Recent and Past Archaeological Looting by Satellite Remote Sensing: Approach and Application in Syria

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Abstract Illegal excavations represent one of the main risks which affect archaeological heritage throughout the world. Actions oriented to quantify damage and prevent looting can be supported by satellite technologies which can provide reliable information to detect and map devastation phenomenon in particular for remote or non-accessible sites. In these cases, it is desirable to use satellite-based semiautomatic or automatic approaches for the mapping and quantification of looting patterns. In this paper, an automatic method for archaeological looting feature extraction approach (ALFEA) has been applied to an archaeological site in Syria, Tell Sheikh Hamad, affected by archaeological looting before and during the civil war. The aim is to evaluate the capability of ALFEA to extract past and recent looting features and patterns using Google Earth images. The results have been assessed through visual inspection, which shows that the rate of success was higher than 90% for recent looting and around the 80% for past archaeological disturbance.

Keywords Satellite remote sensing · Past and recent archaeological looting · Automatic feature extraction · Texture analysis · Google Earth · Syria

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Introduction

Illegal excavations of archaeological sites are part of a global crime system of trafficking in antiquities (Bowman 2008) whose activity tends to grow dramatically during armed conflicts causing irreversible damages to archaeology and history on the human past (Gibson 1997; Brodie et al. 2001). In fact a number of important archaeological areas are located in countries involved in armed conflicts and civil wars, as in the case of Syria, where looting activities have exponentially increased (UNESCO 1956, 1970; United Nations Security Council 2015) since the beginning of the conflict as in many other countries of the Middle East.

Unfortunately, important cultural property disappeared in many countries across the world even in areas not involved in armed conflicts or politic unrest, where looting is phenomenon (Looted Heritage 2016), fed by demand of private collectors and those museums that do not take measures to control the provenance of artefacts (Ganciu 2018; Hart and Chilton 2015). According to analyses conducted by Proulx (2013), 'the archaeological site looting is [...] a globally pervasive problem and is not limited to certain parts of the world respect to others'. This occurs despite the UNESCO recommendations and the repressive measures adopted by many countries which impose the returning of looted objects (UNESCO 1956, 1970; United Nations Security Council 2015). Nevertheless, it must be considered that even returning the refound looted artefacts, the damage to archeology research and the study of the human past cannot be anymore recovered due to the loss of cultural context.

Since the first decade of 2000s, very-high-resolution (VHR) satellite images have shown great potentiality (Lasaponara & Masini 2008) for the identification and the quantification of damage of looting in Syria (Casana and Panahipour 2014; Casana 2015; AAS 2015; Danti et al. 2017), in Iraq (van Ess et al. 2006; Stone 2008, 2015; Danti et al. 2017), in Egypt (Parcak 2007; Bowen et al. 2017), in Afghanistan (Lauricella et al. 2017), in Jordan (Vella et al. 2015), in China (Caspari 2018), and in Peru (Contreras 2010; Lasaponara and Masini 2010; Lasaponara et al. 2012, 2014). Satellite technologies proved to be particularly effective in addressing the current cultural heritage crisis in the conflict zones, as Iraq and Syria, where the worst catastrophe for archaeological heritage is occurred since the Second World War (Danti et al. 2017; Matthiae 2015). In such scenarios, the effectiveness of satellite remote sensing could increase through the application of automatic extraction procedures. Nevertheless, up to now, only a few investigations have been specifically focused on the automatic extraction of archaeological looting features using remote sensing. In particular, van Ess et al. (2006) applied a semiautomatic object-oriented approach based on the segmentation and subsequent supervised classification to the archaeological site of Uruk-Warka in Iraq. Bowen et al. (2017) used a hierarchical categorization and localization algorithm for partially supervised classification of looted areas in Egypt. Lauricella et al. (2017) used a semiautomatic procedure based on principal component analysis for the detection of looting. Cerra et al. (2016) performed an automatic change detection in two archaeological sites in

Syria and Iraq analysing texture features through Gabor filters. Agapiou et al. (2017) used an object-oriented classification for the detection of looted tombs in Cyprus.

