Developing reproducible lidar classifications for Greek archaeology: assessing an area-based verification strategy for lidar-based archaeological prospection in the Cyclades, Greece

Brody W. Manquen
Department of Geography and the Environment, University of Texas, Austin
manquen@utexas.edu

Thomas G. Garrison
Department of Geography and the Environment, University of Texas, Austin
thomas.garrison@austin.utexas.edu

Alex R. Knodell
Department of Classics, Carleton College
aknodell@carleton.edu

Demetrios Athanasoulis
Ephorate of Antiquities of the Cyclades, Hellenic Ministry of Culture
dathanasoulis@gmail.com

Introduction

Over the last decade, archaeologists around the world have increasingly added lidar data from aerial and terrestrial platforms to their project toolkit. As lidar-based archaeology has proliferated, experience with the technology has not been evenly distributed. The technology garnered recognition for its ability to precisely map ground surfaces under dense canopy in the heavily forested regions of Mesoamerica, Southeast Asia, and parts of Europe.[1] In the Maya Lowlands, researchers acknowledged the revolutionary nature of the technology early on.[2] Subsequent years of use have allowed its applications to mature, as seen in studies analyzing patterns of social inequality and redefining ancient Maya rural land use.[3] Importantly, this maturation has allowed for the refinement of survey methods as archaeologists have confronted the mistakes of early applications, for example issues of mismatching verification procedures and representational issues in classified datasets.[4]

Despite persistent archaeological interest, the Mediterranean region boasts relatively few lidar-based archaeological studies, with even fewer extending beyond single-site or small area surveys.[5] Many archaeological landscapes of interest in the Mediterranean are situated in modern agricultural areas, both facilitating research and biasing our understanding away from the forested, hilly regions commonly studied with lidar.[6] Furthermore, most lidar-based research in Europe has been conducted in Spain, Italy, Slovenia, and Croatia, often focused on denser forests than the scrub maquis land cover common in Mediterranean hinterlands.[7] Given the nascence of lidar-

[1] Li 2021.
[2] Chase *et al.* 2011; 2012.
[3] Beach *et al.* 2019; Garrison *et al.* 2019; Thompson *et al.* 2021.
[4] Garrison *et al.* 2023; Fontana 2025.
[5] Fontana 2022.
[6] Campana 2018; Attema *et al.* 2020; Knodell *et al.* 2023.
[7] Vinci *et al.* 2024.

based archaeology in Greece,[8] there is opportunity to adapt the best techniques from mature areas of lidar-based archaeological research to existing Greek archaeological practice, thereby ensuring early applications remain useful as the field grows.

Incorporation of remote sensing methods into archaeological practice has driven scholars to examine critically lidar processing and classification survey procedures as a whole. Pre-processed lidar-derived topographic models, like those available for download on many national GIS platforms, risk obscuring acquisition and processing biases and manual feature classification requires significant documentation to present reproducible research, prompting researchers to develop transparent, open-source processing systems for archaeological contexts.[9] Regional spatial analyses that compare feature distributions between survey regions require comparable datasets, and datasets that use different verification strategies may not provide adequate comparability, a lesson only learned as lidar-based Maya archaeology matured.[10]

This article presents an accuracy assessment of a lidar-based archaeological survey in the Greek Cycladic islands. Following a pilot study on Polyaigos in 2022, the Small Cycladic Islands Project (SCIP) – an intensive pedestrian survey project targeting the uninhabited islets of the Cyclades – implemented an accuracy assessment protocol in 2023 to quantify the reliability of lidar for identifying archaeological features in this maquis-dominated landscape.[11] We advocate for transparency in data processing and interpretation, while arguing that the integration of area-based field verification methods into existing Mediterranean pedestrian survey practices provides an ideal model for lidar-based prospection in Greek archaeology, as this approach aligns well with existing practice and provides robust classification datasets for future regional analyses.

Lidar processing and analysis for archaeological research

Lidar data may be acquired from a variety of aerial, terrestrial, and mobile platforms. Each make and model of sensor collects data differently and has its own benefits and restrictions. Mobile lidar devices are increasingly available on phone and tablets and are being used to record archaeological features everywhere from New Zealand[12] to our own field documentation on SCIP. Higher resolution, tripod-based lidar scanners have been used to document larger spaces, like excavation tunnels in Guatemala.[13] However, airborne laser scanning (ALS) systems are by far the lidar sensors most commonly used by archaeologists and are the focus of the present study. A clearly justified acquisition, processing, and visualization method ensures analysts use a transparent dataset for feature classification. As all processing steps prior to analysis affect accuracy results, this justification enables the accuracy data to inform potential sources of error.

ALS data processing

Consideration of lidar acquisition and processing procedures can improve dataset utility for archaeological prospection. Consultation on flight planning includes consideration of desired ground-point density, often weighted against total area to be covered. To balance areal coverage with costs, the acquisition produced lower density point-clouds for larger islands relative to smaller islands, while also providing an assessment of a range of point densities. In practical terms, the lidar sensor flew at two separate altitudes of 3,000 ft (yielding a point density of 34 pts/sq m) and 4,500ft (8 pts/sq m). Following data acquisition, archaeologist input best informs post-flight

[8] Agapiou *et al.* 2022; Lucas and Sánchez 2022; Vinci *et al.* 2024.
[9] Štular *et al.* 2021; Doneus *et al.* 2022.
[10] Garrison *et al.* 2023.
[11] Athanasoulis *et al.* 2021; Knodell *et al.* 2022; Knodell *et al.* 2025.
[12] Cohen-Smith *et al.* 2022.
[13] Garrison *et al.* 2016.

processing and visualization decisions.[14] Ground-point filtering algorithms classify raw elevation points into descriptive classes, with different algorithms having variable abilities to distinguish archaeological features from ground or vegetation classes. This is especially problematic under dense, low vegetation like the maquis cover common in Mediterranean landscapes, prompting the creation of custom ground-filtering algorithms.[15] The consistent contracting of the same lidar acquisition centers and companies by multiple projects – as with the National Center for Airborne Laser Mapping (NCALM) in Mesoamerica and AeroPhoto Ltd. in Greece – allows the remote sensing technicians to refine their algorithms so that they are tailored better to the needs of archaeologists.[16] After classification, interpolation algorithms create continuous elevation surfaces from classified point-clouds. Digital terrain models (DTMs) are surfaces interpolated only from ground points while digital surface models (DSMs) only include the highest point of a given laser pulse.[17] Štular and colleagues additionally propose a digital feature model (DFM) that interpolates using ground and other archaeologically relevant point classes to provide the most comprehensive single surface model for archaeological applications.[18] Interpolation algorithm choice impacts the topographic fidelity and surface noisiness of the model, potentially limiting archaeological interpretability. The same scholars propose a hybrid algorithm to maximize archaeological utility of elevation models without selecting the most time-consuming algorithms. Visualization algorithms manipulate these interpolated surfaces to enhance their utility for analysis.[19]

Different visualizations are suitable for different landscapes and features, thereby affecting classification quality and reproducibility. Usually, archaeologists use 2.5D visualizations – images that mimic 3-D environments in a 2-D setting – built from elevation models to aid interpretation. Simple illumination models, particularly the basic hillshade, are commonly used due to perceived intuitiveness and ease of computation but risk oversimplification, prompting the creation of alternative models like the multidirectional hillshade.[20] Additionally, topographic filtering algorithms calculate topographic parameters such as slope or local dominance that remove the visual bias of landscape features, emphasizing useful topographic indices.[21] Blends, like the Red Relief Image Map (RRIM) or the Visualization for Archaeological Topography (VAT), combine multiple visualizations into one image to reduce visualization switching, although complex manipulation of the DTM risks obscuring certain topographic features which might cause confusion for the analyst (Figure 1).[22] Consultation of multiple visualizations during feature classification ensures the most robust results.

Feature classification and verification

The company or center responsible for acquiring the data commonly conducts the point classification necessary to create the visualizations described above, though this may be done in consultation with archaeologists. Conversely, archaeologists, ideally with a background in remote sensing and familiarity with the landscape represented in lidar visualizations, typically perform the feature classification necessary to extract archaeological information from lidar data. A description of the classification process and a standardized field verification strategy are necessary to give confidence to classified features across the whole dataset, especially when verification of all features is impractical. The decision-making process for classification is opaque but can be split between 'interpretative mapping',[23] where local and archaeological knowledge

[14] Lozić and Štular 2021.
[15] Doneus, Mandlburger, and Doneus 2020; Štular and Lozić 2020.
[16] Fernandez-Diaz *et al.* 2014.
[17] Dong and Chen 2018.
[18] Štular *et al.* 2021.
[19] Štular *et al.* 2023.
[20] Kokalj and Somrak 2019; Crabb *et al.* 2023.
[21] Štular *et al.* 2012; Doneus 2013; Crabb *et al.* 2023.
[22] Chiba *et al.* 2008; Kokalj and Somrak 2019; Crabb *et al.* 2023.
[23] Doneus, Doneus, and Cowley 2022.

