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Christine L. Jones
Michigan Technological University

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**COMPARING REMOTE SENSING AND GROUND-BASED METHODS OF
QUANTIFYING COVER TYPE AND CARBON STORAGE IN AN URBAN FOREST**

by

CHRISTINE L. JONES

A REPORT

Submitted in partial fulfillment of the requirements for the degree of

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This report, “Comparing remote sensing and ground-based methods of quantifying cover type and carbon storage in an urban forest”, is hereby approved in partial fulfillment of the requirements for the Degree of MASTER OF SCIENCE IN FORESTRY.

School of Forest Resources and Environmental Sciences

Signatures:

Report Advisor

Molly A. Cavaleri

Committee Members

Michael J. Falkowski

Blair D. Orr

Amy M. Marcarelli

Dean

Margaret Gale

Date

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(Under direction of Molly A. Cavaleri)

ABSTRACT

Understanding the canopy cover of an urban environment leads to better estimates of carbon storage and more informed management decisions by urban foresters. The most commonly used method for assessing urban forest cover type extent is ground surveys, which can be both time-consuming and expensive. The analysis of aerial photos is an alternative method that is faster, cheaper, and can cover a larger number of sites, but may be less accurate. The objectives of this paper were (1) to compare three methods of cover type assessment for Los Angeles, CA: hand-delineation of aerial photos in ArcMap, supervised classification of aerial photos in ERDAS Imagine, and ground-collected data using the Urban Forest Effects (UFORE) model protocol; (2) to determine how well remote sensing methods estimate carbon storage as predicted by the UFORE model; and (3) to explore the influence of tree diameter and tree density on carbon storage estimates. Four major cover types (bare ground, fine vegetation, coarse vegetation, and impervious surfaces) were determined from 348 plots (0.039 ha each) randomly stratified according to land-use. Hand-delineation was better than supervised classification at predicting ground-based measurements of cover type and UFORE model-predicted carbon storage. Most error in supervised classification resulted from shadow, which was interpreted as unknown cover type. Neither tree diameter or tree density per plot significantly affected the relationship between carbon storage and canopy cover. The efficiency of remote sensing rather than *in situ* data collection allows urban forest managers the ability to quickly assess a city and plan accordingly while also preserving their often-limited budget.

1. Introduction

The release of carbon dioxide into the atmosphere from both natural ecosystems and urban centers has become a major concern in today's society. The emission of this gas and other pollutants are thought to significantly contribute to the increasing temperatures of the earth's atmosphere, ultimately leading to changes in climate conditions and water levels throughout the world (Nowak, 1993; Pachauri and Reisinger, 2007). Longer commutes and expanding urban centers contribute to the release of carbon into the atmosphere, while areas once considered rich in their ability to store carbon are dwindling due to the growing demand for forest products.

Pools of carbon in urban centers are numerous. Trees, shrubs, non-woody plants, and soils fall under the category of natural pools. Other pools are anthropogenic in nature and include buildings and other structures, books, furniture, waste, and even humans and animals. Within urban areas, soils store the most carbon followed by buildings and vegetation (Churkina et al., 2010). These calculations depend on total area in each category as well as estimated carbon density associated with the type of pool.

Trees, much more than non-woody vegetation, can act as a sink for carbon dioxide by sequestering carbon during photosynthesis and storing it as biomass. Their potential for carbon storage changes as they age, and eventually die and decay (Nowak and Crane, 2002). Understanding the coverage and size of the urban forest can lead to better decisions with regards to urban planning and management. City planners can utilize information regarding urban forests to develop strategies to mitigate heavy pollution levels in certain areas. Potential strategies involve both increasing canopy cover as well as strategically placing trees near buildings to reduce energy costs involved with heating and cooling the facilities (Nowak et al.,

1996). Additionally, specific tree species can be chosen to achieve specific goals. For example, trees with greater leaf area and more complicated structure remove a greater amount of particulate matter from the air (Tiwary et al., 2009).

One way to assess carbon sink potential of urban forest systems involves the use of ground crews to collect vegetation data from a variety of sites throughout a city, and input this ground-based data into models to estimate carbon sequestration and storage. One such model is called the Urban Forest Effects model (UFORE), developed in the late 1990s by David J. Nowak and Daniel E. Crane (Nowak et al., 2003). This model utilizes ground data to calculate carbon storage, carbon flux, air pollutants such as ozone and particulate matter captured by the urban forest, as well as biogenic volatile organic compounds (BVOC) released by these trees. UFORE *in situ* data determines the amount of coarse vegetation cover, a factor that is directly related to carbon storage potential (USDA Forest Service, 2009b).

Other ways of assessing carbon storage potential include evaluating land cover type via remote sensing and aerial images. ArcGIS, specifically ArcMap, can be used to manually delineate an aerial photo into cover type classifications (ESRI, 2010). ERDAS Imagine software allows for a more automated classification of cover type by allowing the user to create signature files which ‘train’ the algorithm to classify an image according to cover type (ERDAS Inc., 2011).

Los Angeles, California, the study site for this project, has been and is currently facing problems with air quality, water shortages, urban heat island effect, and runoff from storm water (Wu et al., 2008). This city began as a struggling agricultural area in the late 1700s. When California joined the Union in 1850, Los Angeles had a population of 1,600 people; however, in only 80 years, this number would jump to 2.3 million making it the 4th most populated city in the

Union (Fogelson, 1993). As of 2006 almost 4 million people live in this metropolis (US Census Bureau, 2009). This number will most likely continue to increase as the population of the world continues to migrate to larger cities. In turn, these already large cities expand and become encompassed by urban sprawl. Los Angeles is a perfect example of this. Unlike other sprawling cities such as Las Vegas, Nashville, or Portland, however, the sprawl of Los Angeles is bound by an ocean on one side and a mountain range on the other (El Nasser and Overberg, 2001). Because of these characteristics, the green cover in Los Angeles will only change from within. Taking stock of what is growing within the city and planning from there will be an important process for this metropolis.

The primary objective of this study was to evaluate the accuracy of several methods of cover type classification in order to better estimate carbon storage potential in the urban forest of Los Angeles, California. Specifically, I aimed to (1) determine how well remote sensing methods of estimating cover type and percent cover (hand delineation and supervised classification) compare with *in situ* measurements; (2) determine how well remote sensing methods estimate carbon storage as predicted by the UFORE model; and (3) whether variables such as tree diameter or tree density affect the accuracy of carbon storage estimates at the plot level. If a relationship is found between the percent cover using either method of analyzing remotely sensed data and the carbon storage calculated from ground-acquired data, a more efficient way of determining the size of a city's carbon storage potential may be implemented across larger scales.

2. Methods

Study area

The city of Los Angeles has a land area of about 121,500 hectares. The majority of this city is non-coastal, however a small part of the city touches the ocean on the west and a small sliver of land connects the larger part of this metropolis to the water on the south (Fig. 1). The average yearly temperature for this city ranges from about 7°C to 24°C, while yearly precipitation is highly variable, ranging from 13.9 cm to 96.5 cm, with an average of 38.4 cm (NOAA, 2011).

UFORE model analysis

UFORE data collection protocol for assessing carbon storage of urban trees involves thorough ground surveys which measure the following data from trees within each plot: species, stem diameter at breast height (dbh), tree and crown height, crown height and width, and canopy condition (light exposure, percent missing, degree of dieback) (Nowak et al., 2003). An average of 200-fixed radius plots, each with an area of 0.039 ha, are assessed per city. According to the literature, 200 plots will typically result in 10% standard error for the total number of trees, and a larger number of plots will increase the accuracy of the study (Phillips, 2006). For this study, 348 plots were assessed, totaling 13.71 ha or about 0.011% of the total land area of Los Angeles. Using GIS software, plots were chosen via a stratified random sample, where strata were land-use categories (Table 1) per UFORE model protocol (Nowak et al. 2003). UFORE protocol gives greater preference to sites assumed to have more trees. For example, residential (R) is more heavily weighted compared with utility (U) or agricultural (A) areas and therefore has a higher

number of plots. This is done in order to get a more accurate interpretation of the tree cover of the city. Depending on the potential natural vegetation of the city (*i.e.* whether it was formerly a forested, a grassland, or a desert area), land use with the most potential for tree cover may differ. Los Angeles is considered a desert area, and therefore much of the tree cover is found in residential areas that are intensively cared for instead of vacant or natural areas, which in formerly forested areas would contain a higher proportion of tree cover (Nowak et al., 2003).

