LiDAR Derived Data to Inform Vegetative Structural Conditions

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Prepared for the U.S. Forest Service by
The Nature Conservancy

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For more information about this report please contact:

Travis Woolley, Forest Ecologist
The Nature Conservancy
114 N. San Francisco Street, Suite 205
Flagstaff, Arizona 86001
(928) 774-0831
twoolley@tnc.org

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Introduction

Restoration of dry forests in northern Arizona, and planning of restoration treatments has recently begun to approach landscape scales. This approach has gained traction because large and uncharacteristically severe wildfires are pushing forests farther from desired conditions and exemplifying the lack of resiliency across these forested landscapes. Ponderosa pine forests of the North Kaibab are generally denser and more continuous than compared to historical reference conditions (Kaibab National Forest Land and Resource Management Plan USDA 2014). Much of the restoration work to move landscapes towards desired conditions and re-establish fire regimes emphasizes mechanical thinning as a tool for reducing tree densities so natural and managed fire can be re-introduced into the system. When planning landscape scale (> 10,000 acres) restoration projects, it can be challenging to obtain site-specific data on existing conditions over these larger areas. The ability of remotely sensed data sets such as LiDAR, and innovative approaches to applying that data, are key to assisting project planners and specialists with large landscape scale restoration projects.

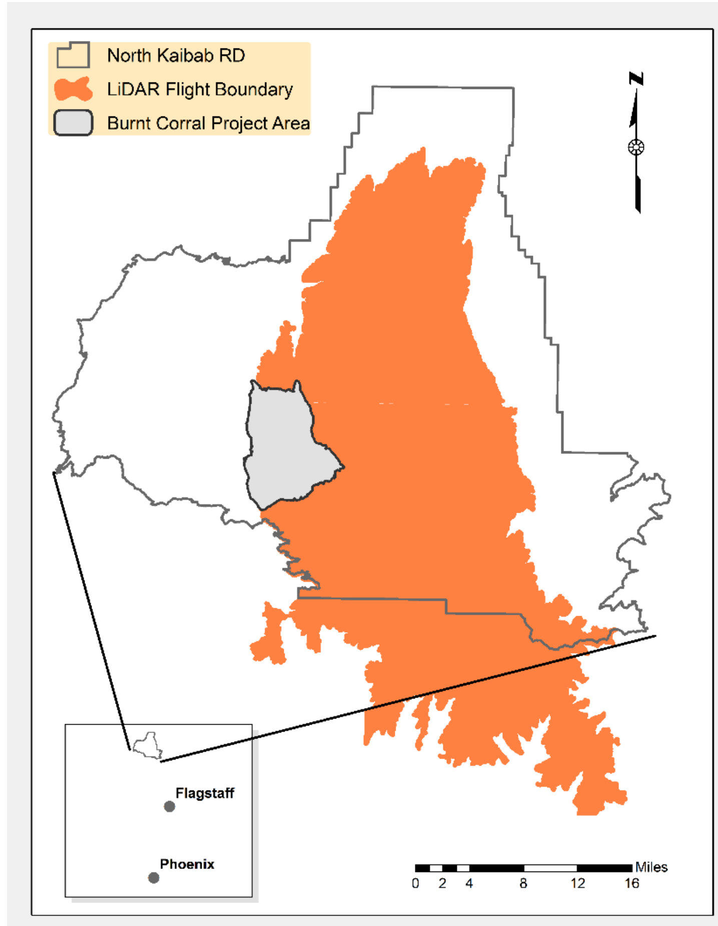

Figure 1 – Burnt Corral Project Area within the LiDAR footprint collected within the North Kaibab Ranger District, Kaibab National Forest

For this project, the Burnt Corral Planning and Analysis area on the North Kaibab Ranger District, Kaibab National Forest in northern Arizona (Figure 1) was used as a case study to develop and provide useful information regarding existing forest structure, particularly related to large tree and canopy cover components. The density and spatial arrangement of large trees influences potential fire behavior (particularly crown fire), enhances water interception, influences carbon sequestration and storage, and provides habitat characteristics for some wildlife species. Across the southwest, large tree occurrence is infrequent compared to historical conditions. Their retention across the landscape is of considerable importance given that the ecosystem services they provide are disproportionately high given their limited abundance on the forest. Prior to the initiation of this project, a collaborative planning process, led by the Landscape Conservation Initiative at Northern Arizona University, was undertaken to "develop a proposed action for vegetative treatment…using a collaborative approach supported by spatial analysis and group deliberation" (Sisk et al., 2014). One of the remaining issues not resolved by the stakeholder process was large tree retention and the use and effectiveness of a diameter cap to achieve project objectives. Whether or not consensus is reached, the identification of areas with a larger and older trees is key to developing alternatives for restoration, principally mechanical thinning prescriptions.

In 2013, Region 3 of the USFS contracted to collect Light Detection and Ranging (LiDAR) data across of the North Kaibab Ranger District (Figure 1: WSI Technical Data Report 2012). The acquisition and subsequent data/products cover 457,925 acres of forest and woodland vegetation types. LiDAR is a remote sensing technology that uses a laser emitter-receiver scanning unit that sends 200,000 pulses of light per second to the ground (Figure 2: McGaughey 2014) while measuring the time for pulses to reflect off of the canopy and ground surfaces. This results in a 3-D model of ground surface, vegetation, roads, and buildings that is spatially explicit and provides highly accurate estimates of vegetation height, cover and canopy structure (Lefsky et al. 2002). This data also lends itself to modeling to estimate forest parameters such as leaf area index (LAI), biomass, volume, and tree density.

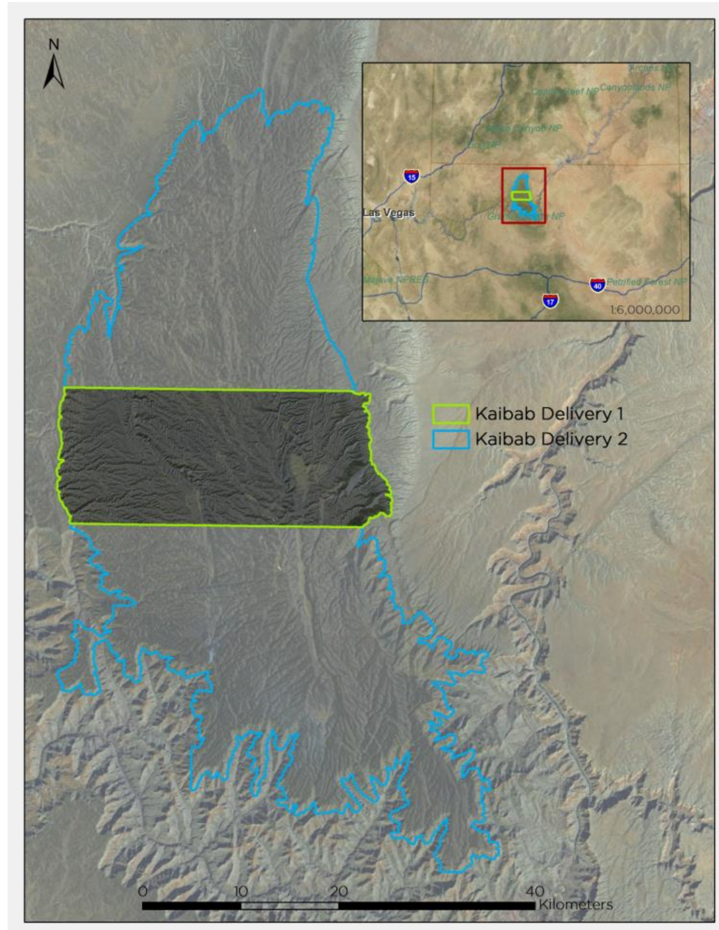

Figure 2 - Kaibab LiDAR data acquisition area. Delivery 1 was a preliminary subset of products delivered and Delivery 2 included a complete ground point shapefile geodatabase.

The overarching objective of the cost-share project between The Nature Conservancy (TNC) and the Kaibab National Forest (KNF) was to develop analytical methods to better integrate existing LiDAR data into project level planning and analysis leading to more informed management, improved transparency, and stakeholder consensus. Using the existing LiDAR dataset and spatial data developed by the Remote Sensing and Applications Center (RSAC), procedures (see Appendix A: Workflow) and resulting data layers can improve the identification of existing forest structural conditions. In particular, the USFS was interested in two sets of products for the Burnt Corral Project area 1) Canopy cover data layers 2) spatial data indicative of large young tree density existing in an even-aged canopy structure. This report elucidates the concepts and methods developed to produce these spatial data, and illustrates the resulting data. This information can provide the USFS with an improved ability to meet forest plan desired conditions, such as large trees (>18 inches in diameter) contributing the largest percentage of basal area in ponderosa pine vegetation types. These empirically defined and data driven methods can also help to inform stakeholder driven planning processes by improving transparency in decision making by the forest service.

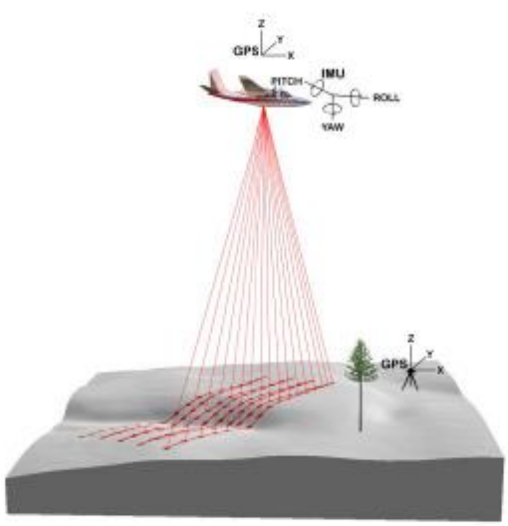

Figure 3- Schematic of an airborne laser scanning system.

