Data-driven Method for the Delimitation of Viticultural Zones: Application in the Mendoza River Oasis, Argentina

Método basado en datos para la delimitación de zonas vitivinícolas: Aplicación en el oasis río Mendoza, Argentina

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Abstract

In viticulture, understanding the spatial variability of natural factors influencing vineyard potential is essential for terroir characterization. In the present study, we present a data-driven protocol that integrates climate, geomorphology, and soil data to delineate viticultural zones. The method combines spatial layers with statistical tools to partition a region into areas with similar characteristics. The protocol comprises: 1) rescaling multiple spatial data layers, 2) applying spatial multivariate analysis to group spatial units, and 3) using machine-learning algorithms to identify key zoning drivers. The approach was applied to the Mendoza River oasis in Argentina. Climate and geomorphology layers were used first, as they varied at a broader spatial scale than soil data. Two climatic zones were identified, mainly differentiated by elevation and thermal indices. Subsequent soil-based zoning within each climatic zone revealed five distinct edaphoclimatic zones. These zones showed statistically significant differences in environmental variables and exhibited spatial coherence aligned with landscape features. Results showed that this protocol facilitates the integration of diverse data sources and supports a deeper understanding of the uniqueness of vineyard zones in wine-producing regions.

Keywords
spatial clustering • edaphoclimatic zoning • zoning drivers

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Resumen

En viticultura, comprender la variabilidad espacial de los factores naturales que influyen en el potencial vitivinícola es esencial para caracterizar el terroir. En este estudio presentamos un protocolo basado en datos de clima, geomorfología y suelo para delimitar zonas vitivinícolas. El método integra capas de datos espaciales con herramientas estadísticas para subdividir una región en áreas con características similares. La metodología comprende: 1) el reescalado de múltiples capas de datos espaciales, 2) el análisis multivariado espacial para agrupar unidades espaciales, y 3) la aplicación de algoritmos de aprendizaje automático para identificar las principales variables determinantes de la zonificación. El protocolo se aplicó al oasis del río Mendoza, en Argentina. Primero se utilizaron los datos climáticos y geomorfológicos, que mostraban variabilidad a una escala espacial mayor, identificándose dos zonas climáticas diferenciadas principalmente por la altitud y los índices térmicos. Posteriormente, dentro de cada zona climática, se realizó una zonificación adicional basada en propiedades de suelo, lo que permitió identificar cinco zonas edafoclimáticas. Estas zonas presentaron diferencias estadísticamente significativas en variables ambientales y una alta coherencia espacial en correspondencia con las características del paisaje. Este enfoque permite integrar datos diversos y contribuye a lograr una comprensión más profunda de los ambientes vitícolas en regiones productoras de vino.

Palabras clave

agrupamiento espacial • zonificación edafoclimática • importancia de variables en zonificación

Introduction

Viticulture is one of the most widespread horticultural activities worldwide, with wine grapes cultivated across diverse climates and landscapes. Sustainable viticulture requires integrating large volumes of soil and climate data to support vineyard management and long-term planning (Visconti *et al.*, 2024). In Argentina, vineyards extend across multiple mesoclimates, landscapes, and soils. National grape and wine production is led by Mendoza province, in the central west of the country, accounting for nearly 70% of the total (INV, 2024). Viticulture in Mendoza province is concentrated in four main oases located between 33° and 36° S. This arid to semi-arid region depends on irrigation from Andean meltwater and shows high variability in climate and soils (Puscama *et al.*, 2025; Straffelini *et al.*, 2023). Recently, the Argentine Viticultural Corporation (COVIAR) conducted a comprehensive soil and climate survey of wine-producing regions, fostering a deeper understanding of natural variability and its influence on productivity and regional differences in grape production. The concept of terroir -used to explain differences in wine style and quality- is fundamentally geographical and supports spatial analysis of edaphoclimatic influences (Van Leeuwen *et al.*, 2010). This concept is also recognized as a socio-ecological construct, shaped not only by natural conditions but also by cultural, technical, and economic factors (Vaudour *et al.*, 2010). Terroir is multifactorial, with climate, topography, and soil as its main environmental pillars (Van Leeuwen *et al.*, 2010; Vaudour *et al.*, 2010). Climatic factors like temperature, radiation, precipitation, and thermal amplitude influence grape phenology and sugar accumulation (Jones *et al.*, 2005). Topographic or geomorphometric factors -particularly elevation, slope, and aspect- influence climate, water dynamics, and solar exposure (Hall & Jones, 2010; Irimia *et al.*, 2014). Soils regulate water and nutrient supply, shaping vegetative growth, yield, and grape composition (Morlat & Bodin, 2006). The interaction among these factors drives spatial heterogeneity in vineyard performance and wine typicity, underscoring the need to integrate them into zoning studies. When referring specifically to areas sharing similar biophysical features that influence vine development and grape composition, the term "edaphoclimatic zones" is commonly used. Advances in proximal and remote sensing technologies now allow the acquisition of large volumes of georeferenced data, which in turn permits delimiting these edaphoclimatic zones. Combined with geostatistical and machine-learning methods, these data are used to develop digital maps of biophysical variables relevant to viticulture (Ferro & Catania, 2023). Nevertheless, many terroir studies still rely on expert-based assessments rather than systematic, data-driven approaches (Bramley *et al.*, 2020). In recent years, data-driven methods have emerged as powerful tools to analyze terroir, enabling subregional classifications and explaining within-region variations in grape quality and vineyard performance (Bramley *et al.*, 2023; Bramley & Gardiner, 2021).

