remote sensing

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Review

Detection of Archaeological Looting from Space: Methods, Achievements and Challenges

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Abstract: Illegal excavations in archaeological heritage sites (namely "looting") are a global phenomenon. Satellite images are nowadays massively used by archaeologists to systematically document sites affected by looting. In parallel, remote sensing scientists are increasingly developing processing methods with a certain degree of automation to quantify looting using satellite imagery. To capture the state-of-the-art of this growing field of remote sensing, in this work 47 peer-reviewed research publications and grey literature are reviewed, accounting for: (i) the type of satellite data used, i.e., optical and synthetic aperture radar (SAR); (ii) properties of looting features utilized as proxies for damage assessment (e.g., shape, morphology, spectral signature); (iii) image processing workflows; and (iv) rationale for validation. Several scholars studied looting even prior to the conflicts recently affecting the Middle East and North Africa (MENA) region. Regardless of the method used for looting feature identification (either visual/manual, or with the aid of image processing), they preferred very high resolution (VHR) optical imagery, mainly black-and-white panchromatic, or pansharpened multispectral, whereas SAR is being used more recently by specialist image analysts only. Yet the full potential of VHR and high resolution (HR) multispectral information in optical imagery is to be exploited, with limited research studies testing spectral indices. To fill this gap, a range of looted sites across the MENA region are presented in this work, i.e., Lisht, Dashur, and Abusir el Malik (Egypt), and Tell Qarqur, Tell Jifar, Sergiopolis, Apamea, Dura Europos, and Tell Hizareen (Syria). The aim is to highlight: (i) the complementarity of HR multispectral data and VHR SAR with VHR optical imagery, (ii) usefulness of spectral profiles in the visible and near-infrared bands, and (iii) applicability of methods for multi-temporal change detection. Satellite data used for the demonstration include: HR multispectral imagery from the Copernicus Sentinel-2 constellation, VHR X-band SAR data from the COSMO-SkyMed mission, VHR panchromatic and multispectral WorldView-2 imagery, and further VHR optical data acquired by GeoEye-1, IKONOS-2, QuickBird-2, and WorldView-3, available through Google Earth. Commonalities between the different image processing methods are examined, alongside a critical discussion about automation in looting assessment, current lack of common practices in image processing, achievements in managing the uncertainty in looting feature interpretation, and current needs for more dissemination and user uptake. Directions toward sharing and harmonization of methodologies are outlined, and some proposals are made with regard to the aspects that the community working with satellite images should consider, in order to define best practices of satellite-based looting assessment.

Keywords: looting; archaeological remote sensing; change detection; feature extraction; pattern recognition; SAR; VHR optical; WordView-2; Sentinel-2; COSMO-SkyMed

1. Introduction

In archaeology and the cultural heritage sector, the term "looting" refers to illegal excavations through digging holes on a site of archaeological or historic significance—usually in areas yet unexcavated by archaeologists—in search of objects and antiquities to sell in the black market.

This anthropogenic phenomenon can be triggered and driven by various economic, social, cultural, and political factors. Especially in poor regions, looting may be on a small scale mainly for subsistence [1]. In Latin America, for example, migration, developmental disparities, and the need of reclaiming land for agriculture or urbanization are factors that often create the socio-economic-cultural context for heritage sites to be looted [2]. In this regard, some modern uses of land, such as terracing, planting of orchards, grazing, ploughing, center pivot and channel irrigation, utilities construction, mining and quarrying, compete with the needs of cultural heritage preservation. A selection of these threats can be found in [3], with examples from the Middle East and North Africa (MENA) region.

On the contrary, large-scale excavation by means of digging tools and machinery is a planned activity, run by well-organized groups [1]. Not rarely, this happens by taking advantage of political instability or lack of site surveillance, although there are studies (e.g., ref. [4] with regard to Syria) that rightly point out that the scope and severity of war-related looting can be best understood if this phenomenon is analyzed in reference to looting that took place prior to the war. Systematic looting by means of bulldozers or other earth-moving machinery can spread in short time across a whole archaeological site, cause often-irreversible damage to the pristine archaeological stratification and context, and distinctively pock-mark the landscape. This effect can be captured from space. A clear example is seen in the Hellenistic towns of Apamea and Dura Europos in Syria, which are among the heritage sites that have been most damaged since the beginning of the Syrian civil war. Various studies have provided evidence through observations made with optical (e.g., refs. [4–6]) and radar (e.g., refs. [7,8]) satellite images. These and other studies help to show how and where satellite imagery can identify looting or site encroachment and can aid in connecting the ongoing looting to larger issues, whether economic, social, political, or environmental [9]. Although satellite technologies do not directly address the trafficking aspects of the illicit trade in cultural goods, monitoring looting from space is important as a way to document damage, estimate the total value (and volume) of the trade in looted objects, and identify looting "hotspots" [10].

