

Socio-Ecological Systems Delineation in Idaho: A Spatially-Explicit Approach

A Spatially-Explicit Approach

Sue Parsons

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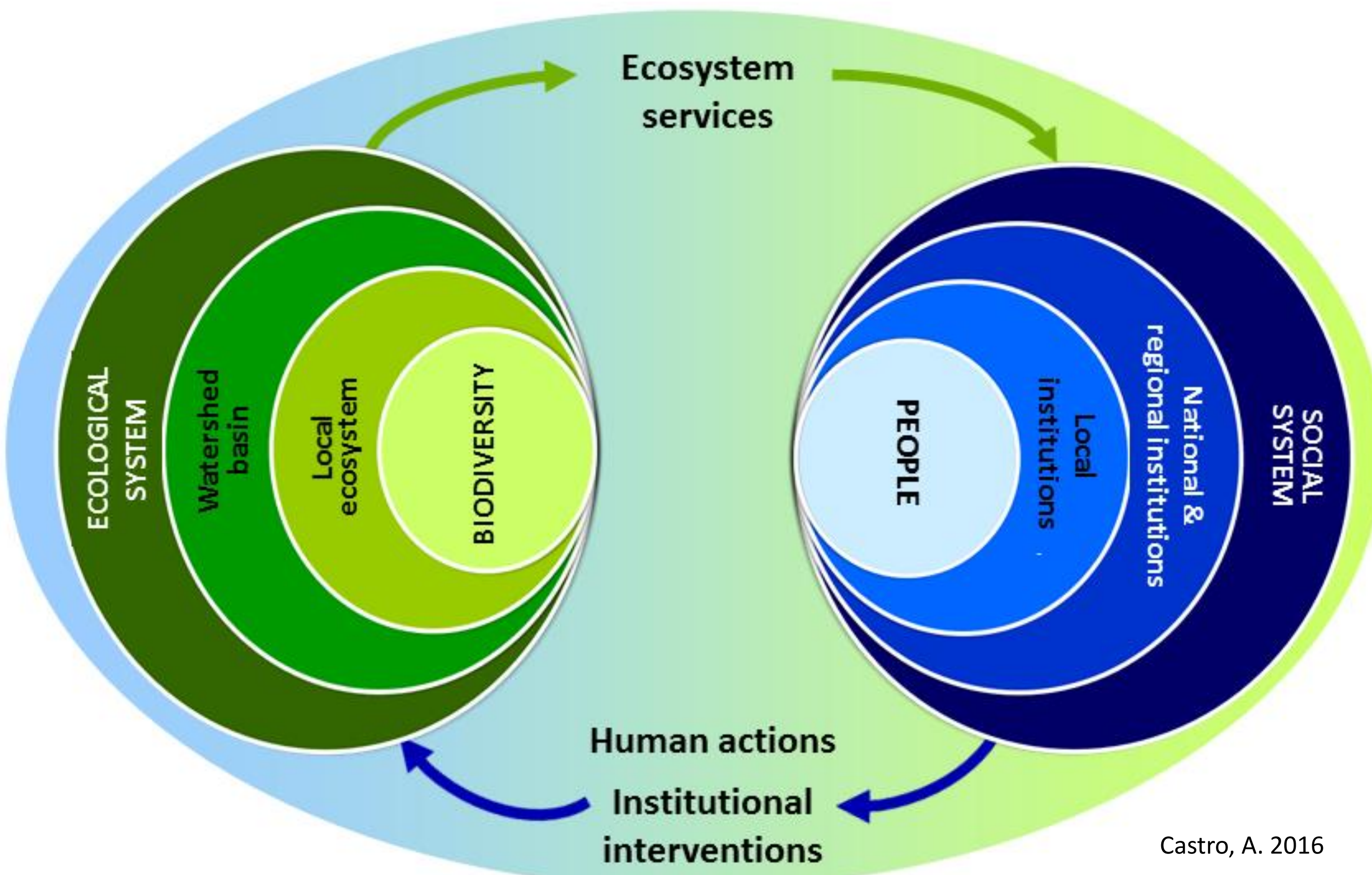
Antonio Castro

