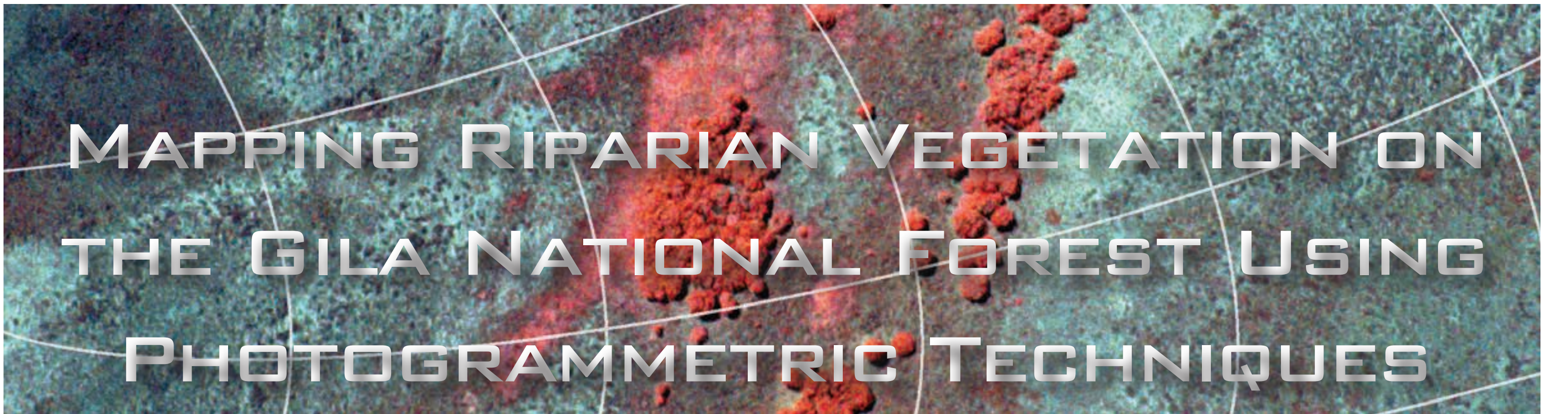
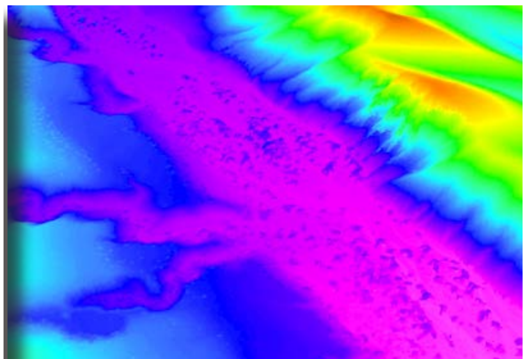
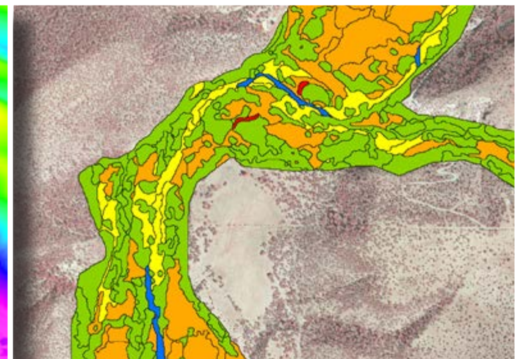
United States Department of Agriculture
Forest Service