However, it would be untrue to state that only poor countries, or regions in warfare, are affected by looting. These damaging activities are also observed in peacetime, even in countries where there is a long-standing culture of heritage conservation. This suggests that we are actually witnessing a phenomenon of more global relevance [11]. Figure 1 shows a sample of looting incidents recorded across the globe. Their scattered distribution is quite illuminating, as it matches not only with the location of unstable countries, but also of cultural landscapes known or suspected to be reservoirs of goods of historical or cultural value. It is to be acknowledged though that Figure 1 cannot (and does not intend to) represent the full complexity or provide a quantification of the scale and extent of this phenomenon. On one side, there is a very large number of sites that are looted at some point, but they are not reported whatsoever. Frequently, this simply happens because it is a type of looting not based on current socio-political events that would provide the context and trigger for reporting. On the other side, there are practices such as metal detection that are legal in some countries and/or dealt with through initiatives aiming, for example, to negotiation and cooperation [12], but are banned and prosecuted in others (see for example the legislation in Italy; [13]). It is outside the scope of this paper to discuss these aspects, though the reader can refer to [14] and the related literature for further information.

Focusing on the use of satellite imagery to identify illegal excavations and assess damage, the following two considerations can be made:

- Looting mostly occurs within sites that are difficult to access due to their geographic location (e.g., rural areas, deserts, forests), or that have become inaccessible due to socio–cultural–political

situations (e.g., warfare, abandonment, lack of surveillance), or that are too large and/or distant from urbanized areas and transport infrastructure to be monitored effectively and regularly based on the available resources, even when they belong to listed and protected sites;

- Looting manifests with distinctive features that are common across different geographic locations, despite the predisposing factors and local contexts.

Looting pits differ very distinctively from other types of archaeological features, and their excavation completely modifies the surface morphology of the affected landscape. Hand-dug pits are frequently scattered or clustered in small groups, are characterized by shallow depth, and are surrounded by mounds of debris that is sifted and then accumulated aside. Ref. [15] provided interesting statistics of average area, perimeter and circularity index of looting holes visible on very high resolution (VHR) optical satellite imagery in sites located in Afghanistan, Jordan, Iraq, and Southern Peru. Ref. [16] found pit depths of around 70–90 cm and 40–50 cm and average diameters of 2.6 m and 3.9 m in Cafetal and Arenal (Lambayeque, northern Peru), respectively. In Cahuachi (southern Peru), ref. [17] reported diameters of looting holes from 2 to 9 m, and depths of around 2 m. In Egypt, ref. [18] measured average size of looting pits of 2 m × 2 m and estimated average depth of 1.24 m with a hemispherical shape. In Lisht, one of the sites most damaged by looting, pits grew larger in size, with one measuring 5 m × 2 m [19]. In Apamea (Syria), ref. [7] combined observations from space and ground-based photographs published online to estimate that the planimetric dimensions of the pit openings ranged between tens of centimeters to a few meters, with depth generally less than one meter or up to a couple of meters. Ref. [5] estimated that in Apamea looting trenches typically measure up to 3 m on a side. Both the studies agree that the size and sheer number of looting holes, as well as the regular pattern of looting clusters, suggest that heavy machinery was used. Indeed, machine-assisted looting generally manifests in the form of regular, highly concentrated and extended series of looting holes, and sometimes includes excavation trenches that can reach a depth up to a few meters.

