Archeologia e Calcolatori
36.2, 2025, 159-178
doi 10.19282/ac.36.2.2025.14

REMOTE SENSING TECHNIQUES AND MACHINE LEARNING ANALYSES IN ARCHAEOLOGY: A METHODOLOGICAL APPROACH TO TERRITORY INVESTIGATIONS

1. Introduction: RS and AI methodologies

The term 'remote sensing' was coined in the 1960s by the American geographer Evelyn Lord Pruitt (Pruitt 1979). In its most general definition, it refers to the acquisition and processing of qualitative and quantitative information about an object without direct contact. The application of remote sensing in archaeology has historically been secondary, despite its initial development for Earth observation (at various scales) and monitoring in military, cartographic, and environmental contexts, among others. Following a period of research that has spanned more than half a century, the scientific community has adopted two different approaches to define this term (Campana 2017). Some archaeologists have described it as a method for obtaining information about objects by analysing data collected by sensors (cameras, scanners, radar systems, etc.) mounted on airborne or satellite platforms, without direct contact with them. In this paper the definition of remote sensing refers to the observation of buried traces without compromising the integrity of the stratigraphy (for a recent study Wang, Liu 2024).

The advent of Artificial Intelligence (AI) and Machine Learning (ML) techniques has led to a considerable augmentation in the analysis of remotely sensed data, thereby expanding and testing the potential of this methodology in archaeological research (Lambers *et al.* 2019; Orengo *et al.* 2020; Bickler 2021; Cacciari, Pocobelli 2021; Argyrou, Agapiou 2022; Karamitrou *et al.* 2022; Zhang, Zhang 2022; Agapiou, Lysandrou 2023; Kadhim, Abed 2023; Canedo *et al.* 2024; Luo *et al.* 2024; Vats, Mehta 2024). Advanced algorithms now allow the processing of large quantities of information with greater precision and speed, enabling the detection of sites and ancient anthropic structures that are sometimes difficult to identify. For instance, these tools can detect hidden patterns in multi- and hyper-spectral or radar data, improving the mapping and interpretation of archaeological landscapes in a fully non-invasive manner and guiding subsequent ground investigations (Canedo *et al.* 2024). Consequently, the integration of remote sensing with AI and ML techniques is becoming increasingly valuable for the sustainable and non-destructive management of cultural heritage.

This paper presents the results of an in-depth research project carried out by the Authors over the last year and a half, which involved the testing of two artificial intelligence software packages: ENVI (v. 4.5) and eCognition (v.

10.4 and 10.5). Both were used for the automated processing and analysis of high- and very high-resolution multispectral remotely data. A particular focus was devoted to eCognition, which was extensively tested during the research, and the main results are presented here. Specifically, imagery acquired by WorldView-2 (4 bands) and WorldView-3 (8 bands) satellites, with ground resolutions of 0.50 m and 0.30 m respectively, was processed and analysed.

The investigations covered various territorial contexts of central and southern Italy, characterized by marked orographic differences[1]. This paper presents data on the Campania region, with particular focus on two geographical and geomorphological distinct areas: the northern sub-region of Irpinia and the Campanian Plain. Methodologically, the research was structured on three levels of investigation: traditional, semi-automated, and automated.

The remotely sensed data were initially processed through the application of Spectral Indices and analysed through photointerpretation method, in order to understand the topography and orography of the area, to identify anomalies and archaeological traces. This process is essential for training ML algorithms and correcting any interpretation errors made by the software.

As several scholars have already emphasized, the integration of remote sensing analysis with modern AI technologies is transforming archaeological research and beyond, making it possible to analyse large datasets and extensive areas. At the same time, however, it is important to emphasize that AI, though powerful, requires continuous monitoring and, above all, the input of human intelligence in order to improve and evolve (Gallavotti 2024).

F.D.P., P.M.

2. State of art: from decision tree to convolutional neural network

2.1 *A comparison of the performance, commonality and differences between the ENVI and eCognition software*

In recent decades, satellite image processing has become a central role to numerous fields of research, from environmental and geological studies to urban monitoring, from land-use planning to archaeological investigations. With the advent of AI, commercial software tools for advanced remotely data analysis have rapidly proliferated (Tab. 1). Among the most widely used applications are ENVI and eCognition, which enable the extraction of complex information, simplifying otherwise laborious tasks and enabling faster and more accurate automated analyses.

[1] As with *Atella* (see Brancato *et al.* in this volume), these experiments are part of two PRIN projects: In.Res.Agri (European Union NextGenerationEU; MUR project code 2022SMJCHX) and ASH (European Union NextGenerationEU; MUR project code P2022NNE72) (see Pacciarelli *et al.* in this volume).

Software	*Analysis ability*	*Analysis accuracy*	*Learning difficulty*	*Interface friendliness*	*Algorithms quantity*	*Design oriented*
ENVI	Very powerful	Higher	Ordinary	Ordinary	Many	Yes
Geomatica	Ordinary	Ordinary	Hard	Unfriendly	Many	Yes
Qmosaic	Ordinary	Ordinary	Ordinary	Ordinary	Many	No
eCognition	Very powerful	Higher	Easy	Friendly	Great many	Yes
ERDAS	Powerful	High	Hard	Friendly	Great many	No

Tab. 1 – A comparison of five commonly used RS image analysis software packages (by Zhang 2008). Although eCognition is rated as 'easy to learn' due to its intuitive interface and graphical tools, its advanced functionalities – including object-based workflows, complex segmentation and customised algorithms – require a steeper learning curve and greater specialist expertise than pixel-based environments such as ENVI.

Since May 2024, the Authors have initiated a study aimed to understand the potential of these two software packages and their application for archaeological purposes. The objective is to develop a methodological framework tailored to specific territorial, geological, and archaeological contexts. Although ENVI's potential in the archaeological applications was already known, a systematic comparison was nevertheless undertaken between the two commercial tools (ENVI and eCognition). The comparison focused on shared features, methodological differences, and potential applications, with particular emphasis on their usability in the archaeological field.

Both software packages can process data acquired from different platforms (satellite, aerial, UAV) and support integration with GIS systems, offering advanced spatial analysis capabilities. Despite both supporting automated methods, their approaches differ: ENVI is based on pixel-based classification (PBC), which is ideal for traditional classification tasks, while eCognition adopts an object-based image analysis (OBIA) methodology, particularly effective in analysing high-resolution images and managing complex spatial features (Del Giglio *et al.* 2019), such as those typical of archaeological sites. In terms of ease of use, ENVI is generally considered more intuitive, while eCognition offers more sophisticated functionalities but requires advanced knowledge of OBIA (Tab. 2).

