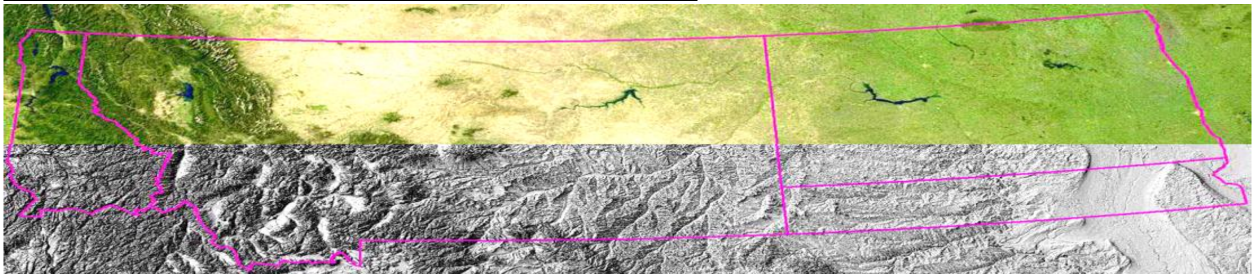
Project Report: NRGG_PR_BITLO_VMAP2016



The Bitterroot and Lolo National Forests Region 1 Existing Vegetation Database (VMap) Revision of 2016.

October 4, 2017

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1.0 Overview

Consistent, continuous, contemporary and accurate vegetation data are essential for effective ecosystem assessment and land management planning. The Northern Region Existing Vegetation Mapping Program (VMap) (USDA 2017) addresses this information need by providing a database of existing vegetation and associated map products that are constructed with an analytical methodology based on the Existing Vegetation Classification and Mapping Technical Guide (Brohman and Bryant, 2005) to support the Region 1 Multi-level Classification, Mapping, Inventory, and Analysis System, R1-CMIA (Berglund et al. 2009).

A VMap database has been published for every Forest in the USDA Forest Service Northern Region, and updated in a cyclical manner since 2003 (Barber et al. 2012, Brown and Barber 2012,). In 2017, an updated VMap database was produced for the Bitterroot and Lolo National Forests (BITLO). The VMap database consists of four primary spatially explicit attributes that include descriptions of 1) lifeform, 2) tree canopy cover class, 3) tree size class, and 4) tree dominance type. These attributes can be mapped and used to support mid and base-level analysis and planning. VMap uses the Region 1 Existing Vegetation Classification System (Barber et al. 2009) in its map unit design. This system defines the logic for grouping entities by similarities in their floristic characteristics. VMap products are derived using remote sensing technology, and are based on a combination of airborne imagery and a nationally available digital topographic and climatic data.

With a foundation of contemporary aerial imagery, a clear view of the project area is essential. For our purposes, high resolution, four-band NAIP imagery, collected in 2013 (USDA Farm Service Agency 2015, 2016) was used in in combination with a 10 meter digital elevation model (DEM) (Gesh 2002), a representation of moisture availability, and a raster based-representation of geographic space, and ground-based measurements of vegetation attributes in the VMap production process. As part of that process, a NAIP composite spanning the entire extent of the BITLO mapping area was used in a segmentation routine to create a vector-based layer of polygons that represent a delineation of stand boundaries across the study area (Haralick and Shapiro 1985, Zaitoun and Aqel 2015). This set of polygons, or stands, are the elements attributed by the VMap process and issued in the final database. In the field, reference information was collected and used to make spatial predictions of the vegetation attributes contained in the database. Predicted raster surfaces of the attributes were summarized to the delineated polygons.

As draft map products were created, they were reviewed and appropriate changes were made in the labeling algorithms. Upon a satisfactory conclusion, the final products were used to populate the VMap database.

After draft products were inspected and adjusted, an accuracy assessment was conducted to provide a quantitative validation of the database. Estimates of overall map accuracy and confidence measures of individual map classes can be inferred from the error matrix derived from the comparison of known reference sites to mapped data, for each attribute. The stated accuracy assessment results are applicable to the entire BILO, and ranged from 62-90%, depending on the attribute in question.

2.0 Source Data

A combination of field reference, recent image, and biophysical data are needed to produce the VMap database. Once collected, ground reference data was used to build relationships between the observed phenomena and the spectral and biophysical information derived from remotely sensed and ancillary data.

2.1 Field Data Collection

Collectively, ground and other reference data are also known as "training data" because they are used to construct algorithms that relate observations to quantified variables, and are used to interpret and label areas that have not been sampled within a study area. Thus, they "train" algorithms to distinguish between and label the unknown areas. For the development of the VMap database, training data was specifically collected to identify and distinguish lifeform, tree canopy cover, tree size, and vegetation dominance type classes.