Ken Aho

Background

Balancing climate change, sustainable growth, and human wellbeing requires understanding of how biophysical and socio-economic landscapes interact with each other (Griggs, et al. 2013). Socio-ecological systems (SES) science attempts to do this by defining and characterizing the boundaries, interactions, and feed-back loops mediating different types of landscapes, whether engineered or naturally occurring. Numerous conceptual frameworks exist to describe SES interactions and evaluate SES characteristics (Binder, et al. 2013, Carpenter, et al. 2008, Ostrom 2009), but questions remain of how to locate and characterize these SES domains.

“Ecosystem services” describe a landscape’s ability to supply resources of value to humans and are a critical component of understanding social ecological systems.



Studies mapping ecosystem service provisioning have increased exponentially since 1995 (Martinez-Harms, et al. 2012), but studies of the underlying social-ecological system boundaries are less abundant (Folke 2007) and detailed methodological information is missing from the majority of them (Martinez-Harms, et al. 2012). Principal Component Analysis (PCA) followed by clustering has been used to define eco-economic regionalization of the Chinese Loess Plateau (Zang, et al. 2011), characterize biophysical and socio-economic functional units in Spain (Castro, et al. 2014, Martin-Lopez, et al. 2017), and define socio-ecological regionalization of urban sub-basins in Mexico (Cervantes-Jimenez, et al. 2016). Despite these advances, approaches to compress multi-dimensional datasets into functional units remain subjective in their interpretations, as the variables, proxies, and techniques used to define different landscapes greatly influence the results.

We report analyses to delineate SES landscapes in Idaho, USA predicated on the assumption that homogenous functional groups will have the same potential for providing ecosystem services. This work presents a methodological improvement on traditional PCA followed by clustering techniques used by other researchers, and explicitly addresses the results and implications of using a non-hierarchical vs. hierarchical approach to clustering SES variables.

Methods

Data. Publically available, authoritative datasets were used.