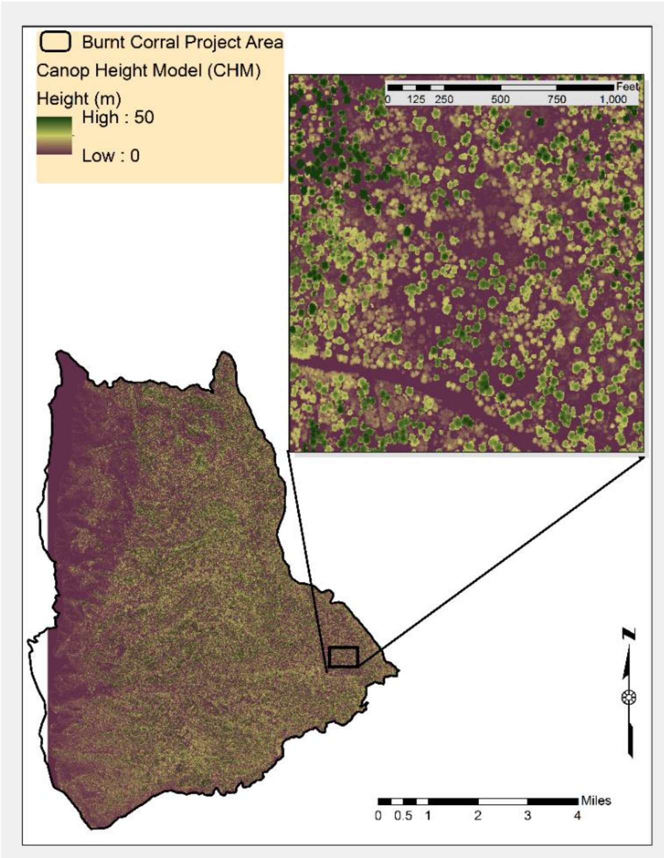

Figure 4 - 1-meter resolution Canopy Height Model (CHM) raster.

Methods

Canopy Cover

Canopy cover is a metric often used to describe the canopy structure of the forest. Defined in the USDA Forest Service Common Stand Exam Users Guide (2010) as "the percent of a fixed area covered by the crown of an individual plant species or delimited by the vertical projection of its outermost perimeter; small openings in the crown are included". This differs from canopy closure in that canopy cover does not take into account light interception and other factors that influence microhabitat (Egan 2010). Canopy cover can be measured in various ways, from ground based measurements of canopy extent to using remotely sensed information such as aerial imagery or LiDAR.

For this project we produced spatial canopy cover products for the Burnt Corral project area using a LiDAR derived 1-meter resolution Canopy Height Model (CHM -Figure 4). This differs from the RSAC produced spatial canopy cover layer (25-meter resolution), which uses the differencing between canopy returns of interest (chosen height threshold) and all returns (Equation 1) to derive a raster of canopy cover values (Figure 5).

Equation 1:

$$Cover = \left(\frac{\text{\# of returns>Threshold}}{\text{Total Returns}}\right) * 100$$

This method of computing canopy cover may be more similar to an estimate of canopy closer (Egan 2010) than canopy cover. In contrast, using the CHM explicitly bases the estimates on a canopy projection. The CHM raster is a 2 dimensional depiction of canopy area. Presumably each pixel with a height value greater than 3 meters is considered tree canopy. This threshold could be altered and applied to derive canopy cover for any canopy strata of interest (e.g., a single diameter class 5-12", or all diameter classes > 18").

A threshold must be chosen that represents height values related to the canopy strata of interest. To apply this threshold, the 1-meter CHM is converted to a raster of 1's and

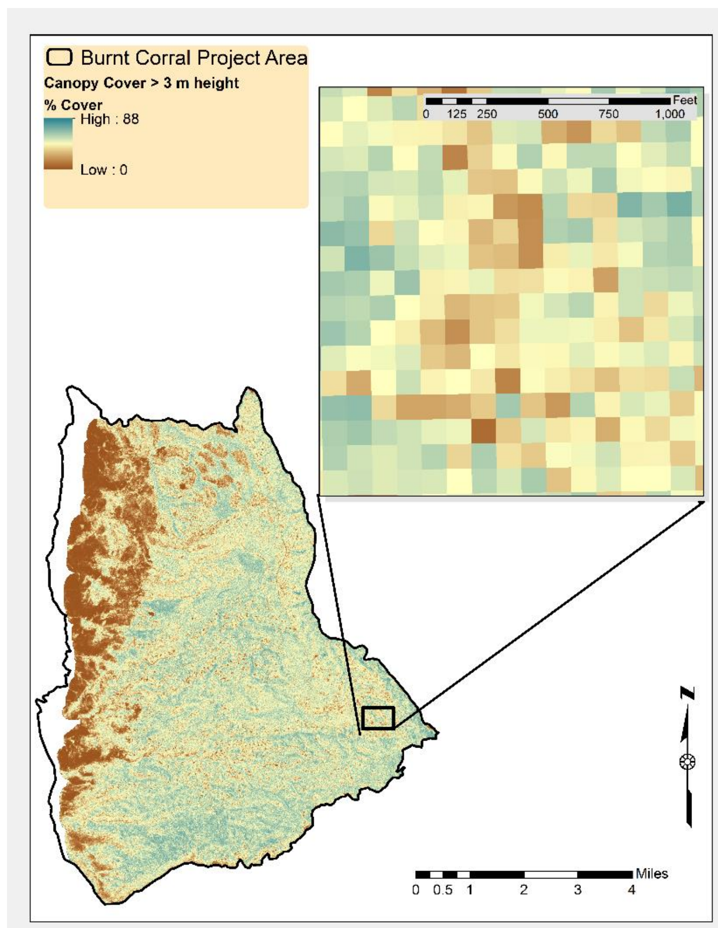

Figure 5 - 25-meter resolution Canopy cover raster derived directly from LiDAR returns (Equation 1)

0's, 1's being raster cells that are canopy height values > threshold, 0's being height values < than threshold. The resulting raster is then scaled up by summing all 1-meter raster cells in a 30 m x 30 m zone together (sum of 900 raster cells). This scale can be changed depending upon the scale desired. If a per hectare estimate is more appropriate/desired, then using 100 m x 100m scale would be applied. Using the new 30-meter raster we then divided each 30-meter raster cell value by 900 (the maximum possible value) and multiplied by 100 to obtain a percent canopy cover value for each 30-meter cell. Figure 6 depicts this as a vector (polygon) layer following reclassification into quartile bins (0-25%, 25-50%, 50-75%, 75-100%).

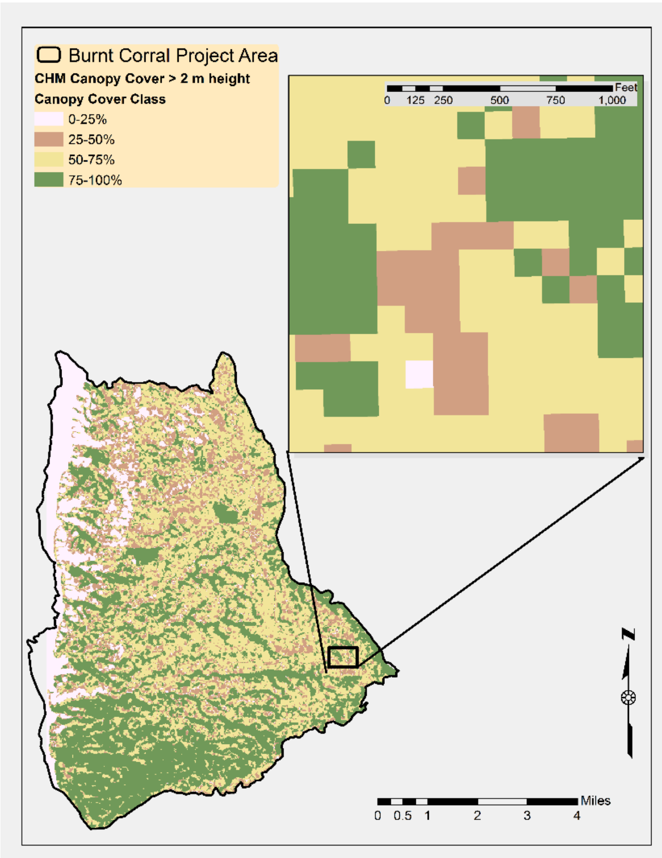

Figure 6 - 30-meter canopy cover layer derived from the Canopy Height Model.

For this project, three canopy cover layers were delivered:

1. *Canopy cover > 3 meters* using RSAC/FUSION methods reclassified into quartiles and converted to vector.
2. *Canopy cover > 2 meters* using CHM method for all canopy reclassified into quartiles and converted to vector.
3. *Canopy cover > 15 meters and < 23 meters* using CHM method for all canopy reclassified in to quartiles and converted to vector.

The third canopy cover product height thresholds were based on a diameter distribution of 12-18", using 15" as the mean of that distribution, and assuming a height range for that distribution of 15-22 m.