Plot-level tree data were analyzed using the Urban Forest Effects (UFORE) model (USDA Forest Service, 2009b) to calculate biomass and carbon content of the urban forest. Various factors were used to determine dry-weight biomass, including average moisture content for the different species of trees. When the species was not known, the trees were categorized into dbh classes. Different adjustment factors were used to keep the general dbh classes to within 2% of the original estimates calculated using individual species equations (Nowak and Crane, 2002). Urban tree growth, its effects on carbon sequestration, and carbon released during decomposition after tree death were also modeled. (Nowak and Crane, 2002). Because this study does not look at the changes each tree undergoes over time, only calculations regarding current carbon storage were utilized.

GIS and Remote Sensing Analysis

The 348 plots used in the UFORE model were assessed using ArcGIS. This assessment involved hand delineation in ArcMap 10.0 (ESRI, 2010) of the cover types present within each plot, followed by a determination of the area in hectares per plot of each cover type. The cover types delineated were as follows: bare ground, fine vegetation (grass and low-lying shrubs), coarse vegetation (trees and larger shrubs), impervious surfaces (cement and buildings), pool

water, and natural water. National Agricultural Imagery Program (NAIP) images with a 1-meter spatial resolution and a 4-band (RGB and near-infrared) spectral resolution used for this delineation were downloaded from CA.gov's Cal-Atlas Geospatial Clearinghouse (California GIS Council, 2010). The digital orthophoto quarter quad tiles (DOQQs) acquired in 2009 were projected in UTM zone 11. Forty-seven DOQQs covering about 4,662 hectares each were needed to cover the entire study site. Because of the grainy nature of the orthophotos downloaded from Cal-Atlas (Fig. 2c), Google MapsTM (Google Maps, 2009) high-resolution images of the study site were used as a reference to better determine the different cover types. An 11.2 m radius buffer was placed around each plot center, which was recorded with a hand-held GPS device during UFORE field data collection. The area under each buffer was hand-delineated according to cover type in ArcMap (Fig. 2c). Once delineated, the new buffer shape file was imported as a feature class into a newly created geodatabase in ArcCatalog. Once in the geodatabase, a new field was added to the attribute table and the area of each new polygon representing cover type in the plot was calculated.

A subset of five DOQQs of the forty-seven were classified via supervised classification in ERDAS (ERDAS Inc., 2011). The NIR property of the images was used to enhance the color of the vegetation, which showed in varying colors of pinks and reds (Fig. 2a). The five DOQQs chosen for supervised classification contained 63 of the total 348 plots and represented 9 of the 12 land uses (Table 1). A different training area was used for each DOQQ during classification to improve accuracy of the program since the images appeared to have been acquired on different days or at the least during different times of the day. In addition to the cover types listed above, the amount of shadow was also determined for these images (Fig. 2b). Because the program cannot determine which cover type the shadow might be, this reduced the overall area

of many of the plots. Additionally, light and dark categories of the major cover types, i.e. light impervious (whites, bright blues, etc) vs. dark impervious (varying shades of grays, darker reds, etc.) were separated for the supervised classification in order to achieve more accurate readings. Once classified, the image was brought into ArcMap, cover types divided into light and dark were merged once again, and the area per plot of each cover type was determined (Fig. 2d).

The UFORE cover type data estimated the coarse vegetation cover type out of 100% cover, while estimates of fine vegetation, bare ground, and impervious surfaces were also each determined out of 100% cover type. Because aerial photos make it impossible to see below the tree canopy, ArcMap and ERDAS calculations were based on all cover types together equaling 100%. The implications of this are small for coarse vegetation, however this might result in a smaller percentage of the other three cover types represented in the non-ground-based assessment methods.

Statistical analysis

Comparisons of the percent cover in each plot for the cover types bare ground, fine vegetation, coarse vegetation, and impervious surfaces were determined between the *in situ*, hand-delineation, and supervised classification assessments. One-to-one lines were used to determine how well the data matched between plots. Simple linear regression to determine R-squared and p-values estimated relationships between the three assessment techniques.

A comparison of mean percent cover for each cover type associated with each land use was graphed. The four major cover types of bare ground, fine vegetation, coarse vegetation, and impervious surfaces were shown for each of the assessment methods. Additionally, the hand-delineation assessment took into account the presence of pool water and natural water, while the

supervised classification included natural water and shadows. The effect of shadow on plots assessed via supervised classification was explored in an effort to determine which land use suffered more 'loss' of cover type due to this potential source of error.

UFORE model results indicated the amount of carbon being stored in the system by coarse vegetation (kg plot^{-1}). These data were plotted against the hectares per plot of coarse vegetation measured using the three different methods. Data were log-transformed to correct for heteroskedasticity. R-squared and p-values were recorded for comparison using simple linear regression.

Further analysis was done to determine if factors such as mean dbh or number of trees within a plot affected the relationship between UFORE-derived carbon storage and hand delineation-derived coarse vegetation coverage. Values of plot-level mean dbh were divided into three classes: less than or equal to 20 cm, between 20 cm and 40 cm, and greater than or equal to 40 cm, which contained 64 plots, 75 plots, and 60 plots, respectively. Values of tree density per plot were also divided into 3 categories: 2 or fewer trees, 3 or 4 trees, and 5 or more trees, which contained 67 plots, 40 plots, and 33 plots, respectively. Visual assessment was used to reveal any relationships. An analysis of covariance was applied to the dbh assessment to determine which dbh category was more strongly correlated with carbon storage as predicted by canopy cover. All statistical analyses were performed using R statistical software (R Development Core Team, 2010).

3. Results

Cover type assessment

Mean percent cover for each cover type by land use was determined using the *in situ*, hand-delineated, and supervised classification data (Fig. 3). The remotely sensed methods of data collection (supervised classification and hand-delineation) utilized more cover type classes than did the *in situ* assessment. All methods accounted for impervious surfaces, fine vegetation, bare ground, and coarse vegetation. Hand delineation in ArcMap accounted for two additional cover types: natural water and pool water (Fig. 3b), while supervised classification using ERDAS accounted for the additional cover types: natural water and shadow (Fig. 3c). After analysis, pool water and natural water were considered negligible because they made up such a small area of the total plots within the study site, <0.1% and 0.1%, respectively. However, it should be noted that the natural water cover type was substantial (25% of the total land cover) in the Wetland land use class.

The mean cover type for each plot according to land use revealed a general trend for where each cover type is dominant. Cover type trends from *in situ* data and hand-delineation, both of which were used to assess all 348 plots, were more closely aligned with each other (Figs. 3a-b) than with trends found using supervised classification, which was used to evaluate a subset of 63 plots (Fig. 3c). Bare ground had a larger presence in the *in situ* data than in the other two collection methods. Coarse vegetation was greatest for all three assessment methods in the No Intended Use land use class. The five land uses with the greatest coarse vegetation percent cover were the same for both *in situ* and hand-delineated data: No intended use, Wetland, Agricultural, Parks, and Residential. The top five land use classes in impervious surfaces were also the same

for the *in situ* and hand-delineated data: Commercial, Institutional, Transportation, Multi-family, and Residential.

Linear regressions of percent cover assessed by UFORE *in situ* methods vs. percent cover assessed by hand-delineation in ArcMap showed significant relationships for each of the four cover types (Fig. 4). The strongest associations between the two assessment methods, as shown by higher R^2 values and regression lines closer to 1:1 lines, were for coarse vegetation cover (Fig. 4c) and impervious surface cover (Fig. 4d).

In situ percent cover was compared with percent cover assessed using a supervised classification (Fig. 5). All cover types show significant yet weak correlations between the two assessment methods. Bare ground (Fig. 5a) appears to be the most accurately represented cover type with a higher R-squared value and a regression line that follows most closely with the 1:1 line. Coarse vegetation and impervious surfaces appear to be under-represented in the supervised classification (Figs. c and d) since many of the points fall above the 1:1 line. Errors in supervised classification of fine vegetation may be present since many plots found to have no fine vegetation according to *in situ* data were classified as having up to 75% cover in the supervised classification (Fig. 5b).

