



Invisible Herders, Visible Traces: A Spatio-Chemical and Remote Sensing Approach to Deciphering Pastoral Landscapes in Dhofar, Oman

RESEARCH ARTICLE

ANTONIOS KOUTROUMPAS

SILVIA LISCHI

ABEL RUIZ-GIRALT

STEFANO BIAGETTI

**Author affiliations can be found in the back matter of this article*

ubiquity press

ABSTRACT

Mobile pastoral communities have inhabited Dhofar, Oman, for over seven millennia, yet they remain systematically underrepresented in the archaeological record due to minimal material traces and lack of permanent structures. As part of the CAMP project, which develops geo-ethnoarchaeological methods to define geochemical fingerprints of pastoral sites, this paper presents preliminary results from an integrated approach designed to address this detection gap. Altogether 1,441 soil samples were collected from 13 seasonal pastoral campsites and two vegetation control locations in the Khor Rori area and analysed using portable X-ray fluorescence (pXRF) spectrometry. Multi-element data were processed with Compositional Data Analysis (CoDA) and combined with satellite imagery to test whether pastoral activity markers are detectable from orbit. Geochemical results revealed distinctive signatures that differentiate pastoral activity areas from natural background, utilising geostatistical interpolation techniques—a step fundamental for the subsequent remote sensing analysis. Hyperspectral imagery from the Wyvern Dragonette constellation was fused with multispectral Sentinel-2 SWIR bands to overcome the spectral limitations of visible-range sensors. A Gradient Boosting model trained on the fused spectral data to predict anthropogenic enrichment regions achieved meaningful discrimination (ROC-AUC = 0.86). These preliminary findings suggest integrated geochemical-remote sensing approaches can enable landscape-scale detection of ephemeral pastoral campsites, though methodological refinement is needed.

CORRESPONDING AUTHOR:

Antonios Koutroumpas

CASEs Research Group,
Universitat Pompeu Fabra, C.
Ramon Trias Fargas 25-27,
08005, Barcelona, Spain
antonios.koutroumpas@upf.edu

KEYWORDS:

pastoralism; geo-ethnoarchaeology; Dhofar; pXRF; remote sensing; Compositional Data Analysis (CoDA)

TO CITE THIS ARTICLE:

Koutroumpas, A, Lisch, S, Ruiz-Giralt, A and Biagetti, S. 2026. Invisible Herders, Visible Traces: A Spatio-Chemical and Remote Sensing Approach to Deciphering Pastoral Landscapes in Dhofar, Oman. *Journal of Computer Applications in Archaeology*, 9(1): 418–435. DOI: <https://doi.org/10.5334/jcaa.272>

1. INTRODUCTION

Pastoralism is nowadays considered an efficient strategy for achieving food security and responding to compelling challenges such as the current climate crisis ([African Union 2010](#); [FAO 2020](#); [FAO 2021](#)). Understanding how pastoral communities have adapted to environmental variability in the past can inform contemporary responses to climate change, yet reconstructing these long-term trajectories requires robust archaeological evidence. However, traditional archaeological methods struggle to capture the subtle material signatures of mobile pastoral communities, resulting in their systematic underrepresentation within the archaeological record (e.g., [Biagetti 2025](#); [Hildebrand et al. 2018](#); [Honeychurch and Makarewicz 2016](#); [Lane 2016](#); [Makarewicz 2013](#); [Marshall and Weissbrod 2011](#); [Wright 2016](#)). Unlike sedentary communities, which leave abundant material traces, mobile pastoralists create ephemeral settlements with shallow deposits, minimal material structures, and sparse artefacts. As a result, the conventional archaeological concept of a ‘site’—typically defined by the presence of dense architectural remains, stratified deposits, or abundant artefacts—is not always appropriate for pastoral contexts. Pastoral occupation is often organised as a network of repeatedly used campsites, livestock enclosures, and activity areas distributed across the landscape rather than as discrete, permanently occupied places. Consequently, the challenge is not that pastoral sites are absent, but that their archaeological visibility relies less on architecture and artefacts than on more subtle signatures produced through repeated occupation ([Biagetti et al. 2026](#)).

Attempts to address this detection problem face three interconnected challenges. First, existing remote sensing studies in dryland regions have focused predominantly on monument detection ([Biagetti and Howe 2017](#); [McCorriston et al. 2025](#); [Williams et al. 2014](#)), vegetation dynamics ([Al-Kindi, Al Nadhairi & Al Akhzami 2023](#); [Arnold et al. 2020](#); [Horisk et al. 2023](#)), and land-use change ([Galletti, Turner & Myint 2016](#); [Ramadan, Al-Awadhi & Charabi 2021](#)), rather than on identifying the ephemeral occupation sites that characterise mobile pastoral communities. Second, although previous studies have investigated the potential of geochemical soil analysis for understanding pastoral campsites ([Biagetti et al. 2026](#); [Seitsonen and Égüez 2021](#)), geochemical characterisation and spectral remote sensing remain disconnected analytical domains. Third, intensive geochemical survey yields high-resolution, site-specific data but cannot feasibly extend across entire landscapes, while remote sensing operates at landscape scales but lacks the specificity to discriminate pastoral activity markers from naturally occurring soil variation.

This work is part of the CAMP (Re)Constructing the Archaeology of Mobile Pastoralism project ([Biagetti et al. 2026](#)), which aims to develop a novel methodology

for investigating archaeological pastoral sites. The project employs a geo-ethnoarchaeological approach, studying contemporary pastoral camps where the relationship between activities and their material traces can be directly observed, thereby establishing reference signatures transferable to archaeological contexts where such links must be inferred. A key challenge, however, lies in scaling site-level geochemical observations to landscape-level detection.

To address this challenge, this paper presents an integrated detection framework combining geochemical analysis with remote sensing, using contemporary pastoral campsites in Dhofar, Oman, as a reference case. The research pursues two primary objectives. First, it seeks to establish a baseline geochemical signature for pastoral habitation by identifying elemental markers—such as enrichments in phosphorus or organic proxies—that distinguish activity areas from the natural background, using portable X-ray fluorescence (pXRF) spectroscopy processed through Compositional Data Analysis (CoDA). Second, the research assesses the feasibility of upscaling this detection to the landscape level by training a machine learning model on the correspondence between ground-truthed geochemical hotspots and fused high-resolution satellite imagery.

This framework is grounded in the hypothesis that repeated animal management activities—specifically livestock penning, dung accumulation, and urine deposition—create diagnostic elemental enrichments (particularly P, K, Ca, and Cl relative to lithogenic elements such as Si, Al, Fe, Ti, and Mg) that can be detected through surface reflectance signatures in satellite imagery. Following [Oonk, Slomp & Huisman \(2009\)](#) and [Lubos, Dreibrodt & Bahr \(2016\)](#), we expect these chemical proxies to remain consistent across sites sharing similar geological substrates, aridity regimes, and livestock management practices. Specifically, we test whether: (1) contemporary pastoral campsites exhibit statistically distinguishable geochemical signatures relative to natural background soils; and (2) these ground-truthed signatures correspond to spectral features detectable from orbital platforms. The findings presented here serve as a technical proof-of-concept, documenting primary results as well as specific analytical limitations. Beyond methodological validation, the proposed framework offers a potential means to reconstruct the spatial logic of Dhofari pastoralism—mapping land-use intensity across the landscape and enhancing our understanding of the material traces of pastoralist occupation that can be traced from the ethnographic present back to earlier periods.

2. MATERIALS AND METHODS

2.1. STUDY AREA: THE KHOR RORI AREA, SW OMAN

The Khor Rori area, located approximately 40 kilometres east of Salalah in the Dhofar Governorate, was selected as the study area for this research ([Figure 1](#)). The area

is situated at the mouth of Wadi Darbat, the largest drainage system feeding into the coastal plain, which empties into a bar-built discharge that historically served as a natural harbour (Steele et al. 2024). The exceptional preservation of this landscape is partly attributable to its early inclusion in the UNESCO World Heritage List as part of the ‘Land of Frankincense’ designation in 2000 (UNESCO 2000).

The Dhofar region presents a compelling setting for studying pastoralism due to its remarkable long-term continuity as a socio-ecological adaptation—a continuity fundamentally enabled by its distinctive monsoon-driven environment. The landscape is shaped by the Southwest Monsoon, locally known as the *Khareef*, a climatic system active for at least 10,000 years (Tigani ElMahi 2001). This seasonal phenomenon, occurring between mid-June and mid-September, brings moisture-laden winds from the southwest Indian Ocean, producing persistent low-level stratus clouds, fog, and intermittent drizzle rather than heavy rainfall. While the region remains generally arid, the *Khareef* transforms the mountains into a verdant refuge surrounded by desert, delivering approximately 300 mm of annual precipitation, with effective moisture availability substantially exceeding this due to fog interception (Arnold et al. 2020; Tigani ElMahi 2001). The terrain extends from coastal lowlands through foothills to mountain escarpments dissected by deep wadis (ephemeral watercourses), producing distinct ecological zones historically utilised by pastoral communities (Ramadan, Al-Awadhi & Charabi 2021; Tigani ElMahi 2001).

Archaeological evidence suggests that Neolithic communities were present in Dhofar by the late 7th to

early 6th millennium BCE, within the broader emergence of pastoral societies in the Omani peninsula from around 6500 BCE or possibly earlier (Charpentier et al. 2023). Although the progressive aridification of the Rub’ al-Khali has been invoked to explain a movement of herding groups towards the more stable environments of the Dhofar mountains (Newton and Zarins 2010; Tigani ElMahi 2001), Neolithic sites are now known across the coastal plain, the mountains, the Nejd and the desert interior. This distribution suggests a more complex system of mobility and interaction between ecological zones (Charpentier et al. 2023). More recent archaeological research in Dhofar has documented a wide range of settlement forms and occupation strategies. Within this broader framework, research conducted by the DHOMIAP project has revealed permanent settlements with monumental architecture alongside seasonal open-air sites, confirming occupation from the Early Iron Age (from the 9th–8th century BCE) through the Late Iron Age (c. 1st century BCE–2nd century CE) and into the Islamic period (c. 10th–11th century CE) (Lischi 2022; Lischi 2025; Rougeulle 2008). Elsewhere in Dhofar, excavations at Iron Age sites such as Shakil and Halqoot revealed material signatures—rooms with bedrock floors, deep accumulations of burnt cattle dung, and a striking scarcity of portable artefacts—more consistent with repeated, long-term pastoral use than with sedentary agricultural occupation (McCorriston et al. 2020).