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2.2 *ENVI and Decision Tree Classification*

ENVI (Environment for Visualizing Images) is a commercial software developed by Harris Geospatial Solutions, now part of L3Harris Technologies. This program is distinguished by its ability to manage substantial image datasets and its sophisticated algorithms, facilitating the extraction of intricate information from remotely sensed data. It is one of the most comprehensive

Feature	ENVI	eCognition
Main Focus	Image processing, data analysis and visualisation of geospatial data.	Object-based image analysis (OBIA), segmentation, and classification.
Core Functionality	Image enhancement, multispectral and hyperspectral analysis, and integrate on with GIS tools.	Segmentation, classification, and spatial analysis of remotely sensed data.
Data Types Supported	Multispectral, hyperspectral, LiDAR. radar, and other geospatial data formats.	Primarily focuses on high-resolution imagery and data from various sources, including drones.
Analysis Type	Pixel-based analysis and classification.	Object-based analysis, focusing on segments of the image rather than individual pixels.
Processing Techniques	○ Image processing ○ Spectral analysis ○ Classification (supervised/unsupervised) ○ Change detection	○ OBIA classification ○ Multi-scale segmentation ○ Rule-based classification ○ ML Integration
Ease of Use	User-friendly with a comprehensive interface, suitable for both beginners and experts.	More complex. requiring a solid understanding of OBIA, but very powerful for high-level tasks.
Integration with the other software	Excellent integrate on with GIS platforms (ArcGIS, QGIS), Python scripting and other geospatial tools.	Integrates well with RS tools and GIS software but is more focused on spatial analysis.
ML Capabilities	Provides basic ML tools for classification, clustering, and regression.	Supports more advanced ML models, especially in OBIA classification.
Automated/Manual Process ng	Offers both manual and automated workflows (e.g. batch processing).	Highly automated with customisable rule sets for segmentation and classification, but also allows manual intervention.
Customization	Customisable through scripting (Python and IDL), plugins, and toolboxes.	Highly customisable with user-defined rulesets and scripting (eCognition Developer).
Potential Applications	○ Environmental monitoring ○ Land use/land cover mapping ○ Agriculture ○ Disaster management	○ Urban planning ○ Agriculture ○ Forestry ○ Environmental monitoring High-resolution imagery analysis
License Type	Commercial license with various tiers for different functionalities.	Commercial license with a focus on professional, large-scale projects.
Cost	Expensive, with a tiered pricing model based on the features	Expensive, geared towards advanced and large-scale professional users.

Tab. 2 – Summary table comparing ENVI and eCognition software for remote sensing (RS) image analysis. ENVI is primarily PBC and user-friendly, whereas eCognition adopts an object-based approach (OBIA), offering more advanced but complex functionalities (elaborated by Francesca Di Palma).

tools available for satellite image processing and geospatial analysis, combining basic functionalities (visualization and corrections) with advanced techniques for multi-/hyperspectral and multitemporal analyses. Its versatility makes it a key software both in scientific research and in professional applications (Teodoro *et al.* 2012; Wang *et al.* 2021).

ENVI supports all the latest data collection platforms (satellite, airborne, drone, terrestrial), more than 200 different data types, and modalities including panchromatic, multispectral, hyperspectral, LiDAR, SAR, and FMV. It can process datasets of any size and provides automated tools to quickly and easily prepare imagery for further analysis (nv5geospatialsoftware.com/Products/ENVI). ENVI offers automated workflows that help users efficiently extract information from all types of geospatial data, such as:

– multitemporal analysis: monitoring territorial changes (deforestation, urbanization, climatic phenomena);
– hyperspectral analysis: identification of minerals, pollutants, or specific crops through hundreds of spectral bands.
– spectral indices: calculation of NDVI (Normalized Difference Vegetation Index), NDBI (Normalized Difference Built-up Index), NDWI (Normalized Difference Water Index).
– thematic classification: identification of different land covers (vegetation, water bodies, urban areas). Among the supervised classification techniques available in ENVI, the Decision Tree method represents a flexible and interpretable approach, particularly suitable for integrating spectral data, derived indices, and ancillary information.

A decision tree is a classification model that iteratively splits a dataset according to logical rules based on threshold values. Each node represents a condition (e.g., NDVI values), each branch a decision, and each leaf corresponds to a thematic class as vegetation, water, bare soil, urban areas, etc. (Breiman *et al.* 1984). The strength of this method lies in its simplicity and transparency: unlike more complex algorithms such as neural networks or parametric methods (e.g., Maximum Likelihood), the decision tree allows users to clearly trace and understand the rules that led to classification (Hansen *et al.* 2013).

The classification process via Decision Tree in ENVI can be summarized in several stages (Friedl, Brodley 1997):

1) data preparation: radiometric and atmospheric correction of images, calculation of spectral indices (e.g., NDVI, NDWI), generation of ancillary layers (e.g., digital elevation models);
2) definition of rules: the user establishes logical conditions based on band or index values (e.g., NDVI threshold);
3) tree construction: rules are hierarchically organized into a decision flow;
4) classification: each pixel is assigned to a class according to the logical path followed within the tree;
5) validation: results are compared with reference data (ground truth, aerial photographs, GIS datasets).

Supervised pixel-based classification (PBC) of multispectral imagery constitutes a valid tool for the production of thematic maps based on the spatial and spectral information contained in individual pixels. This approach, which involves selecting representative sample pixels for each class, is closely integrated with supervised classification through decision trees. The analysis demonstrates the ability to distinguish classes such as 'Archaeological Traces' although classification process is often influenced by spectral similarities between classes. In fact, variations in vegetation or soil chemical-physical properties are often minimal (Merola 2011).

Despite some limitations due to modest separability between the spectral signatures of archaeological contexts and surrounding soils, the results can be considered valid both in terms of accuracy and pixel localization.

P.M.

2.3 *eCognition and the Convolutional Neural Network*

eCognition is a software developed in 2000 by Definiens, specifically designed for the automated analysis of satellite and aerial imagery. In 2014, Trimble acquired Definiens, and the software became part of Trimble's suite of products for image analysis and geospatial data management (https://www.sysdecoitalia.com/prodotti/ecognition/). In the field of remote sensing

