

Compare ESD and ESG Quantitative Benchmarks

Introduction

The development of Ecological Sites (ES) and their descriptions (ESD's) represent an enormous effort on behalf of the Natural Resources Conservation Service (NRCS) (Bestelmeyer (2015)). As mentioned in section XX, they do not yet form a continuous coast to coast, nor even across the field office data set (Twidwell et al. (2013)). In order to allay the significant amounts of effort required to develop these, and to make land management decisions in the interim alternative classification systems have been proposed (Nauman et al. (2022)). One system which incorporates the NRCS ESDs, and which provides continuous coverage across our study area, are the Ecological Site Groups (Nauman et al. (2022)).

The Ecological Site Groups developed largely by United States Geological Survey (USGS) researchers at the Southwest Biological Science Center in Moab Utah, with assistance from BLM Colorado State Office Staff, are meant to both bridge the spatial gap in ESD development, and to provide a framework for land management decisions at a larger scale than that which generally occurs at a BLM Field Office. The Ecological Site Groups were developed by grouping together similar ESD's, akin to the strictly interpretive approach - which seeks to reduce conceptual fineness - in section XX, and which will respond in a similar fashion to management actions (Duniway et al. (2016)). To these initial groups the field data which largely informed the ESD creation, most notably soil physical parameters, and with the use of an objective and quantitative approaches, which make use of simple *Machine Learning (ML)* method *Random Forest* **section XX** were used to identify recurring themes in the dataset into groups, and then project these onto a 'map' which covers the Upper Colorado River Basin.

While for most land management decisions at the UFO ESD's, when available, represent the best available scientific evidence upon which to inform decisions, ESG's provide the best alternative for much of the field office, and in the future are likely to be influential for large scale decisions at the UFO. Herein we address questions regarding the similarity of estimates arising from ESG's and ESD's. In this report, we are using ESD's for the *reference state benchmarks* which they contain, in other words quantitative goals which we seek to compare land to, and seek to visualize the relationship between the standards of ESD's and ESG's.

The goals of this section are to 1) determine which ESD's constitute the ESG's across the UFO? And 2) visualize the similarity in benchmarks within an ESG and the ESD's which it contains. A short investigation of how different methods of extracting the spatial dataset to the ground truthed data, as well as a comparison of the accuracy of the predicted ESG's limited to the UFO area and ground truthed plots, is also included.

In the publication of Nauman et al. 2022 the accuracy of the final product was calculated as being 57.4% (Nauman et al. (2022)). However, In our experience certain groups are often more difficult to reliably predict, and without sufficient testing sample sizes many spatial products will score higher, or lower, than these averages in areas with/without these features.

Methods

The mean fractional cover of vegetation was manually transcribed from Table 3 of Appendix A from Nauman et al. 2022. The spatial data product, a gridded surface of predicted ESG's, which was the outcome of the study was accessed from sciencebase.gov catalog on (Dec. 16, 2022, no internet), three additional layers predicting soil geomorphological groups and another predicting climate zone were also downloaded. ESD

quantitative benchmarks values, and AIM plot locations were cleaned in previous work (Section XX ESD Completion). All analyses were performed in R version 4.2.2 using RStudio on Linux Ubuntu 22.04 LTS (R Core Team (2022), Sobell (2015), RStudio Team (2015)).

Test Raster Extraction Methods

To test whether we were extracting and processing the correct ESG from the gridded surface two comparisons of raster extraction methods were attempted. The first (hereafter: ‘polygon’), which is typically performed at UFO, is to buffer the point to represent the actual area of the entire AIM plot and extract to that area, and choose the categorical class with the most cells per value (in other words the statistical mode). The second (hereafter: ‘point’) option is to extract values from the gridded surface directly to the point geometry. The idea behind this is that the pixels from the gridded surface featured a ‘splotchy’ characteristic, a byproduct of not performing spatial operations to clean up the predictions (e.g. ‘Focal Statistics’); oftentimes these central isolated cells are not artifacts of analysis, but rather true points which are swamped by the adjacent cells. The slightly higher performing method, ‘polygon’, was used for the duration of the analyses.

Test Local Accuracy of Raster Dataset

To determine whether the raster dataset gives a higher or lower performance accuracy in the UFO portion of it’s range the 157 AIM plots in 18 ESD’s which are known to map directly to 10 ESG’s were utilized. These plots were extracted from the ESG gridded surface and the proportion of each ESG which was correctly and incorrectly mapped were calculated.