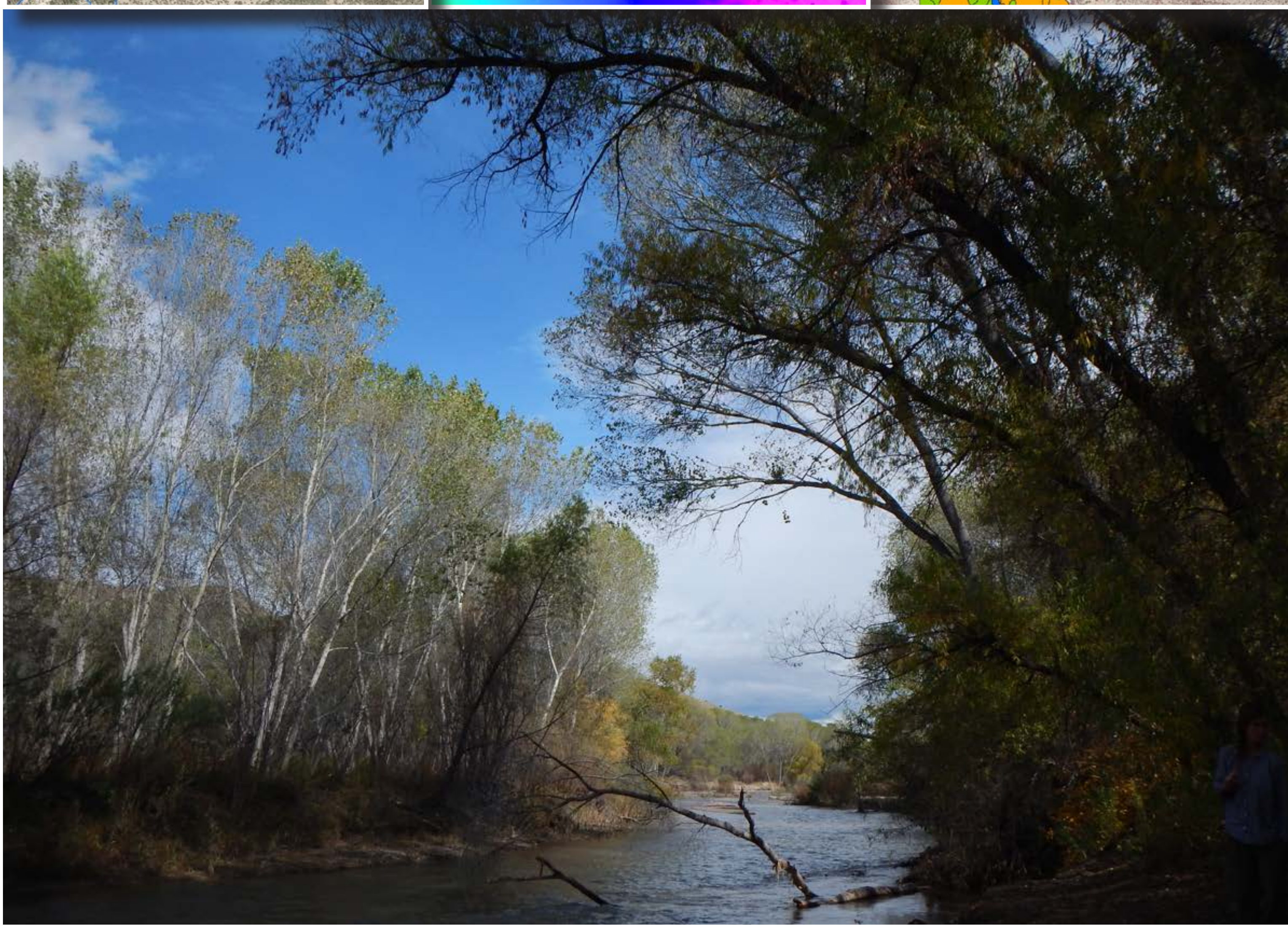


Mapping Riparian Vegetation on the Gila National Forest Using Photogrammetric Techniques

August 2016
RSAC-10121-RPT1







Abstract

A technique for generating a digital surface model (DSM) from stereo 30 cm image pairs was investigated for use in mapping riparian vegetation, canopy cover, and canopy height on the Gila National Forest. Semi-Global Matching (SGM) is a relatively low cost photogrammetric technique used to create a high resolution DSM over a large area using stereo image pairs. For this pilot project, multiple digital elevation model manipulation techniques were used on an image-derived DSM to create a digital terrain model (DTM). The difference between a DSM and a DTM was used to produce a canopy height model (CHM) which was used in mapping land cover, canopy cover, and canopy height. A visual assessment of the CHM, using high resolution imagery, showed agreement with riparian land cover types. The CHM, topographic data, and high resolution imagery were used to segment the study area into objects with similar characteristics for use in vegetation mapping. The effect of the CHM on out-of-bag error in Random Forest classification of vegetation type and canopy height was examined. Generally the largest and smallest canopy height classes were mapped with the least amount of out-of-bag error, and inclusion of the CHM improved the out-of-bag error for the vegetation type map. Possible factors contributing to the results are discussed, including inherent limitations of the SGM technique and challenges related to the terrain of the study area.

Key Words

Digital Surface Model, Digital Terrain Model, Semi-Global Matching (SGM), Image-Derived Surface Model, lidar, Stereo Image Pair, Photogrammetry, Phodar

Authors

Adam Clark is a remote sensing specialist employed by RedCastle Resources at the Remote Sensing Applications Center (RSAC) in Salt Lake City, Utah.

Carson Stam is a remote sensing specialist employed by RedCastle Resources at RSAC.

Wendy Goetz is the vegetation mapping group leader employed by RedCastle Resources at RSAC.

Paul Maus is a contract leader and a principal of RedCastle Resources at RSAC.

Kevin Megown is the Resource Mapping, Inventory, and Monitoring program leader at RSAC.

Jack Triepke is the Regional Ecologist for the Forest Service Southwestern Region in Albuquerque, New Mexico.

Bart Matthews is the Photogrammetry Program Specialist for Forest Service Southwestern Region.

Esteban Muldavin is the Director and Ecologist for Natural Heritage New Mexico, Biology Department, University of New Mexico in Albuquerque.

Clark, A.; Stam, C.; Goetz W.; Maus, P.; Megown, K.A.; Triepke, J.; Matthews, B.; Muldavin, E. 2016. Mapping riparian vegetation on the Gila National Forest using photogrammetric techniques. RSAC-10121-RPT1. Salt Lake City, UT: U.S. Department of Agriculture, Forest Service, Remote Sensing Application Center. 9 p.

Table of Contents

Introduction

Stereo imagery has been used for decades in the production of topographic maps and elevation models using photogrammetric techniques. Due to recent technological advancements, detailed elevation information can now be automatically extracted from digital stereo aerial imagery using a process known as Semi-Global Matching (SGM) (Hirschmüller 2008).

SGM uses overlapping imagery and sensor orientation, location, and correction data from the associated 'block files' to create data points with an x, y, and z coordinate if the same feature is 'matched' in more than one image. The outputs from SGM are in the same file format as a lidar point cloud (.las) and can contain millions of data points. The point cloud can then be fed into a software application to create a digital surface model (DSM). Comparisons between a DSM with a digital terrain model (DTM) can be used to approximate canopy structure. Because of low cost and high accuracy, image-derived DSMs are comparable and in some cases preferred to those created from lidar (Gobakken and others 2015). However, creating a DTM is challenging using SGM.

While there has been research in measuring canopy structure by using data manipulation tools on inverted lidar-derived DSMs, specifically to identify tree crown location and height (Pyysalo and Hyyppa, 2002; Ziegler, Michaela, and others 2000), little has been done to see if these methods work on inverted image-derived DSMs. This project investigated different methods for extracting canopy height and canopy cover information using inverted image-derived DSMs with data manipulation tools and also developed a workflow for creating a riparian vegetation map.

Study Area

The study area is located in the Gila National Forest (NF) in western New Mexico. The area included all riparian corridors within the Gila NF as defined by boundaries created by the Regional Riparian Mapping Project (RMAP), encompassing about 65,484 acres/26,500 hectares and an elevation range from 1,186 to 2,904 meters (3,892 to 9,528 feet). RMAP was produced in 2013 using topographic information and photo-interpretation methods to delineate all riparian corridors in the Forest Service Southwestern Region (Triepke and others 2013).

Data Collection

This project used a wide variety of geospatial data including high resolution resource imagery, Landsat 8 imagery, topographic data, photo-interpreted data, and vegetation field data. All data were projected to a NAD 83 UTM Zone 12 projection.

Resource Imagery

A stereo aerial image dataset of 30 cm resolution covering the Gila NF was collected by an UltraCam Eagle sensor in August and September of 2013. The imagery contained four-spectral bands (blue, green, red, and near-infrared) in 8-bit GeoTIFF format. A Normalized Difference Vegetation Index (NDVI) was also produced to help distinguish vegetated areas. To decrease processing time and memory storage required to develop the DSM, the minimum number of image pairs was chosen for the required coverage of the study area. Where possible, one image pair was chosen as coverage for an area, when 4 could have been included.