Lasaponara and Masini (2010) firstly introduced the use of local indicators of spatial association (LISA) for the identification of looting patterns, near Nasca (in Southern Peru), and later added an unsupervised classification (Lasaponara et al. 2014) step for the automatic extraction of looting features in Ventarron (Northern Peru). This approach was further improved (Lasaponara and Masini 2016) adding a segmentation step, similarly to a feature extraction procedure (Lasaponara et al. 2016), developed for Hierapolis in Turkey. The final refinement of the procedure, recently published (Lasaponara and Masini 2018) and named archaeological looting feature extraction approach (ALFEA), has been applied in desert environment, in two different test cases: Dura-Europos in Syria and Cahuachi (near Nasca) in Peru. These test sites were chosen because they are the representative for two looting features diverse in morphological characteristics and temporal dynamics: frequent in the past for Cahuachi and still ongoing in Dura-Europos.

In this paper, ALFEA has been applied to Tell Sheikh Hamad in western Syria, located in the lower Khabur River and affected by clandestine excavation activities started before the beginning of the civil war (March 2011) and continued with renewed intensity during the years of conflict. Tell Sheikh Hamad has been chosen because it is representative of two looting features/patterns referable to the past and recent looting. The reliability of the results was estimated using both visual inspection and independent investigations (Cunliffe et al. 2014).

Study Area

The Syrian cultural heritage dates back millennia considering that human settlement was recorded at least from around 9000 BC. It is one of the richest and complex heritages in human history being that over the centuries Syria homed a long succession of civilizations starting from the Bronze Age to the Ottoman Empire (Akkermans and Schwartz 2003).

Syria (Abdulkarim 2014; Cunliffe et al. 2014) was strongly affected by clandestine excavations during the ongoing conflict which began 2011 with anti-government protests (BBC 2016) and later enlarged into a full-scale civil war which also facilitated the escalation of the so-called Islamic State (IS). The latter has conducted a systematic destruction of cultural heritage with the aim of erasing the vestiges of the pre-Islamic past and using illegally excavated artefacts to finance their criminal activities (Conversation 2016).

The selected test case is Tell Sheikh Hamad, the modern name of the ancient Assyrian city of Dūr-Katlimmu, which lies on a limestone terrace on the lower Khabur River, tributary of the Euphrates, between the cities of Hassake and Deir ez-Zor in western Syria (North Mesopotamia). Although the oldest remnants of settlements dated back to the end of the fourth millennium BC, Dūr-Katlimmu was founded during the reign of Shalmaneser I (1274 BC–1245 BC), King of Assyria during the Middle Assyrian Empire (1365 BC–1050 BC). The identification of the ancient name was made possible by the discovery of 30 inscribed tablets of the Middle Assyrian period, found in 1977. The excavations, carried out since 1978, have unearthed the remains of a large city, extending over an area of over 100 hectares, and articulated in various suburbs around the tell. Dūr-Katlimmu had its major development in the Middle Assyrian period. In the Neo-Assyrian period, the city was enlarged with the construction of the lower city. At this time, it was an important military base for the Assyrian expeditions towards Syria and countries facing the Mediterranean Sea. In the Persian period, Dūr-Katlimmu lost importance: from the sixth to the fourth century, the lower city was only partially inhabited. Occupancy levels are still attested on the main tell of the site at Parthian and Roman times, after which it was deserted.