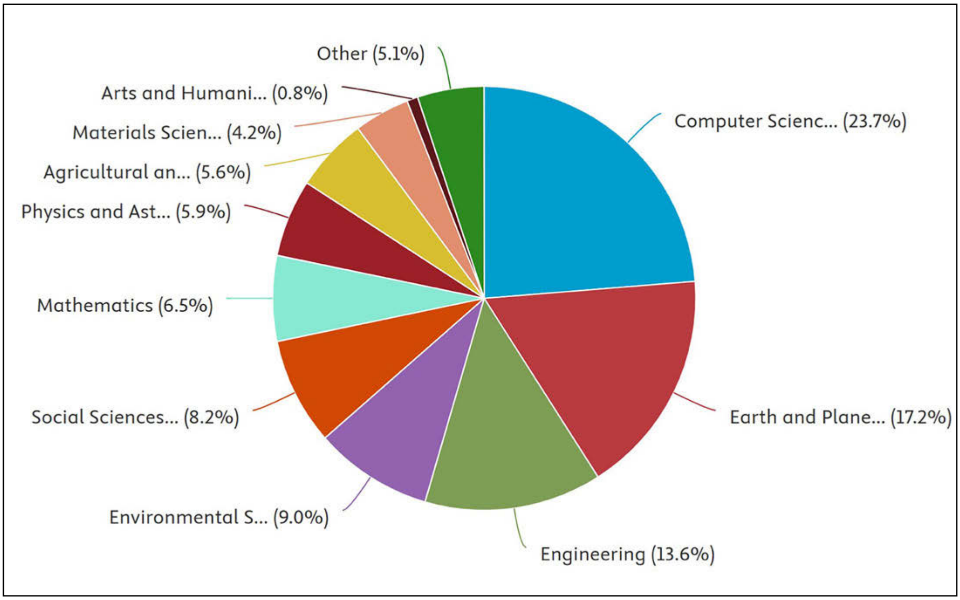

Fig. 1 – The figure presents a graph relating to all publications produced between 2000 and 2024 containing the keyword 'eCognition'. The figure delineates the percentage relating to the disciplinary sectors covered by the aforementioned publications. As is evident, the humanities sector is below 1% (source: Elsevier-Scopus).

software, eCognition is a leading solution for the processing, analysing, and interpreting geospatial data. Compared to ENVI, eCognition enables object-based analyses through segmentation and classification techniques, both semi-automated and automated (Sharma *et al.* 2024). This approach allows the combined extraction of linear and areal objects from multi-sensor image data, made possible by ML algorithms (Argyrou, Agapiou 2022). Although originally developed for environmental and territorial remote sensing data analysis, eCognition has proven extremely versatile for archaeological research (Fig. 1).

Its OBIA approach allows the identification and classification of complex landscape elements with high precision, facilitating the detection of hidden or subtle archaeological sites. Remotely sensed data (multispectral, hyperspectral, LiDAR, etc.) processed with spectral indices and analysed through segmentation and classification not only enhance the understanding of ancient topography, guiding field verification, but also allow the monitoring of site preservation over time. The integration of multispectral, geophysical, and archaeological data deepens our understanding of the historic landscape, reconstructing human-environment interactions in greater detail (Leucci *et al.* 2002; Zamuner *et al.* 2009; Merola 2011; Campana 2017; Valente *et al.* 2023; Cozzolino *et al.* 2025). Therefore, although eCognition was not originally designed for archaeology, it is now a valuable tool for the field, bridging traditional topographic research, Computational Archaeology, and the Digital Humanities.

From the outset, the Authors committed not only to studying the software but also to testing its potential – from basic remote sensing analyses to more advanced ML and Deep Learning (DL) applications. The main analytical operations in eCognition unfold in two stages: a) PBC (Pixel-Based Classification); b) OBIA (Object-Based Image Analysis).

In the first stage, the image is imported and spectral indices are calculated to highlight specific features in the remotely sensed data (in archaeological research, these can emphasize landscape anomalies). A preliminary classification based on spectral pixel values (PBC) can thus be performed. Subsequently, the OBIA approach segments the image into homogeneous objects, aggregating similar pixels into meaningful spatial entities. Statistical and geometric features are then extracted from these objects to enable more accurate, context-based classification.

Both classification types can be enhanced by applying Convolutional Neural Networks (CNNs). Neural networks are a class of algorithms that attempt to recognize underlying relationships within a dataset by mimicking the functioning of the human brain, particularly the neuronal system. CNNs are fundamental for advanced object detection, enabling the automated identification of complex patterns and hidden relationships (for applications in archaeological detection, see Soroush *et al.* 2020). Features such as linear or regular structures can be effectively recognized by training CNNs; once validated, these networks produce stable and reliable models for analysis. The training, however, requires a preliminary learning phase using representative datasets to optimize the model's ability to generalize and accurately identify targets in satellite imagery.

The following methodological section presents in detail the processing protocols and analytical procedures developed through the use of eCognition.

F.D.P.

3. In.Res.Agri project: from the mountain to the plain. The Campania case studies: looking at different areas with different types of elevation

As part of the In.Res.Agri project (Brancato *et al.* 2024), case studies were conducted on selected areas of Campania (Irpinia and the Campanian Plain) and *Apulia* (Tavoliere). These territorial contexts were investigated by methodologically combining traditional topographical research with innovative AI-based experiments, such as ML and DL, for spatial analysis and the automated detection of archaeological traces attributable to ancient land divisions. This paper presents the preliminary results concerning the region of Campania and two distinct and complex areas of investigation, as previously mentioned: Irpinia and the Campanian Plain. Irpinia is a historical-geographical region of the Campanian hinterland, predominantly mountainous and hilly territory, largely coinciding with the current province of Avellino. In the Roman period, Irpinia underwent processes of landscape Romanization, including the construction of roads, settlements, and structured systems of agricultural exploitation such as centuriation (Johannowsky 1987).

The Campanian Plain, by contrast, refers to the flat area known in Roman times as *Campania Felix* (Strabo, *Geographica* V, 4, 3; Plin., *Naturalis Historia* III, 60-61). The region has been continuously inhabited since antiquity. It has hosted heterogeneous settlements from pre-Roman times through the Imperial period. However, the substantial post-World War II urbanization has profoundly altered the historical landscape, often obscuring or obliterating the material traces of antiquity.

The complex orography of Irpinia and the extensive transformations of the Campanian Plain today mean that archaeological research is challenging. This means that advanced investigative and territorial analysis tools are needed. For this purpose, the Authors tested the potential of eCognition (v. 10.4 and 10.5), applying it to high- and very high-resolution multispectral satellite imagery (0.50-0.30 m ground resolution) within an innovative approach for the semi-automated and automated detection of Roman centuriation.

Spectral Indices	Description	Formula	References
NDWI	Normalized Difference Water Index	(G – NIR)/(G + NIR)	McFeeters 1996
SR	Simple Ratio	NIR/R	Jordan 1969
NDVI	Normalized Difference Vegetation Index	(NIR-R)/(NIR+R)	Rouse *et al.* 1974
NDYI	Normalized Difference Yellowness Index	(G-B)/G+B)	Sulik, Long 2016
GRVI	Green Ratio Vegetation Index	N/G	Sripada *et al.* 2005
GNDVI	Green Normalized Difference Vegetation Index	(N-G)/(N+G)	Gitelson *et al.* 1996
NDSI	Normalized Difference Soil Index	(R-B)/(R+B)	Escadafal *et al.* 1994
SAVI	Soil-adjusted vegetation	((NIR - R) / (NIR + R + L))*(1+L)	Huete 1988
OSAVI	Optimized Soil-Adjusted Vegetation Index	(NIR-R)(NIR+R+0.16)	Rondeaux *et al.* 1996
NIRv	Near-Infrared Reflectance of Vegetation	((NIR-R)/(NIR+R))x NIR	Badgley *et al.* 2017
NormNIR	Normalized NIR	NIR/(NIR+G+R)	Sripada *et al.* 2005
VARI	Visible Atmospherically Resistant Index	(G-R)/(G+R-B)	Gitelson *et al.* 2002
VrNIRBI	Visible Red based built-up index	(R-NIR)/ (R+NIR)	Estoque, Murayama 2015
VgNIRBI	Visible Green based built-up index	(G-NIR)/ (G+NIR)	Estoque, Murayama 2015

Tab. 3 – Summary of the spectral indices used (elaborated by F. Di Palma, based on literature).