Landsat Imagery

A Landsat 8 OLI mosaic was created from 6 scenes from June 2014 and 2015 (P34R36, P34R37, P34R38, P35R36, P35R37, and P35R38). Imagery was used from two different years in order to obtain a cloud-free mosaic.

Landsat Seasonal Coefficients

Landsat scenes from 2010-2015 were compiled into a time series using Google Earth Engine. Angle, a derivative from the Tasseled Cap Transformation, was calculated for each scene and a harmonic regression equation was then built for each pixel. These equations used the cosine and sine of time as independent variables and angle values as the dependent variable. These equations then represented the seasonal variability (speed, magnitude, and longevity of green-up and senescence). The equations each had three coefficients (slope of cosine, slope of sine, and y-intercept) which were represented as individual bands in an image.

NED

The National Elevation Dataset (NED) is a seamless elevation dataset for the entire United States provided by the USGS (Siddiqui and Garrett, 2008). Multiple sources such as lidar, contour maps, and data from the Shuttle Radar Topography Mission were used to create this dataset (Gesch, 2002). Although throughout the US different spatial resolutions are available, within the Gila NF the NED data resolution is 1/3-arcsecond (about 10 meters). Slope and tri-shade topographic derivatives were created for use as predictor variables in the modeling phase.

Lidar

Lidar data intersecting 1,000 acres of the RMAP project area were provided by the Southwestern Regional Office. These data were acquired during leaf-free conditions during the fall of 2013 and had a 0.5 meter spacing. Lidar data were used to generate training samples and for model validation.

Reference Data

Reference data for this project were comprised of 337 visited Terrestrial Ecological Unit Inventory (TEUI) field plots, 84 visited field sites from Natural Heritage New Mexico, and approximately 2,400 photo-interpreted sites. These plot data were synthesized to represent project map themes of lifeform, leaf retention, and plant height. A quality check was done to ensure all plots represented the entire mapping segment in which they were located.

Methods

The development and assessment of a canopy height data layer and production of a vegetation map was accomplished in three main phases. First the methods for producing a CHM were tested, assessed, and a final product produced. Second, the riparian area delineated by RMAP was buffered out by 20 meters and segmented to develop the modeling units. Third, a vegetation type map was produced using Random Forest classification and field and photo-interpreted reference data. The final vegetation map was clipped to the RMAP boundary and filtered to a .25 hectare minimum map feature size.

Phase I: Development and Testing Methods for Canopy Height

Creating an image-derived CHM was a multi-step process. A number of techniques and methods were used to investigate the use of stereo image pairs to estimate canopy height.

Imagery was converted into point clouds using Tridicon SGM algorithms in the Erdas Photogrammetry toolbox. Tridicon SGM generates a 3-D point cloud from overlapping aerial imagery. The imagery and block files were provided by the Southwestern Region and were used to create .las file point clouds for all riparian corridors within the Gila NF.

If the difference of a pixel value between the SGM DSM and the NED was more than 50 meters, the program set the pixel value to that of the NED. This resolved many of the noise issues that were present after creating the DSM from the point cloud. It is unclear what causes these noise issues, but it seems that areas of high elevation and slope were most affected.

All elevation models have error. In a hydrologic sense, a pit is a depression in a DEM that has no outlet for water to flow. Pits may cause erroneous results and derived drainage networks may be discontinuous and are generally undesirable in hydrologic modeling. A pit removal tool is usually applied to all DEMs to remove these types of errors before hydrologic processing. This tool will (1) identify all pits, and (2) identify the closest outlet point, and will (3) modify all elevation data within the pit to the height of the outlet point (figure 1).

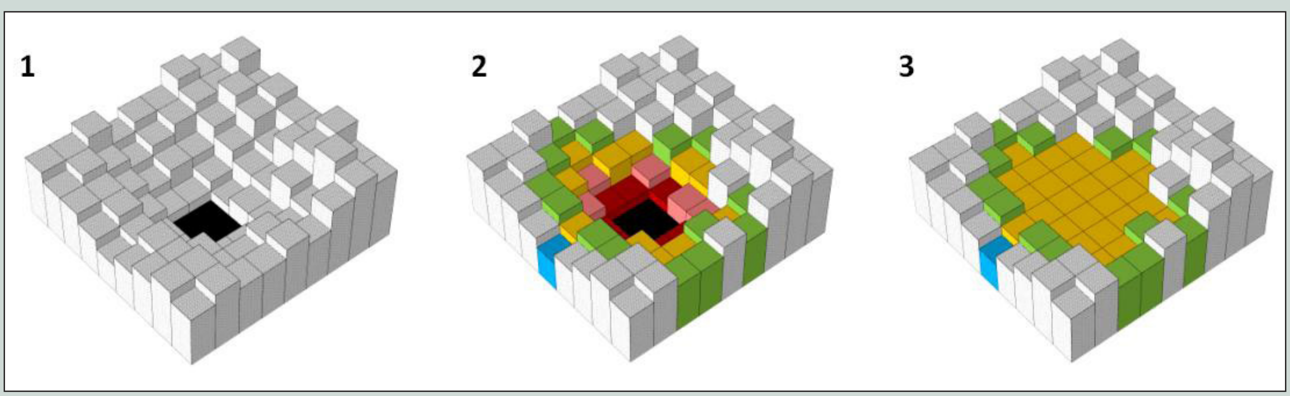


Figure 1—Model showing the 3 main steps used by a pit removal tool (http://wikhydro.developpement-durable.gouv.fr/images/3/31/Fill_Sinks.JPG).

If a DSM has high enough resolution it will be able to model above ground features such as trees or buildings. When a pit removal tool was run on an inverted DSM the tool identified and filled each above ground feature to the lowest pour point. Once the filled DSM had been inverted again it more closely resembled a DTM, referred to as a "Filled DTM". This inverted raster was subtracted from the original DSM. The result was a raster that identified all areas that qualified as pits and were filled, namely trees, hill tops, mountain tops, and buildings as well as a height value.

Above ground features located on a slope had a lower outlet point due to one side of the object being lower in elevation (figures 2 and 3). While not providing accurate canopy height information, the fill was useful for location identification. A conditional statement was run that identified each area in the filled raster and determined whether the Filled DTM or 10m NED DEM was lower in elevation and created a new raster that would reflect the lower of the two, referred to as a "Top Off DTM"—which is alluding to a gas tank that one would "top off" after "filling" it up.

