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A novel machine learning automated change detection tool for monitoring disturbances and threats to archaeological sites

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ABSTRACT

Archaeological sites across the globe are facing significant threats and heritage managers are under increasing pressure to monitor and preserve these sites. Since 2015, the EAMENA project has documented more than 200,000 archaeological sites and the disturbances and threats affecting them across the Middle East and North Africa (MENA) region, using a combination of remote sensing, digitization, and fieldwork methodologies. The large number of sites and their often remote or otherwise difficult to access locations makes consistent and regular monitoring of these sites for disturbances and threats a daunting task. Combined with the increasing frequency and severity of threats to archaeological sites, the need to develop novel tools and methods that can rapidly monitor the changes at and around archaeological sites and provide accurate and consistent monitoring has never been more urgent. In this paper, we introduce the EAMENA Machine Learning Automated Change Detection tool (EAMENA MLACD). This newly-developed online tool uses bespoke machine learning algorithms to process sequential satellite images and create land classification maps to detect and identify disturbances and threats in the vicinity of known archaeological sites for the purposes of heritage monitoring and preservation. Initial testing and validation of results from the EAMENA MLACD in a case study in Bani Walid, Libya, demonstrate how it can be used to identify disturbances and potential threats to heritage sites, and increase the speed and efficiency of monitoring activities undertaken by heritage professionals.

1. Introduction

The heritage of North Africa and the Middle East is under threat from a variety of factors. This includes not only direct attacks on heritage such as the well-publicized examples of armed conflict and large-scale looting, but also countless other issues including urban and agricultural expansion, natural disasters, and the effects of climate change, leading to desertification, coastal erosion, and wildfires, (Huang and Xu, 2022; Jiang et al., 2023; Mamo et al., 2022; Rayne et al., 2017; Vousdoukas et al., 2022). The Endangered Archaeology in the Middle East and North Africa (EAMENA) project was established in 2015 in recognition of the growing number of threats facing heritage sites today. A collaboration between the Universities of Oxford, Leicester, and Durham, and funded by Arcadia, the EAMENA project's main objectives are to document heritage and the damage and threats affecting heritage sites across the Middle East and North Africa (MENA) region and make them available in an online database (Oxford and Southampton, 2024; database.

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eamena.org) for use by heritage professionals, researchers, students, and other stakeholders (Bewley et al., 2016; Zerbini, 2018; see also eamena.org).

The EAMENA project uses an interdisciplinary methodology to record heritage sites and conduct condition assessments, including digitization of published and archival materials, and fieldwork. A primary focus of the project's methodology is on the use of remote sensing and satellite imagery analysis (Rayne et al., 2017). Over the past two decades, remote sensing has become established as an indispensable tool for archaeological survey and documentation, particularly in the MENA region, where it is especially effective due to the dry climate, relatively low levels of vegetation and low population densities outside of the large cities (e.g. Casana et al., 2013; Kennedy, 2011; Luo et al., 2018; Parcak, 2009). It is also an especially valuable tool in the MENA region because it allows both local and foreign archaeologists to conduct surveys and monitor the condition of archaeological sites over time in areas which are unsafe due to conflict or political instability, or otherwise inaccessible.

As of June 2024, the EAMENA database holds over 200,000 heritage records spanning over 20 countries across North Africa and the Middle East, from Mauritania to Iran, and this represents only a fraction of the heritage sites in the region. Site records contain up to c. 90 fields related to the archaeological significance, form, features, location, and date of the heritage site, as well as a condition assessment that documents both visible disturbances and potential threats identified at the time of recording. The database thus provides a baseline inventory of heritage sites, which is the necessary foundation for their protection.

However, effective heritage protection over the long-term requires regular monitoring of sites, to track their condition over time and identify any new disturbances or encroaching threats. There are four main questions which need answering for effective monitoring of archaeological sites:

1. Has a change or a potential threat been observed in the vicinity of the site?
2. What type of change or threat has been observed?
3. When did this change or threat occur?
4. Is the change or threat still ongoing?

All of these questions can be answered through fieldwork or image interpretation using high-resolution imagery, and these remain key tools for heritage monitoring. However, due to the huge number of sites with which we are dealing, and the enormous area being covered, our project has been exploring and developing automated methods to aid heritage managers make this mammoth and never-ending task faster and more efficient.

Remote sensing change detection methods have been developed for a wide range of purposes in many disciplines (Asokan and Anitha, 2019; Bai et al., 2023; Goswami et al., 2022; Lu et al., 2004; Singh, 1989) such as large-scale natural hazard monitoring (Mentaschi et al., 2018), environmental and disaster management monitoring (Szpakowski and Jensen, 2019; Willis, 2015), mapping national-scale mangrove forests (Hu et al., 2020) and for developing early warning systems, for example for monitoring deforestation in Kenya (Roberts et al., 2022); it has also been widely used in the field of archaeological monitoring (Chen et al., 2023; Guo et al., 2023). One tool which is making these methods more accessible is Google Earth Engine (GEE), a free, open-access platform which allows users to deploy a huge archive of satellite imagery and geospatial datasets and write bespoke codes to perform planetary-scale analysis (Gorelick et al., 2017). GEE is increasingly being used as a tool for archaeological and heritage applications (Agapiou, 2017; Herndon et al., 2023; Liss et al., 2017; Rayne et al., 2020).

The EAMENA project's first GEE-based Automated Change Detection (ACD) methodology and workflow was published in 2020 (Rayne et al., 2020). In that version, the user defines the study area, dates of interest, change threshold, and inputs the location(s) of one or more heritage sites, with a user-defined buffer zone. The script compares the pixel values across two Sentinel-2 satellite image composites, to determine where changes have occurred within the area of interest. Any instances where the areas of change intersect with the buffer zones of the heritage sites are highlighted to the user, enabling them to undertake validation and where possible identify the specific cause of the change identified by the ACD, via more thorough visual survey of high-resolution satellite imagery or fieldwork. This method was presented with case studies in Libya and Egypt, and validation showed that the method had an accuracy of between 85 and 91 % (Rayne et al., 2020).

The advantages of this method are its speed and simplicity, allowing the user to quickly analyse dozens or even hundreds of sites at once and then target resources towards those where changes have been highlighted. However, it is limited in the amount of detail that it can provide about the type and timeline of the change that it has identified. It only answers the first question mentioned, presenting a binary result which indicates only whether a change has occurred or not. The second phase of EAMENA's work in this area, has therefore been on the development of an ACD method which would also answer the other three questions, namely what type of change has occurred, when did it occur, and is it still ongoing.

The results of this development and accompanying workflow are presented below, as the EAMENA Machine Learning Automated Change Detection (MLACD) method, which uses machine learning models to produce a time-series of Sentinel-2 images classified by land cover for a user-defined location and time-period, and compares them to determine changes in land cover and use at and around a defined dataset of heritage sites. The workflow and outputs are demonstrated in a case study analysing a series of endangered heritage sites in and around the city of Bani Walid, Libya, and represents the first application of this type of methodology to the protection of Libyan heritage sites. The outputs of the method provide new information and insights into the disturbances and potential threats affecting heritage sites in the region. The development of a bespoke, user-friendly interface and detailed training documentation in both English and Arabic, enabled the training of several archaeologists from the Libyan Department of Antiquities in this method, who then undertook the field validation in Bani Walid. This case study demonstrates how the EAMENA MLACD can be successfully incorporated into the workflows of local antiquity authorities to rapidly identify areas of concern and prioritize the deployment of resources.

2. Data and methods

The EAMENA MLACD has been developed in the cloud computing service platform Google Earth Engine (GEE) using the JavaScript programming language. The implementation of the EAMENA MLACD requires a free Google Earth Engine account as well as basic GIS and remote sensing skills to adapt and implement the tool for new case studies.

The EAMENA MLACD follows sequential steps to process Sentinel-2 satellite images in order to identify the changes and potential threats to the archaeological sites in the region of interest (Fig. 1). The EAMENA MLACD workflow is divided into three main stages: 1) defining variables and inputs; 2) image classification and analysis; 3) identification of disturbances and threats to archaeological sites. The workflow is outlined in summary in the sections below. The code and full step-by-step instructions in English and Arabic for adapting and implementing the EAMENA MLACD can be accessed on the EAMENA GitHub repository (https://github.com/eamena-project/EAMENA-MachineLearning-ACD).