Contemporary pastoralism in Dhofar employs three primary livestock species—cattle (*Bos indicus*), goats (*Capra hircus*), and camels (*Camelus dromedarius*)—each managed within specific ecological zones through dynamic herding strategies calibrated to seasonal

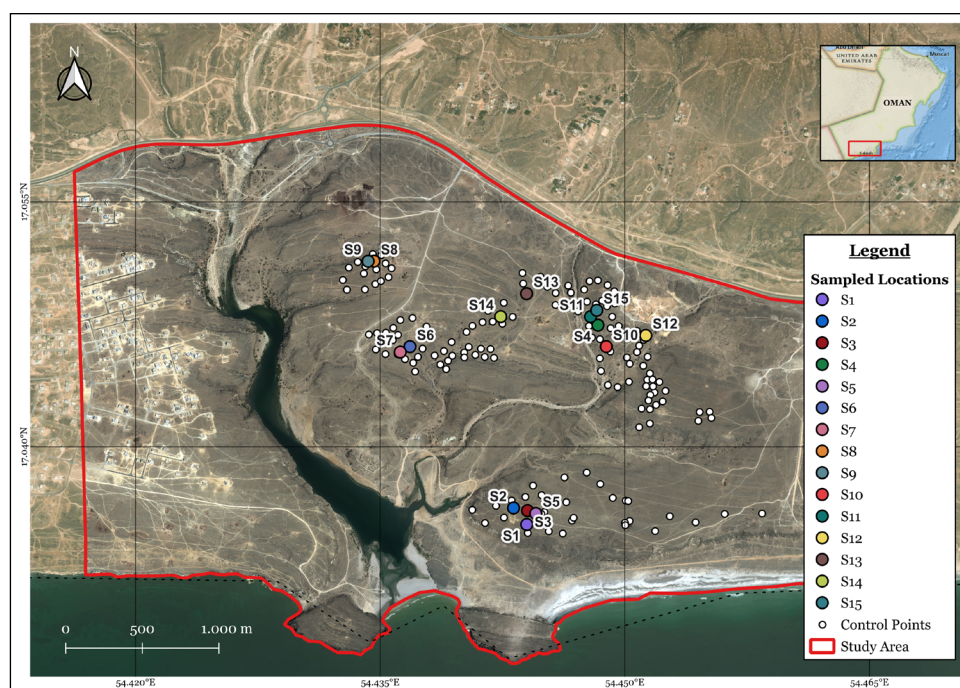


Figure 1 The Khor Rori study area, SW Oman, showing the study area perimeter, the location of the 15 sampled locations (S1–S15), and the distribution of control points across the landscape. Basemap: includes material © CNES (2025), Distribution Airbus DS.

cycles (McCorriston et al. 2020; Tigani ElMahi 2001). The distinct *Khareef* seasonality shapes a transhumant regime in which each species follows specific movement patterns. During winter and summer, cattle remain on the Khatum and Qatan plateaus, while during the *Khareef*, they disperse across the plateaus, foothills, and occasionally coastal plains. Camels occupy the foothills and Qatan during the dry seasons but are moved to the coastal plains and Nejd during the monsoon to avoid the slippery mountain slopes, where these heavy animals risk serious injuries. Goats are herded in the foothills and escarpment for most of the year but relocated to the foothills, coastal plains, and Nejd during the *Khareef* due to their intolerance of wet conditions (Tigani ElMahi 2001; Tigani ElMahi 2011b). Environmental pressures, particularly predation by hematophagous flies, further structure pastoral practice, with herders systematically collecting and burning manure to eliminate fly breeding areas (Tigani ElMahi 2011a). The material culture of these communities reflects adaptation to mobility constraints, characterised by minimal permanent construction: circular habitat areas (*strayat*), livestock enclosures (*duguf*), and small stone enclosures (*al-masadid*) represent the primary architectural features (Tigani ElMahi 2001).

Given this rich presence of active and recently abandoned pastoral camps embedded within a landscape of documented long-term pastoral continuity, this region provides essential ground truth for establishing the methodological approach. Within this landscape, 15 seasonal pastoral campsites were selected and documented following the methodological protocol described in Biagetti et al. (2026). These settlements typically comprise distinct functional zones: a penning area for livestock enclosure, a domestic living space, and associated features such as fireplaces. Campsite selection was based on physical visual inspection, prioritising locations that exhibited diverse activity areas. The documentation process involved GPS mapping, photographic recording, and detailed sketching. Occupation history was assessed through multi-temporal satellite imagery analysis through Google Earth's historical imagery (2003–2023), combined with in situ sediment sampling (January 2025). Campsites were finally revisited in January 2026 to check whether they had been used during the last monsoon season. Two locations initially recorded as campsites (S11, S12) were reclassified during the second field visit as vegetation patches rather than pastoral encampments. Their samples were retained for two reasons: vegetation cover was sparse enough for the sediment surface to remain visible to the sensor, and their compositions extend the range of low-enrichment values against which the anthropogenic–lithogenic balance is calculated. Of the 13 campsites, three (S4, S7, S10) showed evidence of continued seasonal use at the time of the second field

visit in January 2026, while the remaining sites were last visible as active campsites in the historical satellite record between 2016 and 2023, indicating abandonment within roughly the last decade.

A total of 1,441 soil samples were collected following a multi-resolution spatial sampling strategy: a dense 2-metre grid for domestic zones and 4-metre grids in penning areas where geochemical signatures are more homogeneous. Additional targeted sampling was conducted at discrete features such as fireplaces. All samples were collected at a 5 cm depth to capture the anthropogenic horizon while removing superficial aeolian deposits. Spatial coordinates were recorded using a pole-mounted GNSS receiver (UTM Zone 40N, EPSG:32640). Additionally, 150 control samples were collected across the wider pastoral landscape to characterise the regional geochemistry, allowing for a statistically robust estimation of the baseline signal. This follows the standard CAMP protocol of c. 150 off-site control samples per study region (Biagetti et al. 2026), a fixed sampling effort that ensures baselines remain comparable across the project's study area. Control locations avoided visible pastoral activity and disturbed contexts such as tracks, active grazing areas, and recently abandoned structures.

2.2. CASE STUDY: CAMPSITE S4

To test the feasibility of upscaling geochemical detection through remote sensing, the analysis begins with contemporary settlements where anthropogenic signals are expected to be strongest. From the 13 documented campsites, campsite S4 (Figure 2) was selected based on two criteria: it remained in active seasonal use, ensuring strong geochemical signatures; and it was the only site exhibiting the complete range of functional zones characteristic of pastoral settlements in the region.

Campsite S4 is located in the northeastern portion of the Khor Rori area and was identified as a seasonally used camel corral situated on limestone bedrock. The campsite comprises three distinct activity zones: a roughly circular fenced penning area of approximately 170 m² (c. 15 m diameter), a small domestic space of approximately 12 m² positioned to the southeast of the corral, and a fireplace (c. 0.5 m²) located to the southwest (Figure 3). The penning enclosure consisted of a semi-complete metal mesh fence, with some sections collapsed on the ground, while visible dung accumulation within the corral interior confirmed recent animal presence. A total of 61 soil samples were collected across these activity zones, following the multi-resolution sampling strategy outlined in Section 2.1 (Figure 3).

2.3. pXRF SPECTROMETRY FOR MULTI-ELEMENT DETERMINATION

The geochemical analysis of soil samples collected from the Khor Rori area was conducted using portable X-ray



Figure 2 General view of the S4 sampling campsite and the enclosed structure.

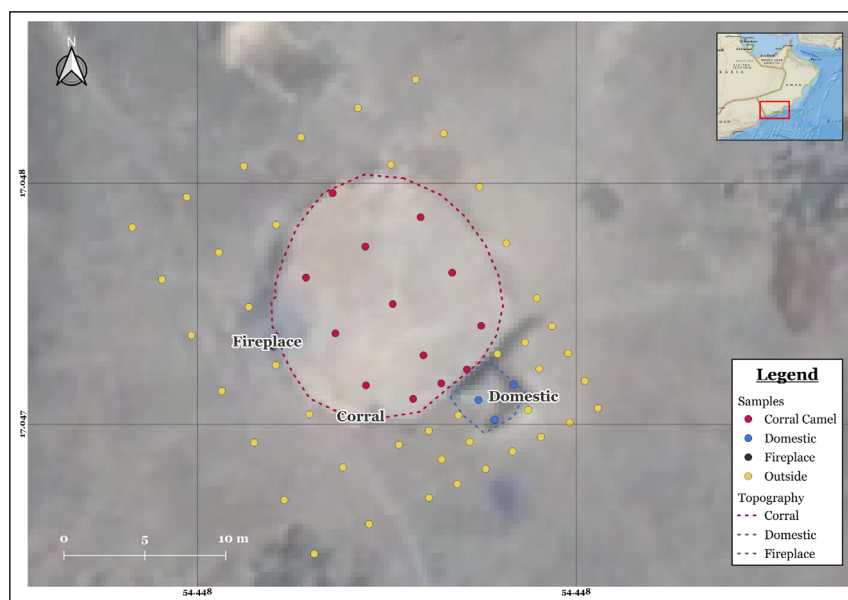


Figure 3 Map of campsite S4 illustrating the functional areas (corral, domestic) and the location of collected soil samples. Basemap: includes material © CNES (2025), Distribution Airbus DS.

fluorescence (pXRF) spectroscopy, following the laboratory protocol established by the CAMP project (Biagetti et al. 2021; Biagetti et al. 2026). The machine used to analyse the samples was a Bruker CTX 800 portable benchtop XRF analyser equipped with a rhodium target X-ray tube, and a large-area silicon drift detector was employed for all measurements. Prior to analysis, air-dried bulk sediment samples were sieved through a 1 mm mesh directly into plastic sample cups prepared with 4.0 μm polypropylene thin film, a preparation method designed to increase reliability and reproducibility while providing sample homogenization (Middleton 2004; Williams, Taylor & Orr 2020). The instrument was configured using the Bruker ‘GeoExploration’ application with the ‘Oxide3phase’ method, combining three measurement phases at

different voltages and filters to detect elements ranging from magnesium to uranium. Integration times were set at 30 seconds each for intermediate and heavy element detection phases, and 100 seconds for light elements such as phosphorus and magnesium, which lie at the edge of pXRF detection limits.

The employment of the pXRF method for identifying anthropogenic signatures in pastoral contexts builds upon foundational multi-element approaches that were primarily introduced by Barba and Ortiz (1992) and Middleton and Price (1996), who demonstrated that repetitive human activities leave characteristic elemental patterns in occupation surfaces. Although pXRF raises technical and methodological concerns that require standardised protocols (Hunt and Speakman 2015; Williams, Taylor &

Orr 2020), its rapid, non-destructive, and cost-effective nature was essential for analysing the 1,441 samples.

2.4. COMPOSITIONAL DATA ANALYSIS (CoDA) AND GEOSTATISTICAL MODELLING

Geochemical data derived from pXRF analysis are inherently compositional, meaning that elemental concentrations represent proportions of a whole rather than independent variables. When one element increases the others must decrease proportionally, creating dependencies that violate the assumptions of classical statistics and can generate spurious correlations (Aitchison 1982). The analysis therefore follows a Compositional Data Analysis (CoDA) framework, in which data reside in the simplex, a space that inherently accounts for the constant-sum and positivity constraints (Filzmoser, Hron & Templ 2018; Greenacre and Wood 2024; Martín-Fernández, Buxeda i Garrigós & Pawlowsky-Glahn 2015). Within this framework the meaningful information lies in the ratios between elements rather than their absolute values.