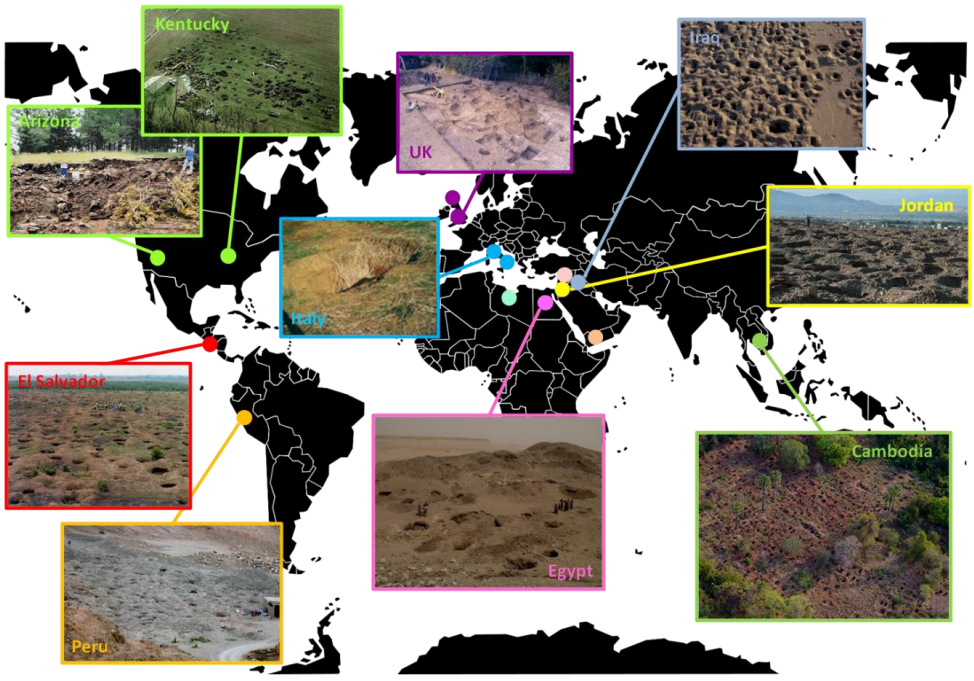

Figure 1. Graphic representation of the widespread phenomenon of looting in archaeological heritage sites and cultural landscapes across the globe. The map is not exhaustive and intentionally provides a sample for demonstration purposes only.

Traditionally, archaeologists and heritage conservators document looting features during their field inspections or, when possible, through airborne surveys that allow a wider view to be captured at

site scale. The use of aerial photographs (including those from declassified military surveys, such as CORONA, ARGON, and LANYARD imagery) has been one of the first remote sensing techniques exploited by archaeologists, for example in the Middle East in the context of dedicated academic projects (e.g., refs. [20,21]), or in the framework of international initiatives since the Iraq war and its aftermath [22]. More recently, archaeologists have started assessing the performance of looting documentation via drones, since these are more cost-effective compared to airborne surveys, allow higher resolution documentation up to 1–2 cm/pixel in mere days, and are capable to capture typologies of excavations that could not be visible from satellite (e.g., sideway diggings into adjacent tombs [23]). However, although drones are currently used in site-specific projects [24], their implementation is still at an experimental stage (e.g., ref. [25]) and may be potentially limited by difficulties in getting airspace authorization to fly over sensitive locations. Moreover, there are not yet published research papers presenting established and shared methodologies for data capture and processing.

Much more developed is, instead, the use of satellite remote sensing to document looting incidents. Since the early 2000s, there has been a more systematic use of satellite images, mostly sourced from commercial providers (e.g., DigitalGlobe) or freely accessible platforms (e.g., Google Earth; [26]). Satellite-based assessment allowed archaeologists to successfully overcome the limitations due to site inaccessibility and substantiate incident reports collected from broadcast and social media, or written based on direct observation on the ground. In this regard, there is indeed a general consensus across the research community about the advantageous properties offered by satellite imagery (e.g., refs. [6,27,28]).

Undoubtedly, some events were catalyzers to stimulate the use of satellite imagery for detecting looting, such as the Syrian conflict during which such data have come of age for archaeological purposes [29]. The impact of satellite imagery on the practice of heritage management and protection was so positive that international organizations, practitioners and heritage bodies nowadays regard satellite-based assessment as a source of objective information allowing a conservative estimate of the condition on site [30]. Further proof is the increasing number of initiatives to deploy satellite imagery to map cultural and natural areas under threat [31], or to protect cultural and natural heritage with the most advanced geo-spatial technologies [32].

In this context, satellite remote sensing has been used so far to address the following questions:

- Identification: Are there newly looted sites? If so, where are they located?
- Substantiation: Is there evidence corroborating reports of looting incidents?
- Monitoring and quantification of damage: Is there evidence that looting is continuing in sites that have been already looted? If so, at what rate and how is looting spatially spreading? At what extent has the site been damaged?

In most cases, satellite-based assessment of looting is carried out in a critical way, with the awareness that, while in some contexts satellite observations work very well, they are not able to capture all forms of looting or vandalism [33]. Furthermore, spatial and temporal resolutions are critical factors to achieve an accurate and granular quantification of damage [7,34].

In this regard, the increasing accessibility to a wider spectrum of space-borne data, particularly very high resolution (VHR) images from commercial optical satellites and, more recently, from synthetic aperture radar (SAR) missions, has encouraged the research community to test new image processing techniques for identification, extraction and counting of looting features, to complement (or even replace) analyst-driven methods of image interpretation and looting mapping. At the same time, researchers and the practitioner community are exploiting facilitated access to imagery to conduct more systematic, regional-scale efforts covering larger regions [34]. This is a circumstance that, in turn, generates the need of developing automated algorithms for looting identification and monitoring. For example, the American Schools of Oriental Research Cultural Heritage Initiatives (ASOR CHI) is one of the leading initiatives that have started researching toward this direction, to automate the change detection analysis to effectively screen hundreds of thousands of satellite images [28].

However, the plethora of methods of image processing that are published in the literature has not been reviewed yet, except for a chapter of state-of-the-art recently published in [17], that broadly separates methods for the identification of looting features in "visual" vs. "automatic". Besides the latter, there are no papers that discuss the achievements in this field of archaeological remote sensing and identify the current challenges to move from research to practice and user uptake.