Over the course of the 2015 field season, a total of 4,404 data plots were collected across the Bitterroot and Lolo National Forests (Figure 1). At each plot, the lifeform, diameter-at-breast-height (dbh), and species of all measured trees were recorded. Trees were measured using a variable radius plot design and a tree selection criteria based on a basal area factor of ten. Thus all trees meeting or exceeding the basal area criteria in a plot were measured and counted. The numbers of all counted trees were converted to measures of relative abundance and associated with plot locations. When summarized, each plot was attributed with a mean basal area weighted dbh, and the abundance percentage of each measured species.

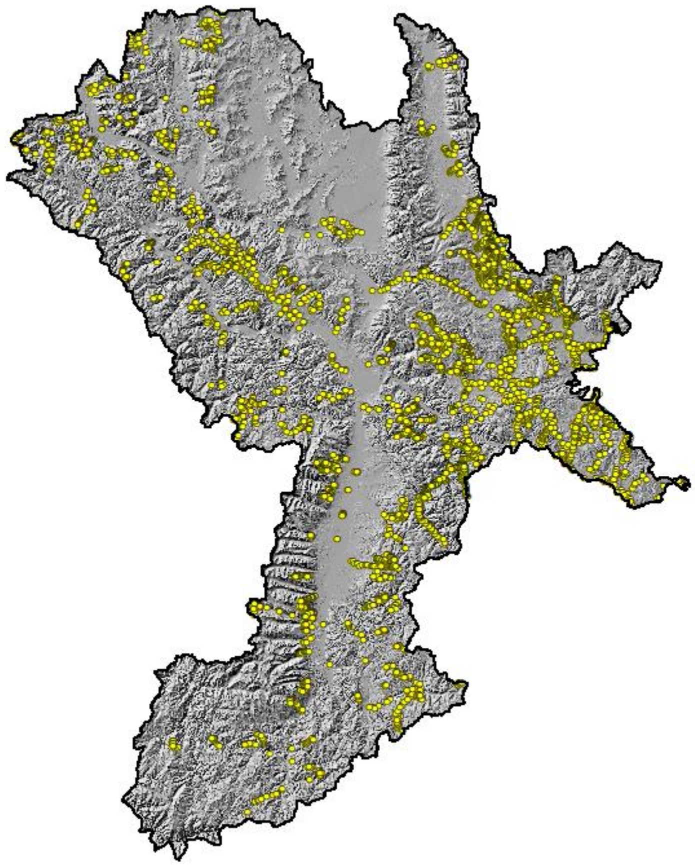


Figure 1. *Spatial distribution of training data plot locations, shown as yellow points, across the Bitterroot-Lolo National Forests, collected in the 2015 field season.*

Table 1 provides a summary of the number of tree abundance records that are greater than zero at all sites, and Figure 2 shows the distribution of abundance records for each species. Figure 3 illustrates the distribution of summarized tree size values, given as basal area weighted dbh, in inches, collected at all sites across the mapping area. Reviewing the abundance distributions one can see that some species tend to dominate sites, while others tend to occur in lower abundances where they are present (Figure 2). The tree size data tends to be normally distributed, although there is a concentration around the minimum value of 0, with a mean around 11, and a maximum plot value of 39 inches (Figure 3).

Table 1. *Summary of relative tree abundance values collected across the Bitterroot-Lolo National Forests in the 2015 field season.*

Dominance Type Code	Dominance Type Description	Number of Records	Relative Abundance (%)
8010	Ponderosa pine	836	13
8020	Douglas-fir	1,917	30
8030	Grand fir	73	1
8040	Western larch	858	13
8050	Lodgepole pine	1,194	19
8060	Subalpine fir	748	12
8070	Engelmann spruce	424	7
8090	Western red cedar	46	1
8110	Mountain hemlock	55	1
8120	Whitebark pine	162	3
8130	Subalpine larch	48	1
8180	Juniper	58	1
		6,419	

In terms of dominance type, training data were collected at plots placed within predefined 70 meter x 70 meter sampling grid cells, in areas that were considered representative of stand conditions. The dimensions of the sampling grid roughly approximate that of an FIA plot (Bechtold and Patterson 2005). In an example given in Figure 4, a plot location is shown in the context of the established sampling grid.