Before the analysis, data preparation addressed zeros and outliers, two fundamental challenges in compositional datasets. Values below detection limits were imputed using methods that respect compositional principles such as scale invariance and subcompositional coherence (Palarea-Albaladejo and Martín-Fernández 2015), while outlier detection employed robust Mahalanobis distances computed on Orthonormal Log-Ratio (OLR) coordinates derived from a balanced basis, using the Minimum Covariance Determinant (MCD) estimator (Filzmoser and Hron 2008); the outlier threshold was set at the chi-squared quantile with $\alpha=0.975$. Outliers representing meaningful subpopulations rather than measurement errors were retained. Furthermore, log-ratio transformations were then applied to convert the data from the simplex into Euclidean space: Centred Log-Ratio (CLR) coordinates for exploratory analyses such as Principal Component Analysis, Orthonormal Log-Ratio (OLR) coordinates, also termed isometric log-ratio (Egozcue et al. 2003), for geostatistical modelling where proper Euclidean covariance structures are required, and symmetric log-ratio balances for correlation analysis, as standard correlations are invalid for compositional data (Kynčlová, Hron & Filzmoser 2017).

Geostatistical techniques were used to model the spatial distribution of elemental signatures. Variogram analysis characterised the spatial structure of the data (Hilal et al. 2024; Matheron 1963), the Linear Model of Coregionalization (LMC), jointly with the variogram analysis, described the spatial autocorrelation of OLR-transformed variables and their cross-correlations (Goulard and Voltz 1992; Tolosana-Delgado and Mueller 2021). Cokriging predicted elemental distributions at unsampled locations, incorporating spatial structure

and cross-correlations while providing uncertainty estimates (Tolosana-Delgado, Mueller & Van Den Boogaart 2019). Finally, Maximum Autocorrelation Factors (MAF) analysis enhanced spatially structured signals by separating coherent patterns from random variation (Tolosana-Delgado and Mueller 2021). A detailed presentation of this workflow is provided in Biagetti et al. (2026), using the code available in the following repository: <https://github.com/project-camp/camp-public>. Model performance was assessed through cross-validation diagnostics.

2.5. MULTISPECTRAL AND HYPERSPECTRAL REMOTE SENSING

Materials interact with electromagnetic radiation in characteristic ways, producing spectral signatures that encode mineralogy, organic matter content, moisture and texture (Clark 1999; Hunt 1977). Hyperspectral sensors resolve these through numerous narrow, contiguous bands, whereas multispectral sensors use broad, discrete bands insufficient for subtle absorption features (Goetz 2009) but often extending into the shortwave infrared, critical for soil mineralogy and moisture.

Hyperspectral imagery was acquired from the Wyvern Dragonette-001 satellite (6U cubesat, ~550 km altitude) on June 10, 2025, capturing 23 spectral bands spanning 503–799 nm at a 5.3 m ground sampling distance. Commercial data were provided through ESA's Network of Resources Initiative and delivered via UP42. To complement this, multispectral imagery was obtained from Sentinel-2 on June 11, 2025 (one day after the Dragonette acquisition). Although soil sampling was conducted in January 2025, both sampling and imaging fell within the extended dry window prior to the *Khareef* monsoon, so surface reflectance properties remained unaffected by seasonal moisture or vegetation cover. Imagery was atmospherically corrected using the 6S radiative transfer model (Py6S interface; Vermote et al. 1997; Wilson 2013) with a maritime aerosol profile, given the study area's proximity to the Arabian Sea coastline. To exploit complementary sensor strengths, Sentinel-2 NIR plateau bands (B8, 842 nm; B8A, 865 nm) and SWIR bands (B11, 1614 nm; B12, 2202 nm) were reprojected onto the Dragonette reference grid by bilinear interpolation and concatenated through layer-stacking, creating a fused dataset of 27 spectral bands. Initial testing indicated that prioritising spectral richness over spatial sharpening yielded superior model accuracy.

The feature space was further enlarged through spectral indices known to correlate with specific biophysical properties (Poggio and Gimona 2017). These include NDVI for vegetation abundance (Rouse et al. 1974) and SAVI for soil brightness adjustment (Huete 1988), and MSAVI2, which removes the need for an externally specified soil-adjustment factor (Qi et al. 1994):

$$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}}, \quad SAVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red} + 0.5} \times 1.5,$$

$$MSAVI2 = \frac{1}{2} [2\rho_{NIR} + 1 - \sqrt{(2\rho_{NIR} + 1)^2 - 8(\rho_{NIR} - \rho_{Red})}]$$

Moreover, specific mineralogical indices were generated, including the Clay Index (SWIR2/SWIR1) responding to clay mineral absorption features (Drury 1987) and the Calcite Index, targeting the mineral alterations often associated with anthropogenic soil compaction and chemical weathering. The Bare Soil Index (BSI), which contrasts the SWIR and red bands against the NIR and blue bands, was also included as a measure of exposed soil relative to vegetation cover (Rikimaru, Roy & Miyatake 2002):

$$Clay\ Index = \frac{\rho_{SWIR2}}{\rho_{SWIR1}}, \quad Calcite\ Index = \frac{\rho_{SWIR1} - \rho_{SWIR2}}{\rho_{SWIR1} + \rho_{SWIR2}}$$

$$BSI = \frac{(\rho_{SWIR1} + \rho_{Red}) - (\rho_{NIR} + \rho_{Blue})}{(\rho_{SWIR1} + \rho_{Red}) + (\rho_{NIR} + \rho_{Blue})}$$

Moisture-sensitive indices such as NDMI (Gao 1996) and NDWI (McFeeters 1996) were included to capture the differential moisture retention capacities of organic-rich corral soils versus the surrounding arid lithology.

$$NDMI = \frac{\rho_{NIR} - \rho_{SWIR1}}{\rho_{NIR} + \rho_{SWIR1}}, \quad NDWI = \frac{\rho_{Green} - \rho_{NIR}}{\rho_{Green} + \rho_{NIR}}$$

This multi-source expansion follows Poggio and Gimona (2017), who report that multi-sensor integration improves soil property model accuracy over single-sensor approaches. Ground sample coordinates were transformed to match the coordinate reference system of the fused raster (WGS 84 / UTM Zone 40N, EPSG:32640).

Where multiple samples fell within a single pixel, compositional aggregation was performed using the geometric mean in simplex space. This procedure reduced the initial dataset of 1,441 discrete samples to 708 unique pixel-level observations (a 51% reduction due to high spatial clustering of sampling points). Because this study implements the CAMP protocol for the specific target of pastoral campsites, sampling was designed around the spatial scale of the geochemical features themselves rather than the pixel grid of the satellite data. A sampling design matched to sensor resolution would retain a higher proportion of independent observations and improve the correspondence between ground and image scales in future applications. In cases of ‘mixed pixels’ containing both pastoral and background samples, we prioritised samples representing pastoral activities. This preserves the integrity of the anthropogenic signal: given that over half the dataset required aggregation, averaging with background samples would have diluted the chemical signature and risked false negatives in training.

A rigorous background removal protocol isolated the anthropogenic signal. A custom script identified control points within a 500-metre buffer zone of each site (see Figure 4). This distance threshold was large enough to extend beyond the ‘anthropogenic halo’ of the campsites (typically <100 m for ephemeral sites) while remaining within the same lithological unit. The geometric mean of these control points—the appropriate measure of central tendency under CoDA—was used to perturb sample values, perturbation being the compositionally valid equivalent of subtraction. This filters out the geological background, leaving residuals representing anthropogenic enrichment.

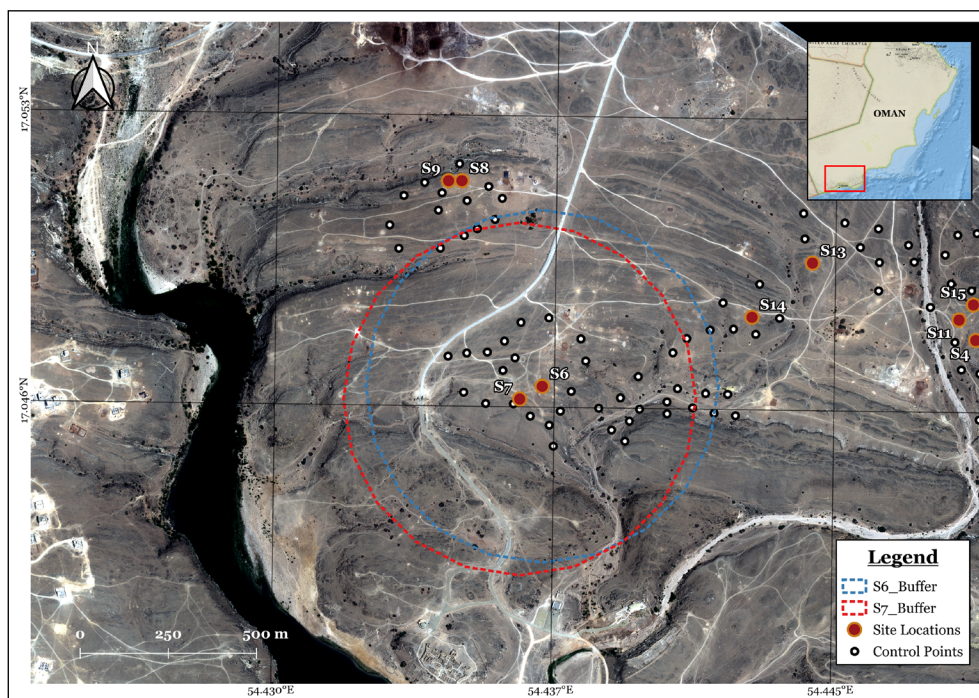


Figure 4 Spatial distribution of control points relative to the buffer boundaries of campsites S6 and S7. Basemap: includes material © CNES (2025), Distribution Airbus DS.

Finally, the target variable followed the CoDA framework (Section 2.4). Rather than predicting raw concentrations, a group balance was constructed through amalgamation: a log-ratio contrast between anthropogenic markers (P, K, Ca) and lithogenic elements (Si, Al, Fe, Ti, Mg) (Kynčlová, Hron & Filzmoser 2017). This gives a target that is mathematically coherent and geochemically meaningful. Chlorine was excluded despite its prominence at S4: the balance requires all constituent elements in both site and control samples, and Cl was absent from the control points, being detected only at the most recently active campsites. Code for the remote sensing analysis is available at <https://github.com/project-camp/camp-remote-sensing>.

3. PRELIMINARY RESULTS

3.1. GEOCHEMICAL SIGNATURES AND GEOSTATISTICS AT CAMPSITE S4

Following pXRF analysis, Spearman rank correlations were computed using symmetric pivot coordinates appropriate for compositional data (Kynčlová, Hron & Filzmoser 2017). The results reveal a coherent lithogenic cluster: Si, Al, Fe, Ti, and Mg intercorrelate strongly ($r_s \geq 0.76$), reflecting the geochemical fingerprint of the local limestone bedrock. Against this geological

background, the most striking result is a set of strong negative correlations between these lithogenic elements and chlorine (Si–Cl $r_s = -0.79$; Al–Cl $r_s = -0.79$; Ti–Cl $r_s = -0.78$; Fe–Cl $r_s = -0.77$) (Figure 5).

This pattern suggests that chlorine from an external source is masking the relative proportion of rock-derived elements in the soil. Animal waste introduces mobile elements that can obscure the geochemical signature of the underlying parent material, complicating the distinction between anthropogenic and natural soil formation processes (Middleton and Price 1996). While dung decomposition enriches phosphorus—derived from its organic component—and calcium, concentrated in the form of spherulites (Marshall et al. 2018; Shahack-Gross et al. 2004), urine is the main pathway through which chlorine leaves the animal's body. This fits ethnographic observations in Dhofar, where pastoralists supplement livestock diets with commercial concentrates containing salt (Tigani ElMahi 2011b). Such supplementation is common in arid pastoral systems, since natural pastures rarely provide sufficient sodium and chloride and heat-tolerant livestock must tolerate high salt intake (Belhadj Slimen et al. 2016; Habeeb, Marai & Kamal 1992). Most of this salt is passed in urine, leaving a chemical trace where animals are repeatedly penned.