In detail, five multispectral satellite images were analysed: two acquired by WorldView-2 (a 4-band image of 9 April 2017, ID 103001006802B800, for Irpinia; and an 8-band image of 9 October 2020, ID 10300500A8F93B00, for the Campanian Plain), and three by WorldView-3 (a 4-band stereo image of 26 April 2018, ID 104001003C24FD00, for Irpinia; and two 8-band images of 27 December 2023, IDs 104005005BDC1C00 and 104005005BDC1B00, plus an 8-band image of 11 May 2024, ID 1040050065DCD900, for the Campanian Plain). The case studies covered areas in the territories of Sturno, Nusco, Ponteromito, Cassano Irpino, and Montella (Irpinia), and Sant'Arpino, Succivo, and Orta di Atella (Campanian Plain). The Irpinia case study was

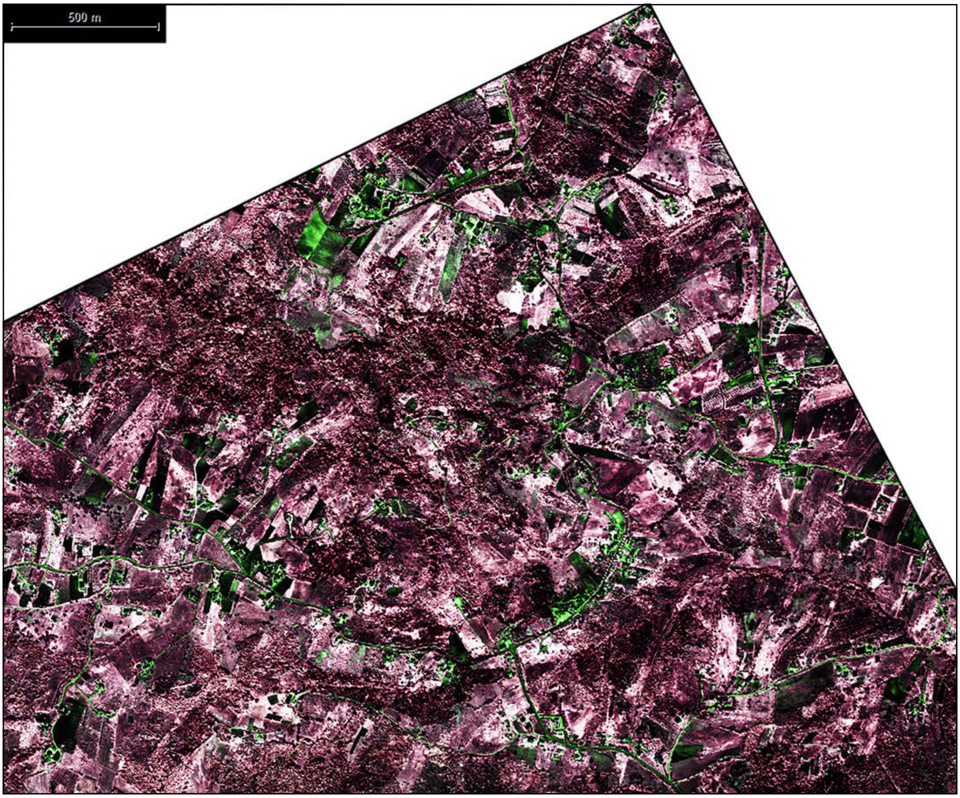

Fig. 2 – Detailed processing of the WV-3 four-band stereo satellite imagery from April 26, 2018 (ID code 104001003C24FD00). The image has been processed using a false-colour composite, with the B, G, and R channels assigned to the respective B, G, and R bands, while the Near-Infrared (NIR) band is displayed across all channels. A series of vegetation and surface indices were derived and visualized: the Normalized Difference Water Index (NDWI) in the G channel, the Simple Ratio (SR) in all channels, the Normalized Difference Vegetation Index (NDVI) in the B channel, the Green Ratio Vegetation Index (GRVI) in the R channel, the Normalized Difference Soil Index (NDSI) in the B channel, and the Normalized NIR (NormNIR) in the R channel.

conducted by the Archaeological Mapping Lab of CNR-ISPC, Lecce, while the Campanian Plain study (*Atella* archaeological site) was carried out by the University of Naples unit.

The multispectral data were processed by applying 14 spectral indices (NDWI, SR, NDVI, NDYI, GRVI, GNDVI, NDSI, SAVI, OSAVI, NIRV, NormNIR, VARI, VrNIRBI, VgNIRBI; Tab. 3). Some were pre-set in the software (NDVI, NDWI, NDSI, NDBI, NDSnI, NBR, SAVI, EVI, and GRVI), while others were calculated manually using raster calculator formulas (Fig. 2). The flexibility to experiment with multiple indices was crucial for advancing the topographical and orographical understanding of the study areas, producing methodologically significant results. For instance, by applying arithmetic functions to bands and selected indices, it was possible to clearly emphasise elevations and microrelief traces. More specifically, combining the panchromatic band (PAN) with the Normalized Difference Water Index (NDWI) and/or Principal Component Analysis (PCA) conditioned on band variance, along with the Near Infrared (NIR) band, enabled the enhancement of relief and microrelief features (see also Cozzolino *et al.* 2025). This formula is currently being verified and systematized into a theoretical framework.

The calculation of spectral indices completed the Pixel-Based Image Analysis (PBIA) phase and provided a foundation for Object-Based Image Analysis (OBIA). This method allows for the segmentation and classification of high-resolution satellite images according to morphological, spatial, and spectral criteria, enabling the detection of regular, linear patterns compatible with ancient land divisions.

The first stage of OBIA was segmentation (eCognition 10.5 provides a wide range of segmentation algorithms, including Chessboard, Contrast Filter, Multiresolution, Multi-threshold, Quadtree-based, SAM, Spectral Difference, Superpixel, Watershed, and Vector-based segmentation). The accuracy of segmentation is directly proportional to the quality of PBIA. Optimal results were obtained by excluding the noisiest bands (Blue and Coastal Blue) and working with the remaining bands (G-R-NIR for 4-band images; G-Y-R-RE-NIR1-NIR2 for 8-band images), along with the calculated indices. This approach significantly reduced atmospheric disturbance, ensuring a more robust basis for OBIA. Segmentation is a crucial step, as the quality of extracted objects directly affects classification accuracy (Hossain, Chen 2019). The most effective algorithms tested included: Multiresolution Segmentation; Multi-threshold Segmentation; Spectral Difference Segmentation; Segment anything Segmentation.

