CLASSIFYING AMERICAN VITICULTURAL AREAS BASED ON ENVIRONMENTAL DATA

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ABSTRACT:

American Viticultural Areas are wine appellation areas in the United States formally and legally defined by the US Alcohol and Tobacco Tax and Trade Bureau (TTB) through a petition process and are used in marketing wine. The TTB's petition process is intended to define areas containing unique environmental conditions. In this paper, I investigate how similar AVA boundaries are in their environmental characteristics though a hierarchical cluster analysis, using the environmental variables required to be described in the petition process. The AVAs fell into six groups, driven largely by their physical features such as topography, elevation, or location on a coastline, rather than into geographic clusters.

1. INTRODUCTION

Legally defined appellation areas are used by governments throughout the world to demarcate geographic areas that produce agricultural products, such as wine, cheese, or preserved meats, with a specific quality or set of characteristics. In the United States, the American Viticultural Areas (AVAs) define wine growing areas that are distinctly different from others. These boundaries are created by the US Alcohol and Tobacco Tax and Trade Bureau (TTB) through a legal process and the definitions are published in the United States Federal Register, in narrative form, defined using United States Geological Survey (USGS) topographic maps for their landmarks. TTB requires all petitions to include evidence the climate, geology, soils, physical features (such as topography and water bodies), and elevation within the proposed boundary are distinct from the area around the proposed AVA (United States Bureau of Alcohol, Tobacco & Firearms, 1980).

AVA boundary definitions can impact the marketability of the wine produced there. AVA boundaries designed with a distinct set of environmental factors, has more appeal for use in marketing. For example, creating smaller and more distinct AVAs in Oregon's Willamette Valley presents an advantage in pricing over more general AVAs (Gokcekus and Finnegan, 2017), as do the smaller AVAs contained within the larger Napa Valley AVA (Keating, 2020). Tobias and Myles (2022) found that the large area and varied environmental conditions present inside the Sierra Foothills AVA made the boundary less culturally significant and less useful for marketing than some of the nearby, more specific AVAs. While classifications of wine and wine-growing areas are a social construct, they, nonetheless, confer and define power and are a tool to differentiate social standing amongst competing wine regions (Zhao, 2005). AVAs may, however, have limited use in regions where the market and tourist traffic do not coincide with preferred growing regions (Myles, Tobias, and McKinnon, 2021).

Exploring the environmental conditions inside of an appellation area with a hierarchical cluster analysis is a useful way to better understand the similarities between different boundaries. This exercise has not been published for the US' AVAs, nor does it seem to have been performed for appellation areas of any product, perhaps because of a lack of openly available spatial boundary data. However, hierarchical clustering has been used to differentiate appellation areas of olive oil (Rial and Falqué, 2003) and cheese (Solís-Méndez, Estrada-Flores, and Castelán-Ortega, 2013) based on characteristics of the products made inside a given boundary.

The TTB's process of proposing and accepting AVA boundary definitions is intended to ensure the creation of boundaries with a unique set of environmental conditions. Using datasets defining environmental characteristics defined by the TTB as a necessary part of the petition text, such as soils, climate, and elevation, this investigation seeks to understand how the characteristics present within the AVA boundaries are similar to one another. The goal of this analysis is to explore the similarities between environments contained in AVAs based on the definition of an AVA as stated by the TTB and determine if this definition produces areas of unique characteristics.

2. METHODS

2.1 Data

For the AVA boundaries, I used the AVA Digitizing Project dataset coordinated by UC Davis which was created by digitizing each AVA's boundary narrative onto the USGS topographic maps described in the legal documents. At the time of analysis, the dataset contained 261 boundaries. The data is open, and the methods are well documented and repeatable. For each boundary, the dataset includes attributes including an identifier, the official name of the AVA, any synonyms for the name, the dates the AVA officially was recognized, the start and end date for the given polygon, who petitioned to define the AVA, which TTB staff member wrote the official documents, the list of approved maps, the list of maps used to digitize the boundary (to record any necessary substitutions), and the official boundary description (American Viticultural Areas Digitizing Project Team, 2022), however, for this analysis, I only used the geometry (spatial boundary) data. The dataset is stored in geojson format in a publically available GitHub repository and updated as AVAs are created or amended. In addition to the AVA boundaries, this analysis used data from the PRISM Gridded Climate Data (PRISM) and POLARIS datasets. PRISM is a collection of spatial climate data for the continental United States (PRISM Climate Group, Oregon State University, 2022). From the PRISM dataset, this analysis used 30-year climate normal for precipitation and temperature as well as PRISM's elevation dataset. POLARIS is a probabilistic soil series spatial dataset for the contiguous United States containing many soil variables (Chaney et al., 2016; 2019). From this dataset, I used the percent sand, silt, and clay at 0-5, 5-15, and 15-30 cm depth, downloaded at 30-meter resolution, using the XPolaris R package (Moro Rosso, de Borja Reis, and Correndo, 2021).