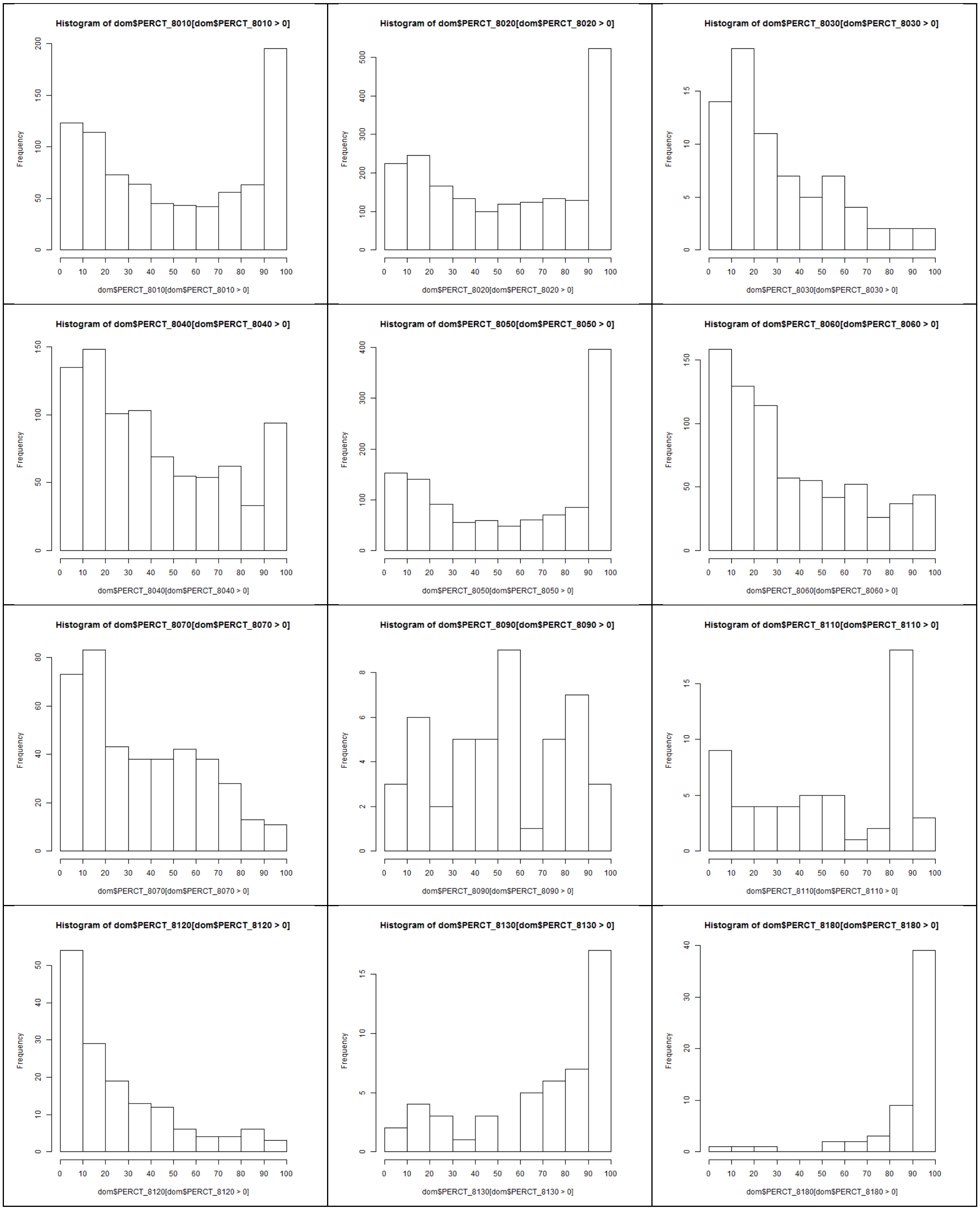


Figure 2. *Distribution of sampled species abundance values*

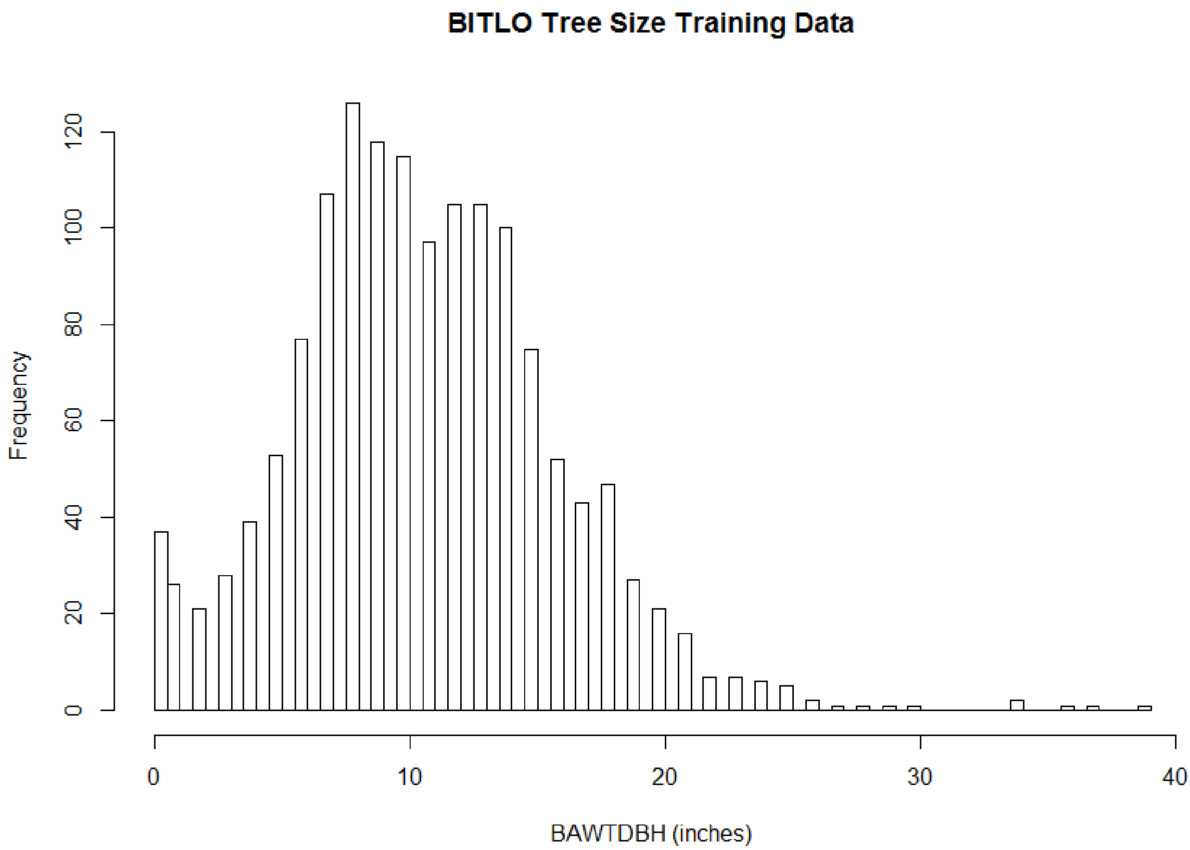


Figure 3. *Distribution of summarized mean basal area weighted dbh values*

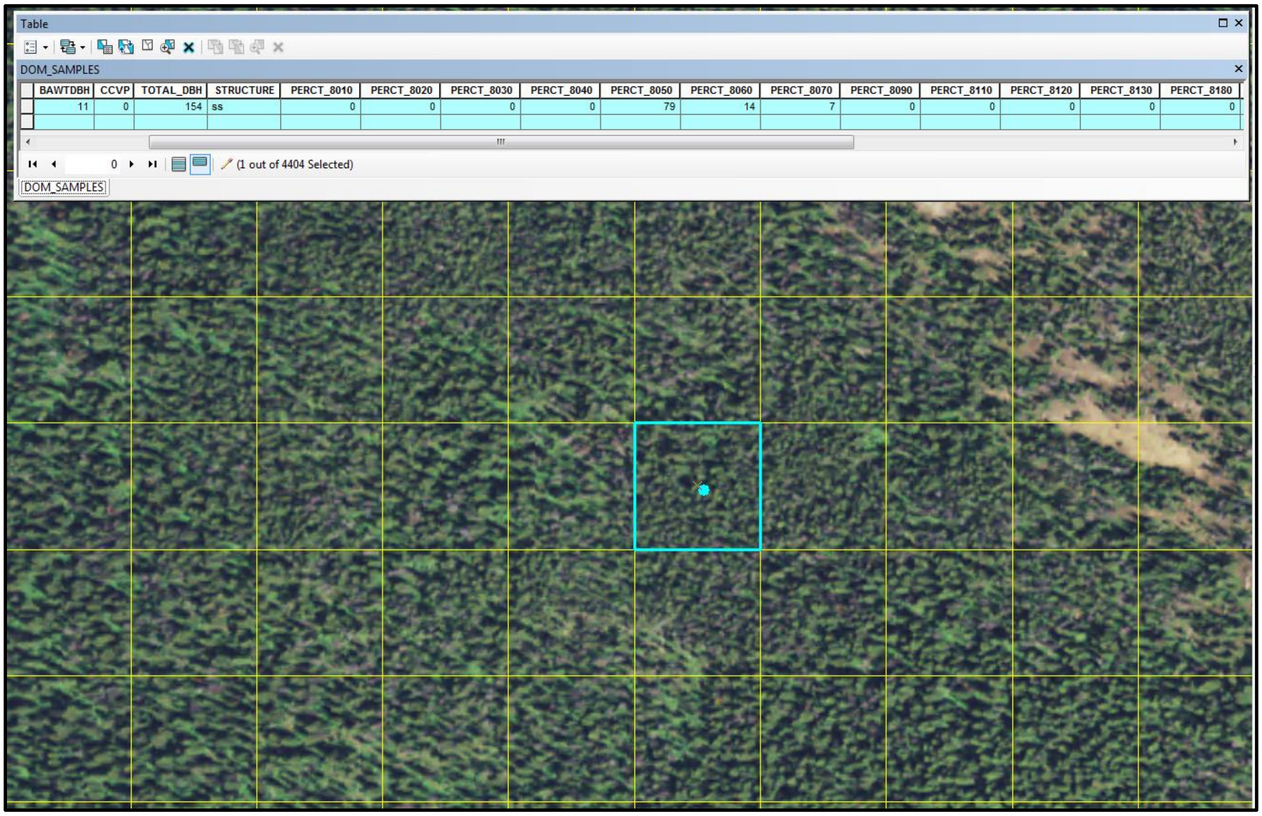


Figure 4. *Reference data collection example, where the plot center is shown within the context of a predefined 70 meter x70 meter sampling grid. Measured tree attributes, including mean basal area weighted dbh, total dbh, canopy cover percentage, structure, and percentage of each present species are shown in the highlighted table at the top of the figure.*

2.2 Image Data Collection and Pre-Processing

High resolution, four band NAIP imagery (USDA Farm Service Agency 2016) with a native pixel size of 1 meter provided the spectral data used in the production of the VMap database.

At 1 meter pixel resolution, NAIP imagery was used for visual inspection by analysts. While it provides clarity and facilitates interpretation at that grain size, image data at such a high resolution a cumbersome to use in algorithm development and application with when they span millions of acres, as was the case in the BITLO mapping project.

