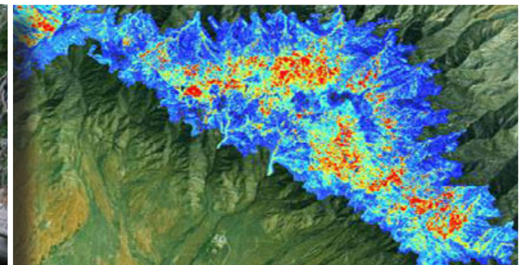
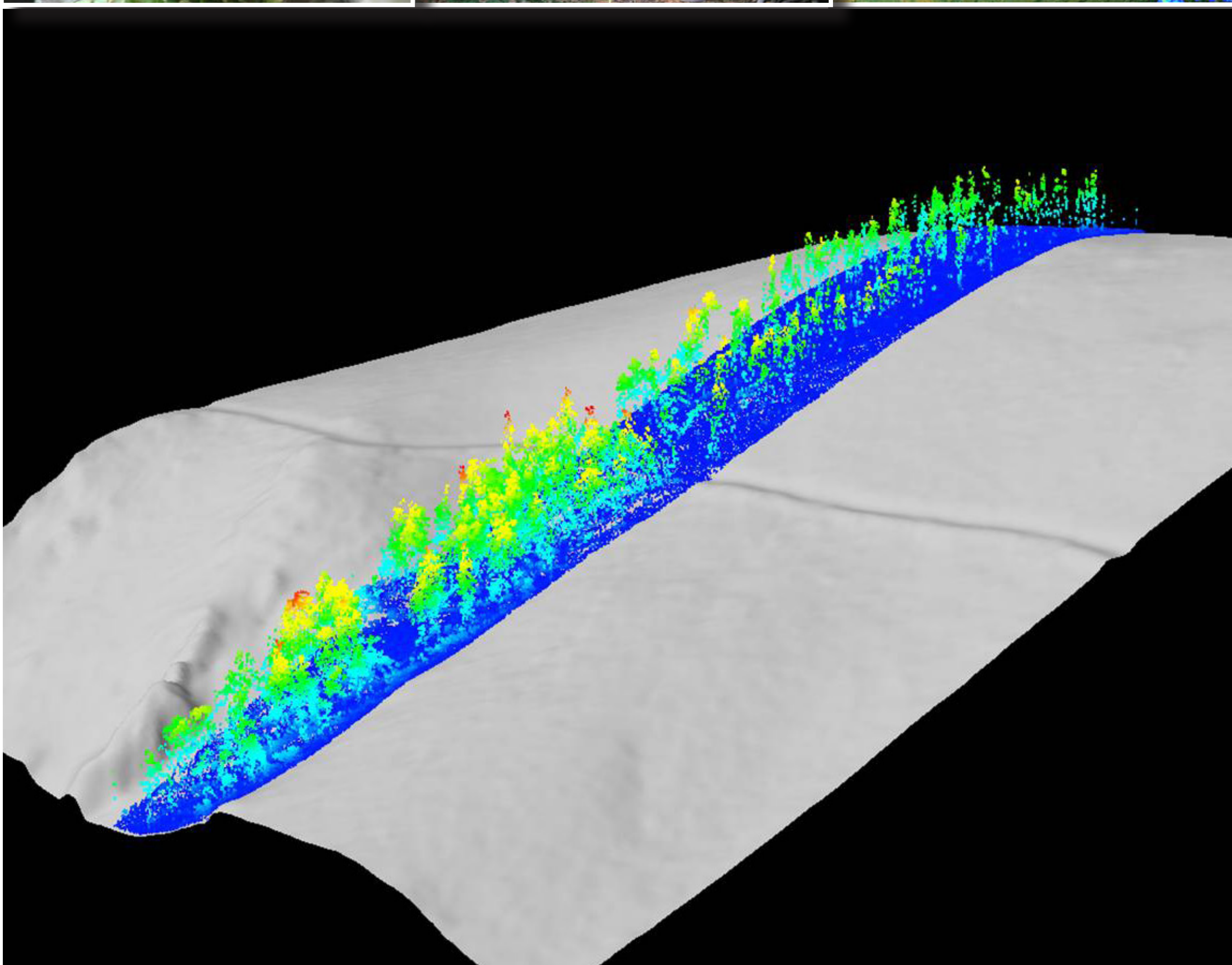
Mapping Vegetation Structure in the Pinaleño Mountains Using Lidar

Phase 3: Forest Inventory Modeling

March 2012

RSAC-10007-RPT1





United States Department of Agriculture

Forest Service

Geospatial Management Office

RSAC Remote Sensing Applications Center

Abstract

Understanding forest structure and how it is affected by management practices and natural events is a critical part of managing natural resources within the Forest Service, U.S. Department of Agriculture. The Pinaleño Mountains of southeastern Arizona represent a Madrean sky island ecosystem and the last remaining habitat for the Mt. Graham red squirrel. This unique ecosystem is threatened by a general shift in species composition and forest structure as well as by high severity fires and insect infestations. Due to these factors, the Coronado National Forest has implemented a forest restoration effort using lidar (light detection and ranging) as a tool for identifying habitat and cataloging forest inventory variables at a landscape level. Forest inventory parameters were modeled by building regression models between forest inventory parameters measured on field plots and their associated lidar canopy metrics. Inventory parameters that could be successfully modeled with R^2 values above 0.6 were calculated for the full extent of the lidar data. This created landscape GIS layers for inventory parameters such as biomass, basal area, Lorey's mean height, and timber volume. The resulting GIS inventory layers were qualitatively validated with local experts and conformed well to trends known to occur on the landscape. The layers are currently being used for additional analysis, project development, and monitoring.

Key Words

lidar, forest inventory modeling, biomass, fusion, fire fuel parameters, Pinaleño Mountains, Mount Graham red squirrel

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Mitchell, B.; Walterman, M.; Mellin, T.; Wilcox, C.; Lynch, A.M.; Anhold, J.; Falk, D.A.; Koprowski, J.; Laes, D.; Evans, D.; Fisk, H. 2012. Mapping vegetation structure in the Pinaleño Mountains using lidar—phase 3: forest inventory modeling. RSAC-10007-RPT1. Salt Lake City, UT: U.S. Department of Agriculture, Forest Service, Remote Sensing Applications Center. 17 p.

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Overview

The Pinaleño Mountains in southeastern Arizona contain the southernmost expanse of spruce-fir forest type in North America. This ecosystem is also the last remaining habitat for the Mount Graham red squirrel *(Tamiasciurus hudsonicus grahamenis)*, a federally listed endangered species. This unique ecosystem is being threatened due to a general shift in species composition and forest structure of the mixed-conifer forest type and a series of large high-severity fires and insect infestations. The Coronado National Forest has begun a forest restoration effort attempting to balance fuels reduction and habitat conservation.

Identifying habitat and cataloging forest inventory variables are two key components to implementing the forest restoration effort. Lidar (light detection and ranging) was identified as an efficient tool for filling the data collection needs, since field data collection is restricted to a limited area due to rugged terrain and safety concerns.

During Phases 1 and 2 of this project, lidar acquisition specifications were determined and the lidar data were collected. The resulting lidar data were assessed for quality, and first order products (such as canopy height and percent canopy cover) were created. In addition to the lidar data collection, eighty .05 hectare forest inventory plots were established during the 2009 field season (Laes and others 2008, 2009).

Objective

The objective for Phase 3 of the Pinaleño lidar project was to model forest inventory parameters at the landscape level. To meet this objective we built regression models between forest inventory parameters measured on field plots and their associated lidar canopy (plot) metrics. The resulting models were applied to the lidar data resulting in continuous GIS raster layers of the forest inventory parameters across the study area. These layers can be used for analysis, project development, and monitoring.

