COMPARING ALTERNATIVE TREE CANOPY COVER ESTIMATES DERIVED FROM DIGITAL AERIAL PHOTOGRAPHY AND FIELD-BASED ASSESSMENTS

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ABSTRACT

A spatially-explicit representation of live tree canopy cover, such as the National Land Cover Dataset (NLCD) percent tree canopy cover layer, is a valuable tool for many applications, such as defining forest land, delineating wildlife habitat, estimating carbon, and modeling fire risk and behavior. These layers are generated by predictive models wherein their accuracy is dependent on the quality of the data used to train the models. This analysis compares several different methods for estimating live tree canopy cover, including ocular, image segmentation, and dot count assessments from digital aerial photography, as well as field-based measurements.

INTRODUCTION

Tree canopy cover is defined as the proportion of the ground covered by a vertical projection of all the live tree canopies. A spatially-explicit representation of live tree canopy cover, such as the 2001 National Land Cover Dataset (NLCD) percent tree canopy cover layer, is valuable for many natural resource applications including: wildlife habitat models (Allen 1982; Kroll and Haufler 2006; Zarnetske and others 2007; Koy and others 2005), atmospheric carbon estimates (Nowak and Crane 2002), and fire applications such as FARSITE (Finney 1998). For strategic level forest inventories, such as the Forest Inventory and Analysis (FIA) program, percent canopy cover is also a very important measurement used for defining forest land.

The NLCD originated in 1992 from the Multi-Resolution Land Characteristics (MRLC) consortium. This multi-agency program was formed specifically to acquire Landsat data across the conterminous U.S. and to generate a 30-m pixel land cover map. In 2001, a second-generation land cover map was produced from more current Landsat imagery purchased by the MRLC. In addition, 30-m pixel maps of imperviousness and percent tree canopy cover were developed. A third generation map of land cover and second generation maps of imperviousness and percent tree canopy are currently in progress and slated for release in 2011.

The NLCD 2001 map of tree canopy cover was produced by modeling a response of tree canopy cover as a function of an extensive database of predictor layers, including 30-m resolution Landsat satellite imagery, digital elevation models, and other ancillary data that were meaningful to the model. Here, the tree canopy cover response (training) data were acquired using an automated classification of 1-m digital orthophoto quadrangles (DOQs), along with extensive post-processing hand editing. Models were developed by mapping zones, dividing the landscape into relatively homogenous regions with respect to landform, soil, vegetation, spectral reflectance, and characteristics of the imagery (Homer and others 2004).

A number of accuracy assessments of the NLCD 2001 tree canopy layer have been conducted, but their findings are inconsistent. For example, Homer and others (2004) reported mean absolute error averaging 10.8 percent based on cross-validation of per-pixel estimates from three different mapping zones. An evaluation of zonal estimates from the tree canopy cover layer compared to photo-interpreted estimates from Google Earth imagery indicated an underestimation of tree canopy cover by an average of 9.7 percent consistently across the conterminous United States (Nowak and Greenfield 2010). The Landscape Fire and Resource Management Planning Tools (LANDFIRE) project found the canopy cover values to be too high for use in existing fire models (Scott 2008). Questions of the accuracy of the NLCD tree canopy layer have led to a reassessment of the model's response data and potential alternative methods for the third generation. As the leading agency for national-level tree data, the United States Department of Agriculture, Forest Service, Forest Inventory and Analysis (FIA) program was identified as a logical candidate for leadership in the third generation product.

This paper compares several techniques for measuring live tree canopy cover for use as training data in predictive mapping efforts, such as the NLCD. Using data collected

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throughout the state of Nevada, the underlying objectives are to: (1) assess variability in ocular estimates of tree canopy cover from multiple observers; (2) compare photo-based methods and field-based methods for measuring canopy cover, an extension from Goeking and Liknes' 2009 analysis; and (3) compare photo-based measurements from 1-m resolution NAIP imagery to higher-resolution imagery acquired in Nevada.