Even-aged Large (Young) Tree Structure

One of the needs of silviculturists when planning restoration treatments, particularly mechanical thinning, is to identify/quantify on the landscape certain structural characteristics that inform the existing condition. Using this spatial data subsequent project design and prescriptions could be developed more precisely to make progress

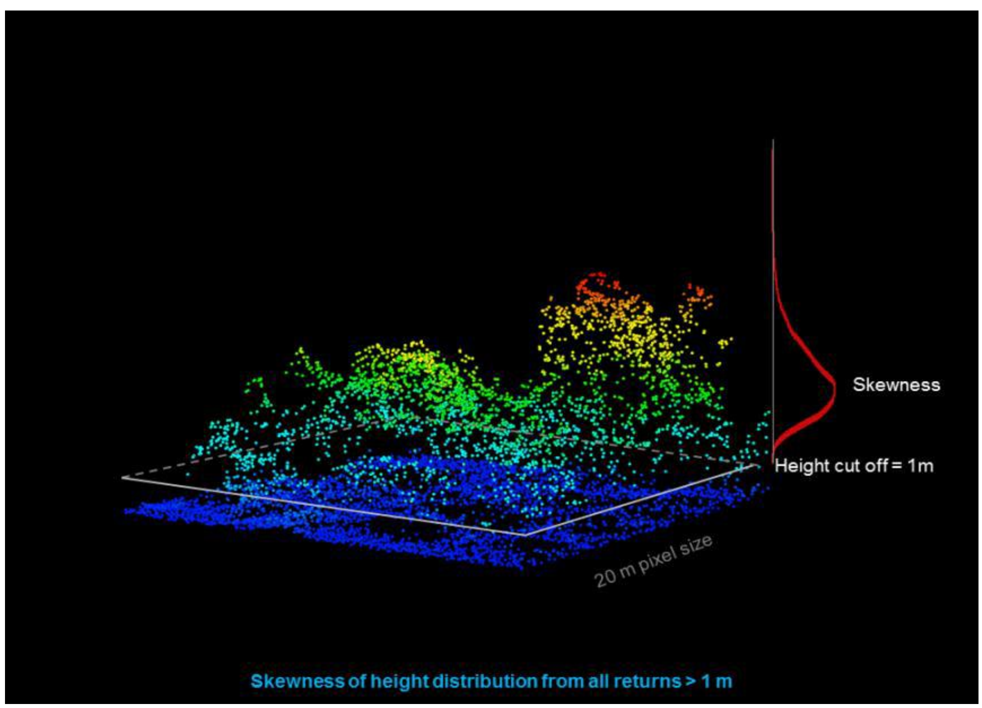

Figure 7 - LiDAR point cloud for a 20-meter cell illustrating skewness in the canopy height distribution.

toward a specific desired condition. In particular, there are areas of interest to both managers and stakeholders that can be defined as having a similar size/age structure (even-aged) while carrying a preponderance of larger trees. In general, LiDAR derived data, particularly the CHM, can be very useful in identifying larger (i.e., taller) trees across multiple scales. The CHM can be used in multiple ways to derive spatial data layers that indicate and/or quantify various tree canopy structure. We used two different approaches to identify density of larger (taller) trees and/or even aged canopy stratification: 1) RSAC delivered metrics derived from the LiDAR point cloud in combination with a 1-meter CHM, and 2) Individual tree segmentation using a 1-meter CHM.

LiDAR Metrics and CHM

To provide spatial data for the Burnt Corral project area that relates to older and larger (taller) trees existing in an even-aged condition we used a 1-meter CHM derived from the raw LiDAR data applying FUSION (McGaughey 2014) methods. To derive a CHM, FUSION subtracts the ground return values from the canopy return values for each 1-meter cell, producing a raster (Figure 4) of canopy height that can then be used to spatially assess where canopy structure relates to height. The workflow developed to create this data was based on several assumptions. First, regarding large trees, we used height as a surrogate for larger tree size often referred to by diameter. LiDAR provides extremely precise estimates of tree height, and there are defined relationships between tree height or canopy area (Sanchez-Meador et. al., 2011) and tree size (i.e., diameter). Secondly, we assumed that an even-aged forest structure can be defined as having a lack of vertical stratification in the canopy, whereas an uneven-aged forest structure would have some degree of vertical stratification or heterogeneity. Two proxies for vertical canopy stratification based on the LiDAR data were examined, 1) the standard deviation of height and 2) the skewness of height (Figure 7). For standard deviation of height, we assumed that a larger standard deviation of height values in the LiDAR canopy return data would represent more vertical stratification/heterogeneity and be indicative of more un-even aged structure. Smaller standard deviation of height values would reflect the opposite and be indicative of even-aged forest structure. Similarly, for skewness of height we assumed that values of skewness that were larger indicated that the canopy was skewed to upper canopy while smaller values reflect canopy height was skewed to shorter

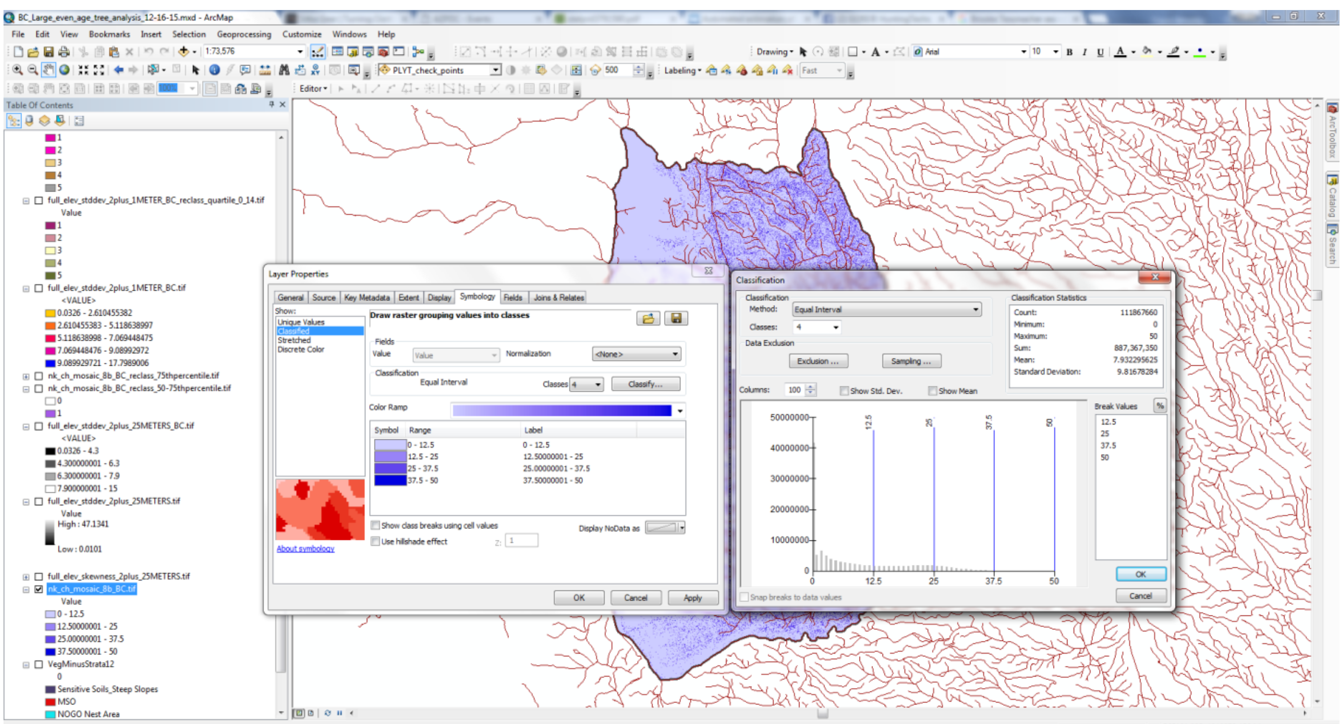

Figure 8 - Screenshot illustrating the use of classification breaks in ArcGIS to determine quartile breaks for height distribution of the CHM.

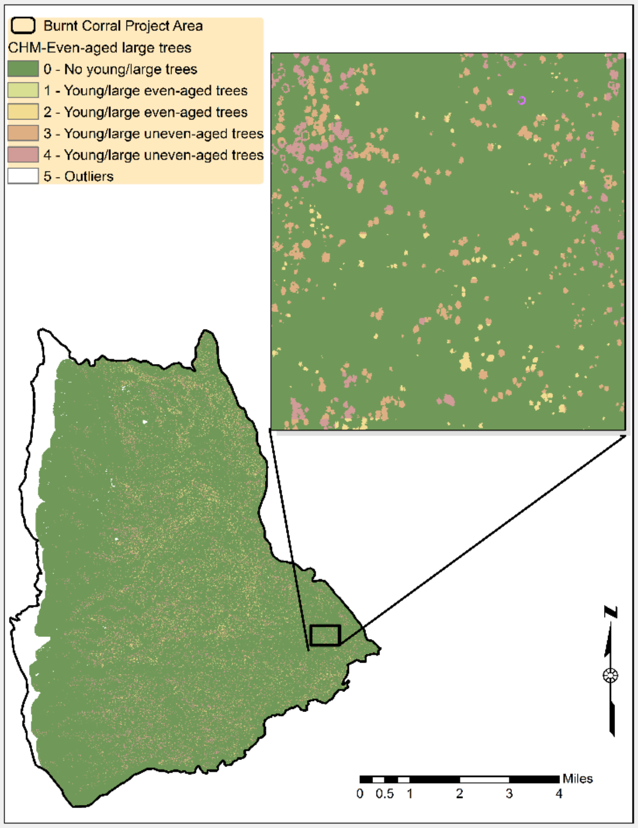

Figure 9 - Raster dataset derived by multiplying the 50th-75th percentile CHM values by the Standard deviation in height values.

canopy structure. For all subsequent analysis and reporting we chose to focus on the standard deviation of height because it is a more intuitive variable to communicate to managers and others.