Tell Sheikh Hamad compared to other sites in Syria, such as Palmyra and Dura-Europos, was less damaged during the civil war even if it presents many areas plundered and destructed by bombing, such as an Assyrian temple, collapsed after shell fire, and other monumental structures heavily damaged when the site was transformed into a battlefield between deserters and army (Cunliffe 2012, p. 6). Two satellite images acquired on March 2011 and March 2014, respectively, show looted areas between the tell and the ancient city (see Fig. 1b, c). The comparison between the two images exhibits changes in terms of looted area and different visibility of past looting. Figure 2 shows details of 2011 and 2014 image. An orange box denotes the area of interest which includes three groups of looting features named A, B and C. The visual comparison between the two images put in evidence two different shapes of looting features:

(i) The first one, in cluster A (in Fig. 2b), is characterized by quadrangular shape with size ranging from 1.5 to 4 m, referable to recently dug pits, completely shadowed (see also zoomed picture in Fig. 2b bordered by red box).
(ii) The second one, in B and C, exhibits rounded-shape holes, partially shadowed and with size ranging from 2 to 5.5 m, which are related to looting activities occurred before 2011. These features are characterized by different visibility of the edges depending on the different depth and consequently excavation phases. In particular, two types of features, named 'x' and 'y', with different edge visibility have been identified. Type 'x' refers to the holes with greater edge contrast, having size ranging from 3.5 to 5 m (as measured from Google Earth). Type 'y' refers to the holes with lower contrast with a size ranging from 2.5 to 4 m. The comparison between the two satellite images (see in particular zooms of cluster B in Fig. 2a, b) evidences a significant decrease in terms of visibility of the looting features in B and C.