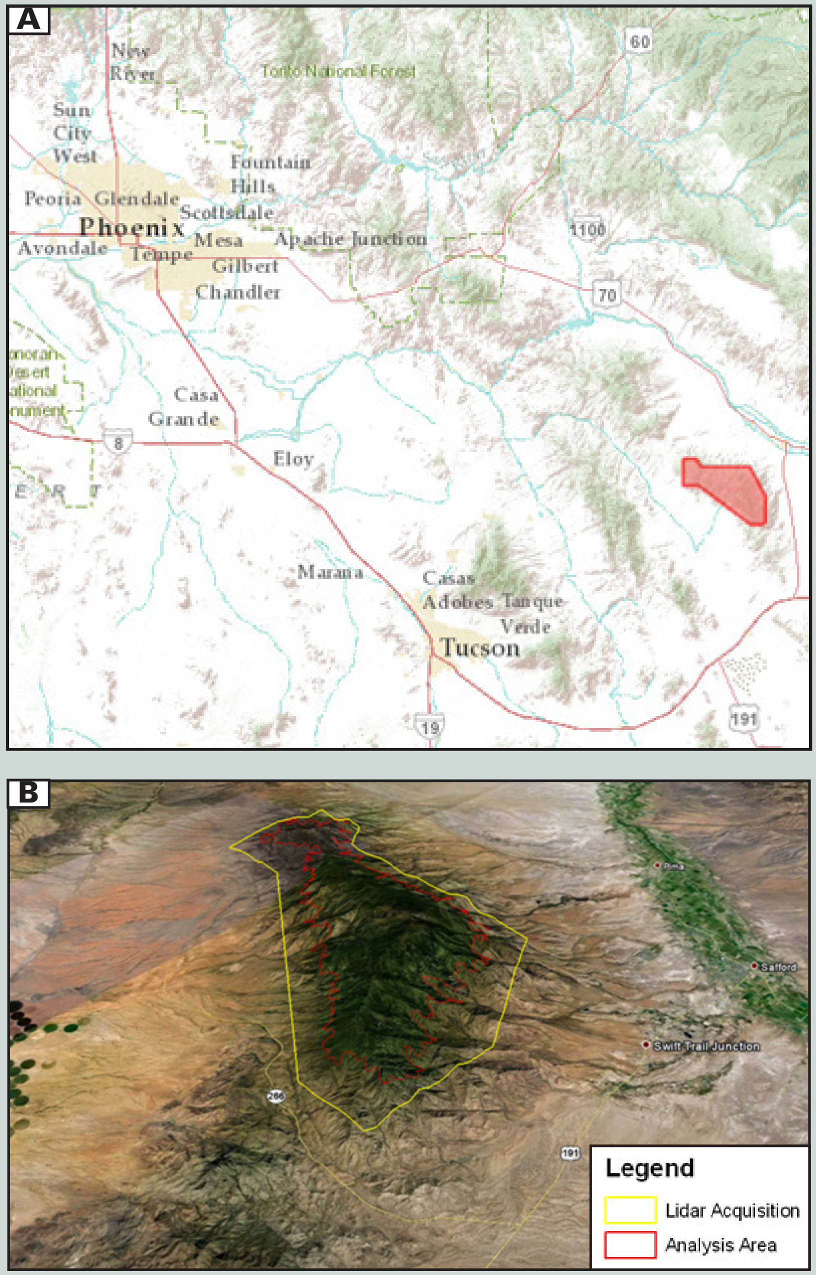

Figure 1—The map *A)* represents the project area in the Pinaleño Moutains in southeastern Arizona; in *B)* the lidar acquisition and inventory modeling area are represented in a 3-D virtual globe environment.

Study Area

The project study area covers approximately 85,500 acres (34,600 hectares) in the mixed-conifer zone above 7,000 feet (2,133 meters) within the Pinaleño Mountains, located southwest of Safford, Arizona (figure 1). The Pinaleño range is an isolated Madrean sky island which contains the southernmost expanse of a spruce-fir forest in North America and one of the most southern extensive mixed-conifer forests. The high-elevation ecosystems have been isolated for the last 11,000 years and support the only habitat for the Mount Graham red squirrel, a federally listed endangered species. The range has experienced similar post–

Euro-American settlement changes in forest composition and structure as other southwestern mixed-conifer forests. The pre-settlement and pre-fire-suppression forests were more open with less forest-floor fuel, favoring more frequent, but less-intense, fires (Covington and Moore 1994). Recent changes have led to several large and uncharacteristically severe wildfires and a series of devastating insect outbreaks. Particularly hard hit have been the Engelmann spruce and Corkbark fir trees, with mortality estimates of more than 80 percent. This was the primary habitat for the Mount Graham red squirrel. The remaining red squirrel habitat is primarily in the lower elevation transitional zone between the spruce-fir and mixed conifer forest, sometimes referred to as wet mixed-conifer forest (Wood and others 2007).

Data

The data required for this phase of the project included fully prepared airborne lidar data and tightly associated field plot data. The two datasets were collected on similar dates and the field data were collected specifically for use with high-resolution lidar data.

Lidar Data

Approximately 85,000 acres of high pulse-density lidar data were acquired between September 22 and 27, 2008. The dataset meets the minimum recommended specifications for forest inventory modeling[1] with a nominal pulse density of greater than or equal to 3 pulses per square meter, greater than 50 percent side lap, and a scan angle within 14 degrees of nadir. The full lidar data collection specifications and quality assessment can be found in the Phase 2 report (Laes and others 2009).

Field Data

Field data were collected with the goal of addressing data needs of not only the lidar modeling but also in support of the Pinaleño demography study being conducted by the University of Arizona and the Rocky Mountain Research Station. Due to multiple objectives a 500 meter grid was chosen as the sample design[2].

Eighty field plots were collected in the summer of 2009 based on the 500 meter grid. Plots were 1/20th hectare (.05 hectare) fixed plots with a 12.62 meter radius. Only 80 of the 200 potential plot locations were sampled due to extreme terrain (the extreme terrain being one of the primary reasons for the lidar project). All plots were permanent and trees tagged.

Field Prep Work

Plot location maps for all plots being measured were created to assist the field crew. A color infrared aerial photo was used as a backdrop with the plots marked by a circle in the predetermined location (figure 2). Lidar subsets were also clipped from the data (based on location and radius) which provided the field crew an additional 3-D visualization of the plot (figure 2). Using map products and predetermined plot coordinates, the field crew navigated to the potential plot location using a GPS and recorded the actual location of the plot, which became the official plot location/coordinate.

Plot Protocol

All trees (live or dead) greater than or equal to 20 centimeters in diameter and all coarse woody debris (downed logs) greater than or equal to 20 centimeters were measured on each plot. To assess seedlings and regeneration three equal-sized wedge shaped 1/60th hectare subplots were created and one was chosen at random to measure all trees (live or dead) less than 20 centimeters in diameter and coarse woody debris less than 20 centimeters and greater than 5 centimeters in diameter. Based on the subplot boundaries, three transects were conducted that included Brown’s Fuel transects, understory transects (shrub, forbs and grasses), and regeneration transects. Three photo points were also collected at each plot location.

GPS Data Collection

When using lidar and field data to model forest inventory parameters it is imperative that sub-meter plot location accuracy is obtained[3]. A relatively high level of positional accuracy is needed to minimize error and maximize correlation between field and lidar data in our modeling methodology.

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1 Discrete lidar data continues to prove useful in many natural resource applications. However, not all lidar datasets are equal. Probably the most important single characteristic that determines the appropriate use of a lidar dataset is the mean number of pulses/m^2. For example, relatively low pulse-density data (0.5 to 1 pulse/m^2) is typically only useful for bare earth or terrain models. Medium pulse-density (1-3 pulses/m^2) data has the additional potential of providing canopy height models. Forest structure information, however, requires relatively high pulse-density data (typically >= 3 pulses/m^2).

2 If the field data was exclusively collected for lidar modeling a stratified random sampling design based on initial lidar derivatives has been shown to be the most effective sampling design for this type of lidar modeling (Hawbaker and others 2009).

3 To ensure sub-meter plot location accuracy a Trimble GeoXH with a Zephyr antenna was used to collect plot center locations. In addition Trimble H-Star technology was used for data collection, post processing and differential correction to ensure sub-meter accuracy.

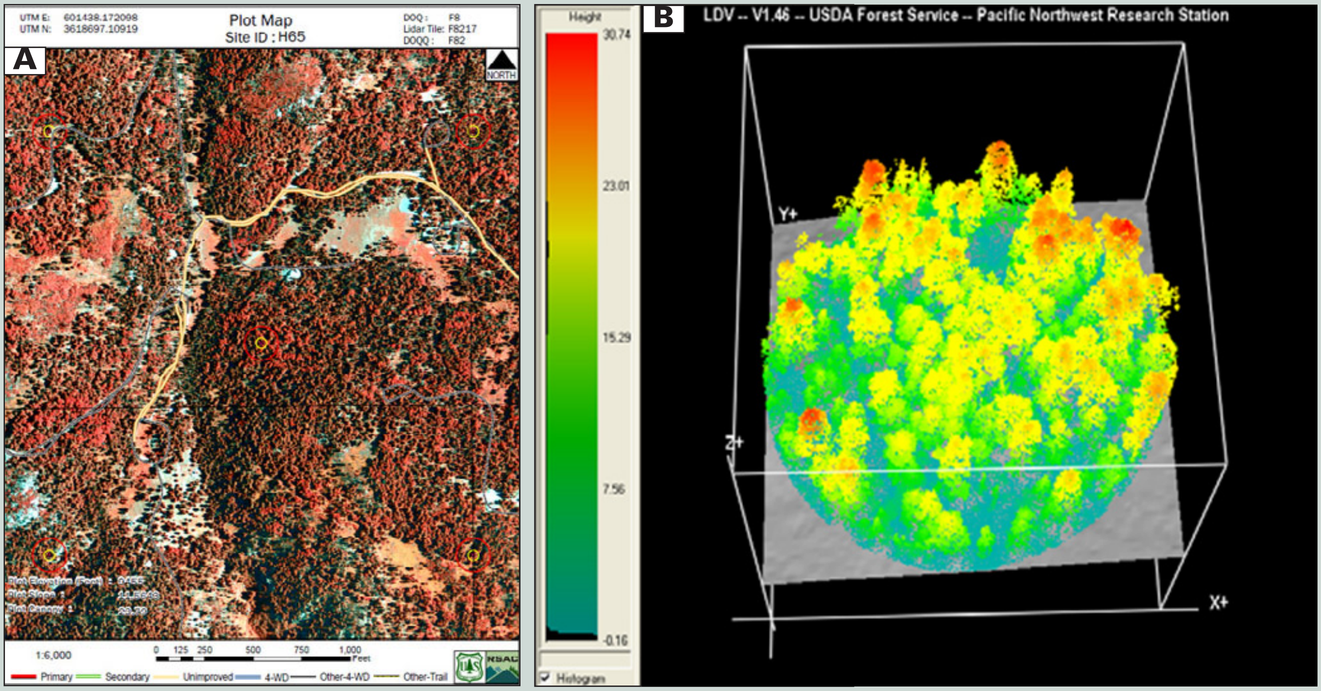

Figure 2—Graphic *A)* is an example of a MapBook page that was created for each plot to aid the field crew in locating the correct plot location. Image *B)* is the 3-D lidar point cloud visualization of the plot also provided to the field crew for each potential plot location.