Using the distribution of height values in the CHM (Figure 8), a reclassification based on quartiles was performed. This step allows an additional reclassification based on values of height for the question of interest. For example, Woolley (2014) showed that in areas tested on the North Kaibab Ranger District the 75th percentile and greater was an adequate threshold to capture old-growth trees (field based determination classified by a set of characteristics indicative of tree age). In this project the 50th-75th percentile was used as it likely represents larger/younger trees that are not yet exhibiting old-growth characteristics, and are a component of the forest structure that managers and stakeholders feel is prime for promoting larger/older forest habitat structure.

Similarly, we classified 5 quantiles based on the distribution of standard deviation of height values. The first four categories represent the majority of the distribution, while the fifth category represented extreme outliers (cliff artifacts, birds, etc.). Using the 50-75th percentile CHM data in combination with the categorized standard deviation data, we created a combination data layer by multiplying these two raster datasets together. The resulting dataset (Figure 9) categorizes the project area into six categories (0-5). Values of 0 represent areas where the tall/young trees do not exist (either too small or too large). Values of 1 or 2 are areas of potentially larger (i.e., taller) trees with very little deviation of height in canopy (0-3.5 meters standard deviation). This condition would be considered more of an even-aged forest structure containing larger trees. Values of 3 and 4 represent areas where larger trees exist with larger deviation in canopy height, potentially representing more of an uneven-aged forest structure condition. This raster was then converted to a point layer in order to run the kernel density tool in ArcGIS (ESRI 2014). This tool calculates a magnitude per-unit-area from point/polyline features using a kernel function to fit a smoothly tapered surface. This results in a raster layer with a "density" estimate (Figure 10). The layers developed by this specific analysis, and used in the kernel density analysis, don't represent individual trees, the default area was used as an example to visually represent how overall "density" of larger trees can be identified on the landscape.

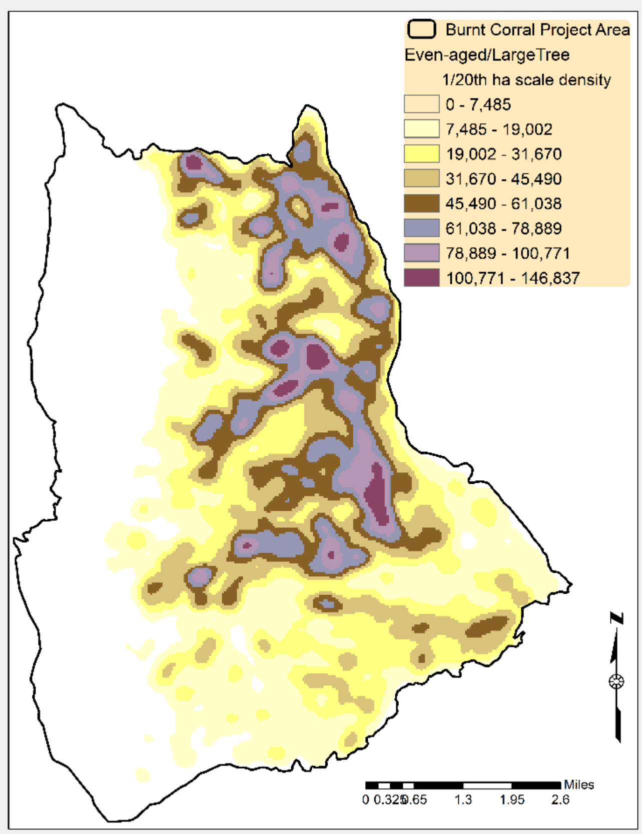

Figure 10 - Raster dataset derived using Kernel Density analysis to illustrate the relative density of even-aged larger trees.

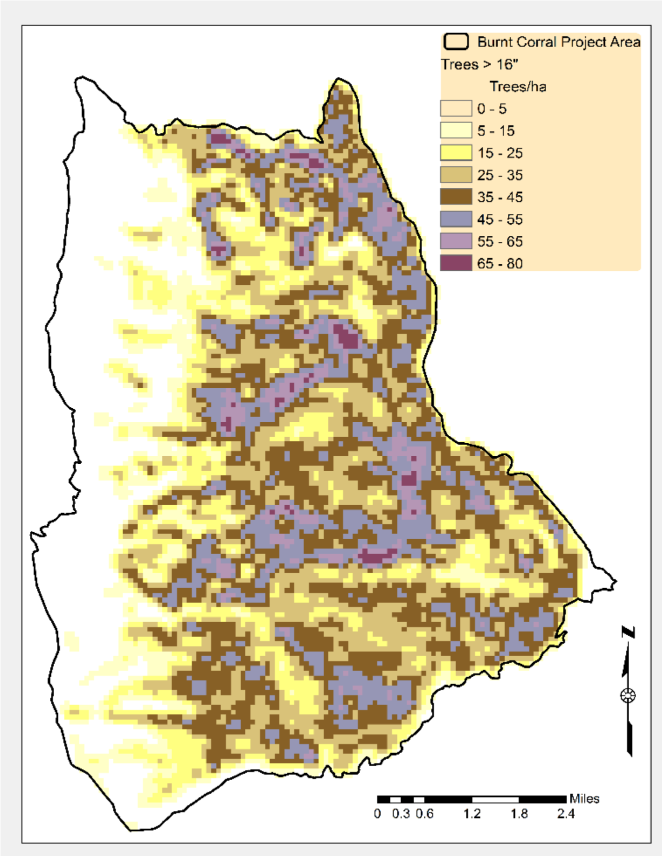

Figure 11 - Large tree density (>16" dbh) derived from individual tree segmentation using Kernel Density analysis.

Individual Tree Segmentation using CHM

A more detailed and quantifiable (i.e., tree/hectare) method for determining the density of large trees for landscape restoration planning and prescription development involves using the canopy height model to identify individual tree crowns using the CHM. There are many methods to accomplish this task, in this project we chose to use methodology from FUSION to identify individual trees. All of the processes described here are available as packages in the statistical package R (R Core Team 2013). First, a smoothing function was applied to the existing CHM produced by RSAC (or a CHM derived using FUSION functions). Following smoothing, a local maximum function with a moving window applied to identify the location and height of each individual tree. The moving window basically takes a set of cells and identifies the highest point within those cells and determines that it is an individual tree. The moving window size is set to be similar to canopy areas for a given tree/forest type. The final step is to identify and segregate the area of individual canopies for each identified tree. This method results in a dataset with locations, heights, and canopy area/radii for each individual tree identified from the CHM. A crown area and diameter relationship (Sanchez-Meador et. al., 2011) was applied to the data to derive diameter at breast height for each tree. Diameter can be derived in other ways, for example, if local data exists that relates diameter to height, the height values for each tree can be used to predict diameter. Similar to the even-aged raster analysis, a kernel density analysis was applied to the individual tree location dataset to quantify the density of larger trees (Figure 11). However, with the individual tree location data we were able to choose the scale at which we applied the kernel density tool. Given trees per acre as a commonly used estimate, the kernel density tool was applied to trees >16" at an acre scale, resulting in estimates of trees >16"/acre. We chose the 16" threshold as this is a common socially derived cut-off for large ponderosa pine trees in the region.

The resulting datasets; individual tree locations, height, crown area, diameter at breast height; and rasters produced from this layer can be extremely useful in quantifying existing condition. Individual tree list data provides spatially explicit inventory data that can be summarized to the desired scale (i.e., stand, restoration unit, watershed etc.) for forest structural parameters such as tree density and basal area. One main benefit of LiDAR data is that it provides information on every square meter of ground for which it is collected. As with all datasets there are sources of error, however, having some uncertainty everywhere on the landscape can at least be supplemental to datasets (e.g., stand exams) where a large degree of uncertainty exists in areas of the landscape that have not been sampled.

Field Verification

Although LiDAR data does represent forest structure (e.g, height, canopy cover) across every square meter of the project area, the methods and products developed for this report, particularly those using the CHM and other metrics related to height, have not been field validated. Initial accuracy assessment for individual tree segmentation has shown confidence in predicting larger trees (e.g., > 10" in diameter), but that sub-canopy trees are difficult to detect with a high level of accuracy. Interestingly, the two layers relating to the density of larger trees (CHM and standard deviation derived vs. individual tree segmentation) resulted in similar patterns of areas predicted to have larger trees in higher densities. This can be seen by comparing Figures 10 and 11. To begin field validation for areas of higher large tree density, a few field sites have been visited to visually assess the general stand structure relative to the two LiDAR derived products. Figure 12 illustrates the current condition in areas visited relative to the LiDAR derived products (Figures 10 and 11) and generally supports the potential of these products to provide valuable information to the planning process. As with any data product, particularly spatial products, it is valuable to make field visits to verify and further refine understanding of existing conditions as this will help to validate restoration treatments that move toward desired future conditions. Further assessment of these data products is ongoing and USFS staff will be apprised of results of this work in the future.

Figure 12 - Field photos illustrating sites predicted to have a high density of large trees (top photos) and sites that were not predicted to have high density (bottom two photos).

Discussion

The impetus for this project was to provide additional spatial information that would inform project level analyses for large scale restoration projects, using the Burnt Corral Project as a pilot. One of the more contentious topics in collaborative discussions of restoration projects involving mechanical thinning is that of larger diameter trees, particularly those that do not meet old-growth criteria (Van Pelt 2008) but do provide unique wildlife habitat characteristics and maintain forest structural attributes that may be lacking on the landscape. To move forward with selective thinning treatments collaborative stakeholder groups must find implementation strategies in which these areas are protected from large uncharacteristically severe wildfires, continue to provide the large tree structural components for wildlife habitat, and produce increased ecological integrity and resilience across the landscape. The first step in this process, to help build trust and more refined treatment options, is to have the best available data and science to base those collaborative decisions on. The quantity and location of areas of special interest can be key to addressing the concerns of stakeholders while giving managers the flexibility to meet multiple objectives across the landscape.