To fill this gap, this paper aims to provide a comprehensive review of space-based methods for detection, monitoring and quantification of looting (Sections 2 and 3). The review accounts for: (i) the different types of satellite data that can be used; (ii) the properties of the looting features that can be estimated and utilized as proxies to assess the damage to a cultural heritage site; (iii) the image processing rationales and methodological workflows that enable the generation of value-added mapping products; and (iv) the rationale for validation.

This review is timely in that it helps to: re-examine the achievements in archaeological remote sensing after more than a decade of developments and experimentation on such a topical challenge (Sections 2 and 3); disseminate methods, approaches and common practices (Section 4); and outline future perspective for further advancement and operational implementation (Section 5). This is also in line with the work promoting sharing and harmonization of methodologies that is currently being undertaken in the framework of ongoing international networks and digital platforms (e.g., H2020 NETCHER project [35]). The intention is that this paper could contribute to the discussions currently animating the debate within the research and practitioner community.

2. Materials and Methods

2.1. Literature Review

The foundation of this scientific study is the evidence gathered from the bibliographic review of the peer-reviewed publications that were indexed in Scopus in the last fifteen years (as of June 2019), and focus on investigating archaeological looting with space-based methods. The production of years 2018 and 2019 was intentionally included, although it is known that the indexing for such recent periods by Scopus could still be not completed yet, so some publications may be later included in the research catalogue. To account for this situation, a cross-check with Google Scholar and wide search on Google was made. Elsevier's Scopus and Clarivate Analytics' (formerly Thomson Reuters') Web of Science (WoS) citation databases were queried through an automated Boolean search based on the technical terms 'looting', 'space', 'satellite', and their combinations within the various bibliographic fields (e.g., *TITLE-ABS-KEY (looting AND satellite)*). The same Boolean search was applied to query internet to capture relevant non-indexed abstracts, conference proceedings and book chapters, as well as the grey literature (e.g., technical reports, white papers), that were published about this subject by international organizations (e.g., UNITAR-UNOSAT) and academia/practitioner-led projects (e.g., EAMENA, ASOR CHI, American Association for the Advancement of Science—AAAS).

The information collected from this automated search was then analyzed through a skim-reading process. Publications that were found not relevant were discarded from the collection used in this paper (e.g., those wherein looting and/or satellite imagery are mentioned only, but not specifically investigated and exploited, respectively). On the other hand, features of the publications that were found relevant for the analysis were noted and classified. Table 1 lists the attributes that were extracted for each relevant publication and the labels adopted for their classification. Full description of how these attributes were classified is provided in Sections 3.1–3.4, to introduce the analysis of the related results.

Table 1. Attributes by which scientific papers, grey literature and relevant information therein were classified for the analysis of methods for archaeological looting investigation with satellite imagery.

Attribute	Label
Year of publication	Year
Spatial focus	Site-specific; Region-specific
Location(s)	Toponym
Spatial scale of analysis	Site; Landscape
Sensor type	Optical; SAR
Space mission	e.g., IKONOS, WorldView, TerraSAR-X, Sentinel-2
Image visualization platform	e.g., Google Earth, Bing Maps
Looting feature observed	Looting pit; Looting pit (circular); Looting mark ensemble; Looting cluster; Filling mark; Change pattern
Looting feature property	Brightness; Density; Homogeneity; Radar backscatter; Radar backscatter ratio; Reflectance; Shape; Similarity; Size; Spatial correlation; Texture
Methodology	Visual; Manual; Image enhancement/filtering; Image processing; Automatic
Technique	Change detection; Contouring; Multi-temporal averaging; Object-based feature detection; Pansharpening; Photo-interpretation; Radar backscatter multi-looking; Segmentation; Spatial Autocorrelation statistics; Spectral analysis; Supervised classification; Temporal variability; Texture extraction; Unsupervised classification
Validation	Literature; Ground truthing; Ground-based incident reports; Third-party in situ inspection; Aerial imagery; Visual inspection of other satellite imagery; Manual mapping on same/other satellite images
Author research domain	e.g., Archaeology, Anthropology, Cultural heritage, Remote sensing, Geography

2.2. Satellite Images and Demonstration Sites

The discussion is supported via a selection of satellite observations and image processing tests that were run on either optical or SAR images, at different spatial, spectral and temporal resolutions, covering known looted heritage sites, as well as examples from visualization platforms such as Google Earth and Bing Maps. Details of the materials and techniques used are reported in Table 2.

3. Results

3.1. Trends in Space-Based Looting Studies

3.1.1. Spatial–Temporal Patterns

A total of forty-seven peer-reviewed studies on space-based assessment of looting were published in indexed journals since 2006 (Figure 2). These papers focus on either the use of satellite imagery for looting assessment at specific archaeological sites of interest, or the development of image processing techniques to detect, monitor and quantify looting. This collection of publications provides clear evidence that there is a substantial body of scientific research of looting assessment using satellite imagery. Some trends can be observed.

