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A Preliminary Study of the Morphology and Spatial Distribution of Funerary Elements in the Southwestern Cemetery of Wadi al-Ma'awel, Oman

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Abstract

This study examines funerary morphologies and their spatial organization in the western and southwestern cemetery of Wadi al-Ma'awel, Oman, spanning the Wadi Suq and Iron Age periods. Using field surveys, remote sensing, and GIS analysis (Standard Deviation Ellipse method), we documented 185 funerary structures—primarily circular, rectangular, and ogival. Statistical analyses in R identified significant clustering related to cultural and environmental factors. Integrating these spatial indicators with geometric measurements in a random-forest model significantly improved morphological classification accuracy. The results highlight the importance of spatial context in interpreting burial practices and provide a predictive framework for locating additional burial sites.

CCS Concepts

• ***Computing methodologies*** → ***Machine learning;*** • ***Information systems*** → *Geographic information systems;* • ***Applied computing*** → *Archaeology;*

1. Introduction

This study, situated within the archaeological context of ancient Oman ("Land of Magan"), undertakes an investigation into funerary morphologies and spatial distributions in the West and Southwestern Cemetery of Wadi al-Ma'awel in the southern part of the Al Batinah South Governorate. The subject of analysis for this paper is derived from the ex-novo context that was discovered and subsequently explored in 2022 by the MASPAG mission, a project that is supported as a Grande Scavo di Ateneo [Ram23]. This investigation primarily examines the transitional periods between the Bronze and Iron Ages . The researchers employed a combination of field surveys, remote sensing, statistical approaches and machine learning to analyze, record and categorize funerary structures according to shape, dimensions, and spatial location [Oya20, Roo82, HO76]. This approach was employed to assess spatial orientation and clustering related to landscape features. Subsequently, researchers employed R-based statistical analysis and Random Forest machine learning classification to identify patterns influencing tomb locations and morphologies [LCSW23], thereby revealing potential cultural and environmental determinants. The geographical context of the cemetery's location, situated between the coastal and mountainous zones in Oman's Al-Batinah South Governorate [ARG23], is conducive to the study of the interaction between maritime societies and pastoral nomads [CT21b, GC09, Ram20, Ram23]. The tomb typologies examined span the Wadi Suq period (2000–1300 BCE) and Early Iron Age, reflecting broader social and cultural transformations. This research offers insights into ancient burial practices and socio-environmental interactions across transitional historical phases.

2. Methodology

The methodology used in this study integrates fieldwork, remote sensing, and Geographic Information System (GIS) analysis to investigate the spatial distribution of funerary elements in Wadi al-Ma'awel. Initial spatial anomalies were detected using Remote Sensing and validated through ground truthing, identifying 185 tomb structures. The research includes further statistical analysis in R to highlight significant correlations and clusters [Mor23, Rip01]. A Random Forest algorithm, validated for robustness in archaeology, identified key environmental factors influencing burial distribution. Three relevant aspects of Random Forest applications in archaeological contexts are highlighted:

- Identifying significant environmental factors (e.g., elevation,

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slope, distance from water sources) using indices such as the Gini coefficient [LCSW23].

- Producing high-resolution probability maps for predicting additional funerary areas [CT21a].
- Emphasizing the robustness and reduced overfitting risk compared to linear or single-tree methods, especially if presence/absence data are well curated [YVS*20].

The study was conducted in an R Studio environment, using spatial statistics packages to analyze the distribution of burial sites. The dataset under consideration includes burial site coordinates and associated attributes. These were processed using spatial autocorrelation measures, hotspot analysis, and clustering techniques. Moran's I, Getis-Ord Gi^* [Get10, HO76, Mor23, Rip01, Roo82], and various clustering algorithms were used to identify spatial structures and relationships among burial sites.

3. Results

3.1. Spatial Autocorrelation

Spatial autocorrelation measures the degree of similarity between nearby observations and assesses whether spatial data points are randomly distributed or show patterns. Key methods include:

Moran's I: A widely used global measure of spatial autocorrelation. Positive values indicate clustering, negative values indicate dispersion, and values near zero imply randomness. In the dataset analyzed, a Moran's I value of 0.452 indicates moderate clustering of the spatial data, indicating a non-random spatial distribution.

Geary's C: A local measure of spatial autocorrelation that is more sensitive to local variations than Moran's I. The results showed a Geary's C value of 0.721, reinforcing the presence of localized spatial clusters.