LiDAR data, applications, and products can help to provide the basis for further collaborative refinement of treatment alternatives, particularly as the cost of the data becomes less prohibitive and the value of the products resulting from this data collection are shown (Hummel et al., 2011). In addition, LiDAR data can readily be used for monitoring at multiple scales (individual tree to stands to landscapes), making it extremely relevant under new planning rules that require broad scale monitoring approaches across forests/regions (National Forest System Land Management Planning 2012). Increased training on potential applications and fundamentals of LiDAR data processing will afford novel approaches to restoration planning by natural resource specialists. The additional information provided by LIDAR can help to achieve the overall goal of moving forward with collaborative decisions based on the best available data and science.

Acknowledgements

Funding was provided for this work by the Kaibab National Forest, and feedback from Valerie Stein-Foster and Ariel Leonard on project components and report drafts were extremely helpful. Discussions and input from Garry Domis (North Kaibab District Silviculturist) was invaluable for producing spatial data layers. This work would not have been possible without the data products that have been derived by Region3 of the U.S. Forest Service. Data Processing for individual tree segmentation outputs was graciously completed by Andrew Sanchez-Meador at Northern Arizona University. GIS processing advice was also provided by TNC-AZ Spatial Analyst Lisa McCauley.

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Deliverables and Outreach

The following deliverables have been provided by TNC to the Kaibab NF based on the Supplemental Project Agreement # 15-CS-11030700-018:

- To inform project level analysis on the Burnt Corral Project area:
    1. Canopy Cover layers derived from 1-meter LiDAR Canopy Height Model (CHM) raster.
    2. Raster layer illustrating areas of higher large (tall) tree density with even-aged structural characteristics
    3. Point layer of all individual trees detected using LiDAR 1-meter CHM.
    4. Raster layer illustrating areas of higher large tree density based on individual tree detections
- Technology Transfer presentation and tutorial for Silviculture, Wildlife, and GIS specialist staff on the Kaibab NF (July 12th, 2016 12pm-4pm).
- Workflow document (Appendix A) outlining data use and processing steps for GIS layer deliverables
- Technology transfer handout and PowerPoint presentation (Delivered with Final Report).
- Final Report outlining project outcomes and deliverables.

Appendices

The following workflow and technology transfer handout outline has been developed based on the development of deliverables for this project. It is followed by a technology transfer handout that provides examples and screenshots to provide an outline for those with less Geographic Information Systems (GIS) experience to follow and produce usable outputs. Familiarity with using ArcGIS raster processing tools is the minimum experience level needed to work through the methods outlined, however assistance from GIS specialists may be needed.

Appendix A: Work Flow (*see Appendix B for screen shots)*

1. **Canopy cover layers**
    a. Overall canopy cover in quartiles
        i. Canopy Height Model Method
        ii. LiDAR Point Cloud Derived Canopy Cover Raster
    b. Upper Canopy Cover – uneven-aged stands - > 55-70' (17 – 22 meters)
    c. Layers to use (all layer files have _BC added to the end since I clipped LiDAR rasters to Burnt Corral (BC) project area).
        i. Canopy Height Model (CHM) **'nk_ch_mosaic_8b_BC.tif'**
        ii. 25 meter Canopy Cover (CC) **'full_all_cover_above3_25METERS_BC.tif'**

    d. Procedures **1 a.i.**
        i. Reclassify CHM raster as canopy or open (1,0) (reclassify tool)
        ii. Sum cells in 30x30 meter area (0-900) (Aggregate tool 30)
        iii. Run Float tool to convert from integer (Spatial Analyst Toolbox)
        iv. (Divide Tool: Cell value divided by 900 to get % Cover value)
        v. Reclassify cells into 0-25, 25-50, 50-75, 75-100%
            1. Classification

a. 1 = 0-25% canopy
b. 2= 25-50%
c. 3= 50-75%
d. 4= 75-100%

vi. Apply Majority filter (8 Neighbors, Half replacement threshold)
vii. Convert to Polygon (Do not Simplify)
viii. Apply simplify or smooth polygon tools if desired (not done for this analysis)

e. Procedures **1 a.ii.**

i. Reclassify RSAC 'full_all_cover_above3_25METERS_BC.tif' raster 0-25, 25-50, 50-75, 75-100%
    1. Classification
        a. 1 = 0-25% canopy
        b. 2= 25-50%
        c. 3= 50-75%
        d. 4= 75-100%
ii. Apply Majority filter (8 Neighbors, Half replacement threshold)
iii. Convert to Polygon (Do not Simplify)
iv. Apply simplify or smooth polygon tools if desired (not done for this analysis)

f. Procedures **1 b.**
i. Reclassify CHM so that heights above 15 meters are classified as 1 and remaining values below 15 meters are 0's.
ii. Sum cells in 30x30 meter area (0-900) (Aggregate tool 30)
iii. Run Float tool to convert from integer (Spatial Analyst Toolbox)
iv. (Divide Tool: Cell value divided by 900 to get % Cover value)
v. Reclassify cells into 0-25, 25-50, 50-75, 75-100%
    1. Classification
        a. 1 = 0-25% canopy
        b. 2= 25-50%
        c. 3= 50-75%
        d. 4= 75-100%
vi. Apply Majority filter (8 Neighbors, Half replacement threshold)
vii. Convert to Polygon (Do not Simplify)
viii. Apply simplify or smooth polygon tools if desired (not done for this analysis)

g. Deliverables PRODUCED
i. Canopy Cover (from RSAC) converted to canopy cover classes
    1. Filename **- 'full_all_cover_above3_25meters_bc_poly'**
ii. Canopy Cover (using CHM) converted to canopy cover classes

            1. Filename **- 'chm_cover_above2_30meters_bc_poly'**
      iii. Canopy cover of upper canopy trees (15-23 meters) using CHM) only converted to canopy cover classes
            1. Filename **– 'chm_cover_above15_30mres_bc_poly'**

2. Layer of Even aged larger preponderance of large young trees (PLYT)

   a. Assumptions
      i. Larger = Taller
      ii. Even aged = Similar height across canopy
   b. Layers to use (all layer files have _BC added to the end since I clipped LiDAR rasters to Burnt Corral (BC) project area).
      i. Canopy Height Model (CHM). **'nk_ch_mosaic_8b_BC.tif'**
      ii. Standard Deviation of point cloud height (SDH). **'full_elev_stddev_2plus_25METERS_BC.tif'** Skewness raster could be valuable as well to determine whether canopy heights are skewed towards taller trees (even aged) or evenly distributed throughout the canopy (uneven-aged)
   c. Procedures
      i. Reclassify CHM in to broader categories.
         1. Use distribution of reasonable height values (ignoring 0's and excluding extremely high values for cliffs) divide distribution into percentiles (0-25, 25-50, 50-75, 75-100%). For this analysis the following quartile cutoffs were used based on the canopy height distribution:
            a. 0-25% = 0 - 12.5 meters
            b. 25-50% = 12.5 – 25 meters
            c. 50-75% = 25 – 37.5 meters
            d. 75-100% = 37.5 – 50 meters
         2. Categories – If tall trees are the target, decide what height values represent taller trees.
            a. For old growth, > 75th percentile is adequate (see Woolley 2014 report to KNF).
            b. For large/tall trees that may still be young a different value should be used. For this analysis I chose 50th-75th percentile height range to reduce the data to PLYT.
      ii. Reclassify CHM with 50-75 percentile value of height – Create category of 0 and 1 (1 being 50-75th percentile values, and 0 everything else).
      iii. Resample SDH (25 m resolution) to 1 meter resolution to match CHM raster.
      iv. Reclassify SDH into 4 categories based on quantiles from 0-14 meters (0-3.5, 3.5-7, 7-10.5, 10.5-14) and a fifth category for outliers of 14+ meters.
      v. Multiply Reclassified CHM ('**nk_ch_mosaic_8b_BC_reclass_50-75thpercentile.tif'**) by reclassified SDH.
         1. Resulting layer is classified from 0-5. 0's represent areas where tall/large trees aren't detected based on CHM percentile classification. 1-5s' represents areas with tall trees with varying ranges in overall canopy.
            a. 1's and 2's = Tall trees with very little deviation in the height of canopy (particularly 1's) and are more likely to be even aged taller trees.
            b. 3's and 4's = Tall trees with much larger deviations in in the height of canopy and likely have more stratification of canopy layers and may have more uneven aged structural characteristics (i.e., multi-layered/aged canopy trees)

            c. 5’s = Likely outliers of high standard deviation based on cliff artifacts, birds, etc.