Data Processing—Preparing the Forest Plot and Corresponding Lidar Variables for Modeling

Collected lidar and field data were then processed and prepared for modeling. The goal was to process the field inventory and lidar data to ensure they corresponded as much as possible. The evaluation process includes summarizing the field inventory data to the plot level (e.g., basal area, stand density index, average tree height, trees per hectare, and quadratic mean diameter are examples of plot data versus tree-level data) and creating corresponding metrics from the lidar data. The end product of this step was a single table containing a record for each of the field plots. Each plot record included the field plot information and the corresponding lidar metrics. The subsequent two sections provide descriptions of the processing performed on each of these datasets.

Generating Lidar Predictor Variables at the Plot Scale

Using the XY coordinates and the plot radius for each field plot, we subset the corresponding lidar returns. During the clipping process the data were normalized to the ground surface so that the returns were expressed in terms of heights above the ground instead of elevation above sea level. After subsetting the lidar plot data, a set of 47 lidar plot metrics (variables) were calculated for each of the plots using FUSION software (McGaughey 2012).

Creating Lidar Subsets

The ClipData FUSION[4] command was used to subset the lidar data. Four input data sources are necessary to complete the processing: plot coordinates, plot radius, lidar-generated bare earth surface covering the project area, and the raw lidar data tiles (.las files). The process produces a separate output lidar data file for each plot.

Creating Lidar Plot Metrics

Lidar metrics were calculated for each plot's point cloud using FUSION's CloudMetrics command. The resulting metrics became the predictor variables for the inventory models. Each record in the output table has a set of variables (fields) that together describe the vertical distribution of the lidar points (representative of the biomass) within the plot (table 1).

4 For a more detailed explanation and technical instructions for using both the CloudMetrics and ClipData FUSION commands please refer to the "FUSION Tutorial" (http://fsweb.geotraining.fs.fed.us/www/index.php?lessons_ID=971) hosted on the FSWeb within the USDA Forest Service Geospatial Training and Awareness Website.

Table 1—Groups of lidar plot and grid metrics generated by CloudMetrics and GridMetrics (McGaughey 2011)

Category	Output Variable
Descriptive	Total number of returns Count of returns by return number Height statistics: • Minimum • Maximum • Mean • Median (output as 50th percentile) • Mode • Standard deviation • Variance • Coefficient of variation • Interquartile distance • Skewness • Kurtosis • AAD (Average Absolute Deviation) L-moments (L1, L2, L3, L4) L-moment skewness L-moment kurtosis
Height percentile values	(1st, 5th, 10th , 20th, 25th, 30th, 40th, 50th, 60th, 70th, 75th, 80th, 90th, 95th, 99th percentiles)
Canopy related metrics (calculated when the "/above:#" switch is used)	Percentage of first returns above a specified height (canopy cover estimate) Percentage of first returns above the mean height/elevation Percentage of first returns above the mode height/elevation Percentage of all returns above a specified height Percentage of all returns above the mean height/elevation Percentage of all returns above the mode height/elevation Number of returns above a specified height / total first returns * 100 Number of returns above the mean height / total first returns * 100 Number of returns above the mode height / total first returns * 100

Generating Lidar Predictor Variables at the Landscape Scale

The lidar metrics (table 1) were generated for the entire project area using FUSION's GridMetrics[5] command. Previously CloudMetrics was used to generate output metrics from the lidar cloud within the boundaries of the 3-D plot, but in this process we used GridMetrics to generate the same output metrics based on the lidar cloud within the boundaries of each 3-D grid cell—across the entire grid. In other words, the output of GridMetrics is the same as CloudMetrics but it is a continuous raster grid for each of the output variables across the entire project area.

These grids are the input, or predictor, variables, to which the regression models are applied resulting in an estimated forest inventory parameter—also in grid format—at the landscape scale. We used a cell size of 25 meters which approximates the same area as the .05 hectare plots. It is recommended to select a cell size that corresponds to the plot size used to build the regression models to ensure consistency of scale when applying such models across the landscape.

Figure 3 represents an example of the percent Canopy Cover grid metric produced using the GridMetrics FUSION command. A similar grid was produced for each output variable listed in table 1.

5 For a more detailed explanation and technical instructions for using the GridMetrics FUSION command please refer to the "Large Lidar Acquisition Processing Tutorial" (http://fsweb.geotraining.fs.fed.us/www/index.php?lessons_ID=971) hosted on the FSWeb within the USDA Forest Service Geospatial Training and Awareness Website.

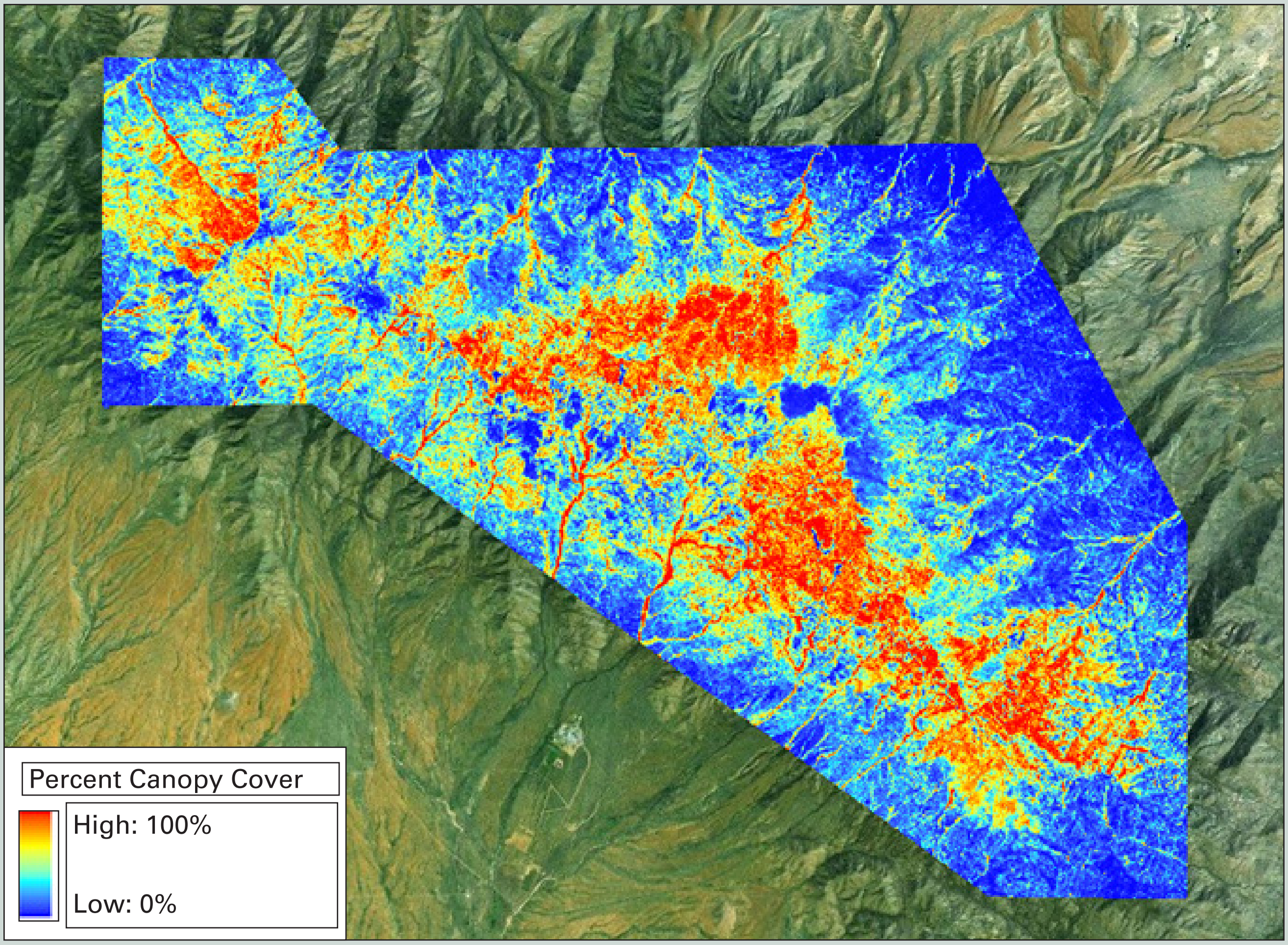

Figure 3—The figure represents the percent canopy cover grid produced at a 25 meter cell size across the Pinaleños sky island project area of approximately 85,000 acres. All the metrics listed in table 1 can be exported to a grid format and integrated into a GIS as illustrated in this figure.