Phase 2: Image Segmentation

After the CHM was developed the modeling units (segments) were produced in eCognition using resource imagery, NDVI derived from resource imagery, and the Top Off CHM as input raster data. A minimum size filter of approximately 40 square meters was used to screen out the segments that were too small to be useful. A visual inspection, using the 30 cm imagery, determined that the CHM layer increased the quality of the modeling units. Quality was determined by assessing the modeling unit's homogenity in lifeform, leaf retention, canopy cover, and canopy height.

Phase 3: Modeling

The modeling phase developed the statistical relationships between the reference data and the geospatial predictor data. These statistical relationships were then applied to the full extent of the census data to build a map. The first step involved producing zonal statistics (minimum, maximum, mean, and standard deviation) for each modeling unit using Landsat 8 imagery and seasonal coefficients, resource imagery, Top Off CHM, and the topographic data. Random Forest algorithm was then used to assign lifeform, leaf retention, woody lifeform, canopy cover, and canopy height classes (Breiman 2001) (table 1). Each model output was carefully evaluated for inconsistencies or misclassification using the high resolution imagery. Areas that were misclassified were reassessed, new training data added, and new models developed. This modeling procedure was repeated until the maps were considered satisfactory. The map was finalized by clipping it to the RMAP boundary and aggregating and filtering the map features to the minimum feature size.

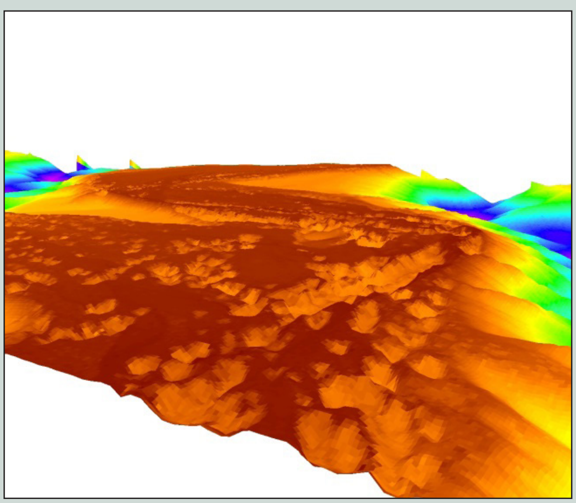


Figure 2—Inverted DSM.

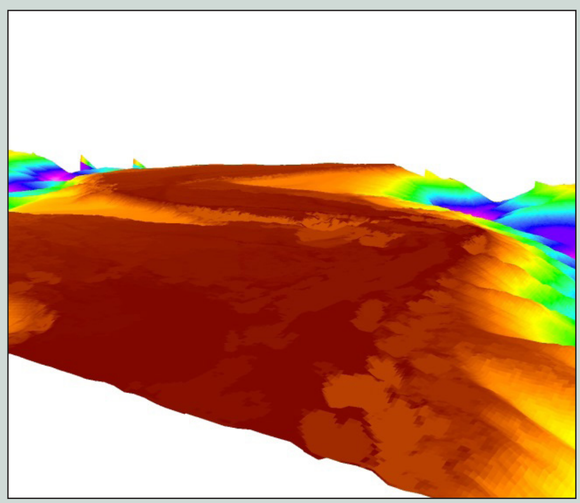


Figure 3—Filled inverted elevation model.

Table 1—Lifeform, leaf retention, woody lifeform, canopy cover, and canopy height classes

Lifeform	Leaf Retention	Woody Lifeform	Canopy Cover	Canopy Height
Tree-Shrub	Evergreen	Tree	10-25%	0-0.5 m
Grass Forb	Deciduous	Shrub	25-50%	0.5-5 m
Bare soil	Mixed Evergreen-Deciduous		50-75%	5-12 m
Water			75-100%	>12 m
Shadow				

Results and Discussion

Canopy Height Data Layer

Using stereo image pairs to model canopy height is quickly becoming one of the best vegetation mapping options available because of the low cost, potential for future data collection, and the availability of historical photography. However, one of the main disadvantages of image-derived elevation models are the inability to penetrate dense vegetation cover and model the ground surface. Without any bare earth elevation data it is difficult to create a DTM in areas with dense canopy cover. Since a DTM is necessary to calculate canopy height this can present a major obstacle.

To quantify the accuracy of the CHM, a linear regression analysis comparing lidar was completed using the canopy height values from 1,000 random points. Canopy heights derived from lidar filled DTM, top off DTM, and NED bare earth model rasters were compared. Using NED as a standalone bare earth model for deriving CHM resulted in a low R^2 value (0.58) when compared to lidar canopy height data. Because of the difference in spatial resolution between these datasets, some height values were returned as negative, and when all negative values were set to zero the strength of the relationship increased R^2 value of (0.66) (figure 4). Using the Filled DTM for deriving CHM resulted in an R^2 value of 0.71 with most canopy height calls underestimated. It was found using the Top Off method, which uses the Filled DTM as a mask with NED filling in for higher elevation areas, further increased the R^2 values to 0.80, with most calls overestimating canopy heights.

While it was decided that a 1 meter DSM could have more accurately modeled the canopy structure of the forest, a 3 meter raster was created because of the high processing and storage required in creating a 1 meter model. Choosing a resolution of 3 meters exponentially reduced processing time and the storage required for this project. Using higher resolution DSMs is one potential avenue for greater accuracy and further study.

Data Processing Consideration

A higher pyramid level signified that more data were consolidated into fewer pixels. At pyramid level 0 there is no consolidation. It was found that pyramid level 1 had no major visual difference over level 0, but took half the time to process and occupied one quarter of the stored memory. A higher pyramid level also created the desired effect of smoothing the DSM, which may have filtered out unneeded data and made processing simpler in the long run.

Data gaps in the image-derived point cloud were present as expected, especially in rough terrain and high altitudes. For this project, the minimum number of image pairs for each area were chosen to produce the DSM, which resulted in occasional data gaps. A better practice may be to pick the maximum number of image pairs to increase the amount of data for an area, though more image pairs will lead to increased processing time and memory storage requirements. As some areas can have up to 4 image pairs, this is a decision that needs to be considered with the costs in mind. If data processing increases, the analyst time and the space needed to manage the data are increased.