2.2 Analysis

The analysis was caried out using R (R Core Team, 2022). For this analysis, I excluded the single AVA from Hawaii because it is outside the geographic extent of the PRISM and POLARIS datasets. Presumably, this AVA would have significantly different environmental characteristics, given the tropical climate of Hawaii, and should be considered in its own cluster.

The POLARIS data was resampled to 800-meter cells to match the resolution of the PRISM data. For each AVA, I summarized each environmental datasets from PRIMS and POLARIS over the area of the polygon, calculating the mean and the range of the measurements in R, to create an estimate of the central tendency as well as the spread of the measurements.

For each attribute, the value at each AVA was assigned a z-score, calculated as the mean of the attribute field subtracted from the value and divided by the standard deviation of the field. This was done to normalize the data and reduce the effect of differing scales of measurements (for example, depth of precipitation compared with temperature in degrees Celsius).

To assess how similar any given AVA is to other AVAs, I performed a hierarchical clustering analysis using R's hclust() hierarchical clustering function. This tool uses a dissimilarity matrix to assign each polygon to a hierarchical series of groups based on how similar (or dissimilar) each polygon is to each other. The advantage of hierarchical clustering is the output that allows investigators to see the structure of the data (Abdolreza Eshghi et al., 2011). The results can be displayed in a dendrogram to visualize the structure of the classes produced by the hierarchical cluster analysis. The classes can also be used to create a map of the AVAs to help interpret the groups. The full code for this analysis is available in the author's GitHub repository (Tobias, 2022).

To ease interpretability, I chose to cut the dendrogram into a relatively small number of groups, but because of the visible structure of the dendrogram, it is still possible to understand relationships among the leaves at other levels of similarity. The goal was to strike a balance between specificity and regionality. Making many groups creates fewer sites in each group, and perhaps it would be easier to find commonalities this way, but having many small groups reduces the potential to identify regional patterns. Ultimately, the dendrogram allows us to see the relationships between sites at multiple scales.