For analytical purposes and ease of processing, the original NAIP image data were resampled to 5 meter pixel resolution. At 5 meter resolution, the NAIP imagery was used to create a suite of derivatives which were reprocessed to 10 meter resolution and stored as 8-bit unsigned integer data.

2.3 Creation of image derivatives

Image derivatives are transformations of raw image data that provide spectral and texture-based information useful for land cover mapping. Before their use as independent predictors in a modeling framework, each raster dataset was processed in a number of ways, with a pixel resolution of 10 meters and stored as 8-bit unsigned data.

A raster stack representing the spectral components is based on 1meter, four band NAIP imagery, collected in 2013. As a first step, NAIP was resampled to 5 meter and focal min, max, mean, and standard deviations were computed on a 15 meter x 15 meter window. The resulting raster outputs were then resampled to a 10 meter pixel resolution. A principal component analysis was conducted on this output stack of 16 bands, and the top five components were retained and used to represent the spectral signature of the landscape. This dataset is considered the spectral input for modeling.

2.4 Biophysical characterization data

Elevation is related to many physical and biological phenomena, and to account for those processes, a 10 meter DEM was used to represent elevation (Gesch 2002).

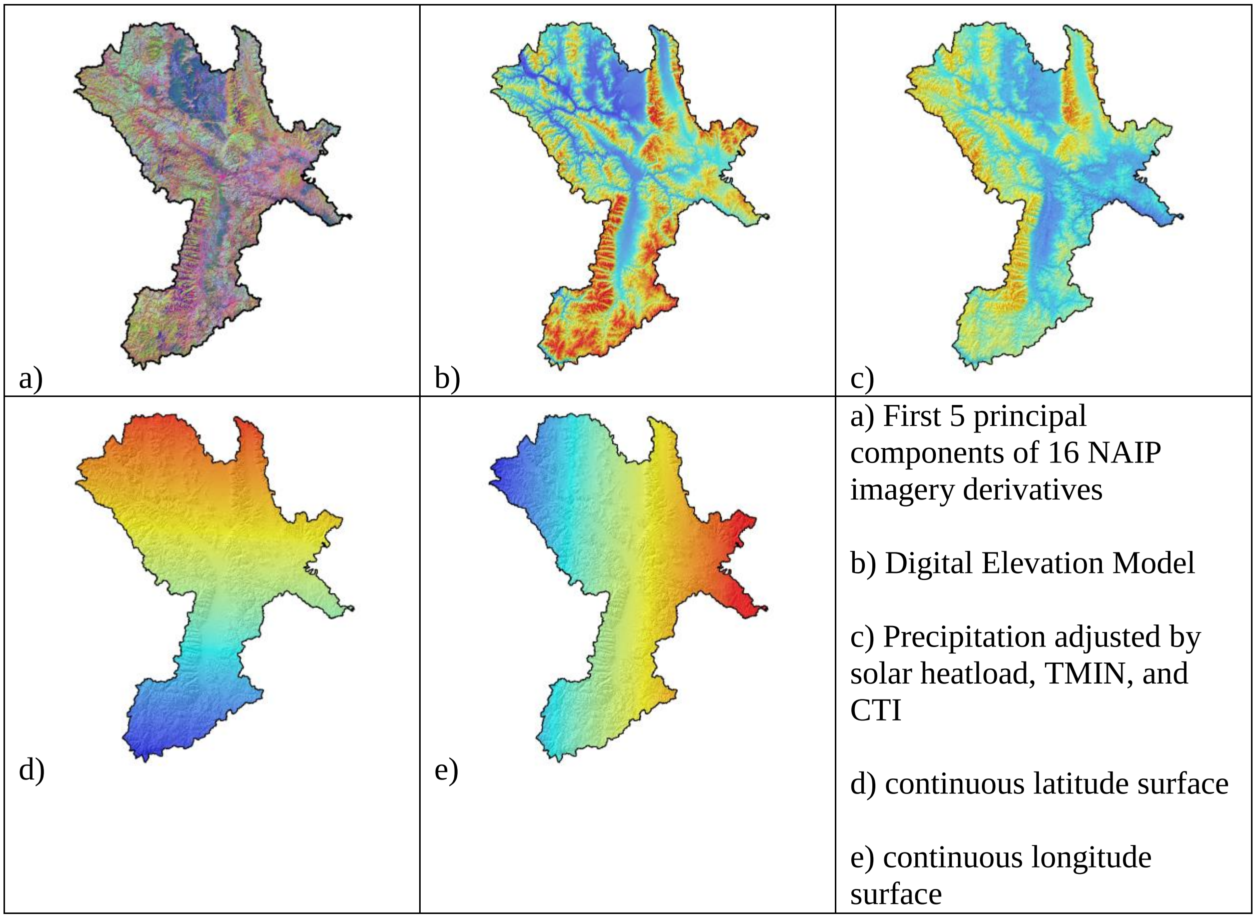
Moisture availability is often the limiting factor in vegetative growth, productivity and species distribution. To account for precipitation, temperature, and water holding capacity an integrated biophysical raster layer was also created. Because it integrates precipitation, heat load from the sun, and water routing by topographic elements, this dataset is called PHEAT which stands for **P**recipitation **H**eat & **E**levation **A**djusted **T**opography, and is produced at 10 meter pixel resolution.