Data-driven delineation of edaphoclimatic zones requires: 1) statistical methods that integrate the spatial distribution of multiple variables, and 2) clustering algorithms that group sites with similar attributes and identify the key drivers defining each zone. The success of such zoning depends on the spatial resolution, type, and quality of input data (Van Leeuwen *et al.*, 2010). Although several zoning approaches exist (Ghilardi *et al.*, 2023), few address the dual challenge of handling high-dimensional environmental datasets while accounting for the spatial autocorrelation typical of edaphoclimatic variables. Many studies have classified viticultural areas by using soil, climate, and topographic variables (Ferretti, 2020; Ghilardi *et al.*, 2023), yet most rely on conventional multivariate techniques that do not explicitly incorporate spatial structure. Ignoring spatial dependence can result in fragmented zones or biased interpretations of terroir. Integrating spatially explicit methods -such as spatial principal components or geostatistical models- remains limited but offers a promising path toward more robust and geographically coherent zoning. Thus, this study describes a data-driven approach to delineate edaphoclimatic zones in a viticultural region by integrating multiple environmental variables across spatial scales. In this approach, spatial principal components are first computed and used in a hierarchical clustering process to delineate zones. Because soil variables typically exhibit greater spatial heterogeneity than climatic and geomorphometric variables, we adopted a nested clustering strategy: initial zoning was based on climate and geomorphology -variables occurring at a broader spatial scale- followed by refinement with soil data to capture finer-scale variability.

Spatial principal components were applied to ensure that spatial autocorrelation was explicitly considered in the clustering process (Córdoba *et al.*, 2012). Although the loadings of input variables on each component provide insights into spatial correlations, they do not always identify the main drivers of zoning- particularly when multiple correlated factors shape the results (Jolliffe & Cadima, 2016). For this reason, we complemented the spatial principal component analysis with machine-learning-based feature selection. This approach allowed us to quantify the relative importance of each predictor while handling high-dimensional, multicollinear datasets. The full analytical workflow was applied to climatic, geomorphometric, and soil data from the Mendoza River oasis in Argentina. The resulting maps and descriptions of the edaphoclimatic zones identified are publicly available through an open-access website (https://caracterizacion-fisico-ambiental-coviar.hub.arcgis.com/), which provides interactive visualizations and detailed zone characterizations.

Materials and Methods

Study area

The study area (figure 1, page 60) is located in the Mendoza River Oasis, Argentina, and includes the departments of Lavalle, Capital, Las Heras, Guaymallén, Maipú, and Luján de Cuyo. Elevations range from 600 to 1,200 meters above sea level (m a. s. l.). The region has a warm-temperate arid climate with low annual precipitation (228.8 mm, minimum 148.8 mm in Lavalle), low humidity, and moderate winds. The annual mean temperature is 15.8°C, with higher values in the north and urban areas. The mean diurnal temperature variation is 14.3°C. Extreme heat (>35°C) occurs on 15.4 days per year on average, reaching 36 in Lavalle, with 3.9 heatwave events. The area records 1,536.6 annual cold hours, being the highest in Luján de Cuyo. Frost and hailstorms are major meteorological risks. Frost occurs on 43.4 days on average, peaking in Perdriel-Agrelo (87 days) and northern Lavalle (57 days). Rainfall is highest in February (42.1 mm), which increases the risk of cryptogamic disease before grape maturation.