The cumulative curve (blue line in Figure 2) shows that, until 2013, one to three papers per year were published, thus resulting in a steady increase of the total number of publications on this subject. However, no immediate correlation is found between the number of papers and two of the key historical events that happened during the period 2006–2018. These are the Arab Spring (conventionally lasting from 17 December 2010 to 1 December 2012) and the start of the Syrian civil war (conventionally beginning on 15 March 2011), in conjunction of which a significant number of incidents of looting were recorded across the MENA region. In this regard, it is worth recalling that [4] found an increase in the frequency of looting by nearly an order of magnitude in Syrian heritage sites, although war-related looting was similar in proportion to the record of pre-war looting. Whereas, the results published by [18] evidenced a statistically significant upward trend in site damage and

indicated a greater frequency of intensive looting in Egypt, immediately following the recession in 2008–2009, but prior to the Arab Spring.

The absence of an immediate correlation between the number of publications and the events occurred across the MENA region could have been expected, considering that these events were regional and the body of publications analyzed in this study also included papers focusing on other regions in the world. There is also a temporal shift between the event occurrence and the time required from manuscript preparation to final publication after peer-review, that needs to be accounted for and could have well contributed to the absence of a clear temporal association.

A clear ramp up of the cumulative curve is observed starting from 2013 (Figure 2). Thirty-seven out of the forty-seven publications analyzed in this work (i.e., ~79%) were published since then, with a peak of fourteen papers in 2017 (i.e., ~30%).

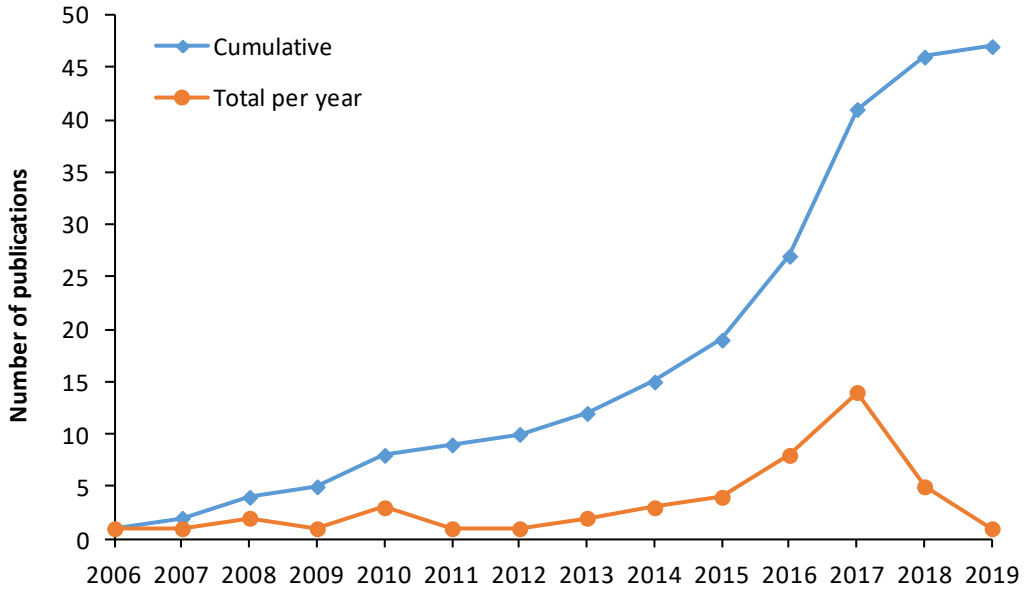

Figure 2. Peer-reviewed publications indexed in Scopus as of June 2019, wherein satellite images were used to detect looting at specific archaeological sites and/or image processing methods aimed to detect looting were presented.

Looking at the geographic distribution where the authors of these papers found evidence of looting using satellite images, Iraq and Syria appear to be the most studied countries with 13 and 12 papers, respectively, followed by Peru (7), Egypt (6), Libya (5) and Afghanistan (5) (Figure 3). These numbers must not be read as an indication that a country has been affected by looting more than another. Instead, they indicate which countries were the geographic focus of a higher number of publications, particularly in the last five years. Precise location of the sites and landscapes studied by scholars is reported in Figure 4.

Table 2. Summary of looted heritage sites presented in this paper for demonstration and discussion purposes, satellite imagery used and image processing technique applied. Notation: CSK—COSMO-SkyMed; GE—Google Earth; GE-1—GeoEye-1; GSD—ground sample distance; IK2—IKONOS-2; IR—Infrared; NIR—Near-Infrared; NDVI—Normalized Difference Vegetation Index; PS—pansharpened; QB-2—QuickBird-2; S2—Sentinel-2; SP—Spotlight Enhanced imaging mode; WV-2—WorldView-2; WV-3—WorldView-3.