Lastly, to account for species or process variation due to eastings and northings, two raster layers representing continuous units of latitude and longitude were also created at 10 meter pixel resolution.

2.5 Synthesized Modeling Input

The five bands of NAIP image derivatives, and single layer of elevation, a single layer representing biophysical integration of moisture potential, a layer of latitude and a layer of longitude were all combined to yield a nine band raster stack, at 10 meter pixel resolution, to be used as independent inputs for regression modeling (Figure 5).

All nine bands of the input raster data were sampled at plot locations, and associated point files were attributed with values of the independent raster variables. Using the measured tree values as response variables, and the raster values as independent variables, a suite of ten Random Forest (Breiman 2001, Liaw and Wiener 2002, Liaw 2015) regression models were produced for each model type, including lifeform, tree canopy cover, tree size, and tree dominance. Algorithm parameters were set to run 100 regression trees, using a random selection of 0.66 percent of the training data, and 4 randomly selected input variables for each regression tree. For each attribute, the model for the suite of 10 runs with least error was selected to produce the output surfaces.



a) First 5 principal components of 16 NAIP imagery derivatives

b) Digital Elevation Model

c) Precipitation adjusted by solar heatload, TMIN, and CTI

d) continuous latitude surface

e) continuous longitude surface

Figure 4. *Tree species abundance modeling independent variable data inputs*

2.6 Image segmentation

Image segmentation is the process of combining unique picture elements, or pixels, within digital images into spatially cohesive regions. These individual regions are called image objects and represent distinct areas within the image that generally correspond to patches of similar vegetation type/conditions (Haralick and Shapiro 1985, Zaitoun and Aqel 2015). Ultimately, the raster-based image objects are converted to vector-based polygons. These image objects depict elements of vegetation and other patterns on the landscape, and all VMap attributes are associated with the polygons derived from the segmentation process. In the production of the BITLO database, the NAIP-based image derivative principal component stack, and PHEAT layers were used were used for segmentation.

3.0 Mapping Process

3.1 Lifeform Classification

The lifeform attribute is mapped with a combined process of image object classification and refined with manual image interpretation and editing, following the rules established by the R1 Existing Vegetation Classification document. Labeling of the lifeform groups is accomplished with the Random Forest classification algorithm (Breiman 2001, Liaw and Wiener 2002, Liaw 2015) using field collected reference information and summarized image derivative, biophysical derivative, and vegetation index derivative statistics associated with the polygons obtained from the segmentation process. Mapped lifeforms classes include tree, shrub, herbaceous, sparsely vegetated, and water with precedence order being tree, shrub, herbaceous in the lifeform key.

3.2 Tree Canopy Cover Classification

For polygons where a tree lifeform has been assigned, tree canopy cover values were estimated. Traditionally the tree canopy cover values in the VMap database were only available in four classes: low (10-24.9% Cover), moderate low (25-39.9% Cover), moderate high (40-59.9% Cover) and high (60%+ Cover). In this VMap update, however, canopy cover estimates were produced as continuous variables that were distributed into the stated classes.