A comparison of cover types assessed by hand-delineation and supervised classification showed significant relationships for each of the four cover types ($p < 0.0001$) (Fig. 6). The strongest association between the two assessment methods, as shown by higher R^2 values and regression lines closer to the 1:1 lines, were impervious surface cover (Fig. 6d) and fine vegetation cover (Fig. 6b). Supervised classification appears to be under-estimating percent cover in comparison to hand-delineation for both coarse vegetation and impervious surfaces as shown by almost all of the plot points falling below the 1:1 line. Supervised classification may

also be overestimating bare ground and fine vegetation cover as shown by the large number of plot points on the zero line for hand-delineation percent cover, but between zero and forty % cover for supervised classification (Fig. 6a-b).

Coarse vegetation cover vs. carbon storage

Carbon storage in kilograms per plot, calculated from coarse vegetation using the UFORE model had a significant relationship (p-value <0.0001) with the hectares per plot of coarse vegetation canopy cover assessed by UFORE ground crews (Fig. 7a). The relationship, according to visual assessment, is strongest when both axes are log-transformed to reduce heteroskedasticity. The relationship was weaker when coarse vegetation was assessed using hand-delineation (R^2 value of 0.23 vs. 0.69 for UFORE) although the relationship was still highly significant (p-value < 0.0001, Fig. 7b). There was a slight trend, but no significant relationship ($\alpha = 0.05$) between coarse vegetation measured using supervised classification and carbon storage per plot (p-value = 0.062, Fig. 7c).

Influence of tree diameter and tree density on carbon storage estimates

The correlation between carbon storage and hand-delineated coarse woody cover area was explored with low, medium and high mean dbh classes as well as low, medium and high trees per plot classes (Fig. 8). An analysis of covariance was used to determine whether either dbh or tree count per plot played a significant role in affecting the relationship between carbon storage and canopy cover. The results of this analysis indicate that neither factor is significant.

4. Discussion

Cover type assessment using remotely sensed data

I set out to evaluate the accuracy of several cover type classification methods in an urban forest using remotely sensed aerial images and *in situ* data.

In our study we used two different methods of processing aerial images to determine cover type. One method involved the use of hand-delineation of cover-type for each plot using ArcMap 10.0. This method was somewhat labor intensive, but also relatively user friendly. My data classifications corresponded well with ground collected UFORE data especially for coarse vegetation and impervious surfaces (Fig. 4 and Fig. 6b). This method of cover type assessment is dependent upon the user's skill at determining what cover type is shown on the aerial image. Also important is the quality of the aerial image being processed (Swain, 2007). Better spatial resolution (1-meter vs. 30-meter) will result in a more easily readable image. By using the downloaded DOQQs in conjunction with Google Maps TM, I was able to increase readability of the study site image while hand-delineating. The supervised classification, however, was still run on the lower-resolution DOQQ images. This may account for the increased accuracy of hand-delineation over supervised classification.

There are other ways of processing aerial images via ArcMap that are worth exploring in further study. One method involves designing an algorithm that can use something such as color on a near-infrared aerial image to identify cover type. Wu, et al. (2008) used a computer program developed in ArcGIS environment to assess the city of Los Angeles, CA, for potential tree planting sites. This program first classified land cover type and then proceeded to virtually plant trees starting with largest projected canopy trees and filling in with medium and then small

throughout the city in an effort to determine how many potential trees could be planted in this urban center. After testing for accuracy by ‘ground-truthing’ a number of sites, it was determined that most errors came from the original land cover-type assessment, *i.e.* bare ground was mistaken for an impervious surface (Wu et al., 2008). Because of this common error, it is necessary to check the accuracy of images that are classified before land mapping of an area can be considered complete (Karaburun et al., 2010). This is true whether the classification is done in ArcMap, ERDAS or some other classification program. For this study, the in situ data considered to be the most accurate was used

Another tool in ArcGIS software is Feature Analyst, an objects-oriented extension that can be used to classify features such as cover type on a landscape (ESRI, 2010). Unlike pixel-based classification methods, which use spectral qualities such as color, object-oriented classifications examine spatial relationships as well. Swain (2007) found that object-oriented classifications were more accurate than both hand delineation and pixel-based classification methods, because the pixels are classified in context with the rest of the image rather than individually. Unfortunately the learning curve to using Feature Analyst is steep requiring more time initially (Swain, 2007).

The other method for assessing cover type that was evaluated in this study used a supervised classification in ERDAS Imagine 2010 to delineate multi-spectral images of the study site. A major source of error in this method was the shadow present in the aerial images. Shadow was negligible or not present in land use areas like cemeteries and golf courses, but was almost 25% of the cover in residential areas and almost 50% of the cover in transportation areas (Fig. 3c), resulting in a large portion of unknown cover type for these sites. These ‘shadow’ areas may explain the tendency of the supervised classification to underestimate coarse

vegetation and impervious surfaces while overestimating fine vegetation and bare ground when compared with hand-delineation (Fig. 6).

Residential areas, found to contain a high proportion of canopy cover, however not the highest amount as was assumed prior to in situ sampling, were also found to contain a lot of shadow. This may explain the lack of significance between supervised classification canopy cover and UFORE carbon storage (Fig. 7c). Determining the cover type below the shadow by hand delineation would most likely improve this correlation.

A supervised classification such as the one we used in this study involves creating and using a training area to identify cover type from an aerial image. Each pixel is classified according to the spectral reflectance it is ‘taught’ indicates a certain cover type. Myeong, *et al.* (2006) used a classification type method to assess canopy cover from Landsat Thematic Mapper (TM) imagery of Syracuse, New York, and found that errors in this method can come from cloud cover above as well as shadows cast from buildings and trees increasing the area of unknown cover types. This study, however, showed there to be only a 0.2% difference in carbon storage estimates using aerial images compared with field collected data (Myeong et al., 2006). My study showed a much greater difference between these two methods of assessment and their predicted percent cover.

Another consideration when using spectral reflectance for cover type assessment is edge effect, which can often confuse pixels between adjoining cover types resulting in erroneous classifications (Wu et al., 2008). Because the urban surface is so varied, this error could be substantial.

Remote sensing vs. ground-based assessment of cover type

The UFORE model, developed in the late 1990s, has gone through several adaptations all of which, however, still rely on ground-collected (*in situ*) data. Street Tree Resource Analysis Tool for Urban Forest Managers (STRATUM) not only assesses the urban landscape for structure and function, but also determines the monetary benefit the tree canopy provides for a city, *i.e.* energy saved on heating and cooling ((US Forest Service: Pacific SW Research Station, 2009); (Maco and McPherson, 2003). The most recent derivations of UFORE and STRATUM are i-Tree Eco and i-Tree Streets, respectively, both of which were developed by the US Forest Service and now offer publically accessible applications downloaded free from itreetools.org in which ground-collected data can be entered and site assessments derived (USDA Forest Service, 2009a).

Ground surveys can be time consuming and require a large number of relatively skilled field crews, making them also somewhat expensive. Using community volunteers to collect ground data would help defray some of the cost. In a recent study volunteers used digital cameras to collect images that were later run through the PhotoModelerTM software package to correctly locate the sites on a Google MapsTM (Google Maps, 2009) framework called the Urban Forest Inventory Web Application (UFIA). This study determined that although it is much cheaper to use volunteers, it is necessary to have several volunteers visit and assess each site in order to cross-check the accuracy of the data (Abd-Elrahman et al., 2010).

Ground surveys can have other limitations. It was found in a study by Millward and Sabir (2010) in Toronto, Canada, that STRATUM might overestimate tree value when the health of a

tree is in decline. This study also stressed the importance of leaf area even more than canopy size when it comes to ecological benefits (Millward and Sabir, 2010).

Because of the need for faster site assessment, the use of remote sensing and aerial images to assess cover type is growing, even though ground-based evaluation of plots is still considered the most accurate method of assessment (Myeong et al., 2006). Using Google MapsTM images along with other aerial photos available free through GIS data repository websites is an economical approach to quantifying cover type in an urban area. This method of assessment requires fewer personnel, is less time intensive than performing ground surveys, and can cover a larger area in a shorter amount of time (Abd-Elrahman et al., 2010).