- d. Deliverables PRODUCED
    - i. Raster layer denoting areas where larger (taller) trees exist with varying stratification of the canopy (even-aged and uneven aged).
        1. **‘CHM_SDH_multiply_BC.tif’**
    - ii. Kernel Density Raster
        1. Convert **‘CHM_SDH_multiply_BC.tif’** to point shapefile (Raster to point Conversion tool)
        2. Clip point shapefile file to only include 1’s and 2’s (see C.V.1. above)
        3. Run Kernel density tool (default settings used) on subsequent shapefile to produce raster that indicates where the highest density of “even-aged” tall tree areas exist.
        4. Resulting density raster of potential ‘even aged large tree’ structure ‘**KernelD_Even aged_LargeTree.tif**’

3. Individual Tree Segmentation tree list

- a. Using Canopy Height Model (CHM) Raster this process applies several steps to identify individual tree crowns, their local maximum (top of tree), and determines crown area. The analysis was performed using R software and the package rLiDAR (https://cran.r-project.org/web/packages/rLiDAR/rLiDAR.pdf).
    - i. Methods (see manual for specific functions)
        1. Derive a CHM from LIDAR .las data (or use RSAC developed CHM) and run smoothing function.
        2. Identifies the location and height of individual trees using a local maximum function with a fixed moving window. This identifies the highest point within a set of pixels and determines the highest point is the top of an individual tree.
        3. Derives ground-projected canopy area of each individual tree using the CHM.
        4. Using published equation (Sanchez-Meador et al. 2011) predict diameter from crown radius value for each individual tree
    - ii. Output data set(s)
        1. Point Shape file of individual tree records (rLiDAR_CHMSeg)
            - a. X,Y,Z coordinates for tree location and height (Z)
            - b. Ca (canopy area in square meters)
            - c. Crad (Crown radius in meters)
            - d. DBH_cm_pre (predicted diameter in centimeters)
            - e. DBH_in_pre (predicted diameter in inches)
            - f. Predicted diameter is derived from a regression equation relating crown radius and diameter (Sanchez-Meador et al. 2011).
        2. Kernel Density raster
            - a. Large (tall with large canopy)
    - iii. Uses/products
        1. This dataset can be summarized at any scale desired. Stand or compartment boundary layers can be used to summarize to the stand level, or 1-acre grid cells can be created to use for summary at a smaller scale.

2. Kernel Density maps as described above can also be created to quickly summarize and visualize areas with higher densities of larger trees.

iv. Limitations

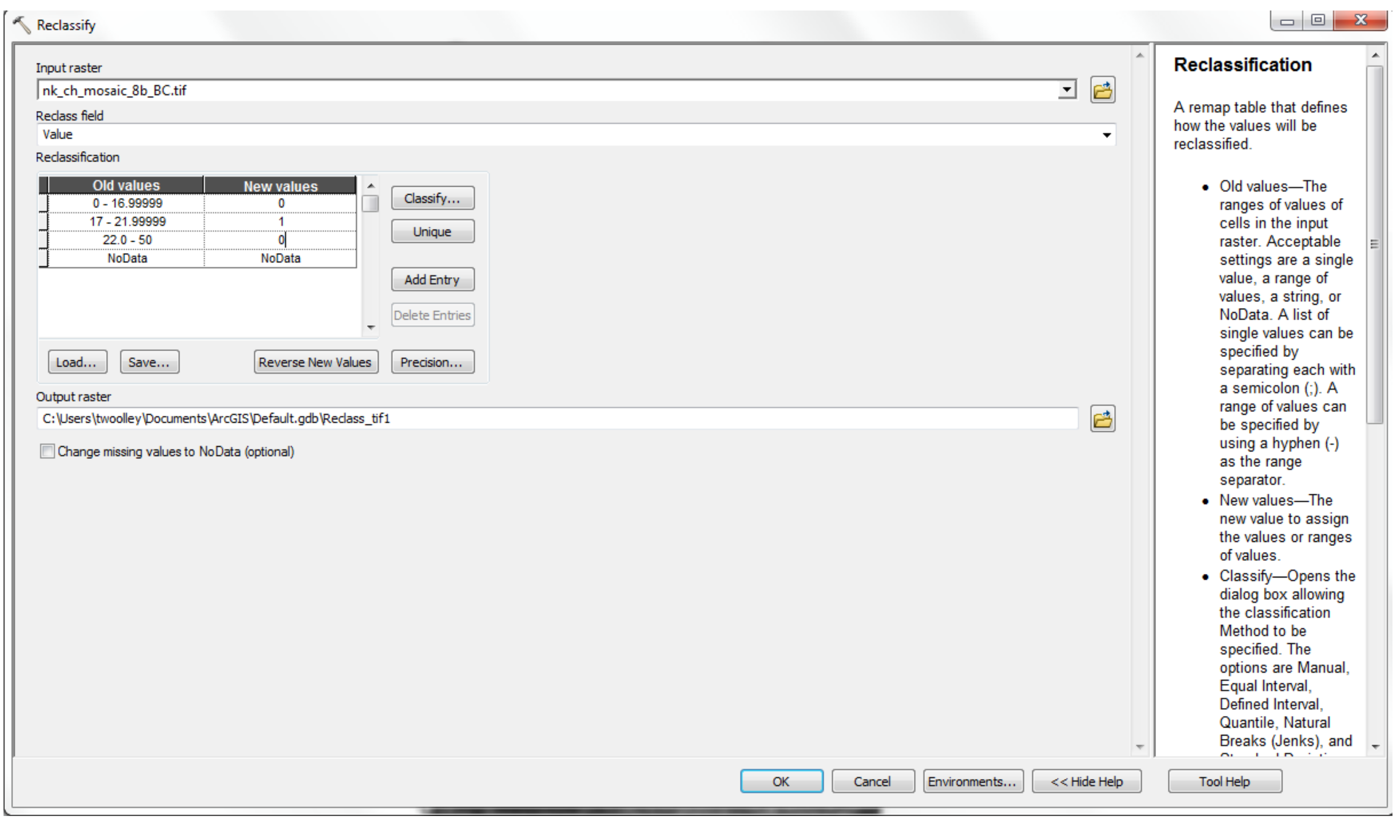
1. Recent work by NAU (funded by TNC) has shown that Individual Tree Segmentation does not predict individual small (<8-10" DBH) trees accurately. This layer should be used as a larger scale planning tool to determine relative tree density of trees > 8-10" diameter.

Appendix B: *Technology Transfer Handout/Tutorial*

Exercise #1 – Using a LiDAR derived Canopy Height Model (CHM) to create a Canopy Cover Raster layer

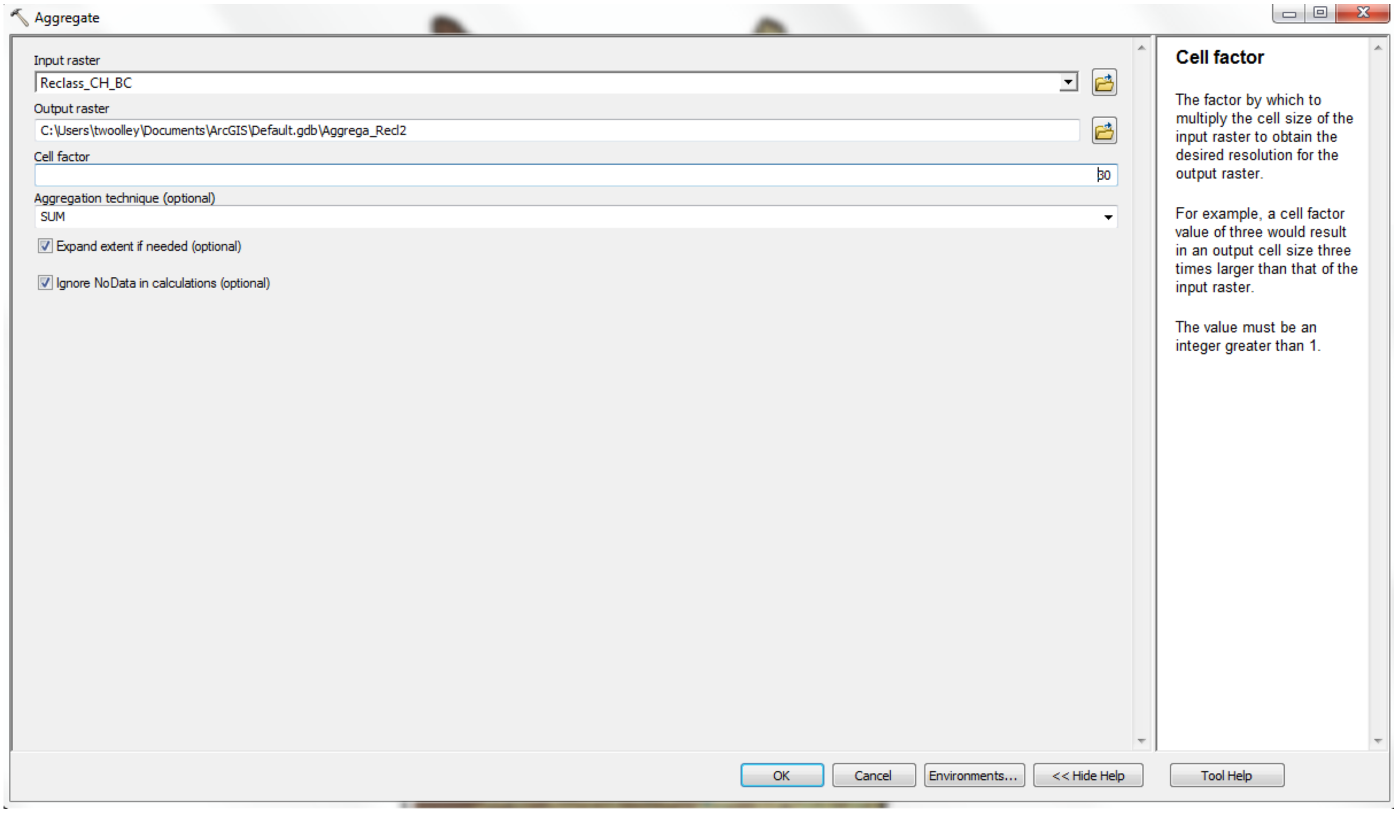
Procedures

1. Reclassify CHM Raster as either Canopy (1) or no canopy (0)
   a. Use Reclassify tool: *Spatial Analyst Tools>Reclass>Reclassify*
   b. Choose height threshold for canopy layers of interest
      i. Example: Canopy cover of "upper canopy"
         1. 12"-18" dbh - using an average of 15" a height threshold might be 55'-70' (***15-22 meters***) in height.
      ii. < 55' height or >70' height = 0
      iii. >55' and <70' = 1