Canopy cover models were based on reference data obtained through analyst-based image interpretation, and a Random Forests regression algorithm (Breiman 2001, Liaw and Wiener 2002, Liaw 2015). In the development process, the NAIP based image derivatives, the elevation raster, the biophysical description raster, and geographical raster data were incorporated. Using a 70 meter by 70 meter grid, which resembles the dimensions of an FIA plot (Bechtold and Patterson 2005), an image analyst randomly selected 1,000 grid cells across the mapping area and then used the 1 meter NAIP imagery to assign a percent canopy cover estimate to each cell. A full range of canopy cover values, ranging from a minimum of 10% to values greater than 60%, were generated and used as training data in the modeling process. The selection of reference sites were used in combination with the stack of image derivatives, elevation, biophysical, and geographical representation raster data in a Random Forest regression model to estimate the full range of canopy cover values across the mapping area.

The resulting continuous canopy cover values were summarized to the image segmentation and then grouped into canopy cover classes based on the specifications of the Region 1 Existing Vegetation Classification System, as described above.

3.3 Tree Size Class

Tree size class is modeled from field collected data that quantifies basal area weighted average tree diameter at breast height (BAWDBH), as described in the Region 1 Exiting Vegetation Classification System. BAWDBH was computed from a variable radius plot to the nearest full inch. In a process similar to canopy cover modeling, data from reference sites were associated with image derivatives, an elevation raster, a biophysical derivative, and geographical rasters, and used in a Random Forest regression model (Breiman 2001, Liaw and Wiener 2002, Liaw 2015) to estimate continuous tree size values for every pixel.

For all polygons classified as the tree lifeform, individual BAWDBH pixel values were summarized and the mean BAWDBH was associated with those polygons. The resulting mean values in all tree class polygons were grouped into the Region 1 Existing Vegetation Classification System tree size classes ranging from 0-4.9, to 5.0-9.9, 10.0-14.9, 15-19.9, 20.0 – 24.9, and greater than 25 inches dbh mean values for stands.

3.4 Tree Dominance Type

Similar to canopy cover, and tree size, tree dominance type was modeled using a Random Forest regression (Breiman 2001, Liaw and Wiener 2002, Liaw 2015) based on individual tree species abundance information collected at the field plot level, NAIP image derivatives, elevation raster, biophysical representation and geographical raster data. The plot data were used as the response variable, and the raster data were used as the independent variables in the regression modeling process.

A separate raster surface was built for each species, where a continuous range of percent abundance values represent the potential abundance of a given species in any given pixel. Finally, a raster surface was created for each species of interest. The suite of species abundance raster data were then summarized to the VMap polygons to determine percent composition and a dominance type label was assigned based on R1 Existing Vegetation Classification System tree dominance type rules.

4.0 Accuracy Assessment

An independent accuracy assessment of the VMap products was conducted across the entire BITLO mapping area to provide a validation of the issued data. An estimate of overall map accuracy and confidence of individual map classes was computed with a standard error matrix derived from the comparison of known reference sites to mapped data. Overall, the delivered BITLO map products were validated with accuracies generally exceeding national standards, ranging from 62-91% depending on the attribute.

4.1 Error Matrices

Following the recommendations of Stehman and Czaplewski (1998), a stratified random sample design was used to select comparison sites across the BITLO mapping area and construct a standard accuracy assessment matrix (Congalton 1991) for each attribute being assessed. The assessed attributes include lifeform, tree canopy cover, tree size class, and tree dominance type.

For the lifeform attribute, the overall map accuracy was assessed at 91%. A stratified random sample of 3,801 reference sites was drawn from six strata that include herbaceous, shrub, conifer tree, water, sparse vegetation, and deciduous tree classes. An error assessment matrix that displays falsely committed map errors, and falsely omitted classification errors is given below.

Errors of commission describe the probability that a feature on the map actually represents that category on the ground, and is calculated by dividing the number of agreements for a category by the total number of sites that were mapped into that category. Errors of omission relate to the probability of a reference site being correctly classified, and is calculated by dividing the total number of correctly mapped sites for a class by the total number of reference sites for that class.

				Reference Sites				
Lifeform	*Herbaceous*	*Shrub*	*Conifer*	*Water*	*Sparse*	*Deciduous*	*Total*	*Comission*
Herbaceous	918	91	3	3	16	5	1036	89%
Shrub	30	749	5	1	6	20	811	92%
Conifer	27	24	476	0	14	11	552	86%
Water	3	3	0	486	4	1	497	98%
Sparse	9	9	6	5	435	0	464	94%
Deciduous	1	28	4	1	0	407	441	92
Total	988	904	494	496	475	444	3,801	*Overall*
Omission	93%	83%	96%	98%	92%	92%		**91**%

For the tree canopy cover attribute, the overall map accuracy was assessed at 84%. In this assessment the four standard canopy cover classes were considered, and 100 sites were randomly selected from each of the classes for evaluation. The standard canopy cover classes include low cover (10-24.9%), moderate low cover (25-39.9%), moderate high cover (40-59.9%), and high cover (greater than or equal to 60%), and the accuracy assessment error matrix is given below.