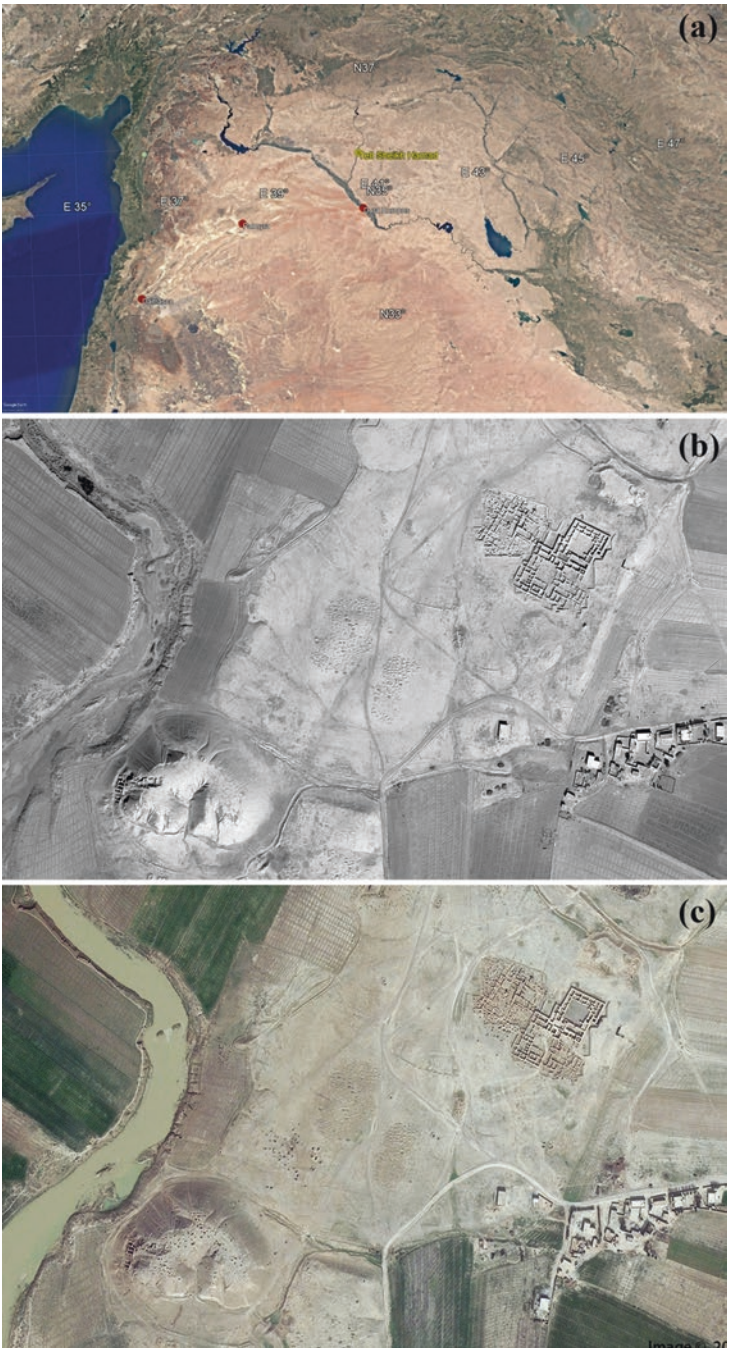

Fig. 1 (**a**) Location of Tell Sheikh Hamad, modern name of the ancient Dūr-Katlimmu, in Eastern Syria, located in one of the tributaries of the Euphrates River; (**b–c**) satellite images of Tell Sheikh Hamad acquired on March 1, 2011, and on March 3, 2014. (Courtesy by Google Earth)

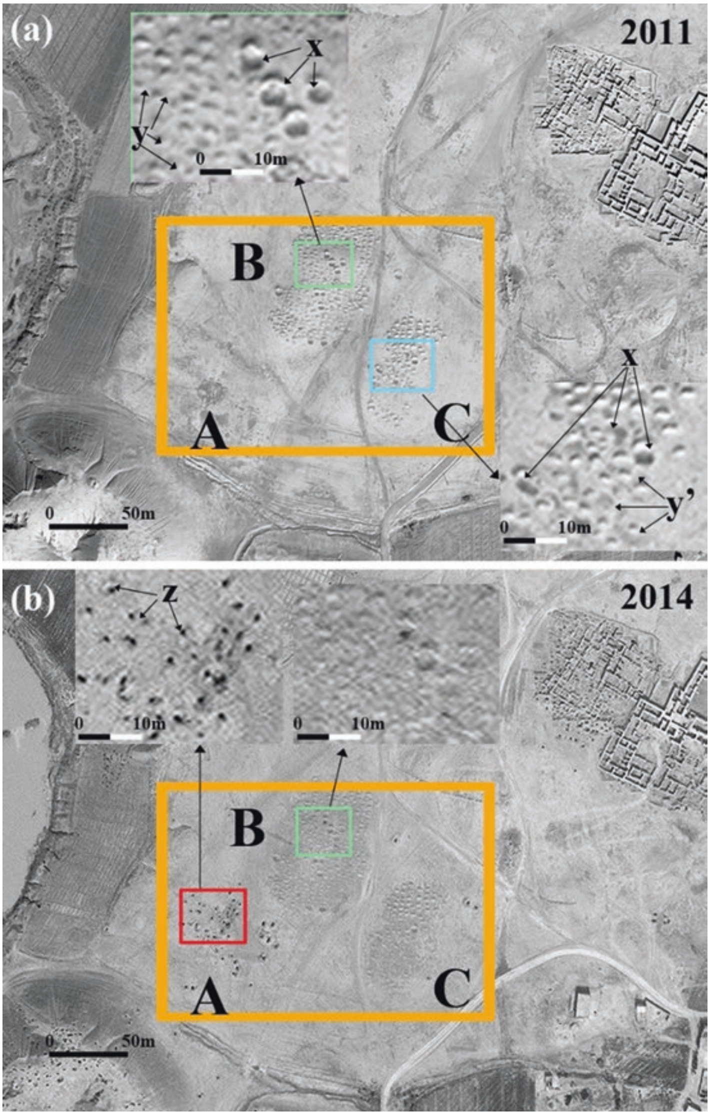

Fig. 2 Details of 2011 and 2014 images (**a** and **b**, respectively). The orange box denotes the test site which ALFEA has been applied to. A, B and C indicate three groups of holes and pits related to two diverse looting phases, before the 2011 (B and C) and in 2014 (A). The holes in B and C are less visible in 2014 than in 2011. In (**a**) zooms of B and C (bordered by green and light blue box, respectively) evidence two different looting features (labelled 'x' and 'y') which exhibit a different visibility of their circular edges, being that they were probably excavated in different periods. In (**b**) the same zoom of B evidences a less significant discriminability of the holes in 2014 with respect to 2011. Finally, the red box denotes a zoomed image of A which depicts the presence of rectangular pits excavated some month before the satellite image acquisition

Material and Method

Satellite Dataset

The automatic extraction of looting features (explained in section 'Method') has been done using Google Earth images to encourage the use of automatic procedures to a wide community of users, also considering the opportunity of civic crowd sourcing activities (Pringle 2010; Ur 2006).

