| Existing UTC | 55,096,547,745 | 13,122,208,529 |
| Additional UTC | 38,460,379,529 | 12,956,888,913 |
| Existing + Additional UTC | 93,556,927,274 | 26,079,097,442 |

## SUMMARY & CONCLUSION

Metropolitan Denver's urban forest is extensive, covering 15.7 percent of the 721 square mile region. Urban tree canopy (UTC) for the 29 cities ranged from 5 to 37 percent. Impervious surfaces, such as roads, buildings and parking lots, accounted for 34 percent of the land area, while irrigated grass, bare soil and dry vegetation covered 48 percent. The accuracy assessment found that UTC was classified with 91.5 percent accuracy, above the 90 percent standard set for the study.

Hot spots, areas with surface temperatures elevated more than 1.25$^{o}$F above the mean, occupied 21 percent of the region. Not surprisingly, the mean UTC was only 4.5 percent for these areas. These urban heat islands are associated with higher summer air conditioning demand, increased ozone concentrations and greater risk of illness and death to residents, especially to vulnerable populations.

There are approximately 10.7 million trees in the Metro Denver urban forest, assuming an average crown diameter of 19-ft per tree. The mean tree density of 23.2 per acre compares favorably with values reported for other large cities such as Chicago (24), Philadelphia (25) and New York City (26). The average number of trees per capita is 4, less than 5.2 reported for California cities (McPherson and Simpson, 2003) but more than values reported for most other cities.

Metro Denver's urban forest produces ecosystem services valued at $551 million annually. The largest benefit, $436.5 million, is for increased property values and other intangible services. Reduced stormwater runoff management costs from 21,141 acre feet (6.9 billion gals) of rainfall intercepted by the existing canopy is valued at $91 million. Air temperature reductions from evapotranspirational cooling reduce residential air condition demand by 182,000 MWh, saving $21.8 million in cooling costs each year. If carbon dioxide sequestered and emissions avoided from cooling savings by the existing trees (172,272 tons) were sold at $10 per ton, the revenue would be $1.72 million. Finally, Metro Denver's urban forest filters 1,396 lb of air pollutants from the air at an estimated annual value of $7,465.

There are approximately 10 million vacant planting sites in the Metro Denver urban forest. This number assumes plantable space for a 30-ft crown diameter tree and that about 30 percent of the vacant sites are not plantable because of physical limitations such as utilities. Seventy percent of these plantable vacant sites are in single family residential and mixed land uses, while 16 percent are in public and institutional land uses. Potential tree planting sites (PTPS) are nearly evenly distributed between lawn areas already irrigated (56%) and unirrigated grass and bare soil (44%). Approximately 1.5 million vacant sites are located in hot spots. Shading parking lots, arterial streets, dark roofs and other sites where people work outdoors and recreate can provide significant health benefits.

Setting realistic targets for additional UTC is not straightforward because each city has a different land use mix, as well as different existing UTC and potential UTC (PUTC) that reflect historical patterns of development and tree stewardship. After discussion with partners it was decided to fill 50 percent of the calculated PTPS in non-agricultural land use zones. Setting a target for each city of filling 50 percent of its PTPS acknowledged that cities with the most vacant planting sites will achieve the greatest relative increase in UTC, whereas those with higher stocking levels will gain less UTC. Also, each city can do its “fair share” by filling 50 percent of its available tree planting sites, thus contributing to the common Metro Denver goal.

Filling 50 percent of the plantable vacant sites region wide will require planting 4.25 million more tree sites. This will result in about 14 million planted sites and is projected to increase UTC from 16 to 31 percent assuming that current UTC remains stable and program tree sites remain fully stocked with 30-ft crown diameter trees. There is adequate space in irrigated lawn areas to achieve the target. The gradual conversion of agricultural land to urban land uses will provide additional opportunities for planting.

Achieving the targeted 15 percent UTC increase will pay dividends. The value of ecosystem services will nearly double, increasing by $449.7 million, from $551 million to $1.0 billion. The value of increased annual property values and other intangible services is projected to be $351.7 million. Annual savings for reduced stormwater management costs will accrue from an additional 20,180 acre feet of rainfall interception (6.6 billion gals) and are projected to be $86.8 million. Reduced demand for 86,370 MWh of electricity for air conditioning is expected to save another $10.4 million in cooling costs. Trees in the additional sites will reduce atmospheric carbon dioxide by 81,984 tons, valued at $819,843 annually. The additional UTC will reduce another 1,332 lb of pollutants from the air. Expansion of the UTC from 16 to 31 percent is projected to result in provisioning of ecosystem services valued at over $1.0 billion annually from approximately 14 million trees. The average annual value of $67 per tree is comparable to results for the same services reported for street and park trees in Boulder and Fort Collins, CO (McPherson et al. 2001, 2003). This is a very conservative estimate of service value, as it does not fully capture all benefits associated with increased UTC, such as job creation, improved human health and fitness, wildlife habitat and biodiversity.