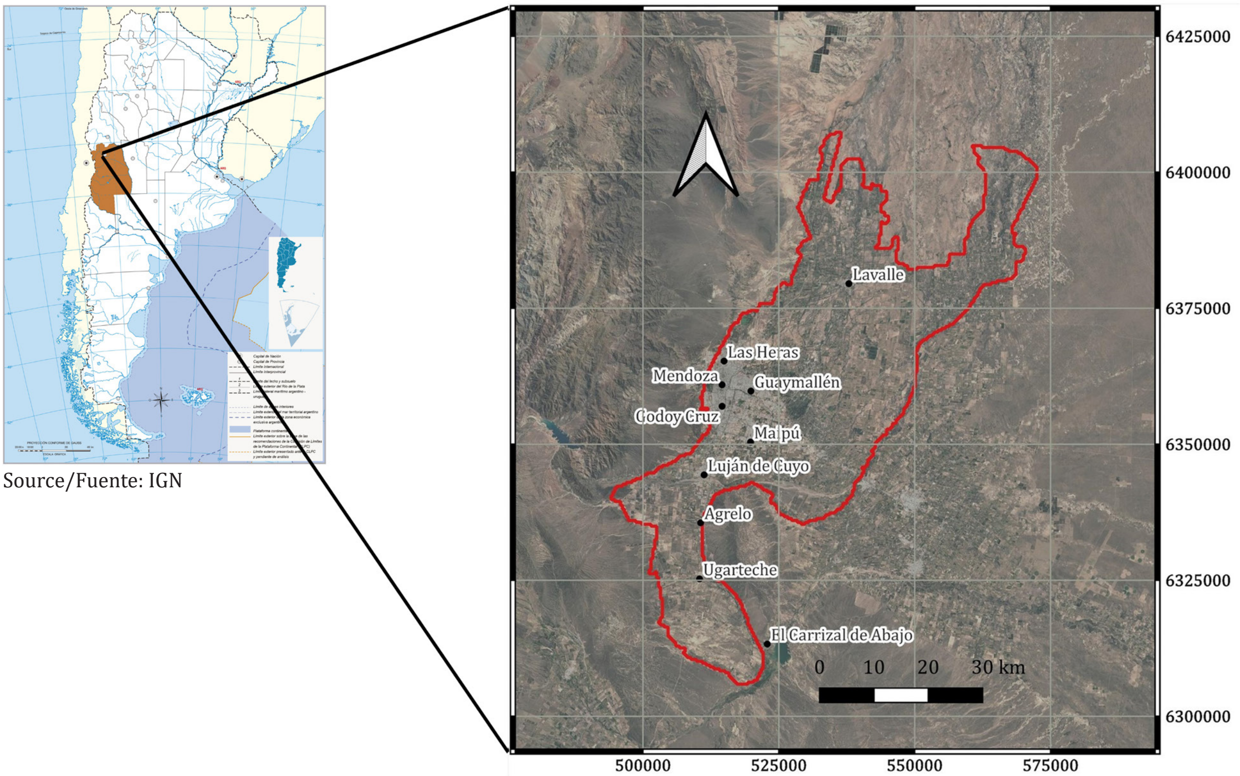

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Figure 1. Study area: Mendoza River oasis, Mendoza province, Argentina.

Figura 1. Área de estudio, oasis río Mendoza, provincia de Mendoza, Argentina.

Spatial Data Layers

The study area boundaries were defined using digital maps of geomorphometric and soil variables from vineyard test pits (Vallone *et al.*, 2023), combined with bioclimatic indices. Bioclimatic maps were derived from a national survey of Argentina's wine regions (Cavagnaro *et al.*, 2023). Weather records were obtained from nine World Meteorological Organization (WMO)-certified stations with 41 years of data (1980-2020), supplemented by public and private networks. Climatic maps were generated using kriging interpolation for variables such as cumulative seasonal precipitation (CSP) (September-April). Standard viticultural indices included: a) Growing Degree Days (GDD) (Mullins *et al.*, 1992), b) Winkler Index (WI) (Amerine & Winkler, 1944), c) Huglin Heliothermal Index (HI) (Huglin, 1983), d) Cool Night Index (CNI) (Tonietto & Carbonneau, 2004), and e) Thermal Integral above 13°C (TIB13). Shuttle Radar Topography Mission (SRTM) elevation data were processed with SAGA GIS to derive geomorphometric variables: slope, aspect, curvature, convergence, slope length factor (L-S), topographic wetness index, multiresolution valley bottom flatness, and vertical distance to drainage. Additional land suitability maps and geomorphometric studies from COVIAR were incorporated (Vallone *et al.*, 2007). A total of 153 soil samples were analyzed for physicochemical properties. Digital soil maps were generated (McBratney *et al.*, 2003) and harmonized into 0-50 cm and 50-100 cm horizons (Malone *et al.*, 2009). Plant available water (PAW), field capacity (FC), permanent wilting point (PWP), and saturated hydraulic conductivity (Ksat) were estimated from field data (bulk density, particle size) and pedotransfer functions. A soil water storage capacity map was produced using geostatistical interpolation. All spatial layers were resampled to a 4-ha grid (200 × 200 m).

Analytical Method

Step 1. Delimitation of Climatic Zones

Climatic zones were delimited using the KM-sPC algorithm (Córdoba *et al.*, 2012), which combines fuzzy k-means clustering with spatial principal components (sPCs) to account for spatial autocorrelation. Input variables included climatic and bioclimatic indices and elevation, which strongly influence viticultural potential. The first two sPCs were retained because they explained at least 80% of the total climatic variance; that is, they captured the main patterns in the data. Clustering was performed for 2 to 6 classes (*i.e.*, five clustering runs), with the optimal number determined using the partition coefficient, classification entropy, and a combined summary index (Albornoz *et al.*, 2018). The clustering was conducted on a 4-ha grid, resolution value to which all spatial layers were previously resampled. The analysis was implemented in R (R Core Team, 2024) using the “paar” package (Paccioretti *et al.*, 2024).