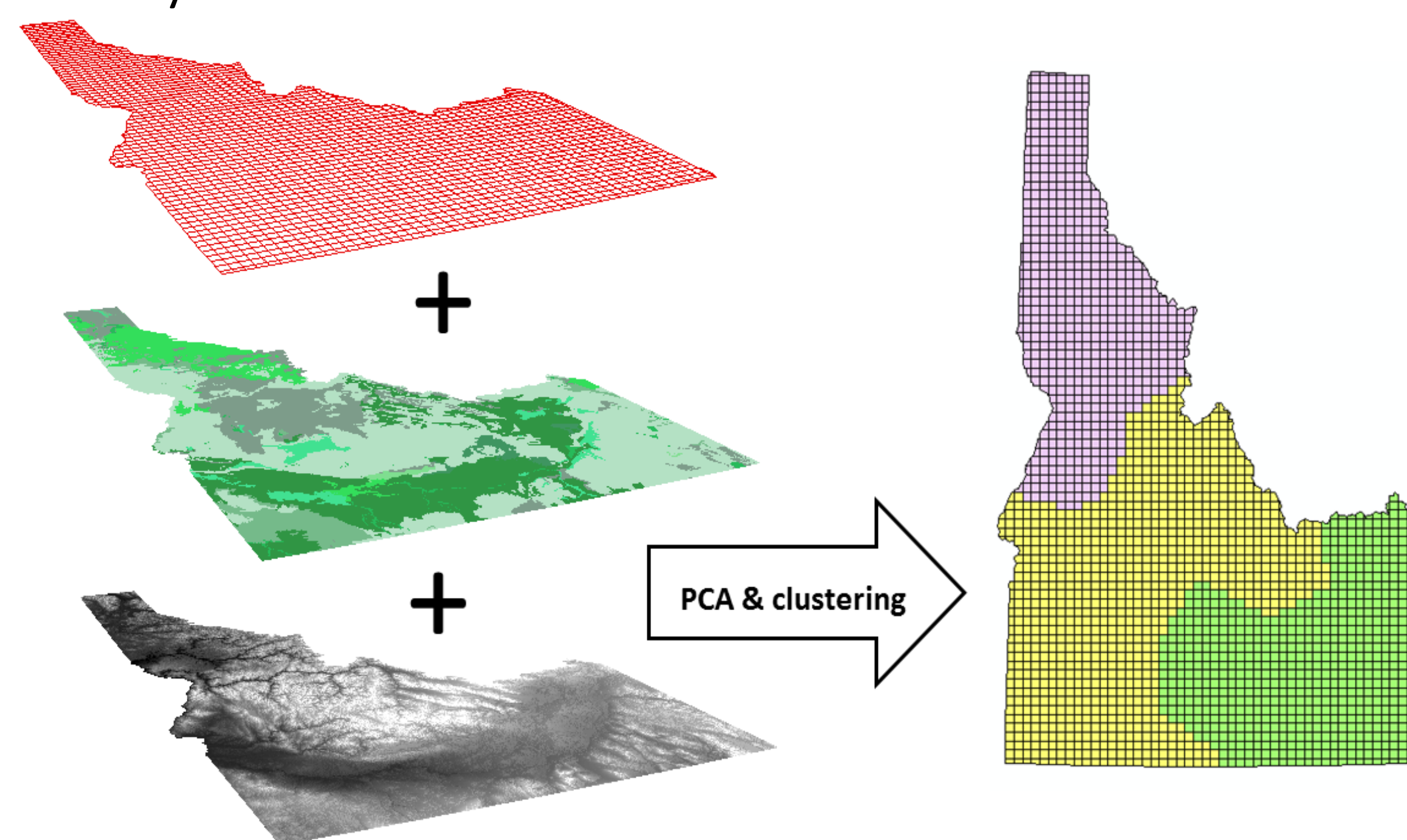
- **Biophysical Variables:** elevation, slope, dew temperature, air temperature, vapor pressure deficit, precipitation, potential evapotranspiration, NDVI, land cover, lithology, soil order, biodiversity.
- **Socio-Economic Variables:** population density, percent Caucasian, median age, high school degrees, bachelor degrees, aggregate income/household, housing density, owner occupied homes, percent traditionally married with children families, percent divorced, traffic density, human modification index, industry occupations, surface management agency, land use.

Nested PCA. Categorical variables were numericized and concatenated via an initial, nested PCA approach. Selected principal components from this step were included with the continuous data for a second PCA.