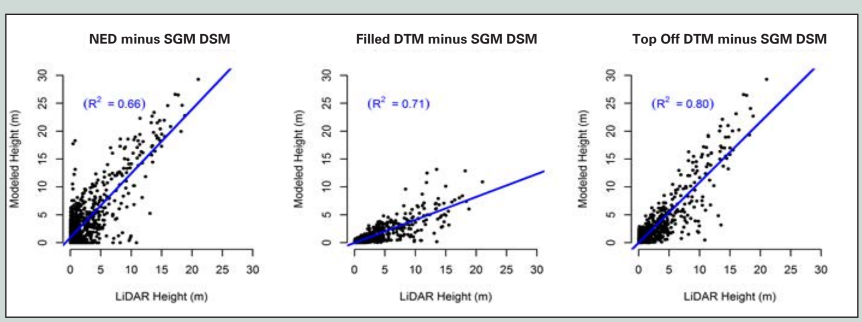


Figure 4—Plotted results of linear regression analysis showing comparison from lidar, NED, and image-derived DTMs.

One disadvantage of the inverted DSM approach to deriving a DTM is that the tops of hills, mountains, and rock features were identified as pits and subsequently filled. The pit removal tool has a parameter that only allows the tool to fill pits that have minimum drainage area; this is normally used for excluding actual bodies of water. Lowering this parameter excluded most of the hilltops. A visual inspection was made for the riparian areas within the Gila NF to check for these types of problems, and manual edits were made to remove these which were concentrated along cliff edges in steep canyon areas. As riparian areas by definition low hilltops, mountaintops, and rock features, this was not a large obstacle to overcome, usually by exclusion using RMAP boundaries.

Mapping

Map attributes characterizing lifeform, leaf retention, woody lifeform, canopy cover, and canopy height were developed using the Random Forest algorithm. Random Forest is an advanced machine-learning algorithm based on the recursive generation of classification and regression trees. The resulting map products provide for continuous vegetation information for the RMAP area. These maps were produced using all of the geospatial data, including the image-derived canopy height information, and field and photo-interpreted training data. The lifeform map was produced first, followed by leaf retention, woody lifeform, canopy cover, and canopy height classes. The final map was aggregated and filtered to the .25 hectare minimum map feature size.

When a Random Forest model was created, it produced an estimate of the importance of each predictor variable to the accurate modeling of the dependent variable. This analysis consistently identified the canopy height layers as the most important predictors for accurate classification. The maximum, mean, and standard deviation canopy height statistics were the top three variables for mapping canopy height (figure 6). Mean canopy height also ranked the highest when mapping the woody lifeform map.

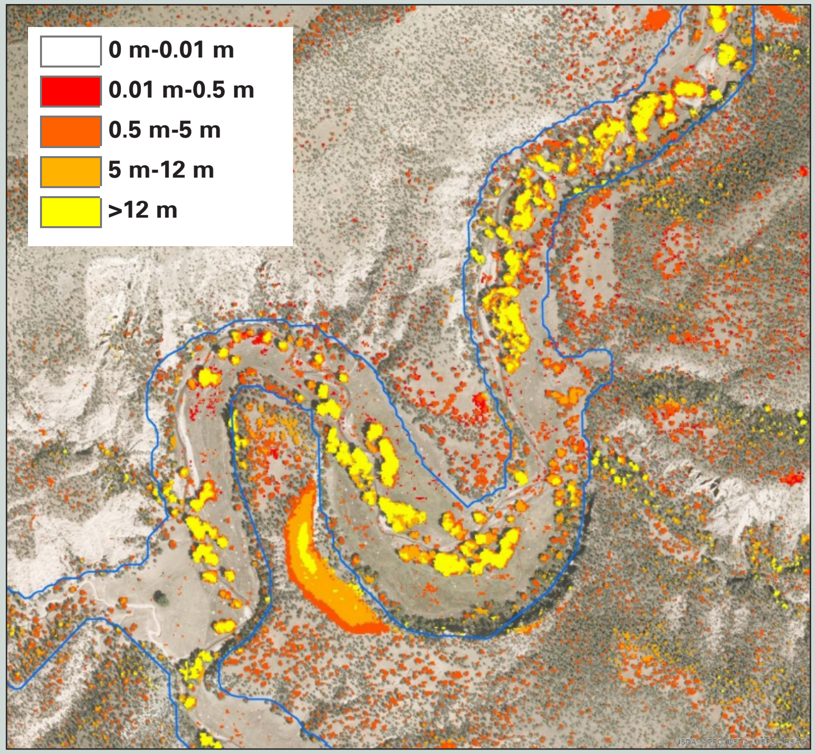


Figure 5—Top Off CHM classified according to map legend and overlaid onto 30 cm resource imagery. Notice that a hilltop was caught as an above ground feature, but falls outside of the riparian boundary.

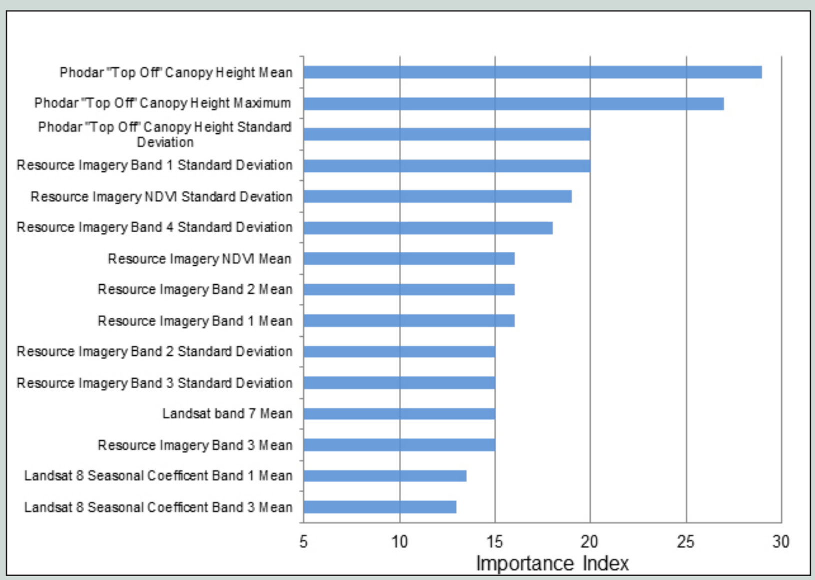


Figure 6—Variable importance plot in the creation of the canopy height layer. In this graph "phodar" refers to SGM or Semi-Global Matching.