Step 2. Soil Zoning within each Climatic Zone

Within each climatic zone, a finer edaphic partition was performed using KM-sPC with soil and geomorphometric variables. This nested clustering approach reflects the natural hierarchy between broader climatic-geomorphological controls and finer edaphic variability.

Step 3. Characterization of Delimited Edaphoclimatic Zones

Radar Plots

Radar plots were used to visualize the multidimensional attributes of each zone. Each axis represents a variable, with spoke lengths scaled to relative magnitudes. These plots enabled comparison between individual zones and the overall mean profile. Radar plots were generated using the “fmsb” package (Nakazawa, 2023).

Random Forest (RF)

RF is an ensemble method that builds multiple decision trees from bootstrap samples and aggregates their predictions to improve accuracy and reduce overfitting (Breiman, 2001). In this study, RF classification was applied to evaluate the relative importance of each variable in distinguishing individual zones by contrasting one zone against all others. Variable importance was quantified as the mean decrease in accuracy after permuting the values of each predictor in the out-of-bag samples. This analysis identified the predictors that most contributed to zone distinctiveness. Model tuning involved optimizing the number of variables randomly selected at each split (mtry) through grid search. The number of trees and the minimum terminal node size were fixed at 500 and 5, respectively. Model performance was evaluated using 10-fold cross-validation. The RF model was implemented in R using the “caret” (Kuhn & Max, 2008) package.

Identification of Key values for each Zone

Key characteristics of each zone were summarized into “zone notes”, describing typical climatic, geomorphological, and soil attributes. These summaries were developed in collaboration with domain experts to emphasize the distinctive features of each viticultural zone.

Step 4. Zone Validation

The appropriateness of the delineated zones was evaluated by comparing the means of the most important variables identified by the RF analysis. A permutation-based statistical test accounting for spatial correlation was applied to evaluate whether these variables differed significantly among zones. The analysis was performed using the “ofemeantest” package (Córdoba *et al.*, 2024) in R.

Results and Discussion

Delimitation of Climatic Zones

Figure 2 shows the first two components of the sPC analysis (sPCA), which explained 96.5% of the total climatic variability. The most influential variables for differentiating climatic zones were WI, TIB13, and HI. These indices were positively correlated, as indicated by the small angles between their vectors. In contrast, these variables were negatively correlated with Digital Elevation Model (DEM), as shown by the angle close to 180°. GDD and CSP contributed to spatial variability but were less important, being primarily associated with the second axis.

CNI: Cool Night Index, HI: Huglin Index, (°GDD), TIB13: Thermal Integral with Base 13°C (°GDD), WI: Winkler Index (°GDD), CSP: Cumulative Seasonal Precipitation (mm), GDD: Growing Degree Days (days), DEM: Digital Elevation Model (m a. s. l.).

CNI: Índice de Frescor Nocturno, HI: Índice Huglin (°GDD), TIB13: Integral Térmica con Base 13°C (°GDD), WI: Índice Winkler (°GDD), CSP: Precipitación Estacional Acumulada (mm), GDD: Duración del periodo activo (días), DEM: Modelo Digital de Elevación (m s. n. m.).

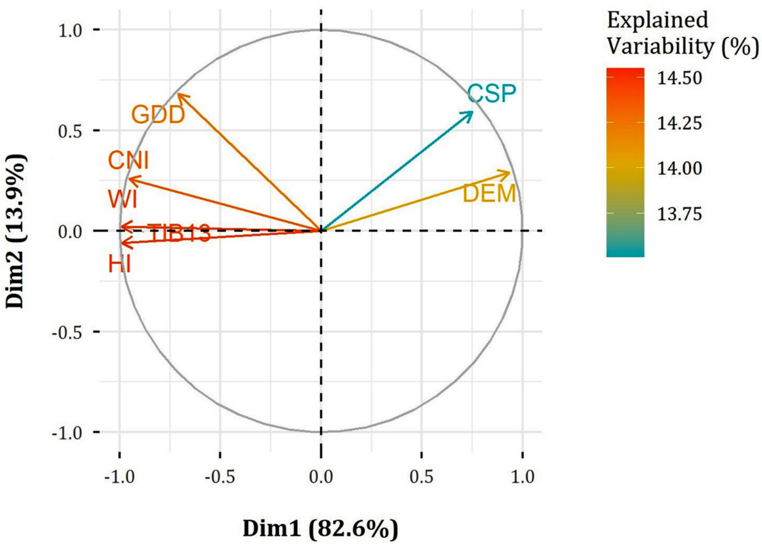


Figure 2. Graphical representation of the first two axes of the spatial principal components analysis, which together explained 96.5% of the total variance. The percentage contribution of each variable to the variance explained by these components is shown.