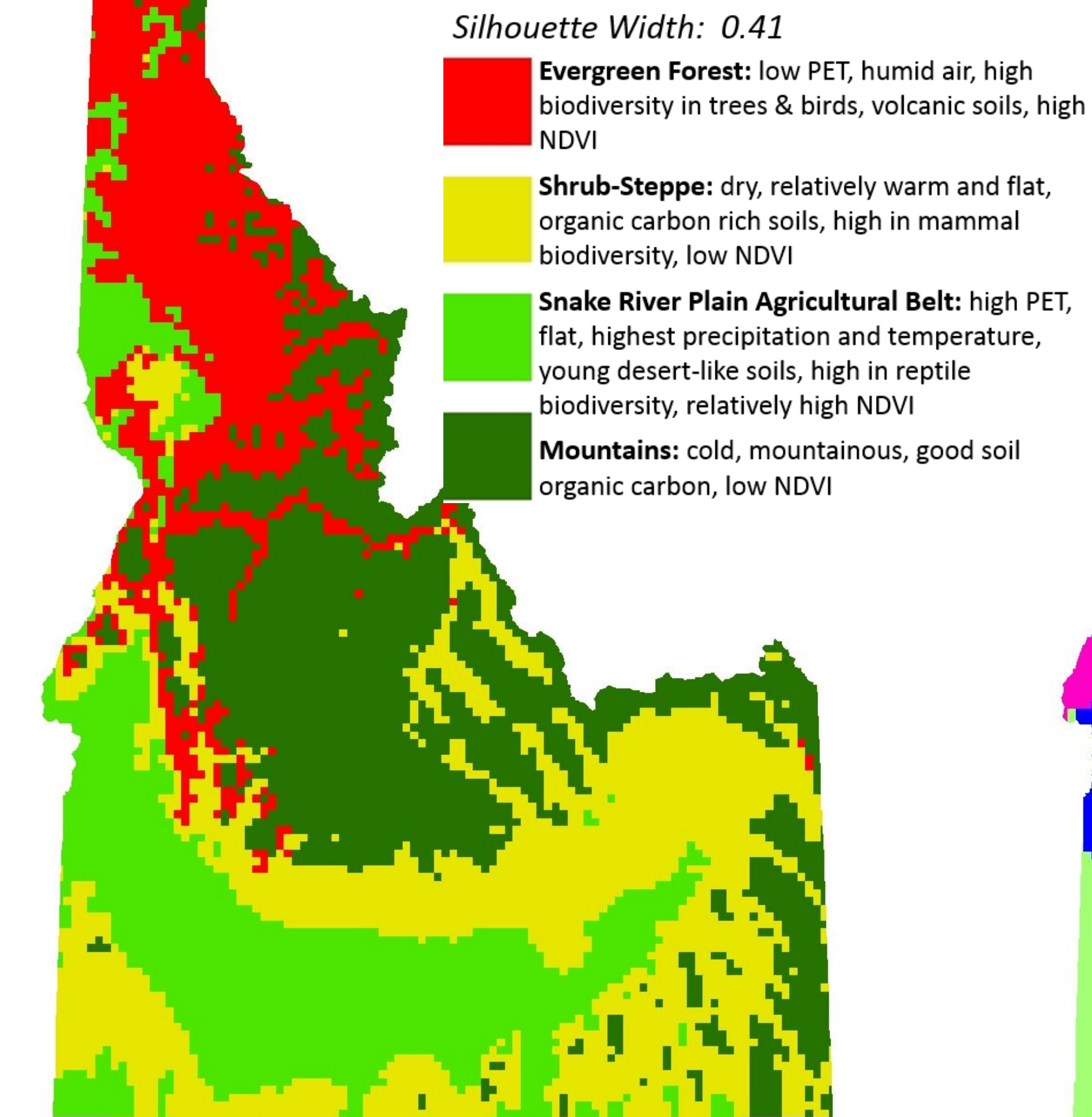
- **Biophysical Variables:** **biodiversity** PC1-3, 80.6 % (originally 6 categories), **landcover** PC1-2, 89 % (originally 9 categories) **soil order** PC1-3, 87.1% (originally 7 categories), **lithology** PC1-2, 80.8% (originally 4 categories).
- **Socio-Economic Variables:** **industry occupation** PC1-7, 70.5 % (originally 17 categories), **surface management agency** PC1-2, 87.3% (originally 9 categories), **land use** PC1, 93.7% (originally 6 categories).

Modified PCA. Modified PCA was performed with XY spatial coordinates of analysis grid centroids included in the dataset. The coordinates were then omitted for score calculations, thereby holding spatial location constant while not explicitly including them in subsequent clustering analysis.