Determine ESD and ESG Groupings

To inform a strategy for mapping individual ESDs directly to ESG’s a bipartite network was created using all AIM plots with verified ESD’s, all statistics (**not reported in text**) were calculated using the package ‘bipartite’ (Dormann et al. (2008)). This approach was deemed necessary given how many erroneous relationships were returned by the ESG extraction method.

All observed ESD’s were matched to ESG’s in an incremental fashion. 1) ESD’s which were used directly in the creation of ESG’s were removed based upon a noted association in Appendix 6 of Naumen et al. 2022. 2) ESD’s for which only a single AIM plot existed, had the ESG which values were extracted from it listed as it’s ultimate mapped association. 3) ESD’s with greater than 1 AIM plots associated with them, and which had all plots match an ESG were classified as such. 4) ESD’s with over 65%, our local accuracy of the gridded surface, of their AIM plots mapping to a single ESG.

Following the removal of these ESDs from the initial dataset, the three Soil Geomorphologic Units (SGU) surfaces, and the Climate Zone surface were used to match the remaining ESDs to an ESG. Each of the remaining points had values extracted from each layer of the SGU surfaces, each representing the classification prediction from the three top performing classifier models. The most commonly occurring ESG (in others words the statistical mode), was then calculated considering each of the SGU layers per point, across all points in the ESD simultaneously. All climate zones were also extracted to the points, and the most commonly occurring climate zone per ESD was selected as the climate zone to classify these sites in the SGU framework, thus forming the ESG.

The results of these analyses led to the development of a draft ESD-ESG lookup table for the Uncompahgre Field Office for this project.

Results

157 AIM points were in the 18 ESD’s which were directly involved in the creation of 10 ESG’s and could be used for assessing the results from the alternative raster data extraction methods and for assessing the

accuracy of the ESG gridded surface in the area of analysis. The method of extracting the ESG from the gridded surface to plot had little influence on the accuracy of the ESG. Regardless the method of buffering the point to the real size of the AIM plot was used as it slightly outperformed plot centers on the 157 known sites, 0.65 to 0.637. 157 AIM points were in the 18 ESD's which were directly involved in the creation of 10. The ESG gridded surface was able to correctly place 0.65 plots to the appropriate ESG, rather than the 57.4% reported for the entire study area (*Figure 1*). A caveat associated with this result is that our value is likely to be biased towards more common ESG classes. We accept this bias as the scale at which we make management decisions is so great.

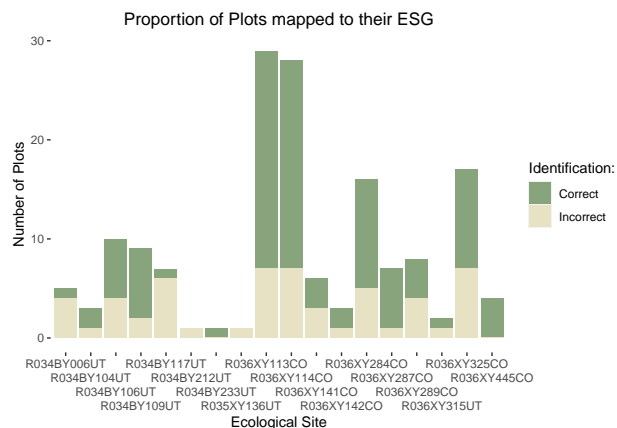


Figure 1: Proportion of Plots in ESDs which were included in the ESGS and should map over unequivocally to an ESG