Figura 2. Representación gráfica de los dos primeros ejes del análisis de componentes principales espaciales, los cuales explican el 96,5% de la varianza total. Se muestra el porcentaje de contribución de cada variable a la varianza explicada por estas componentes.

Based on the three indices, the climate zoning identifies two zones (figure 3, left, page 63). Zone 1, located on the left bank of the Mendoza River, between 600 and 900 m a. s. l., encompasses the transition and low areas of the river basin, including peri-urban areas of the Capital, Godoy Cruz, and the departments of Guaymallén, Maipú, Las Heras, and Lavalle (zone 1). This zone exhibits the highest temperatures and the lowest precipitation levels within the oasis. Zone 2, covering the river basin and right bank between 900 and 1,100 m a. s. l., is characterized by cooler temperatures and higher rainfall.

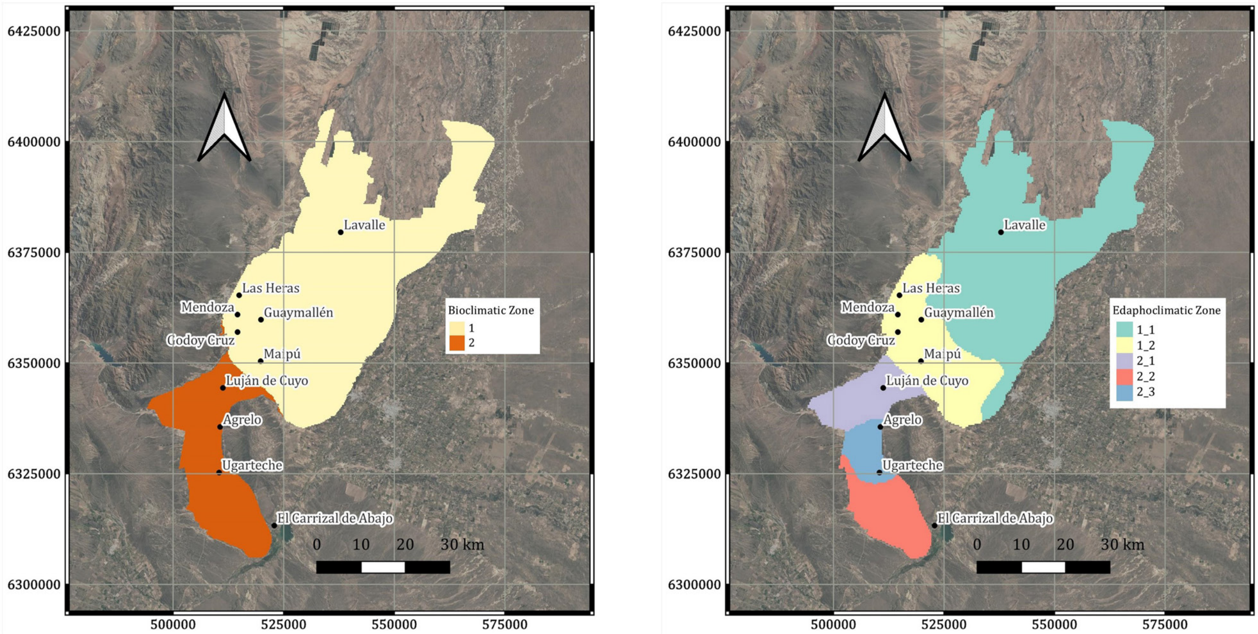


Figure 3. Bioclimatic zoning (left) and edaphoclimatic zoning (right) of the Mendoza River oasis, Argentina.
Figura 3. Zonificación bioclimática (izquierda) y edafoclimática (derecha) del oasis río Mendoza, Argentina.