Estimating carbon storage

The second objective was to determine how well remote-sensing methods estimated carbon storage as predicted by the UFORE model. UFORE *in situ* data and hand delineation in ArcMap were significantly correlated to UFORE predicted carbon storage, while the supervised classification using ERDAS was not. The correlation between the *in situ* assessment and UFORE predicted carbon storage is not surprising since the data used to calculate carbon storage comes directly from the ground surveys done during *in situ* assessment.

Unlike the UFORE model, however, remote sensing and satellite images do not take into account specific tree details such as species. Nowak and Crane (2002) determined that carbon storage can be predicted for trees whose species is unknown using a general species formula which would bring the total carbon storage for the urban forest being assessed to within 2% of the total predicted using species specific calculations (Nowak and Crane, 2002). Therefore a

small part of the error in our study between the assessment methods may be due to unknown tree species.

Canopy condition, including dieback and decay, is another variable that is difficult to determine using aerial assessments. To try to overcome this problem, Franklin and Hiernaux (1991) used the Li-Strahler reflectance model to determine crown size and density of unknown trees with only minimal error (a factor of 1.5) (Franklin and Hiernaux, 1991). Ground surveys allow for the proper assessment of tree health, the location of dead, decomposing trees which are releasing carbon back into the atmosphere and their removal and replacement (Nowak and Crane, 2002). Additionally, invasive species can be better accounted for during ground surveys as can the location of endangered or rare plant communities (Abd-Elrahman et al., 2010).

The ever-changing urban center may be another reason for the discrepancies between the aerial assessments and UFORE predicted carbon storage (Myeong et al., 2006). The UFORE ground data was collected in 2007 and 2008. The images used in ERDAS classifications were from 2009, while the images used in ArcMap classifications were also from that year, but with the help of GoogleMaps™ whose images were from an unknown year. It is unknown in which season any of the images were taken, however this may not matter as much in a city like Los Angeles compared to a more seasonal city like Buffalo, NY. The urban landscape in any city, however, can change significantly within a year and year to year.

Influence of tree diameter and density

The third objective was to determine whether variables such as tree diameter or tree density correlated more closely with carbon storage estimates at the plot level. The literature has shown that more carbon is stored in trees with a larger dbh (McPherson et al., 1997). The data

from my study lends further support to this theory given the significant DBH class term (Fig. 8) indicating that more carbon is indeed stored in plots with larger trees. Also significant is the tree count term indicating that more carbon is stored in plots with more trees. Both variables appear to be important but neither significantly affect the relationship between carbon storage and canopy cover. Further support for the maintenance of older, larger trees, however, can be found in the literature which estimates that up to 40% of young, newly-planted trees die within their first 10 years. This highlights both the ecological and economical benefits of older, well-established trees (Millward and Sabir, 2010).

5. Conclusion

The primary objective of this study was to evaluate the accuracy of several methods of cover type classification in order to better estimate carbon storage potential in the urban forest. *In situ* data, considered to be the most accurate, were compared with remotely sensed data hand-delineated in ArcMap and delineated via supervised classification in ERDAS. I found that hand-delineation in ArcMap was overall more accurate than the supervised classification in ERDAS. Error associated with the supervised classification was due mostly to shadows reducing the amount of classifiable cover type within each plot. This study also confirmed the importance of both tree dbh and tree density, but found neither to significantly affect the relationship of carbon storage and canopy cover.

Remotely sensed data can be a useful tool for the urban forest manager. Although not as accurate as *in situ*-collected data, this method is more economical and will still give a relatively good representation of canopy cover. Using ground crews to assess a small portion of plots

within each land use type is a way to ground-truth the remotely sensed data. The benefits of larger, more well established trees can be stressed to promote the maintenance of trees already present and careful planning when new plantings are performed.

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Tables:

Table 1. Land use descriptions used for random stratification of plots in study site.

Land Use	Code	Description	Number of Plots
Residential	R	1-4 families, free-standing	163
Commercial	C	commercial areas includes parking lots	49
No Intended Use	V	land with no clear, intended use	50
Transportation	T	limited access roadways, airports, railroads, green spaces	23
Institutional	I	schools, hospitals, colleges, government buildings, religious buildings	21
Multi-family	M	4+ families, attached	19
Parks	P	parks	8
Golf Course	G	golf courses	7
Wetland	W	wetlands, streams, rivers, lakes	3
Cemetery	C	cemeteries	2
Agricultural	A	pastures, nurseries, vineyards	2
Utility	U	power facilities, sewage treatment centers, reservoirs, storm water retention areas, flood control channels	2

Figures:

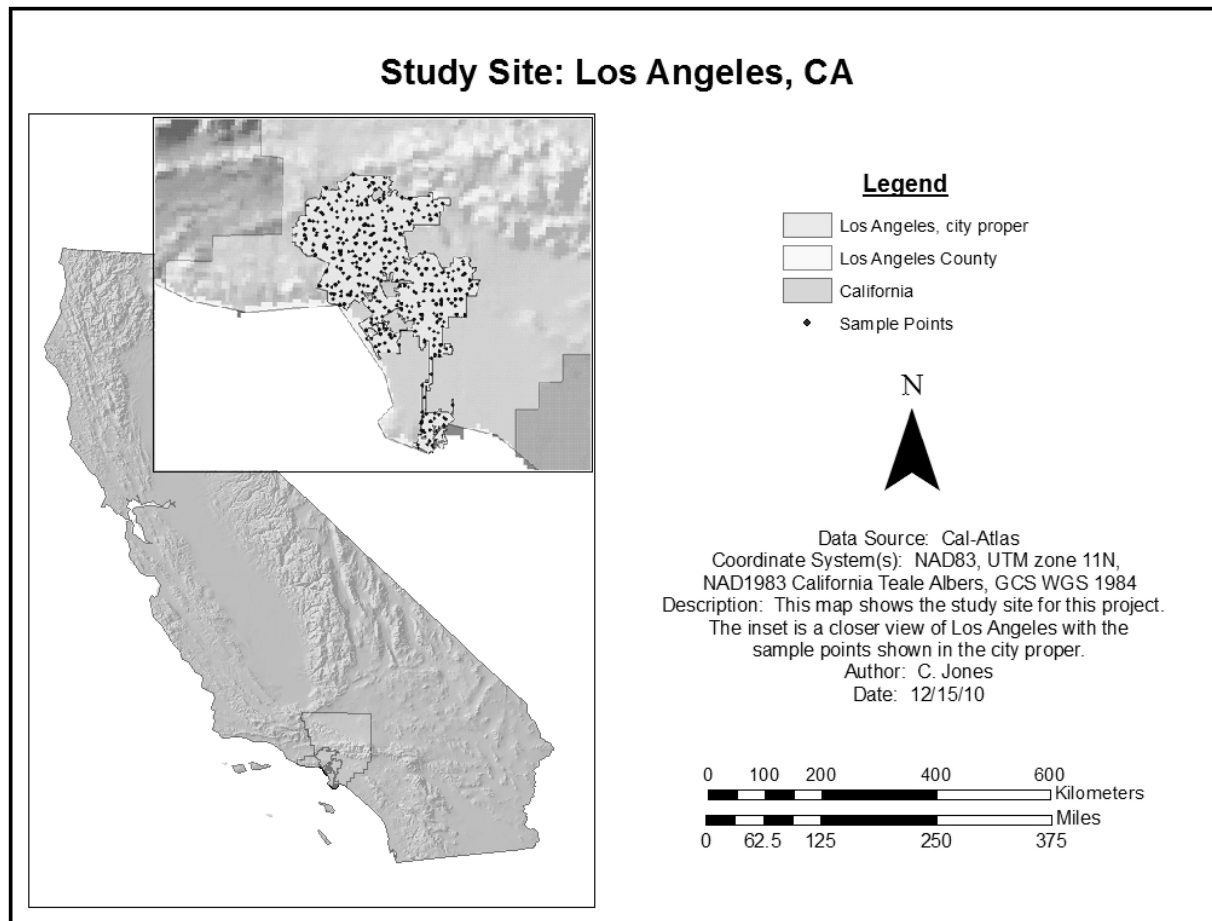


Figure 1. The study site is located in the city of Los Angeles, California. Plots (labeled as sample points) fall throughout the city proper. Also indicated is the county of Los Angeles. Note that the scale bar corresponds with the larger image and not the inset.