METHODS

Analyses were conducted throughout the state of Nevada using a subset of field-sampled FIA plots from the 2004 and 2005 inventory years. A total of 150 plots, or approximately 45 percent, were randomly selected from the population of 328 FIA plots collected during these years that sampled at least one forested condition. Field sampling determined that 128 of the 150 plots had a woodland forest type, 8 plots had a timber forest type, and 12 plots were nonstocked (see http://socrates.lv-hrc.nevada.edu/fia/ab/issues/pending/glossary/Glossary_5_30_06.pdf for definitions). Two plots were removed from the analysis because of geographical inconsistencies. On each of the remaining 148 plots, three photo-based methods and two field-based methods were applied to construct alternative measures of live percent tree canopy cover. This process followed that of Goeking and Liknes (2009), where similar methods of remotely estimating crown cover were compared to field transect data across five states in the interior west: Arizona, Colorado, Idaho, Montana, and Utah, in an attempt to expand the utility of the pre-field operations for the national FIA program.

The photo-based methods involved interpreting one-acre circular plots, coinciding with the 148 FIA plot locations, using three methods applied to large scale aerial photographs: an ocular estimate; a dot count method; and an image segmentation method using Feature Analyst software. Ocular estimates were collected by three photo interpreters for each type of photography. Three interpreters were used to examine variability in the subjective measurements among interpreters based on findings from Goeking and Liknes (2009), where ocular estimates varied widely among three photo interpreters. A crown cover callibration key was used to assist in determining the crown coverage within the acre circle. Although the individual observer values were analyzed for variability, the average value of the three interpreters was used as the single ocular estimate for each plot to compare to other methods. The dot count method involved photo-interpreting 50 randomly distributed points within the acre circle, with a restriction of having a minimum distance of 2 meters between points. Percent cover was calculated by counting the number of points that fell on live tree crowns and dividing by the total number

of points. The image segmentation procedure entailed digitizing a few live tree crowns, or polygons, within the acre circle and using these polygons as training data in the Feature Analyst extension to ArcMap. Feature Analyst® is an automated feature extraction software that uses inductive learning algorithms and techniques to model object recognition (Opitz and Blundell 2008). Training information is assigned by the user and the software automatically generates a model, correlating the known data to target objects, and applies the model to the entire area of interest.

These three photo-based methods were applied to two different types of large scale aerial photography to help understand the effect of resolution on estimating canopy cover. The types of photography included: 1.0-meter (39-inch) resolution, National Agriculture Imagery Program (NAIP) natural color, orthorectified photography for year 2006 that is freely available from the USDA Forest Service Image Server extension of ArcMap (http://fsweb.rsac.fs.fed.us/imageserver/image_server_home.html); and 0.15-meter (6-inch) resolution, natural color, georeferenced, direct-to-digital or scanned-digital photography that was acquired by contract for a photo-based inventory pilot study throughout the state of Nevada in years 2004 and 2005 (NPIP; Frescino and others 2009).

The field-based methods included a line-transect method and a modeled method based on field measurements obtained from FIA's extensive database of field measurements. For the field-transect estimates, live tree crown cover was measured using sixteen 25-ft transects, totaling 400 feet, with intercepts of all live trees 1.0 inch and greater recorded at one-foot intervals (O'Brien 1989). These data were aggregated to the plot level. For the field-model estimates, predictive models of tree canopy cover were previously generated from field measurements of tree species and diameter using over 12,000 FIA plots across the Interior West (Toney and others 2009). These models were applied to the plots in this study using the FIA field plot measurements as parameters in the models.