The Google Earth images available for Tell Sheikh Hamad were acquired in 1.03.2011, 12.08.2013, 3.03.2014, 6.11.2016, and 30.09.2017. They make possible to observe a plundering activity before the civil war which continued between 2013 and 2014 and is still today ongoing. For testing the ALFEA method, we used the satellite image acquired in 2011 and 2014 which evidences a variety of looting features in terms of shapes, dimensions and depth, and consequently visibility of edges.

Method

Remote sensing-based identification of looted areas of archaeological interest poses serious challenges related to data processing and interpretation due to the diverse physical characteristics from one site to another one, from one image to another one of the same site or from an area to another in the same image. The complexity of the problem is more evident in case of weak spatial/spectral signals which affect the edge visibility as in the case of archaeological sites located in desert environment. Actually, the holes and pits, created by grave robbers to plunder past treasures, are partially covered over time by desert sand, especially in windy areas, making the detection of looting features by remote sensing difficult (Lasaponara and Masini 2016). In this context, procedures based on textural analysis which take into account both the pixel spectral values and the spatial relationships among the neighbouring pixels may be more effective (Richards and Jia 2006). A similar approach has been recently proposed by Lasaponara and Masini (2018) and applied to two archaeological sites in Syria and in Peru for extracting in an automatic way looting features and patterns. It is based on three steps: (i) local spatial autocorrelation to provide a first clusterization of features, (ii) unsupervised classification to categorize classes linked to looting features, and, finally, (iii) segmentation to refine the feature extraction.

Spatial autocorrelation measures the degree of dependency among pixel reflectance values, considering at the same time their similarity and distance relationships (Bao 1999). The basic formulation of the presence of autocorrelation in a spatial distribution is based on two contributions, generally denoted as first- and second-order effects that could be well defined, but not easily separated (Gatrell et al. 1996). Both of them produce clustering and smooth variations in density, but their relationships and interaction mechanisms with other variables are very different. The first-order effects measure how the expected value (mean of pixel number) varies in the space, and the second-order effects concern local interactions between pixels and are measured by covariance variations. There are many indicators of spatial autocorrelation generally denoted as global and local indicators, the latter are more suitable to identify second-order effects. Global statistics inform us (by a single value) about the magnitude of autocorrelation for the whole region under investigation. The local statistics relies on the information distance captured in distance matrix and informs us about edges and clusters. These indicators measure if and how much the dataset is autocorrelated on the basis of distance used to define the neighbourhood of a given region (Anselin 1995; Getis et al. 1992). The widely local indicators are Getis-Ord Gi, Moran's I, and Local Geary's *C*. They allow us to uncover hidden local patterns that global statistics may lose. Results from these indices provide diverse maps which, for each pixel, inform us about the presence of local clusters, as well as variations in texture or the presence of edges (Anselin 1995; Getis et al. 1992; Geary 1954). For the purpose of our investigations, we used Local Geary's *C* index which identifies edges and areas characterized by a high variability compared to the values of its neighbouring pixels and determines if adjacent observations of the same phenomenon (in our case looting features) are correlated (Geary 1954).

Local Geary's *C* index is defined according to formula 1.

$$C = \frac{n-1}{\sum_{i=1}^{n}\left(X_i - \bar{X}\right)^2} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(X_i - X_j\right)^2}{2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{1}$$

where n is the total number of pixels, X_i and X_j are intensity in points i and j (with $i \neq j$), $\bar{X}$ is the average value, and w_{ij} is an element of the weight matrix.