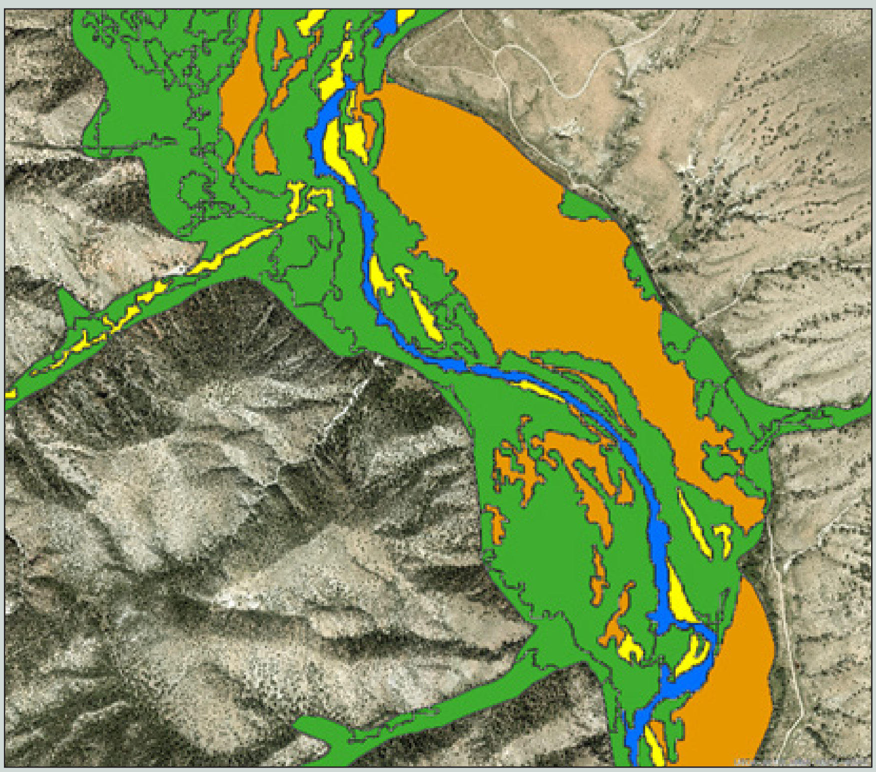
The canopy height layers were also assessed by examining the out-of-bag (OOB) error rates in Random Forest for models that were developed with and without the Top Off CHM layer. Random Forest OOB estimates are good estimates of map accuracy only when the training data have been randomly selected. The training data in this project were mostly purposively sampled and therefore the OOB estimates only serve to give a general idea of the map accuracy. The OOB error rate was 36 percent when run without the layer and decreased to 25 percent when the Top Off CHM layer was used. This test is not wholly appropriate in assessing the effectiveness of the CHM since the segment being modeled were created using the canopy height data as ancillary information. A more appropriate test would have objects and classifications created with and without the Top Off CHM. There is potential for future analysis on this subject. The OOB error rates for all map attributes using the canopy height layers is found in figure 7.

Lifeform Attribute

The final map contained five lifeform classes (figure 8). Of the total 65,483 acres, 74 percent percent or approximately 49,000 acres were mapped as tree-shrub. The grass-forb class was more common in lower elevation, wide riparian corridors, adjacent ot or near private land used for grazing. The bare soil class was typically found along the river banks as sand bars or as dry stream beds for ephemeral streams. The shadow class was the least dominant, occurring only in areas with tall vegetation or large cliffs along the edges of riparian corridors. The acreage summaries are shown in figure 8.

Out-of-Bag errors		
Lifeform Overall		9.37%
	Tree Shrub	19%
	Grass Forb	20%
	Sparse Veg	5%
	Shadow	7%
Substrate Overall		2.97%
	Bare Soil, Rock	2%
	Water	7%
Leaf Retention Overall		22.92%
	Evergreen	7%
	Mix	91%
	Deciduous	20%
Woody Lifeform Overall		12.12%
	Tree	8%
	Shrub	21%
Canopy Cover Overall		38.05%
	1 (10%-25%)	30%
	2 (25%-50%)	43%
	3 (50%-75%)	31%
	4 (75%-100%)	42%
Canopy Height Overall		25.51%
	1 (0-.5 meters)	38%
	2 (.5-5 meters)	29%
	3 (5-12 meters)	31%
	4 (12+ meters)	5%

Figure 7—Out-of-Bag errors for each mapped class.



Lifeform	Acres	%
Bare Soil	5,245	8.01%
Grass-Forb	10,516	16.06%
Shadow	284	0.43%
Tree-Shrub	48,718	74.40%
Water	720	1.10%

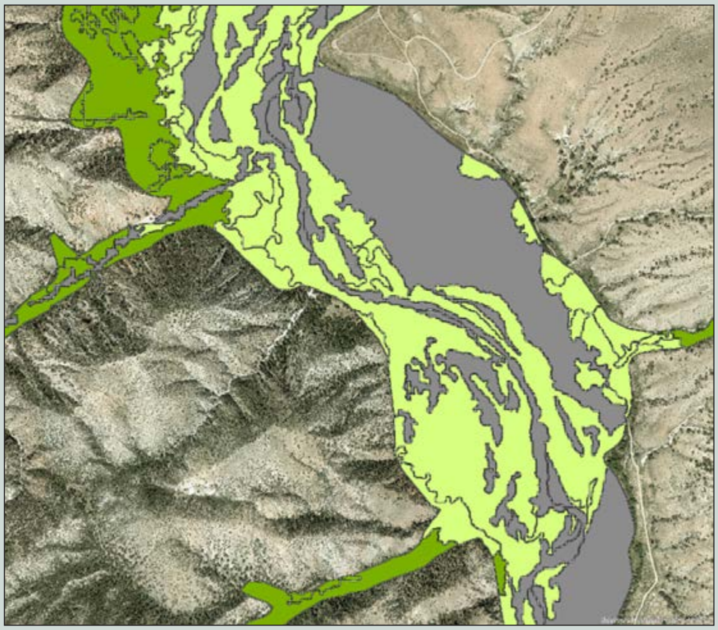
Figure 8—Lifeform map showing bare soil, grass-forb, shadow, tree-shrub, and water classes with associated acre summaries.