Following segmentation, classification was performed using both Unsupervised Classification (USC) and Supervised Classification (SC) (see Alcaras *et al.* 2025 for a recent comparison). Automated classification, also known as Unsupervised Classification (USC) is a process in which statistical-computational algorithms and models autonomously categorise pixels or objects in remote sensing images, assigning each to a predefined target class (e.g., land cover, water, built-up areas). For the case studies presented, USC was performed using PCA, calculated on the variance of the bands (with Coastal Blue/Blue isolated depending on whether 4- or 8-band imagery was used, plus the 14 indices). This operation made it possible to reduce the dimensionality of the dataset and emphasise the most significant components, enabling rapid and efficient classification.

The Supervised Classification (SC) method, on the other hand, permits human intervention to define or orient the target classes, as established during the research presented here. Conversely, automatic tools apply the rules. This approach reduced interpretation errors evident in USC (e.g., frequent misclassification of watercourses as dirt roads due to similar reflectance in the visible spectrum). Research is ongoing to refine methods that minimize these errors.

In conclusion, this methodological phase achieved a solid level of processing and analysis. Although OBIA applications have been successfully developed using shape- and object-extraction algorithms, advancing further requires moving toward Deep Learning (DL) analysis with CNNs. To improve automated classification and specifically detect regular linear features potentially corresponding to centuriation grids – hypothesized from historical cartography and partially verified in the field – the Authors are currently training a CNN model.

The eCognition workflow can be summarised in five main steps for developing a mature operational model for automated identification of linear archaeological features such as centuriation traces (Fig. 3):

1. image segmentation – using the Segment Anything Model (SAM) to identify and flexibly segment features across varied data types and landscapes;
2. creation of training samples – manually selecting representative areas of centuriation traces and other classes of interest, then generating labeled patches for training ('Generate labeled sample patches' algorithm);

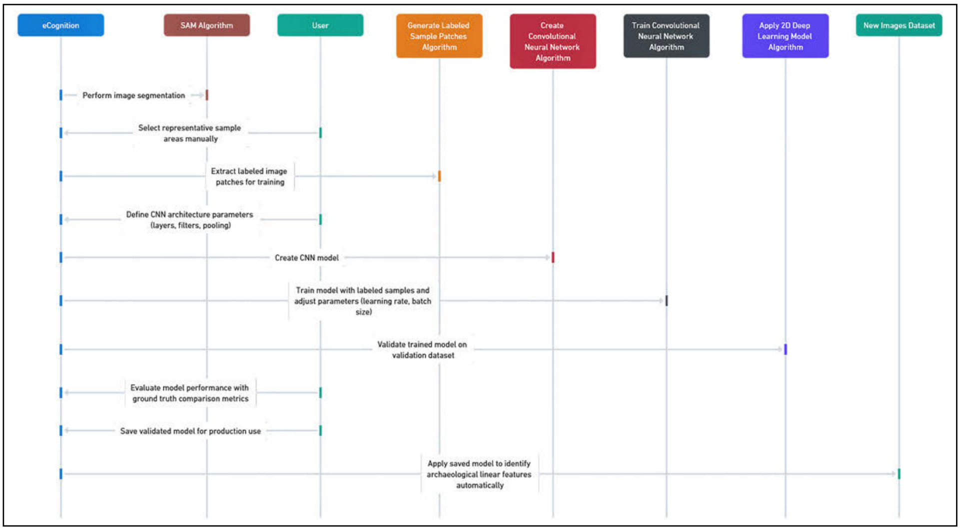

Fig. 3 – The operational workflow in eCognition for the automatic identification of archaeological linear features, from image segmentation and training sample creation to model application in production.

3. neural network training – defining the CNN architecture ('Create convolutional neural network' algorithm), increasing complexity as needed, and training ('Train convolutional neural network' algorithm) with sample data (adjusting parameters such as learning rate and batch size);
4. model validation – applying the trained model to independent validation datasets and evaluating performance against ground truth using appropriate metrics;
5. operational application – once validated, the model can be deployed to automatically detect archaeological traces in new satellite images.

At present, the research is at step 3-CNN training. The ultimate goal, closely tied to the In.Res.Agri project, is to achieve a fully operational model for the automatic identification of Roman centuriation grids.

F.D.P.

4. Results

Experiments conducted in the eCognition environment demonstrated the software's effectiveness in detecting archaeological traces plausibly related to ancient land divisions. In several cases, the analyses confirmed the existence of grid systems previously reconstructed through cartographic methods and only partially verified in the field. Furthermore, the software enabled the identification of additional anthropogenic and archaeological anomalies. The application to mountainous landscapes, such as those in Irpinia, highlighted the challenges of photo-interpretation in areas where terrain morphology and dense vegetation obscure archaeological features. Despite these difficulties, eCognition proved useful in outlining possible alignments even in complex contexts.

In Irpinia, two agrarian layouts were identified: one associated with a grid model defined by an intersection near the settlement of Fioccaglia (Fig. 4), and another oriented NE-SW (Fig. 5). These results corroborate hypotheses advanced through cartographic research and only partially confirmed on the ground (see Ditaranto, Giordano in this volume and references therein). In the Campanian Plain, analysis focused on the area surrounding the archaeological site of *Atella*. In this instance, eCognition facilitated the identification of potential archaeological evidence related to agricultural division as well as ancient structures and infrastructures. The study used eight-band multispectral data from the WV-3 satellite. Among the anomalies identified, the most promising appears to be a possible road alignment oriented NE-SW and seemingly directed towards the archaeological site (Fig. 6). Field verification is currently in progress, guiding survey activities conducted by the University of Naples Federico II.

Overall, eCognition not only confirmed previous hypotheses but also revealed new archaeological traces requiring further investigation. The