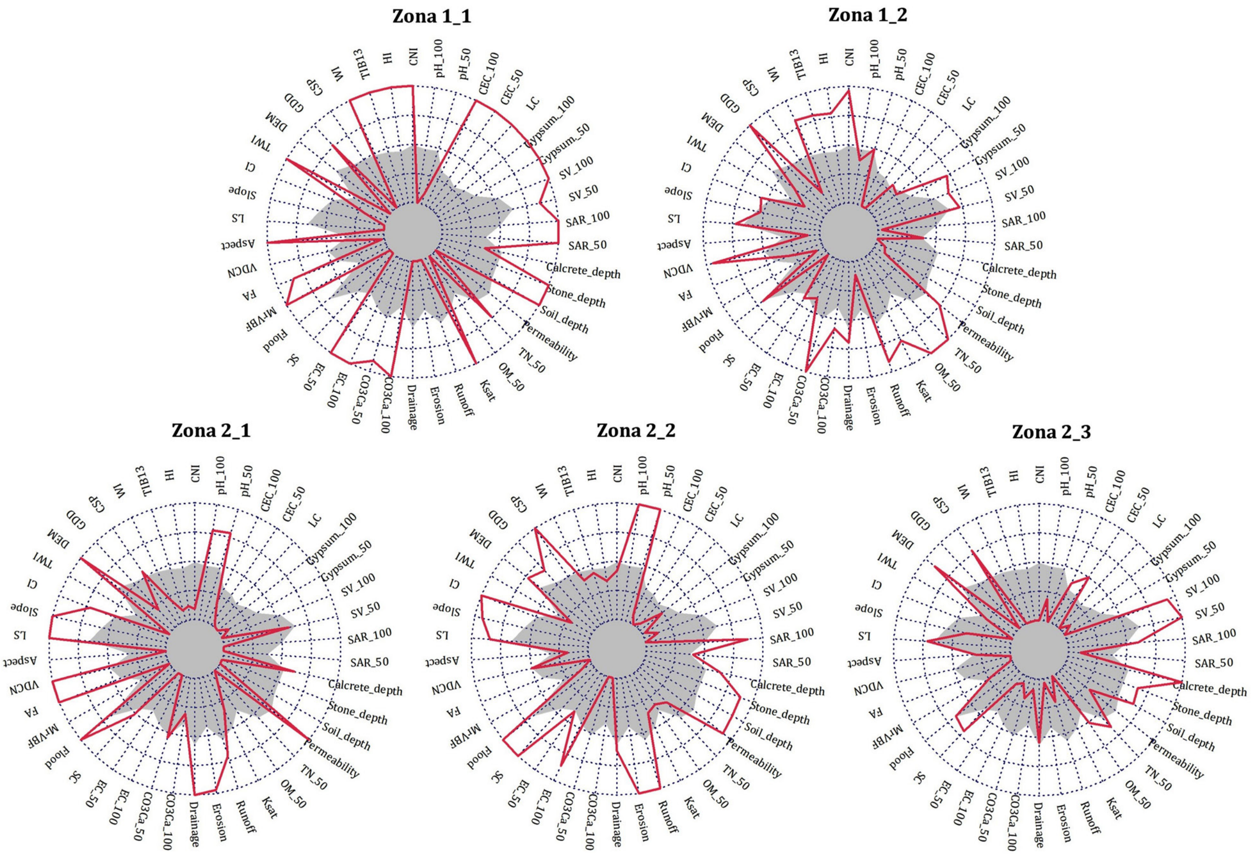
Soil Zoning within each Climatic Zone

Clustering based on geomorphometric and edaphic properties showed that topography strongly influences soil variation in the oasis. The relative importance of variables for differentiating the finer partitions indicated that DEM was one of the most important predictors, especially for differentiating areas within climatic zone 1. In zone 2_1, DEM was again influential, together with the CNI. In contrast, in zones 2_2 and 2_3, the most discriminative variables were CSP and Sedimentation Volume at 50-100 cm depth (SV_100), respectively. The eigenvector loadings from the sPCA described the contribution of each variable to overall variance (Córdoba *et al.*, 2013). We complemented this with RF classification to evaluate variable importance in terms of their discriminatory power for clustering. RF is advantageous for handling complex, non-linear relationships and interactions among variables, which are common in environmental datasets (Fox *et al.*, 2020). Combining sPCA and RF enabled a nuanced understanding of variable influence, both from a structural and predictive perspective.

Characterization and Validation of Edaphoclimatic Zones

Figure 3 (right) shows the multivariate zoning of the Mendoza River oasis. The edaphoclimatic zoning delineated five zones. Figure 4 (page 64) presents star plots summarizing the main characteristics of each zone. The five delimited zones showed statistically significant differences for most key soil and climatic variables ($p<0.05$).

Zone 1_1 is characterized by bioclimatic indices placing it in a very warm viticultural climate with mild nights. Annual precipitation in this zone is the lowest in the oasis (140 mm), while the active period lasts more than 260 days. Morphometric indicators revealed gentle slopes throughout most of the zone, with terrain aspects oriented mainly northeast and north in the final stretch of the river in the Lavalle sector. Topography-related factors (convergence, surface flow accumulation, and slope length) suggest a lower risk of water erosion in this alluvial plain compared with the lower Mendoza River basin, where defined channels are absent. Evidence of gully erosion is observed along the Mendoza River, Leyes Stream, and Tulumaya Stream. Soils in zone 1_1 show high effective rooting depth, with loamy to sandy loam texture. In addition, they show lower permeability and more restricted natural drainage than soils of the other zones. Soil salinity reaches the highest levels in the oasis. Accumulations of limestone and gypsum can be observed at both surface and subsurface horizons. Mean comparison of key variables indicated statistically significant differences between zone 1_1 and the other zones ($p<0.05$).