Principal component analysis reinforces these findings: the first two components account for 92.2% of

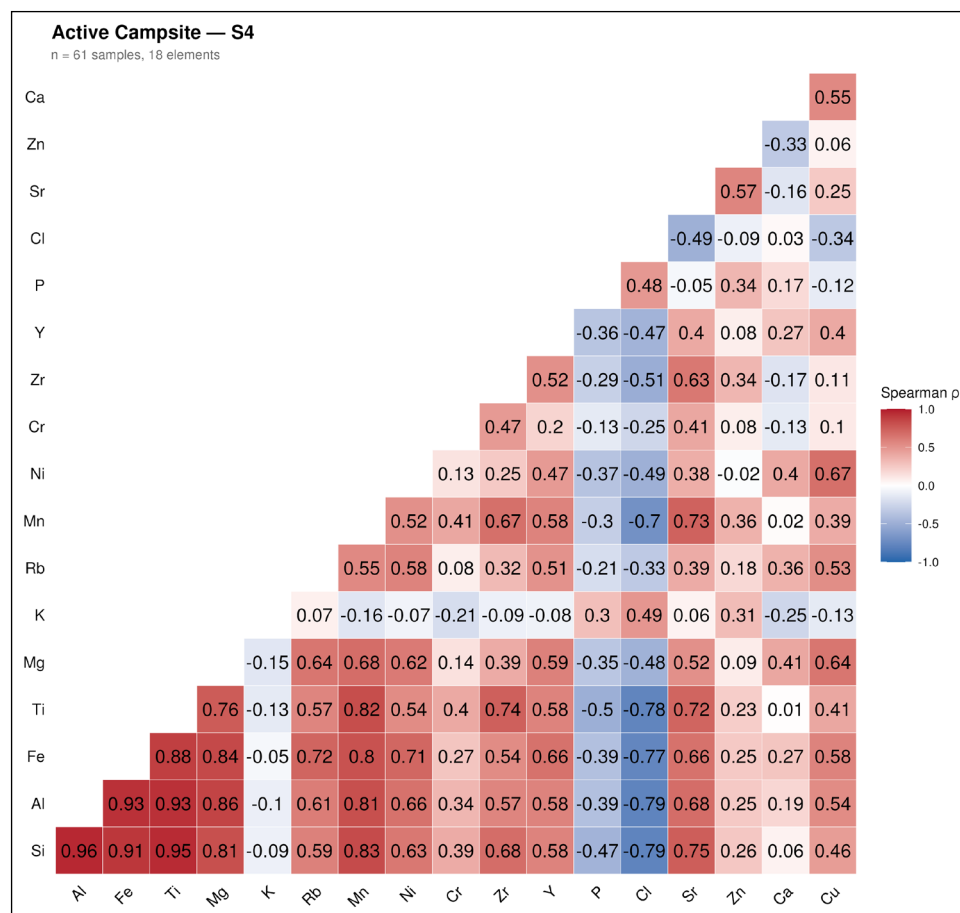


Figure 5 Spearman correlation matrix of the elemental concentrations analysed from S4 soil samples.

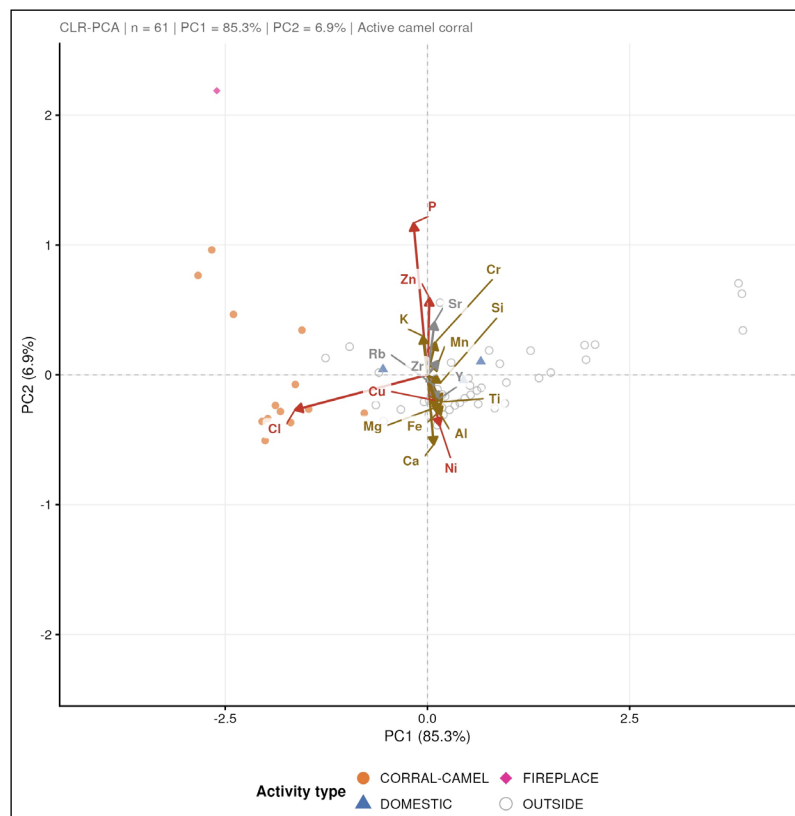


Figure 6 PCA biplot displaying sample scores and elemental loadings on the first two principal components (PC1 and PC2).

total variance, with PC1 alone capturing 85.3%, driven predominantly by chlorine. This confirms that chlorine variation represents the dominant source of geochemical differentiation within the site, which can be interpreted as a urine marker. PC2 (6.9% of variance) isolates a secondary gradient driven by P, Zn and Sr loadings, which might indicate a signal from organic-waste accumulation associated with dung decomposition. A biplot of the first two components resolves samples into two tight clusters corresponding to corral-interior versus exterior locations, while a single fireplace sample plots as a distinct outlier (Figure 6). Notably, the overlap between DOMESTIC and OUTSIDE samples was anticipated, given the low-intensity use of domestic areas compared to the corral enclosure.

These compositional patterns translate into spatially coherent structures suitable for geostatistical modelling. To address the constant-sum constraint of compositional data, cokriging was applied to transformed balances. The analysis compared a direct OLR-based model against a Maximum Autocorrelation Factors (MAF) rotation. Leave-one-out cross-validation indicated that the MAF-transformed model achieved superior performance: the omnidirectional model yielded 95% multivariate accuracy with 47% precision, while directional variogram analysis at four azimuths (0°, 45°, 90°, 135°) produced comparable accuracy (95%) with improved precision (73%). The gain in precision suggests that although the overall spatial structure is largely isotropic, subtle directional dependencies in the variance structure are

captured more effectively by directional modelling, giving more reliable predictions with reduced uncertainty even in a roughly circular corral. In addition, cokriging interpolation was employed to visualise the spatial geochemical distribution across the site (Figure 7). As expected from the prior Spearman and PCA analysis, chlorine concentrations peak in the central corral area and decline sharply beyond the enclosure boundary, mirroring the pattern expected from concentrated urine deposition. Within the same framework, phosphorus and calcium exhibit a more diffuse enrichment centred on the corral interior, reflecting the broader spatial footprint of dung accumulation. Apart from that, potassium closely tracks chlorine, reinforcing the interpretation that both elements derive from the same urinary source. The lithogenic elements (Al, Fe, Ti, Si, Mg) display the inverse pattern, with the highest values in exterior samples and progressive decrease towards the corral's centre.

3.2. REMOTE SENSING: SPECTRAL DIFFERENTIATION AND TECHNICAL CHALLENGES

The Dragonette sensor (503–799 nm) lacks Short-Wave Infrared (SWIR) coverage, a limitation for detecting pastoral geochemical signatures. Model performance using Dragonette bands alone was unsatisfactory, indicating that this range was insufficient to capture the relationship between surface reflectance and geochemistry. The multi-sensor fusion described in Section 2.5 was therefore implemented to expand the

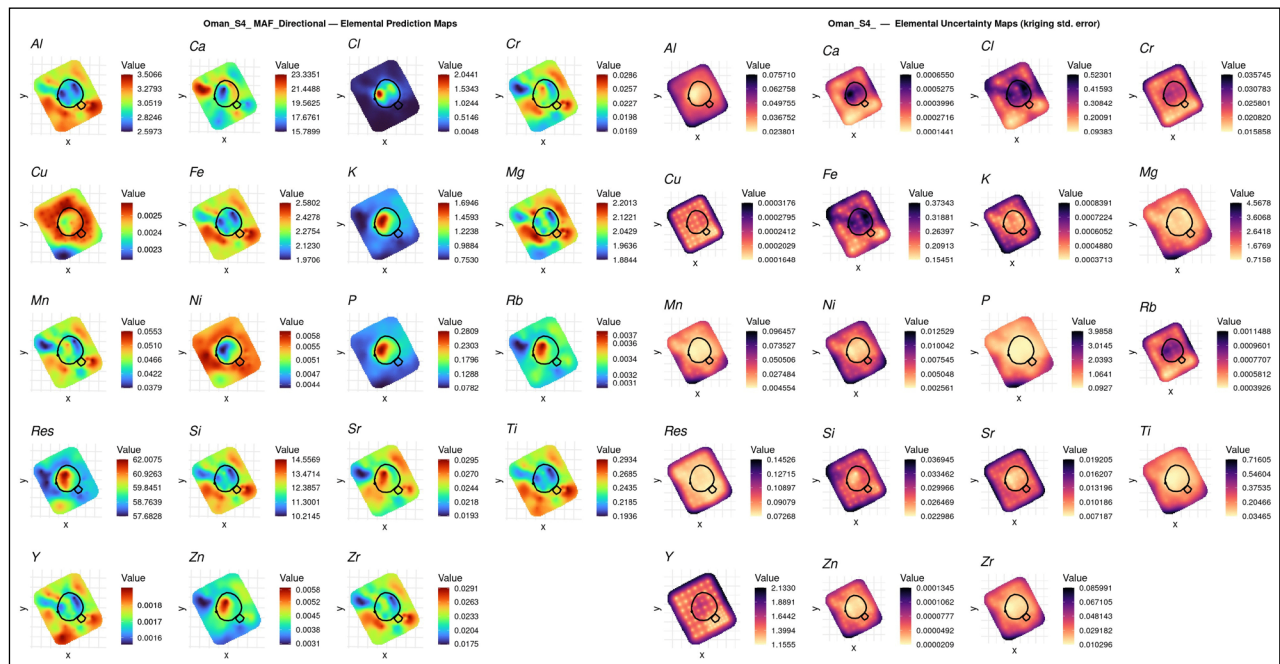


Figure 7 Back-transformed MAF-cokriging results for campsite S4. (Left) Predicted elemental concentrations (%) for each analysed element; (right) corresponding kriging standard errors (delta-method propagated).

feature space. Before model training, a background removal protocol was applied to isolate the anthropogenic signal from local geological variability.