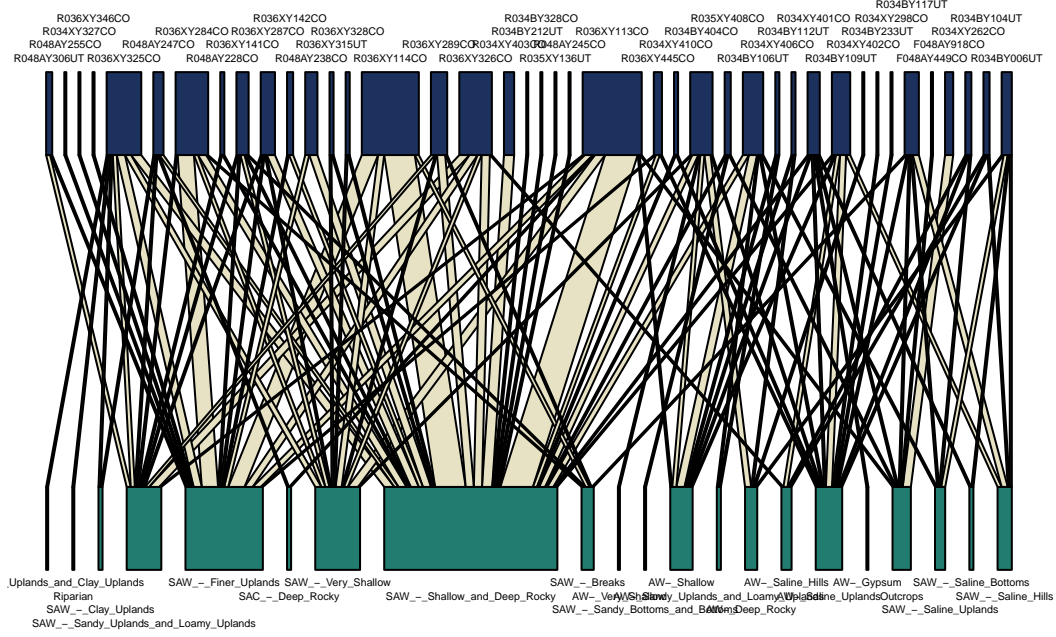


Figure 2: Initial Relationship Between Field Verified ESD and ESG extracted from the gridded surface

The initial extraction of ESG to AIM points was problematic, Figure 2. Ideally, if ESD's were the entities which defined the ESG's, then each ESD (the upper boxes in the panel) would link to a single ESG (the lower boxes in the panel), an image of this relationship is displayed in Figure 4. As is apparent, this was not the case, however much of the error in these classifications lay with the classification of the gridded surfaces, rather than with the ESG concepts themselves.

In order to map these relationships we utilized a step-wise process. 1) 18 ESD's, associated with 157 plots, which were used directly in the creation of 10 ESG's were removed based upon a noted association in Appendix 6 of Naumen et al. 2022. 2) 8 ESD's for which only a single AIM plot existed, had the 5 ESG which values were extracted from it listed as it's ultimate mapped association. 3) There were 2 ESD's with greater than 1 AIM plot associated with them, which had all plots match the same ESG 2. These ESD's, F048AY918CO, R034XY403CO, were associated with 9 AIM plots, and mapped to: *Outcrops, SAW Shallow and Deep Rocky*. 4) Finally, 2 ESD's with over 65%, our local accuracy of the gridded surface, of their AIM plots mapping to a single ESG were recovered. These ESD's , R048AY238CO, R048AY306UT, were associated with 9 AIM plots, and mapped to: *SAW Shallow and Deep Rocky, SAW Sandy Uplands and Loamy Uplands*. At this point the classified ESD's and non-classified ESD's appeared as Figures 3 and 4 respectively.