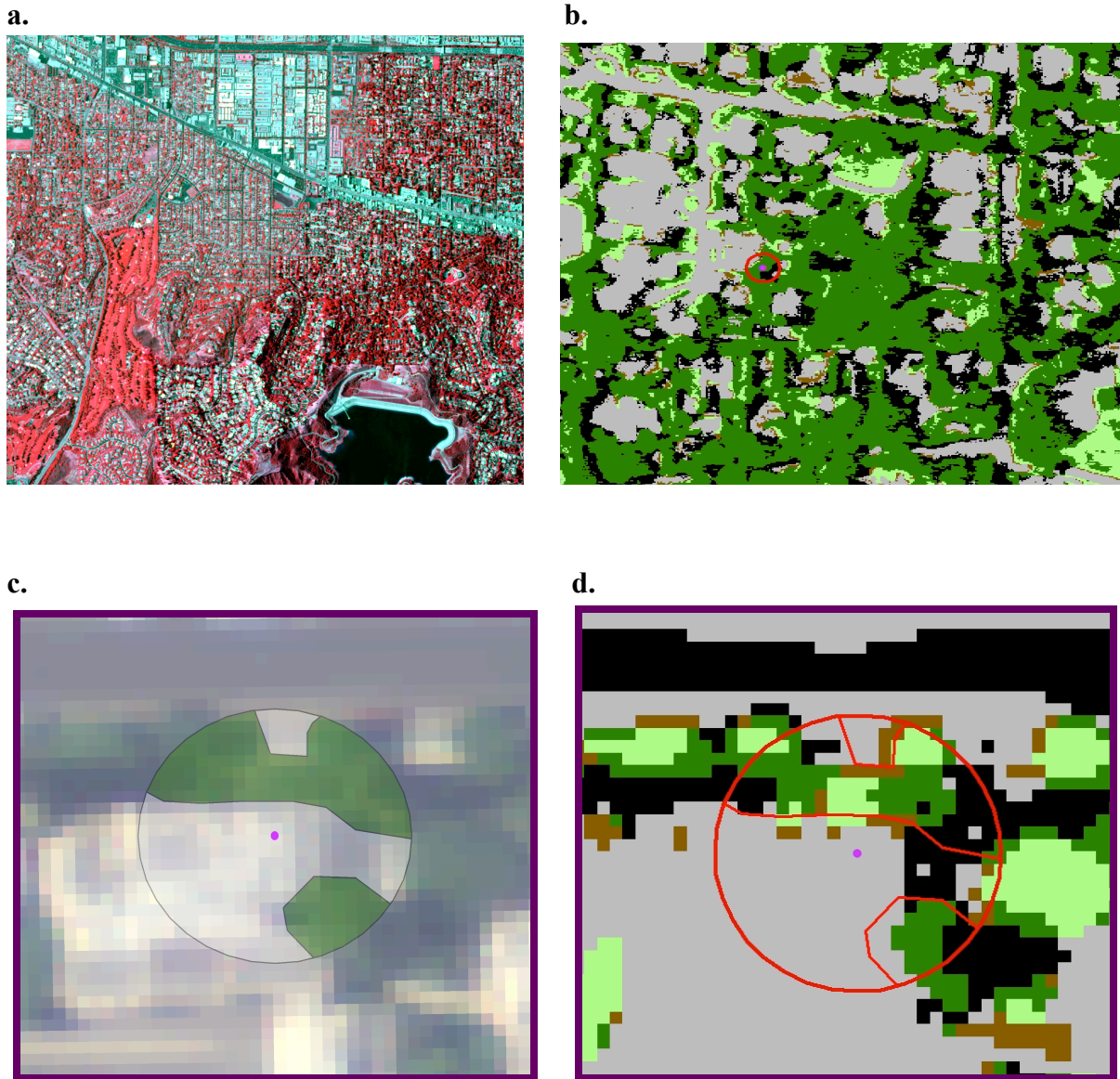


Figure 2. (a.) A near-infrared image of the study site, zoomed out. Note the vegetation shown in varying reddish hues, while impervious surfaces are varied in color. The large dark area on the lower right is a reservoir. (b.) A zoomed in view showing one plot (plot 128, land use is residential) after supervised classification and color adjustment. Note that the black color indicates shadow. (c.) Plot 137 in the multi family land use has been hand-delineated. Two cover types are shown for this plot: coarse veg (green) and impervious surface (grey). (d.) The same plot, 137, after supervised classification with hand-delineation layer (shown in red) over top. More cover types are represented: coarse veg. (dark green), fine veg. (light green), bare ground (brown), impervious (grey). Shadow (totalling 18% cover) shown in black represents the unknown.

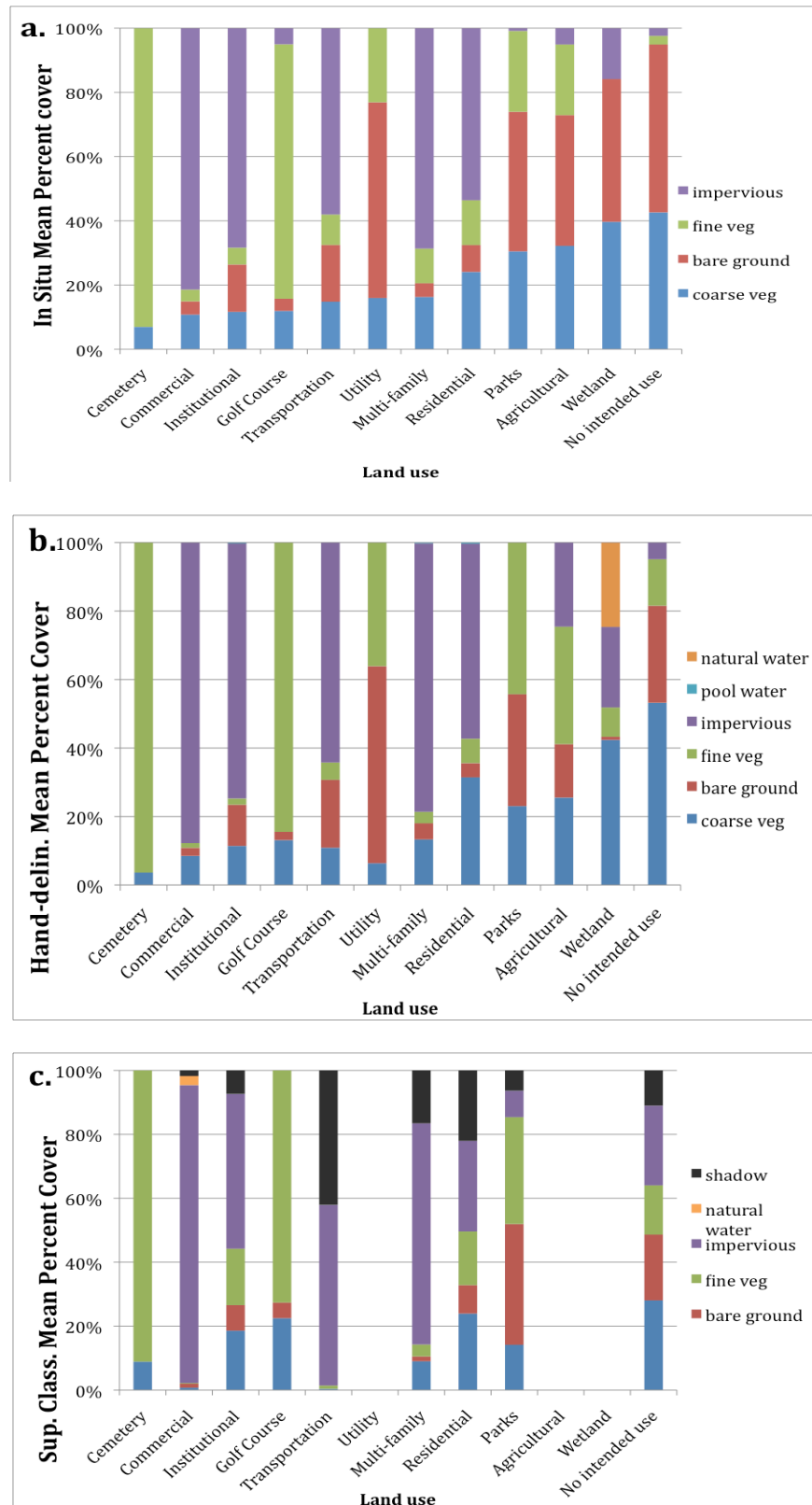


Figure 3. Mean percent cover of each cover type within each land use type. Percent cover was measured using in situ data in Fig. 3a, hand-delineated data in Fig. 3b, and supervised classification in Fig. 3c. Cover types are defined as coarse vegetation, bare ground, fine vegetation, impervious surfaces, pool water, natural water, and shadow. Not all assessment methods delineated the same cover types. The plots assessed via supervised classification (Fig. 3c) contained no plots within the land use categories of utility, agricultural or wetland.