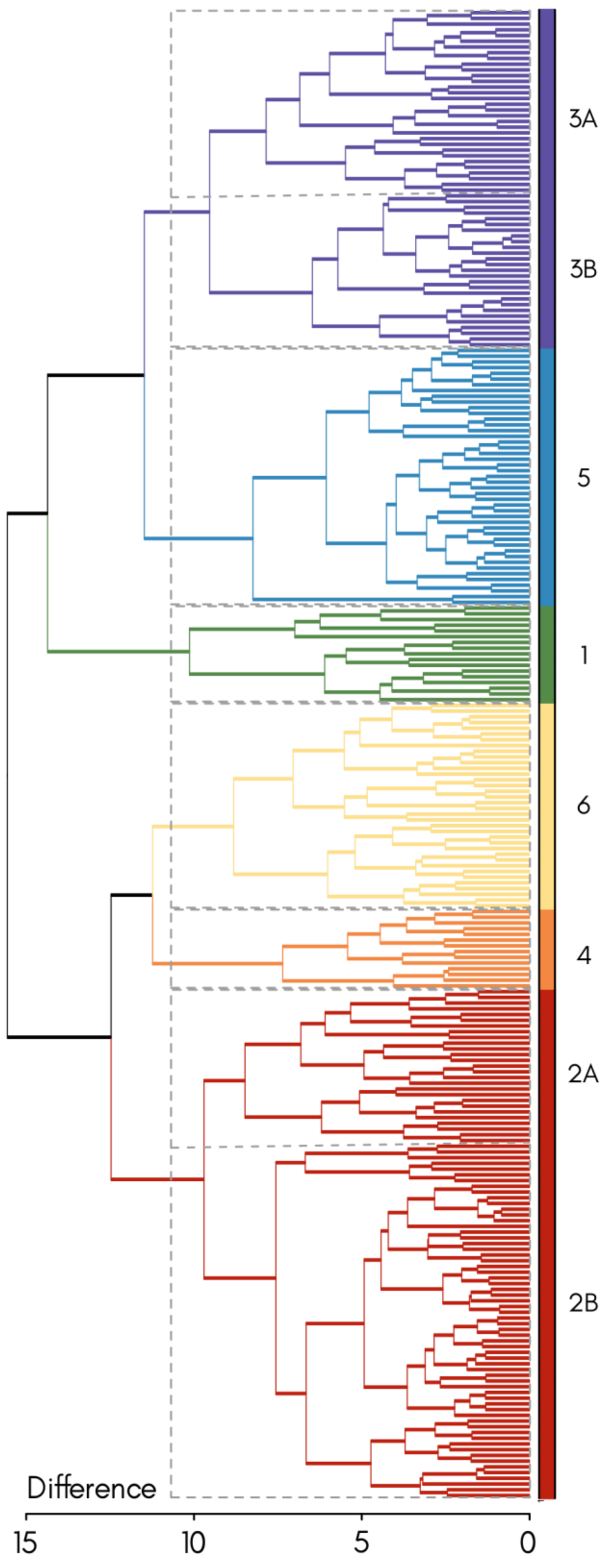

Figure 1. Dendrogram

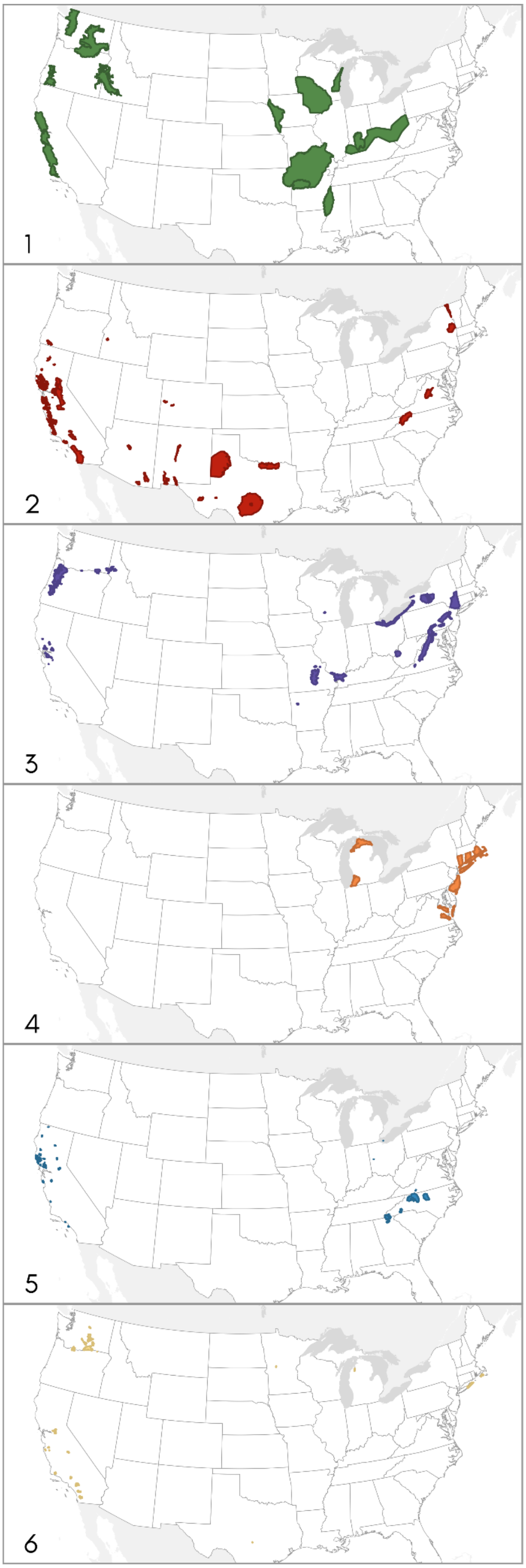

Figure 2. Maps of AVAs in each group

3. RESULTS

The analysis produced a hierarchical set of clusters that can be visualized as a dendrogram to show how similar each AVA to the others (Figure 1). Cutting the dendrogram at a height of about 11 produces six clusters, a good number of groups to understand in a geographical representation (Figure 2). The membership of each group is listed in Table 1. A heatmap illustrates the relationship between the sites and the environmental measurements (Figure 3).