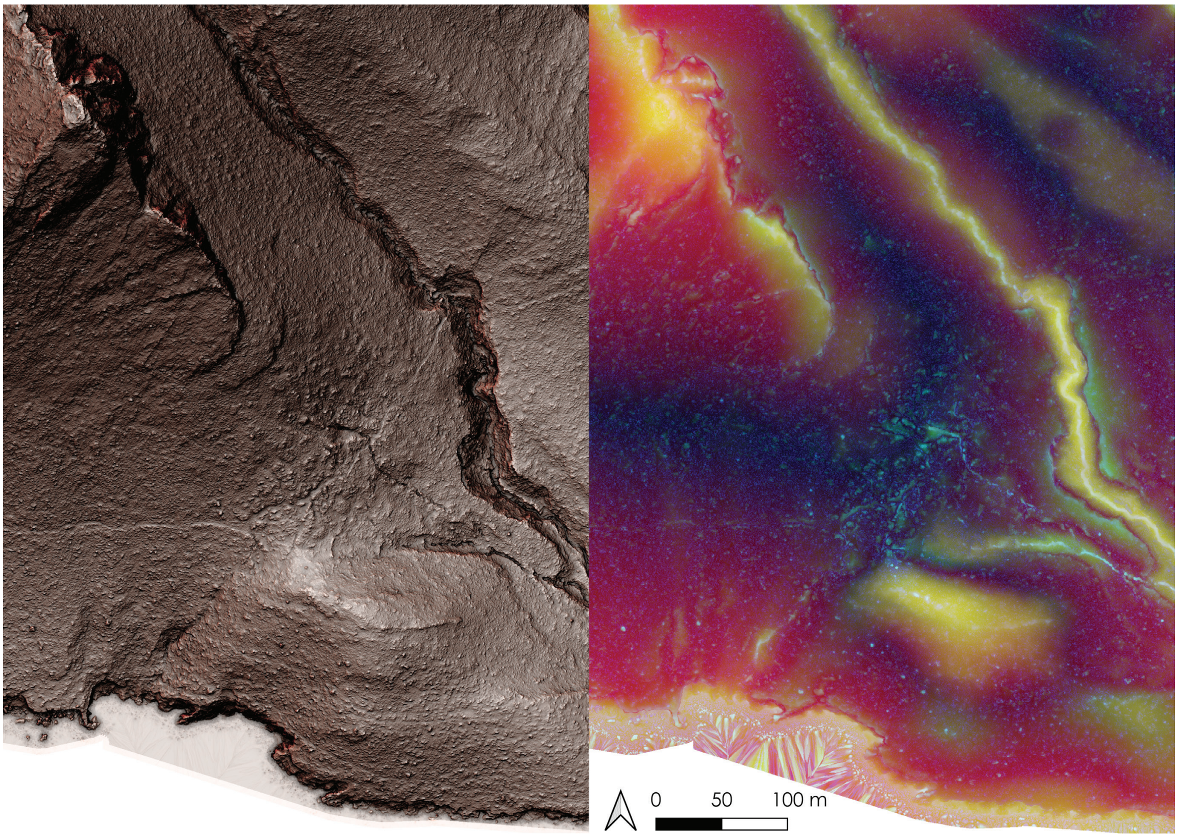

Figure 1. Comparison of the multiscale topographic position index (MSTP), a complex blend visualization representing each pixel's relative position at three scales, with a slope raster overlaying a simpler VAT blend. Distinguishing between high and low elevations is difficult in the MSTP without training. (Map by B. Manquen).

informs feature classification, and geospatial parameter calculations.[24] Although easy to record, geometric parameters do not remove classification subjectivity, as classification rarely relies on the convergence of multiple parameters. Conversely, the archaeological or remote sensing experience that influences visual interpretation is not readily parametrized and reported. It is thus difficult to reproduce precisely how analysts interpret visualizations, especially if descriptions of parameters are missing.[25] Each attribute must be considered as a tradeoff between analytical utility and time added to the classification process, which will depend on project needs. Furthermore, both the feature category choices and the analyst's skill and experience introduce bias into the classification,[26] with multi-analyst methods requiring significant resources to conduct.[27] Beyond human analysts, artificial intelligence models hold potential for replacing or augmenting reliance on individual analysts altogether, although research using these tools remains highly localized at present and still require an archaeologist familiar with the region being analyzed in order to implement correctly and assess accuracy.[28]

Once classified, results must be verified. Garrison and colleagues describe three methods commonly used for verifying classified archaeological features: map-based verification, where the verification team compares the classification to maps of known features from previous work in a region, target-based verification, where the verification team selects features for field visitation, and area-based

[24] Grammer *et al.* 2017; Hutson 2015.
[25] Doneus, Doneus, and Cowley 2022; Lozić and Štular 2021 suggest standardized analytic templates.
[26] Cowley 2016; Grammer *et al.* 2017; Garrison *et al.* 2023.
[27] See Quintus *et al.* 2017 for a robust multi-analyst workflow. Overlap in classification area assigned to individual analysts reduces accuracy biases, but redundancy limits the time-saving benefits of employing multiple analysts.
[28] See Bickler 2021 for a brief overview of the applications of machine learning to remote sensing archaeology.

verification, where a verification team mixes a target-based system a systematic ground survey to find missed features.[29] The same authors argue that the area-based method most comprehensively assesses the classification system because it systematically identifies both false negatives and false positives, giving a clear sense of both under- and overidentification issues in the classification methodology. They warn that inattention to classification assessment practices early in lidar-based research affects later studies, as differences in feature densities between regions might be skewed by the verification method of each regional project, not by a real difference in features.

Fortunately, intensive pedestrian survey methods that are common in Mediterranean landscape archaeology are readily transferable to area-based verification methods.[30] The side-by-side coverage of survey grid cells is functionally the same design as the area-based verification strategy. Integration of lidar prospection into an existing intensive survey or expansion of side-by-side fieldwalking methods to the scale of a larger-scale lidar survey can help achieve robust, verified lidar datasets. Additionally, the overlap in design reflects shared concerns about data biases and comparability between practitioners of both methodologies.[31] This beneficial conversation between fields mirrors how lidar methods can benefit Mediterranean survey archaeology. Survey projects are commonly biased against the steep, scrub-covered landscapes that inhibit visibility and mobility, what Campana calls 'emptyscapes' due to the temporal and spatial patterns of past land use lost due to this phenomenon.[32] Remote sensing methods have been proposed to mitigate this bias.[33] The SCIP team confronted many of the challenges described above during the integration of lidar data into the pre-lidar database, as the project had three seasons of data collection prior to the first lidar acquisition flight in May of 2022.[34]

Regional setting

The Small Cycladic Islands Project is a regional archaeological survey of the many small, uninhabited islets across the Cyclades. The diachronic intensive survey of these islets investigates human interactions with these dry, remote island landscapes, from periods of occupation to ephemeral visitations, as well as their relative integration into cultural and economic networks at multiple scales.[35] The project seeks to understand how both material resources and evolving cultural conceptions of marginality and nodality have shaped islet habitability, following calls from island archaeologists to focus on small islands networks for their sensitivity to regional trends.[36] Fieldwork in 2023, the subject of the verification program of this paper, focused on the islets around Andros, Tenos, Mykonos, and Amorgos (Figure 2).

Methods

We developed a systematic feature classification protocol to map and describe all archaeological features on each islet surveyed in the 2023 field season using lidar-derived visualizations and orthophotographs, following preliminary uses of lidar survey during the 2022 field season.[37] AeroPhoto Ltd. collected lidar point-clouds for about 100 Cycladic islands covering 84 km^2 of land. All visualizations derived from lidar as part of SCIP use these data. AeroPhoto collected lidar data

[29] Garrison *et al.* 2023.
[30] Knodell *et al.* 2023 detail the widespread application of this method in Greece and the Mediterranean. See also Attema *et al.* 2020; Knodell 2025.
[31] Knodell and Leppard 2018; Attema *et al.* 2020 describe the breadth of the representation biases common among intensive survey projects, along with some remedies.
[32] Campana 2018; see also Attema *et al.* 2020; Knodell *et al.* 2023 show that few intensive surveys in the Mediterranean occur outside of low elevation, open, agricultural landscapes. See Caraher *et al.* 2020, Roussos 2020, and Wiersma *et al.* 2022 for examples of 'emptyscapes' in Greek landscape archaeology.
[33] Agapiou *et al.* 2022; Meyer 2023. Canuto *et al.* 2018 address a similar situation in Maya landscape archaeology using lidar.
[34] Knodell *et al.*, this volume.
[35] Athanasoulis *et al.* 2021; Knodell *et al.* 2022.
[36] Fitzpatrick *et al.* 2016; Braje *et al.* 2017; Dawson 2019; Athanasoulis *et al.* 2021; Knodell *et al.* 2022.
[37] Knodell *et al.* 2025.