	Reference Sites					
Cover	*10-25%*	*25-40%*	*40-60%*	*>60%*	*Total*	*Comission*
10-25%	69	8	3	0	80	86%
25-40%	7	66	14	3	90	73%
40-60%	1	2	73	17	93	78%
>60%	0	0	2	95	97	98%
Total	77	76	0	115	360	*Overall*
Omission	90%	87%	92%	83%		**84**%

For the tree size class attribute, the overall map accuracy was assessed at 62%. In this assessment the standard tree size classes of seedling (0-4.9” dbh), small (5-9.9” dbh), medium (10-14.9” dbh), and large/ very large (15” and greater dbh) were considered. For evaluation, 10% of the reference sites in each class were randomly drawn from the population, yielding a total of 2,854 points of comparison. The resulting error matrix is given below.

	Reference Sites					
Size	*0–5 dbh*	*5-10 dbh*	*10-15 dbh*	*15-20+dbh*	*Total*	*Comission*
0–5 dbh	126	39	0	0	165	76%
5-10 dbh	117	755	355	46	1273	59%
10-15 dbh	5	167	497	188	857	58%
15-20+dbh	1	17	148	393	559	70%
Total	249	978	1,000	627	2,854	*Overall*
Omission	51%	77%	50%	63%		**62**%

For the tree dominance type attribute (DOM40), the overall map accuracy was assessed at 71%. For DOM40 12 classes were evaluated, and they include MX-PIPO, MX-PSME, MX-ABGR, MX-LAOC, MX-PICO, MX-ABLA, MX-PIEN, MX-THPL, MX-TSME, MX-PIAL, MX-LALY, and MX-JUSC. For each class 10% of the collected training sites were withheld and assessed. The total number of assessment sites was 3,075, and the error matrix is given below.

	Reference Sites												
Type	*MX-PIPO*	*MX-PSME*	*MX-ABGR*	*MX-LAOC*	*MX-PICO*	*MX-ABLA*	*MX-PIEN*	*MX-THPL*	*MX-TSME*	*MX-PIAL*	*MX-LALY*	*MX-JUSC*	*Total*	*Co-mission*
MX-PIPO	342	154	1	17	22	2	15	0	0	0	0	3	556	62%
MX-PSME	51	731	11	70	68	17	35	3	0	0	0	0	986	74%
MX-ABGR	1	1	5	0	0	0	0	0	0	0	0	0	7	71%
MX-LAOC	13	50	0	219	41	6	8	1	0	0	0	0	338	65%
MX-PICO	3	62	0	16	506	21	10	1	0	3	0	0	622	81%
MX-ABLA	0	49	0	9	43	187	34	0	4	9	1	0	336	56%
MX-PIEN	2	7	0	2	2	5	53	0	0	0	0	0	71	*75%*
MX-THPL	0	0	0	0	1	0	0	14	0	0	0	0	15	93%
MX-TSME	0	0	0	0	2	1	1	0	25	0	0	0	29	86%
MX-PIAL	0	0	0	0	3	0	0	0	0	15	1	0	19	79%
MX-LALY	0	0	0	0	1	3	0	0	0	4	34	0	42	81%
MX-JUSC	1	1	0	0	0	0	0	0	0	0	0	52	54	96%
Total	413	1055	17	333	689	242	156	19	29	31	36	55	3,075	*Overall*
Omission	83%	69%	29%	66%	73%	77%	34%	74%	86%	48%	94%	95%		**71%**

4.2 Discussion

Since not all of the map attributes are suitable for visual interpretation, such as tree size class and tree dominance type, it is useful to withhold a certain amount of field collected reference information and compute an independent estimate of the map class accuracy. The draw back to using withheld data is that there may not be enough data to withhold to provide a meaningful quantification of the error.

In the tree canopy cover and tree size class attributes, most of the error occurs between adjacent classes and can easily be attributed to either interpretation error or just the inherent fact that when a continuous world is parceled into discrete classes not everything fits as expected. For example, if a given polygon is estimated to have 61% tree canopy cover, but the analyst estimates that it has 59%, the true difference is only 2%, but 59.9% is the cutoff between two classes so that the polygon would then be assessed as incorrect.

While the accuracy assessment attempts to quantify the error structure in the BITLO map products, there is no substitute for map evaluation prior to its use in any analysis.

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