Field Data

To use the field data for modeling inventory parameters in conjunction with the lidar data, we calculated the desired inventory parameters from our field data for all individual trees and then summed all values to the plot level (table 2).

The Pinaleño sky island study area includes a variety of ecosystems ranging from dry savannah at the lower elevations to spruce-fir at the upper elevations. However, plots were only collected at elevations above 7000 feet which primarily represents the mixed-conifer and spruce-fir zones (our area of interest) and a small amount of ponderosa pine type. The plots can be categorized into four plant association series as defined in the Plant Associations of Arizona and New Mexico Field Guide (Stuever and Hayden 1997):

- **Spruce-Fir** (dominant late seral species is subalpine fir and Engelmann spruce,
- **Wet Mixed-Conifer** (dominant late seral species is white fir),
- **Dry Mixed-Conifer** (dominant late seral species is Douglas fir) and
- **Upper Pine-Oak** (dominant late seral species is ponderosa pine).

Table 3 summarizes the number of plots collected in each plant association series. As highlighted in the table, a majority of the field plots were collected in the Spruce-Fir and Wet Mixed-Conifer plant association series.

Attempts to stratify the data based on plant associations were not feasible due to the limited number of plots in each association and the lack of a plant association map of the project area.

Table 2—Inventory parameters calculated for individual trees and summed to plot level

Parameter	Description
Basal Area	Units: square meters per hectare • Calculations do not include stumps • Basal Area was calculated for live, dead, conifer, deciduous and total
Trees per hectare	• Calculated for live conifer, live deciduous, live total, dead, total live and dead
Stand Density Index	• Used Ziede's summation method • Based on live trees only
Tree height	Units: meters
Lorey's Mean Height	Units: meters • Also known as Tree Height Weighted by Basal Area (HGTwBA)
Height of tallest tree	Units: meters
Standard deviation of tree heights	Units: meters
Average tree height based on trees per hectare	Units: meters
Quadratic mean diameter	Units: DBH in cm of the tree of average BA • Based on live trees only
Standard deviation of DBH	Units: standard deviation of DBH
Average tree crown base height	Units: meters
Timber volume	Units: cubic meters • Calculated for live conifer, live deciduous, total live, and total dead • Equations taken from Zhou and Hemstrom 2010 • Calculations do not include stumps
Total biomass	Units: kilograms per hectare • Biomass calculated above ground; includes bark and branch biomass, but does not include foliage or stumps • Equations taken from Zhou and Hemstrom 2010
Canopy fuel load	Units: kilograms per square meter • Represents the mass of available canopy fuel per unit ground area • Canopy fuel formulas from Cruz and others 2003
Canopy bulk density	Units: kilograms per cubic meter • Represents the mass of available canopy fuel per unit canopy volume • Canopy fuel formulas from Cruz and others 2003
Canopy base height	Units: meters • Base heights estimated as a function of average plot tree height and plot basal area • Canopy fuel formulas from Cruz and others 2003
Down woody fuels	Units: kilograms per hectare • 1 hour fuels (1HrKgHa) • 10 hour fuels (10HrKgHa) • 100 hour fuels (100HrKgHa) • 1000 hour fuels (1000HrKgHa) • Total down woody fuels (TotDWFKgHa) • Down woody fuel formulas from Brown and others 1982

Table 3—Number of field plots collected in each Plant Association Series

Plant Association Series	Number of Field Plots Collected
Spruce/Fir	24
Wet Mixed-Conifer	32
Dry Mixed-Conifer	17
Upper Pine-Oak	7

Model Development

For the Pinaleño project, predictive models were created for 22 different forest and fuel inventory parameters (table 2). Since all parameters being modeled are represented by continuous values, regression techniques were used to perform the modeling. Non-linear regression was used to provide adequate predictive functions for each of the modeled parameters. All models created and applied to the landscape, along with the selected lidar predictor variables, are displayed in table 4.

The modeling process was conducted in three principle stages: 1. identify best predictors, 2. create appropriate modeling masks, and 3. generate forest inventory models.

Find Best Linear Predictors

We used a "leave one out" cross validation with a generalized linear regression model to find the lidar-derived parameters that best predicted the plot parameters. Both single and pairs of lidar parameters were examined. Parameters with the lowest Root Mean Squared Errors (RMSE) were selected for use in the final model[6]. In all but one case (live basal area) two lidar parameters showed a lower RMSE error then one lidar parameter. In agreement with current literature (Reutebuch and others 2010), the lidar-derived predictor variables chosen for the models (table 4) represent some measurement of vegetation height, the variation or distribution of vegetation height and vegetation density.

Find Best Non-Linear Fit Using the Best Linear Predictors

Once selected, the best linear predictor values from the lidar derivatives were entered into the online curve fitting application ZunZun (Phillips, 2012) to identify the best non-linear functions to correlate the lidar predictors with the modeled parameter of interest. Functions were not only evaluated in terms of overall correlation (R^2 test), they were also selected to avoid over-fitting (i.e. selected based on smoothness). The final models that were deemed adequate to apply to the landscape based on a smoothness of fit and an R^2 value greater than or equal to 0.6 are displayed in table 4. The models for quadratic mean diameter (QMD) and canopy bulk density (CBD) were included for further investigation based on interest from the project cooperators, even though they didn't meet the R^2 threshold.

All remaining models deemed unfit (based on their R^2 values) for further exploration and application to the landscape are displayed in appendix A. Some of the forest inventory parameters that performed poorly included downed woody fuels, trees per hectare, and quadratic mean diameter. The poor performance of downed woody fuels models probably reflects lidar's limitation at distinguishing between the bare earth surface and woody debris lying directly on the ground. Trees per hectare (TPH) are difficult to estimate based on lidar height and density metrics due to the large variation in tree size; modeling only tree density of trees larger than 20 centimeters may have yielded better results. We suspect that modeling QMD might be more successful in a more homogeneous forest stand where heights to DBH relationships are more consistent. QMD is best thought of as the diameter of the average tree (based on tree basal area). Lorey's Mean Height is similar, in that it is the height of the average tree (also based on basal area) and may prove to be a better lidar forestry parameter since tree height is easier for lidar to estimate. The R^2 of the Lorey's Mean Height was 0.83. Both QMD and TPH layers can be derived from the Basal Area (live) and stand density index (SDI) layers, however this was not within the scope of the project.

Lidar might be superior to field estimates at measuring parameters that are indirectly measured in the field, such as CBD, but will require more intensive studies. For example, CBD is estimated from very costly whole tree clipping studies and mathematically modeled using more easily measured tree attributes (height, diameter, and species). Clipping studies utilizing lidar data may be required to develop better models.

6 The R Statistical Computing Package (http://cran.r-project.org/) was used to accomplish this task.

Table 4—The table summarizes the best non-linear forest inventory models created, using lidar predictor variables to model field derived forest inventory parameters. All models in this table were deemed acceptable for further exploration and application at the landscape level. Models are sorted by descending nonlinear fit R^2 values.

Predicted	Parameter 1	Parameter 2	Cross Val RMSE	Linear Fit R^2	Nonlinear Fit R^2	Fit Difference
TotBMKg (biomass kg per hectare)	Elevation mean	(All returns above mean) / (total first returns) * 100	3.51E+09	0.7416	0.8780	0.1364
HGTwBA (Lorey's mean height)	Elevation mean	Elevation Skewness	5.3452536	0.8123	0.8265	0.0142
CUMVolTot (volume)	Elevation P60	(All returns above mean) / (total first returns) * 100	14750.004	0.7026	0.8216	0.1190
BATotal (total basal area)	Elevation P75	(All returns above mean) / (total first returns) * 100	262	0.7024	0.7782	0.0759
SDItotal (stand density index)	Percentage all returns above 3.00	(All returns above mode) / (total first returns) * 100	58787.843	0.6994	0.7614	0.062
HGTmax (height of tallest tree)	Elevation L2	Percentage all returns above 3.00	29.979735	0.6919	0.7529	0.0610
CUMVolD (volume dead)	Percentage all returns above mean	(All returns above mean) / (total first returns) * 100	9921.26	0.4038	0.7361	0.3323
SdHGT (standard tree height)	Elevation variance	Elevation P50	1.7235131	0.5802	0.6817	0.1015
BALive (live basal area)	Percentage all returns above mean		256.12185	0.5993	0.67	0.61007
CBH (canopy base height)	Elevation variance	Elevation CV	6.1674894	0.4855	0.6187	0.1331
CFL (canopy fuel load)	Percentage all returns above mean	(All returns above mode) / (total first returns) * 100	0.421073	0.512	0.6	0.0880
***QMD (quadratic mean diameter)**	Elevation minimum	Elevation P10	56.991829	0.3932	0.4909	0.0976
***CBD (canopy bulk density)**	Elevation P20	Percentage all returns above mean	0.0261966	0.3724	0.4378	0.0655

Prepare Data to Generate GIS Products

Our models for estimating continuous forest inventory measurements across the lidar acquisition area performed poorly in two areas: areas that fell outside the range of plot measurements and thus require the model to extrapolate estimates, and nonforest areas. Predicted data outliers were masked and clipped in the first circumstance, and in the latter nonforested areas were excluded from the modeling process.