The asset value of Metro Denver’s existing urban forest is $13 billion, calculated at a 4.125 percent discount rate for the next 100 years. At zero discount rate, the Metro Denver urban forest asset value is estimated at $55 billion. If UTC is increased to 31 percent over the next 30 years, the urban forest’s asset value increases to $26.1 billion and $93.6 billion, assuming 4.125

and zero percent discount rates, respectively. Hence, the ecosystem services produced by Metro Denver's urban forest provide a considerable stream of benefits over time, just as a freeway or other capital infrastructure does. Quantifying the asset value of this "green infrastructure" can help guide advancement towards a sustainable green economy by shifting investments towards the enhancement of natural capital.

Metropolitan Denver is a vibrant region that has invested in its urban forest as it has grown. The task ahead is to better integrate the green infrastructure with the gray infrastructure by targeting tree planting and stewardship activities to maximize their environmental and human health impacts. This study provides information that can be used to plan, prioritize and implement new urban forestry programs. In so doing, Metro Denver's urban forest will become larger, more resilient and better able to meet the challenges of tomorrow.

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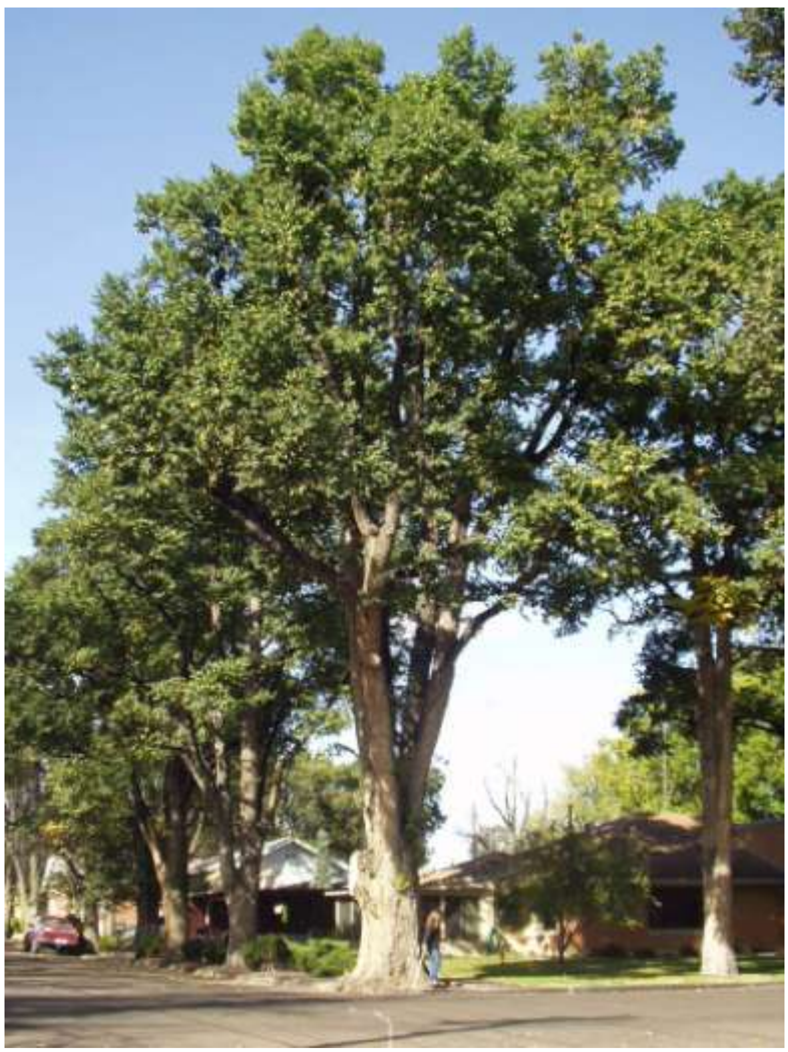

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# APPENDIX I URBAN LAND COVER MAPPING POSTCLASSIFICATION PROTOCOL

The goal of post classification processing is the correction of obvious classification errors. These errors are either caused by NAIP's spectral confusion of different land cover classes (more than one land cover class within a pixel) or land cover mixing of minimum mapping unit. During post classification these misclassified polygons will be manually reclassified to their actual land cover class based on visual interpretation of NAIP imagery.

Data require: Input data are organized by tile (PCQAGrids.shp). Each tile has its unique ID number. There are two files for each tile; multispectral NAIP imagery (example, NAIP_16_6.tif) and a land cover map from imagery analysis (example, LC_16_6.shp).

Products: the product from this process is a post-classification land cover map.
Software: ArcMap
Method: A 3-step approach will be used as described in detail below.