Variables are listed clockwise from 12 o'clock. Suffixes _50 and _100 indicate values for the 0-50 cm and 50-100 cm soil layers, respectively. Variables include: Cool Night Index (CNI), pH_50, pH_100, Cation Exchange Capacity (CEC_50), Gypsum_50, Gypsum_100, Sedimentation Volume (SV_50, SV_100), Sodium Adsorption Ratio (SAR_50, SAR_100), Calcrete depth, Stone depth, Soil depth, Permeability, Total Nitrogen (TN_50), Organic Matter (OM_50), Saturated Hydraulic Conductivity (Ksat), Runoff, Erosion, Drainage, Calcium Carbonate ($CaCO_3$_50, $CaCO_3$_100), Electrical Conductivity (EC_50, EC_100), Storage Capacity (SC), Flooding, Multi-resolution Valley Bottom Flatness (MrVBF), Flow Accumulation (FA), Vertical Distance to Drainage Network (VDCN), Aspect, Longitudinal Slope (LS), Slope, Convergence Index (CI), Topographic Wetness Index (TWI), Digital Elevation Model (DEM), Growing Degree Days (GDD), Cumulative Seasonal Precipitation (CSP), Winkler Index (WI), Thermal Integral with Base 13°C (TIB13), Huglin Index (HI).

Las variables se enumeran en el sentido horario desde las 12 en punto. Los sufijos _50 y _100 indican valores correspondientes a las profundidades de 0-50 cm y 50-100 cm, respectivamente. Las variables incluyen: Índice de Frescor Nocturno (CNI), pH_50, pH_100, Capacidad de Intercambio Catiónico (CIC_50), Yeso_50, Yeso_100, Volumen de Sedimentación (VS_50, VS_100), Relación de Adsorción de Sodio (RAS_50, RAS_100), Profundidad de tosca, Profundidad de piedra, Profundidad del suelo, Permeabilidad, Nitrógeno Total (NT_50), Materia Orgánica (MO_50), Conductividad Hidráulica Saturada (Ksat), Escorrentía, Erosión, Drenaje, Carbonato de Calcio (CO_3Ca_50, CO_3Ca_100), Conductividad Eléctrica (CE_50, CE_100), Capacidad de Almacenamiento (CA), Anegamiento, Índice de Multiresolución del Fondo de Valle (MrVBF), Acumulación de Flujo (AF), Distancia Vertical a la Red de Drenaje (VDCN), Orientación, Pendiente Longitudinal (PL), Pendiente, Índice de Convergencia (IC), Índice Topográfico de Humedad (TWI), Modelo Digital de Elevación (DEM), Grados-Día Acumulados (GDD), Precipitación Estacional Acumulada (CSP), Índice de Winkler (WI), Integral Térmica con Base 13°C (TIB13), Índice de Huglin (HI).

Figure 4. Star plots illustrating the average profile of each edaphoclimatic zone in the Mendoza River oasis.
Figura 4. Gráficos de estrellas que ilustran el perfil promedio de cada zona edafoclimática en el oasis del río Mendoza.

Zone 1_2 is characterized by a very warm climate with mild nights and low precipitation (170 mm annually). It shows the highest GDD in the oasis. Morphometric indices suggest a generally lower risk of water erosion than in zone 1_1, except for the cone area in the Barrancas sector. This zone comprises higher lands transitioning towards zone 1_1. It includes the areas of Maipú and Guaymallén. Soils are constrained by shallow groundwater and surface accumulations of calcium carbonate (locally known as "tosca" in Mendoza). At depth, soils transition to clayey loam with higher organic matter and total nitrogen, especially in the green belt area at district of Km 8 and Corralitos. These soils derive from former lagoons and are classified as intrazonal. Salinity levels are moderate, lower than in zone 1_1.

Zone 2_1 includes the highlands of the Mendoza River basin and the right bank of the river (Chacras de Coria, Las Compuertas, Vistalba, Perdriel, and Lunlunta). The climate is warm with cold nights. Annual precipitation averages 230 mm. This is the highest zone and, according to geomorphometric indicators, is at risk of water erosion. Soils are loamy and sandy loam at depth. They show the lowest values of Electrical Conductivity (EC) and Sodium Adsorption Ratio (SAR), both superficially and at depth, with slight salinity. Soil permeability is high, and drainage is somewhat excessive. Soils are the shallowest in the oasis, averaging 115 cm, due to rocky subsoil.

Zone 2_2 includes the southern part of Ugarteche and the area of El Carrizal. Bioclimatic indices classify it as a warm zone with cold nights. Average minimum night air temperature in March ranges between 12 and 14°C. Seasonal precipitation is the highest in the oasis, with an annual average of 295 mm.