2.1. Defining variables and inputs

Before running the script, the first step of using the EAMENA MLACD is to define the variables and inputs. This includes defining the geographical extent of the study area, importing a vector layer for the archaeological sites under investigation within the region of interest, defining the visualization parameters, bands, and setting the labels which will be used for the outputs. The user can also define

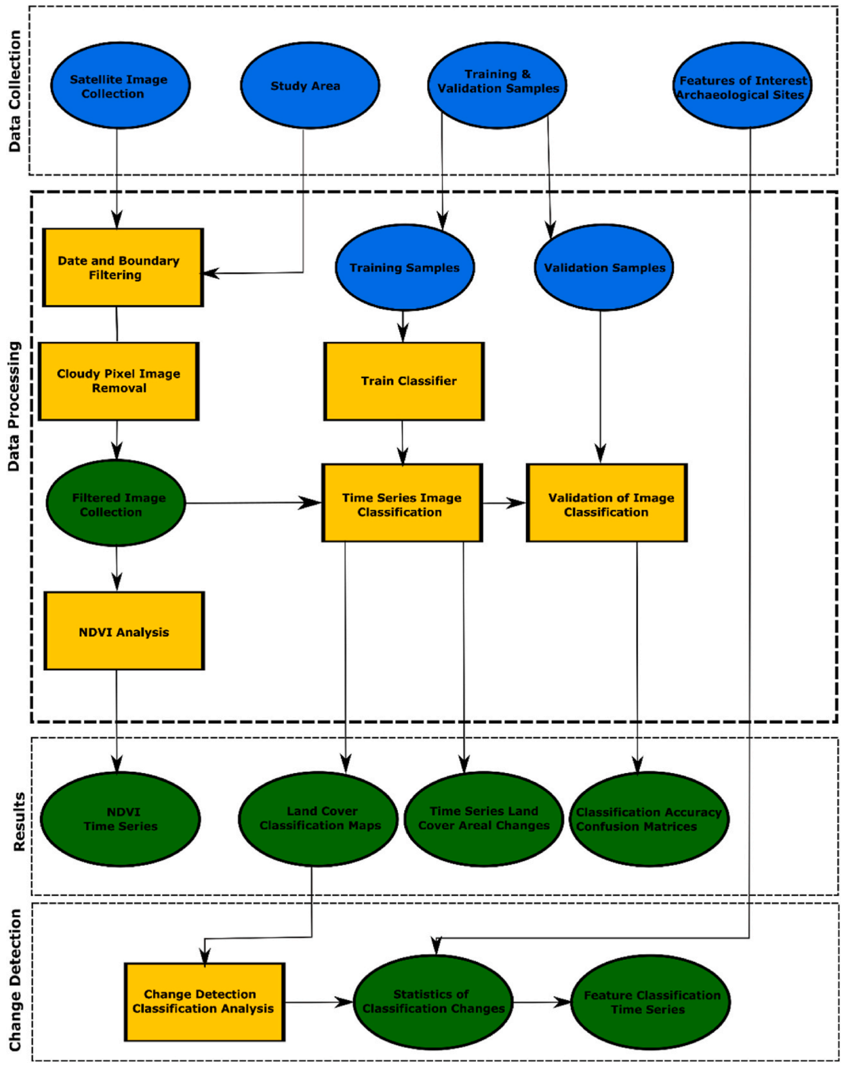

Fig. 1. EAMENA machine learning automated change detection processing framework.

a location (P), either a point or polygon, which will produce an additional, more in depth analysis of the changes encountered in this particular location. The study area and the location (P) can be defined using the Geometry Tool which is built into the Google Earth Engine or imported as a pre-defined vector layer.

The user must also collect training and validation datasets which will be used to train the classification model to distinguish the different land cover classes in each satellite image and detect the changes and threats within the study area.

2.1.1. *Training samples*

The EAMENA MLACD works by creating a series of land classification maps for the area of interest and time period defined by the user. Training samples must be collected for each new case study to train the machine learning model to distinguish the spectral variation between the different land cover types and enable the classification. The selection of training datasets has a significant role in the accuracy of the classification results (Zhang et al., 2023).

The user must first define the number and labels of the land cover classes they wish to use directly in the code, based on the environment in which they are conducting their analysis, before creating the training sample data. Training samples can be defined directly in Google Earth Engine, using the Geometry Tool and the high-resolution base map provided, or using satellite imagery accessed via other platforms and imported into the script. We recommend that users create several training dataset polygons for each class. The EAMENA MLACD tool applies a stratified sampling method which ensures that the training datasets are divided homogeneously into strata with adequately representing each stratum in the sample and captures the variability within different strata (Ramezan et al., 2021). The model is developed to select 500 points for each class from the training dataset where 70% of these selected stratified samples are used as training samples and the remaining 30% are used to validate the accuracy of classification of the machine learning model.

2.1.2. *Filtering and mosaicking satellite images*

The EAMENA MLACD is developed to automatically process and analyse Sentinel-2 Level 2A harmonized satellite images. These images comprise multispectral satellite data with an applied surface reflectance correction and has multiple bands with variant spectral reflectance such as Red, Green, Blue and the Near Infra-red with 10 m pixel spatial resolution. The Sentinel-2 L2A Harmonized imagery has global revisit time of the satellite of between 5 and 10 days at the equator which makes it ideal for monitoring purposes (ESA, 2015).

The EAMENA MLACD code filters the Sentinel-2 images based on the user-defined area and period of interest, as well as the defined cloud coverage percentage, excluding images which are too cloudy. To further improve the accuracy of the classification results, collected images are passed through a cloud mask to remove all the remaining cloudy pixels in the images. This mask relies on the Scene Classification Layer (SCL) which is provided with each Sentinel-2 image to filter out pixels of cloud and shadows which can lead

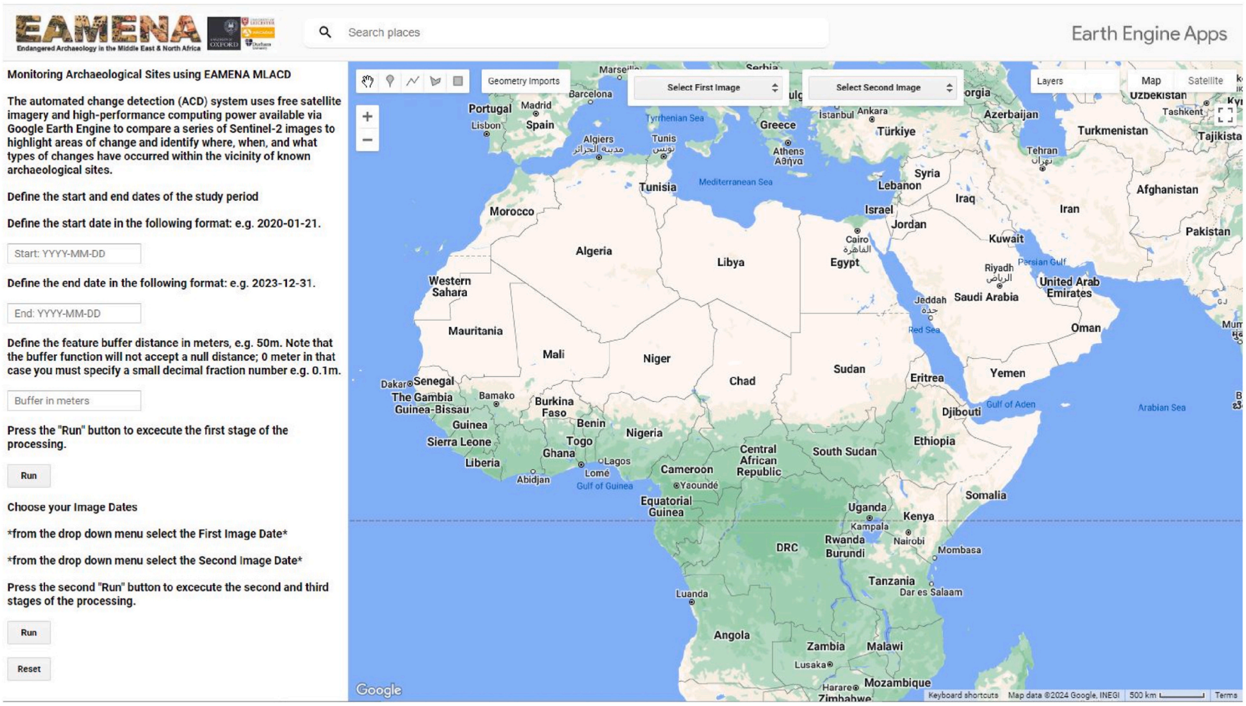

Fig. 2. EAMENA MLACD User Interface. The user interface allows archaeologists to easily execute the process of monitoring archaeological sites in areas of interest.

to misclassification. A mosaicking step is also implemented to ensure that the area of interest is fully covered and analysed in cases where it spans two or more satellite scenes.

2.1.3. User interface

The variables discussed in the previous sections must be edited directly within the code before it runs in order to set the parameters. However, we have developed a bespoke user interface in which to enter additional variables, to help users with limited knowledge or comfort with coding interfaces carry on with the workflow (Fig. 2). At this point, the user inputs directly into the interface the start and end dates for the period of interest and sets the size of a buffer zone around each of the defined archaeological sites in which to conduct the analysis and detect the changes and threats within the defined boundary.

2.2. Land cover classification and change detection

Land cover classification of satellite images is the main processing step in this tool. The EAMENA MLACD uses a machine learning algorithm to perform supervised classification to distinguish pixels that represent each of the defined classes and land cover types identified in the variables and input step as the training dataset.

