Vegetation\_Classification

steppe

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The initial AIM sample design for a field office utilized stratified random sampling within classified vegetation types which the plots could make inference to. The vegetation types were composed of alliances and communities from the GAP-Landfire National Terrestrial Ecosystems spatial data set (PUBLISHER 2011). Alliances and communities were aggregated, by an expert at each field office, to form broader vegetation groups in order for them to have more samples per unit area.

However, the GAP data set erroneously classifies many vegetation types at a non-negligible rate. Accordingly, a number of areas stratified as one vegetation type through the project may not feature the intended target vegetation. Thus, several of the stratified zones are in error, and may sensibly have their plots and acreage reallocated to inform inference of conditions in the larger vegetation types.

For example, of the nine vegetation types which the AIM project was stratified across, a couple were seldom seen, such as ‘Mixed Conifer’ vegetation. The study area does contain this vegetation type, however it represents a fraction of a percent in the Field Office, and the designated stratified area did not coincide with it’s actual presence. As the stratified area did not correlate with the vegetation type, neither could the random plots drawn within it. Accordingly the acreage of these areas should be reclassified into their appropriate vegetation types, alongside the plot, in order that these data are interpreted in the correct context.

Additional problems were inherited with a vegetation types known as ‘Other’. This is an aggregate developed from the *need* to classify the entirety of the field office. It functions as a catch-all designation for vegetation types which do not have adequate cover to form a broader classification. For example, a small patch of Blackbrush (*Coleogyne ramossisima*) on 90, gypsum terraces in the Paradox Valley, and escarpment vegetation with Stansbury’s Cliffrose (*Purshia stansburyiana*) across the entire study area were placed into this designation. As ‘Other’ is not a group wherein the members have any inherit similarities to themselves, we argue they should align with other groups which they share, even if only weak, affinities. Affinities between the gysum terraces, to the salt desert, both soils which reduce the availability of free water for plant usage and result in barren to salt-tolerant vegetation are evident. Similarities between the escarpments of mesa’s and the Pinyon-Juniper which occupies both the thin soil at the edges of the mesa, and the Pinyon-Juniper woodlands on the rocky soils at the toes of the escarpments, as well as are scattered throughout the Stansbury Cliffrose areas make this a tangible target for placement of these ‘other’ plots.

A final problem is associated with the need to classify bodies of water. Our field office the ‘Uncompahgre’, is named after a word of Ute origin which has various translations, but a central element of them is a reference to ‘Red Rocks’ and ‘flowing water’. Our design stratum had 4% of the survey area designated as riparian, in part to hold surface rivers. However, given the allowance to shift plots 50m in the cardinal directions, the tri-spoke design of aim plots requiring a 60m diameter, and the deployment of Lotic AIM during the sampling period, few to none plots remained in the riparian vegetation type.

In order to resolve these issues with the analysis of the AIM 2017-2022 sample design, we reclassify the field office into four major, and one very minor, vegetation groups which may accommodate a major swath of the lands in the field office to make inference too. To accomplish this we use over 1600 random points across the entire extent of the field office, classified in Google Earth, NAIP aerial imagery and a couple simple spatial data products, as inputs to a simple random forest model which is projected onto the aerial extent of the field office.

# Methods

Colorado 2019 NAIP Imagery were downloaded from the official repository at Box in Fall 2022. While decoding from MrSID to tif file formats, their resolution was reduced by a factor of four using the ‘mrsiddecode’ program (Vers. 9.5.1.4427) from LizardTech. This effectively reducing their resolution to 9.6 meters. Following decompression of MrSID data, all spatial data processing occurred using R version 4.2.1, all computing performed on linux Ubuntu (20 & 22) on multiple hardware. These raster tiles were united via mosaic, cropped to the extent of the Field Office’s ownership, and masked to BLM administered surface areas. These data were then aligned with previously generated raster data sets derived from a 10m DEM; when required all re-sampling of these tiles were achieved using cubic spline interpolation.

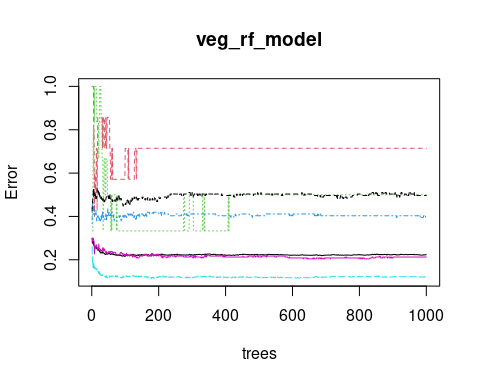
A Gray Level Co-occurrence Matrix (GLCM) was created using the ‘glcm’ package to create a texture raster layer to aid in classification. Texture bands are, among other properties, capable of indicating the amounts of heterogeneity of habitat types across the landscape. Texture layers were produced using both NAIP natural color and infrared imagery. Texture statistics: mean, variance, homogeneity, contrast, dissimilarity, with windows of 5 in both direction, shifts in all directions (**Queen’s case**), and the default value of 32 grey levels. NAIP data were processed to create an NDVI band. NDVI is well suited for identifying sparsely vegetated areas, it may be useful in distinguishing salt desert from all other strata, and help in distinguishing between MMS and PJ.