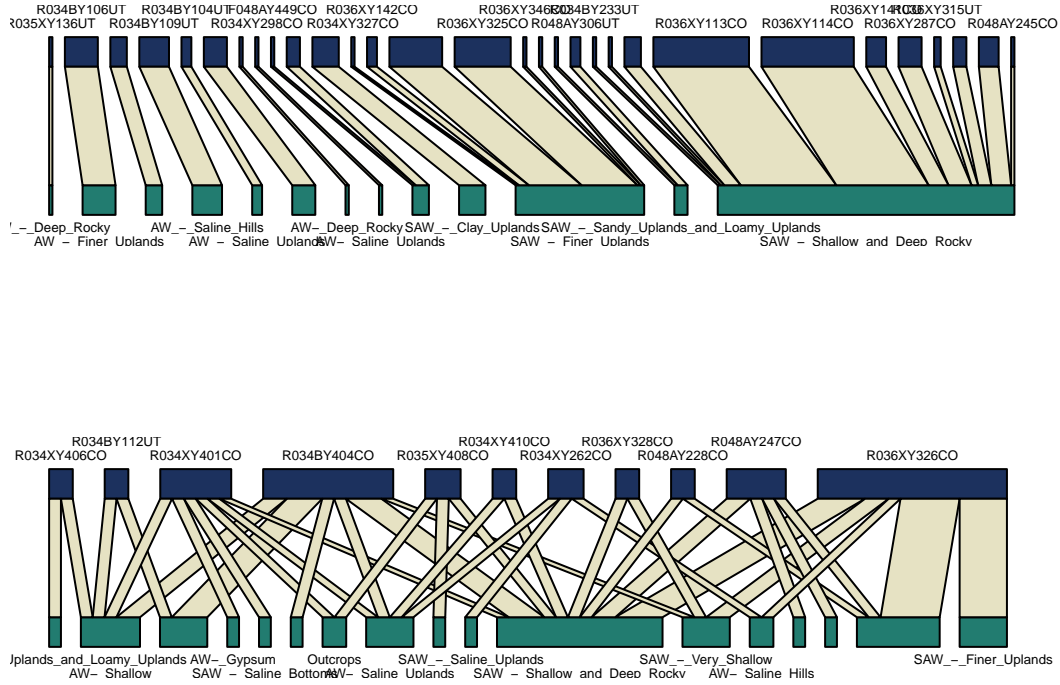


Figure 3: Relationships Between ESDs and ESGs midway through the cleaning process

The remaining 11 ESD's, associated with 54 AIM Plots, were all mapped to 6 ESGs via the methods of summarizing both all three SGU layers in conjunction with climate zones. The final lookup table of ESD to ESG mapping is in Figure 4. 11 of the 35 ESGs were present in the UFO, the number of plots per ESG ranged from 5 (AW Saline Bottoms and Bottoms) to 97 (SAW Shallow and Deep Rocky).

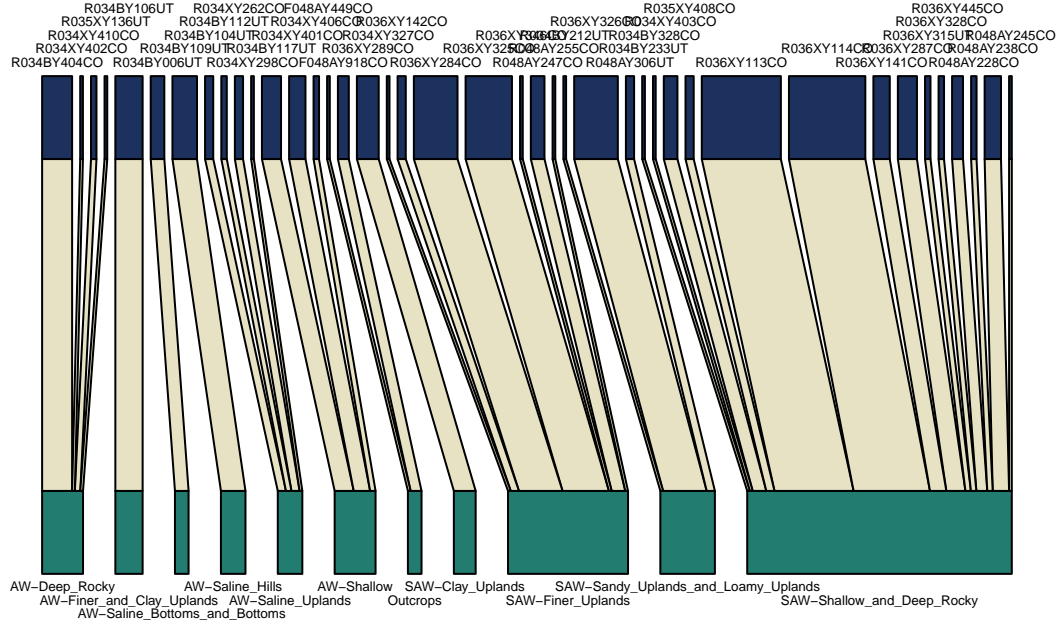


Figure 4: Relationship between ESDs and ESGs at end of process

Of the three climate zones defined in Nauman et al. 2022, the UFO does not contain the Semiarid-Cool zone.

The quantitative estimates for the cover of major vegetation types by group are presented in figure 6. Note this figure does not contain ‘outcrops or riparian esg’ both of which do not have ESD, nor are they target areas for management considerations. Riparian areas fall within the domain of Lotic AIM, and the ecology of outcrops is a management action over the geologic time scale.