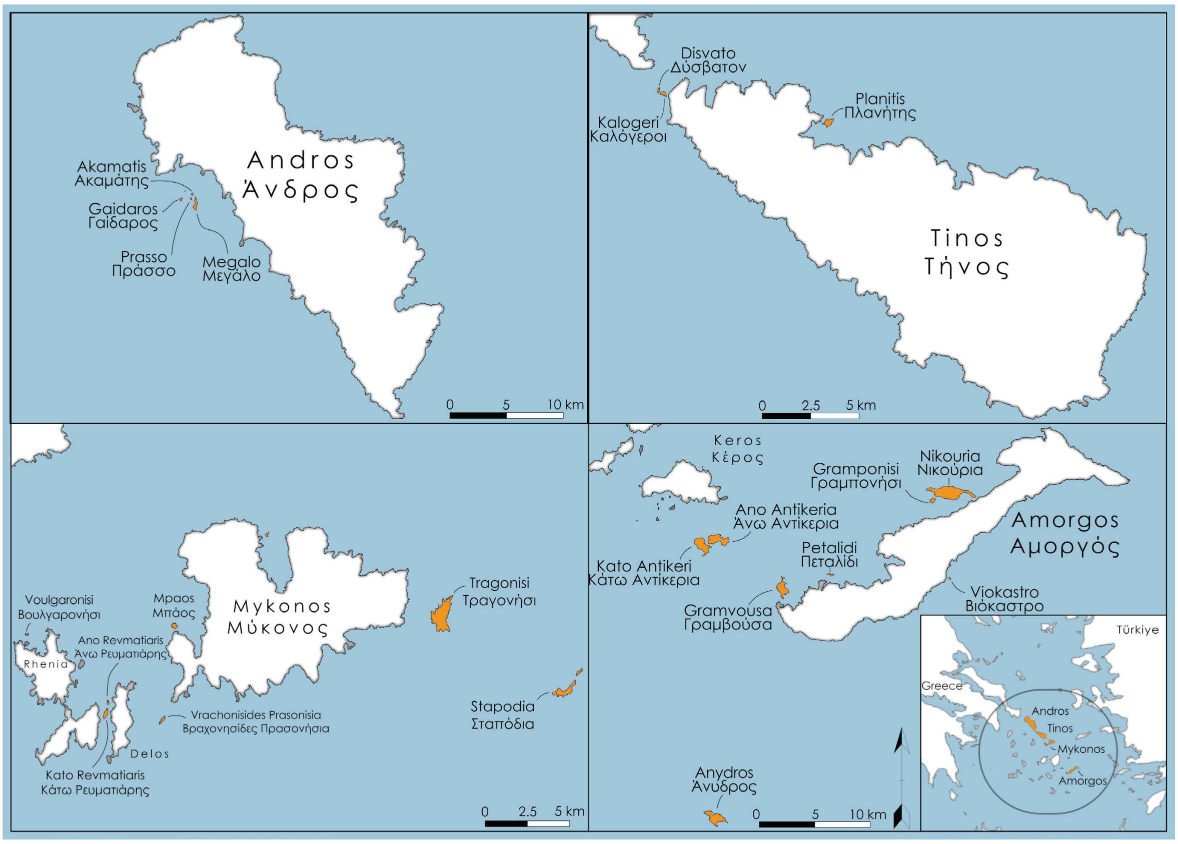

Figure 2. Map of islets surveyed around Andros, Tinos, Mykonos, and Amorgos during the 2023 field season of the Small Cycladic Islands Project (SCIP) using lidar methods. (Map by B. Manquen).

with a RIEGL VQ-1560i sensor with 30% sidelap at 58.52-degree field-of-view in late April 2022 after consultation between AeroPhoto, Knodell, and Garrison. For the 2022 data, two flight altitudes achieved two target point densities: 3000ft for 34pt/m^2 and 4500ft for 8pt/m^2. Laser pulse repetition rate (PRR) maxima were 2x2MHz and 2x800kHz for each altitude, respectively. AeroPhoto carried out a second set of flights in the spring of 2023 using a RIEGL VQ1560II with integrated Applanix 610/IMU-57 and PhaseOne iXU-RS 1000 50mm RGB 100MP camera; the mean AGL for this flight was 3600 ft with 25pt/m^2 resolution. The data cover a mix of previously surveyed islands, islands with planned pedestrian surveys, and test islands without plans for pedestrian survey. Of the 84 islands, SCIP selected 23 islets covering 9.48km^2 for both lidar and pedestrian survey during the summer 2023 field season. The aggregate dataset point density for these 23 islands is 20.5pt/m^2. AeroPhoto provided 0.25m-resolution DSMs and DTMs, as well as orthophotos ranging in resolution between 0.08m–0.12m.

We processed each point-cloud with a standardized processing pipeline. First, Manquen created a DFM interpolating ground, building, and archaeological feature lidar point codes (2, 6, and 19, respectively) using lidR[38] package for R version 4.3.2 and employing an ordinary kriging interpolation method (k=20) at 0.25m resolution for most islets. We created the DFM for Nikouria, Amorgos using the inverse distance weighted (IDW) interpolator due to processing power limitations. We then created a suite of five visualizations for the DFMs and DSMs (Figures 3 and 4) using the Relief Visualization Toolbox[39] Python library in JupyterNotebook. The processing and visualization pipeline produced 23 0.25m DFMs and 230 visualizations, five per DFM and five per DSM. These visualizations balance analysis time and analytical power by having multiple, complementary

[38] Roussel *et al.* 2020.
[39] Zakšek *et al.* 2011; Kokalj and Somrak 2019.

Visualization	Composition	Strengths	Weaknesses
Basic	DFM (topographical color ramp; 80% opacity; Multiply blend mode) **over** Hillshade (315 azimuth, 35 elevation; singleband gray; 100% opacity; Normal blend)	**Landscape-scale topography**	Microtopography
Slope-VAT	Slope (White-Red color ramp; 80% opacity; Multiply blend mode) **over** VAT (singleband gray; 100% opacity; Normal blend)	**Microtopography; landscape-scale topography**	Relief
Red Relief Image Map	Openness Index (Green-Yellow color ramp; 80% opacity; Multiply blend mode) **over** Slope (White-Red color ramp; 100% opacity; Normal blend)	**Relief, microtopography**	Gentle features
Local Dominance	Local Dominance (Rainbow color ramp; 80% opacity; Multiply blend mode) **over** Hillshade (315 azimuth, 35 elevation; singleband gray; 100% opacity; Normal blend)	**Relative elevation (large-scale)**	Landscape-scale topography
Gradient Relief Model	Simple Local Relief Model (Radius: 16 px; Blue-Yellow-Red color ramp; 60% opacity; Normal blend mode) **over** Gradient Relief Base (three-band color composite; 100% opacity; Normal blend)	**Relative elevation (small-scale)**	Landscape-scale topography

Figure 3. Visualization suite used for lidar-based classification. Strengths and weaknesses are reported from user experience. (Table by B. Manquen).

representations of the landscape.[40] We loaded the generated rasters into QGIS Version 3.28 *Firenze* for feature classification.

We conducted manual archaeological feature classification for each islet prior to visitation for intensive survey. Two analysts divided the dataset, with three islets (Am-AA, Am-KA, and Am-AN) analyzed by Rosie Campbell, the rest by Manquen. Typically, the orthophoto and Slope-VAT visualizations were the base visualizations used to start the identification process, after which the local dominance and the gradient relief model enabled fine-tuned feature classification (Figures 5A and 5B). The analyst drew identified features as line vector geopackage files (.gpkg) with multiple attributes, most importantly the feature type category (Figure 6). We also used the 'lidar notes' field to describe characteristics that justified classification or expressions of uncertainty. The 'Area of Interest' (AOI) classification marked features with high uncertainty as a precaution, as the full coverage of the field verification strategy afforded visitation of highly unlikely features as a precaution. Both line and polygon vectors marked structures, terrace complexes, enclosure systems, and quarries (Figure 5C).

We verified all classified features during the 2023 SCIP field season using a mixed target-based and area-based methodology, which seamlessly integrated into the existing intensive pedestrian survey. A feature documentation team conducted a target-based verification for each classified feature using QField for Android. Additionally, the intensive pedestrian survey teams noted any missed features discovered during side-by-side survey, providing the area-based coverage necessary to identify false negatives in lidar feature classifications.[41] All verified features were labelled as false positive (FP), false negative (FN), or true positive (TP).

After verification, we removed weak classifications and split multipart features into individual vectors. We defined weak classifications as those features labelled as highly uncertain during the

[40] Kokalj and Somrak 2019.
[41] Garrison *et al.* 2023.