Input data are located in Chelsea Wu's computer (\\RP1731-xiao2\share2) under Denver\zpostClassification. One subfolder is NAIP image, one folder is land cover shape file.

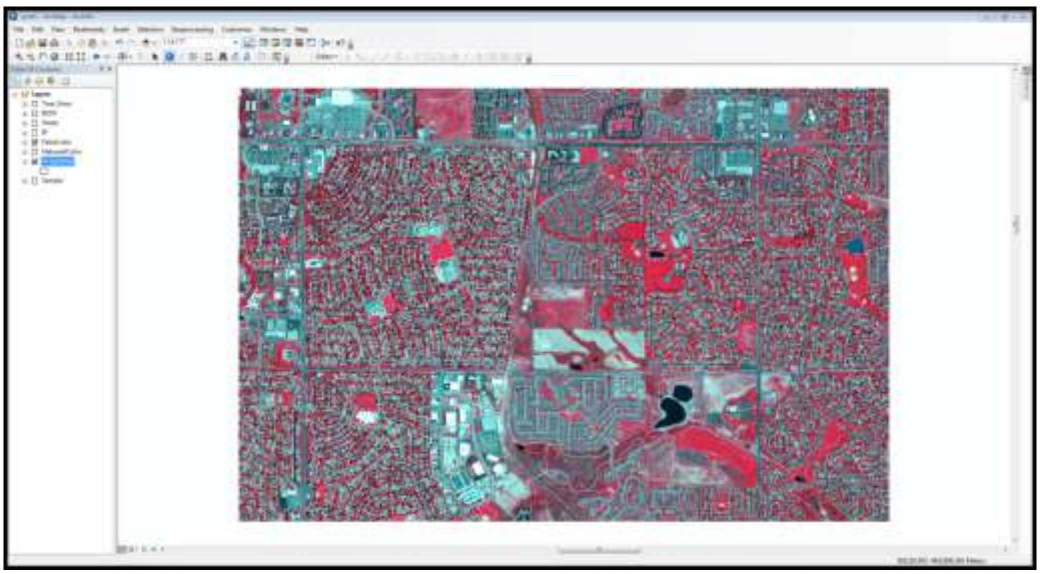
**Step 1: Get data**

1. Open excel file: PostclassificationTileList.xlsx, check tile names that are available and need postclassification. Fill in your name (checkout) and date and save the file.
2. Copy NAIP image and land cover layer of selected tile to your local computer.
3. Close the excel file.

**Step 2: Data preparation**

1. Start ArcMap
2. File-> open-> postc.mxd
3. Replace the FalseColor image with the tile you want to work on (example, NAIP_16_6.tif). You can do this by changing the data source of the example NAIP image. The symbology setting is RGB=412. Go into properties and symbology, change 'stretch' to "standard deviation" and 'Statistics' to "from current display extent"
4. Replace the NaturalColor image with the tile you want to work on (example, NAIP_16_6.tif). You can do this by changing the data source of the example NAIP image. The symbology setting is RGB=123

5. Change the land cover layers' data sources (example, LC_16_6.shp). You need to do this for Tree_Grass, BSDV, Water, and IP.
6. Open any land cover layer's attribute table. Add one field to this table. Name = ELC, type = text, do a field calculation: ELC = class_name
7. Identify tile ID of the tile to be edited (example, LC_16_6.shp) from PCQAGrids.shp, Use "definition query" to set: "Status" = '' AND "TileID" = '16--6'
8. Set the layer property's clip options: specify shape file = PCQAGrids.shp
9. Turn all layers off except FalseColor. This is the starting point for manual editing. Your screen should looks like this:



The view scale may vary with your computer monitor size and setup.

**Step 3: Editing**

In this step, you are going to correct land cover classes that were obviously mapped incorrectly based on visual NAIP image interpretation. You are not digitizing/modifying polygon boundaries. The corrections are made by changing land cover class layers' attributes. You are only making changes in the [class_name] field. Keep the field ELC intact (you can hide the ELC field).

1. Start editing the land cover shape file (example, LC_16_6.shp). Open the attribute table from the editor's tool set.
2. Open PCQAGrids' attribution table.
3. Select any row from PCQAGrids' attribution table and "zoom to select"
4. Turn Tree_Grass on.