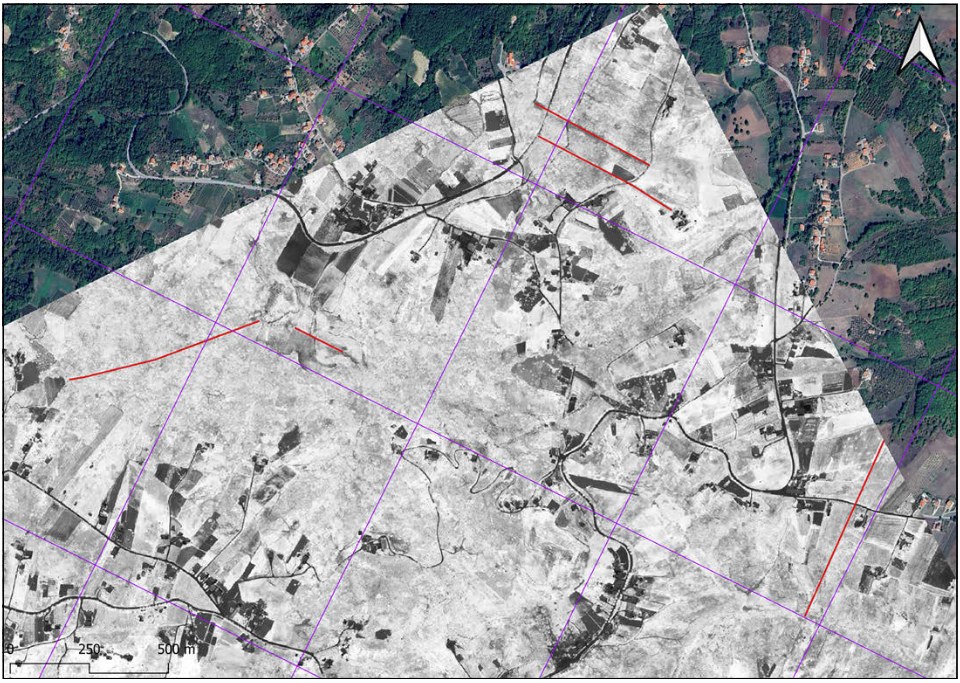

Fig. 4 – Irpinia, image WV-3 from April 26, 2018 (ID code 104001003C24FD00). Example of traces identified and associated with the grid model oriented NE-SW. The trace identification and vectorization were performed using eCognition v. 10.4 and v. 10.5, based on the SAVI index, enabling precise delineation of archaeological features in the landscape.

integration of high- and very-high-resolution multispectral data with traditional cartographic approaches proved particularly effective in complex contexts such as Irpinia and the Campanian Plain, enhancing our understanding of the archaeological landscape.

F.D.P., P.M.

5. Discussion and conclusion

The Campania region, with its two case-study areas, Irpinia and the Campanian Plain, selected within the framework of the In.Res.Agri project, served as an authentic experimental laboratory for testing the potential of artificial intelligence software in combination with more traditional approaches in ancient topography and landscape archaeology. Among the software employed, eCognition proved to be the most effective and, together with ENVI, functioned as an interface and mediation tool, simplifying access to the

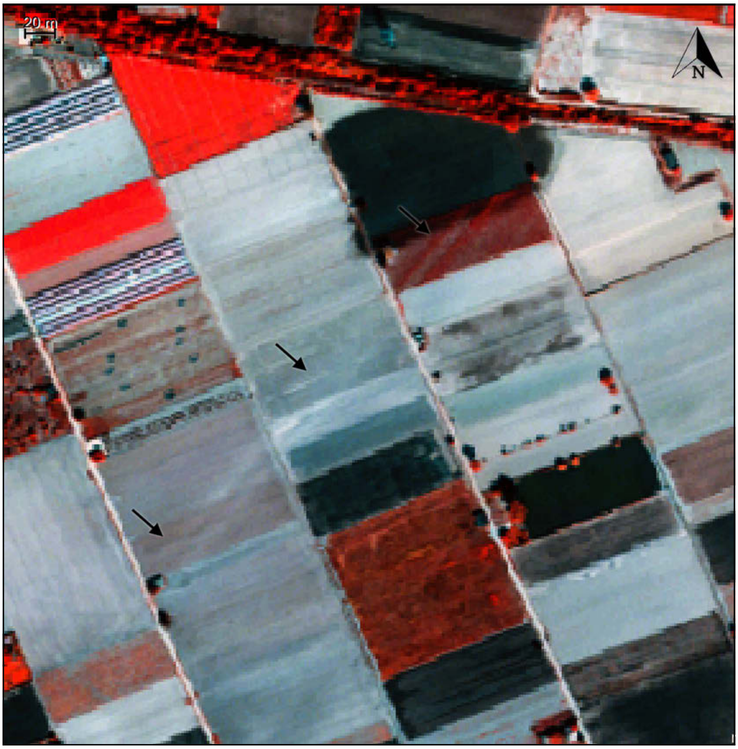

Fig. 5 – Campanian Plain, Acerra (NA), image WV-3 from December 27, 2023 (ID code: 104005005BDC1B00). A possible road trace with NE-SW orientation, seemingly aligned toward the archaeological area of ancient *Atella*. The trace identification and vectorization were performed using eCognition v. 10.4 and v. 10.5, based on the false-color composite derived from the calculated spectral indices.

complex analytical operations that characterize Computational Archaeology and the Digital Humanities.

Analysis of high- and very-high-resolution multispectral data using eCognition v. 10.5 demonstrated the effectiveness of innovative approaches in detecting archaeological traces of ancient land divisions. This made it possible to integrate information derived from cartographic investigations with new discoveries, particularly in morphologically complex contexts such as the mountainous landscapes of Irpinia and the heavily urbanized areas of the Campanian Plain.

In Irpinia, the experiments confirmed the presence of agrarian layouts that had been hypothesized in previous studies (see Ditaranto, Giordano in this volume and references therein), but were here validated through the combined use of satellite analyses and field surveys. The identification of linear traces attributable to Roman centuriation enhanced our understanding of the Romanization of the landscape and of modes of agricultural exploitation. In the Campanian Plain, particularly in the area of the ancient settlement of *Atella*, further archaeological traces were identified, including a possible ancient road, which is currently being verified through targeted field surveys.

The results confirm the potential of the software not only to consolidate previously advanced hypotheses but also to highlight new questions through the detection of previously unknown archaeological traces. These questions may form the basis for future and promising lines of research. The adoption of these advanced techniques, however, has not been without challenges. The main issues concern the quality of the input data, the accuracy of image segmentation, and the constant need for field validation. Accurate segmentation is fundamental for the subsequent phases of classification and automatic object identification; in complex orographic contexts such as Irpinia, the spatial resolution of the imagery is also crucial to avoid distortions caused by vegetation or other natural factors. Despite these limitations, the results demonstrated that the integration of traditional methods with advanced AI tools, particularly convolutional neural networks (CNNs), can provide effective support for archaeological research, paving the way for faster and more efficient investigation strategies. The project has achieved a substantial level of data processing; however, full automation in the identification of centuriation traces will require further development and refinement of deep learning (DL) models. The ongoing process of neural networks training is expected to consolidate and enhance the model, with the ultimate goal of fully automating the identification of ancient agrarian structures.

In conclusion, the work carried out within the In.Res.Agri project confirmed the potential of modern technologies in improving the understanding of archaeological landscapes and in supporting field research. This innovative approach has two main benefits. Firstly, it increases the efficiency and accuracy of archaeological investigations, and secondly it offers a new perspective on the interpretation of ancient landscapes. The integration of sophisticated geospatial analysis techniques with the long established tradition of topographical studies has resulted in significant advances, although further field validation is required to confirm the results and to refine the predictive capacity of the algorithms employed.