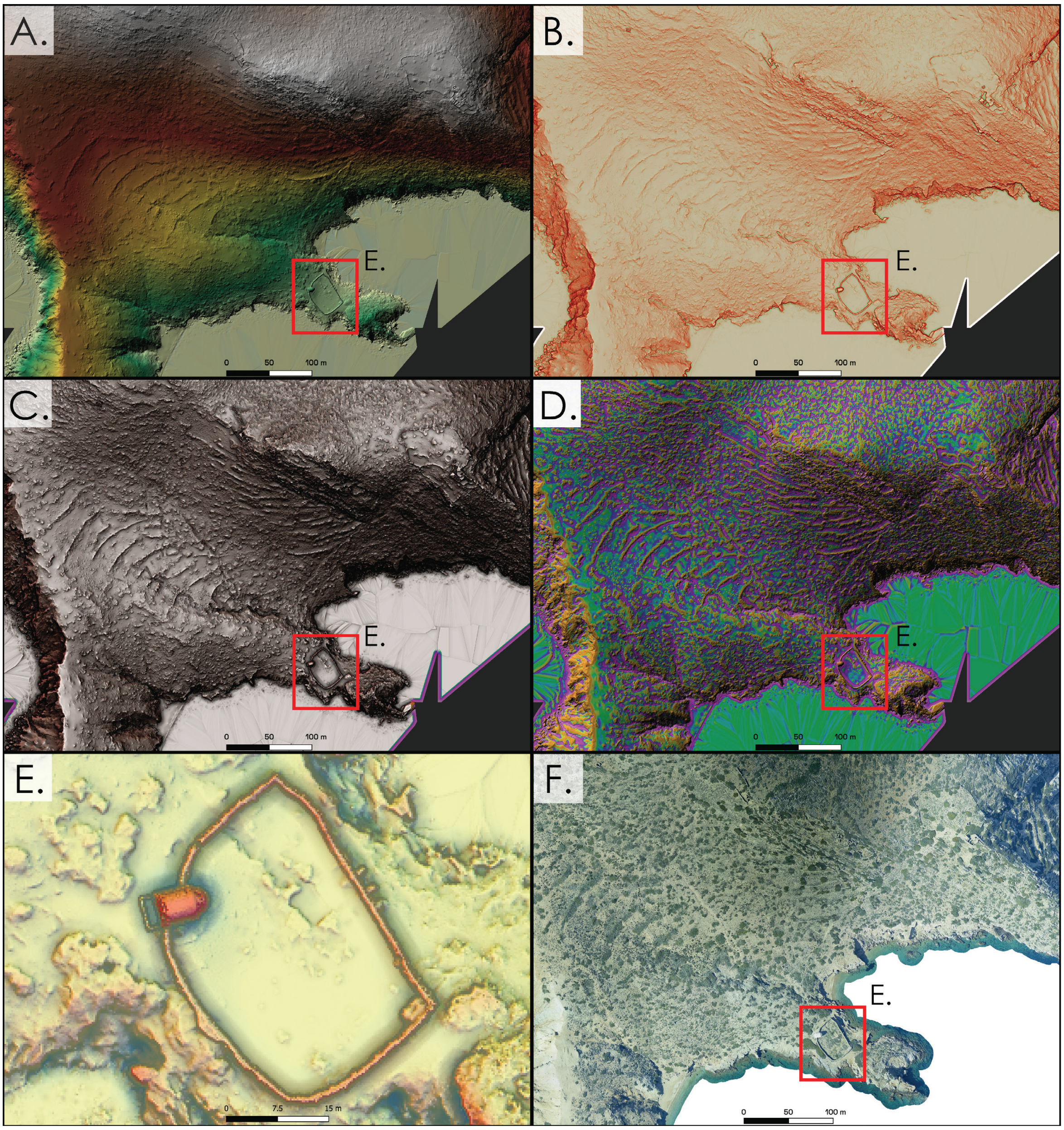

Figure 4. Examples of visualization methods applied to the islet of Gramvousa, near Amorgos: (A) Basic Visualization; (B) RRIM; (C) Slope-VAT; (D) Local Dominance; (E) Gradient Relief Map; (F) Orthophoto. (Map by B. Manquen).

initial classification. None of these highly uncertain features were true features. We then cleaned multipart vectors with significant separation between parts by splitting them into individual segments in QGIS to reflect the classification of individual features in the visualizations. This rule only applied to agricultural terrace complexes and pastoral systems where analysts identified wall segments as independent objects. Segment splitting aimed at assessing lidar's ability to detect individual objects.

We then exported feature vectors from QGIS as a comma-separated values file (.csv). These vectors contained error data used to create an error table with the dplyr package for RStudio (R Version 4.3.1) (Figure 7). We calculated four accuracy metrics for each feature category. 'Accuracy' is the ratio of true positives to total feature count. 'Precision' (or 'User's Accuracy') accounts for commission errors (Type I) and is the ratio of true positives to both true and false positives. 'Recall' (or 'Producer's Accuracy') accounts for omission errors (Type II) and is the ratio of true positives

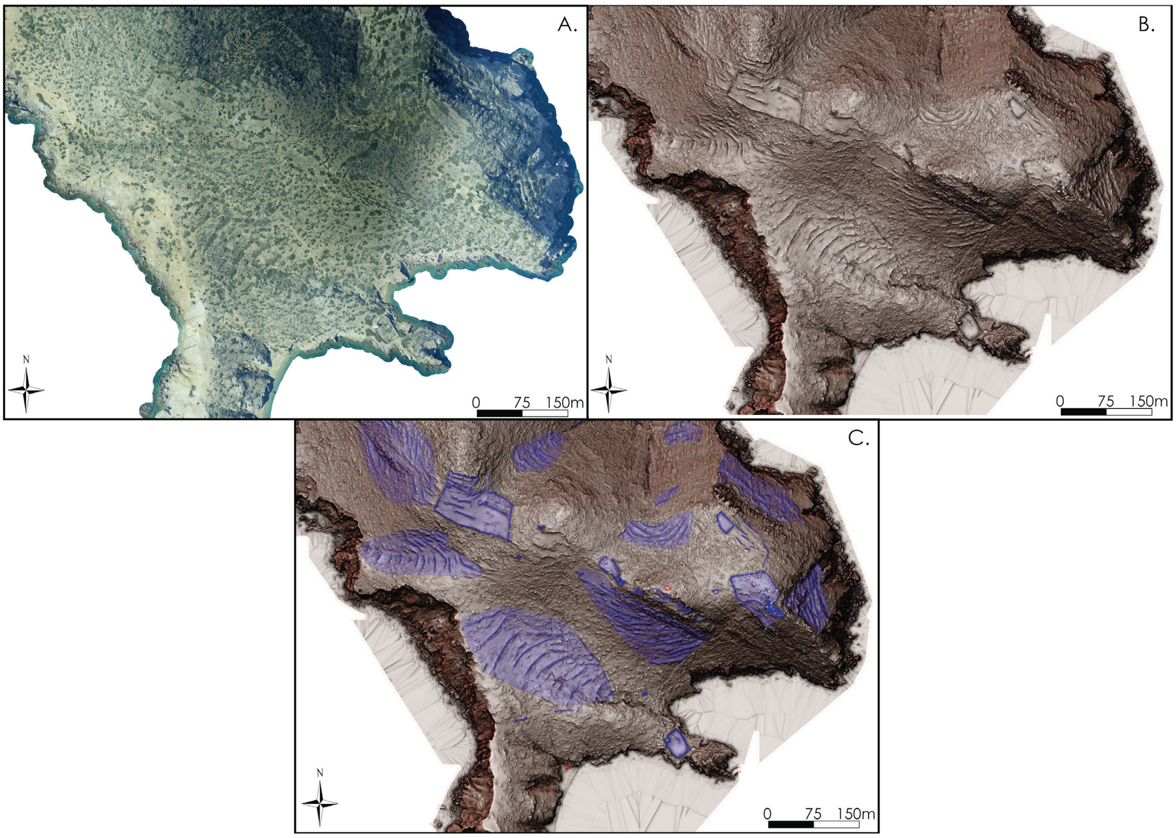

Figure 5. Sample classification inputs and results for the islet of Gramvousa, Amorgos: (A) Orthophoto; (B) Slope-VAT; (C) Final classification as multiline and polygon vectors. (Map by B. Manquen).

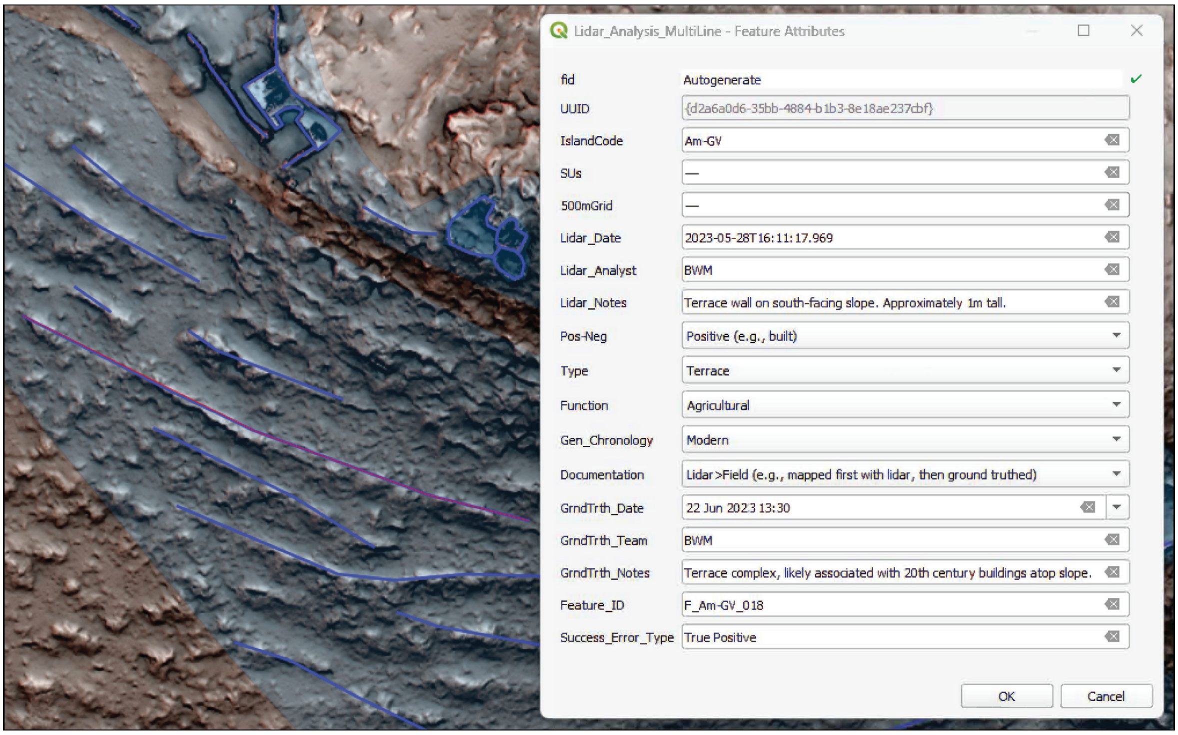

Figure 6. Attribute input pop-up used to digitized features during manual classification. (Image by B. Manquen).