The model was trained and evaluated on the geochemical data from all 13 campsites and the two locations recharacterised as vegetation patches. Following aggregation to pixel resolution, the dataset was split into training (80%) and testing (20%) subsets by stratified random sampling. Stratification was necessary because functional zones (e.g., fireplaces, middens) are not present at every site, and all activity classes had to be proportionally represented in both subsets. This introduces a risk of spatial autocorrelation between adjacent pixels, but we prioritised sampling density so that the full range of geochemical variance within each class was captured.

To establish a predictive baseline using the fused imagery, a Random Forest regressor was tuned by randomised search, yielding a test-set R^2 of 0.51. The modelling strategy then advanced to an Extreme Gradient Boosting (XGBoost) framework, leveraging sequential residual learning and built-in regularization ($R^2 = 0.62$). The XGBoost implementation was tuned using Optuna Bayesian optimisation, with the final configuration employing a learning rate of 0.066, maximum tree depth of 4, and 195 estimators, with L2 regularisation ($\lambda = 0.0008$) and subsampling parameters calibrated to mitigate overfitting. The final performance metrics for the optimised regression model are summarised in Table 1.

The regression results reveal a gap between training ($R^2 = 0.95$) and test set performance ($R^2 = 0.62$). This gap suggests that while the model captures internal variance and spectral-geochemical relationships within the training data, it fits those data closely, and

METRIC	TRAINING SET	TEST SET
R^2 Score	0.95	0.62
RMSE	0.14	0.33
MAE	0.09	0.23

Table 1 Quantitative performance metrics for the XGBoost regression model.

generalisation to unseen pixels is further constrained by the landscape's lithological heterogeneity. The moderate test R^2 indicates that while the model captures general regional geochemical trends and identifies anomalous enrichment zones, it exhibits higher uncertainty when predicting fine-scale concentration values. Since prospection relies on detection rather than precise quantification, we assessed the model's ability to simply distinguish 'enriched' pixels from 'background' pixels. Crucially, this did not involve training a separate classifier; instead, ground-truth pixels were labelled as enriched or background at a balance of zero, the point at which anthropogenic markers exceed the lithogenic reference. The continuous values predicted by the regression model (Table 1) were then binarised against this labelling, with the optimal prediction threshold of 0.10 determined by maximising Youden's J statistic (Sensitivity + Specificity – 1) (Youden 1950). The diagnostic performance of this approach is presented in Table 2.

The resulting ROC-AUC score of 0.86 indicates substantial discriminative capacity. Bootstrap confidence intervals (1000 iterations) give a 95% CI of 0.78–0.92, confirming performance statistically distinct from chance. At the Youden-optimised threshold, the model successfully identified 80 out of 96 enrichment pixels

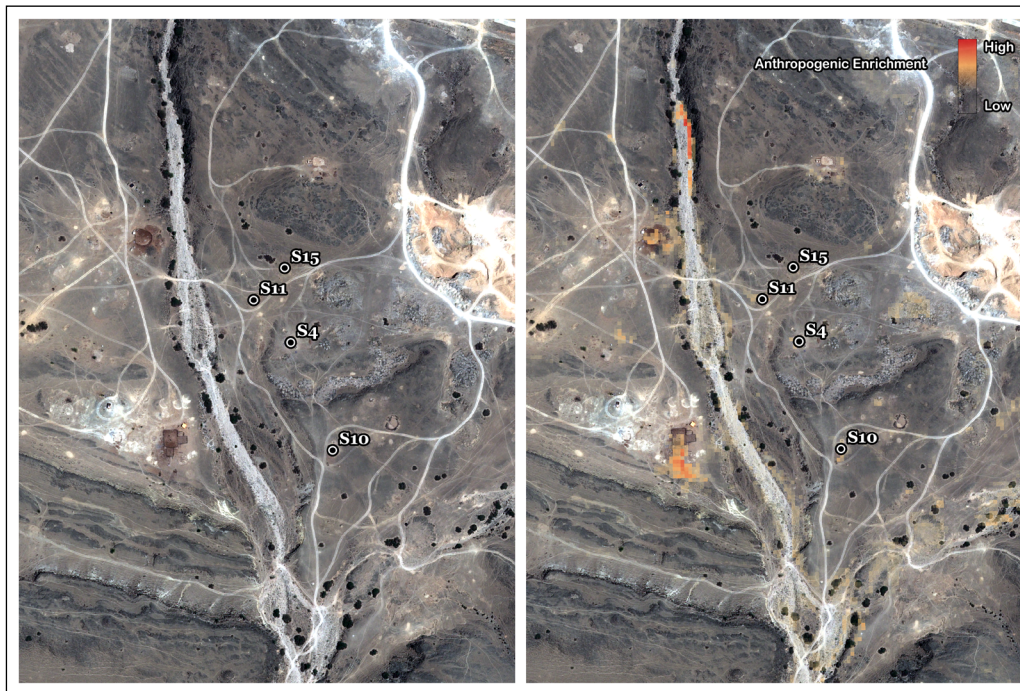


Figure 8 Visualisation of the model classification performance, highlighting the identification of high-enrichment pixels in the vicinity. Basemap: includes material © CNES (2025), Distribution Airbus DS.

METRIC	VALUE
ROC-AUC	0.86
Recall (Sensitivity)	83.33%
Precision	87.91%
F1-Score	0.86
Overall Accuracy	81%
True Positives	80
False Negatives	16

Table 2 Diagnostic performance of the regression model when evaluated as a binary anomaly detector.

(Recall: 83.33%) alongside a specificity of 76%. The high recall ensures that few genuinely enriched areas are missed, while the moderate specificity means a proportion of background pixels are also flagged, an acceptable trade-off in a prospection context, where candidate locations are subsequently verified on the ground. The classification output (Figure 8) identifies high-enrichment pixels in areas where no ground-truth samples were collected, suggesting the learned relationships generalise beyond the training locations rather than memorising site-specific patterns.

Model performance was additionally assessed at the level of individual sampled locations (Table 3). Within-site Spearman correlations between measured and predicted enrichment balance were computed for 14 of the 15 locations (S11 and S12, reclassified as vegetation patches, are included as low-enrichment references), ranging from 0.54 (S15) to 0.89 (S4) with a median of 0.69. S12 is excluded owing to insufficient samples (n

SITE	n	MEASURED (MEAN $\pm$ SD)	PREDICTED (MEAN $\pm$ SD)	BIAS	RMSE	ρ
S1	135	0.24 ± 0.17	0.21 ± 0.15	-0.03	0.13	0.67
S2	20	-0.01 ± 0.12	0.02 ± 0.11	0.03	0.10	0.62
S3	75	0.04 ± 0.19	0.08 ± 0.15	0.04	0.14	0.75
S4	31	0.30 ± 0.35	0.28 ± 0.27	-0.02	0.10	0.89
S5	53	0.11 ± 0.16	0.14 ± 0.11	0.03	0.13	0.56
S6	32	0.55 ± 0.67	0.50 ± 0.49	-0.05	0.30	0.61
S7	52	0.39 ± 0.47	0.44 ± 0.30	0.04	0.24	0.69
S8	40	0.76 ± 0.60	0.70 ± 0.47	-0.06	0.19	0.82
S9	31	1.07 ± 0.80	1.06 ± 0.71	-0.01	0.29	0.87
S10	14	0.52 ± 0.51	0.52 ± 0.34	-0.00	0.27	0.68
S11 ¹	14	0.06 ± 0.21	0.10 ± 0.09	0.04	0.16	0.78
S12 ¹	5	0.16 ± 0.17	0.13 ± 0.10	-0.02	0.08	—
S13	39	0.66 ± 0.46	0.61 ± 0.30	-0.05	0.31	0.76
S14	33	0.23 ± 0.14	0.23 ± 0.14	-0.01	0.12	0.69
S15	31	-0.09 ± 0.16	-0.02 ± 0.12	0.06	0.16	0.54

Table 3 Site-level model performance. Measured and predicted enrichment balance (mean $\pm$ SD), bias (predicted – measured), RMSE, and within-site Spearman correlation (ρ) for each sampled location. ρ not reported for S12 ($n = 5$). n = pixels per location; the remaining 103 pixels are off-site samples.

= 5). Site-level bias remains within ± 0.06 throughout, indicating no systematic over- or under-prediction at particular locations.

The landscape-scale prediction (Figure 9) reveals spatially coherent patterns, with elevated values clustering around several sites, particularly near S8–S9 in

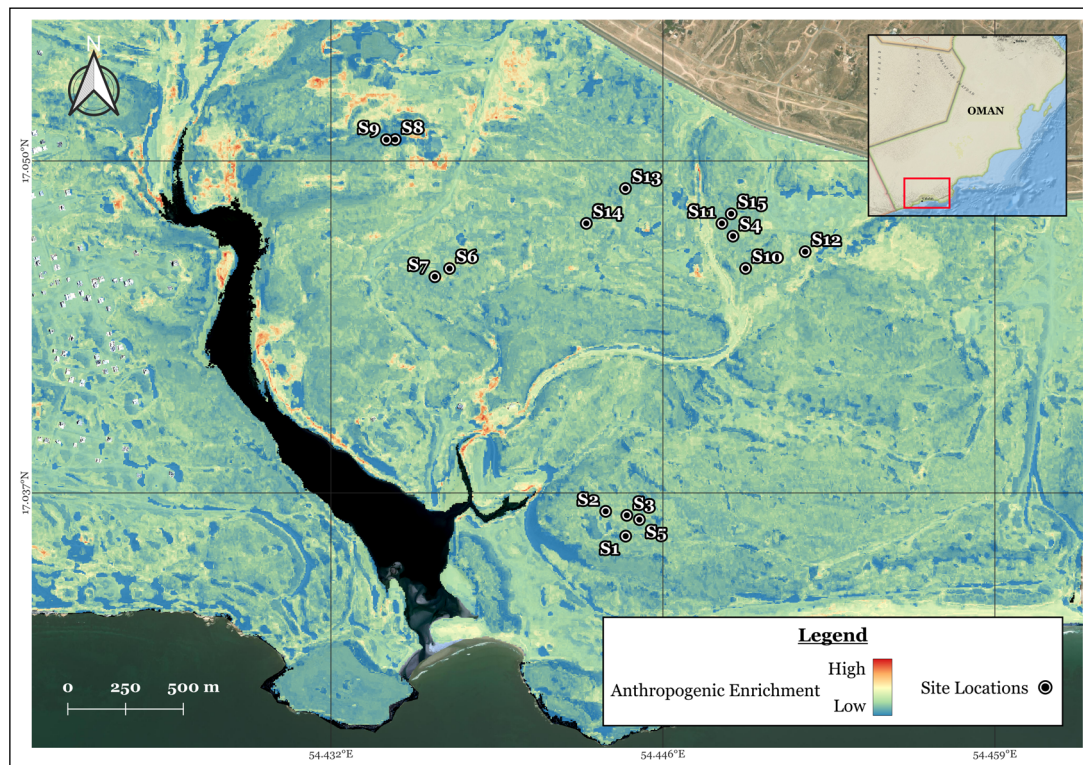


Figure 9 Predictive model of anthropogenic soil enrichment across the study area, highlighting zones of high (red) and low (blue) potential human activity.

the north-west and S10–S11 in the north-east. Isolated hotspots in the northern and eastern sectors indicate possible activity beyond the sampled locations; whether these are true pastoral signatures or artefacts of lithological variation requires ground-truth verification.