Mask and Clip Predictor Data Outliers

Within the study area, there were small regions that were not well represented by the field plot measurements. One example occurred in groves of old growth Douglas-fir forest, i.e., dense groups of very large trees. The gridded plot system did not include plots in these areas and the lidar-derived parameters fell well outside the range measured in any of the field plot data. These locations were identified, flagged in a mask layer, and their associated lidar output grid metrics truncated (clipped) to the closest lidar values associated with existing field plot measurements. This process ensured that predictions made by the non-linear regression models did not create completely unrealistic values in these outlying areas, though as a consequence it does over or under estimate some values. For example, the clipping process was applied to less than 0.7 percent of the modeled area when the mean height lidar metric was used as a predictor in the models (figure 4).

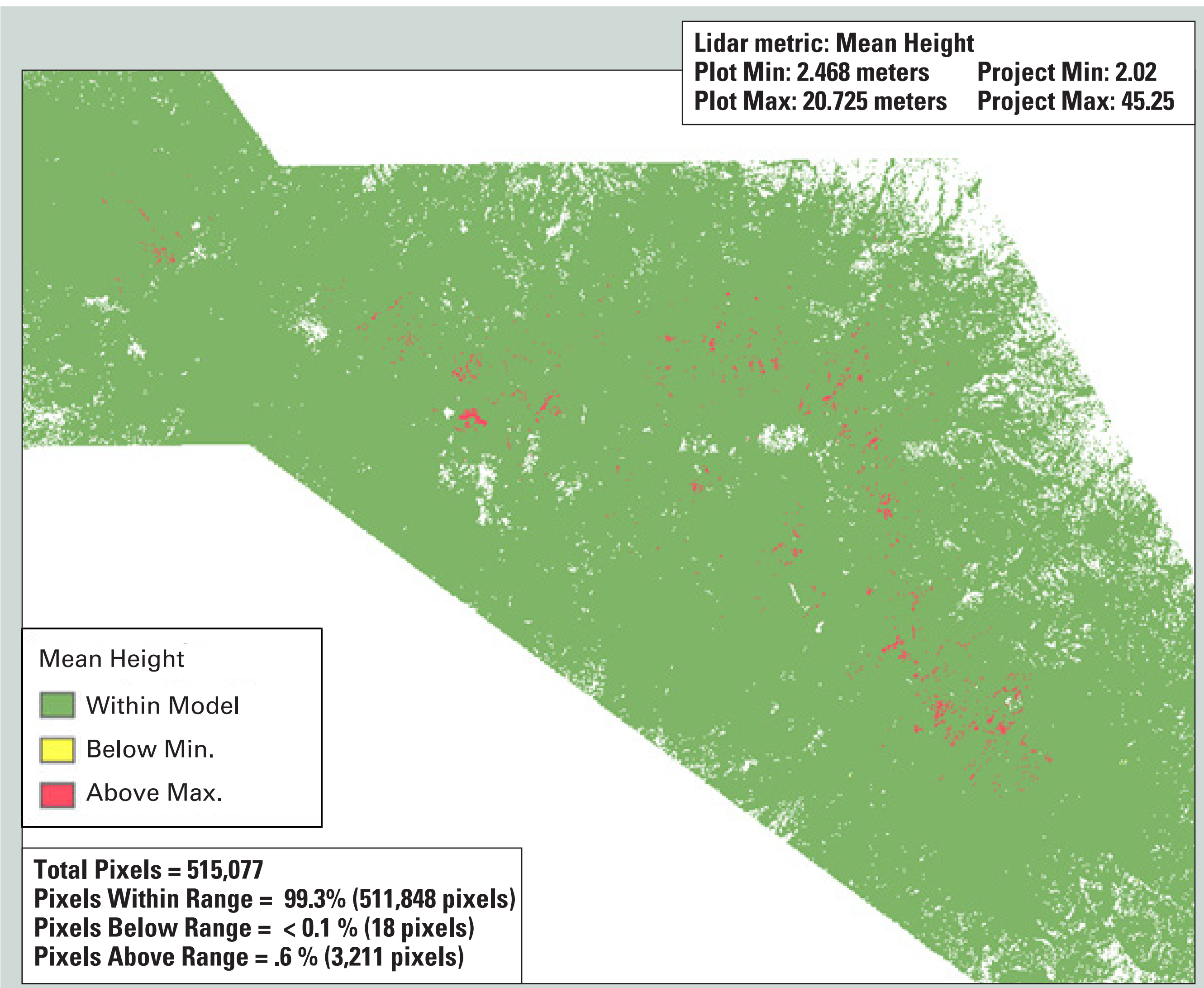

Figure 4—The mask layer above highlights the number and spatial location of pixels representing the mean height grid metric across the project area that fell outside the range of the training data used to create a number of the forest inventory models. Only 0.7 percent of the pixels across the project area were clipped back to the closest lidar values contained in the training data.

Create a Forest/Nonforest Analysis Mask

Before we applied the forest parameter models at the landscape level, we created a forest/nonforest mask to exclude nonforest areas. To create the mask, a forested area was defined as having greater than or equal to 2 percent canopy cover and a canopy height of greater than or equal to 3 meters. Each 25 meter pixel in the study would have to meet both these conditions to be considered a forested pixel. The percent canopy cover and 95th elevation percentile height grid metric outputs were used to identify all pixels that met both conditions and to create the forest/nonforest grid (figure 5).

Generate Forest Inventory GIS Products at the Landscape Scale

Estimate Forest Attributes at Landscape Level

Continuous inventory parameters were created at the landscape scale by applying the derived equations (table 4) to the lidar GridMetrics layers. Each calculation produced a new grid in which each 25-meter cell spatially represents the estimated forest parameter of interest derived from the lidar data (figure 6).

Quality Check and Validation of Models

Models were validated qualitatively using local biological, silvicultural, and ecological knowledge of the study area alongside ancillary GIS data and imagery. For example, a mature forest adjacent to Riggs Lake, and a previously burned area that contains a large quantity of standing dead biomass, both well-known and familiar areas, were used to qualitatively validate models with local experts (figures 7 and 8). The lidar inventory models conformed well to trends known to occur on the landscape.