Type	Total	True Positive	False Positive	False Negative	Accuracy	Precision	Recall	F1
Terrace Walls	406	358	43	5	88.2%	89.3%	**98.6%**	93.7%
Structures	193	158	13	22	81.9%	**92.4%**	87.8%	90.0%
Walls	140	107	22	11	76.4%	82.9%	**90.7%**	86.6%
Other	157	77	46	34	49.1%	62.6%	69.4%	65.8%
Total (w/ Other)	896	700	124	72	78.1%	85.0%	90.7%	**87.8%**
Total(w/o Other)	739	623	78	38	84.3%	88.9%	94.3%	**91.5%**

Figure 7. Validated accuracy results of the 2023 lidar survey. (Table by B. Manquen).

to true positives and false negatives. 'F1 Score', or the harmonic mean of precision and recall, is a single statistic that evaluates the classification method's ability to correctly identify features while minimizing both false positives and negatives.[42]

Results

After data cleaning and splitting, the final feature dataset contained 896 feature segments corresponding to 234 unique features. Figure 7 presents the accuracy table for all feature classes with more than 50 occurrences. Only three feature classes have more than 50 occurrences. Both the 'terrace' and 'wall' classes have higher recall than precision, with the 'structures' class displaying the reverse. The field team typically verified extensive terrace complexes as units, with any falsely identified or missed segments added if detected. During classification, we placed walls that were not clearly part of a terrace complex or structure – typically pastoral enclosures or check dams – in the 'wall' class. The tendency to classify uncertain linear features as 'wall' rather than 'terrace' may explain the lower accuracy rate for 'wall' compared to 'terrace'.

The 'other' class in Figure 7 represents feature classes containing fewer than 50 instances. Figure 8 presents these classes separately because they should be interpreted cautiously due to low sample size. The most common features are the 'pit' and 'mound' categories, which we consider true positives only if anthropogenic in origin. Miscellaneous features include rock cairns, graffiti, salt pans, rock cuttings, debris, and construction equipment. While these features are important for understanding human behavior on the islets, they are usually too small and indistinct to register in the lidar visualizations.

Type	True Positive	False Positive	False Negative	Accuracy	Precision	Recall	F1
Cave or Shelter	0	0	3	0.0%	NA	0.0%	NA
Cistern	0	0	1	0.0%	NA	0.0%	NA
Mine	11	2	1	78.6%	84.6%	91.7%	**88.0%**
Misc.	12	6	23	29.3%	66.7%	34.3%	45.3%
Mound	6	13	2	28.6%	**31.6%**	75.0%	44.4%
Pit	8	19	1	28.6%	**29.6%**	88.9%	44.4%
Quarry	3	4	1	33.3%	37.5%	75.0%	50.0%
Roads and Paths	32	2	1	91.4%	94.1%	97.1%	**95.6%**
Threshing Floor	5	0	1	83.3%	100%	83.3%	90.9%

Figure 8. Validated accuracy results for feature classes composing the 'other' group in Figure 7. (Table by B. Manquen).

[42] Campbell *et al.* 2023.

Our method did not systematically assign chronological periods during the lidar classification, following SCIP's diachronic interest in documenting all features present on each islet. Our method did not measure misclassifications, or features identified but assigned an incorrect class. Finally, we dropped the AOI category (15 occurrences) from analysis because we did not identify AOIs systematically but instead marked them as precautionary areas to investigate if time permitted.

Discussion

The inclusion of both false positive and false negative features in the systematic classification verification facilitates reflection on the relative strengths of the classification methodology for each feature type. A key strength of the area-based method is the ability to generate precision, recall, and F1 scores.[43] Our methodology confidently produced this information for the 'terrace', 'wall', and 'structure' classes, and for other smaller classes. Furthermore, the full island coverage of the intensive pedestrian survey and area-based verification enabled our method to prioritize feature detection over classification precision, which is reflected in the overall higher recall compared to precision, though this trend varies somewhat by feature class.

Classification accuracy

The 'terrace' and 'wall' classes, both linear features with similar profiles in the remote sensing imagery, present similar accuracy trends. Since we are interested in evaluating the classification method by its success in identifying features while balancing false positives and false negatives, we prioritize using the F1 score to interpret classification performance. The 93.7% F1 score achieved for the 'terrace' class reflects the recognized strength of lidar prospection for detecting archaeological terraces both within the Mediterranean and in other regions.[44] Specifically, recall scores are significantly higher than precision scores for both types, indicating that the analysts rarely missed these features during classification. A recall of 98.6% for terraces suggests that terrace complexes are highly visible under Mediterranean maquis land cover. Conversely, the lower precision scores suggest that this methodology produces false positives for these linear wall features. A likely source of this error are the linear erosional patterns commonly found on these landscapes (Figures 9A and 9B). In these cases, analysts mistook natural bedrock patterns for fragmented, aggraded walls or agricultural terraces assuming that the messy signatures in the visualizations represented older, poorly preserved anthropogenic constructions. The source of these geomorphic features is likely related to the complex extensional geology of the region[45] combined with aeolian and/or coastal erosional processes,[46] although we did not collect geomorphological information during the field verification.

Classification accuracy remained high for the 'structure' class overall but reversed the precision and recall pattern of linear features. The 90% F1 score reflects the high overall accuracy, but unlike the total trend, this category has higher precision compared to recall. This indicates that the classification methodology produced fewer false positive identifications of structures compared to other features. Instead, it more commonly failed to identify verified structures. This is likely due to the prevalence of small structures, some of which were obscured by slope and low vegetation (Figures 9 C and 9D), although our method did not statistically test causality. However, for many structures left unmarked during remote classification, only georeferenced photographs from field verification allowed for detection in the GIS, because the structures were indistinguishable from normal terrain in the lidar visualizations. Hutson and colleagues demonstrated that lidar prospection techniques for archaeology face a 'small buildings problem', defined as when lidar-

[43] Garrison *et al.* 2023.
[44] Chase *et al.* 2011; Godone *et al.* 2018; Agapiou *et al.* 2022.
[45] Searle and Lamont 2022.
[46] Evelpidou *et al.* 2021.

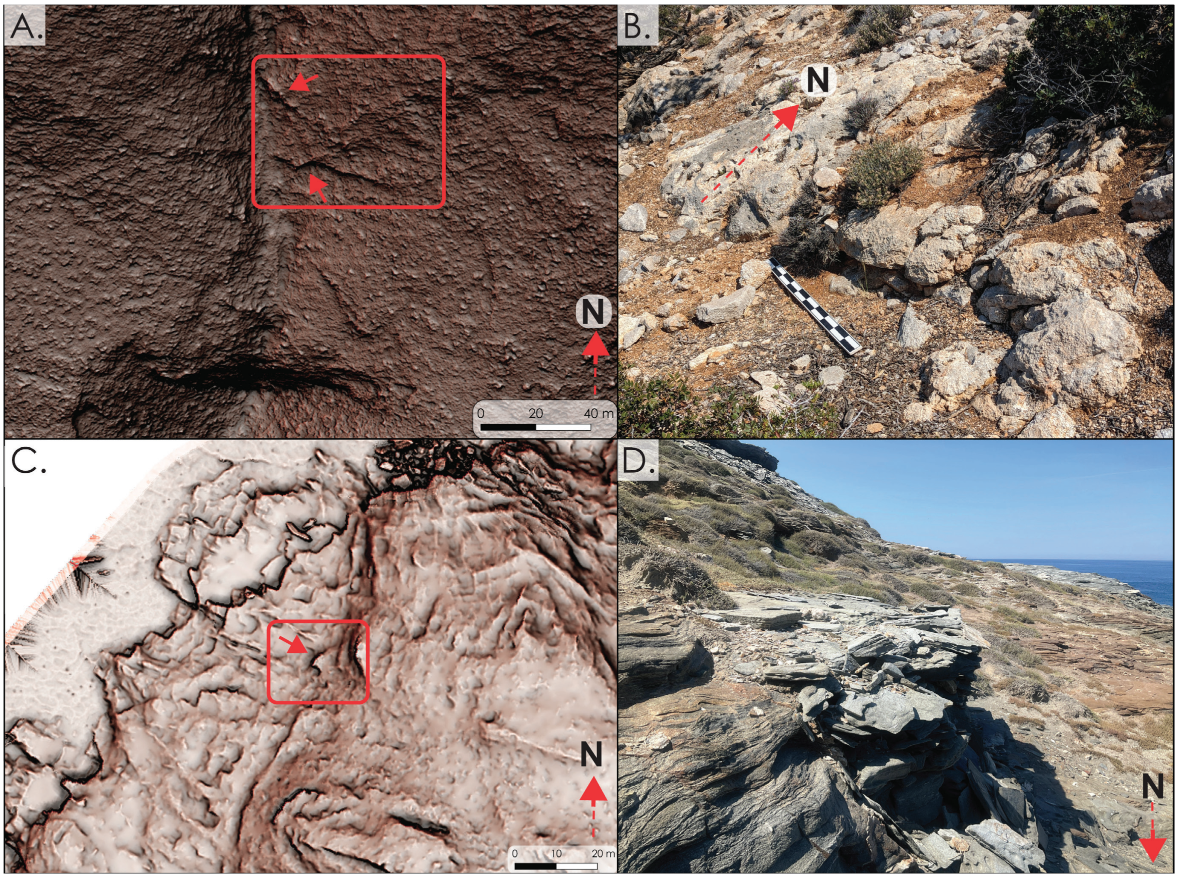

Figure 9. Examples of false positive 'terrace' classification (A-B) and false negative 'structure' classification (C-D). (Map by B. Manquen).