The EAMENA MLACD employs the Random Forest machine learning classifier that works by generating multiple decision trees from randomly selected subsets of the training samples. Each decision tree votes to predict or classify unknown samples and the final prediction or classification is aggregated from the majority of votes from the individual trees (Breiman, 2001). This method has proved to be robust in dealing with large training datasets and reducing overfitting and outliers in the training samples (Belgiu and Drăguţ, 2016), in addition to being less sensitive to mislabelled training data (Mellor et al., 2015). The Random Forest model is found to be suitable for the classification of hyperspectral data (Chan and Paelinckx, 2008) and multi-source remote sensing data (Corcoran et al., 2013; Li et al., 2022). Moreover, it also performs well in arid and semi-arid regions, making it an ideal algorithm for change detection applications. To ensure a robust analysis and accurate classification model, the MLACD was tested using a series of different Random Forest model parameters to optimize the model for the classification.

After defining the variables and running the script as described in the previous sections, two dropdown menus appear which finally enable the user to choose two individual images from within the specified period of interest for the script to compare. The script conducts the change detection by computing a new change class which identifies which pixels have retained the same land cover class and which have changed to a different land cover class between the two selected images. As illustrated in Table 1, for example, if the initial analysis is run with four land cover classes (e.g. Bare, Disturbed Earth, Urban, and Vegetation, the classes identified in the case study presented in Section 3), this results in 16 new classes, four of which represent no change, and 12 representing each different permutation of change from one class to a different one. If the user identifies five land cover classes, there would be 25 change classes, and so on.

The script identifies the changes within the defined buffer area of each site of the study area, and calculates the mode, i.e., the most commonly occurring change class within the buffer zone of each site. A chart which then presents the distribution of sites by mode is produced as an output, giving an overview of the most commonly observed change classes. The proportion of each change class which appears within the buffer zone is also calculated as a histogram for each individual site and presented in the outputs.

To help the user refine the best combination of bands to use for the land cover classification, the script also computes the spectral reflectance response of each land cover class and compares it to the different image bands in the optical Sentinel 2 multispectral images. Fig. 3 illustrates the output that this analysis produces for an example involving four land cover classes. In this example, the spectral reflectance recorded for bare class and urban class overlaps in bands B1, B2 and B3 which could generate mislabelling and inaccurate classification of images. Therefore, users can choose to exclude any band that results in that to reduce the likelihood of misclassification and then re-execute the analysis before moving forward.

Table 1
Classification change table for the changes in pixels between two selected satellite image dates.

Class in Image 1	Class in Image 2	Change Class Value	Change Class Label
C1	C1	1	Bare_to_Bare
C1	C2	2	Bare_to_DisturbedEarth
C1	C3	3	Bare_to_Urban
C1	C4	4	Bare_to_Vegetation
C2	C1	5	DisturbedEarth_to_Bare
C2	C2	6	DisturbedEarth_to_DisturbedEarth
C2	C3	7	DisturbedEarth_to_Urban
C2	C4	8	DisturbedEarth_to_Vegetation
C3	C1	9	Urban_to_Bare
C3	C2	10	Urban_to_DisturbedEarth
C3	C3	11	Urban_to_Urban
C3	C4	12	Urban_to_Vegetation
C4	C1	13	Vegetation_to_Bare
C4	C2	14	Vegetation_to_DisturbedEarth
C4	C3	15	Vegetation_to_Urban
C4	C4	16	Vegetation_to_Vegetation

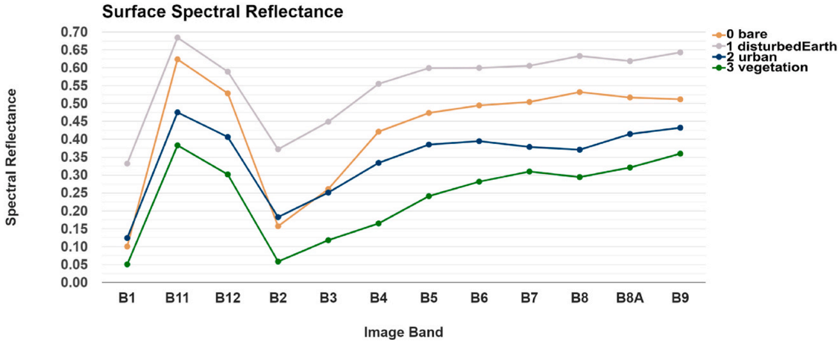

Fig. 3. Example of Surface Spectral Reflectance illustrating the response of each land cover class to the different electromagnetic waves and bands. There is overlap between the Bare class and Urban class in bands B1, B2 and B3 which could generate mislabelling and inaccurate classification. Therefore, these bands are excluded from the analysis.

2.3. EAMENA MLACD outputs

The MLACD produces several different outputs in the form of visual and statistical data. This includes land cover classification maps, a binary change map, change class map, and an animated gif map displaying the changes in the defined study area over the period of interest. Time series analysis charts show the changes in the proportions of each land cover class over time for the entire study area, as well the changes in land cover class and NDVI for a specific user-defined location within the study area. It generates histograms which provide the relative frequency of each change class within the buffer zone of each site, and the user can choose which particular change class they are interested in to visualize the pixels and sites affected by only that particular change. It also produces different vector and raster data for the areas and sites where changes have been identified which the user can download to use in a GIS software for further analysis or validation activities. Finally, it also produces accuracy data including confusion matrices to help the user determine how successful the analysis has been and if, for example, they need to refine their validation data further.

3. Case study: Bani Walid, Libya

In order to demonstrate and test the land cover classification based MLACD method and its workflow, we adapted and applied the EAMENA MLACD to a case study in the area of the city Bani Walid in the north-west region of Libya known as Tripolitania. Located about 150 km southeast of Tripoli, in Misrata District, Bani Walid is one of the largest cities in Libya's pre-desert region, extending approximately 20 km along the north and south banks of a major tributary of the Sofeggin basin, which ultimately flows north and eastwards into the Mediterranean Sea (Fig. 4). Situated at the northern edge of Libya's desert zone, it receives on average less than 100 mm of rain per year, well below the limit for dry farming. Unless aided by advanced irrigation techniques, agriculture is primarily limited to the seasonal river beds or wadis, which flood during the rainy seasons. Local inhabitants have practised floodwater farming techniques for more than 2000 years, building walls across the wadi beds to slow down the speed of the floods, trapping the water and fertile soils to maximize the potential for agriculture.

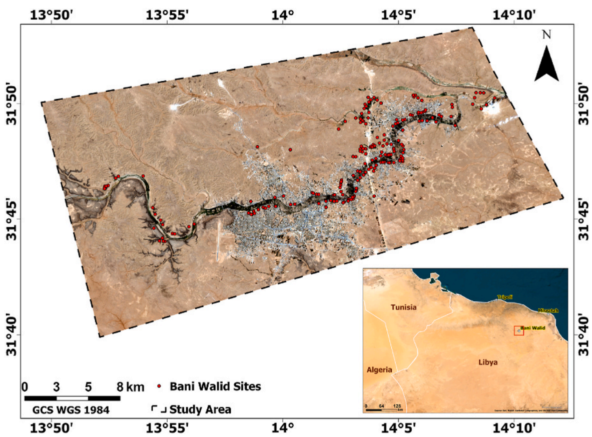

Fig. 4. Study area of Bani Walid located in the north-west of Libya; where 211 archaeological sites recorded in the EAMENA database were monitored using the EAMENA Machine Learning Automated Change Detection (EAMENA MLACD).

3.1. Archaeological background

A total of 211 archaeological sites were recorded in the EAMENA database within the study region and exported for analysis, extending along a c. 30 km stretch of the wadi (Fig. 4) (EAMENA database, 2024). The study area is located near the northern limits of a major archaeological survey which took place in the late 1970s and early 1980s (Barker et al., 1996a, 1996b). The majority of these sites (129) were recorded and digitized from the published gazetteer of this survey, the UNESCO Libyan Valleys Survey (ULVS), comprising the sites recorded in the Wadi Garjuma, Wadi Beni Ulid [sic] (West), and the western part of the Wadi Merdum (Sites Md201–299) (Barker et al., 1996a). However, detailed pedestrian survey was limited in this area; according to the original project notes, the majority of the sites within what is now the modern city of Bani Walid (sites Md201-299) were recorded through reconnaissance along the main road through the area and not visited or recorded individually (BILNAS Archive, ULVS Papers, D54/1/26/2). The remainder of the sites included in this study (82) were identified and recorded via various remote sensing investigations carried out by EAMENA staff members, partners, and volunteers and recorded directly in the EAMENA database, and until recently most had not been recorded in the field.

The majority of datable archaeological remains in the study area date from the Roman to Medieval and Early Modern periods, but archaeological investigations have shown that the Sofeggin basin and the wider pre-desert zone of Tripolitania has been utilized and occupied by people for millennia (Barker et al., 1996b, pp. 83–110). The stretch of the wadi which the modern city of Bani Walid now occupies is no exception, and has been more or less continuously occupied and the wadi cultivated for at least two millennia. Flint scatters and possible funerary cairns could represent even earlier use of the area by local peoples moving through the region, even if they were not permanently settled there (Barker et al., 1996a, pp. 121–123).