The three photo-based methods (ocular ("oc"), dot count ("dot"), and Feature Analyst ("fa")) applied to two scales of aerial photography ("NAIP" and "NPIP") plus the two field based methods (field transects ("Field") and models developed by Chris Toney and others 2009 ("CTmodel")) gave a total of 8 different estimates of tree canopy cover over the 148 plots, summarized in Table 1. Analyses comparing these different estimates included exploratory displays of data distributions using boxplots, histograms, and scatterplots. Simple linear regression analyses were conducted using combinations of the eight canopy estimates to describe the relationship between the different methods. The regression line slopes that were visually closer to the 1:1 line indicated the canopy measures were more closely

related. The differences in the slope and intercept values were examined for understanding potential bias across the range of percent canopy values. The Pearson correlation coefficient was also shown to measure the association between variables.

RESULTS

VARIABILITY IN OCULAR ESTIMATES

Figures 1 and 2 show the results of the ocular estimates from each observer using both the NAIP photography and the NPIP photography. Similar to findings from Goeking and Liknes (2009), the ocular estimates are highly variable among interpreters with an overall mean difference of 22 percent for estimates using NAIP photography and 16 percent for estimates using NPIP photography (Figure 1). Figure 2 illustrates a number of results. First, scatterplots and regression lines for each pair of ocular estimates are shown in the lower diagonal half of the figure, where the method associated with each axis is the label in the diagonal box corresponding to the row and column of interest. For example, the scatterplot seen in row 4, column 2 of Figure 2 is a graph of observations obtained from observer #2 using NAIP photography in the x-axis, versus observer #1 using NPIP photography in the y-axis. Similarly, the upper diagonal half of the graphic displays the correlations between the estimation pair labeled in the diagonal box corresponding to the row and column of interest. Scatterplots of observers using NAIP photography (seen in the (row, column) pairs of (2,1), (3,1), and (3,2)) reveal regression slopes are closer to 1 than those from observers using NPIP photography ((5,4), (6,4), and (6,5)). In general, estimates using the NAIP photography are higher and more variable than the estimates using NPIP photography (Figures 1 and 2) and estimates from observer #2 are higher than the other observers using both photography sources. We used the mean estimate by plot from the three observers for comparison with the other methods for the rest of the analyses.

ESTIMATION METHOD COMPARISON

Figures 3 and 4 show results comparing all methods using both the NAIP and NPIP photography, including the mean estimates from the ocular method. The modeled estimates (CTmodel) are highly correlated (0.84) with the field transect estimates (Field) but, in general, the modeled estimates are slightly lower than the field transect estimates, with an overall mean difference of 4 percent (Figure 3). These differences are more emphasized in the higher canopy ranges (Figure 4).

All other estimation methods using both NAIP and NPIP photography tend to be lower than the field transect method, except the dot count method using NPIP, having an overall

mean difference of 3 percent; and the mean ocular estimates using NAIP photography, having an overall mean difference of 9 percent. Similar results are seen when comparing the modeled versus field estimates (Figures 3 and 4). The estimation method most highly correlated to the field transect method is the mean ocular estimate using NPIP photography followed by the dot count method using NPIP photography. Again, similar results are found by comparing the modeled and field estimates (Figure 4).

PHOTOGRAPHY COMPARISON

When looking at the differences in estimation methods using only NAIP photography, the mean ocular estimates tend to be higher overall than all the other methods, with an overall mean of 39 percent (Figure 3). Regardless, the regression slope is the closest to 1 compared to the other methods when related to the field transect method. The Feature Analyst estimates are generally higher than the dot count method, although the dot count method has no estimates greater than 50. The correlation is highest between the mean ocular method and the dot count method (Figure 4).

The estimates using NPIP photography show much different results than the estimates using NAIP photography. In general, the correlations are higher, the regression slopes are closer to 1, and the regression intercepts are smaller. The highest correlation (0.84) is between the ocular method and the dot count method, with the ocular method having slightly lower estimates. The correlation is also high between the ocular method and the Feature Analyst method (0.81) with a regression slope closer to 1.0, followed by the dot count and the Feature Analyst method having correlation of 0.80, although the Feature Analyst estimates are slightly lower overall (Figure 4).