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Acknowledgements

The project 'In.Res.Agri – Investigating Resilient Roman Agricultural Landscapes in Southern Italy. An Integrated and Open IT Approach to Modelling Centuriation through Archaeology, Remotely Sensed Data, Palynology and Ancient Texts' was funded by the European Union – NextGenerationEU – Piano Nazionale di Ripresa e Resilienza (PNRR) – Missione 4 'Istruzione e Ricerca' – Componente C2 – Investimento 1.1, 'Fondo per il Programma Nazionale di Ricerca e Progetti di Rilevante Interesse Nazionale' (PRIN) – Project Code: 2022SMJCHX, CUP: B53D23001910006.

REFERENCES

Agapiou A., Lysandrou V. 2023, *Interacting with the Artificial Intelligence (AI) language model ChatGPT: A synopsis of earth observation and remote sensing in archaeology*, «Heritage», 6, 5, 4072-4085 (https://doi.org/10.3390/heritage6050214).

Alcaras E., Amoroso P.P., Falchi U., Figliomeni F.G., Morale D., Prezioso G. 2025, *Comparative analysis of supervised and unsupervised classification methods for Sentinel-2 Imagery*, in *2025 5th International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET) (Fez, Morocco 2025)*, 1-6 (https://doi.org/10.1109/IRASET64571.2025.11007978).

Argyrou A., Agapiou A. 2022, *A review of Artificial Intelligence and remote sensing for archaeological research*, «Remote Sensing», 14, 6000 (https://doi.org/10.3390/rs14236000).

Badgley G. 2017, *Canopy near-infrared reflectance and terrestrial photosynthesis*, «Science Advances», 3 (https://doi.org/10.1126/sciadv.1602244).

Bickler S. 2021, *Machine Learning arrives in archaeology*, «Advances in Archaeological Practice», 9, 186-191 (https://doi.org/10.1017/aap.2021.6).

Brancato R., Ferrari V., Ditaranto I., Merola P., Rossi I. 2024, *Investigating resilient Roman agricultural landscapes in southern Italy. An integrated and open IT approach to modeling centuriation*, «Archeologia e Calcolatori», 35.2, 387-400 (https://doi.org/10.19282/ac.35.2.2024.41).

Breiman L., Friedman J.H., Olshen R.A., Stone C.J. 1984, *Classification and Regression Trees*, Belmont, Taylor & Francis.

Cacciari I., Pocobelli G.F. 2021, *The contribution of Artificial Intelligence to aerial photointerpretation of archaeological sites: A comparison between traditional and machine learning methods*, «Archeologia e Calcolatori», 32.1, 81-98 (https://doi.org/10.19282/ac.32.1.2021.05).

Campana S. 2017, *Remote Sensing in archaeology*, in A.S. Gilbert (ed.), *Encyclopedia of Geoarchaeology. Encyclopedia of Earth Sciences Series*, Dordrecht, Springer, 703-725 (https://doi.org/10.1007/978-1-4020-4409-0_122).

Canedo D., Hipólito J., Fonte J., Dias R., Pereiro T., Georgieva P., Gonçalves-Seco L., Vázquez M., Pires N., Fábrega-Álvarez P., Menéndez-Marsh F., Neves A. 2024, *The synergy between Artificial Intelligence, remote sensing, and archaeological fieldwork validation*, «Remote. Sensing», 16, 1933 (https://doi.org/10.3390/rs16111933).

Cozzolino M., Di Palma F., Gabrielli R., Mauriello P., Scardozzi G. 2025, *A top-down, multi-method and multi-scale approach to studying the Byzantine-Umayyad settlement of Umm ar-Rasas (Amman, Jordan)*, «Heritage», 8, 5, 177 (https://doi.org/10.3390/heritage8050177).

Del Giglio M., Greggio N., Goffo F., Merloni N., Dubbini M., Barbarella M. 2019, *Comparison of pixel- and object-based classification methods of unmanned aerial vehicle data applied to coastal dune vegetation communities: Casal Borsetti case study*, «Remote Sensing», 11, 12, 1416 (https://doi.org/10.3390/rs11121416).

Estoque R.C., Murayama Y. 2015, *Intensity and spatial pattern of urban land changes in the megacities of Southeast Asia*, «Land Use Policy», 48, 213-222 (https://doi.org/10.1016/j.landusepol.2015.05.017).

Friedl M.A., Brodley C. 1997, *Decision tree classification of land cover from remotely sensed data*, «Remote Sensing of Environment», 61, 399-409 (https://doi.org/10.1016/S0034-4257(97)00049-7).

Gallavotti B. 2024, *Il futuro è già qui*, Milano, Mondadori.

Gitelson A.A., Kaufman Y.J., Merzlyak M.N. 1996, *Use of a green channel in remote sensing of global vegetation from EOS-MODIS*, «Remote Sensing of Environment», 58, 3, 289-298 (https://doi.org/10.1016/S0034-4257(96)00072).

Gitelson A.A., Kaufman Y.J., Stark R., Rundquist D. 2002, *Novel algorithms for remote estimation of vegetation fraction*, «Remote Sensing of Environment», 80, 1, 76-87 (https://doi.org/10.1016/S0034-4257(01)00289-9).

Hansen M.C., Potapov P.V., Moore R., Hancher M., Turubanova S.A., Tyukavina A., Thau D., Stehman S.V., Goetz S.J., Loveland T.R., Kommareddy A., Egorov A., Chini L., Justice C.O., Townshend J.R.G. 2013, *High-resolution global maps of 21st-century forest cover change*, «Science», 342, 6160, 850-853.

Hossain M., Chen D. 2019, *Segmentation for Object-Based Image Analysis (OBIA): A review of algorithms and challenges from remote sensing perspective*, «ISPRS Journal of Photogrammetry and Remote Sensing» (https://doi.org/10.1016/J.ISPRSJPRS.2019.02.009).

Huete A.R. 1988, *A Soil Vegetation Adjusted Index (SAVI)*, «Remote Sensing of Environment», 25, 295-309 (https://doi.org/10.1016/0034-4257(88)90106-X).

Johannowsky W. 1987, *L'abitato tardo-ellenistico a Fioccaglia di Flumeri e la romanizzazione dell'Irpinia*, in M. Salvatore (ed.), *Basilicata. L'espansionismo romano nel sud-est d'Italia. Il quadro archeologico, Atti del Convegno (Venosa 1987)*, Venosa, Osanna Edizioni.

Jordan C.F. 1969, *Derivation of leaf area index from quality of light on the forest floor*, «Ecology», 50, 663-666 (http://dx.doi.org/10.2307/1936256).

Kadhim I., Abed F. 2023, *A critical review of remote sensing approaches and deep learning techniques in archaeology*, «Sensors (Basel, Switzerland)», 23 (https://doi.org/10.3390/s23062918).

Karamitrou A., Sturt F., Bogiatzis P., Beresford-Jones D. 2022, *Towards the use of artificial intelligence deep learning networks for detection of archaeological sites*, «Surface Topography: Metrology and Properties», 10 (https://doi.org/10.1088/2051-672X/ac9492).