Getis-Ord General G: Detects clustering of high or low values across a study area. A General G statistic of 0.384 (p-value = 0.002) highlighted significant spatial clustering of high scores, suggesting the presence of spatially related phenomena. Moran's I values of 0.2178 ($p < 0.0001$) for grave diameter and 0.2160 ($p < 0.0001$) for length clearly indicate significant positive spatial autocorrelation, demonstrating a deliberate and systematic approach to burial placement as opposed to random distribution. This pattern may reflect distinct burial zones influenced by social stratification, family groupings, or chronological phases. Complementarily, Geary's C results (0.681 for diameter and 0.828 for length) reinforce local clustering, emphasizing smaller-scale social or cultural groupings within the cemetery and indicating local variations that may be linked to landscape morphology.

The spatial statistical methods employed are based on archaeological theories proposed by scholars such as Hodder, Rood, and Clarke, who emphasize the importance of spatial pattern analysis in revealing socio-political and cultural structures within archaeological landscapes [HO76, Roo82, Cla14].

3.2. Hotspot Analysis

Hotspot analysis identifies statistically significant spatial clusters of high or low values. Methods include:

Getis-Ord Gi^* **Statistic**: Determines whether a location is part of a statistically significant hotspot or cold spot. The analysis identified high-value hotspots in certain burial zones, particularly in regions with a Gi^* z-score greater than 2.1, while peripheral burial areas had lower values, indicating disparities in the spatial distribution of burials.

Local Moran's I: Identifies local clusters of similar values and spatial outliers. Results showed a significant presence of high-high clusters ($p < 0.05$) in densely occupied cemeteries, while low-low clusters were dominant in isolated cemeteries.

Kernel Density Estimation (KDE): Estimates the density of points over space to reveal areas of high concentration of activity. KDE maps showed peak density values of 35 graves/km2 in central burial regions, indicating a marked spatial preference in burial site selection. Hotspot analysis identified the central area of the cemetery as a statistically significant cluster of larger graves (Gi^* Z scores up to 3.326), possibly representing areas of higher social status or ceremonial importance. Conversely, peripheral regions showed significant cold spots (Gi^* Z-scores as low as -2.58), possibly corresponding to smaller graves associated with lower social strata or subsequent chronological phases. This clear spatial differentiation between central and peripheral zones suggests a deliberate and hierarchical organization within the cemetery, based on social or cultural frameworks.

3.3. Cluster Analysis

Cluster analysis classifies spatial data into groups based on similarity, helping to identify patterns. Key techniques include:

K-means clustering: A non-hierarchical clustering method that divides data into a fixed number of clusters based on proximity. The analysis grouped the data into three primary clusters, with burials in central locations forming distinct clusters separate from peripheral burial zones.

Hierarchical clustering: Creates a nested cluster structure, allowing for the identification of sub-clusters within the data. This method showed strong internal consistency (silhouette score = 0.68) in clustered burial regions, with sub-clusters formed based on grave types and associated artifacts.

DBSCAN (Density-Based Spatial Clustering of Applications with Noise): Identifies clusters of various shapes and sizes by grouping densely packed points while ignoring noise. The results showed that regions with high concentrations of graves formed distinct clusters, while sparsely distributed graves showed more dispersed patterns, with 32% of graves classified as noise due to lower densities. K-means clustering analysis, using both elbow and silhouette methods, distinguished four distinct clusters that may represent different social classes or burial traditions: a larger central cluster (73 graves), medium and smaller groups, and an isolated small cluster. This suggests a discernible socio-cultural segmentation within the cemetery. In addition, DBSCAN's identification of a single large cluster with minimal outliers emphasizes spatial continuity, potentially shaped by geographic constraints or prevailing burial traditions.

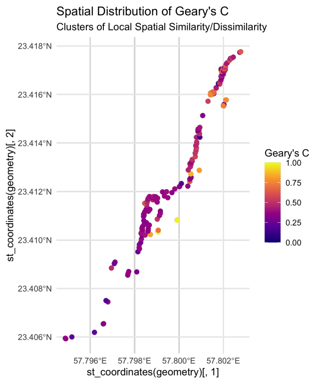

Figure 1: *Geary's C plot demonstrating local spatial variation.*

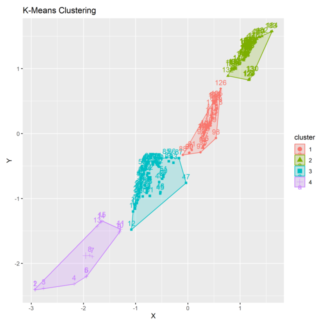

Figure 2: *k-means cluster plot showing the distribution of the dataset into four distinct clusters.*