After the edge extraction, using Local Geary's *C*, textural analysis has been focalized on looting features carried out by unsupervised classification and segmentation.

Unsupervised classifications enable not only to obtain an automatic clusterization but also to overcome the need of a priori predefining known classes. A number of unsupervised classification approaches can be found in literature, even if the most common used algorithms are (i) K-means clustering and (ii) ISODATA (Iterative Self-Organizing Data Analysis Technique). These two approaches are quite similar. Both of them require a few parameters to be set, as (i) the number of predefined classes (clusters) and (ii) the number of iterations to be carried out. In the K-means classification, the number of clusters is known a priori, whereas in the ISODATA approach, the number of clusters is 'dynamically assigned'. Compared to the K-means method, ISODATA is considered more flexible (Memarsadeghi et al. 2007).

A segmentation tool was applied to the classification maps, to select among all the clusters those that exhibited a roughly circular shape (according to the expected looting features). The output from the classification is the input of the segmentation step made to obtain meaningful feature classes as well as to improve the interpretation. Each segment is characterized by a set of attributes, which enable the extraction of specific features characterized by (i) close proximity on the basis of the Geary analysis and (ii) similar spectral characteristics, on the basis of the classification. The processing steps based on the sequence of Local Geary's *C*, ISODATA, and segmentation have been performed by using routines of ENVI software.

With respect to Local Geary's *C*, it is crucial to select two parameters, (i) neighbourhood rule and (ii) maximum lag:

(i) Neighbourhood rule is the adjacency rule used in the calculation; therefore, it defines which adjacent pixels must be compared to the central pixel.
(ii) Maximum lag (pixels) specifies the maximum distance in pixels at which autocorrelation statistics must be calculated.

Given the texture to be extracted, linked to the morphology of the looting features and their dimensions (1.5–4 m on average), we used, respectively, (i) Queen rule, because it selects all eight neighbouring pixels, (ii) and lag distance equal to 1.

As regards ISODATA the following parameters were selected: the number of classes ranging from 5 to 10, change threshold = 5%, and minimum class distance = 5.

The final step is the segmentation aimed at partitioning the ISODATA classes to facilitate the texture discrimination. To this aim it is crucial:

(i) To adequately select the ISODATA classes which better represent the texture to be extracted.
(ii) To set the minimum population (MP) and the number of neighbours (NN) in order to enhance the 'looting texture'. Given the dimension of the looting pits and their shape (most of them roughly circular), we assumed the following values of MP and NN equal to 10 and 4, respectively.

Results and Discussion

Figures 3 and 4 show the results of different steps of the data processing chain for the subset, bordered in orange depicted in Fig. 2a, b for 2011 and 2014 images, respectively. As regards the 2011 image (Fig. 3), the result of Local Geary's *C* index (Fig. 3b) enables the extraction of clusters related to looting holes in areas indicated as B and C (subarea A does not exhibit any disturbance). Local Geary's *C* index also enables the removal of some tracks on the desert pavement. Output from ISODATA classification, shown in Fig. 3c, provides seven classes, among them one (class 7, magenta coloured) refers to looting holes. Consequently, this class has been selected for the following step of segmentation that enabled the extraction of looting pits and the removal of other features not related to looting activity (see Fig. 3d).