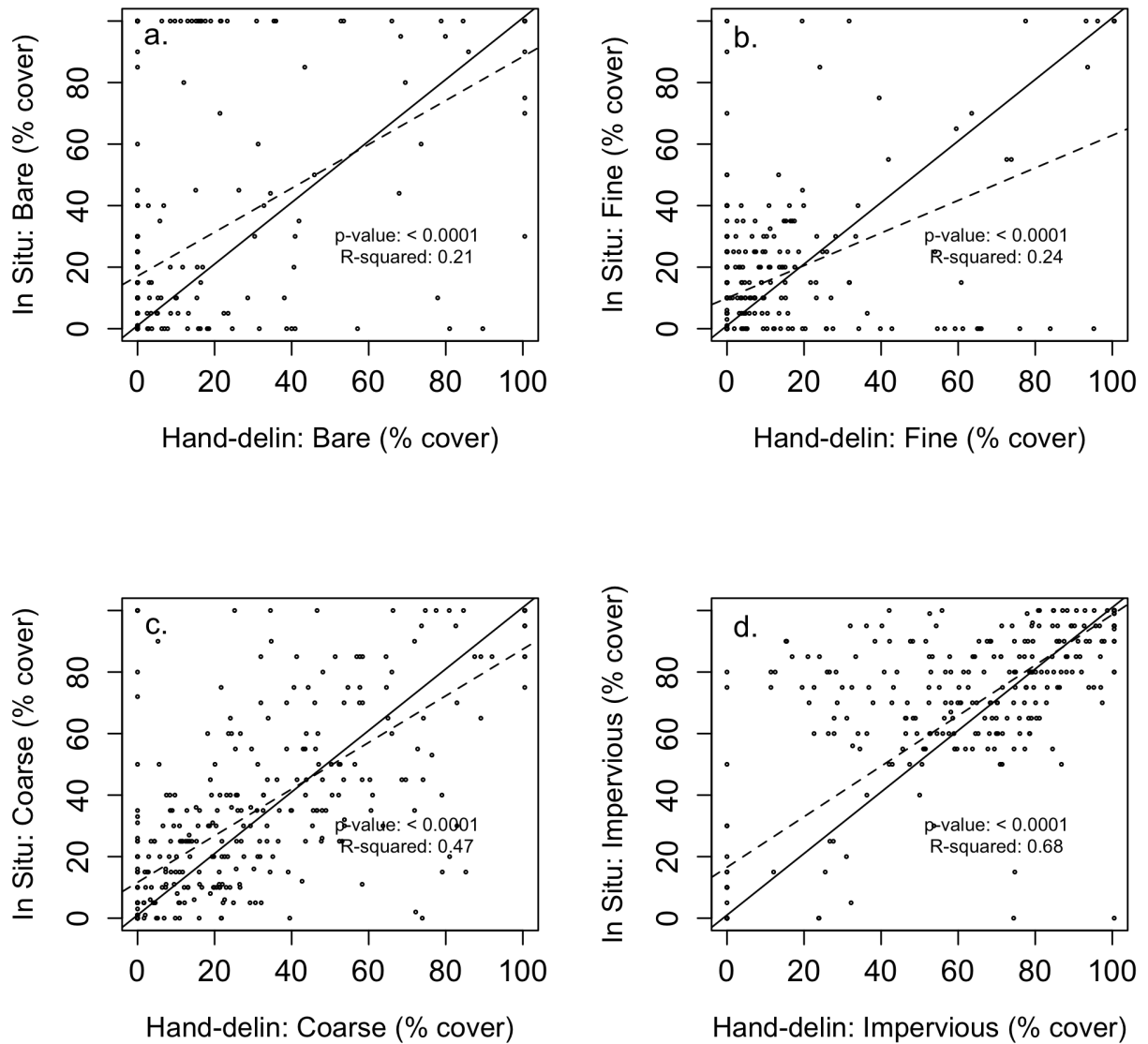


Figure 4. A comparison of percent cover for the 4 major cover types: (4a.) bare ground, (4b.) fine vegetation, (4c.) coarse vegetation, and (4d.) impervious surfaces for 348 plots as determined using hand-delineation in ArcMap and ground data collected for the UFORE model. The solid line represents the 1:1 ratio, while the dotted line is the regression line. Regression equations are as follows:

- (4a.) $\text{In situ} = 17.10 + 0.71 \cdot \text{hand-delin}$; RMSE: 31.9; F-stat: 91.61; DF: 347
- (4b.) $\text{In situ} = 9.94 + 0.53 \cdot \text{hand-delin}$; RMSE: 19.26; F-stat: 110.1; DF: 347
- (4c.) $\text{In situ} = 11.63 + 0.76 \cdot \text{hand-delin}$; RMSE: 22.56; F-stat: 131.1; DF: 347
- (4d.) $\text{In situ} = 16.55 + 0.82 \cdot \text{hand-delin}$; RMSE: 20.44; F-stat: 739.4; DF: 347