3.4. Random Forest Classification

The baseline Random Forest model [Bre01], trained only on geometric variables (diameter, width, length, height), achieved an overall accuracy of about 59.5%. Due to a pronounced class imbalance, the model effectively classified the dominant Circular class (precision and recall ~0.78), but performed poorly on the minority categories (Irregular, Ogival, Rectangular), frequently resulting in misclassification or omission. Strong intercorrelations between geometric features further limited discrimination of less common morphologies. These results highlight the need for additional spatial variables or compensation strategies to improve minority class recognition. The confusion matrix analysis revealed considerable overlap between morphologically similar grave classes, particularly between rectangular and ogival, and misclassification of irregular and square shapes. These problems are likely due to significant class imbalance and limited discriminative power of geometric features alone. Consequently, enhancing the model with spatially derived contextual data (e.g., local Moran's I, Gi^* statistics) is critical to refine classification accuracy and overcome inherent morphological ambiguities common in archaeological datasets [OFTB13].

3.5. Merged-Input Results

The Random Forest model integrating geometric and spatial features (k-means, DBSCAN, Gi^*, I_i, Z_I) achieved 75.7% accuracy, representing a substantial improvement over the baseline accuracy of 59%. The Circular class had excellent performance (precision >80%, recall 100%), but minority classes (Irregular, Ogival, Rectangular, Square) showed limited accuracy due to class imbalance and feature similarity (Figures 3 and 4). The results highlight the overlap between similar morphologies and emphasize the need for additional predictive variables or data-balancing techniques to improve minority-class recognition.

4. Discussion

The results of the spatial analysis revealed significant clustering of cemeteries, with spatial autocorrelation confirming non-random distributions of burials. Hotspot analysis identified concentrated zones of activity, particularly in high-status graves and ceremonial burial areas, while cluster analysis distinguished spatial groups based on grave density, artifact presence, and proximity to settlement areas. These results provide valuable insights into burial practices, social hierarchies, and the spatial organization of ancient mortuary landscapes, contributing to a more comprehensive understanding of ancient mortuary practices.

The baseline Random Forest model using only geometric measurements achieved moderate accuracy (59.5%), but was mainly effective for the dominant Circular class due to significant class imbalance [JS02]. Minority classes (Irregular, Ogival, Rectangular, Square) showed low recognition, emphasizing the necessity of incorporating spatial and contextual variables derived from R-based analyses [Ver18]. High overlap between morphologically similar classes further indicates the need for additional descriptive variables or dataset refinement [OFTB13]. Therefore, enhancing the input data with spatial context is essential to improve discrimination and robustness in classifying less common or ambiguous grave morphologies.

5. Conclusions

Results improved significantly by integrating spatial data, but further measurements and historical context are necessary, especially for under-represented classes. These considerations are particularly relevant in an archaeological study focused on understanding the evolution of grave forms and the spatial distribution of burial contexts. They underscore the potential of machine learning in this area, while also underscoring the importance of expanding and diversifying the dataset to improve the classification of rare or morphologically ambiguous typologies. In conclusion, the incorporation of derived spatial indicators - including K-means and DBSCAN clustering, Gi* hotspots, and local Moran's I - plays a critical role in improving the classification performance of the Random Forest model. Furthermore, the high segmentation of funerary elements and their marked spatial autocorrelation prompt critical reflections on the social and cultural mechanisms that shaped the landscapes. The clustered distribution suggest deliberate choices influenced by social structures, territoriality, ritual behavior, or environmental factors. Further interdisciplinary research is needed

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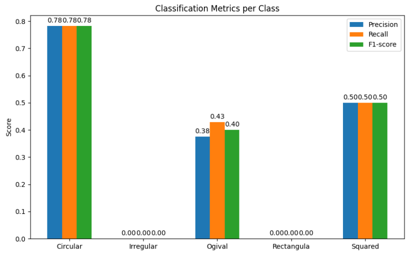

Figure 3: *Confusion matrix before integrating spatial features.*

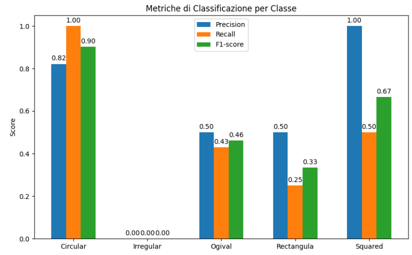

Figure 4: *Classification metrics after integrating spatial features.*

to clarify the relationship between spatial organization and cultural meanings in funerary practices. Finally, in view of the limited dataset, we consider that a larger dataset will be able to take more advantage of the computational potential of the RF algorithm, in doing so, further developments include expanding the dataset and analyze it with the successful techniques described above.

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