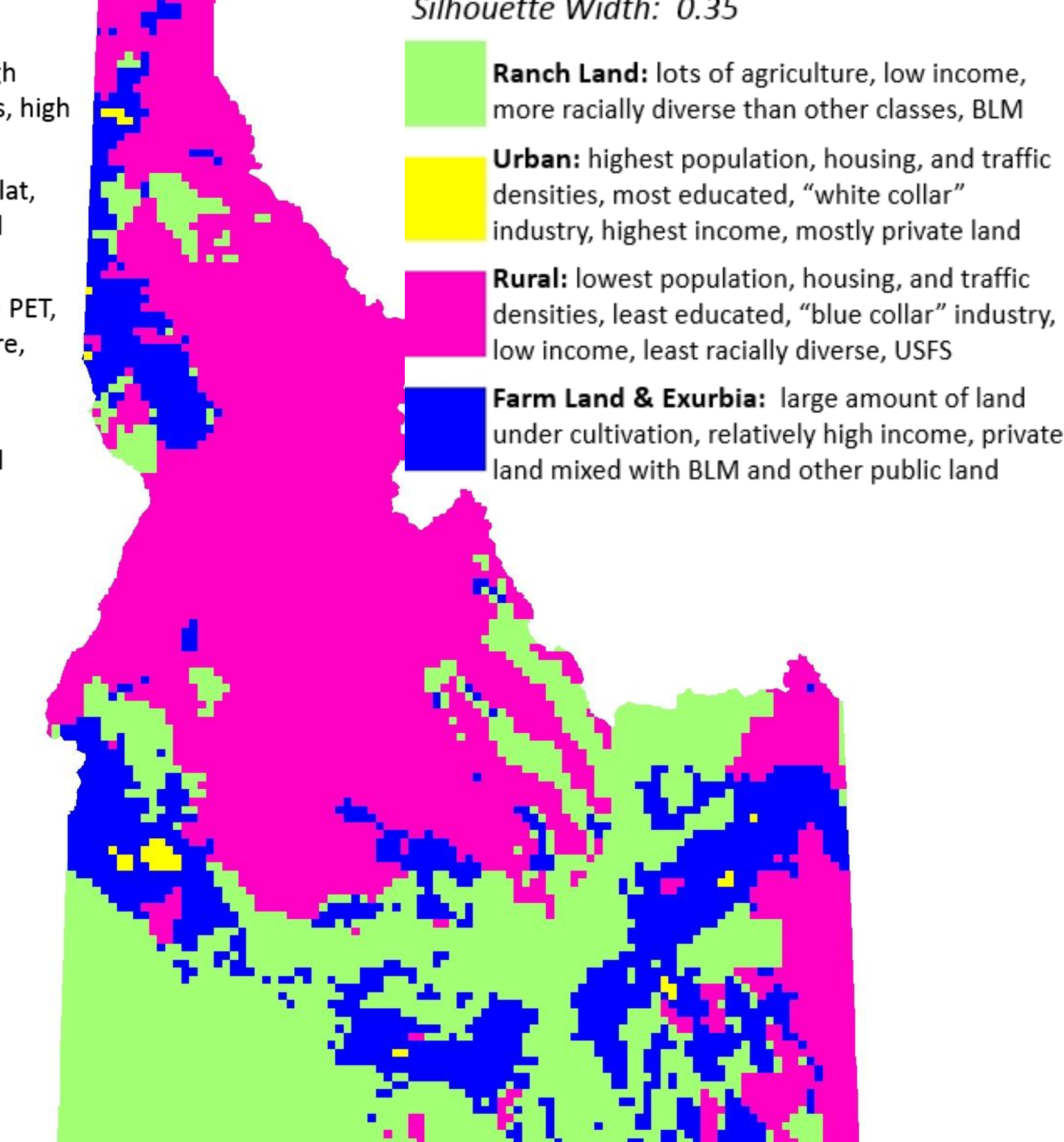
Clustering & Validation. Both kmeans (Lloyd 1957) and Agglomerative Hierarchical Clustering (AHC) (Rokach, et al. 2005) are standard, broadly used approaches to clustering landscape variables, and have specifically been used to cluster PCA results of landscape variables. In order to explore how different clustering approaches might affect delineation outcomes we used both techniques with the intention of comparing and contrasting findings. Choosing the optimal number of clusters generated by kmeans and AHC was done using two validation indices, the silhouette width and the gap statistic, respectively.