In the first group (Figure 1), the range for soil variables is high, meaning the measurements for soil variables has a fair degree of variation within the boundary. They generally have a low mean sand content and are higher in silt. Given the large area of these boundaries, the temperature ranges of this group is surprisingly low as larger areas have a greater potential for variability. The mean temperature is also consistently low across the group. The mean precipitation for this group is also low – these are fairly dry AVAs – but the range of the precipitation measurements is somewhat high meaning there is variation in the precipitation levels within the polygons. The mean elevation of these AVAs is low, but the range is variable across the group meaning some AVAs have larger differences in elevation but others are flat. The second group (Figure 1) has high temperature ranges and moderate mean temperature. The members of this group are moderate to high range in precipitation, but a mix of low and high mean precipitation. Both the elevation range and mean is highly variable in this group, which is consistent with their geographic location in and on the edge of mountainous areas. This group can be subdivided based on soil characteristics. Group 1A has larger ranges of soil characteristics, and lower mean silt. Group 1B generally has fairly balanced soils, if not slightly higher in clay, but ranges of soil factors are moderate. Group 3 (Figure 1) has a large number of AVAs, and, like Group 2, can also be split by soil variables. Group 3A has higher mean silt, and group 3B has higher mean clay, but the group as a whole has low mean silt. The range of the soil variables is inconsistent across the whole group. Group 3A has a higher range in silt while 3B has higher range in clay. Group 3A has low temperature means and ranges, while 3B has high temperature means and ranges. For the group as a whole, the precipitation range is moderate to high and the mean is variable across the group. Mean elevation is low to moderate and the ranges in elevation are also moderate. The fourth group (Figure 1) has high mean sand, and a moderate range for soil characteristics in general. The group has a low range in temperature with low to moderate mean temperatures, as well as higher mean precipitation and moderate range in precipitation. This group has low mean elevations and low range in elevations. The fifth group (Figure 1) has low range in soil variables, probably because these are rather small areas. These soils are a balanced mix of sand, silt, and clay. The group has moderate to high mean temperatures with variation in the temperature ranges as well as high mean precipitation and the range in precipitation is moderate. This group is at mid-level mean elevations with some higher elevations and moderate ranges in elevation. The sixth group (Figure 1) has the highest mean sand content and fairly low mean clay content. The range of the soil variables is low to moderate, and is particularly low for the clay measures. There are moderate range in temperature and variability in mean temperature as well as low mean precipitation, moderate range in precipitation and consistent

Group 1			
Arkansas Mountain	Mississippi Delta	Rogue Valley	Wisconsin Ledge
Central Coast	North Coast	San Francisco Bay	Yakima Valley
Columbia Valley	Ohio River Valley	Snake River Valley	
Indiana Uplands	Ozark Mountain	Southern Oregon	
Loess Hills District	Puget Sound	Upper Mississippi River Valley	
Group 2			
Subgroup 2A			
Antelope Valley of the California High Desert	Mesilla Valley	Santa Clara Valley	Texas High Plains
Champlain Valley of New York	Middle Rio Grande Valley	Santa Cruz Mountains	Texas Hill Country
Eagle Foothills	Mimbres Valley	Santa Maria Valley	Texoma
Fredericksburg in the Texas Hill Country	Mokelumne River	Santa Ynez Valley	Upper Hudson
Grand Valley	Monterey	Sonoma Coast	Verde Valley
Lodi	Paso Robles	South Coast	Willcox
Madera	Petaluma Gap	Tehachapi Mountains	
Subgroup 2B			
Adelaida District	Dry Creek Valley	Pacheco Pass	San Miguel District
Alexander Valley	Edna Valley	Paicines	Santa Lucia Highlands
Alisos Canyon	El Dorado	Paso Robles Estrella District	Santa Margarita Ranch
Alta Mesa	El Pomar District	Paso Robles Geneseo District	Sierra Foothills
Appalachian High Country	Escondido Valley	Paso Robles Highlands District	Sloughhouse
Applegate Valley	Fountaingrove District	Paso Robles Willow Creek District	Sonoita
Arroyo Grande Valley	Hames Valley	Potter Valley	Sonoma Valley
Arroyo Seco	Inwood Valley	Red Hills Lake County	St. Helena
Ballard Canyon	Kelsey Bench-Lake County	River Junction	Sta. Rita Hills
Bennett Valley	Knights Valley	Russian River Valley	Stags Leap District
Calistoga	Malibu Coast	San Antonio Valley	Templeton Gap District
Capay Valley	Mendocino	San Benito	Texas Davis Mountains
Chalk Hill	Monticello	San Bernabe	Trinity Lakes
Clear Lake	Mt. Veeder	San Juan Creek	West Elks
Covelo	Napa Valley	San Lucas	
Creston District	Northern Sonoma	San Luis Obispo Coast	
Group 3			
Subgroup 3A			
Altus	Finger Lakes	Laurelwood District	Shawnee Hills
Augusta	Grand River Valley	Lehigh Valley	Shenandoah Valley
Catoctin	Hermann	Linganore	The Burn of Columbia Valley
Cayuga Lake	Hudson River Region	Middleburg Virginia	Umpqua Valley
Central Delaware Valley	Kanawha River Valley	Niagara Escarpment	Walla Walla Valley
Chehalem Mountains	Lake Erie	North Fork of Roanoke	Warren Hills
Cumberland Valley	Lake Wisconsin	Ozark Highlands	Willamette Valley
Elkton Oregon	Lancaster Valley	Seneca Lake	
Subgroup 3B			