Heritage site	Satellite	Spatial Resolution [1]	Time	Image Processing	Figure
Lisht (Egypt)	GE-1	46 cm	13/05/2013		
Dashur (Egypt)	Pléiades	50 cm	15/02/2013	Visual identification (GE)	6
Abusir el Malik (Egypt)	WV-3	36 cm	10/12/2018		
Tell Qarqur (Syria)	WV-3	37 cm	17/12/2017	Visual identification (GE)	7
Tell Jifar (Syria)	GE-1	48 cm	04/04/2012		
Sergiopolis (Syria)	QB-2	1 m	05/10/2014	Visual identification (ArcGIS basemap)	8
	CSK	1 m (SP)	31/08/2018–13/02/2019	Multi-temporal averaging	
Apamea (Syria)	GE-1	48 cm	04/04/2012	Visual identification (GE)	7
	WV-2	60 cm	29/04/2018		15
	WV-2	30 cm	03/04/2017	Pansharpening (Gram-Schmidt), false colored IR, NDVI, VIS-NIR spectral profiles	9, 10, 12, 13
	S-2	10 m (VIS, NIR)	21/04/2017, 16/04/2018	True color VIS, false colored IR, NDVI, VIS-NIR spectral profiles	9, 11, 12, 15
	CSK	1 m (SP)	16/07/2018–04/08/2019	Multi-temporal averaging, sigma nought profile	13
			16/07/2018, 04/08/2019	Amplitude change detection, sigma nought ratio profile	15, 16
Dura Europos (Syria)	QB-2	77 cm	12/12/2007	Visual identification (GE)	20
	GE-1	44 cm	07/04/2011		
	WV-2	52 cm	04/08/2011		
	WV-2	58 cm	11/04/2015		
	GE-1	43 cm	23/01/2017		
	CSK	1 m (SP)	11/01/2019	SAR texture extraction	14
Tell Hizareen (Syria)	IK2	84 cm	06/09/2012	Visual identification (GE)	19
	Pléiades	50 cm	03/12/2015		

[1] GSD for optical imagery (panchromatic); ground resolution for synthetic aperture radar (SAR) images.

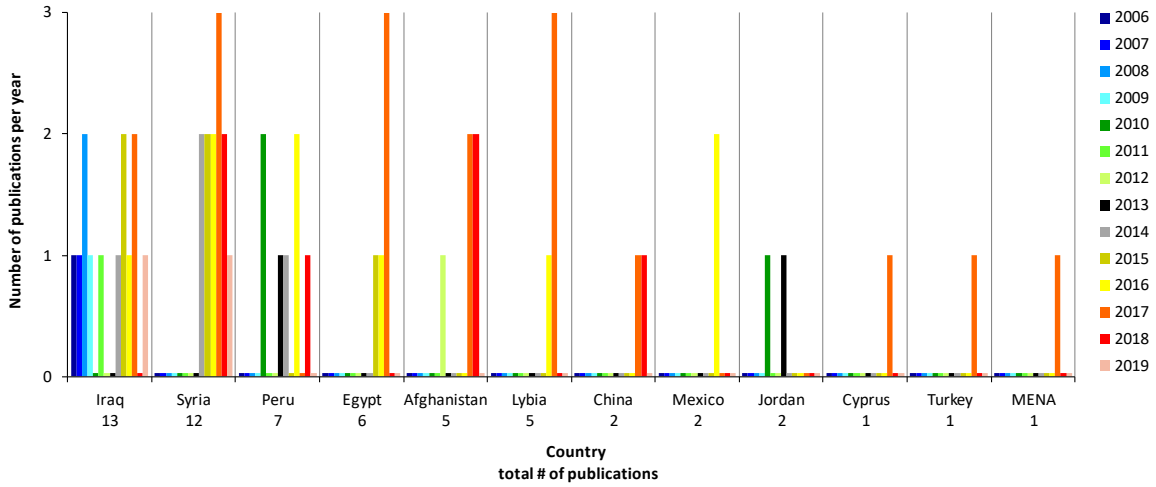

Figure 3. Geographic and temporal distribution of documented looting in the peer-reviewed publications of Figure 2. Publication database updated as of June 2019.

Figure 4. Location of the archaeological sites and cultural landscapes where evidence of looting from satellite imagery was reported in the peer-reviewed papers analyzed in this study (see Figure 2). Publication database updated as of June 2019.

By analyzing the temporal distribution of the papers for each country (Figure 3), it is apparent that papers investigating looting in Iraq and Peru with satellite data were published more regularly from 2006 to 2019. Differently, Syria, Afghanistan, Egypt and Libya were covered more unevenly, with the majority of the publications dated after 2014.