based survey consistently struggles at identifying buildings of certain size thresholds.[47] The authors argue that this issue can best be corrected by selective intensive pedestrian surveys – akin to area-based verification – to establish correction factors to the feature count. More broadly, this research suggests that area-based verification could help correct systematic biases against certain feature types or chronological periods, a known issue in lidar classification analyses.[48] Additionally, statistically assessing the effectiveness of visualizations for subtle feature types such as small buildings may optimize visualization selection.[49]

Among the feature types with fewer than 50 occurrences, 'pits' and 'mounds' represent large sources of error in this study but are in-line with the project's prioritization of feature detection over precision. Both feature types have low precision, likely because natural landscape elements like rocky terrain and patchy vegetation created relative elevation anomalies which easily can be mistaken as anthropogenic (Figure 10). The emphasis placed on these minute elevation differentials by the local dominance visualization, potentially in conjunction with its rainbow color scheme,[50] might have exacerbated the false positive incidents. Among the low-count feature types, the classification of 'mines' and 'roads and paths' was highly accurate. While the latter two follow the general strength of lidar for linear features, the former reflects the scars of mining systems on the landscape, which lidar has been effective in detecting at larger scale elsewhere in the Mediterranean.[51]

[47] Hutson *et al.* 2016.
[48] Fontana (2025) assesses the sampling representation problem in lidar-based classifications.
[49] For examples of studies analyzing visualization effectiveness, see Masini *et al.* 2022 and Crabb *et al.* 2023
[50] Gołębiowska and Çöltekin (2022) note that rainbow color schemes may present data more noisily than other options, impeding interpretation.
[51] E.g., the detection Roman hydraulic gold mining scars in NW Spain by Fernández-Lozano *et al.* 2019.

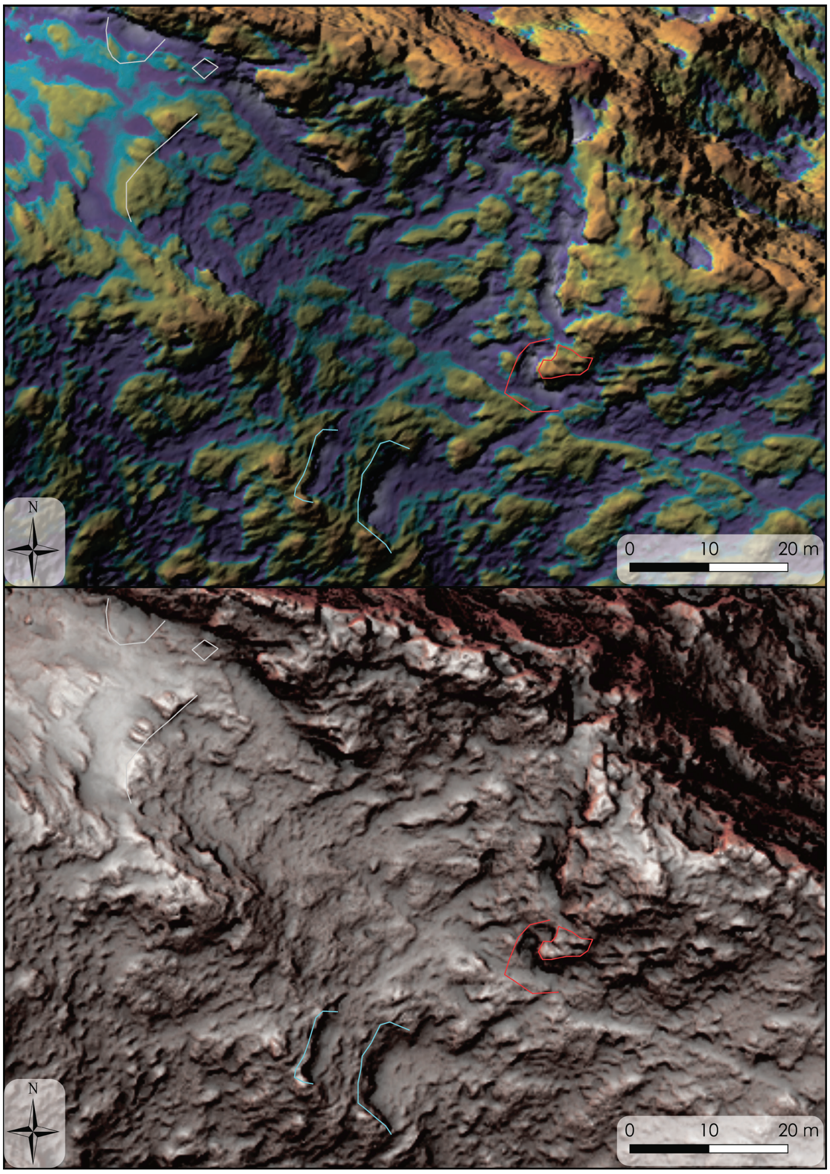

Figure 10. Comparison of Local Dominance visualization (top) with Slope-VAT visualization (bottom). False positive 'quarry' features are in red, true positive 'quarry' features are in blue. (Map by B. Manquen).

Lidar archaeology in marginal Mediterranean landscapes

The high accuracy demonstrated in this study suggests lidar classification and area-based verification may benefit the study of marginal archaeological landscapes in Greece and the Mediterranean. The dry, hard-to-reach small Cycladic islets fit the 'emptyscape' concept proposed by Campana, which theorizes that our spatial and temporal conceptions of ancient landscape engagements are biased against marginal environments by a lack of efficient survey mechanisms suited to such places. While intensive pedestrian survey alone has helped fill in these gaps in the Cyclades,[52] our results confirm the capacity for lidar-based remote sensing methods to quickly map features indicative of engagements with past marginal landscapes.[53]

The high accuracy for terraces and pastoral structures in this study provides evidence for the utility of lidar-based prospection methods for the study of terraced agropastoral landscapes. Abandoned, overgrown terraced slopes are relatively understudied, largely due to historical difficulties

[52] Roussos 2020; Athanasoulis *et al.* 2021; Knodell *et al.* 2022.
[53] Campana 2018; Fontana 2022.

obtaining clear chronologies for terrace use.[54] Paired with recent developments in terrace dating,[55] high accuracy lidar surveys of terraced landscapes can facilitate more comprehensive understandings of the extent of unknown, marginal agricultural land use, further elucidating spatiotemporal patterns of agricultural production and landscape investment that may not be reflected in agricultural valleys.[56]

Additionally, area-based verification results provide useful insights toward the study of lesser-known landscapes. First, map-based verification is impossible in regions without high quality archaeological maps, such as the 'emptyscapes' where lidar may be used. Gaining the spatial distributions of true positives, false positives, and false negatives for each feature type enables use of a lidar-derived dataset as a sample area for regional spatial analyses, permitting extrapolation over similar, understudied landscapes.[57] Error analysis is critical to assessing the overall efficacy of a lidar dataset and acknowledging its limitations. However, we also recognize that target-based or map-based approaches may be suitable for specific project designs, for example for surveys of specific feature types only found in known locations or in regions with high quality maps.[58] Furthermore, area-based verifications performed across larger landscapes could occur over subsets of the lidar dataset rather than the full coverage achieved here, considering variables such as existing archaeological knowledge and lidar sensor capabilities in planning the sampling strategy.[59]

Conclusions

This article has sought to demonstrate the benefits of area-based feature verification for lidar-derived survey datasets in Greek archaeological landscapes. In support of this, we present the results of our own lidar verification program, which we successfully integrated into the intensive pedestrian survey of the Small Cycladic Islands Project. Lidar-based survey has great potential to uncover previously obscured Greek archaeological landscapes.[60] To maximize its utility, landscape-scale surveys would benefit from exploiting lessons learned from mature archaeological fields of lidar-based research to refine transparent, reproducible research. Along with using advanced processing and visualization techniques, incorporating robust feature verification protocols that can detect sources of classification error in Mediterranean ecosystems and facilitate future comparative research is an essential component to any project design looking to include lidar data.[61] Area-based verification designs that detect true positive, false positive, and false negative accuracy provide useful data for such comparisons.