When comparing the different types of photography by estimation method, the mean ocular estimate shows the highest correlation of 0.86, followed by the Feature Analyst method at 0.72, and the dot count method at 0.68. Conversely, the dot count method has the regression slope closest to the 1:1 line. For both the ocular method and the Feature Analyst method, the NAIP estimates are quite a bit higher than the estimates using NPIP photography, especially at the higher end, where as the dot count method shows the NAIP estimates slightly lower than the NPIP estimates (Figure 4). The average overall mean for the NAIP estimates is 29 percent compared to the average overall mean of the NPIP at 28 percent (Figure 3).

DISCUSSION

OCULAR COMPARISON

The first objective of this paper was to assess consistency between photo-interpreters' estimates of tree canopy cover using the ocular method. Ocular estimates, although the

fastest of the methods analyzed, may be quite biased and/ or inconsistent depending on the experience level of the observers. In this study, the ocular estimates were shown to be highly variable between observers, with the estimates using NAIP photography almost always higher when compared to estimates from NPIP photography, especially at higher canopy cover values. Possible reasons for this are discussed under the third objective below. The correlations were slightly higher and the regression slopes closer to 1.0 for the NAIP estimates compared to the NPIP estimates, suggesting a tighter relationship between NAIP observers, but the higher intercepts suggest more bias between these same observers (Figure 2).

Similar results of bias can be seen when comparing the mean ocular estimates with estimates from the other methods. The ocular estimates using NAIP photography tended to be consistently higher than the other methods. The NPIP estimates, on the other hand, had lower estimates and higher correlations between estimates from the other methods, with regression slopes, in general, closer to 1.0 (Figure 4).

METHOD COMPARISON

The second objective of the paper was to compare photo-based methods and field-based methods for measuring canopy cover. For other comparison studies of canopy cover, the field-based method is often used as a control or a source of truth (Goeking and Liknes 2009; Paletto and Tosi 2009; O'Brien 1989). We found all estimation methods using both NAIP and NPIP photography to be lower than the field-transect method as well as the field-modeled method, except the dot count method using NPIP and the ocular method using NAIP, which tended to have slightly higher estimates (Figure 4). Perhaps this reflects the fact that small trees (down to 1.0 inches in diameter) are included in the field-based methods, but small trees are difficult to detect in the photos, especially in NAIP. Alternatively, there is a potential bias in the field-based methods.

For the NAIP estimates, the ocular method tended to be higher than the other methods and the dot count estimates were on the low side with no estimates greater than 50. The NPIP estimates showed higher correlations compared to all methods, indicating greater consistency between methods (Figure 4). The resolution and quality of the photography play a big factor in these results and are discussed in the following section.

PHOTOGRAPHY COMPARISON

The third objective of the paper was to compare photo-based measurements from 1-m resolution NAIP imagery to a higher resolution imagery acquired for NPIP. Using different resolution photography added interesting value to the analysis with the higher resolution photography from

NPIP representing a potential greater source of truth than the lower resolution NAIP photography. Here, we found the NAIP to estimate higher cover relative to the estimates from the NPIP photography.

In general, the lower resolution, NAIP photography has more shadows, especially when the total canopy cover is high or the terrain is steep. It is harder to distinguish tree versus shrub lifeform characteristics of a vegetative object, as well as to discriminate seedlings and saplings from shrub lifeforms. It is also harder to see regeneration of tree species in areas supporting larger trees or areas that have no recognizable trees present. These characteristics lead to overestimations and errors when estimating canopy cover.