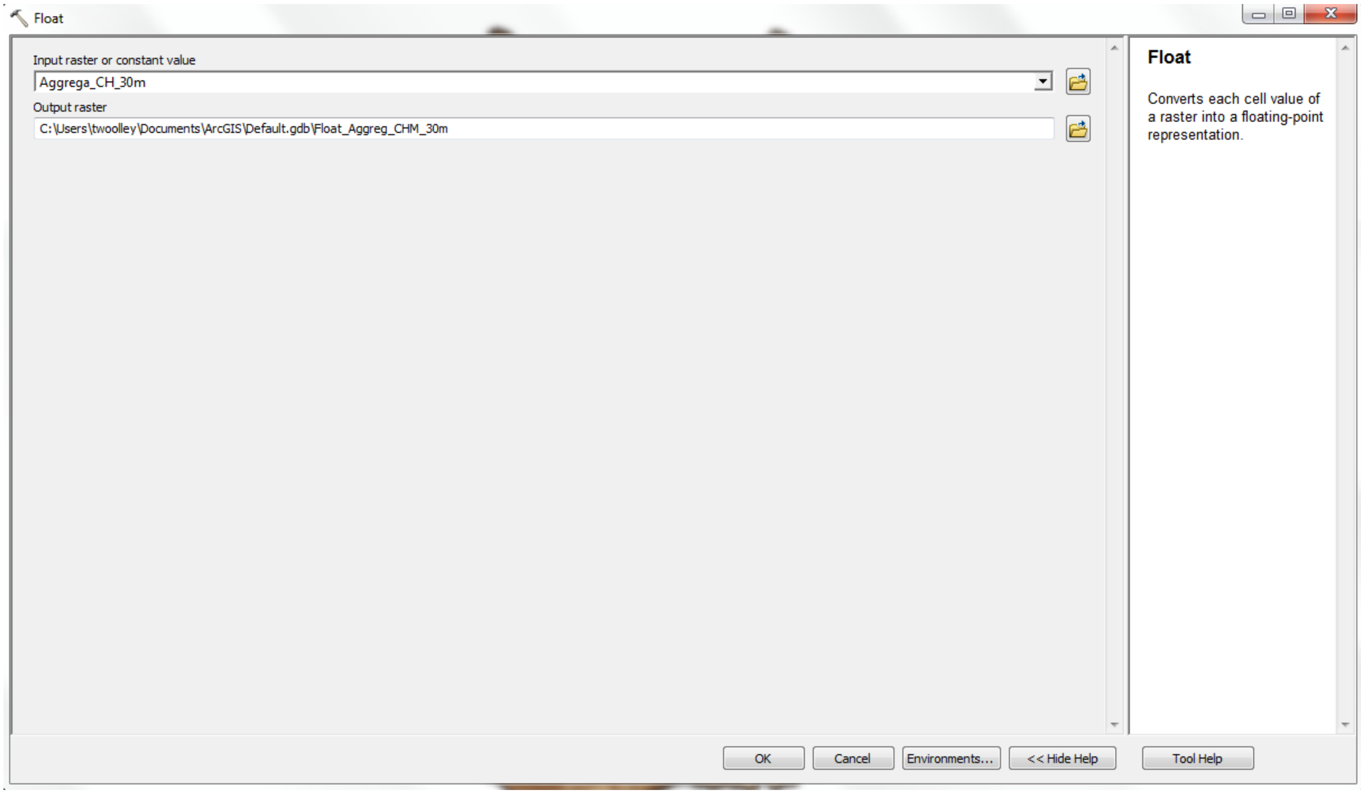
c. **Result**: CHM Raster reclassified of only desired canopy height (i.e., 55-70')

2. Sum cells within 30x30 m area (900m^2)
   a. Use Aggregate tool: *Spatial Analyst > Generalization > Aggregate*
      i. Cell Factor of 30 (makes it a 30 meter resolution raster output)

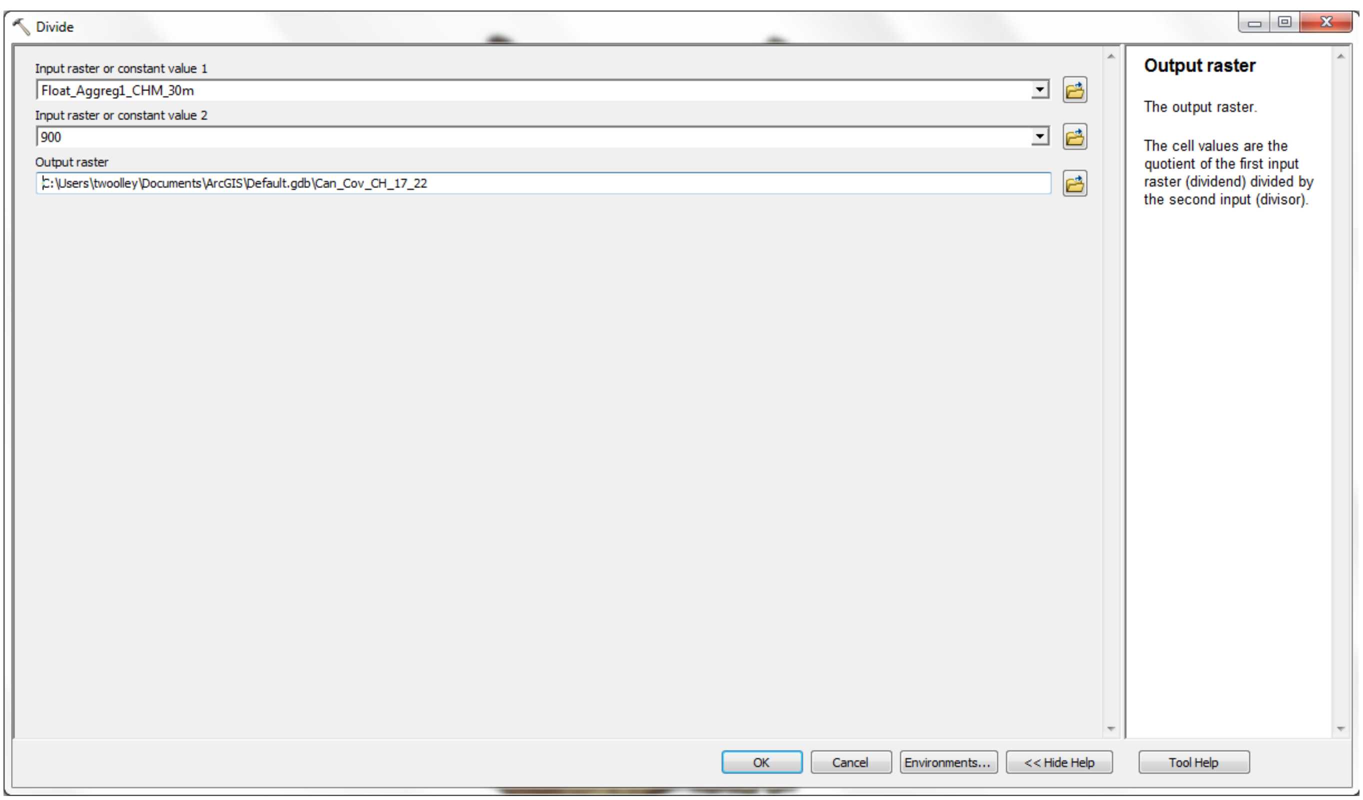


   a. **Result:** 30-meter resolution aggregation of 1's and 0's
      ii. Largest possible value is 900 (all canopy) and lowest is 0 (no canopy)

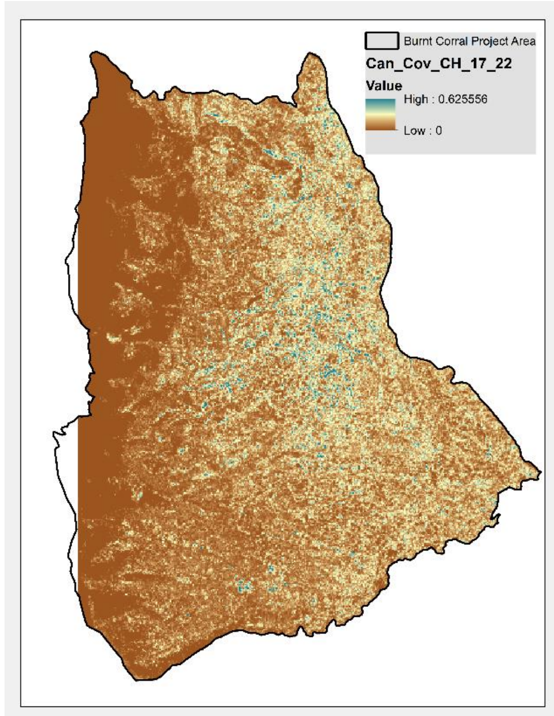
3. Convert raster to integer
   a. Use Float Tool: *Spatial Analyst > Math > Float*



4. Divide cells by 900 to obtain % canopy cover values for each 30-meter cell
    a. Use Divide tool: *Spatial Analyst > Math > Divide*



5. **Result:** Percent Canopy cover raster for canopy > 17 m and < 22 m in height (i.e., “upper canopy”)