SCIP's field-verified dataset allows for useful insights into the properties of the lidar-based classification. Detailed discussion of acquisition, processing, and visualization methods facilitated the interpretation of accuracy results of linear features as potentially linked to the local dominance visualization and/or the rainbow color scheme. In addition to identifying the classification accuracies of each feature class, the specific inclusion of both false positive and false negative information confirmed the pattern of a 'small building problem'[62] for this research area. More broadly, well-founded, verified feature datasets help lidar-based archaeological prospection

[54] Whitelaw 1991; Bevan and Conolly 2011; Brown *et al.* 2020.
[55] Brown *et al.* 2020; Turner *et al.* 2021.
[56] For example, the potential link between climate cooling and terrace investment in between the 12th- to early 16th-centuries AD in southeastern Turkey suggested by Turner and colleagues (2021).
[57] Garrison *et al.* 2023; Fontana 2025.
[58] For example, the target-based verification of hillforts by Fontana (2022) would not have benefitted from an area-based survey of the whole lidar DTM area, since hillforts will not be found on the valley floor.
[59] Garrison *et al.* 2023; see Štular, Lozić, and Eichert (2021) for their Confidence Map rasters which estimate lidar data quality across a given DFM.
[60] Knodell *et al.* 2023; Fontana 2025.
[61] Garrison *et al.* 2023.
[62] Hutson 2016.

address existing survey biases against marginal, hard-to-reach landscapes in the Mediterranean,[63] by enabling treatment of classification results as representative samples of the broader, otherwise poorly known landscapes.[64]

Fortunately, area-based designs can be readily integrated into traditional intensive pedestrian survey techniques common in Mediterranean survey archaeology.[65] The area-based verification conducted as part of SCIP utilized the side-by-side fieldwalking strategy to detect false negatives while a separate team verified remotely classified features. While the comprehensive coverage achieved as part of this survey is unrealistic for larger landscape surveys, the design principle is likely transferable to future lidar-based surveys when appropriate. In addition to scale, research questions may also impact lidar verification methods.[66] Most importantly, scholars looking to integrate lidar into Mediterranean research must communicate with one another to produce lidar-enhanced survey results that are comparable between projects – as exemplified by the contributions to this special issue – facilitating justifiable and meaningful regional interpretations at increasing scales of analysis.

Acknowledgements

Lidar data were provided by Carleton College and the Ephorate of Antiquities of the Cyclades, funded by a US National Science Foundation Senior Archaeological Research Grant (Award ID 2150873, PI: Alex Knodell), with additional support from the University of Texas at Austin, the University of Oklahoma, the Ephorate, and Carleton. Manquen and Garrison's participation was additionally supported with funding provided by the University of Texas at Austin's Lidar and Landscapes of the Ancient Mediterranean and Americas (LLAMA) Lab and graduate student funds from the Department of Geography and the Environment. We are also grateful to all members of the SCIP team who participated in the lidar analysis and ground verification components of the project, especially Sue Alcock, Rosie Campbell and Evan Levine.

References

Agapiou, A., A. Dakouri-Hild, S. Davis, E. Andrikou and W. Rourk 2022. The Kotroni Archaeological Research Project (KASP): evaluating ancient Aphidna using multimodal landscape analysis. *Journal of Greek Archaeology* 7: 413–434.

Athanasoulis, D., A. Knodell, Ž. Tankosić, Z. Papadopoulou, M. Sigala, C. Diamanti, Y. Kourayos and A. Papadimitriou 2021. The Small Cycladic Islands Project (2019–2020): a comparative survey of uninhabited landscapes near Paros and Antiparos, Greece. *Antiquity* 95: 12.

Attema, P., J. Bintliff, M. Van Leusen, P. Bes, T. De Haas, D. Donev, W. Jongman, E. Kaptijn, V. Mayoral, S. Menchelli, M. Pasquinucci, S. Rosen, J. García Sánchez, L. Gutierrez Soler, D. Stone, G. Tol, F. Vermeulen, A. Vionis 2020. A guide to good practice in Mediterranean surface survey projects. *Journal of Greek Archaeology* 5: 1–62.

Beach, T., S. Luzzadder-Beach, S. Krause, T. Guderjan, F. Valdez, J.C. Fernandez-Diaz, S. Eshleman and C. Doyle 2019. Ancient Maya wetland fields revealed under tropical forest canopy from laser scanning and multiproxy evidence. *Proceedings of the National Academy of Sciences* 116: 21469–21477.

Bevan, A. and J. Conolly 2011. Terraced fields and Mediterranean landscape structure: An analytical case study from Antikythera, Greece. *Ecological Modelling* 222: 1303–1314.

Bickler, S.H. 2021. Machine Learning Arrives in Archaeology. *Advances in Archaeological Practice* 9: 186–191.

Blanton, R.E. 2001. Mediterranean myopia. *Antiquity* 75: 627–629.

Braje, T.J., T.P. Leppard, S.M. Fitzpatrick and J.M. Erlandson 2017. Archaeology, historical ecology and anthropogenic island ecosystems. *Environmental Conservation* 44: 286–297.

[63] Campana 2018.
[64] Fontana 2025.
[65] Knodell *et al.* 2023.
[66] Inomata *et al.* 2021 used publicly available lidar data to identify hundreds of new clearly visible archaeological sites in lowland Mesoamerica for a study focused on site plan comparisons, requiring minimal ground verification efforts.

Brown, A., K. Walsh, D. Fallu, S. Cucchiaro and P. Tarolli 2020. European agricultural terraces and lynchets: from archaeological theory to heritage management. *World Archaeology* 52: 566–588.

Campbell, J.B., R.H. Wynne and V.A. Thomas 2023. *Introduction to remote sensing* 6. edition. New York: Guilford Press.

Campana, S.R.L. 2018. *Mapping the Archaeological Continuum*. Cham: Springer International Publishing.

Canuto, M.A., F. Estrada-Belli, T.G. Garrison, S.D. Houston, M.J. Acuña, M. Kováč, D. Marken, P. Nondédéo, L. Auld-Thomas, C. Castanet, D. Chatelain, C.R. Chiriboga, T. Drápela, T. Lieskovský, A. Tokovinine, A. Velasquez, J.C. Fernández-Díaz, R. Shrestha 2018. Ancient lowland Maya complexity as revealed by airborne laser scanning of northern Guatemala. *Science* 361.

Caraher, W., S. Gallimore, D. Nakassis and S.A. James 2020. Survey and the 7th century in the western Argolid. *Journal of Greek Archaeology* 5.

Chase, A.F., D.Z. Chase, C.T. Fisher, S.J. Leisz and J.F. Weishampel 2011. Airborne LiDAR, archaeology, and the ancient Maya landscape at Caracol, Belize. *Journal of Archaeological Science* 38: 387–398.

Chase, A.F., D.Z. Chase, C.T. Fisher, S.J. Leisz and J.F. Weishampel 2012. Geospatial revolution and remote sensing LiDAR in Mesoamerican archaeology. *Proceedings of the National Academy of Sciences* 109: 12916–12921.

Cherry, J.F. 2003. Archaeology Beyond the Site: Regional Survey and Its Future, In J.K. Papadopoulos and R.M. Leventhal (eds) *Theory and Practice in Mediterranean Archaeology*: 137–160. Cotsen Institute of Archaeology Press at UCLA.

Chiba, T., S. Kaneta and Y. Suzuki 2008. Red Relief Image Map: New Visualization Method for Three Dimensional Data. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* 37: 1071–1076.

Cohen-Smith, H., S.H. Bickler, B. Jone, B. Larsen and A. Apfel 2022. New Tech for Old Jobs: Handheld LiDAR for Feature Recording. *Archaeology in New Zealand* 65: 14–27.

Cowley, D.C. 2016. What Do the Patterns Mean? Archaeological Distributions and Bias in Survey Data, In M. Forte and S. Campana (eds) *Digital Methods and Remote Sensing in Archaeology*: 147–170. Cham: Springer International Publishing.

Crabb, N., C. Carey, A.J. Howard and M. Brolly 2023. Lidar visualization techniques for the construction of geoarchaeological deposit models: An overview and evaluation in alluvial environments. *Geoarchaeology* 38: 420–444.

Dawson, H. 2019. As Good as It Gets? 'Optimal' Marginality in the *Longue Durée* of the Mediterranean Islands. *Journal of Eastern Mediterranean Archaeology and Heritage Studies* 7: 451–465.

Dawson, H. 2021. Network science and island archeology: Advancing the debate. *The Journal of Island and Coastal Archaeology* 16: 213–230.

Doneus, M. 2013. Openness as Visualization Technique for Interpretative Mapping of Airborne Lidar Derived Digital Terrain Models. *Remote Sensing* 5: 6427–6442.

Doneus, M., N. Doneus and D. Cowley 2022. Confronting Complexity: Interpretation of a Dry Stone Walled Landscape on the Island of Cres, Croatia. *Land* 11: 1672.

Doneus, M., G. Mandlburger and N. Doneus 2020. Archaeological Ground Point Filtering of Airborne Laser Scan Derived Point-Clouds in a Difficult Mediterranean Environment. *Journal of Computer Applications in Archaeology* 3: 92–108.

Dong, P. and Q. Chen 2018. *LiDAR remote sensing and applications*. Boca Raton, FL: Taylor and Francis.

Evelpidou, N., A. Petropoulos, A. Karkani and G. Saitis 2021. Evidence of coastal changes in the west coast of Naxos Island, Cyclades, Greece. *Journal of Marine Science and Engineering* 9: 1427.

Fernandez-Diaz, J.C., W. Carter, R. Shrestha and C. Glennie 2014. Now You See It… Now You Don't: Understanding Airborne Mapping LiDAR Collection and Data Product Generation for Archaeological Research in Mesoamerica. *Remote Sensing* 6: 9951-10001.