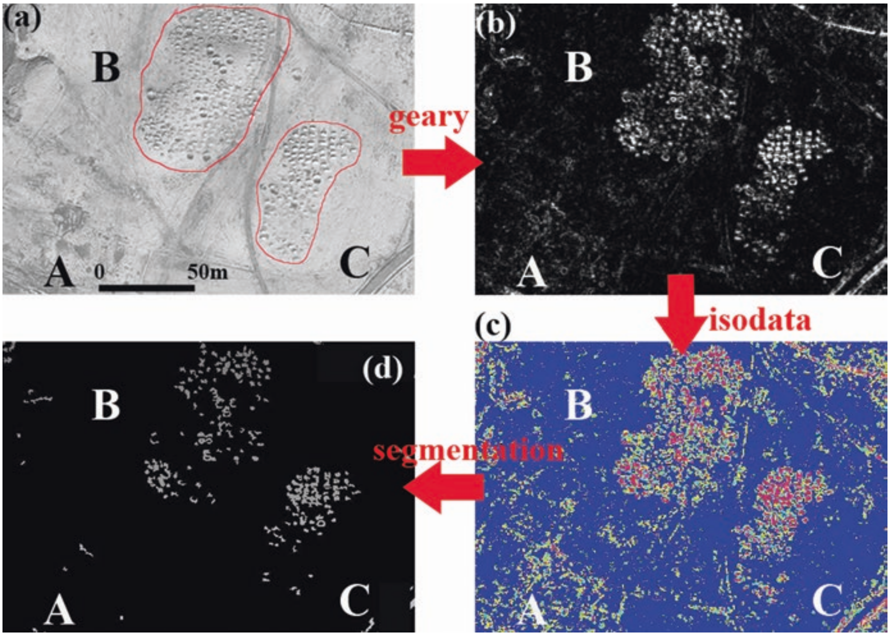

Fig. 3 Results of data processing chain applied to the subset, indicated in Fig. 2a, b, of 2011 image. From up left to bottom left clockwise: non-processed image, Geary result, ISODATA map, and segmentation. Parameters assumed: number of ISODATA classes, 5–10; segmentation applied to classes 6 and 7, population minimum, 10; number of neighbouring, 4

Being that the classification is unsupervised, it is not possible to have statistics related to the assessment that is performed by visual inspection, using the following parameters:

- NH is the number of holes identified from observing Google Earth image.
- TD indicates the number of targets (looting pits) detected.
- TnD is given by the number of targets not detected.
- FA are the false alarms.
- N_{FA} is the normalized false alarm index given by FA/(FA + TD).

Table 1 summarizes the results from the assessment procedure. In particular, the rate of success of targets detected is between 79.41% and 83.58% for clusters C and B, respectively; NFA is around 5%.

Considering that the visual discriminability of looting features is in some points not good, the results of automatic procedure of feature extraction in terms of targets detected and false alarms are to be considered satisfactory.

The rate of success of targets detected strongly increases for the most recent looting pits observed in A of the 2014 image as shown in Fig. 4 and Table 2. In particular, the percentage of targets detected is around 95%. On the contrary the rate of