Big Valley District-Lake County	Lamorinda	Oak Knoll District of Napa Valley	Solano County Green Valley
Clarksburg	Lewis-Clark Valley	Oakville	Suisun Valley
Coombsville	Livermore Valley	Red Hill Douglas County, Oregon	Tracy Hills
Cosumnes River	Los Carneros	Ribbon Ridge	Tualatin Hills
Dundee Hills	Lower Long Tom	Rutherford	Van Duzer Corridor
Dunnigan Hills	McMinnville	Salado Creek	Yamhill-Carlton
Eola-Amity Hills	Merritt Island	San Ysidro District	Yountville
Group 4			
Cape May Peninsula	Leelanau Peninsula	Outer Coastal Plain	Virginia’s Eastern Shore
Eastern Connecticut Highlands	Long Island	Southeastern New England	Western Connecticut Highlands
Fennville	North Fork of Long Island	Tip of the Mitt	
Lake Michigan Shore	Northern Neck George Washington Birthplace	Virginia Peninsula	
Group 5			
Anderson Valley	Eagle Peak Mendocino County	Manton Valley	Sonoma Mountain
Atlas Peak	Fair Play	McDowell Valley	Spring Mountain District
Ben Lomond Mountain	Fiddletown	Mendocino Ridge	Swan Creek
Benmore Valley	Fort Ross-Seaview	Moon Mountain District Sonoma County	Upper Hiwassee Highlands
California Shenandoah Valley	Green Valley of Russian River Valley	North Yuba	Wild Horse Valley
Chiles Valley	Guenoc Valley	Palos Verdes Peninsula	Willow Creek
Cole Ranch	Haw River Valley	Pine Mountain-Cloverdale Peak	Yadkin Valley
Crest of the Blue Ridge Henderson County	High Valley	Redwood Valley	York Mountain
Dahlonega Plateau	Howell Mountain	Rockpile	Yorkville Highlands
Diablo Grande	Isle St. George	Rocky Knob	
Diamond Mountain District	Loramie Creek	Saddle Rock-Malibu	
Dos Rios	Malibu-Newton Canyon	Seiad Valley	
Group 6			
Alexandria Lakes	Columbia Gorge	Los Olivos District	San Pasqual Valley
Ancient Lakes of Columbia Valley	Cucamonga Valley	Martha's Vineyard	Sierra Pelona Valley
Bell Mountain	Goose Gap	Mt. Harlan	Snipes Mountain
Borden Ranch	Happy Canyon of Santa Barbara	Naches Heights	Squaw Valley-Miramonte
Candy Mountain	Horse Heaven Hills	Old Mission Peninsula	Temecula Valley
Carmel Valley	Jahant	Ramona Valley	The Hamptons Long Island
Chalone	Lake Chelan	Rattlesnake Hills	The Rocks District of Milton-Freewater
Cienega Valley	Leona Valley	Red Mountain	Wahluke Slope
Clements Hills	Lime Kiln Valley	Royal Slope	White Bluffs