4. DISCUSSION

The geochemical analysis demonstrates that contemporary pastoral sites in the Khor Rori area exhibit distinctive elemental signatures reliably distinguishable from the baseline geological variability. Although detailed spatial analysis focused on Campsite S4, the activity areas identified reflect the standard spatial logic observed throughout Dhofar (Biagetti et al. 2026). This structuring mirrors ethnoarchaeological findings from sub-Arctic Sámi contexts (Seitsonen and Égüez 2021), suggesting a convergent pastoral spatial logic independent of environmental setting.

The strong negative correlations between lithogenic elements (Si, Al, Fe, Ti, Mg) and chlorine and, to a lesser extent, phosphorus provide compelling evidence for soil modification. While equifinality must be acknowledged, the strict spatial confinement of these anomalies to visually identified penning areas argues against a pedogenic origin, aligning with foundational multi-element approaches (Barba and Ortiz 1992; Middleton and Price 1996) while extending their applicability to arid pastoral contexts.

The elemental suites also offer insight into management practices. Chlorine enrichment may reflect a urinary signature, consistent with ethnographic documentation of salt supplementation in Dhofar (Tigani ElMahi 2011b), while phosphorus, potassium and calcium within corral interiors suggest dung accumulation, their more diffuse footprint reflecting the broader distribution of faecal matter relative to urine. Although prominent at S4, chlorine was excluded since the balance requires elements to be present in both site and control samples.

Connecting these ground-truth realities to satellite imagery revealed both promise and significant challenges. As Gomez et al. (2019) noted, ‘insufficient spectral information’ often limits prediction accuracy in multispectral approaches, a concern validated here by the initial poor performance of Dragonette hyperspectral bands alone (503–799 nm). This range is insufficient because soil organic matter and phosphorus absorb diagnostically in the NIR and SWIR (Ben-Dor, Irons & Epema 1999; Curran 1989; Ramoelo et al. 2011; Stenberg et al. 2010). The fusion of Dragonette’s spatial resolution with Sentinel-2’s spectral coverage was therefore a pragmatic compromise, consistent with evidence that combining Vis-NIR and SWIR enhances soil property prediction (Kim et al. 2022).

While the drop from training ($R^2 = 0.95$) to test performance ($R^2 = 0.62$) indicates that predictive skill is reduced on unseen pixels—echoing Thabeng, Merlo & Adam’s (2019) caution regarding spectral signature universality—the spatial distribution of the model’s

predictions offers an interpretive nuance. The site-level fits (Table 3) show that the measured–predicted relationship is consistent across the study area rather than driven by one or two locations: within-site correlations are positive at all 14 locations for which they could be computed ($\rho = 0.54\text{--}0.89$, median 0.69), and site-level bias remains within ± 0.06 throughout, indicating no systematic over- or under-prediction at particular locations. These are in-sample values and do not themselves demonstrate generalisation, but they rule out the alternative reading that the aggregate metrics are carried by a small number of well-sampled sites. Rather than strictly distinguishing ‘recent’ from ‘abandoned’ sites, the model appears to selectively highlight zones of maximum cumulative intensity instead of reproducing signals across entire sites. The model therefore appears to respond to the magnitude of soil modification rather than memorising site-specific patterns, though absolute dating is lacking. Notably, the highest enrichment values occur at abandoned locations (S9, S8, S13) rather than at the three in active use (S4, S7, S10), indicating that the geochemical signal reflects cumulative soil modification rather than recency of occupation, and that it persists after abandonment. This discriminative behaviour, combined with a ROC-AUC of 0.86, demonstrates a meaningful, albeit qualitative, prospection capacity.

Two methodological constraints warrant consideration. First, integrating Dragonette (5.3 m) and Sentinel-2 (20 m SWIR) data involves a trade-off in spatial fidelity. Resampling the coarser SWIR bands to the Dragonette geometry introduces smoothing, which likely dilutes the signatures of discrete sub-pixel features such as hearths or small refuse pits. While the model detects the broader ‘geochemical halo’ of the campsite complex, it may lack the spatial acuity to resolve fine-scale internal compartmentalisation, relying heavily on SWIR-responsive variables. The remote sensing component was also developed after the ground campaign rather than jointly with it, so sample distribution was not optimised for pixel-level correspondence; a subsequent iteration would benefit from designing the two together.

Second, the analysis relies on a single acquisition, a static snapshot of a dynamic landscape. The Dhofar region is defined by the seasonal *Khareef* monsoon, which drives rapid vegetation flushes that obscure soil surfaces and alter moisture content, both of which modify spectral reflectance (Stenberg et al. 2010). Dry-season imagery was prioritised to maximise soil exposure, but the effect of post-monsoon conditions on detection thresholds remains unquantified and requires multi-temporal analysis.

The relationships reported here are conditioned by the environmental setting in which they were developed. Khor Rori combines an arid climate, sparse vegetation, and limestone bedrock, conditions favouring both the preservation of surface enrichment and its spectral

expression. Elsewhere, leaching, vegetation cover, and different lithogenic backgrounds would be expected to alter these balances. The trained model is therefore specific to this setting, but the framework is not. Since the balances are computed against a locally derived baseline rather than in absolute terms, the same procedure can be recalibrated to a different geology. This is currently being tested at the other CAMP pastoral study areas.

Beyond methodological validation, these results offer a preliminary framework for bridging the critical ‘integration gap’ in the archaeology of Dhofar. Previous remote sensing efforts have focused on monumental architecture (McCorriston et al. 2025) or vegetation dynamics (Al-Kindi, Al Nadhairi & Al Akhzami 2023); this work suggests the ‘invisible’ majority of the region’s occupation history may be rendered visible through an integrated approach, though further validation is required. If ancient mobility mirrored the seasonal cycles of the ethnographic present, the framework offers a means to reconstruct the spatial logic of Dhofari pastoralism.

5. CONCLUDING REMARKS

The integration of geochemical analysis with ethnoarchaeological fieldwork demonstrates the potential of geo-ethnoarchaeological approaches to pastoralism, opening new pathways for bridging contemporary pastoral practices with archaeological inquiry. The fundamental challenge of distinguishing pastoral signatures from natural background variability persists, and model generalisation requires further investigation. Future improvements should focus on the acquisition of hyperspectral imagery with native extended SWIR coverage (e.g., PRISMA, EnMAP) to eliminate sensor fusion uncertainties. Validation of the current findings through additional fieldwork remains essential. The ongoing CAMP project provides an opportunity to test whether chemical proxies generated by pastoral activities remain consistent across sites regardless of ecological setting. Extending this approach to archaeological deposits would further assess whether spectral-geochemical relationships documented in contemporary contexts can truly inform the identification of ancient pastoral sites.

GENERATIVE AI DISCLOSURE

Generative AI tools (Claude, Anthropic) were used to assist with manuscript structuring and code development for data analysis workflows. All AI-generated outputs were critically reviewed, verified, and substantially revised by the authors to ensure accuracy and adherence to scientific standards.

DATA ACCESSIBILITY STATEMENT

Geochemical data (pXRF measurements) collected as part of the CAMP project are available upon reasonable request to the corresponding author, subject to conditions of the research agreement with the Ministry of Heritage and Tourism of the Sultanate of Oman. Satellite imagery (Wyvern Dragonette hyperspectral) is a commercial product provided through ESA's Network of Resources Initiative and cannot be redistributed. Sentinel-2 data are freely available through the Copernicus Data Space Ecosystem (<https://dataspace.copernicus.eu>). Analytical code for compositional data analysis and geostatistical modelling is available at <https://github.com/project-camp/camp-public>, and for the remote sensing analysis at <https://github.com/project-camp/camp-remote-sensing>.

NOTE

- 1 S11 and S12 were reclassified as vegetation patches during the second field visit (Section 2.1) and are retained here as low-enrichment references rather than pastoral campsites.

ACKNOWLEDGEMENTS

Satellite data was provided by the ESA Network of Resources Initiative through the UP42 platform. Research in Oman was conducted under the agreement established between the Ministry of Heritage and Tourism of the Sultanate of Oman and the DHOMIAP Project. The authors thank the two anonymous reviewers for their constructive comments and insightful suggestions, which significantly improved the quality and clarity of this manuscript.

FUNDING INFORMATION

This work is supported by the European Research Council (ERC) grant CAMP (ERC-CoG, n. 101088842, PI: Stefano Biagetti), funded by the European Union. Views and opinions expressed are, however, those of the authors only and do not necessarily reflect those of the European Union or the European Research Council. Neither the European Union nor the granting authority can be held responsible for them.

COMPETING INTERESTS

The authors have no competing interests to declare.

AUTHOR CONTRIBUTIONS

Conceptualisation: AK, SB
Methodology: AK, ARG, SB

Software: AK
Formal analysis: AK
Investigation: AK, SL, ARG, SB
Data Curation: AK, SL, SB
Visualisation: AK
Writing – Original Draft: AK
Writing – Review and Editing: AK, SL, ARG, SB
Resources: SB
Supervision: SB
Funding Acquisition: SB

AUTHOR AFFILIATIONS

Antonios Koutroumpas  orcid.org/0000-0001-5017-9975
CASEs Research Group, Universitat Pompeu Fabra, C. Ramon Trias Fargas 25–27, 08005, Barcelona, Spain

Silvia Lisch  orcid.org/0000-0003-0038-7332
Centre de Recherche Archéologique Jaussen et Savignac, Université Paris 1 – Panthéon-Sorbonne, 3 rue Michelet 75006, Paris, France; CNRS – UMR 8167 Orient & Méditerranée, 7 rue Guy Môquet 94800 Villejuif, France

Abel Ruiz-Giralt  orcid.org/0000-0002-8472-043X
CASEs Research Group, Universitat Pompeu Fabra, C. Ramon Trias Fargas 25–27, 08005, Barcelona, Spain

Stefano Biagetti  orcid.org/0000-0003-0936-3070
CASEs Research Group, Universitat Pompeu Fabra, C. Ramon Trias Fargas 25–27, 08005, Barcelona, Spain; ICREA, Passeig Lluís Companys 23, Barcelona, Spain; School of Geography, Archaeology and Environmental Studies (GAES), University of the Witwatersrand, 1 Jan Smuts Avenue, Braamfontein 2000, Johannesburg, South Africa

REFERENCES

- African Union.** 2010. *Policy Framework for Pastoralism in Africa: Securing, Protecting and Improving the Lives, Livelihoods and Rights of Pastoralist Communities*.
- Aitchison, J.** 1982. 'The statistical analysis of compositional data'. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 44(2): 139–160. DOI: <https://doi.org/10.1111/j.2517-6161.1982.tb01195.x>
- Al-Kindi, KM, Al Nadhairi, R and Al Akhazmi, S.** 2023. 'Dynamic change in normalised vegetation index (NDVI) from 2015 to 2021 in Dhofar, southern Oman in response to the climate change'. *Agriculture*, 13(3): 592. DOI: <https://doi.org/10.3390/agriculture13030592>
- Arnold, R, Haug, J-K, Lange, M and Friesen, J.** 2020. 'Impact of forest cover change on available water resources: long-term forest cover dynamics of the semi-arid Dhofar cloud forest, Oman'. *Frontiers in Earth Science*, 8: 299. DOI: <https://doi.org/10.3389/feart.2020.00299>
- Barba, L and Ortiz, A.** 1992. 'Análisis químico de pisos de ocupación: un caso etnográfico en Tlaxcala, México'. *Latin American Antiquity*, 3(1): 63–82. DOI: <https://doi.org/10.2307/971930>
- Belhadj Slimen, I, Najar, T, Ghram, A and Abdrrabba, M.** 2016. 'Heat stress effects on livestock: molecular, cellular and