The constant attention that scholars paid on investigating Peruvian incidents of looting from space, as well as on heritage sites and cultural landscapes of Egypt, demonstrate that looting is a phenomenon that often happens in ordinary times, regardless of political instability that may create favorable conditions for looting to spread. The logistical difficulties to access remote regions and manage cultural heritage spreading across huge territories, make satellite remote sensing ideal to produce damage and looting maps and incident reports.

On the other side, the scale of damage and intentional destruction in Iraqi and Syrian heritage sites that were reported by broadcast and social media, can be reasonably considered facts and contexts that contributed to trigger academic-led exercises, as well as international initiatives, of space-based assessment of looting over these countries. In the scientific literature this is evidenced by the increase of studies on Syria and Iraq published between 2014 and 2019, with nearly 13% of the total papers

presenting both Iraqi and Syrian case studies within the same publication. Not surprisingly, the densest concentration of looted sites published in the body of peer-reviewed publications analyzed in this study is found in Syria and Iraq (Figure 4).

Jordan is the second country with the highest number of looted sites studied in the published literature, and provides an interesting example to discuss the advantage of using the '*Spatial focus*' and '*Spatial scale of analysis*' as different attributes extracted from the bibliographic metadata of each publication (see Section 2.1, Table 1). In this study, geo-tagging of each publication was made based not only on the geographic indication as per the bibliographic fields (i.e., title, abstract, keywords), but also on the systematic check of the figures of each publication showing the study area(s) and the extent of the satellite observations. This allowed the identification of whether: (i) the observations of looting from space were made at the spatial scale of single site or cultural landscape (see Figure 4), and (ii) the analysis of the results was made with site-specific or region-specific spatial focus. For instance, in [36], looting was documented for twenty-three individual sites in Jordan, so the observations were made at single-site scale (source for site locations: [37]). However, the authors analyzed their results as part of a wider overview of archaeological looting across the whole country, though acknowledging that the aim was not to represent a comprehensive catalogue for Jordan. The approach of attribute extraction implemented in the present paper therefore accounted for such aspects to comprehensively understand the spatial focus and scale of the analysis of all the publications analyzed.

Of the twenty-three publications with a region-specific focus, seven present inventories of looting incidents covering large landscapes (green squares in Figure 4). Except for one case, the authors of these papers relied only on free-access satellite image visualization platforms (mostly Google Earth and Bing Maps) or high volumes of high-resolution satellite imagery. The latter were often sourced through partnerships with government agencies or private foundations (e.g., [38]). Although studies with site-specific spatial focus still predominate the literature, it is to be noted that papers presenting more systematic region-specific exercises of looting recording increased since 2016. This proves how the scope and methodologies of this field of archaeological remote sensing are gradually changing (see also Section 1; [34]).

3.1.2. Satellite Sensors

So far, the majority of the analyzed publications exploited optical images (42 out of 47 papers, i.e., 89%; Figure 5), in some cases by processing them to extract looting features, in others through visual inspection and subsequent manual digitization of looting features (see Section 3.4 for the discussion about methods). Of these 42 papers, 41 used optical data at very high resolution (VHR), i.e., less than 1 m, chiefly sourced from commercial providers. Only one paper is based on the use of Sentinel-2 images at 10-m spatial resolution to assess the spatial and temporal spread of looting at site scale [6]. Therefore, VHR optical images are nowadays well-established data in the archaeological community. Conversely, the use of high resolution (HR) data—such as free-of-charge Sentinel-2 and Landsat imagery—is still at the very early stage. Yet it is to explore at what extent these datasets can be utilized for regional mapping, owing to their large spatial coverage per single frame and availability for the entire landmass, as well as their short revisit time.

In this regard, although five papers state to have made use of Landsat images, these data were not utilized to identify looting features. Landsat images were either used as a good backdrop for site locations and land cover—land use information [39], to derive the environmental setting in geomorphological and regional studies [40] or for land use mapping to identify areas where different processes of encroachment (e.g., building development, cemetery growth, agricultural expansion) are already happening or are likely to happen, and may anticipate incidents of looting of cultural heritage and destruction of archaeological records [41,42].

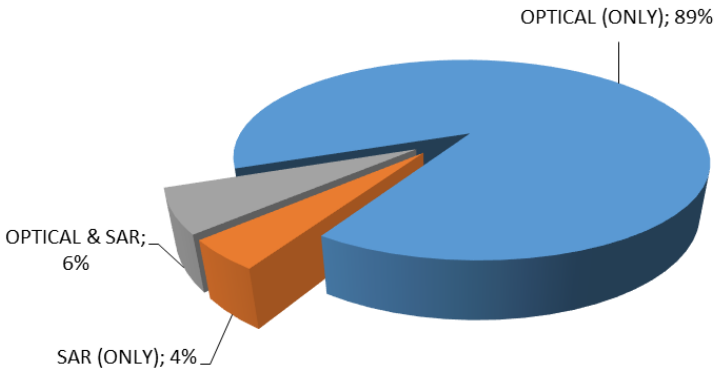

Figure 5. Distribution of peer-reviewed publications by type of satellite images used for looting assessment, either optical, synthetic aperture radar (SAR) or a combination of both. Publication database updated as of June 2019.