Leaf Retention Attribute

Classes describing leaf retention were assigned to tree-shrub polygons identified in the lifeform classification (figure 9). Evergreen was the most common leaf retention type and was mainly mapped in higher elevations surrounding headwater streams, while the deciduous type was more commonly found in the wide flat riparian corridors. Mixed evergreen-deciduous occurred the least. This may have been a result of limited training points, as well as segments that succesfully captured leaf retention homogeneity.

Woody Lifeform Attribute

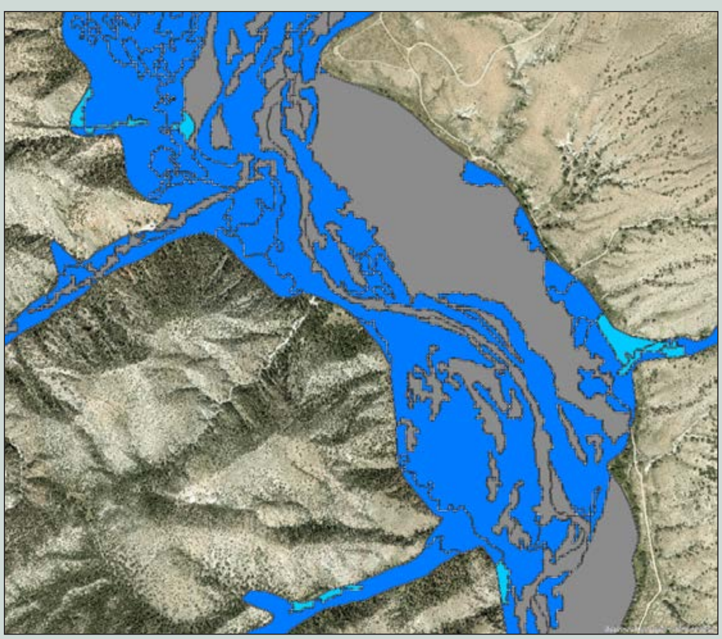
Woody lifeform types were assigned to tree-shrub lifeform polygons (figure 10). The shrub lifeform was commonly mapped in areas also identified as deciduous leaf retention type. These were lower elevations and wide flat riparian corridors of 3rd order streams. The tree type was the most dominant woody lifeform, occupying approximately 35,000 acres or 54 percent of the project area.



Leaf Retention	Acres	%
Non Tree-Shrub	16,765	25.60%
Deciduous	15,159	23.15%
Evergreen	32,889	50.23%
Mixed Evergreen-Deciduous	669	1.02%

- Non Tree-Shrub
- Deciduous
- Evergreen
- Mixed Evergreen-Deciduous

Figure 9—Leaf retention map showing non tree-shrub, deciduous, evergreen, and mixed evergreen-deciduous classes with associated acre summaries.



Woody Lifeform	Acres	%
Non Tree-Shrub	16,765	25.60%
Shrub	13,488	20.60%
Tree	35,230	53.80%

- Non Tree-Shrub
- Shrub
- Tree

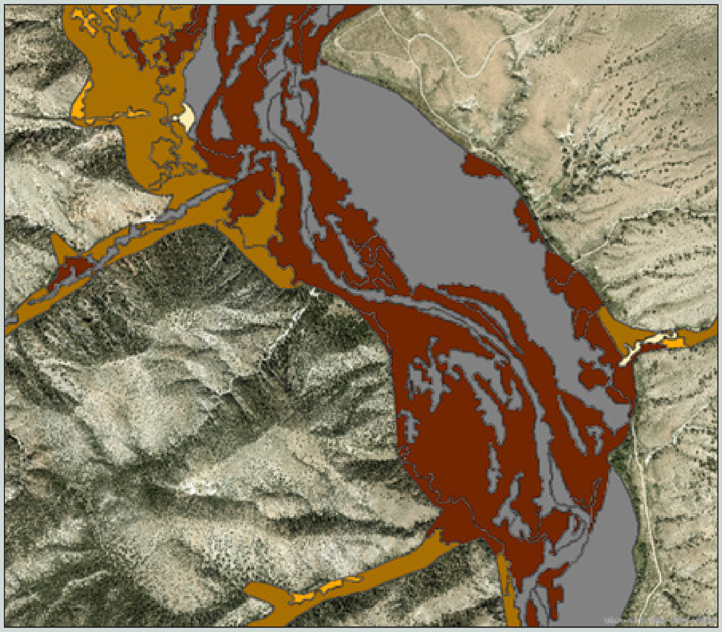
Figure 10—Woody lifeform map showing non tree-shrub, shrub, and tree classes with associated acre summaries.

Canopy Cover Attribute

Canopy cover classes were assigned to tree-shrub lifeform polygons (figure 11). The 50-75 percent class was the most dominant, occupying approximately 21,000 acres or 32 percent of the project area. Both the 25-50 percent and the 75-100 percent class occupied about 8,500 acres or 13 percent of the project area.

Canopy Height Attribute

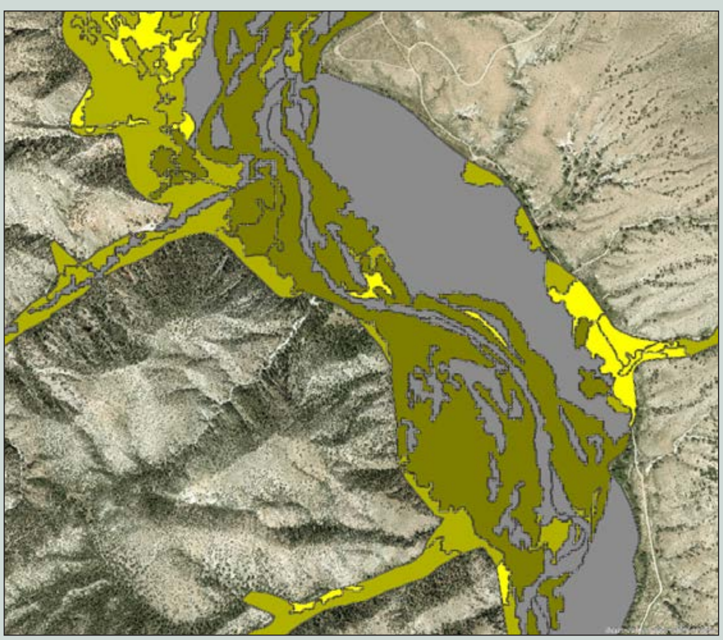
Canopy height classes were assigned to tree-shrub lifeform polygons (figure 12). The least dominant class was the 0-.5 meter class, occupying about 3,000 acres and 4 percent of the project area. The 12+ meters class was the most dominant, occupying approximately 18,000 acres or 27 percent of the project area.