- metabolic aspects, a review'. *Journal of Animal Physiology and Animal Nutrition*, 100(3): 401–412. DOI: <https://doi.org/10.1111/jpn.12379>
- Ben-Dor, E, Irons, JR and Epema, GF.** 1999. 'Soil reflectance'. In: Rencz, AN (ed.) *Remote Sensing for the Earth Sciences, Manual of Remote Sensing*, pp. 111–188. New York: Wiley.
- Biagetti, S.** 2025. 'The long road: ethnoarchaeology, pastoralism and the reconfiguration of archaeological knowledge'. *Cambridge Prisms: Drylands*, 2: e15. DOI: <https://doi.org/10.1017/dry.2025.10011>
- Biagetti, S, Alcaina-Mateos, J, Ruiz-Giralt, A, Lancelotti, C, Groenwald, P, Ibañez-Insa, J, Gur-Arie, S, Morton, F and Merlo, S.** 2021. 'Identifying anthropogenic features at Seoke (Botswana) using pXRF: expanding the record of southern African stone walled sites'. *PLoS ONE*, 16(4): e0250776. DOI: <https://doi.org/10.1371/journal.pone.0250776>
- Biagetti, S and Howe, T.** 2017. 'Variability is the key: towards a diachronic view of pastoralism'. *Nomadic Peoples*, 21(2): 167–172. DOI: <https://doi.org/10.3197/np.2017.210201>
- Biagetti, S, Ruiz-Giralt, A, Rix, KS, Koutroumpas, A, Ibañez-Insa, J, Lancelotti, C, Garcia-Tuset, N, Kerfant, CE, Grillo, KM, Hildebrand, EA, Lonyala, J, Mvimi, M, Merlo, S, Lucarini, G, Lischi, S and Madella, M.** 2026. 'Developing geo-ethnoarchaeological methods for studying archaeological pastoral sites: the CAMP project'. *Journal of Archaeological Method and Theory*, 33(1): 29. DOI: <https://doi.org/10.1007/s10816-025-09759-9>
- Charpentier, V, Maiorano, MP, Marchand, G, Vosges, J and Borgi, F.** 2023. 'Twelve years of the Arabian Seashores project: how the extensive investigation of coastal Oman changed the paradigm of the Arabian Neolithic'. *Arabian Archaeology and Epigraphy*, 34(S1): S1–S21. DOI: <https://doi.org/10.1111/aae.12236>
- Clark, RN.** 1999. 'Spectroscopy of rocks and minerals, and principles of spectroscopy'. In: Rencz, AN (ed.) *Manual of Remote Sensing, Volume 3, Remote Sensing for the Earth Sciences*, pp. 3–58. New York: John Wiley and Sons.
- Curran, PJ.** 1989. 'Remote sensing of foliar chemistry'. *Remote Sensing of Environment*, 30(3): 271–278. DOI: [https://doi.org/10.1016/0034-4257\(89\)90069-2](https://doi.org/10.1016/0034-4257(89)90069-2)
- Drury, SA.** 1987. *Image Interpretation in Geology*. London: Allen and Unwin. DOI: <https://doi.org/10.1007/978-94-010-9393-4>
- Egozcue, JJ, Pawłowsky-Glahn, V, Mateu-Figueras, G and Barceló-Vidal, C.** 2003. 'Isometric logratio transformations for compositional data analysis'. *Mathematical Geology*, 35(3): 279–300. DOI: <https://doi.org/10.1023/A:1023818214614>
- FAO.** 2020. *Innovative Pastoralism: Achieving Productivity and Sustainability for Food Security*. DOI: <https://doi.org/10.4060/ca9261en>
- FAO.** 2021. *Pastoralism – Making Variability Work*. DOI: <https://doi.org/10.4060/cb5823en>
- Filzmoser, P and Hron, K.** 2008. 'Outlier detection for compositional data using robust methods'. *Mathematical Geosciences*, 40(3): 233–248. DOI: <https://doi.org/10.1007/s11004-007-9141-5>
- Filzmoser, P, Hron, K and Templ, M.** 2018. *Applied Compositional Data Analysis: With Worked Examples in R*. Springer Series in Statistics. Cham: Springer International Publishing. DOI: <https://doi.org/10.1007/978-3-319-96422-5>
- Galletti, CS, Turner, BL and Myint, SW.** 2016. 'Land changes and their drivers in the cloud forest and coastal zone of Dhofar, Oman, between 1988 and 2013'. *Regional Environmental Change*, 16(7): 2141–2153. DOI: <https://doi.org/10.1007/s10113-016-0942-2>
- Gao, B.** 1996. 'NDWI-a normalized difference water index for remote sensing of vegetation liquid water from space'. *Remote Sensing of Environment*, 58(3): 257–266. DOI: [https://doi.org/10.1016/S0034-4257\(96\)00067-3](https://doi.org/10.1016/S0034-4257(96)00067-3)
- Goetz, AFH.** 2009. 'Three decades of hyperspectral remote sensing of the earth: a personal view'. *Remote Sensing of Environment*, 113(S1): S5–S16. DOI: <https://doi.org/10.1016/j.rse.2007.12.014>
- Gomez, C, Dharumarajan, S, Féret, J-B, Lagacherie, P, Ruiz, L and Sekhar, M.** 2019. 'Use of Sentinel-2 time-series images for classification and uncertainty analysis of inherent biophysical property: case of soil texture mapping'. *Remote Sensing*, 11(5): 565. DOI: <https://doi.org/10.3390/rs11050565>
- Goulard, M and Voltz, M.** 1992. 'Linear coregionalization model: tools for estimation and choice of cross-variogram matrix'. *Mathematical Geology*, 24(3): 269–286. DOI: <https://doi.org/10.1007/BF00893750>
- Greenacre, M and Wood, JR.** 2024. 'A comprehensive workflow for compositional data analysis in archaeometry, with code in R'. *Archaeological and Anthropological Sciences*, 16(10): 171. DOI: <https://doi.org/10.1007/s12520-024-02070-w>
- Habeeb, AAM, Marai, IFM and Kamal, TH.** 1992. 'Heat stress'. In: Phillips, CJC and Piggins, D (eds.) *Farm Animals and the Environment*, pp. 27–47. Wallingford: CAB International.
- Hilal, A, Bangroo, SA, Kirmani, NA, Wani, JA, Biswas, A, Bhat, MI, Farooq, K, Bashir, O and Shah, TI.** 2024. 'Geostatistical modeling-a tool for predictive soil mapping'. In: *Remote Sensing in Precision Agriculture*. Elsevier. pp. 389–418. DOI: <https://doi.org/10.1016/B978-0-323-91068-2.00011-4>
- Hildebrand, EA, Grillo, KM, Sawchuk, EA, Pfeiffer, SK, Conyers, LB, Goldstein, ST, Hill, AC, Janzen, A, Klehm, CE, Helper, M, Kiura, P, Ndiema, E, Ngugi, C, Shea, JJ and Wang, H.** 2018. 'A monumental cemetery built by eastern Africa's first herders near Lake Turkana, Kenya'. *Proceedings of the National Academy of Sciences*, 115(36): 8942–8947. DOI: <https://doi.org/10.1073/pnas.1721975115>
- Honeychurch, W and Makarewicz, CA.** 2016. 'The archaeology of pastoral nomadism'. *Annual Review of Anthropology*, 45: 341–359. DOI: <https://doi.org/10.1146/annurev-anthro-102215-095827>
- Horisk, KE, Ivory, SJ, McCorriston, J, McHale, M, Al Mehri, A, Anderson, A, Anderson, RS and Al Kathiri, AA.** 2023. 'Vegetation dynamics in Dhofar, Oman, from the late Holocene to present inferred from rock hyrax middens'.