Figure 5 shows an example of a plot where the lower resolution photography led to a large discrepancy in the cover estimate. For this example plot, one interpreter said there was zero percent cover using the dot count method and three percent cover using the Feature Analyst method, where another observer estimated 96 percent using the dot count method and 10 percent using the Feature Analyst method. The plot consists of dense aspen (*Populus tremuloides*) cover, and this species may be confused with shrubs at lower resolutions. In general, the resolution and quality of the photo are more influential to the photo interpreter than the method itself. Here, the Feature Analyst method lends itself better to an automated process that is less subjective than the interpreter's eye. Figure 6 presents another example of differences in photo resolution which affect percent canopy calls. For this plot, one observer said there was 0 percent cover using the dot count method and another observer said 12 percent for the same plot. The plot has a large percentage of dead trees that were not noticeable on the lower resolution image.

CONCLUSION

These analyses illustrate that consistent and accurate measurement of tree canopy cover is challenging. Photo-interpreter experience level, method of canopy estimation, and scale of photography all play interrelated roles in determining the quality and consistency of tree canopy estimates over training or sample plots. Certainly, there are many advantages to using NAIP photography for a national project like the NLCD 2011 tree canopy cover map: it is free, it is relatively high resolution, it has extensive continuous coverage, it is updated frequently, and photo quality continues to improve through time. It is especially effective when used through the ArcGIS Image Server extension (http://www.esri.com/software/arcgis/serverimage/index.html), where it is easy to move from plot to plot. However, more research is needed to understand the limitations in the use of this photography, to develop

methods to improve training methods to ensure consistency between interpreters, and to explore the potential of automated classification algorithms to improve objectivity in interpretations.

ACKNOWLEDGMENTS

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Table 1—Variable short names by estimation method type

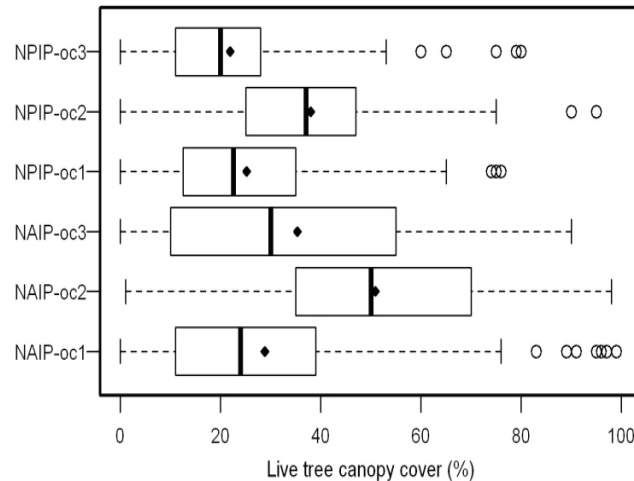| Method Type	Short Name	Description
Field-based	Field	IW-FIA field transects
	CTmodel	Toney and others (2009) field-based stem-map models
Ocular	NAIP-oc	Mean ocular estimate using NAIP photography
	NPIP-oc	Mean ocular estimate using NPIP photography
Dot count	NAIP-dot	Dot count estimate using NAIP photography
	NPIP-dot	Dot count estimate using NPIP photography
Feature Analyst	NAIP-fa	Feature Analyst estimate using NAIP photography
	NPIP-fa	Feature Analyst estimate using NPIP photography