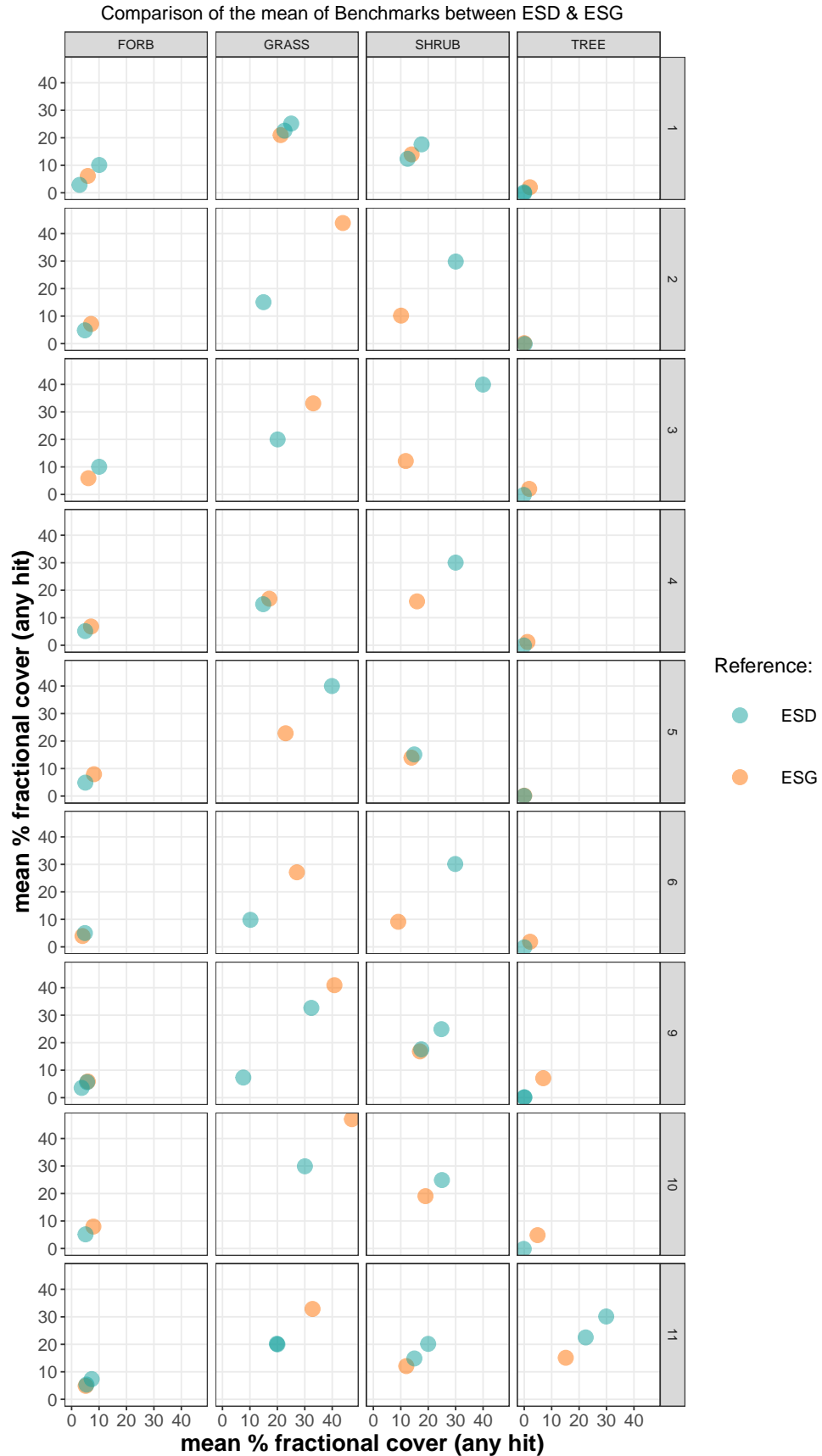


Figure 5: Fractional cover, note the provisional ESGs for Outcrops and Riparian, groups 7 & 8, have been removed.

The covers of forbs, with both perennial -and to an extent annual- life cycles varies the least across lifeforms, their cover ranges from 4 to 8. Given the variability inherent within the concept of an Ecological Site, and the years from which a large amount of the data for which the ESG cover values were calculated a marked majority of this cover should be constituted of perennial rather annual forbs. The cover of trees per Ecological Site Concept has the next least variability (*Figure 5, Column 4*). 6 of 9 sites have < 5 % tree cover, with the exception to this being the FINER??? Uplands, conceptually a very large ESG, which includes nearly all of the Pinyon-Juniper Woodlands, along with high notable amounts of Sagebrush sites (VERIFY). We presume that the inclusion of Sagebrush sites into this ESG is the reason that for this concept alone the tree cover in the ESG exceeds that noted in the ESD.