During the 1st c. CE, there was a rapid sedentarization of the region. For the first time, permanent and often substantial stone farm buildings began to appear along the banks of the most fertile wadis, suggesting at least a perceived incentive for people to practice sedentary agriculture, though it is clear that pastoralism also continued to play an important role (Barker et al., 1996a, 1996b; Mattingly, 2023, p. 472; Sheldrick, 2021, pp. 100–105). Around Bani Walid, due to its near continuous occupation since the early first millennium, however, few of these early Roman farm sites have survived, or at least not in their original forms. More commonly recorded were fortified sites (*qsur*), from the later Roman and medieval periods, dating from the 3rd c. CE onwards (Barker et al., 1996a, pp. 127–133; Sheldrick, 2021, pp. 107–165). Well-preserved examples still remain at the western and eastern ends of the study area, which for now, at least, sit outside the edges of the modern town.

By the 11th c. CE, Bani Walid had become one of the main centres of the Tripolitanian interior, ultimately becoming the base of the Orfella confederation, which encompassed both Libyan and Arab groups which had come to occupy the region (Mattingly, 1987, pp. 91–93). Many of the sites still surviving in and around Bani Walid date from the medieval period, in the form of nucleated villages, comprising multiple houses, sometimes one or more *qsur*, and often a mosque or marabout. Most of these sites have not been examined in any detail, so it is not possible to be more precise in terms of dates in most cases, and further investigations are sorely needed. One of the largest of these medieval settlements was Ben Telis (EAMENA-01164450). Archaeological investigations of the site suggest that its primary phases of occupation were from the 14th to 15th c. CE, and that it was abandoned not long after this (Barker et al., 1996a, p. 192; Barker and Jones, 1981, p. 42). However, it is very likely that at least some sites have earlier origins than this, while others continued to be occupied well beyond this period, into the Early Modern period, with some still occupied today.

3.2. Modern threats

The heritage of Libya is under threat from a variety of modern factors (Munzi and Zocchi, 2017; Rayne et al., 2017). The disturbances to the archaeological sites under investigation in the case study and identified through the MLACD analysis will be discussed further below, but two major, previously identified threats are worth highlighting here.

In the area of Bani Walid in particular, the main threat to heritage sites is the rapid and substantial urbanization of the modern city which has taken place over the past 50 years. Comparison of modern satellite imagery with declassified satellite images collected in the early 1970s shows that the extent of urban areas has increased substantially during this time (Fig. 5). Following the 2011 revolution, urban expansion increased in speed and scale, as the restrictive regulations on property ownership that had been imposed by Qaddafi

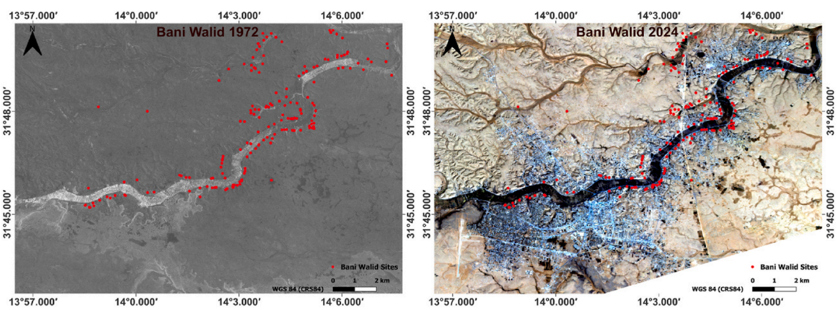

Fig. 5. Substantial level of urban expansion observed in the city of Bani Walid between 1970s and 2024. (a) KH-9 Corona satellite imagery acquired on the July 08, 1972 © USGS D3C1203-100014A008; (b) PlanetScope imagery acquired on February 23, 2024 Image © 2024 Planet Labs PBC.

were no longer being enforced (Fitzgerald et al., 2015). This has already had a significant impact on many of the heritage sites within the boundaries of modern Bani Walid described in the previous section, and the continued expansion of the city poses an imminent threat to sites on its outskirts.

Another activity which has affected heritage sites in this particular region was the Great Man-Made River project (GMRP), which was developed to bring fresh water from the fossil ground-water sources deep beneath the Sahara to the coast for a variety of uses and to address the issue of water scarcity in Libya. The Phase II or Western Pipeline, constructed between 1986 and 1996, brings water from the Jebel Hasounah to Tripoli and the surrounding coastal region, cutting directly through the eastern part of Bani Walid on its route through the pre-desert and is clearly visible on satellite imagery (El-Maiar and Allan, 2006). El Maiar and Allan noted that the pre-desert region was the area in which there was the highest potential for impact on heritage, but as no in-depth investigations had been carried out at the time of publication, they could not comment any more specifically (El-Maiar and Allan, 2006, p. 39). In 2022, a placement student with the EAMENA project compared modern high-resolution satellite imagery to historic KH9 Hexagon satellite imagery from the 1970s to identify what impact the GMRP had had on heritage sites along a 60 km stretch north and south of Bani Walid. His analysis showed that of 411 sites identified within 1 km of the pipeline in this area, 34 sites appeared to have been disturbed as a direct result of the GMRP (Millington, 2022). Given the significant threats facing the important heritage of Bani Walid, it was agreed with the Libyan Department of Antiquities that this would be an ideal area in which to test the EAMENA MLACD method.

3.3. MLACD results

In order to apply the MLACD analysis to the Bani Walid area, we first uploaded shapefiles defining the study area and the dataset of 211 archaeological sites. As each site was geolocated by a single central point, the buffer zone was set at a 100 m radius, in order to include as much of the site extent as possible and ideally some buffer area beyond it (although some of the village sites were even larger than this). The period chosen for analysis was January 2019 to February 2024, resulting in the processing of a sequential series of 135 Sentinel-2 L2A satellite images.

3.3.1. Land cover classification results

Four land cover types were identified for the Bani Walid study area which the machine learning model was trained to identify: Bare, Disturbed Earth, Urban and Vegetation (Table 2). These classes were selected based on inspection of high-resolution satellite imagery to assess the main classes of land cover present, as well as in consultation with our Libyan partners who are familiar with the local environment.

As described in Section 2.2.1 above, the script was run first as a test to calculate the spectral reflectance of each class, in order to further refine the results and reduce misclassification. Bands B1, B2, and B3 were excluded due to the overlapping spectral reflectance levels, for instance between the Bare and Urban classes. The remaining bands used in the analysis therefore were B4, B5, B6, B7, B8, B8A, B11, and B12.

Training sample datasets were collected for each class from high-resolution satellite images including PlanetScope, SkySat and Google Earth archived imagery (Table 3). To ensure high quality of the training dataset and to reduce any potential mislabelling in the training samples which could influence the accuracy of the image classification, all of the training samples were then validated on 11 PlanetScope images collected twice a year across the 5-year period of interest to account for any changes in the study area due to seasonality. Additionally, the training samples were also validated with historical high-resolution images available in Google Earth Pro and/or SkySat imagery.

Having established the variables, the selected images were filtered, processed and classified according to the methods described in Section 2 (Fig. 6a–b). Two individual satellite images were selected to analyse and visualize the changes observed between those specific dates, in this case the earliest and latest available images of the period of interest: January 25, 2019 and February 23, 2024, producing individual land cover maps (Fig. 6c–d), a binary change map (Fig. 6, e) and a change classification map (Fig. 6,f).

In addition to the visualizations, the EAMENA MLACD provides a series of statistical outputs to help the user interpret the results. The first output is at the landscape scale and calculates the area in square kilometres covered by each land cover class for each image within the period of interest, illustrating how the proportions of each class have changed over time (Fig. 7). Understanding the extent and rate at which different types of land cover, such as urban or agricultural areas, are expanding or contracting is crucial information for heritage managers to understand how heritage sites have been affected or may be affected in the future, and enable heritage managers to co-ordinate with other governmental departments and local communities regarding any planned or predicted projects which endanger heritage sites.

Table 2
Land cover types used for the Bani Walid case study.

Class Value	Class Name	Description
C1	Bare	Bare and rocky soil
C2	Disturbed Earth	Areas of recently disturbed earth, exposing sub-surface soils and geology, due to activities such as bulldozing, quarrying and looting
C3	Urban	Buildings and roads
C4	Vegetation	Areas of natural or agricultural vegetation

Table 3
Characteristics of Sentinel-2, PlanetScope, and SkySat images used in this study.