5. Visually inspect trees and grass, see if there are any missclassifications between these two classes. Correct the wrong class by changing its attributes. Pay attention to polygons greater than 25 pixels.
6. Visually inspect trees and grass, pay attention if there are red colored (- using false color image!) patches outside tree and grass classes. Note that trees and shrubs are combined in the same land cover class.
7. Manually change each red colored patch outside tree/grass classes to tree or grass. If needed turn Falsecolor off and turn NaturalColor on to help you identify tree or grass.
8. Visually inspect trees and grass within parking lots and along streets. Correct misclassification if needed.
9. Turn Tree_Grass off, and turn BSDV on.
10. Visually inspect the BSDV class. Make corrections of misclassified patches. Pay attention to roofs and parking lots.
11. Turn BSDV off, and turn Water on.
12. Visually inspect the water class. Make corrections of misclassified patch. Pay attention to large water bodies, building shadows, and parking lots. Swimming pool can be classified as either water or IP.
13. Turn Water off, and turn IP on.
14. Visually inspect the IP classes (i.e., building, road, and other impervious). Make corrections of misclassified polygon. Pay attention to roads, vacant lots, parks, and undeveloped areas. BSDV may be misclassified as impervious, make corrections for misclassified impervious polygons if their area exceeds 100 pixels.
15. Turn IP off, and Tree_grass on. Change the status of the selected row in PCQAGrids' attribute table to "1".
16. Repeat step 3 to 16 until the PCQAGrids' attribution table is empty.
17. Save the edited work and start next tile.

# APPENDIX II REFERENCE LAND COVER DATA PROTOCOL

For each of the 2,000 sample point, one to three land cover classes will be noted. For those sample points that are located somewhat far inside a clearly discernible land cover class, with this land cover class being larger thanMMU (minimum mapping unit) one land cover class will be noted. For sample points close to a land cover class boundary or those within small land cover class areas (i.e., less than MMU), two or three classes will be noted. This will be done since the land cover classification does not result in smooth boundaries but rather along pixels. Thus points close to boundaries might be classified as either land cover class. Similarly with points within small land cover classes. The minimum mapping unit is 4 pixels (4 $m^2$) thus points in small areas might be classified as other land cover classes surrounding the point. The third situation that requires noting multiple land cover classes is for areas not easily identifiable as any class. Those classes (max. three) that most closely or likely describe the point will be noted. These points might later be excluded from accuracy assessment.

The land cover maps below show a section of urbanized area within the greater Denver region. Both maps show the same region; point 1, left, in natural color (bands 1, 2, 3), point 2, right, in infrared (bands 4, 1, 2) to better identify vegetation. Both maps show the same two sample points; the left sample point being located within a land cover class less than 4 pixels (4 $m^2$), the right sample point on the border of multiple classes.

**<u>Land cover class interpretation</u>**

**Point 1, left:**
Since the minimum mapping unit of the maps to be delivered is 4 pixels, or 4 square meters, very small areas will be dissolved into surrounding land cover classes. Thus even though one might be able to identify the land cover class of a small area based on aerial images the accuracy assessment would be misleading. One question to be answered is which of the surrounding land cover classes a given sample point will fall into, once the maps are converted into minimum mapping units. To resolve this confusion, not only the land cover class of the sample point has to be noted but also the surrounding land cover classes based on length of land cover class boundary.

Point A is located on a small group of pixels light brown in color; image left. Thus, the primary land cover class would be bare soil dry grass. However, it is surrounded by vegetation, trees and grass. Looking at the length of the boundary to the surrounding classes one would notice that the sample point is surrounded by grass on three sides and also possibly surrounded by a tree. Thus, the secondary land cover class would be grass and the tertiary tree.

**Point 2, right:**

The classification will result in land cover class boundaries that are somewhat coarse, land cover classes will include entire pixels. Thus, pixels on the border of land cover classes might include properties of all land cover classes; especially since our data have a resolution of 1m and it is unknown, how the land cover classification will classify these particular pixels. Similarly as above, three land cover classes will be noted for each sample point. Looking at point B, right, the primary class is the class the point falls into, here grass. The secondary class is the spatially closest class, here impervious (sidewalk), the tertiary is the next closest class, here tree.

| Sample ID | Primary LCC | Secondary LCC | Tertiary LCC |
|---|---|---|---|
| 1 | BSDV | grass | Tree |
| 2 | Grass | Other impervious | Tree |

Fig 1) Left: natural color image with two sample points. Right: same image as on the left in infra-red to highlight vegetation.

<u>Stepwise process:</u>

Step 1: Display imagery in natural color.

Step 2: Display imagery in false color (infra-red).

Step 3: Locate sample point .

Step 4: Determine the land cover class of the point and record the class

Step 4a: If the point is located in a large (i.e., greater than MMU) land cover class area and it is at least 2 pixels away from the closest land cover class boundary, move to next sample point.

Step 4b: If the point is located within 2 pixels of a land cover class boundary, also determine and record the adjacent land cover class, and move to next sample point.

Step 4c: If the point is located on an area where multiple land cover classes mix, also determine and record the first top two land cover classes this point is surrounded by based distance (closest first) then length of sharing boundary (longest first), and move to next sample point.

Step 4d: If the point is located in a shaded area (i.e. from a building) where land cover can't be determined record shadow as your first land cover class as well as the most likely actual land cover class and move to next sample point.