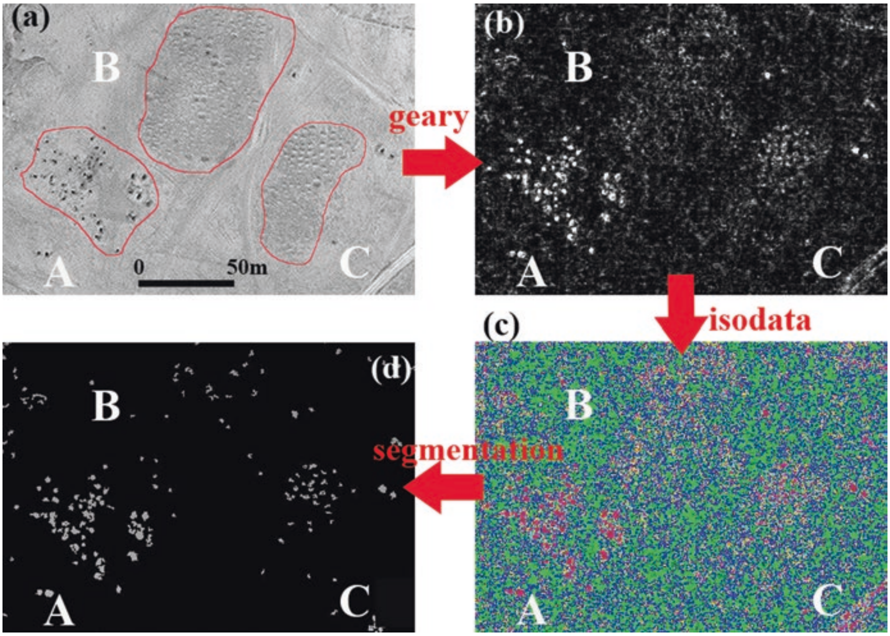

Fig. 4 Results of data processing chain applied to the same subset of Fig. 3 of 2014 image. From up left to bottom left clockwise: non-processed image (**a**), Geary result (**b**), ISODATA map (**c**), and segmentation (**d**). Parameters assumed: number of ISODATA classes = 5–10; segmentation applied to classes 6 and 7, population minim = 10; number of neighbouring = 4

Table 1 Assessment carried out in the test sites of 2011 image

2011					
Group	NH	TD	TnD	FA	N_{FA} = FA/(FA + TD)
A	0				
B	134	112	22	5	
	100.00%	83.58%	16.42%		4.27%
C	102	81	21	5	
	100.00%	79.41%	20.59%		5.81%

Legend. *NH* number of holes identified from visual interpretation, *TD* target (holes/pits) detected, *TnD* target not detected, *FA* false alarms, N_{FA} normalized false alarm index (N_{FA} = FA/(FA + TD))

Table 2 Assessment carried out in the test sites of 2014 image

2014					
Sector	NH	TD	TnD	FA	N_{FA} = FA/(FA + TD)
A	78	74	4	3	
	100.00%	94.87%	5.13%		3.90%
B	23	16	7	5	
	100.00%	69.57%	30.43%		23.81%
C	36	31	5	3	
	100.00%	86.11%	13.89%		8.82%

Legend. *NH* number of holes identified from visual interpretation, *TD* target (holes/pits) detected, *TnD* target not detected, *FA* false alarms, N_{FA} normalized false alarm index (N_{FA} = FA/(FA + TD)) success of the automatic feature extraction is much lower for the looted areas B and C whose discriminability strongly reduced from 2011 to 2014.

Conclusions

Looting represents one of the main risk factors which affects the archaeological heritage throughout the world. The damage is not only the loss of artefacts and monuments but also of the archaeological context, thus denying the knowledge of human past to new generations (O'Neil 1972). To contrast and limit this phenomenon, a systematic monitoring is required. The protection of archaeological heritage from illegal diggings is generally very complex to be approached using only direct (in situ) surveillance. Moreover, it is expensive, time-consuming, and not operatively applicable to desert areas or regions involved in wars and conflicts as, for example, in Syria. In these cases, the use of VHR satellite remote sensing is mandatory along with the use of automatic procedures for the reconnaissance of looting features.

In this paper, we applied a procedure (ALFEA by Lasaponara and Masini 2018) devised for the automatic identification of archaeological looting performed using Google Earth images. This method is made up of three steps: (i) spatial autocorrelation based on Geary index for the extraction of edges, (ii) unsupervised classification, and (iii) segmentation which enabled us to focalize the texture analysis on the targets of interest. The procedure was already tested in desert conditions (Lasaponara and Masini 2018) for two sites located in different geographic areas (Dura-Europos in Syria and Cahuachi in Peru) and characterized by diverse looting features and temporal dynamics. In this paper, ALFEA has been again applied to the site of Tell Sheikh Hamad (in Syria) selected because it is affected by a long plundering activity conducted before and during the civil war.

ALFEA has been assessed in three test areas of Tell Sheikh Hamad characterized by diverse looting features and patterns and, consequently, by different visibility and complexity in the identification of looting edges. As a whole, the adopted methodology provided satisfactory results for the diverse looting features, and it is important to highlight that the methodology is easy and can promptly be reapplied to other geographic areas. This can provide a reliable low-cost tool for a preliminary identification and quantification of clandestine excavations in desert areas. ALFEA represents a contribution to set automatic approaches for looting monitoring using Google Earth operationally.

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