Figure 1—Boxplots of ocular estimates of percent live tree canopy cover using both NAIP and NPIP photography. The points represent the overall mean value. See Table 1 for short name descriptions. Numbers in the name correspond to the three different observers.
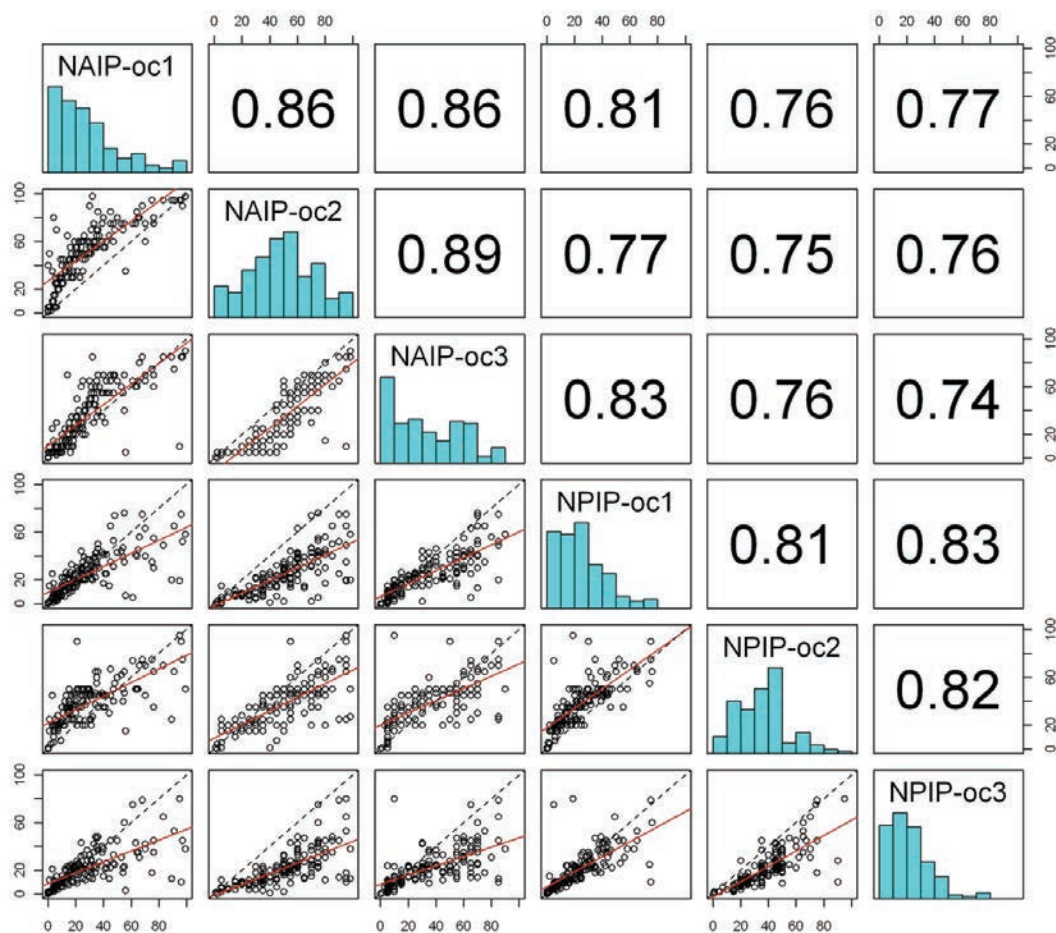