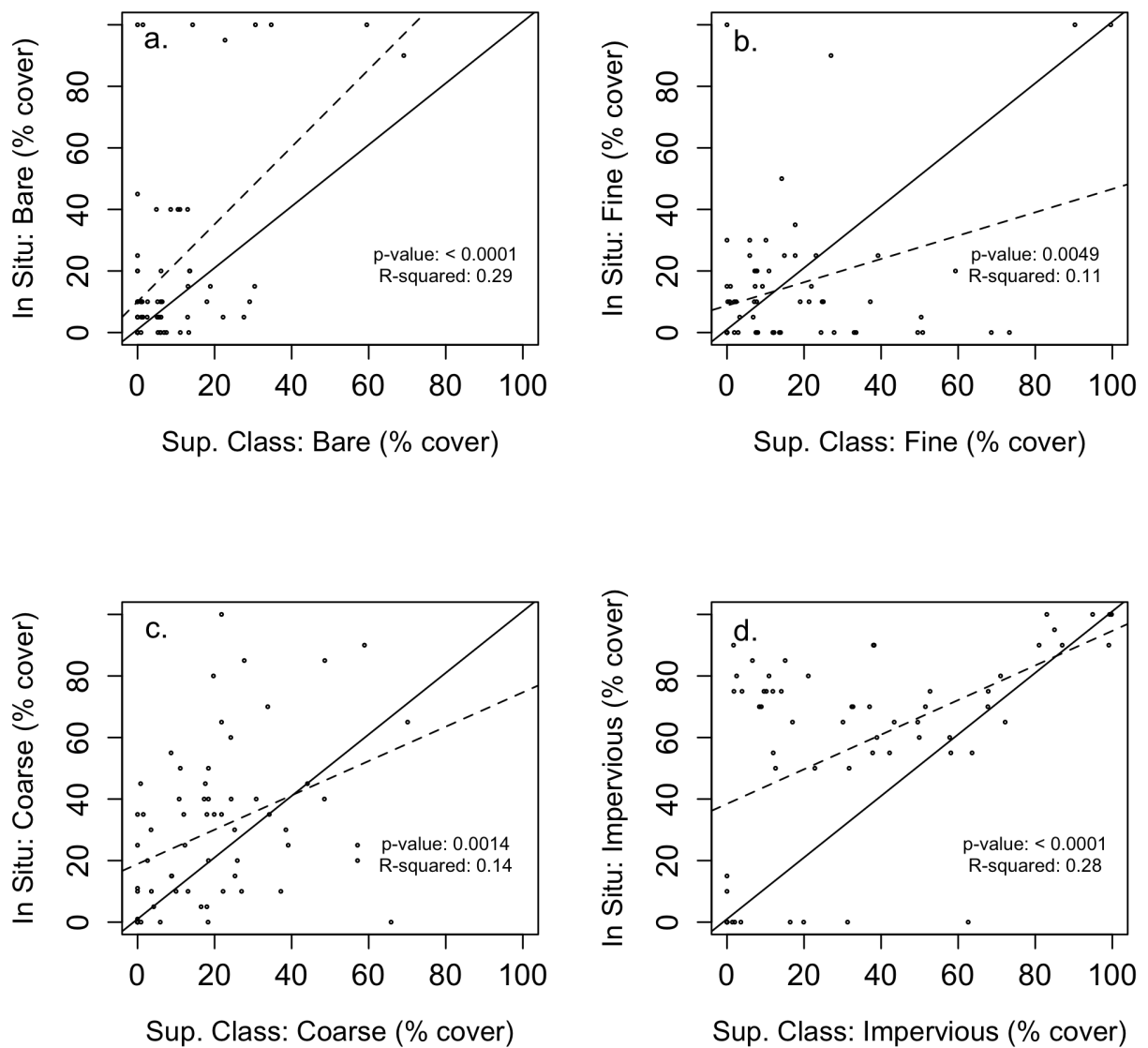


Figure 5. A comparison of percent cover for the 4 major cover types: (5a.) bare ground, (5b.) fine vegetation, (5c.) coarse vegetation, and (5d.) impervious surfaces in 63 plots as determined by in situ collected data and supervised classification in ERDAS. The solid line represents the 1:1 ratio, while the dotted line is the regression line.

Regression equations are as follows:

(5a.) In situ = $10.02 + 1.26 * \text{sup. class}$; RMSE: 26.88; F-stat: 24.86; DF: 61

(5b.) In situ = $8.75 + 0.38 * \text{sup. class}$; RMSE: 22.88; F-stat: 8.52; DF: 61

(5c.) In situ = $18.88 + 0.56 * \text{sup. class}$; RMSE: 23.53; F-stat: 11.28; DF: 61

(5d.) In situ = $38.43 + 0.56 * \text{sup. class}$; RMSE: 28.17; F-stat: 24.78; DF: 61

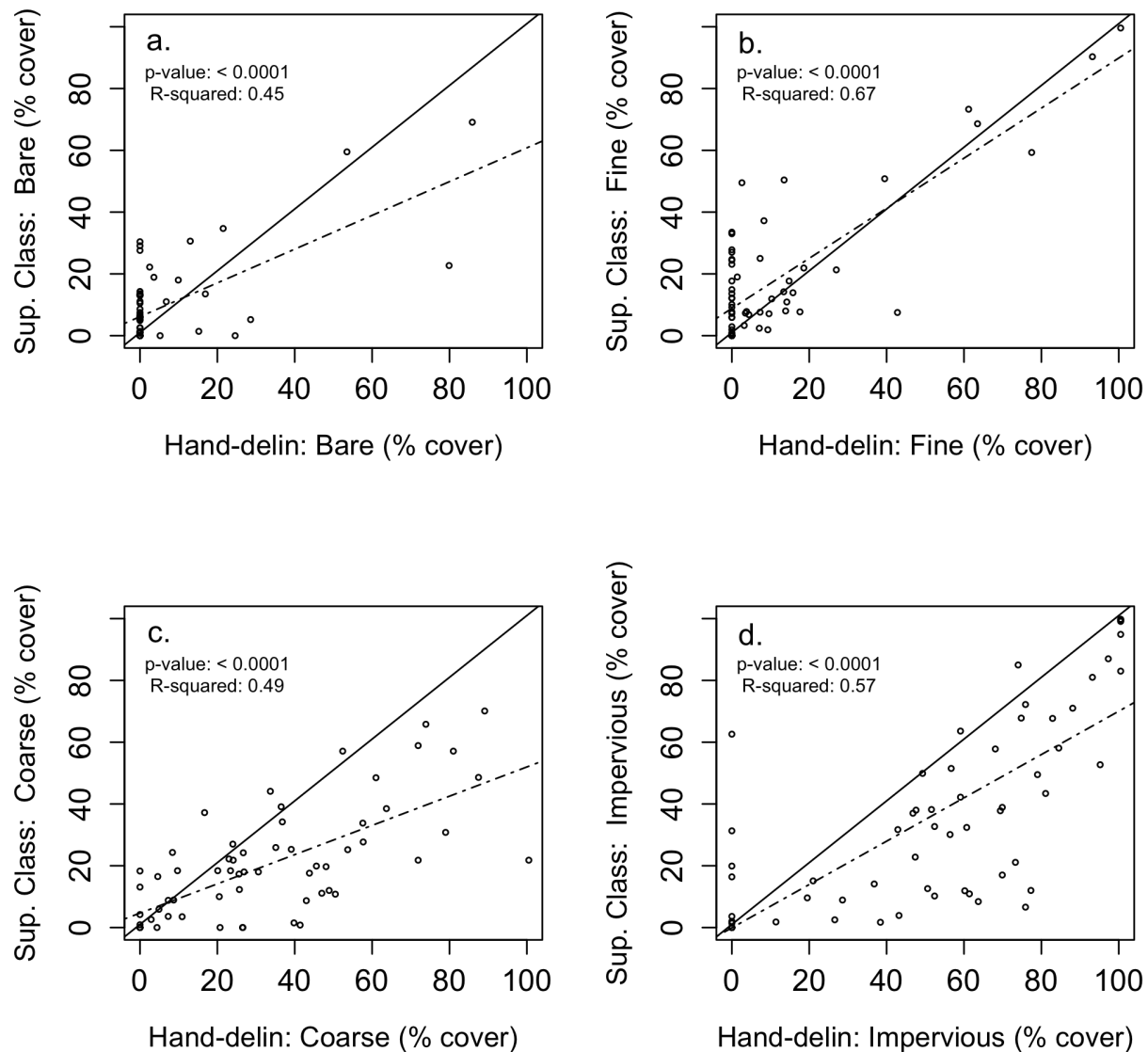


Figure 6. A comparison of percent cover for the 4 major cover types: (6a.) bare ground, (6b.) fine vegetation, (6c.) coarse vegetation, and (6d.) impervious surfaces in 63 plots as determined by hand-delineation in ArcMap and supervised classification in ERDAS. The solid line represents the 1:1 ratio, while the dotted line is the regression line. Regression equations are as follows:

(6a.) Sup. Class = $6.14 + 0.55 * \text{hand-delin}$; RMSE: 10.09; F-stat: 50.58; DF: 61

(6b.) Sup. Class = $8.83 + 0.81 * \text{hand-delin}$; RMSE: 13.04; F-stat: 120.3; DF: 61

(6c.) Sup. Class = $4.67 + 0.47 * \text{hand-delin}$; RMSE: 12.92; F-stat: 59.19; DF: 61

(6d.) Sup. Class = $-0.10 + 0.70 * \text{hand-delin}$; RMSE: 20.82; F-stat: 82.6; DF: 61