To create data set for training a random forest model, all 469 sampled AIM and LMF points LMF points, from 2018-2022, as well as all drawn 2022 AIM points, were exported to Google Earth and 440 were classified. 400 random points were generated across the field office and 377 classified in Google Earth via the vegetation ecologist which lead the AIM sampling in 2022. An additional 885 regularly placed plots were drawn across the extent of the field office and 854 were classified. Unclassified computer generated points were generally those that fell upon a wide road, or were outside BLM Ownership. Unclassified AIM/LMF points were LMF points which must have represented the re-visitation of a single plot, under distinct record elements in the TerraDat database. In all instances points were buffered by a 30m radius, to create the dimensions of an AIM plot, and the single most influential vegetation type was recorded.

To develop a random forest model, the dataset of 1657 classified points were partioned into a 0.3 test and training set 0.7 using caret, the data set was not balanced, see table XX for sample sizes.

Variable Importance in Random Forest Model

| Variable | Importance |
| --- | --- |
| GLCM\_PC2 | 176.028 |
| DEM | 173.738 |
| NDVI | 109.820 |
| Slope | 91.389 |
| NAIP\_blue | 49.249 |
| NAIP\_red | 38.504 |
| GLCM\_PC1 | 32.012 |
| NAIP\_IR | 25.261 |
| NAIP\_green | 22.819 |



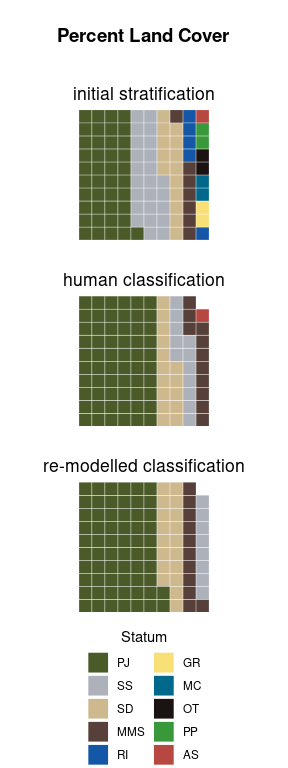
The number of mtry in the random forest model were tuned using the function ‘tuneRF’ with the number of try’s set to 1000, a step factor of 1.5 and a relative minimum improvement in Out of Bag (OOB) error rate set at 0.01. The random forest model was then trained using 4 mtry and 1000 trees, all using the RandomForest package.

While the accuracy for the model was 0.773 (range 0.73 - 0.81), due to an imbalance in the number of observations per group a more appropriate for evaluating the overall performance of the model, is the Kappa metric, 0.628.

Notably, the model has high rates of Specificity (median = 0.96), showing that when it predicts a vegetation type onto a pixel cell, the prediction is usually correct; less so for prediction of Pinon-Juniper (0.766). However, the model suffers from low Sensitivity, indicating that it is unable to detect all occurrences of a vegetation type. For example, the model is only able to appropriately classify half of the occurrences of Sage Steppe (0.475 ) and Mixed Mountain Shrub (0.596). Accordingly this model is susceptible to over-predicting the occurrence of Pinyon-Juniper, at the expense of Mixed Mountain Shrub and Sagesteppe. This is to be expected given the sample imbalance, which contained many more plots PJ than other types. However numerous trials of reducing the number of Pinyon-Juniper plots did not significantly increase the quality of predictions. Further indicating, that the features used are not adequate for distinguishing between the transitional points enough Pinons and Junipers are present where Sagesteppe phases into Pinyon-Juniper, and where shrubs increase in Pinyon-Juniper and it phases into Mixed-Mountain Shrub.

The Random Forest classification model was predicted onto a raster surface using the package ‘Terra.’ This raster was then smooth using focal statistics, with a window of 5 cells, using the mode as the value to return.

# Comparison of New and Old vegetation classification models.



Changes in Predicted Land Cover

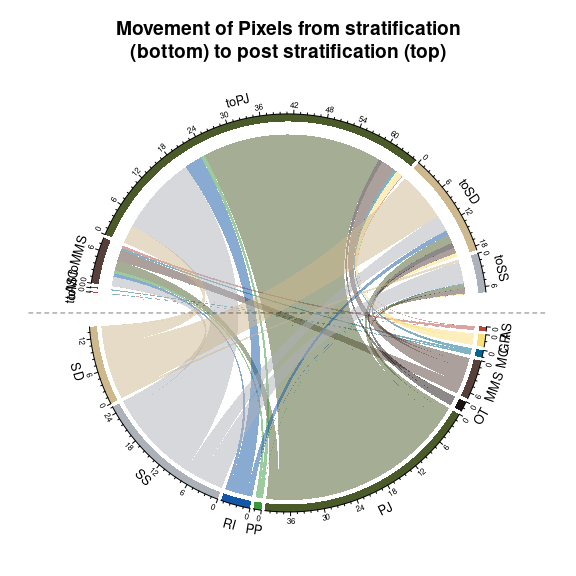
a ton of test words that should wrap right…. seem like needs more work

this town is coming

like a ghost

town

bands wont play no more too much fighting on the dance floor



This diagram shows how raster cells in the UFO are redistributed from the original sample design, to the the reclassified spatial product for the sample design

The initial AIM sample design was based upon a stratification which included r communities. This design was based on a manual reclassification of the GAP/LANDFIRE National Terrestrial Ecosystems 2011 data set.

# Citations

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