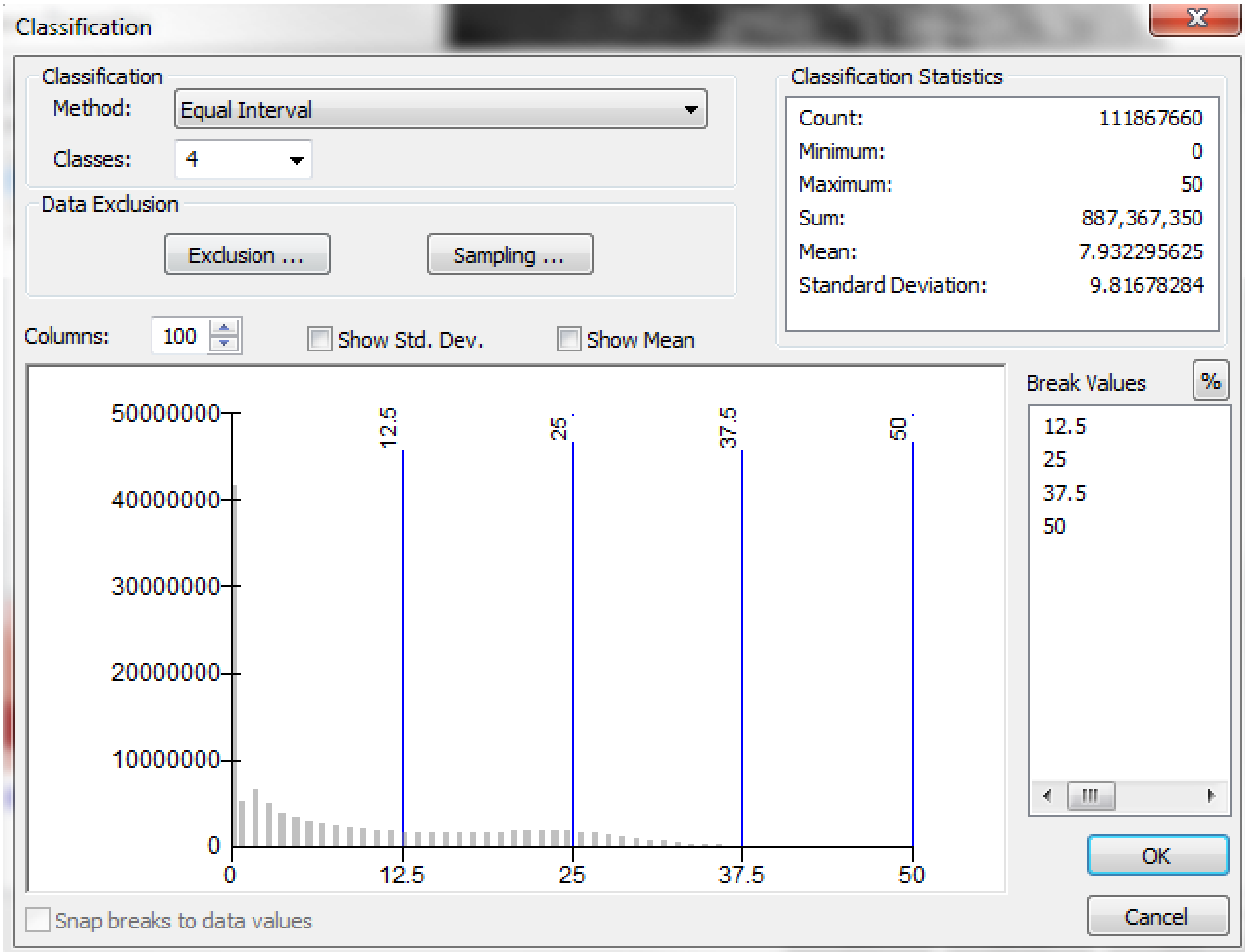


6. ***Optional***
   a. Reclassify to percentile classes of interest (e.g., 0-25, 25-50, 50-75, 75-100%)
   b. Convert to vector (polygon)

Exercise #2 – Using LiDAR derived CHM to identify areas of younger and larger (taller) trees existing in an even-aged structure

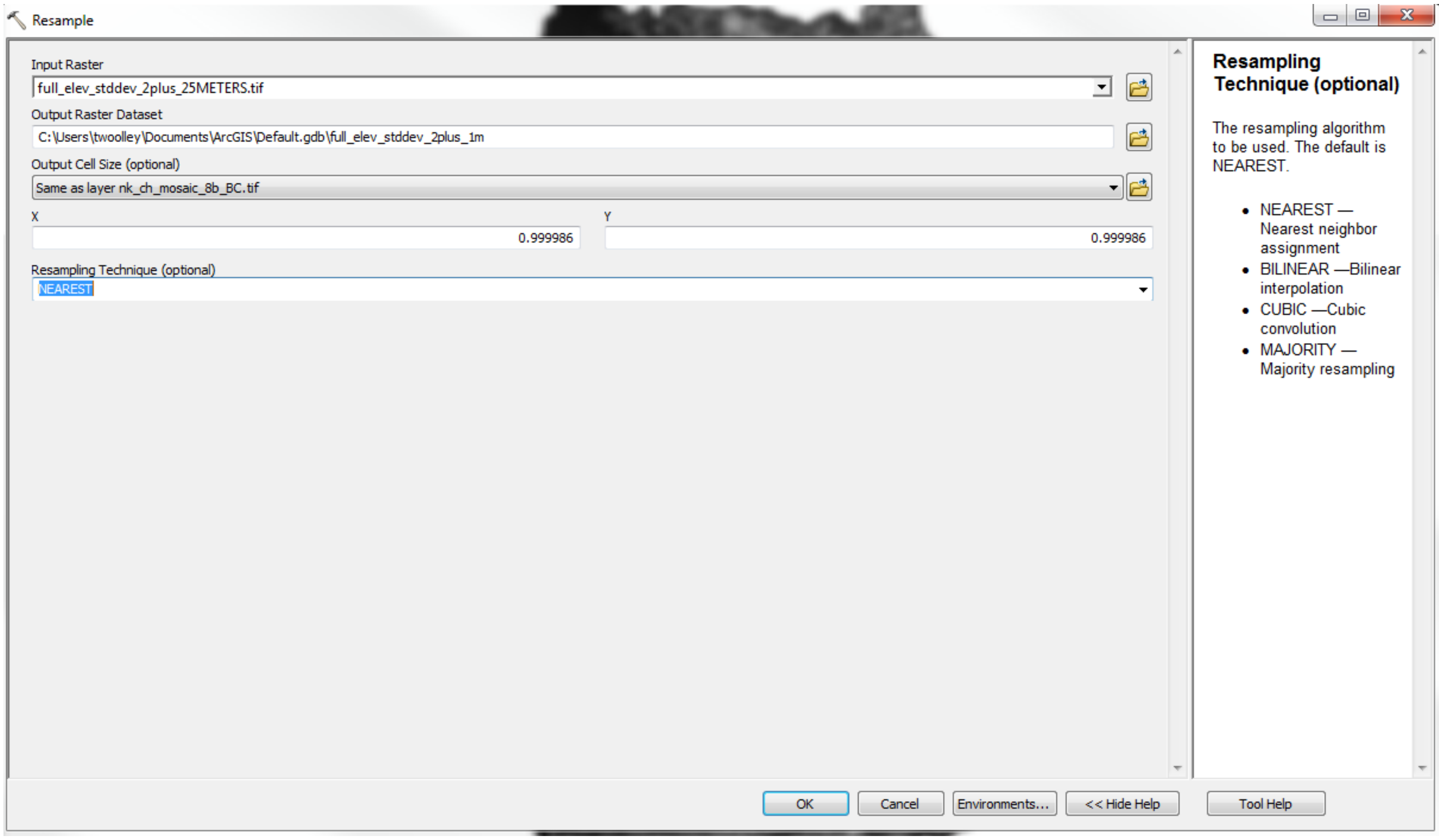
Procedures

1. Reclassify/examine CHM into broader height categories based on quartiles
   a. Use Reclassify tool: *Spatial Analyst Tools>Reclass>Reclassify*
      i. 0-25% = 0 - 12.5 meters
      ii. 25-50% = 12.5 – 25 meters
      iii. 50-75% = 25 – 37.5 meters
      iv. 75-100% = 37.5 – 50 meters
   b. Use histogram to determine percentile height values and skip to Step C.



c. Height Values that represent young AND large
   i. Example 50th-75th percentile (25 - 37.5 meters)
d. Reclassify/CHM into 2 categories
   i. 1 = 25-37.5 meters
   ii. 0=<25 meters or > 37.5 meters

2. Resample Standard Deviation of Height (SDH) raster to same resolution as CHM (1 meter)
   a. Use Resample tool: *Data Management > Raster > Raster processing*
      i. *Use CHM raster as output cell size*



3. Reclassify SDH into 5 categories based on distribution and outliers
    a. 1 - 0-3.5 meters
    b. 2 - 3.5-7 meters
    c. 3 - 7-10.5 meters
    d. 4 - 10.5-14 meters
    e. 5 - > 14.0 meters (outliers)

4. Multiply Reclassified CHM and Reclassified SDH

5. Use Times tool: *Spatial Analyst > Math > Times*

6. **Result:** Raster layer of:
    c. 0's = young large trees are not present
    d. 1's and 2's = Tall trees with very little deviation in the height of canopy (particularly 1's) and are more likely to be even aged taller trees.
    e. 3's and 4's = Tall trees with much larger deviations in in the height of canopy and likely have more stratification of canopy layers and may have more uneven aged structural characteristics (i.e., multi-layered/aged canopy trees)
    f. 5's = Likely outliers of high standard deviation based on cliff artifacts, birds, etc.

7. To Visually assess this more easily:
    a. Convert Raster cells of interest (for even-aged large young trees use values of 1 and 2) to points
        i. Use Raster to Point tool: *Conversion Tools > From Raster > Raster to Point*

b. Use Kernel Density Tool to identify areas with a “higher density” of young, large, uneven aged structure.

   i. Use Kernel Density Tool: *Spatial Analyst Tools > Density > Kernel Density*

      1. Choose units and cell size for desired output