Finally, zone 2_3 is the coolest zone, with cold nights. The WI classifies it as temperate-warm. Minimum night air temperatures in March are below 12°C. Average annual seasonal precipitation is 260 mm. The active period is the shortest in the oasis. Morphometric indicators revealed a higher risk of water erosion in the proximal sector of Agrelo, with signs of gully erosion. Soil water storage capacity is the highest (160 mm on average). Soils are sandy loam with rocky subsoil limiting effective depth. The predominant slope orientation is southeast. The edaphoclimatic zone map (figure 3, page 63) closely matches field observations (Vallone *et al.*, 2023).

The methodological approach used here integrates bioclimatic, soil, and geomorphometric variables while accounting for their spatial correlation. By combining the original variables into sPCs and clustering them, the method reduces the effects of spatial autocorrelation on total variability. As a result, the delineated zones are more contiguous and geographically coherent, minimizing fragmentation and better reflecting landscape continuity (Córdoba *et al.*, 2013). This approach addresses a common limitation of traditional terroir studies that rely on non-spatial multivariate methods (Ghilardi *et al.*, 2023). The primary link between wine and soil lies soil regulating water and nutrient availability for vines. Soil heterogeneity over space and time, and complex soil-climate interactions are widely recognized as major drivers of terroir differentiation, especially at regional to sub-regional scales (Lanyon *et al.*, 2004; Piraino & Roig, 2024). In this study, soil properties emerged as a fundamental component of zoning, reinforcing their central role in the terroir concept. Our findings confirm the importance of soils in defining viticultural zones. However, the direct relationships between soil characteristics, vine performance, and wine sensory attributes remain a key area for future validation.

Beyond the overarching effect of altitude, other key variables identified during the zoning process included soil depth, depth to stone or hardpan layers, soil permeability, and thermal indicators. Soil depth influences root development, water retention, and nutrient uptake, ultimately shaping vine vigor and overall water status (Morlat & Bodin, 2006). The presence of stones or calcareous hardpans ("tosca") can constrain root penetration, modify drainage, and influence nutrient availability, often creating moderate water stress conditions that are beneficial for grape quality (Pracilio *et al.*, 2006). Soil permeability controls water movement and aeration within the root zone, with direct consequences for vine vigor and fruit composition (Lanyon *et al.*, 2004). Elevation, in turn, regulates microclimatic conditions like temperature regimes and rainfall distribution, both critical for grape development and ripening (Ferretti, 2020).

Temperature accumulation, expressed through indices such as the WI and HI, also emerged as an important climatic factor. These indices are widely used to characterize grapevine phenology, berry composition, and ripening dynamics, all of which have direct implications for sugar accumulation, acidity, and aromatic potential (Jarvis *et al.*, 2017). Topography -including elevation, slope, and aspect-, although not explicitly detailed among the most influential variables here, is well established as a determinant of local microclimatic conditions and wine characteristics (Biss, 2020). Other soil properties, although not primary drivers of clustering in this study, remain essential to vine growth and contribute to intra-zone variability. These include soil pH and nutrient availability, both influenced by the underlying geological substrate (Retallack & Burns, 2016). While grapevines tolerate a relatively wide pH range, deviations from the optimal levels can hinder nutrient uptake, reduce growth, and affect yield. Soil organic matter and localized precipitation play pivotal roles in soil fertility and water availability. Vineyards exposed to high runoff and erosion risk may experience reduced grape and wine quality due to the loss of topsoil and organic matter (de Sosa *et al.*, 2023). Furthermore, gypsum-rich soils influence soil structure and nutrient balance, thereby affecting vine performance and grape composition (Lanyon *et al.*, 2004).

From a practical perspective, the successful implementation of this zoning approach depends on the availability and quality of spatial input data. While some viticultural regions benefit from long-term climate records and detailed soil surveys, others lack the resolution or coverage required. Defining a minimum dataset -including soil depth, topographic indices, and key climate metrics- has been suggested as a way to enhance the transferability and operational use of zoning protocols (Bramley *et al.*, 2023). Moreover, the reproducible workflows applied in this study facilitate wider adoption and ensure transparency. Importantly, the method provides more than just classification: by identifying and characterizing zones based on influential biophysical drivers, it offers a framework for site-specific vineyard management, land-use planning, and even the development of appellation criteria. Future work should integrate vine performance metrics -such as yield, grape composition, and sensory attributes- to validate and refine the delineated zones in relation to the terroir concept.

Conclusion

This study presents a data-driven approach for delineating edaphoclimatic zones that ensures spatial coherence and identifies areas according to the most influential climatic, geomorphometric, and soil variables driving regional variability. By integrating spatially explicit clustering with visual and statistical tools -such as star plots and the random forest algorithm- the method enables the simultaneous assessment of variable importance and the detailed characterization of each zone. This framework provides a robust basis for terroir identification and supports a deeper understanding of the uniqueness of vineyard environments, offering practical guidance for viticultural zoning, vineyard management, and regional planning in wine-producing regions.

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