Greater divergences are observed between the estimates of cover for Grass and Shrub. The cover of grasses in XX ESG's, XX, are conceptually identical, however in the other XX ESG's the cover of grass notably exceeds that noted in the ESD's. The reasons for this are perhaps ... The relationships between the shrub cover values are more nuanced, XX ESG's have conceptually identical cover values, however for the remaining ESG's the cover of Shrubs is less than noted in the ESD's. That the cover of shrubs would be less than expected is unanticipated, given the noted movement of much of the vegetation in the arid portions of Western North America moving towards a 'shrub state', a condition whereby the cover of shrubs has increased relative to uncommon parcels of undisturbed land (CITE).

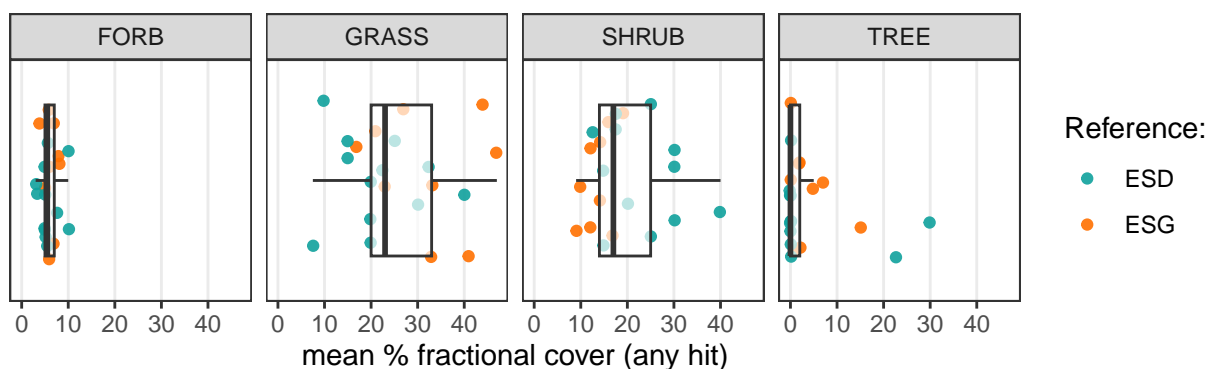


Figure 6: Fractional cover across all ESG's and the ESD's with quantitative Benchmarks within them.

The distributions of covers for each lifeform regardless of ESG are reported in the bottom of (figure 5, Pane B.).

Conclusions

The relationship between the novel ESG's and the ESD's are less straightforward than may be offered by simple extraction of values from gridded surfaces. We find that Nauman et al. 2022 were largely hampered by the same issues as ourselves, Section XX, in trying to map ESD's into meaningfully similar groups. We believe that we are the first persons to attempt to operationalize the ESG concepts which they utilize in their publication.

“We emphasize the need to corroborate mapped classes with field confirmation for site-specific management.”

— Nauman et al. 2022, P. 24

In regards to using ESG's we feel that the best option is to continue verifying the ESD at all sites, and then using a spatial approach as above to determine which ESG an ESD is allied to. The additional use of the Dichotomous Key (Figure 3 of Nauman et al. 2022), with ocular estimates of Electrical Conductivity via ‘sparkling’ parameters of the soil may be used by crews in the future to develop a larger ground truthed data set for the UFO.

References

- Bestelmeyer, B. T. (2015). National assessment and critiques of state-and-transition models: The baby with the bathwater. *Rangelands*, 37(3), 125–129.
- Dormann, C. F., Gruber, B., & Fruend, J. (2008). Introducing the bipartite package: Analysing ecological networks. *R News*, 8(2), 8–11.
- Duniway, M. C., Nauman, T. W., Johanson, J. K., Green, S., Miller, M. E., Williamson, J. C., & Bestelmeyer, B. T. (2016). Generalizing ecological site concepts of the colorado plateau for landscape-level applications. *Rangelands*, 38(6), 342–349.
- Nauman, T. W., Burch, S. S., Humphries, J. T., Knight, A. C., & Duniway, M. C. (2022). A quantitative soil-geomorphic framework for developing and mapping ecological site groups. *Rangeland Ecology & Management*, 81, 9–33.
- R Core Team. (2022). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. <https://www.R-project.org/>
- RStudio Team. (2015). *RStudio: Integrated development environment for r*. RStudio, Inc. <http://www.rstudio.com/>
- Sobell, M. G. (2015). *A practical guide to ubuntu linux*. Pearson Education.
- Twidwell, D., Allred, B. W., & Fuhlendorf, S. D. (2013). National-scale assessment of ecological content in the world’s largest land management framework. *Ecosphere*, 4(8), 1–27.