Fernández-Lozano, J., J.J. Palao-Vicente, J.A. Blanco-Sánchez, G. Gutiérrez-Alonso, J. Remondo, J. Bonachea, M. Morellón and A. González-Díez 2019. Gold-bearing Plio-Quaternary deposits: Insights from airborne LiDAR technology into the landscape evolution during the early Roman mining works in north-west Spain. *Journal of Archaeological Science: Reports* 24: 843–855.

Fitzpatrick, S.M., V.D. Thompson, A.S. Poteate, M.F. Napolitano and J.M. Erlandson 2016. Marginalization of the Margins: The Importance of Smaller Islands in Human Prehistory. *The Journal of Island and Coastal Archaeology* 11: 155–170.

Fontana, G. 2022. Italy's Hidden Hillforts: A Large-Scale Lidar-Based Mapping of Samnium. *Journal of Field Archaeology* 47(4): 245–261.

Fontana, G. 2025. Issues of Sampling and Representativeness in Large-Scale LiDAR-Derived Archaeological Surveys in Mediterranean Contexts. *Archaeological Prospection*: 32: 103–117.

Garrison, T.G., D. Richmond, P. Naughton, E. Lo, S. Trinh, Z. Barnes, A. Lin, C. Schurgers, R. Kastner, S.E. Newman 2016. Tunnel Vision: Documenting Excavations in Three Dimensions with Lidar Technology. *Advances in Archaeological Practice* 4: 192–204.

Garrison, T.G., A.E. Thompson, S. Krause, S. Eshleman, J.C. Fernandez-Diaz, J.D. Baldwin and R. Cambranes 2023. Assessing the lidar revolution in the Maya lowlands: A geographic approach to understanding feature classification accuracy. *Progress in Physical Geography: Earth and Environment* 47: 270–292.

Garrison, T.G., S. Houston and O. Alcover Firpi 2019. Recentering the rural: Lidar and articulated landscapes among the Maya. *Journal of Anthropological Archaeology* 53: 133–146.

Godone, D., D. Giordan. and M. Baldo 2018. Rapid mapping application of vegetated terraces based on high resolution airborne LiDAR. *Geomatics, Natural Hazards and Risk* 9: 970–985.

Gołębiowska, I. and A. Çöltekin 2022. What's wrong with the rainbow? An interdisciplinary review of empirical evidence for and against the rainbow color scheme in visualizations. *ISPRS Journal of Photogrammetry and Remote Sensing* 194: 195–208.

Grammer, B., E. Draganits, M. Gretscher and U. Muss 2017. LiDAR-guided Archaeological Survey of a Mediterranean Landscape: Lessons from the Ancient Greek Polis of Kolophon (Ionia, western Anatolia): LiDAR-guided Archaeological Survey of Kolophon. *Archaeological Prospection* 24: 311–333.

Hutson, S.R. 2015. Adapting LiDAR data for regional variation in the tropics: A case study from the northern Maya Lowlands. *Journal of Archaeological Science: Reports* 4: 252–263.

Hutson, S.R., B. Kidder, C. Lamb, D. Vallejo-Cáliz and J. Welch 2016. Small Buildings and Small budgets: making lidar work in northern Yucatan, Mexico. *Advances in Archaeological Practice* 4: 268–283.

Inomata, T., J.C. Fernandez-Diaz, D. Triadan, M. García Mollinedo, F. Pinzón, M. García Hernández, A. Flores, A. Sharpe, T. Beach, G.W.L. Hodgins, J.J. Durón Díaz, A. Guerra Luna, L. Guerrero Chávez, M. de Lourdes Hernández Jiménez, M. Moreno Díaz 2021. Origins and Spread of Formal Ceremonial Complexes in the Olmec and Maya Regions Revealed by Airborne Lidar. *Nature Human Behaviour* 5: 1487–1501.

Knodell, A.R. 2025. Survey and landscape archaeology in Greece in the 21st century. *Archaeological Reports* 71.

Knodell, A. and T. Leppard 2018. Regional approaches to society and complexity: Setting an agenda. In A.R. Knodell and T. Leppard (eds) *Regional approaches to society and complexity: Studies in honor of John F. Cherry*: 1–23. Sheffield.

Knodell, A.R., D. Athanasoulis, Ž. Tankosić, J.F. Cherry, T.K. Garonis, E.I. Levine, D. Nenova and H.Ç. Öztürk 2022. An island archaeology of uninhabited landscapes: Offshore islets near Paros, Greece (the Small Cycladic Islands Project). *The Journal of Island and Coastal Archaeology* 17: 475–511.

Knodell, A.R., D. Athanasoulis, J.F. Cherry, D. Nenova, H.Ç. Öztürk and Z. Papadopoulou 2025. A regional survey of the uninhabit 94(4): 619–717. ed islands of the western Cyclades: The Small Cycladic Islands Project 2021-2022. *Hesperia* 94.4.

Knodell, A.R., T.C. Wilkinson, T.P. Leppard and H.A. Orengo 2023. Survey Archaeology in the Mediterranean World: Regional Traditions and Contributions to Long-Term History. *Journal of Archaeological Research* 31: 263–329.

Kokalj, Ž. and M. Somrak 2019. Why Not a Single Image? Combining Visualizations to Facilitate Fieldwork and On-Screen Mapping. *Remote Sensing* 11: 747.

Li, X., C. Liu, Z. Wang, X. Xie, D. Li and L. Xu 2021. Airborne LiDAR: state-of-the-art of system design, technology and application. *Measurement Science and Technology* 32: 032002.

Lozić, E. and B. Štular 2021. Documentation of Archaeology-Specific Workflow for Airborne LiDAR Data Processing. *Geosciences* 11: 26.

Lucas, T. and J.G. Sánchez 2022. Opération LiDAR à Akraiphia et au Val des Muses, Béotie (2021). *Bulletin archéologique des Écoles françaises à l'étranger*. http://journals.openedition.org/baefe.

Masini, N., N. Abate, F. Gizzi, V. Vitale, A. Minervino Amodio, M. Sileo, M. Biscione, R. Lasaponara, M. Bentivenga, F. Cavalcante 2022. UAV LiDAR Based Approach for the Detection and Interpretation of Archaeological Micro Topography under Canopy – The Rediscovery of Perticara (Basilicata, Italy). *Remote Sensing* 14: 6074.

Meyer, N. 2023. Finding Sites in Mediterranean Survey. *Journal of Mediterranean Archaeology* 35: 143–168.

Quintus, S., S.S. Day and N.J. Smith 2017. The Efficacy and Analytical Importance of Manual Feature Extraction Using Lidar Datasets. *Advances in Archaeological Practice* 5: 351–364.

Roussel, J.-R., D. Auty, N.C. Coops, P. Tompalski, T.R.H. Goodbody, A.S. Meador, J.F. Bourdon, F. de Boissieu and A. Achim 2020. lidR: An R package for analysis of Airborne Laser Scanning (ALS) data. *Remote Sensing of Environment* 251: 112061.

Roussos, K. 2020. Understanding the Medieval Cyclades through landscape archaeology (8th –

12th century AD). *Journal of Greek Archaeology* 5: 426-447.

Searle, M.P. and T.N. Lamont 2022. Compressional origin of the Aegean Orogeny, Greece. *Geoscience Frontiers* 13: 101049.

Štular, B., Ž. Kokalj, K. Oštir and L. Nuninger 2012. Visualization of lidar-derived relief models for detection of archaeological features. *Journal of Archaeological Science* 39: 3354–3360.

Štular, B. and E. Lozić 2020. Comparison of Filters for Archaeology-Specific Ground Extraction from Airborne LiDAR Point Clouds. *Remote Sensing* 12: 3025.

Štular, B., E. Lozić and S. Eichert 2021. Airborne LiDAR-Derived Digital Elevation Model for Archaeology. *Remote Sensing* 13: 1855.

Štular, B., E. Lozić and S. Eichert 2023. Interpolation of airborne LiDAR data for archaeology. *Journal of Archaeological Science: Reports* 48: 103840.

Thompson, A.E., G.M. Feinman, M. Lemly and K.M Prufer 2021. Inequality, networks and the financing of Classic Maya political power. *Journal of Archaeological Science* 133: 105441.

Turner, S., T. Kinnaird, G. Varinlioğlu, T.E. Şerifoğlu, E. Koparal, V. Demirciler, D. Athanasoulis, K. Ødegård, J. Crow, M. Jackson, J. Bolòs, J. Carlos Sánchez-Pardo, F. Carrer, D. Sanderson, A. Turner 2021. Agricultural terraces in the Mediterranean: medieval intensification revealed by OSL profiling and dating. *Antiquity* 95: 773–790.

Vinci, G., F. Vanzani, A. Fontana and S. Campana 2024. LiDAR Applications in Archaeology: A Systematic Review. *Archaeological Prospection*: 1–21.

Whitelaw, T.M. 1991. The ethnoarchaeology of recent rural settlement and land use. In J.F. Cherry, J.L. Davis and E. Mantzourani, *Northwest Keos. Landscape Archaeology as Long-Term History*: 403–454. Los Angeles: Institute of Archaeology, University of California, Los Angeles.

Wiersma, C., P. Bes, M.W. Van IJzendoorn, A. Wiznura and S. Voutsaki 2022. The site of Ayios Vasileios in Laconia from the prehistoric to the early modern period. Results of the pedestrian field survey. *Journal of Greek Archaeology* 7: 122–172.