Lambers K., Vaart W., Bourgeois Q. 2019, *Integrating remote sensing, Machine Learning, and citizen science in Dutch archaeological prospection*, «Remote Sensing», 11, 794 (https://doi.org/10.3390/RS11070794).

Leucci G., Negri S., Ricchetti E. 2002, *Integration of high resolution optical satellite imagery and geophysical survey for archaeological prospection in Hierapolis (Turkey)*, in *IEEE International Geoscience and Remote Sensing Symposium*, Toronto, ON, Canada, vol. 4, 1991-1993 (https://doi.org/10.1109/IGARSS.2002.1026423).

Luo L., Wang X., Guo H. 2024, *Transitioning from remote sensing archaeology to space archaeology: Towards a paradigm shift*, «Remote Sensing of Environment» (https://doi.org/10.1016/j.rse.2024.114200).

McFeeters S.K. 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 (https://doi.org/10.1080/01431169608948714).

Merola P. 2011, *Classificazione dei dati da remoto per la ricerca archeologica*, in *Volume III di Ricerche di Dottorato*, Facoltà di Lettere e Filosofia, Seconda Università degli Studi di Napoli.

Merola P., Allegrini A., Guglietta D., Sampieri S. 2006, *Study of buried archaeological sites using vegetation indices*, «Proc. SPIE 6366, Remote Sensing for Environmental Monitoring, GIS Applications and Geology», 6, 636609 (https://doi.org/10.1117/12.689727).

Orengo H., Conesa F., Garcia-Molsosa A., Lobo A., Green A., Madella M., Petrie C. 2020, *Automated detection of archaeological mounds using machine-learning classification of multisensor and multitemporal satellite data*, «Proceedings of the National Academy of Sciences of the United States of America», 117, 18240-18250 (https://doi.org/10.1073/pnas.2005583117).

Pruitt E.L. 1979, *The office of naval research and geography*, «Annals of the Association of American Geographers», 69, 1, 103-108.

Rondeaux G., Steven M., Baret F. 1996, *Optimization of soil-adjusted vegetation indices*, «Remote Sensing of Environment», 55, 2, 95-107 (https://doi.org/10.1016/0034-4257(95)00186-7).

Rouse J.W., Haas R.H., Schell J.A., Deering D.W. 1974, *Monitoring the vernal advancement and retrogradation (green wave effect) of natural vegetation*, «NASA/GSFCT Type III Final Report, Greenbelt», MD, USA.

Sharma S., Beslity J., Rustad L., Shelby L., Manos P., Khanal P., Reinmann A., Khanal C. 2024, *Integrating remote sensing, GIS, AI, and machine learning for natural resource management: Comparative analysis of tools and the critical role of in-situ validation data*, «Remote Sensing», 16, 4161 (https://doi.org/10.20944/preprints202409.2466.v1).

Soroush M., Mehrtash A., Khazraee E., Ur J.A. 2020, *Deep learning in archaeological remote sensing: Automated qanat detection in the Kurdistan region of Iraq*, «Remote Sensing», 12, 3, 500 (https://doi.org/10.3390/rs12030500).

Sripada R.P., Heiniger R.W., White J.G., Weisz R. 2005, *Aerial color infrared photography for determining late-season nitrogen requirements in Corn*, «Agronomy Journal», 97, 1443-1451 (https://doi.org/10.2134/agronj2004.0314).

Sulik J.J., Long D.S. 2016, *Spectral considerations for modelling yield of canola*, «Remote Sensing of Environment», 184, 161-174 (https://doi.org/10.1016/j.rse.2016.06.016).

Teodoro A.C., Ferreira D., Sillero N. 2012, *Performance of commercial and open source remote sensing/image processing software for land cover/use purposes*, «Proc. SPIE 8538, Earth Resources and Environmental Remote Sensing/GIS Applications», 3, 85381K (https://doi.org/10.1117/12.974577).

Valente R., Iamoni M., Maset E. 2023, *Multispectral and high-resolution images as sources for archaeological surveys. New data from Iraqi Kurdistan*, «Archeologia e Calcolatori», 34.2, 207-223 (https://doi.org/10.19282/ac.34.2.2023.11).

Vats S., Mehta S. 2024, *Revolutionizing archaeological discoveries: The role of artificial intelligence and machine learning in site analysis*, in *2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, 1-5 (https://doi.org/10.1109/ICCCNT61001.2024.10724869).

Wang M., Huang Z., Zhang X., Zhang Y., Chen M. 2021, *Altered mineral mapping based on ground-airborne hyperspectral data and wavelet spectral angle mapper tri-training model: Case studies from Dehua-Youxi-Yongtai Ore District, Central Fujian, China*, «International Journal of Applied Earth Observation and Geoinformation», 102, 102409 (https://doi.org/10.1016/j.jag.2021.102409).

Wang Y., Liu Y. 2024, *Development trend of remote sensing archaeology based on scientific literature*, «Electronic Engineering and Infoirmatics», 51, 247-254 (http://dx.doi.org/10.3233/ATDE240083).

Zamuner D., Piro S., Marasco L., Dabas M., Campana S. 2007, *Integration of remote sensing, geophysical surveys and archaeological excavation for the study of a medieval mound (Tuscany-Italy)*, «Archaeological Prospection», 16, 167-176 (https://doi.org/10.1002/arp.366).

Zhang L., Zhang L. 2022, *Artificial intelligence for remote sensing data analysis: A review of challenges and opportunities*, «IEEE Geoscience and Remote Sensing Magazine», 10, 270-294 (https://doi.org/10.1109/mgrs.2022.3145854).

Zhang X.L. 2018, *Practice teaching of landscape survey course based on eCognition remote sensing image interpretation technology*, «Educational Sciences: Theory & Practice», 18, 5, 1411-1423 (https://doi.org/10.12738/estp.2018.5.038).

ABSTRACT

This research, conducted within the framework of the In.Res.Agri project, explores the integration of advanced remote sensing and artificial intelligence techniques to investigate archaeological landscapes in the Campania region (Italy), with a focus on the regions of Irpinia and the Campanian Plain. The study utilises high- and very-high-resolution multispectral satellite imagery, processed through software such as eCognition, with the objective of identifying and analysing land divisions, including Roman centuriation, and other archaeological features. The methodology combines traditional topographical analysis with both semi-automated and fully automated deep learning approaches, notably the training of convolutional neural networks (CNNs) for the automated detection of linear features. Preliminary results demonstrate the software's capacity to validate known archaeological layouts while revealing previously unidentified structures, such as ancient road networks, in challenging terrain. The continuous enhancement of CNN models is intended to achieve fully automated detection, with the objective of accelerating landscape analysis and enabling field validation. The project under discussion demonstrates the considerable potential for the integration of geospatial analysis and AI-driven technologies to enhance our comprehension of archaeological landscapes. It is important to acknowledge, however, that such endeavours are not without their limitations, and that there is a necessity for ongoing refinement and on-site verification.