Satellite	Description
Sentinel 2	Freely accessible. Launched 2014/2015, multispectral instrument with 13 bands with different wavelength (443–2190 nm), spatial resolution (i. e., RGB&NIR 10m, Vegetation Red Edge & SWIR (20m), with a revisit time of 5 days–10 days across the globe
PlanetScope	Launched 2015, multispectral instrument with 8 bands wavelength (431–885 nm), spatial resolution (3m), temporal resolution (Daily), licensed
SkySat Archive	Launched 2013, five bands Blue, Green, Red, NIR and Panchromatic, spatial resolution (0.5 m), licensed

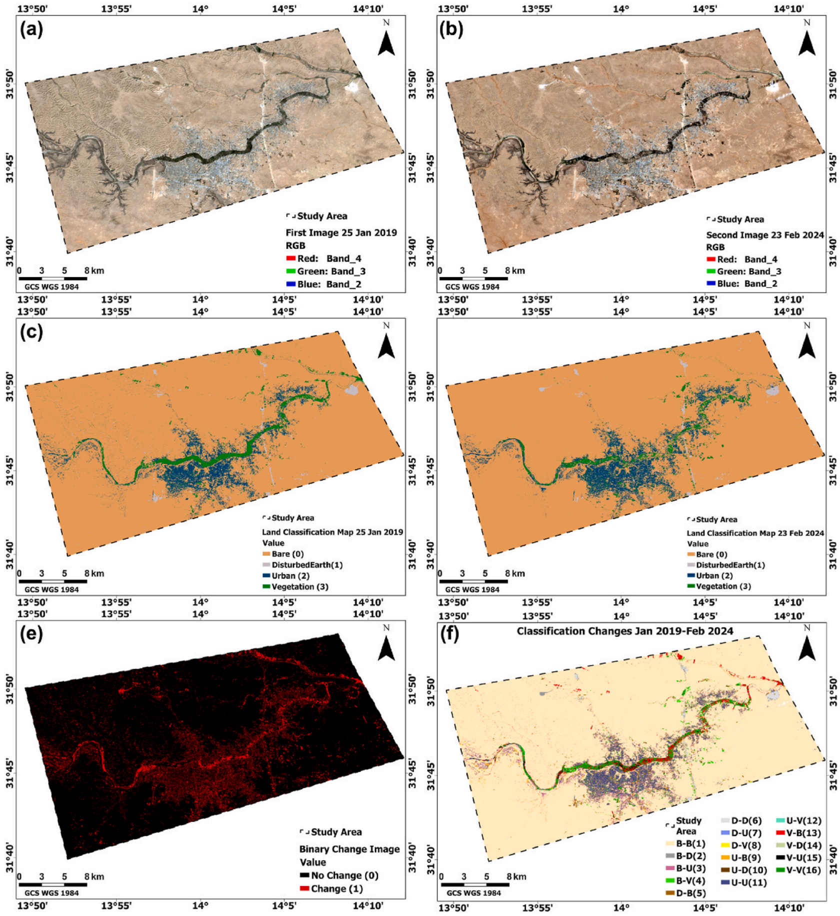

Fig. 6. Change detection between to selected Sentinel-2 images (a) January 25, 2019 (b) and February 23, 2024; (c) land cover classified image of January 25, 2019; (d) land cover classified map of February 23, 2024; (e) binary change map assigns a value of 1 where change has been detected (red) and a value of 0 where there has been no change (black); (f) classification change map between January 25, 2019 and February 23, 2024 (B, D, U and V respectively represent the Bare, Disturbed Earth, Urban and Vegetation land cover classes).

For the study area of Bani Walid, Fig. 7 shows that the class identified as Bare is consistently the dominant class during the period under study, covering an area varying between 470 and 500 sq km. The area covered by the Urban class varies between 18 and 45 sq km during the time period investigated; this is likely in part due to the expansion of the modern urban buildings experienced in Bani Walid. However, it is also important to note that at times the variation between images may also be as a result of misclassification between the Bare and Urban classes; many of the building materials used for construction are sourced from local quarries, resulting in an overlap in the surface reflectance signature of both classes. The Disturbed Earth class covers an area of c. 2 to 10 sq km, related mainly to quarrying and bulldozing activities within and around Bani Walid. The Vegetation class area fluctuates between 6 and 18 sq km depending on the seasonality and vegetation growth mainly within the wadi bed, where most of the agricultural activity in Bani Walid is concentrated. While in this example the overall proportion of each of the land cover classes has remained relatively steady, in the event of any major increases in urban or agricultural development in the study area, this chart would clearly signal these changes to users.

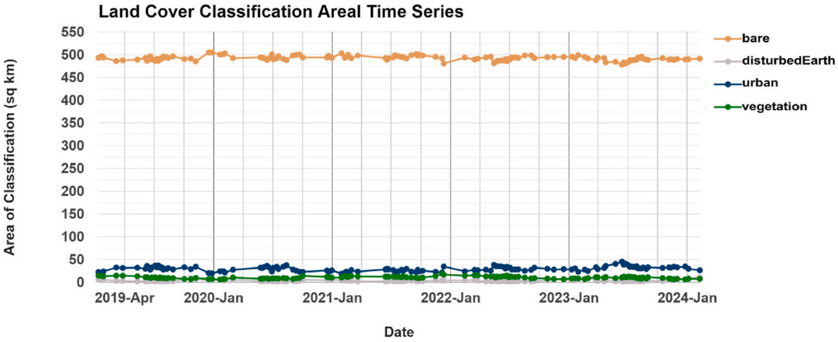

Fig. 7. Land cover classification areal time series.

3.3.2. Change and threat detection results

The next set of outputs provide statistics related to the archaeological sites which were uploaded for analysis and any changes in land cover observed within the buffer zones. As discussed above, changes within the buffer zone of each site are identified at the pixel level in the form of new change classes as illustrated, for example, for site EAMENA-0189582 (Fig. 8, c).

Two outputs which provide different summaries of the MLACD change results are calculated and presented to the user. The first computes the most commonly identified class change (i.e. the mode) within the defined buffer zone of each site. Fig. 8a illustrates the results of this analysis for the case study, showing that for the vast majority of sites (191), the most frequently occurring change class was 'Bare to Bare', that is the majority of pixels within the buffer zone of each site were Bare class in both the earlier and later image analyses. Similarly in the remaining sites, the mode was either the 'Urban to Urban' class (16 sites) or the 'Vegetation to Vegetation' class (4 sites).

This analysis gives a broad summary based on the most commonly observed changes across the sites under investigation, but by only identifying the dominant class it glosses over smaller areas of change, which may be just as detrimental to sites, for example, due to a slight expansion of urban areas or vegetation growth. A second output is therefore generated which tallies the number of sites where even a single pixel of each change class has been identified within the buffer zone of a site, which presents a very different picture, making it clear that a variety of changes, even if only represented by one pixel, have been detected within the buffer zones of most sites (Fig. 8, b). For example, in Fig. 8, b we can see that 164 sites had at least one pixel which changed from the Bare to Urban class, indicating possible new construction within the 100 m buffer zone of the sites. This includes not only instances where the class

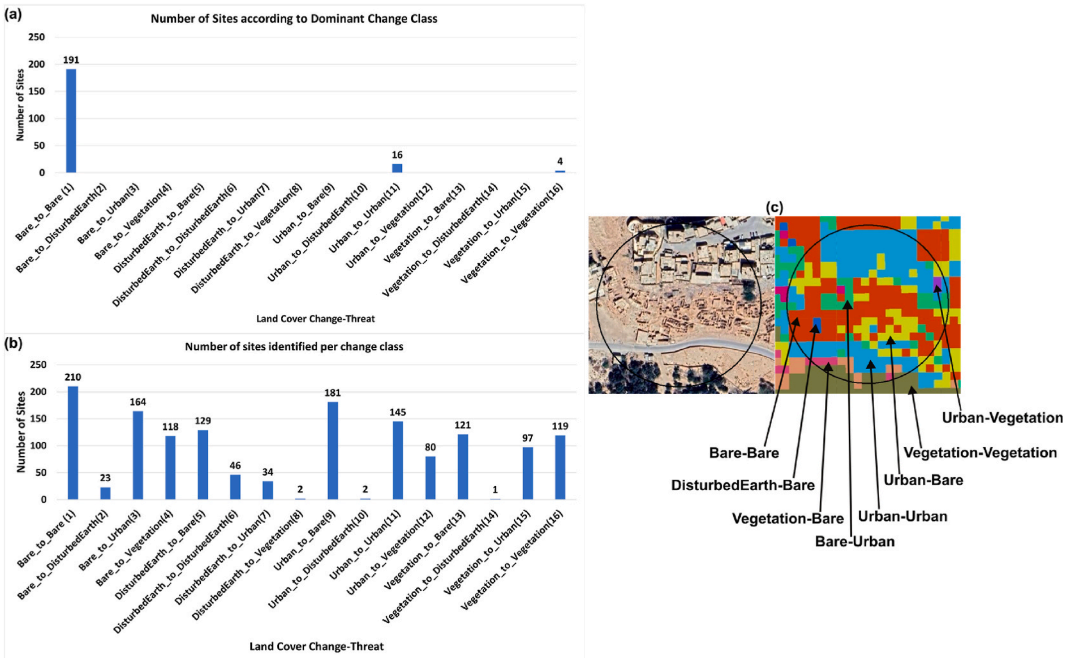

Fig. 8. Statistics based on land cover change classes for archaeological sites within the study area: (a) sites according to dominant land cover change class; (b) number of sites identified with one or more pixels of each change class; (c) example of classification change on a pixel level within the buffer zone of site EAMENA-0189582.

has changed, but also records where the class has remained the same, such as in the case of 145 sites which have pixels which have remained Urban, indicating where a past disturbance, e.g. from urban or agricultural expansion, is already present within the buffer zone of the site, dating to before the period of study, and could be indicative of an on-going disturbance or future threat.