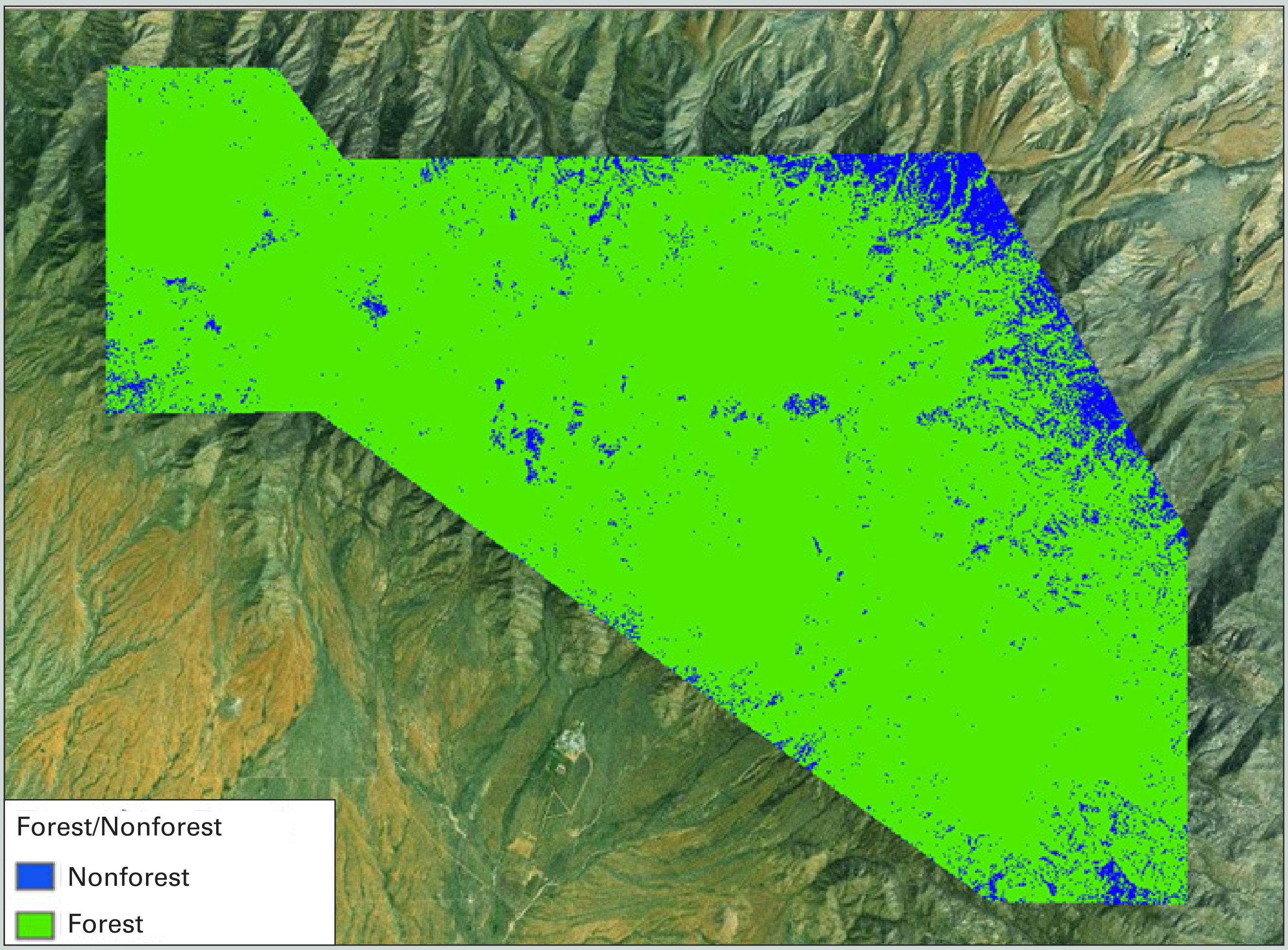

Figure 5—The figure represents the forest/nonforest mask created at the landscape level. All 25 meter pixels that did not meet both forested area conditions (3 m canopy height and 2 percent canopy cover) were designated as no data (blue pixels in graphic) and masked out from the final forest inventory landscape products.

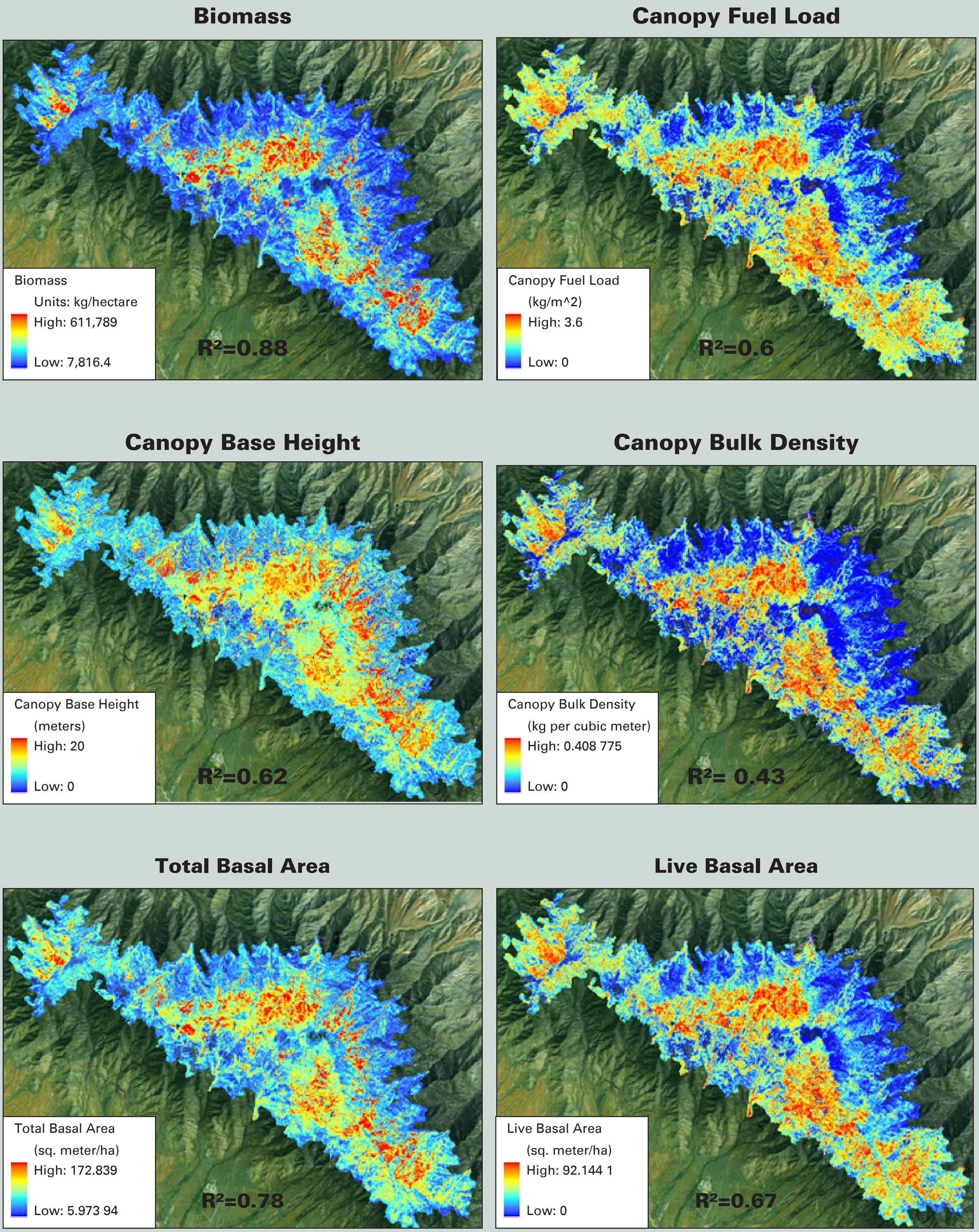

Figure 6—The GIS grid layers (25 m cell size) represent the forest inventory parameter models applied at the landscape level. These GIS layers are the end user products that will be used for future decision making, analysis and monitoring for the Pinaleño sky island study area *(continued on next page)*.

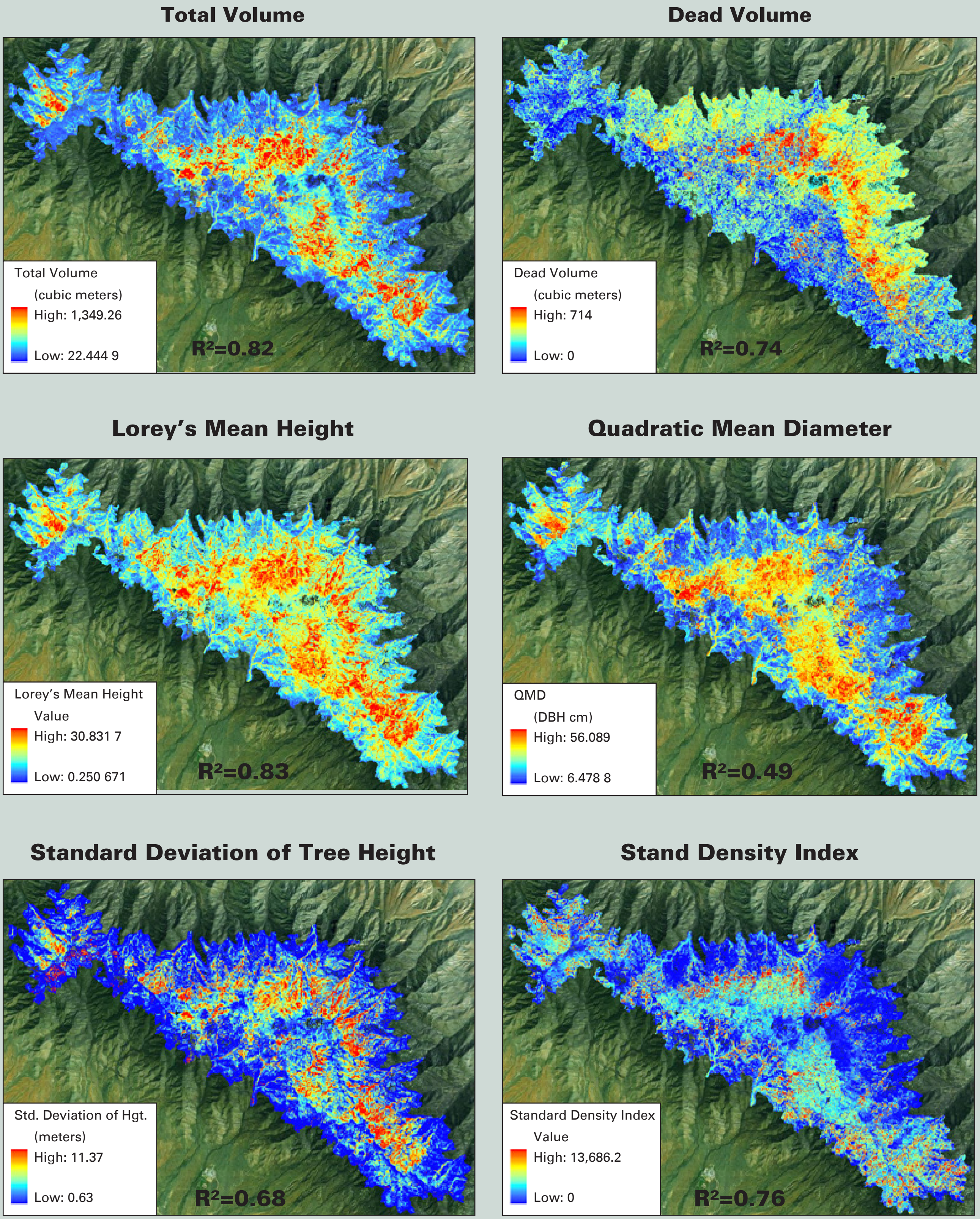

Figure 6 *(continued)*—The GIS grid layers (25 m cell size) represent the forest inventory parameter models applied at the landscape level. These GIS layers are the end user products that will be used for future decision making, analysis and monitoring for the Pinaleño sky island study area.