Table 1. AVAs in each group

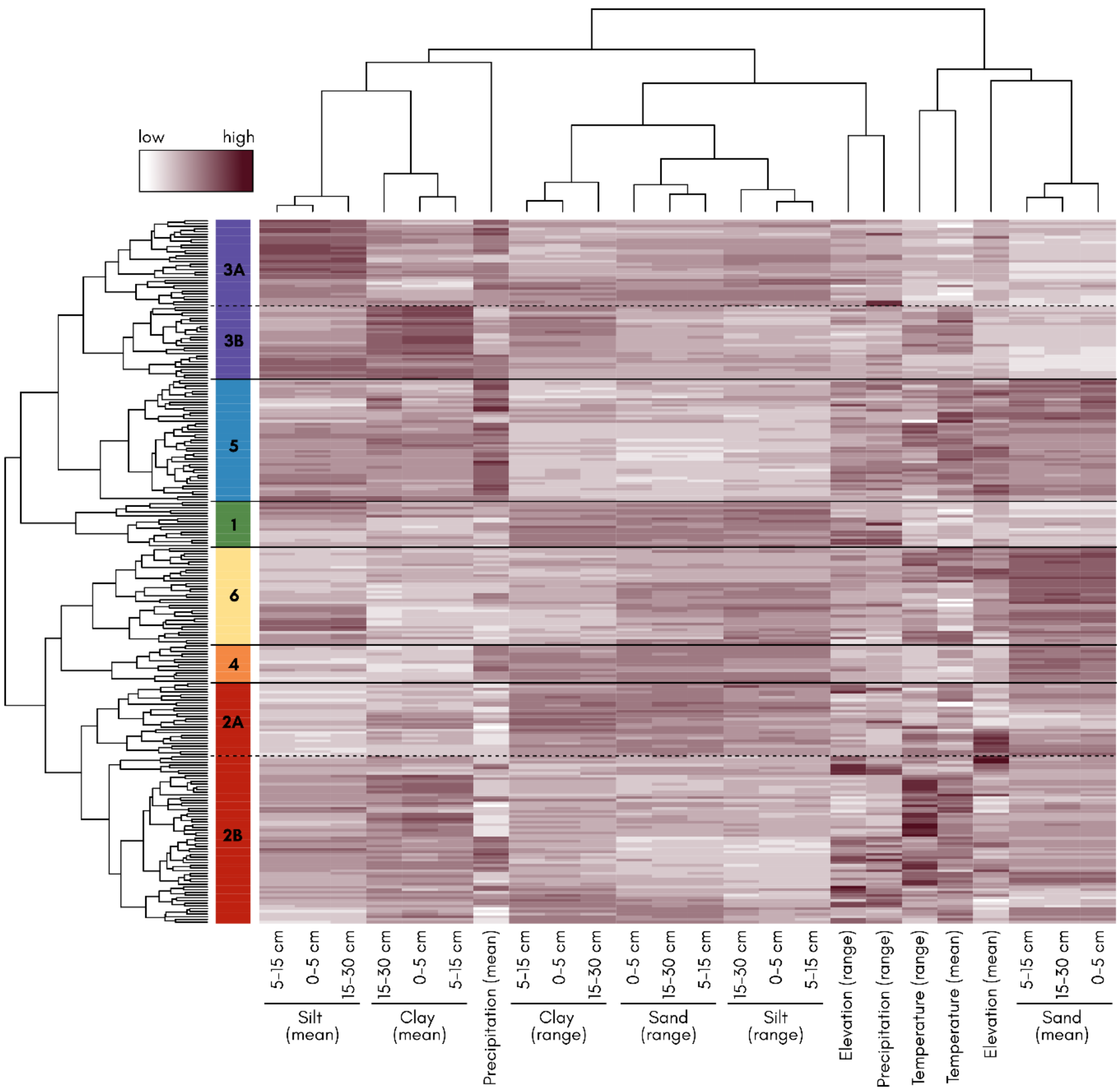

Figure 3. Heatmap illustrating the relationship between the sites and the environmental measurements.

across the group. These AVAs generally have a moderate range and mean elevation.