Finally, the MLACD also produces outputs which illustrate the change over time according to land cover class as well as normalized difference vegetation index (NDVI) at the location (P) defined by the user. In one example, location (P) was a polygon located within the buffer zone of site EAMENA-0189408, a village probably dating to the medieval period. At the start of the period of analysis, the west side of the site had already been encroached upon by the expansion of a modern farm (Fig. 9, a), and the polygon (P) was placed there to monitor any further change. The classification time series calculated at location (P) illustrated that the land cover class at location (P) was either Bare or Urban before June 2021, while after that date it changed to Vegetation (Fig. 9, g). This was also verified by the NDVI time series, which shows that the NDVI value at location P has increased from about 0.05 to 0.17 between January 2019 and January 2021 (indicating bare soil), to about 0.25–0.6 (indicating sparse vegetation) (Fig. 9, h). Validation using high-resolution imagery from Google Earth Pro (Fig. 9b–f) confirmed these results, clearly showing new vegetation growth beyond the boundaries of the modern farm, encroaching eastwards onto the archaeological site, probably an unintentional result of run off from irrigation within the modern farm. This is a direct threat to the site as there is a high likelihood that both the run-off and resulting vegetation will have a detrimental effect on the integrity of the site.

A second example illustrating the issue of urban expansion is shown at site EAMENA-0087052, another probably medieval village. Since 2009, a number of new buildings have been constructed within the buffer zone of the site, resulting in its partial destruction (Fig. 10a–d). The EAMENA MLACD has also identified continuing construction activity within the case study period, where the classification time series of location (P) showed land cover class changes changing between the Bare class and Urban class between 2019 and the end of 2023, after which point it remained steadily urban (Fig. 10, g). Historic imagery consulted in Google Earth Pro confirms that the period in which the class changed between Bare and Urban reflected the ongoing construction, starting in September 2018 and ending in late 2023 (Fig. 10e and f). Moreover, historical images illustrated construction activity on the north and south sides of the site, documented during the fieldwork survey in February 2024 (Fig. 10, h).

In addition to identifying changes which have occurred within the defined time period, the MLACD can also identify where disturbances have occurred at an earlier date, and may present an on-going threat. For instance, pixels with the change class ‘Urban to Urban’ were identified within the buffer zone of site EAMENA-0087047, and the time-series analysis confirms that for the chosen location (P), there was no change in land cover class during the period of study, with the class at location (P) remaining Urban throughout the period (Fig. 11, d). Historical images in Google Earth were subsequently examined which showed that a mosque had been built in the south section of the site at location (P) sometime before 2009. As previously discussed, rapid urbanization and construction is a known source of disturbance and on-going threat to heritage in Bani Walid. Fieldwork which placed in February 2024, found evidence of disturbed earth, heaps of rubbles and evidence of the construction of new buildings within the 100 m buffer zone of site EAMENA-0087047 (Fig. 11a–c), confirming that this continues to be an active issue that needs to be addressed.

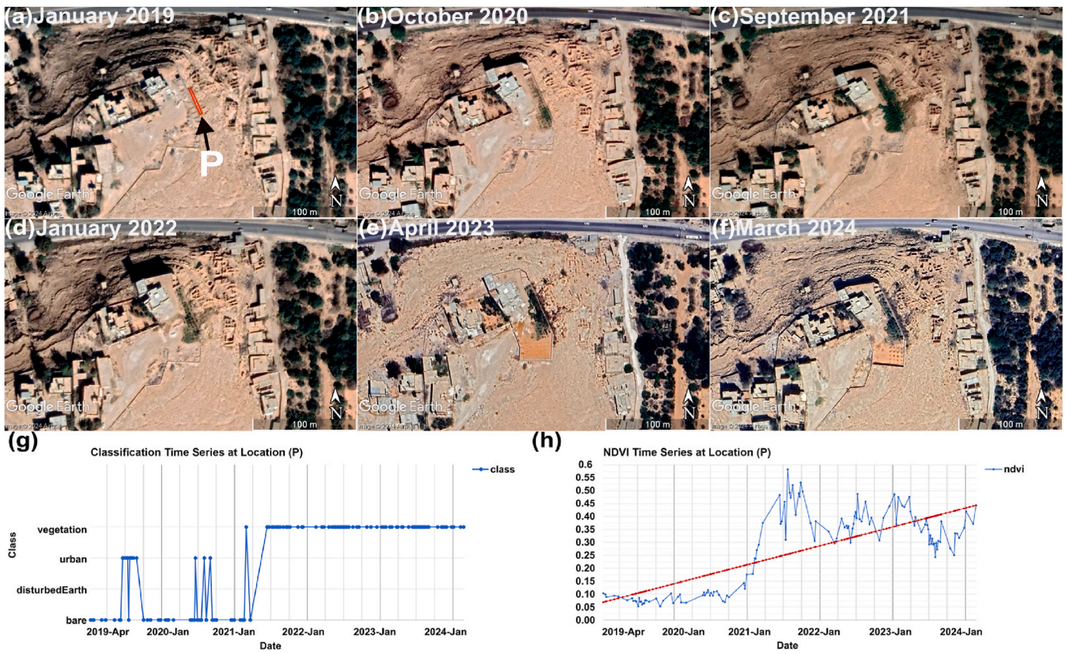

Fig. 9. Results of MLACD analysis at polygon (P) on site EAMENA-0189408, indicating vegetation growth originating from the modern farm. Images (a)–(f) high-resolution images from Google Earth, showing encroaching vegetation; (g) classification time series at polygon location (P); (h) normalized difference vegetation index (NDVI) time series at location (P).

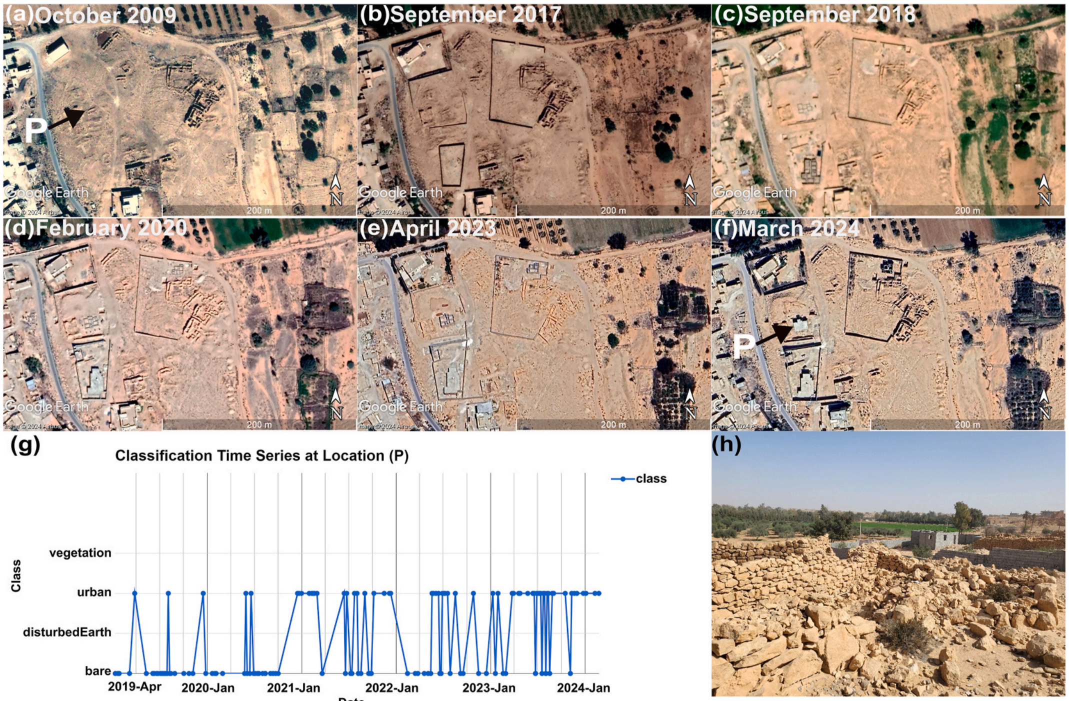

Fig. 10. Urban expansion detected at site EAMENA-0087052. Images (a)–(f): High-resolution images from Google Earth showing the construction activity between 2009 and 2024; (g) classification time series at location (P); (h) Image of a newly built house in the north side of the site in February 2024.