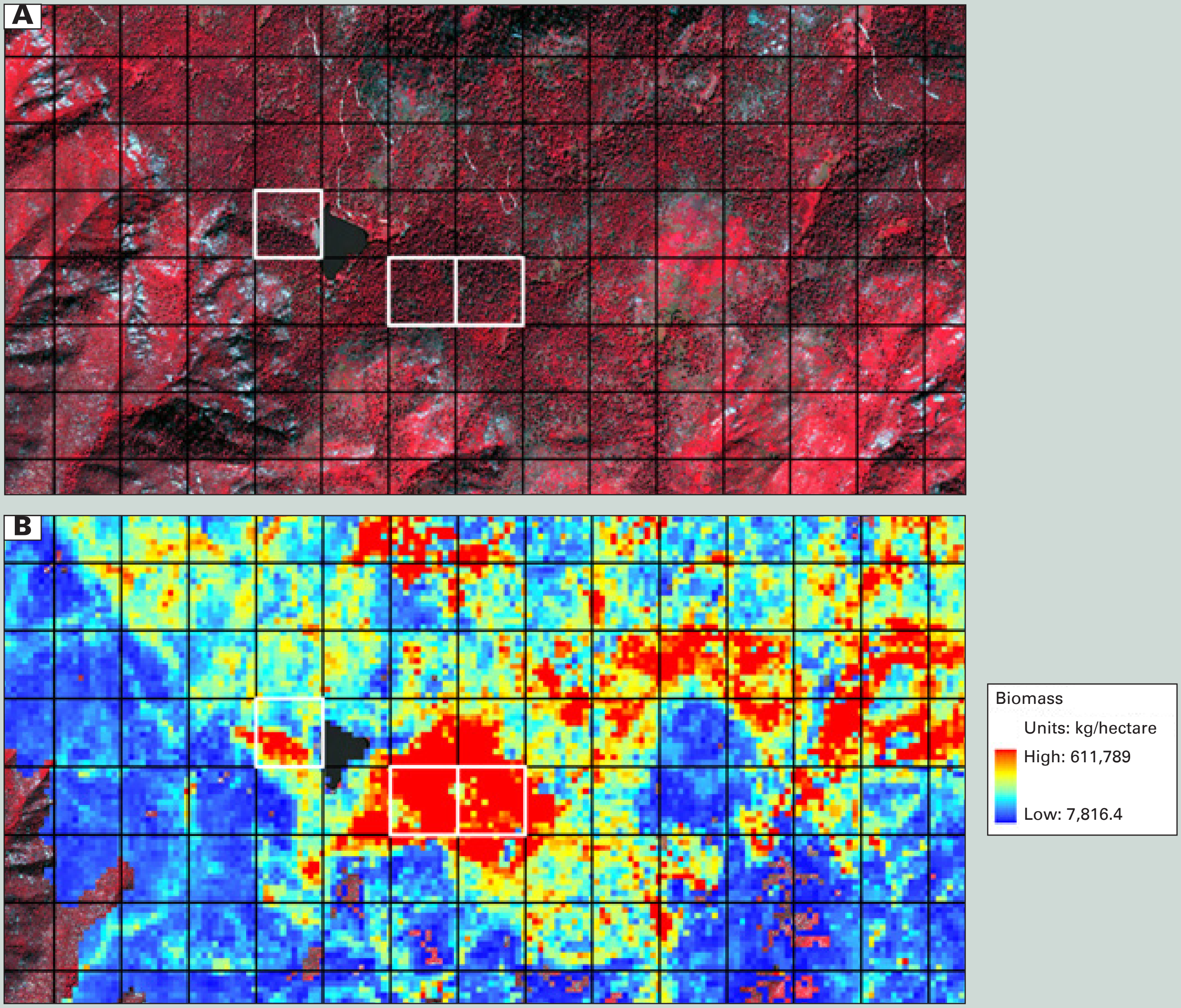

Figure 7—The lidar-derived biomass model accurately reflects the trends in biomass surrounding Riggs Lake. Areas highlighted with the white grid cells represent known areas where large mature forests exist. *A)* Riggs Lake is visible in the color infrared satellite imagery. *B)* Represents the lidar-derived biomass model estimate.

A limiting factor for this type of modeling methodology and the resulting products is the range of structural variation covered by the field plots used to create the models. For example, based on the limited number of plots (only seven) collected in the Upper Pine-Oak plant association series, we observe the Live Basal Area model performing poorly in certain areas as illustrated in figure 9. In contrast the Biomass model performs relatively well in the same area.

Because lidar technology directly and continuously measures the structural characteristics of the forest vegetation across the landscape, and the modeling methodology used has been replicated and accepted internationally (Means and others 2000, NÆSSET 2002), we are cautiously optimistic that our statistically-validated models provide reasonable results representing trends known to exist on the landscape—in those plant association series that had sufficient field plot data.

Conclusions

Phase 3 of the Pinaleño Canopy Mapping Project illustrates that forest inventory parameters measured in the field can be successfully modeled across the landscape with continuous lidar data. Parameters such as biomass (above ground), basal area, Lorey's Mean Height, and timber volume appear to lend themselves to this methodology, which is not surprising as they are directly related to the size and density of the vegetation. We can see that this