4. DISCUSSION

No single environmental measure (or related group of measures) seems to be driving the six groups defined in this analysis. In some cases, groups can be explained by their geographic distribution, but more often, the AVAs in a particular group may contain similar features such as rivers or mountains but are not necessarily related geographically. Some of the groups have a regional distribution, but region or location does not seem to be a major driver of the groups; neighboring AVAs can end up in different groups. The heatmap (Figure 3) indicates that no two AVAs are identical in their environmental conditions and these measures vary quite a bit between boundaries. Group 1 contains large boundaries but comprises a small number of AVAs. Their position on rivers or lakeshores explains their low elevation with silty soils. The AVAs in Group 2 are mostly situated west of the Mississippi River, with the exception of four AVAs. Generally, these are higher elevation AVAs. They correspond with mountainous or hilly areas. Group 3 is a mix of large and small AVAs distributed in the northern half of the country in valleys or other low elevation areas. Group 4 is the most specific groups of AVAs formed in this analysis. These are coastal (ocean and great lakes) AVAs in the northeast. Their locations on the coast explains their environmental measures. Group 5 has a split geographic distribution. These are small AVAs in foothill areas in California and the southern Appalachian Mountains. Group 6 is small AVAs in lower elevation areas. These are mainly in the west coast states, California, Oregon, and Washington, but also contains members scattered across other states.

It is clear to anyone who is familiar with the official AVA boundary descriptions that other factors aside from the environmental conditions can be and are used to define the boundaries of AVAs. Tobias & Myles (2022) explore this concept in California's Sierra Nevada region. It is evident from the boundary descriptions of individual AVAs that use human-created features such as roads, buildings, or property lines in their descriptions rather than natural features such as rivers and lines of topography that not all AVAs are defined with a focus purely on environmental conditions (*Approved American Viticultural Areas*, 2022). In spite of this, the boundaries do create a unique set of environmental conditions, if not truly meaningful with respect to environmental conditions. How to test for that will have to be left to future work.

This analysis represents a complex set of environmental conditions with a discrete set of variables, which cannot completely describe all of the factors and interactions between those factors. For example, a low mean or range of precipitation does not necessarily mean low soil moisture availability. Clay soils hold moisture better than sandy soils and water may be available from other sources like surface water, groundwater, or irrigation. This analysis also does not account for every possible variable. For example, it does not account for soil characteristics such as rocky soil or soil chemistry, nor does it account for variables that might help explain plant vigor such as degree days or solar radiation. These were excluded because they do not address the TTB's suggested variables for consideration in forming an AVA. Tonietto and Carbonneau (2004) use more sophisticated environmental measures more closely related to growing conditions to describe the climate of vineyards. Using measures like these in a hierarchical classification could produce a more robust set of groupings aligned more closely with the growing conditions experienced by the grapes and those that are important factors for quality fruit production. This analysis could also be useful at different geographic scales. For some markets, AVAs may not matter as much as other geographic description. In some places, the region or county of origin for the wine is more important (Atkin and Johnson, 2010) so repeating this analysis at the regional or county level could be useful. Clearly there is room for future work in this vein of research.

5. CONCLUSIONS

Investigating the relationship between the AVA boundaries is an important exercise. With the availability of the AVA boundaries as a geographic dataset, we are now able to combine this data with other existing open datasets to better understand the relationship and differences between these areas. All of the datasets used in this analysis are freely available and demonstrates not only the usefulness of the AVA Digitizing Project dataset but also the depth of the work possible with open data.

The TTB's AVA designation process does create boundaries containing a unique profile of environmental conditions, as called for in their published legal process. The AVAs can be grouped into clusters of similar boundaries, most of which exhibit a low degree of similarity. In this investigation, I have not addressed the concept of terroir, as this pertains to the environmental conditions experienced by the grape vines (van Leeuwen, 2022), of which there are better measures and indexes to quantify these, but rather, I have addressed the measures mandated by the TTB. The importance of this assessment with respect to the product created and the concept of terroir remains to be established.

Ultimately, this research could be the start of a larger body of work enabling researchers to interrogate the underlying concept of terroir and the usefulness of AVAs as a marketing tool. Additional work could include quantifying the use of AVA designations on wine labels as a measure of perceived importance of each AVA boundary. Additionally, it would be interesting to consult an expert in the characteristics of wine from the United States to ascertain if the groups defined in this research corresponded with similar characteristics in the wines produced in these AVAs.

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