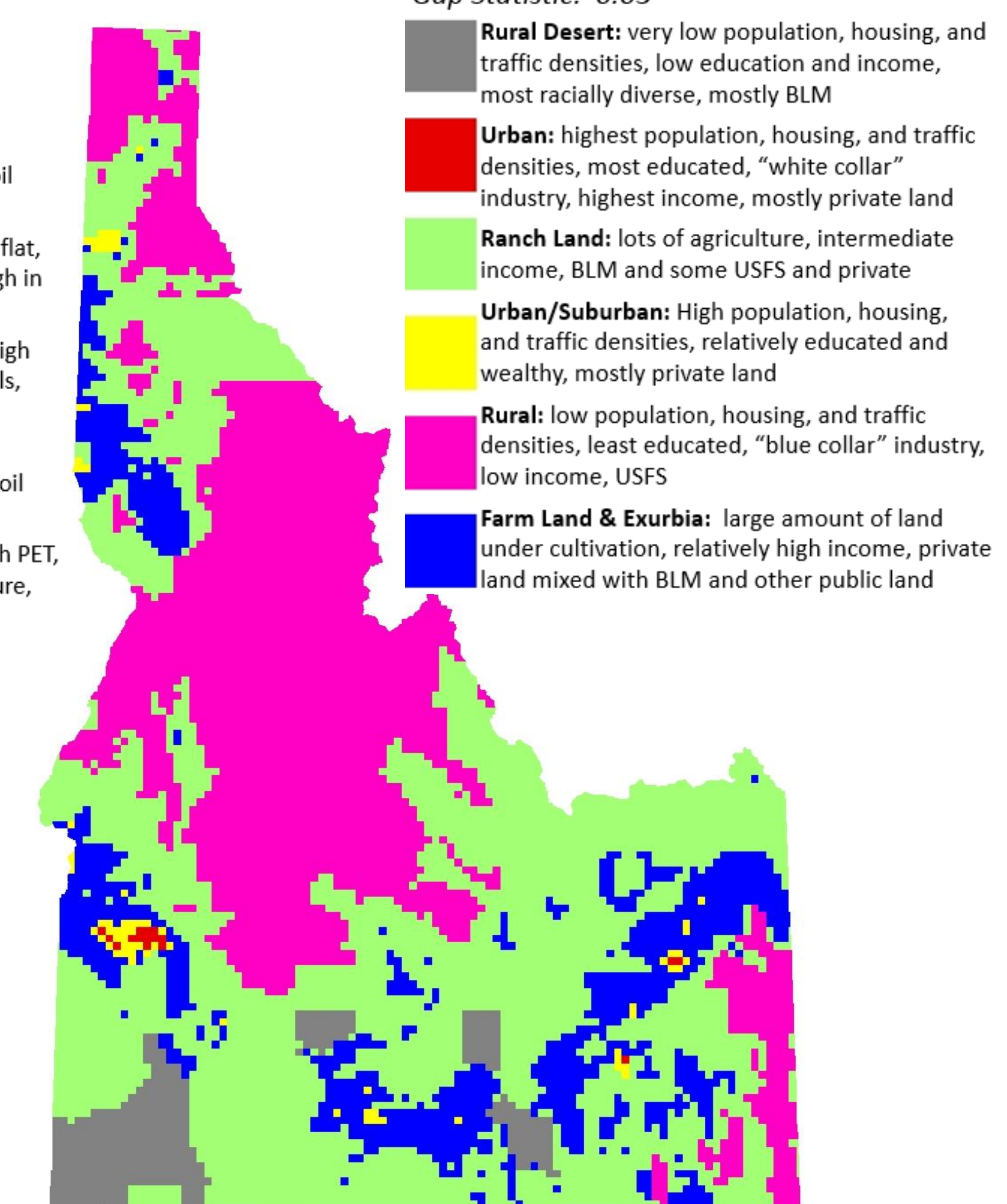
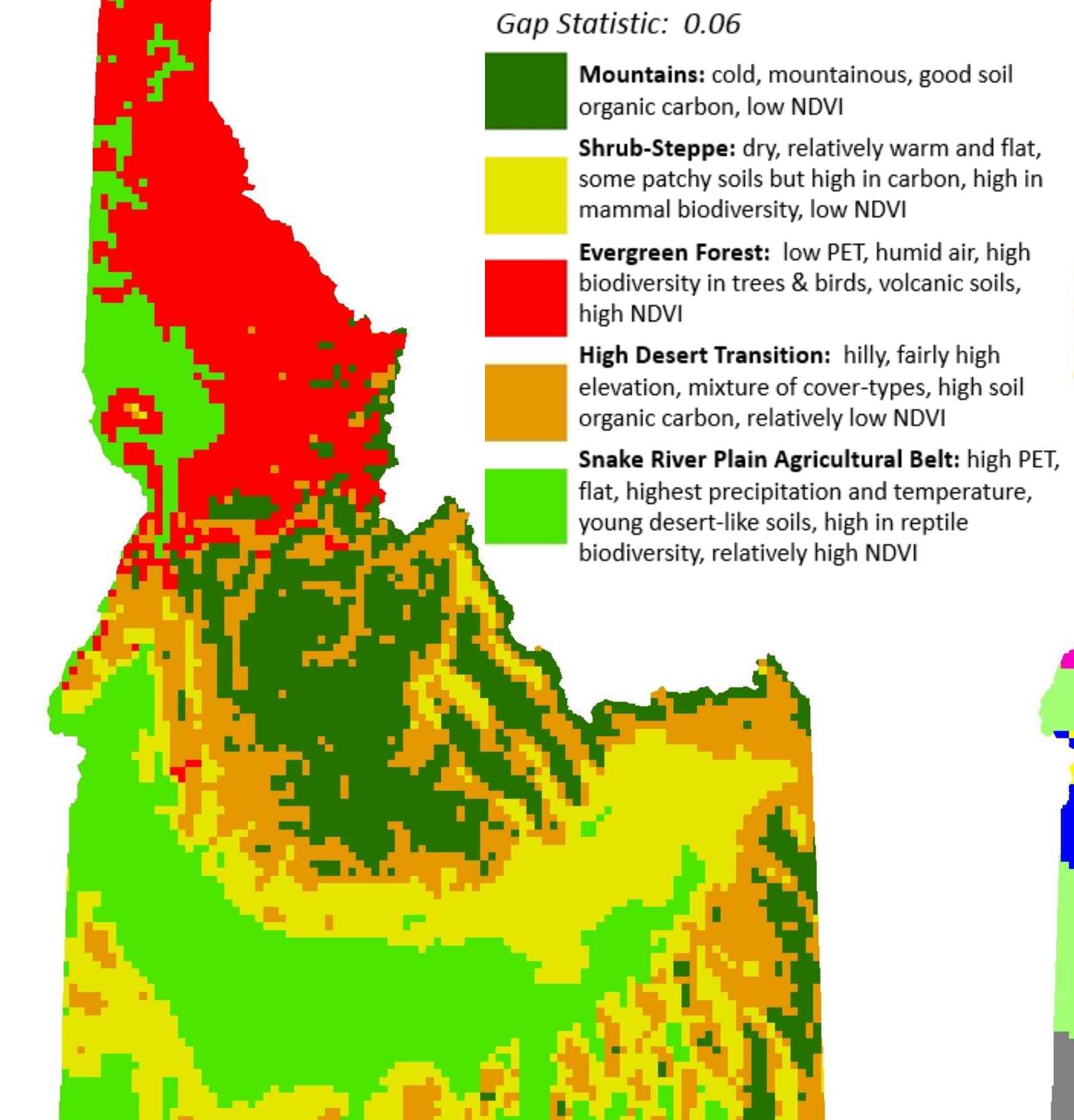
Kmeans, non-hierarchical



Results



AHC, hierarchical



Both clustering techniques generated intuitive and robust maps for subsequent SES studies in Idaho, especially those pertaining to ecosystem service supply and sustainability. The hierarchical approach, AHC, generated a higher number of likely clusters for both the biophysical and socio-economic landscapes, providing finer resolution than did the non-hierarchical method, kmeans. We intend to provide all map sets generated by these analyses for clusters 3-10; however, percent agreement between maps for a given number of clusters varied from 47% to 81%, so we recommend exploring additional validation criteria when selecting map sets not presented here. Preliminary spearman correlations between the biophysical and socio-economic datasets (right) show the strongest coupling along the agricultural belt and developed areas, indicating an opportunity to explore this relationship and how the strength of the association has changed over time at different spatial and temporal scales.

Future Directions