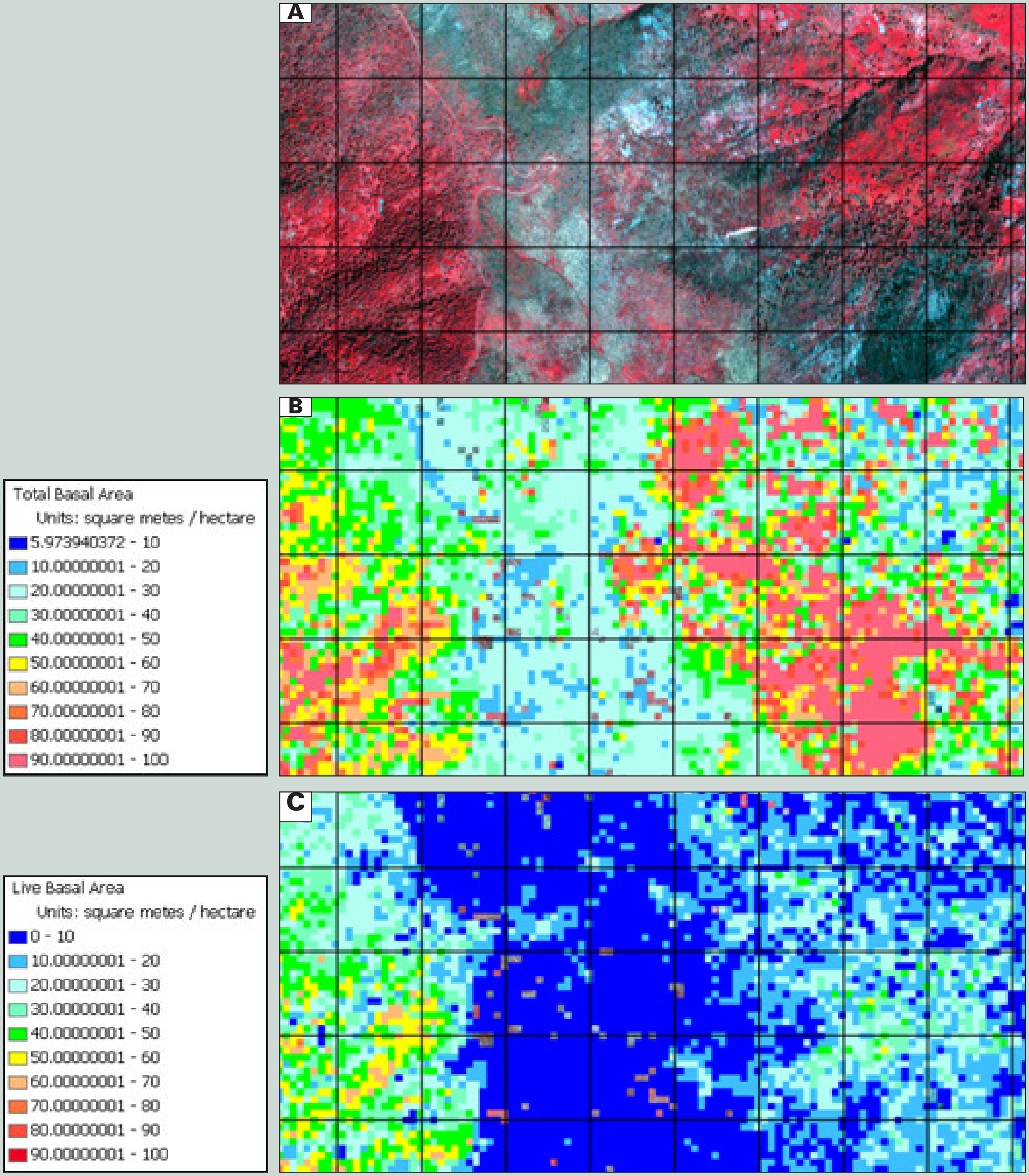

Figure 8—The lidar models accurately reflect the trend of standing dead basal area—within the Spruce-Fir plant association series. The burned area in figure *A* is clearly visible in the WorldView 2 high resolution satellite image. The two figures below represent total *(B)* and live *(C)* basal area respectively. Both images are scaled the same and a grid has been draped on the images for easier comparison. This model was not as accurate in other plant associations series.

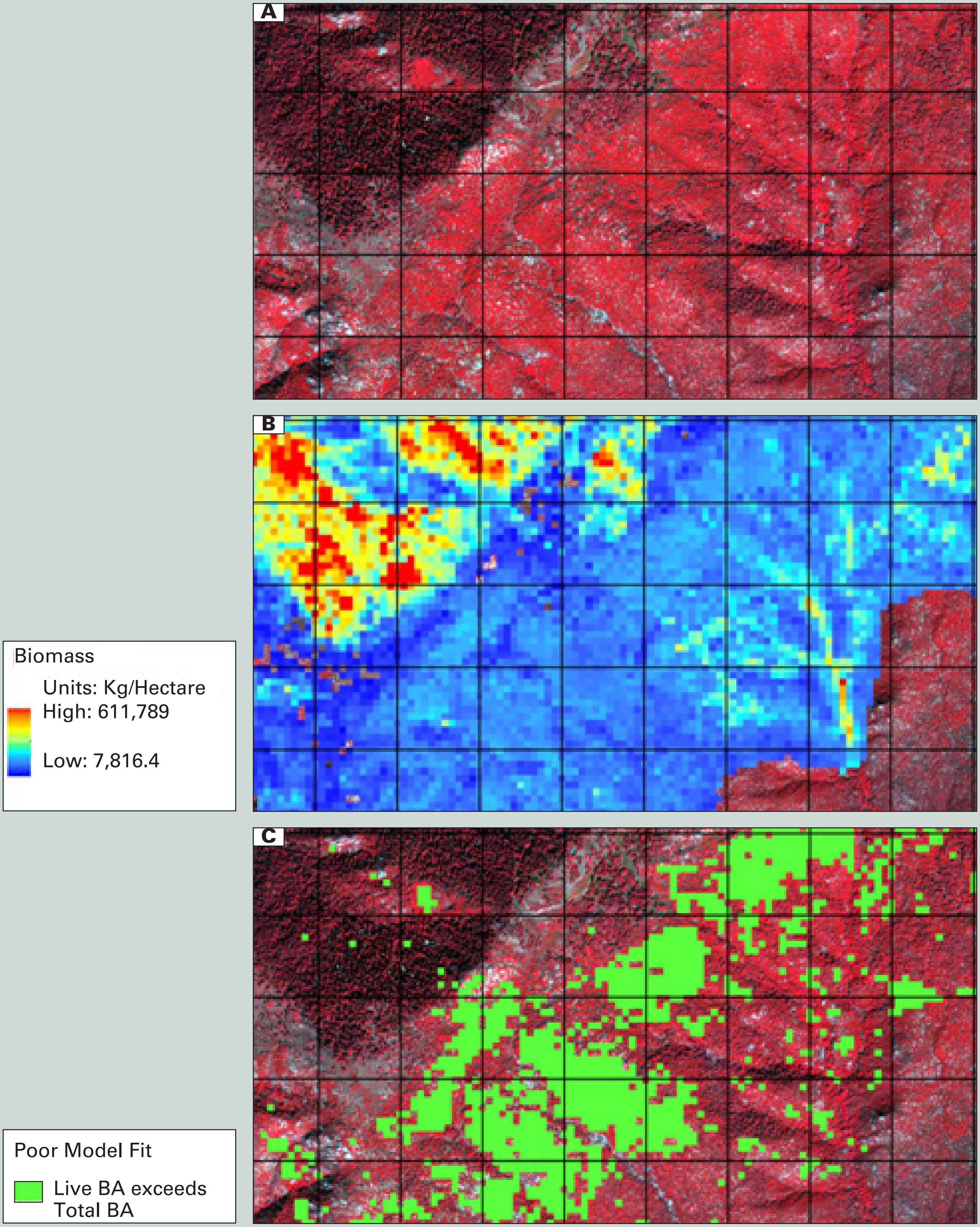

Figure 9—An example area of poor live basal area model fit. The bright red vegetation in *A)* represents lower-elevation oak brush. Figure *B)* represents modeled total biomass, which appears to be accurate in both the oak brush and the pine forests. However, live basal area (which accurately portrays forest biomass in the Spruce-Fir plant association series) over estimates biomass in the oak brush communities. Figure *C)* highlights areas where live basal area was modeled as higher than total basal area (an obvious error). The likely cause for poor model fit in the oak brush areas is the paucity of field plot data in those areas.

logical relationship is reflected in the lidar predictor metrics selected, one describing the height and one describing the density, as the best predictors for these inventory parameters (table 4). These models also appear to be the most robust across plant associations with differing forest structures. Our methodology failed to adequately model trees per hectare or any of the down woody debris parameters.

The first order lidar derivatives and the landscape GIS inventory layers created from this project are currently being incorporated into habitat characterization studies for the Mt. Graham red squirrel and the Pinaleño Demography study. The landscape GIS layers are also being used by the Coronado National Forest to create better strategies for managing and conserving the Pinaleño Sky Island ecosystem.

The three phases of the Pinaleño Canopy Mapping Project, from scoping and data acquisition to production of usable GIS layers took approximately 65 weeks (table 5). This project demonstrated that first order lidar derivatives, such as canopy height and percent canopy cover, can be used in natural resource management activities without the added cost of field data collection and the in-depth modeling

Table 5—Project timeline summarizing all efforts from the Pinaleño Lidar Canopy Mapping Project

Project Phase	Duration (weeks)	Comments
Project initiation	4 to 52	Based on the project coordinator's existing knowledge and experience. Can also depend on clearly defining objectives and what resource managers are interested in contributing to the acquisition
Determine lidar acquisition specifications	1	Once a decision has been made on what management objectives will be addressed with the technology the appropriate specifications can be identified and documented
Contracting phase (RFQ posting and evaluation)	6	This time estimate includes creating contract specifications, and posting the request for quotation. It does not include additional amendments to the contract
Acquisition	1	
Vendor post processing	8	
Data delivery and client quality assessment	4	Client generally has six weeks to perform an independent quality assessment and determine if the contractor delivered acceptable products
Initial data processing	6	GIS analysis with vendor deliverables and the creation of first order lidar derivatives (canopy cover, vegetation density, canopy height, etc.) *The first order derivatives can be used as standalone information products to assist in natural resource management without proceeding any further into the advanced modeling explored in Phase 3. This includes all project phases below
Field data collection	12	Depends on crew size and access
Summarize forest inventory plots	6	
Extract lidar plot metrics	1	
Create forest inventory models	12	Assumes a skilled modeling analyst on staff or available to assist in project
Apply models at the landscape level to create GIS products	1	
Model validation	2	Review initial GIS products with local experts
Make model adjustments	1	
Total modeling project budget	**65 to 113**	

described in this report. The lidar approach to obtaining forest structure data had several benefits over a ground-based approach. First, it provided continuous coverage of all forested areas, rather than stand or plot-level estimates of various parameters created from stratified sampling methods. Second, it sampled areas that field crews could not safely measure due to extreme terrain. Third, it was very cost effective. The Coronado National Forest estimates that obtaining data sufficient to implement the Pinaleño Ecosystem Restoration Project and other anticipated projects would cost approximately $500,000 (assuming that crews could safely work in all areas, which is not the case). By comparison, the Pinaleño Lidar Mapping Project cost $250,000 including acquisition, processing, and analysis.

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