Canopy Cover	Acres	%
0) Non Tree-Shrub	16,765	25.60%
1) 10-25%	10,153	15.50%
2) 25-50%	8,819	13.47%
3) 50-75%	21,194	32.37%
4) 75-100%	8,551	13.06%

0) Non Tree-Shrub
1) 10-25%
2) 25-50%
3) 50-75%
4) 75-100%

Figure 11—Canopy Cover map showing non tree-shrub, 10-25 percent, 25-50 percent, 50-75 percent, and 75-100 percent classes with associated acre summaries.



Canopy Height	Acres	%
0) Non Tree-Shrub	16,765	25.60%
1) 0-0.5 m	2,837	4.33%
2) 0.5-5 m	12,366	18.88%
3) 5-12 m	15,943	24.35%
4) >12 m	17,571	26.83%

0) Non Tree-Shrub
1) 0-0.5 m
2) 0.5-5 m
3) 5-12 m
4) > 12 m

Figure 12—Canopy height map showing non tree-shrub, 0-0.5 m, 0.5-5 m, 5-12 m, and >12 m classes with associated acre summaries.

Conclusion

Understanding the current structure and composition of riparian areas is key to riparian resource management. This study revealed some of the uses and limitations of using surface models derived from 30 cm imagery using Semi-Global Matching to model vegetation in riparian corridors. Our results for image-derived canopy height showed high correlation with lidar-derived canopy heights as an indication of acceptable accuracy for end users. These results had a higher correlation, and by inference higher accuracy, in areas with low slope. Further analysis is needed to understand the potential for mapping canopy heights in other varieties of topography and vegetation density.

References

Breiman, L. 2001. Random Forests. Machine Learning. 45: 5–32.

Gesch, D.; Oimoen, M.; Greenlee, S.; Nelson, C.; Steuck, M.; Tyler, D. 2002. The national elevation dataset. Photogrammetric engineering and remote sensing. 68(1): 5–32.

Gobakken, T.; Bollandsås, O.M.; Næsset, E. 2015. Comparing biophysical forest characteristics estimated from photogrammetric matching of aerial images and airborne laser scanning data. Scandinavian Journal of Forest Research. 30(1): 73–86.

Hirschmüller, H. 2008. Stereo processing by semiglobal matching and mutual information. Pattern Analysis and Machine Intelligence. IEEE Transactions on. 30(2): 328–341.

Pyysalo, U.; Hyyppa, H. 2002. Reconstructing tree crowns from laser scanner data for feature extraction. International Archives of Photogrammetry Remote Sensing and Spatial Information Sciences. 34(3/B): 218–221.

Siddiqui, Y.; Garrett, M. 2008 Datadoors: a system for cataloging, accessing, processing, and delivering large amounts of image data.

Triepke, F.J.; Wahlberg, M.M.; Cress, D.C.; Benton, R.L. 2013. RMAP: Regional riparian mapping project. USDA Forest Service project report. Southwestern Region, Albuquerque, NM. http://www.fs.usda.gov/main/r3/landmanagement/gis.

Ziegler, M.; Konrad, H.; Hofrichter, J.; Wimmer, A.; Ruppert, G.S.; Schardt, M.; Hyyppae, J.M. 2000. Assessment of forest attributes and single-tree segmentation by means of laser scanning. In AeroSense 2000. International Society for Optics and Photonics.

For additional information, contact:

Kevin Megown, RMIM Program Leader
Resource Mapping, Inventory, & Monitoring
Remote Sensing Applications Center
2222 West 2300 South
Salt Lake City, UT 84119

phone: (801) 975-3826
email: kamegown@fs.fed.us

This publication can be downloaded from the RSAC Web site: http://fsweb.rsac.fs.fed.us

Non-Discrimination Policy

The U.S. Department of Agriculture (USDA) prohibits discrimination against its customers, employees, and applicants for employment on the bases of race, color, national origin, age, disability, sex, gender identity, religion, reprisal, and where applicable, political beliefs, marital status, familial or parental status, sexual orientation, or whether all or part of an individual's income is derived from any public assistance program, or protected genetic information in employment or in any program or activity conducted or funded by the Department. (Not all prohibited bases will apply to all programs and/or employment activities.)

To File an Employment Complaint

If you wish to file an employment complaint, you must contact your agency's EEO Counselor within 45 days of the date of the alleged discriminatory act, event, or personnel action. *Additional information can be found online at http://www.ascr.usda.gov/complaint_filing_file.html.

To File a Program Complaint

If you wish to file a Civil Rights program complaint of discrimination, complete the USDA Program Discrimination Complaint Form , found online at http://www.ascr.usda.gov/complaint_filing_cust.html, or at any USDA office, or call (866) 632-9992 to request the form. You may also write a letter containing all of the information requested in the form. Send your completed complaint form or letter to us by mail at U.S. Department of Agriculture, Director, Office of Adjudication, 1400 Independence Avenue, S.W., Washington, D.C. 20250-9410, by fax (202) 690-7442 or email at program.intake@usda.gov.

Persons with Disabilities

Individuals who are deaf, hard of hearing or have speech disabilities and who wish to file either an EEO or program complaint please contact USDA through the Federal Relay Service at (800) 877-8339 or (800) 845-6136 (in Spanish).

Persons with disabilities who wish to file a program complaint, please see information above on how to contact us by mail directly or by email. If you require alternative means of communication for program information (e.g., Braille, large print, audiotape, etc.) please contact USDA's TARGET Center at (202) 720-2600 (voice and TDD).