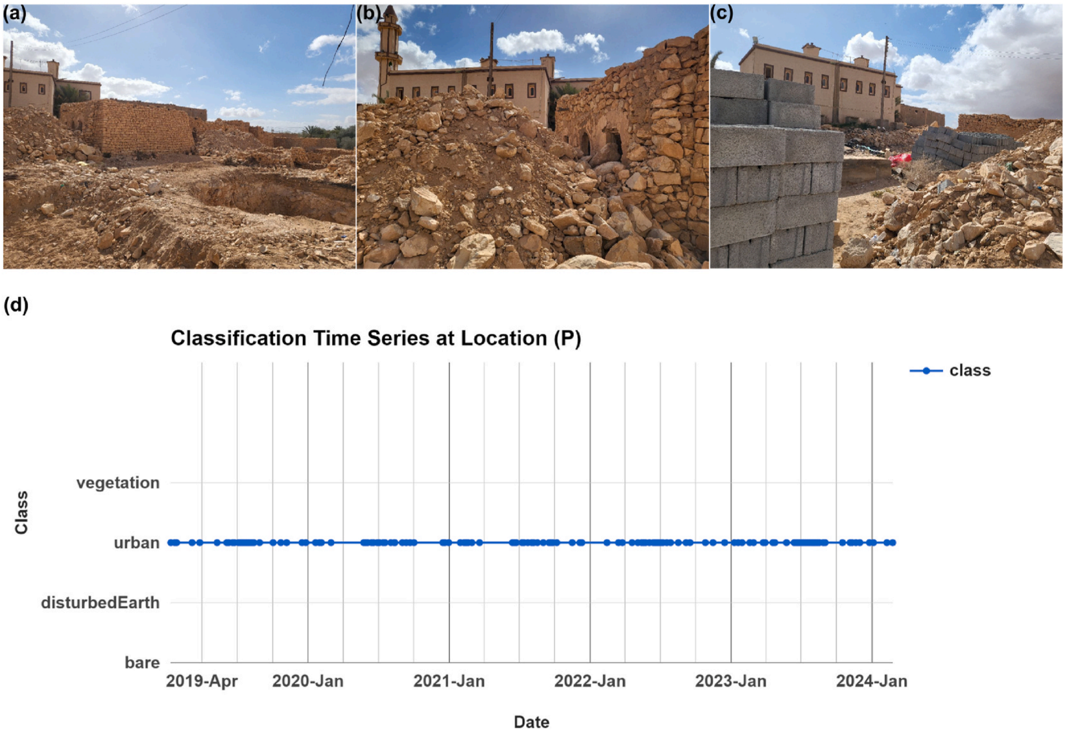

Fig. 11. Identification of previous and on-going disturbance to site EAMENA-0087047 from construction activities. Images (a)–(c) showing evidence of new construction recorded during 2024 fieldwork; d) classification time series at location (P) at site EAMENA-0087047 (the mosque area).

Another on-going issue in and around Bani Walid is quarrying, which has seen significant growth since 2009, related to the growing demand for building materials. Sites EAMENA-0262301, a possible late Roman period qasr, and EAMENA-0262302 a possible funerary site, have already been impacted by and remain under significant threat from a large quarry on the eastern outskirts of Bani Walid. This quarry poses a significant threat to those two archaeological sites as it has expanded to cover an area of about 1.2 sq km in 2024, more than double its size of c. 0.55 sq km from in 2009 (Fig. 12a–d). The classification time series of location (P), a polygon set within the buffer zone of each site, identifies the land cover class is both instances as Disturbed Earth, picking up the quarrying and bulldozing activities, for the entire study period between 2019 and 2024 (Fig. 12e and f).

3.4. Validation fieldwork

Following the MLACD analysis, it is important to conduct validation using high-resolution satellite images from the period under investigation and/or fieldwork to confirm and contextualize the results. In February 2024, a team of heritage professionals from the Libyan Department of Antiquities under the direction of Muftah Ahmed undertook a field survey of the archaeological sites used in this case study, not only to validate the MLACD results, but also to document the sites, which as discussed above have not previously been recorded in detail, as well as assess their condition, and record any disturbances and potential threats. The survey documented significant damages and threats to the archaeological sites in Bani Walid, such as agricultural expansion, urbanization, bulldozing, looting and garbage dumping (Fig. 13). The results of the fieldwork survey will be published more fully in a separate article.

The fieldwork team visited 157 of the 211 archaeological sites analysed in the MLACD; the remaining 54 were not accessible for various reasons. As shown in Table 4, the field survey documented 63 sites as having been impacted by urbanization (i.e. modern buildings or construction activities within the buffer zone of the site), 35 by vegetation, and 34 sites were disturbed by bulldozing activities. Table 4 also shows the number of sites that the MLACD identified as affected by these issues, either before or during the period under study, within different sizes of buffer zone. The MLACD system identified a larger number of sites affected by each of these issues because the analyses covered a larger number of archaeological sites and was able to more consistently include the entire buffer zone that was set. The fieldwork focussed on the core area of the sites, which varied due to constraints on both time and accessibility. The results demonstrate the importance of the method to provide evidence of ongoing disturbances and early warning of approaching threats as most sites had two or more disturbances or threats recorded within the buffer zone.

The fieldwork also recorded a number of disturbances and threats to sites which were not identified by the MLACD, including 32 sites which were affected by dumping and trash, and looting activities recorded at 13 archaeological sites. An additional 15 archaeological sites were found to have been completely destroyed, most of which were small marabout tombs which had been deliberately destroyed following the 2011 revolution. These types of disturbances are usually not identified by the EAMENA MLACD because they have not been assigned separate land cover classes. These disturbances also tend to be small in size and therefore are not detectable in the Sentinel-2 imagery, as its spatial resolution is 10 m per pixel. If users are able to access and upload higher-resolution

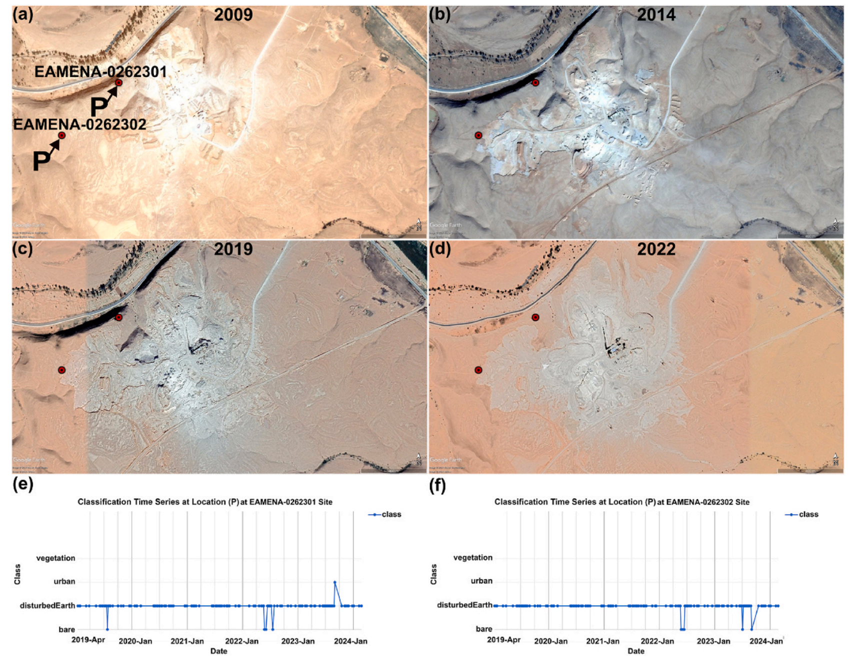

Fig. 12. Quarrying activity detected near sites EAMENA-0262301 and EAMENA-0262302 east of Bani Walid city. Images (a)–(d): High-resolution images from Google Earth showing the quarry encroaching on the two archaeological sites between 2009 and 2022; (e): classification time series at location P at site EAMENA-0262301; (f) classification time series at location P at site EAMENA-0262301.

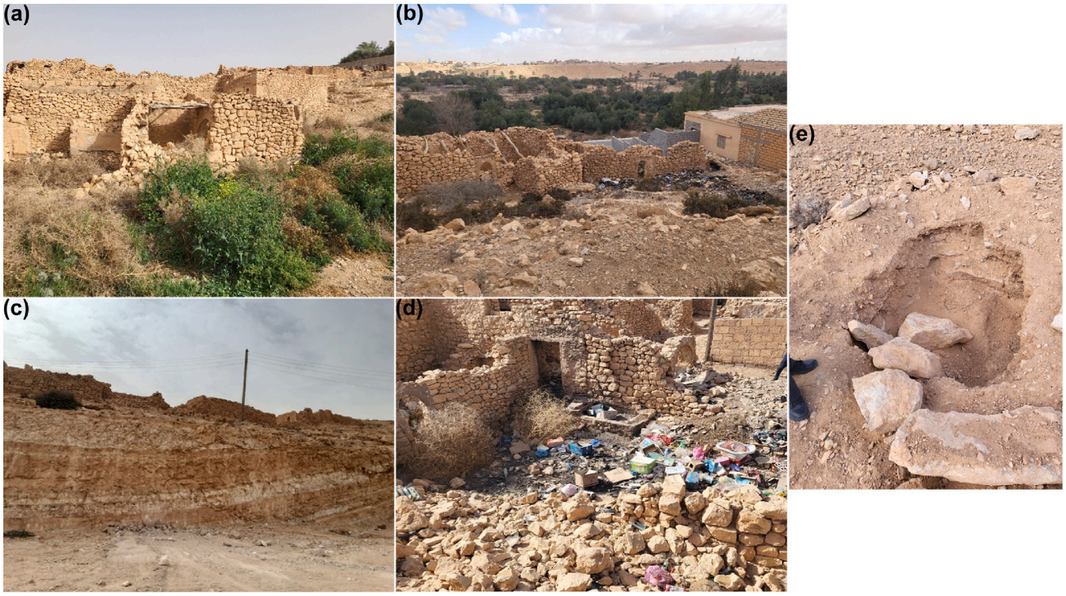

Fig. 13. Examples of documented disturbances to archaeological sites in Bani Walid: (a) vegetation growth (b) construction (c) substantial earth moving and quarrying (d) trash dumping (e) looting pit.