- Quaternary Research*, 116: 12–29. DOI: <https://doi.org/10.1017/qua.2023.42>
- Huete, AR.** 1988. 'A soil-adjusted vegetation index (SAVI)'. *Remote Sensing of Environment*, 25(3): 295–309. DOI: [https://doi.org/10.1016/0034-4257\(88\)90106-X](https://doi.org/10.1016/0034-4257(88)90106-X)
- Hunt, AMW and Speakman, RJ.** 2015. 'Portable XRF analysis of archaeological sediments and ceramics'. *Journal of Archaeological Science*, 53: 626–638. DOI: <https://doi.org/10.1016/j.jas.2014.11.031>
- Hunt, GR.** 1977. 'Spectral signatures of particulate minerals in the visible and near infrared'. *Geophysics*, 42(3): 501–513. DOI: <https://doi.org/10.1190/1.1440721>
- Kim, M-J, Lee, H-I, Choi, J-H, Lim, KJ and Mo, C.** 2022. 'Development of a soil organic matter content prediction model based on supervised learning using vis-NIR/SWIR spectroscopy'. *Sensors*, 22(14): 5129. DOI: <https://doi.org/10.3390/s22145129>
- Kynčlová, P, Hron, K and Filzmoser, P.** 2017. 'Correlation between compositional parts based on symmetric balances'. *Mathematical Geosciences*, 49(6): 777–796. DOI: <https://doi.org/10.1007/s11004-016-9669-3>
- Lane, PJ.** 2016. 'Entangled banks and the domestication of East African pastoralist landscapes'. In: Fernandini, F and Der, L (eds.). *Archaeology of Entanglement*, pp. 127–150. Walnut Creek, CA: Left Coast Press.
- Lischi, S.** 2022. *Settlement Dynamics and Territorial Organization in Dhofar between the Bronze Age and Late Antiquity: Understanding the Settlement Process of the Khor Rori Area and Development of a New Regional Cultural Model*. Unpublished thesis (PhD). University of Pisa.
- Lischi, S.** 2025. 'DHOMIAP project (2022–23): new archaeological discoveries in Dhofar'. *Athar – Bulletin of Archaeological Research in the Sultanate of Oman*, 1: 134–140.
- Lubos, C, Dreibrodt, S and Bahr, A.** 2016. 'Analysing spatio-temporal patterns of archaeological soils and sediments by comparing pXRF and different ICP-OES extraction methods'. *Journal of Archaeological Science: Reports*, 9: 44–53. DOI: <https://doi.org/10.1016/j.jasrep.2016.06.037>
- Makarewicz, CA.** 2013. 'A pastoralist manifesto: breaking stereotypes and re-conceptualizing pastoralism in the Near Eastern Neolithic'. *Levant*, 45(2): 159–174. DOI: <https://doi.org/10.1179/0075891413Z.00000000023>
- Marshall, F, Reid, REB, Goldstein, S, Storozum, M, Wreschnig, A, Hu, L, Kiura, P, Shahack-Gross, R and Ambrose, SH.** 2018. 'Ancient herders enriched and restructured African grasslands'. *Nature*, 561(7723): 387–390. DOI: <https://doi.org/10.1038/s41586-018-0456-9>
- Marshall, F and Weissbrod, L.** 2011. 'Domestication processes and morphological change: through the lens of the donkey and African pastoralism'. *Current Anthropology*, 52(S4): S397–S413. DOI: <https://doi.org/10.1086/658389>
- Martín-Fernández, JA, Buxeda i Garrigós, J and Pawlowsky-Glahn, V.** 2015. 'Logratio analysis in archeometry: principles and methods'. In: Barceló, JA and Bogdanovic, I (eds.). *Mathematics and Archaeology*, pp. 178–189. Boca Raton, FL: CRC Press. DOI: <https://doi.org/10.1201/b18530>
- Matheron, G.** 1963. 'Principles of geostatistics'. *Economic Geology*, 58(8): 1246–1266. DOI: <https://doi.org/10.2113/gsecongeo.58.8.1246>
- McCorriston, J, Ball, L, Harrower, MJ, Hamilton, IM, Ivory, SJ, Senn, MJ, Steimer-Herbet, T, Buffington, AF, Al-Kathiri, AA and Al-Mahri, AM.** 2025. 'South Arabia's prehistoric monument landscape shows social resilience to climate change'. *PLoS One*, 20(5): e0323544. DOI: <https://doi.org/10.1371/journal.pone.0323544>
- McCorriston, J, Buffington, A, Olson, K, Martin, L, Abu-Azizeh, W, Everhart, T, Al Maashani, A, Al Kathiri, AA and Al Mehri, A.** 2020. 'Ancient pastoral settlement in the Dhofar mountains: archaeological excavations at Shakil and Halqoot'. *Journal of Oman Studies*, 21: 152–171.
- McFeeters, SK.** 1996. 'The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features'. *International Journal of Remote Sensing*, 17(7): 1425–1432. DOI: <https://doi.org/10.1080/01431169608948714>
- Middleton, WD.** 2004. 'Identifying chemical activity residues on prehistoric house floors: a methodology and rationale for multi-elemental characterization of a mild acid extract of anthropogenic sediments'. *Archaeometry*, 46(1): 47–65. DOI: <https://doi.org/10.1111/j.1475-4754.2004.00143.x>
- Middleton, WD and Price, TD.** 1996. 'Identification of activity areas by multi-element characterization of sediments from modern and archaeological house floors using inductively coupled plasma-atomic emission spectroscopy'. *Journal of Archaeological Science*, 23(5): 673–687. DOI: <https://doi.org/10.1006/jasc.1996.0064>
- Newton, LS and Zarins, J.** 2010. 'Preliminary results of the Dhofar archaeological survey'. *Proceedings of the Seminar for Arabian Studies*, 40: 247–266.
- Oonk, S, Slomp, CP and Huisman, DJ.** 2009. 'Geochemistry as an aid in archaeological prospection and site interpretation: current issues and research directions'. *Archaeological Prospection*, 16(1): 35–51. DOI: <https://doi.org/10.1002/arp.344>
- Palarea-Albaladejo, J and Martín-Fernández, JA.** 2015. 'zCompositions – R package for multivariate imputation of left-censored data under a compositional approach'. *Chemometrics and Intelligent Laboratory Systems*, 143: 85–96. DOI: <https://doi.org/10.1016/j.chemolab.2015.02.019>
- Poggio, L and Gimona, A.** 2017. 'Assimilation of optical and radar remote sensing data in 3D mapping of soil properties over large areas'. *Science of The Total Environment*, 579: 1094–1110. DOI: <https://doi.org/10.1016/j.scitotenv.2016.11.078>
- Qi, J, Chehbouni, A, Huete, AR, Kerr, YH and Sorooshian, S.** 1994. 'A modified soil adjusted vegetation index'. *Remote Sensing of Environment*, 48(2): 119–126. DOI: [https://doi.org/10.1016/0034-4257\(94\)90134-1](https://doi.org/10.1016/0034-4257(94)90134-1)

- Ramadan, E, Al-Awadhi, T and Charabi, Y.** 2021. 'Land cover/land use change and climate change in Dhofar governorate, Oman'. *International Journal of Geoinformatics*, 17(4): 41–47. DOI: <https://doi.org/10.52939/ijg.v17i4.1949>
- Ramoelo, A, Skidmore, AK, Schlerf, M, Mathieu, R and Heitkönig, IMA.** 2011. 'Water-removed spectra increase the retrieval accuracy when estimating savanna grass nitrogen and phosphorus concentrations'. *ISPRS Journal of Photogrammetry and Remote Sensing*, 66(3): 408–417. DOI: <https://doi.org/10.1016/j.isprsjprs.2011.01.008>
- Rikimaru, A, Roy, PS and Miyatake, S.** 2002. 'Tropical forest cover density mapping'. *Tropical Ecology*, 43(1): 39–47.
- Rougeulle, A.** 2008. 'A medieval trade entrepôt at Khor Rori? The study of the Islamic ceramics from al-Hamr al-Sharqiya'. In: Avanzini, A (ed.) *A Port in Arabia between Rome and the Indian Ocean, 3rd c. BC–5th c. AD: Khor Rori Report 2*, pp. 645–667. Arabia Antica 5. Rome: L'Erma di Bretschneider.
- Rouse, JW, Haas, RH, Schell, JA and Deering, DW.** 1974. 'Monitoring vegetation systems in the Great Plains with ERTS'. In: *Third Earth Resources Technology Satellite-1 Symposium*, Volume I, NASA SP-351, pp. 309–317. Washington, DC: NASA.
- Seitsonen, O and Égüez, N.** 2021. 'Here be reindeer: geoarchaeological approaches to the transspecies lifeworlds of the Sámi reindeer herder camps on the tundra'. *Iskos*, 24: 124–145.
- Shahack-Gross, R, Marshall, F, Ryan, K and Weiner, S.** 2004. 'Reconstruction of spatial organization in abandoned Maasai settlements: implications for site structure in the pastoral Neolithic of East Africa'. *Journal of Archaeological Science*, 31(10): 1395–1411. DOI: <https://doi.org/10.1016/j.jas.2004.03.003>
- Steele, RE, Reinhardt, EG, Boyce, J, Gabriel, JJ and Vosmer, T.** 2024. 'Closure of Khor Al Balid and Khor Rori harbours/estuaries with coastal uplift and aridity in the 12th–15th c. CE and evidence for an extreme overwash event in the 18th–19th c. CE: implications for ancient port sites in southern Oman'. *Marine Geology*, 471: 107282. DOI: <https://doi.org/10.1016/j.margeo.2024.107282>
- Stenberg, B, Viscarra Rossel, RA, Mouazen, AM and Wetterlind, J.** 2010. 'Visible and near infrared spectroscopy in soil science'. In: *Advances in Agronomy*. Elsevier, pp. 163–215. DOI: [https://doi.org/10.1016/S0065-2113\(10\)07005-7](https://doi.org/10.1016/S0065-2113(10)07005-7)
- Thabeng, OL, Merlo, S and Adam, E.** 2019. 'High-resolution remote sensing and advanced classification techniques for the prospection of archaeological sites' markers: the case of dung deposits in the Shashi-Limpopo confluence area (southern Africa). *Journal of Archaeological Science*, 102: 48–60. DOI: <https://doi.org/10.1016/j.jas.2018.12.003>
- Tigani ElMahi, A.** 2001. 'The traditional pastoral groups of Dhofar, Oman: a parallel for ancient cultural ecology'. *Proceedings of the Seminar for Arabian Studies*, 31: 131–143.
- Tigani ElMahi, A.** 2011a. 'Hematophagous flies in Dhofar (Sultanate of Oman): a limiting factor and a potential pathogenic vector'. *Journal of Agricultural and Marine Sciences*, 16: 65–73. DOI: <https://doi.org/10.24200/jams.vol16iss0pp65-73>
- Tigani ElMahi, A.** 2011b. 'Old ways in a changing space: the issue of camel pastoralism in Dhofar'. *Journal of Agricultural and Marine Sciences*, 16: 51–64. DOI: <https://doi.org/10.24200/jams.vol16iss0pp51-64>
- Tolosana-Delgado, R and Mueller, U.** 2021. *Geostatistics for Compositional Data with R. Use R!* Cham: Springer International Publishing. DOI: <https://doi.org/10.1007/978-3-030-82568-3>
- Tolosana-Delgado, R, Mueller, U and Van Den Boogaart, KG.** 2019. 'Geostatistics for compositional data: an overview'. *Mathematical Geosciences*, 51(4): 485–526. DOI: <https://doi.org/10.1007/s11004-018-9769-3>
- UNESCO.** 2000. *Land of Frankincense*. Available at <https://whc.unesco.org/en/list/1010> [Last accessed 30 January 2026].
- Vermote, EF, Tanre, D, Deuze, JL, Herman, M and Morcette, J-J.** 1997. 'Second simulation of the satellite signal in the solar spectrum, 6S: an overview'. *IEEE Transactions on Geoscience and Remote Sensing*, 35(3): 675–686. DOI: <https://doi.org/10.1109/36.581987>
- Williams, KD, Steimer-Herbet, T, Gregoricka, LA, Saliège, J-F and McCorriston, J.** 2014. 'Bioarchaeological analyses of 3rd millennium BC high circular tower tombs in Dhofar, Oman'. *Journal of Oman Studies*, 12: 153–173.
- Williams, R, Taylor, G and Orr, C.** 2020. 'pXRF method development for elemental analysis of archaeological soil'. *Archaeometry*, 62(6): 1145–1163. DOI: <https://doi.org/10.1111/arcm.12583>
- Wilson, RT.** 2013. 'Py6S: a Python interface to the 6S radiative transfer model'. *Computers and Geosciences*, 51: 166–171. DOI: <https://doi.org/10.1016/j.cageo.2012.08.002>
- Wright, J.** 2016. 'Households without houses: mobility and moorings on the Eurasian steppe'. *Journal of Anthropological Research*, 72(2): 133–157. DOI: <https://doi.org/10.1086/686297>
- Youden, WJ.** 1950. 'Index for rating diagnostic tests'. *Cancer*, 3(1): 32–35. DOI: [https://doi.org/10.1002/1097-0142\(1950\)3:1<32::AID-CNCR2820030106>3.0.CO;2-3](https://doi.org/10.1002/1097-0142(1950)3:1<32::AID-CNCR2820030106>3.0.CO;2-3)

TO CITE THIS ARTICLE:

Koutroumpas, A, Lisch, S, Ruiz-Giralt, A and Biagetti, S. 2026. Invisible Herders, Visible Traces: A Spatio-Chemical and Remote Sensing Approach to Deciphering Pastoral Landscapes in Dhofar, Oman. *Journal of Computer Applications in Archaeology*, 9(1): 418–435. DOI: <https://doi.org/10.5334/jcaa.272>

Submitted: 09 February 2026 **Accepted:** 01 September 2026 **Published:** 19 October 2026

COPYRIGHT:

© 2026 The Author(s). This is an open-access article distributed under the terms of the Creative Commons Attribution 4.0 International License (CC-BY 4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited. See <https://creativecommons.org/licenses/by/4.0/>.

Journal of Computer Applications in Archaeology is a peer-reviewed open access journal published by Ubiquity Press.