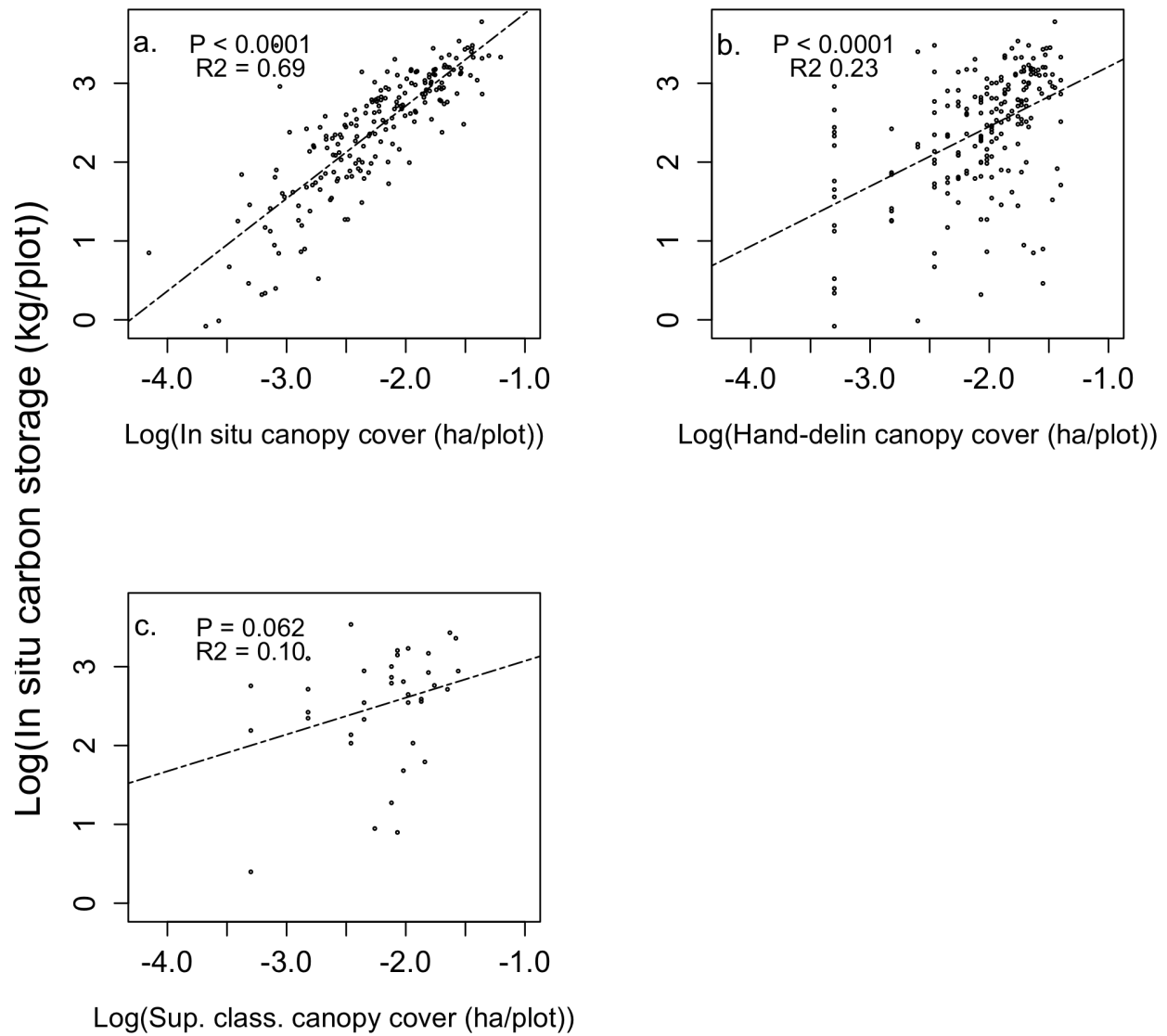


Figure 7. Carbon Storage (in kg) for each of the plots as compared to hectares of coarse vegetation determined using (7a) in situ ground collected data (for UFORE model), (7b) hand-delineation in ArcMap, and (7c) supervised classification in ERDAS. Regression equations:

- (7a.) $\text{Log (Carbon stored)} = 5.06 + 1.17 \cdot \text{Log (In situ)}$; RMSE: .43; F-stat: 437.4; DF: 198
 (7b.) $\text{Log (Carbon stored)} = 3.97 + 0.76 \cdot \text{Log (Hand-delin)}$; RMSE: .67; F-stat: 59.03; DF: 198
 (7c.) $\text{Log (Carbon stored)} = 3.33 + 0.35 \cdot \text{Log (Sup. class)}$; RMSE: .71; F-stat: 3.52; DF: 35

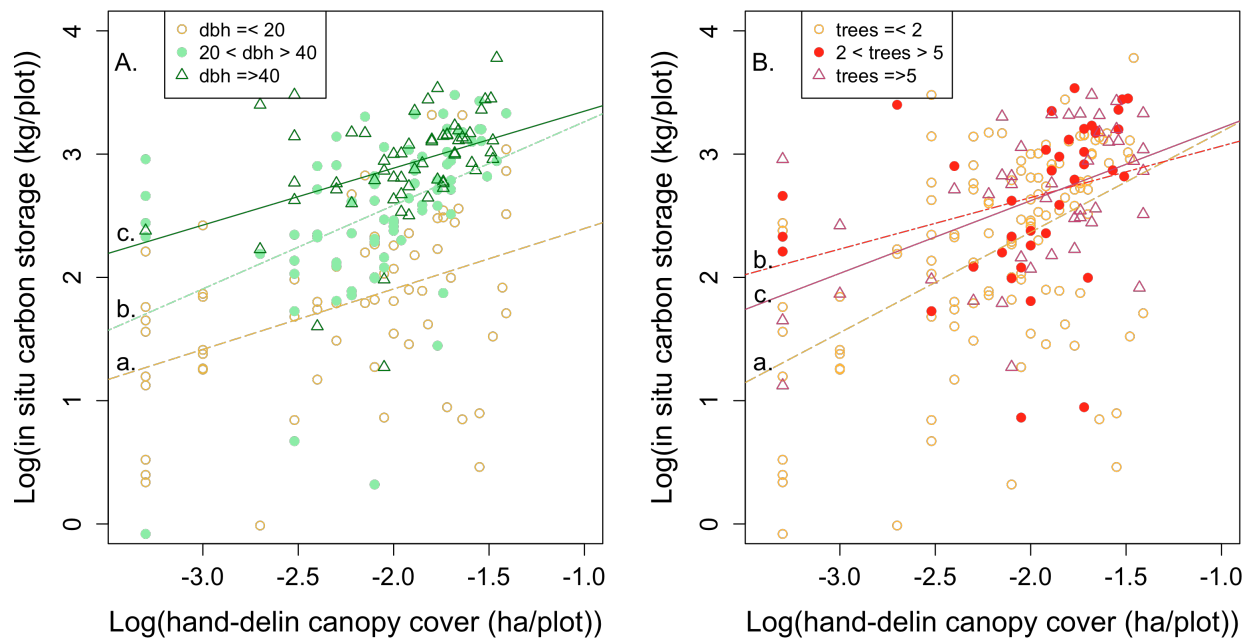


Figure 8. An analysis of covariance of the dbh categories (A.) and tree count classes per plot (B.) and their relationship to carbon storage and canopy cover predicted by hand-delineation was performed (Fig. 8). Regression equations for each dbh category (Fig. 8A) are as follows followed by the ANOVA statistics for this data:

- (a.) Tree diameter 20cm or less: $\text{Log (Carbon stored)} = 2.89 + 0.27 \cdot \text{Log (Hand-delin)}$;
 (b.) Tree diameter between 20cm and 40cm: $\text{Log (Carbon stored)} = 3.94 + 0.68 \cdot \text{Log (Hand-delin)}$;
 (c.) Tree diameter over 40cm: $\text{Log (Carbon stored)} = 3.81 + 0.46 \cdot \text{Log (Hand-delin)}$.

	Df	Sum Sq	Mean Sq	F-stat	p-value
dbh class	2	42.04	21.02	67.61	< 0.0001 ***
canopy cover	1	13.73	13.73	44.17	< 0.0001 ***
dbh class : canopy cover	2	0.38	0.19	0.61	0.54
Residuals	194	60.31	0.31	--	--

Regression equations for each tree count class (Fig. 8B) are as follows followed by the ANOVA statistics for this data:

- (a.) Tree count 2 or less: $\text{Log (Carbon stored)} = 4.00 + 0.82 \cdot \text{Log (Hand-delin)}$;
 (b.) Tree count between 2 and 5: $\text{Log (Carbon stored)} = 3.48 + 0.53 \cdot \text{Log (Hand-delin)}$;
 (c.) Tree count 5 or more: $\text{Log (Carbon stored)} = 3.80 + 0.50 \cdot \text{Log (Hand-delin)}$;

	Df	Sum Sq	Mean Sq	F-stat	p-value
tree count	2	8.16	4.08	9.36	0.00013 ***
canopy cover	1	22.77	22.77	52.27	< 0.0001 ***
dbh class : tree count	2	1.03	0.52	1.18	0.31
Residuals	194	84.51	0.44	--	--