Table 4
Number of sites that have been identified with different changes detected during fieldwork and the MLACD when in 20 m, 50 m, and 100 m buffer zones are applied.

Disturbances recorded	Fieldwork	MLACD – 20 m Buffer Zone	MLACD – 50 m Buffer Zone	MLACD – 100 m Buffer Zone
Urbanization	63	126	136	164
Vegetation	35	18	34	119
Bulldozing (Disturbed Earth)	34	17	32	69
Garbage dump	32	N/A	N/A	N/A
Looting	13	N/A	N/A	N/A
Destroyed	15	N/A	N/A	N/A

imagery, however, it would be possible to adapt the script, for example by training additional classes, to allow for the identification of such change. However, it is important to bear in mind that increasing the land cover classes will increase the possibility of overlap in surface reflectance between the different classes which results in a higher likelihood of misclassification.

Different limitations of both fieldwork and the MLACD highlight the importance of a hybrid methodology. The MLACD enables the detection of disturbances and threats more quickly within a larger buffer area around the heritage site, without being limited by issues of time or accessibility. In addition, generally speaking, fieldwork can only record the current condition of archaeological sites and landscapes, while the MLACD demonstrates how the land cover present at sites and landscapes have changed over a defined period of time. However, fieldwork provides valuable information about site conditions and smaller disturbances that cannot be detected from the remote sensing images.

4. Discussion

The EAMENA MLACD is an effective tool for rapid assessment and monitoring of archaeological sites and landscapes. The case study in Bani Walid has demonstrated the outputs produced by the tool which provide information at both the landscape and individual site level on land cover and change over time. It is important to note, however, that the tool also has some limitations which must be taken into account by users. To assess the accuracy of the land cover classification, the EAMENA MLACD provides the confusion matrices for both images used in the change detection analysis. The confusion matrix is the error matrix that summarizes the performance of a classification algorithm by comparing its predicted classifications to the actual ground truth (Stehman, 1997). It consists of four key metrics: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). An additional metric to evaluate the performance of the classification machine learning model is also provided: the F1-score. The F1-score is the harmonic mean of precision (the proportion of all the model's positive classifications that are actually correct) and recall (the true positive rate or the proportion of all actual positives that are classified correctly as positives) (Maxwell et al., 2021). Table 5 shows the confusion matrices and F1-score for the two images used in the Bani Walid case study, which assesses the performance of the Random Forest machine learning supervised classifier in labelling the different land cover classes in both dates.

Table 5
Confusion matrices for the two classified images of January 25, 2019 and the February 23, 2024.

First Image January 25, 2019							
Class	Bare	Disturbed Earth	Urban	Vegetation	Precision	Recall	F1-score
Bare	135	1	3	0	0.944	0.971	0.957
Disturbed Earth	3	151	0	0	0.980	0.980	0.980
Urban	3	2	58	0	0.950	0.920	0.935
Vegetation	2	0	0	36	1	0.947	0.972
Second Image February 23, 2024							
Class	Bare	Disturbed Earth	Urban	Vegetation	Precision	Recall	F1-score
Bare	135	0	4	0	0.950	0.971	0.960
Disturbed Earth	0	154	0	0	1	1	1
Urban	4	0	59	0	0.907	0.936	0.921
Vegetation	3	0	2	33	1	0.868	0.929

A high overall accuracy of over 96 % was observed for both the first and second classified images. Overall accuracy is a measure of how well a classification algorithm correctly identifies all classes within a dataset. It is calculated by dividing the total number of correctly classified pixels (TP + TN) by the total number of pixels in the dataset (TP + TN + FP + FN). We have also computed the F1-score for each classified image to evaluate the performance of the classification model. High F1 scores were obtained indicating a well-performing model and high classification accuracy. It is possible that the high classification accuracy could be a result of overfitting between the classification training and validation samples. To mitigate this issue, it is important to ensure the training and validation datasets are geographically separated to reduce the risk of overestimating the model's performance quality due to spatial autocorrelation.

There are also a number of issues which can cause misclassification. One that has been observed particularly in arid regions is misclassification between bare soil and urban built-up areas as many of the natural building materials, such as stone, mud brick, or pisé are often acquired from local sources, which results in similarities in the spectral surface reflectance of the different land cover classes. A similar problem has been observed with misclassification of areas in shadow around vegetation or buildings. Seasonality is another issue which is particularly problematic for classification in arid regions which can lead to misclassification, for example, in places like Bani Walid where the watercourse floods seasonally but is dry the rest of the year, resulting in dramatic changes in vegetation cover. These variations can be interpreted as seasonal changes or threats, which are important for heritage professionals to recognize in order to implement appropriate protection and conservation measures.

The accuracy of detection of the EAMENA MLACD can be improved by ensuring that the training sample dataset is collected with as much precision as possible. In addition, the tool can be adapted to process different types of satellite imagery for improved results, depending on the goals of the user. For example, it is possible to adapt the script for LandSat imagery, which is also available open-access via GEE, and is generally lower resolution but allows for a much longer time series analysis, with some imagery available as early as the 1970s. Higher-resolution imagery such as PlanetScope and SkySat can be uploaded into GEE to improve the land cover classification and potentially identify disturbances and threats happening on a smaller scale, such as looting pits. Moreover, to reduce false alarms in change detection, composite images can be generated on a monthly basis to mitigate the effect of seasonality. However, this method may fail to detect changes that occur during the month. Therefore, the EAMENA MLACD tool was developed to accommodate all available images of the study area, providing a comprehensive analysis of time series changes in land cover.

The EAMENA MLACD was developed in Google Earth Engine in order to leverage its powerful processing capabilities to handle large amounts of data and the detection of changes and threats to large numbers of heritage sites over wide areas. In its current iteration, it is optimised for use in the arid regions of North Africa and the Middle East, and has been applied to case studies in other parts of Libya (Lefakat, South Derna, and Fazzan), Algeria, and Morocco. The results of these case studies will be published in separate articles. In theory, the tool could be adapted for any part of the world, and is scalable for regional, national, and even global applications, by adjusting the relevant parameters. In addition to its main application for monitoring disturbances and threats on archaeological sites, the land cover classification capabilities of the EAMENA MLACD mean that it could also be adapted for further applications in the earth observation and environmental fields such as time series analysis for deforestation, wildfire impact analysis, and coastal erosion.

However, since land cover classification is the primary processing step used by the EAMENA MLACD for detecting changes and threats to heritage sites, challenges arise when analysing large areas with significant variations in land cover classes. This can reduce detection accuracy and lead to false alarms due to class overlap. Moreover, the variation and availability of satellite imagery across different regions and time periods can affect the consistency and accuracy of classification results. Finally, the computational load of processing high-resolution images over large areas can be intensive, leading to longer processing times and potential crashes when using machine learning algorithms.

5. Conclusion

The EAMENA Machine Learning Automated Change Detection tool is a novel geospatial tool that allows heritage professionals and researchers to rapidly identify changes and threats to sites. The case study of Bani Walid, undertaken in partnership with the Libyan Department of Antiquities has demonstrated how the dissemination and adoption of the EAMENA MLACD into the methodologies of heritage agencies in the MENA region has the potential to improve and increase the speed of assessment and monitoring of archaeological sites. The case study has also shown the range of valuable information that the MLACD method can provide, which can be used to better understand how and when disturbances have occurred on heritage sites. This is crucial in helping local authorities and heritage professionals to also identify future threats so that they can co-ordinate with other governmental agencies and local communities regarding any planned works that might endanger heritage sites.

The user-friendly interface and workflow, which requires only basic knowledge of GIS and remote sensing make it a powerful tool which can be adopted by local authorities and heritage professionals in their own regions. To aid in the adoption of this method by heritage authorities in the MENA region, the EAMENA team has developed detailed training documentation in both English and Arabic. Supported by the British Council's Cultural Protection Fund, the EAMENA project team has already provided training to over twenty heritage professionals in Libya and Algeria on how to use and adapt the EAMENA MLACD tool for the purpose of heritage preservation in their countries.

CRediT authorship contribution statement

Ahmed Mutasim Abdalla Mahmoud: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Nichole Sheldrick:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Investigation, Funding acquisition, Conceptualization. **Muftah Ahmed:** Writing – review & editing, Validation, Project administration, Investigation.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The EAMENA MLACD code can be accessed from the EAMENA GitHub repository (https://github.com/eamena-project/EAMENA-MachineLearning-ACD).

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