Figure 2—Pairwise comparisons of ocular estimates of percent live tree canopy cover using both NAIP and NPIP photography. See Table 1 for short name descriptions. The diagonal boxes display histogram distributions of each of the eight estimates. The left side shows scatterplot distributions for pairs of estimates with percent canopy cover on each axis. For each scatterplot, the dotted black line represents the 1:1 line and the red line is a linear regression line. The right side displays the Pearson correlation coefficient for each pair.
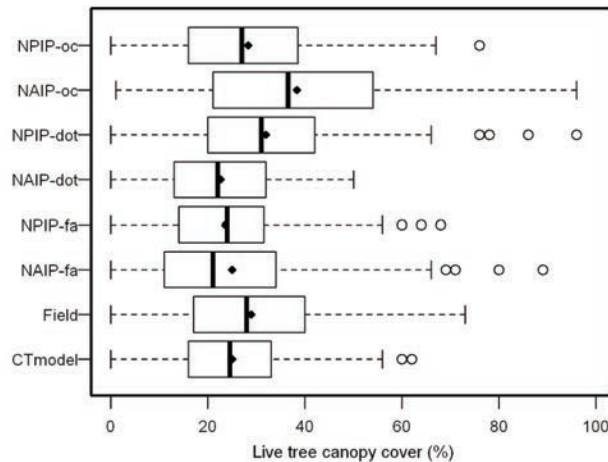
Figure 3—Boxplots of all estimation methods of percent live tree canopy cover using both NAIP and NPIP photography. The points represent the overall mean value. See Table 1 for short name descriptions.
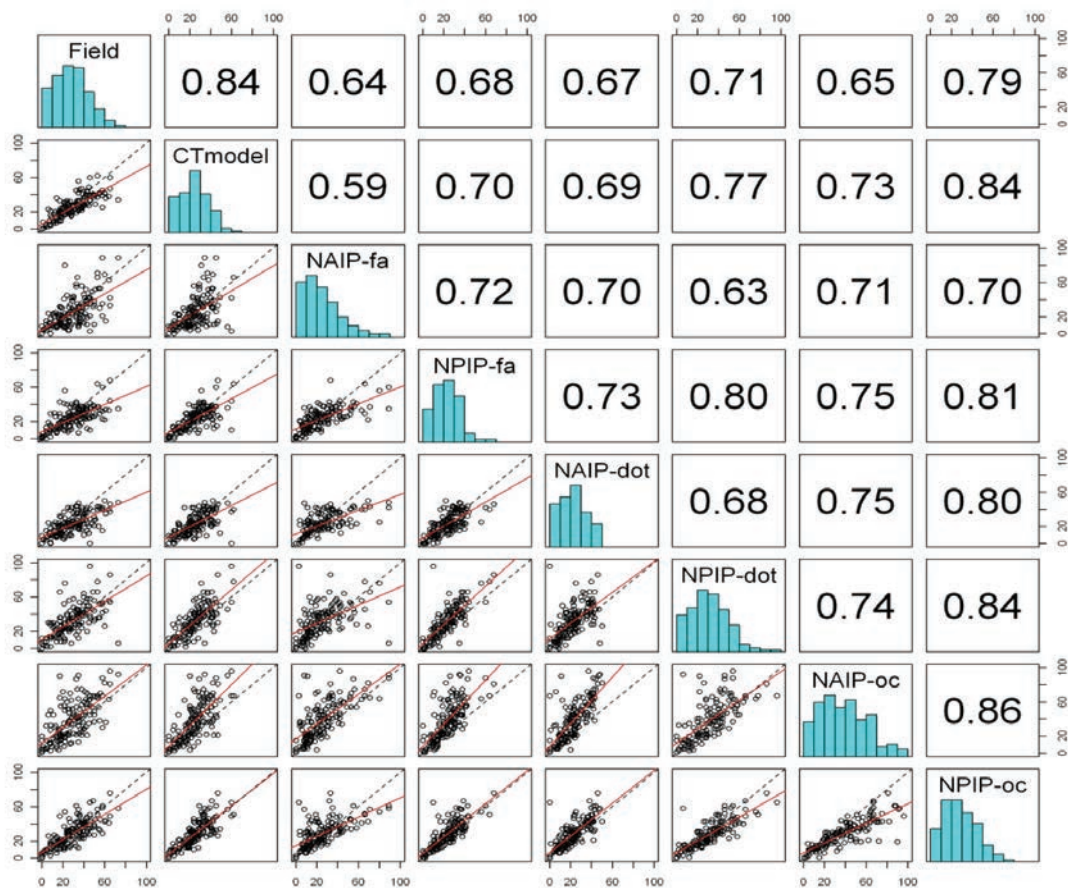

Figure 4—Pairwise comparisons of stimates from all methods including the mean ocular estimates of percent live tree canopy cover using both NAIP and NPIP photography. See Table 1 for shortname descriptions. The diagonal boxes display histogram distributions of each estimate. The left side shows scatterplot distributions between all of the eight estimates with percent canopy cover on each axis. For each scatterplot, the dotted black line represents the 1:1 line and the red line is a linear regression line. The right side displays the Pearson correlation coefficient for each pair.
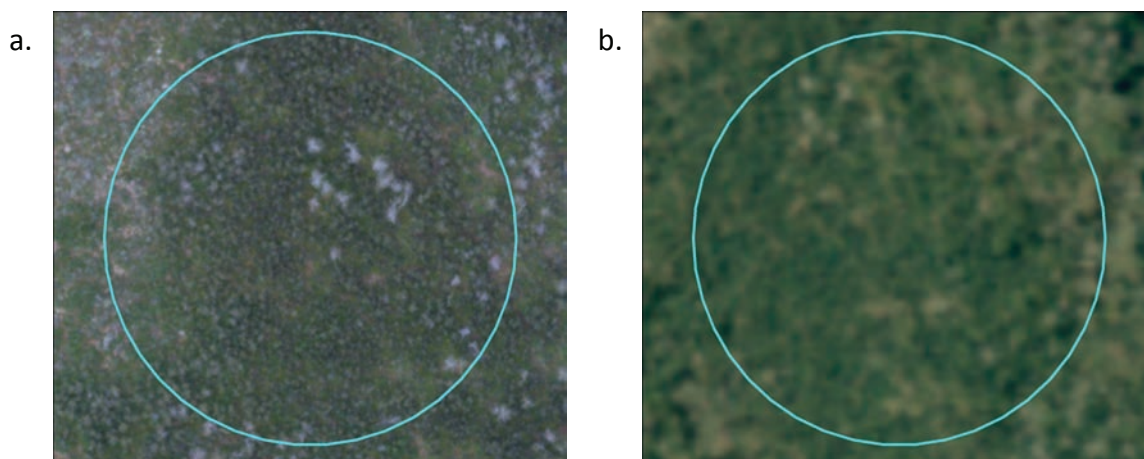
a.

b.

Figure 5—Plot 07-1352. a. NPIP photography with 1-ac plot boundary overlay. b. NAIP photography with 1-ac plot boundary overlay. The plot is covered with aspen (*Populus tremuloides*) seedlings.
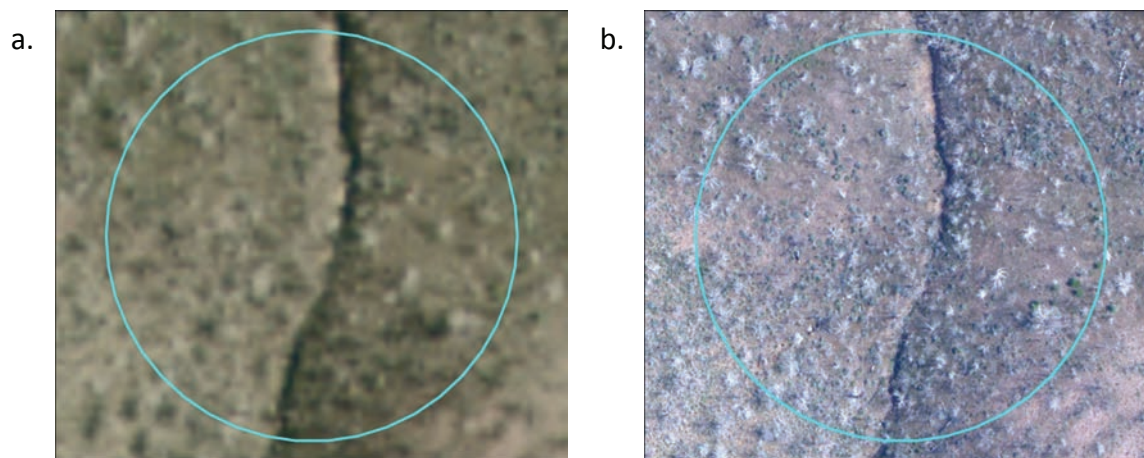
a.

b.

Figure 6—Plot 17-153. a. NPIP photography with 1-ac plot boundary overlay. b. NAIP photography with 1-ac plot boundary overlay. The plot is covered with dead juniper (*Juniperus* spp.).