Similarly, very limited is the exploitation of SAR data (4% and 6% of the analyzed publications, as unique data source and in combination with optical images, respectively; Figure 5), but due to different reasons. The VHR SAR acquisition modes that can offer the adequate spatial and temporal resolution were released relatively recently. We specifically refer to the sub-meter resolution Staring Spotlight imaging mode of the TerraSAR-X mission, available since 2013, as opposed to optical VHR offered by commercial providers since the early 2000s. The first implementation of Staring Spotlight technology for looting monitoring was even more recent [7]. In other cases, even if the VHR SAR technology was available for long and made accessible via dedicated announcements of opportunities by the space agencies, only remote sensing experts exploited this type of data, and the heritage community is still not aware of their usefulness for looting assessment [8]. This is the case of the Spotlight mode provided by the TerraSAR-X mission (i.e., HR Spotlight at 1 m resolution, and Spotlight at 2 m) and the COSMO-SkyMed constellation (i.e., Spotlight-2 or Enhanced Spotlight at 1 m), both available since the launch of the first satellites of the two constellations in 2007. Not to forget the skills gap in handling SAR data across the broader archaeological (remote sensing) community, that contributes to the common misperception that SAR data do not have adequate resolution for archaeological applications, are difficult to process and interpret, and therefore are not useful [43].

From an operational point of view, satellite images are selected by scholars according to technical requirements that are strongly dependent on the spatial focus and scale of analysis. At equal spatial conditions (i.e., size of looting features, scale of looting, total area to survey), temporal resolution and availability of image archives can further drive the input image selection. In Section 3.3, criteria to select space sensors and observation solutions are proposed.

3.2. Looting Features in Satellite Images

This section reviews how looting features are seen and detected in optical and SAR satellite images. This aims to: (i) provide the background to understand better the reasons for the apparent preference of image analysts for optical vs. SAR images in satellite-based studies of looting; and (ii) outline the methods with which all these data can be more exploited than currently done.

Figures 6 and 7 display a selection of looting features as they appear in optical VHR images covering different parts of the world (Table 2), in arid/desert and vegetated sites, respectively. More specifically, the following looting features/morphologies are taken into account:

1. Looting pit, single, isolated, of either circular or irregular shape, in arid or vegetated grounds;
2. Cluster of looting pits, where pits are either in a close formation but each of them is distinguishable, or are so contiguous that they form an overlapping coalescence.

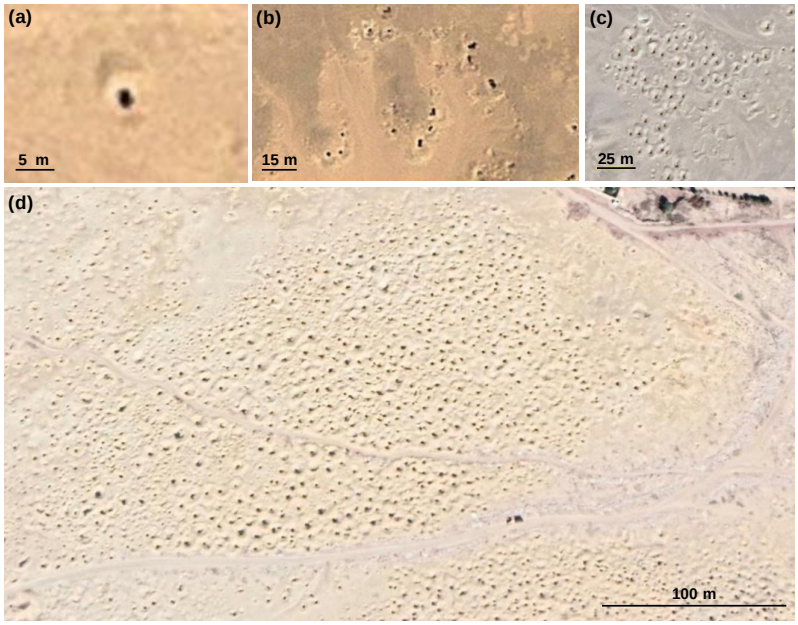

Figure 6. Examples of typical looting features in satellite very high resolution (VHR) optical images covering arid and desert sites: (**a**) single, isolated, circular looting pit; (**b**) low density clusters of looting pits; (**c**) high density cluster of looting pits; (**d**) extended looted areas with coalescence of looting pits. Google Earth images © 2019 Maxar Technologies.

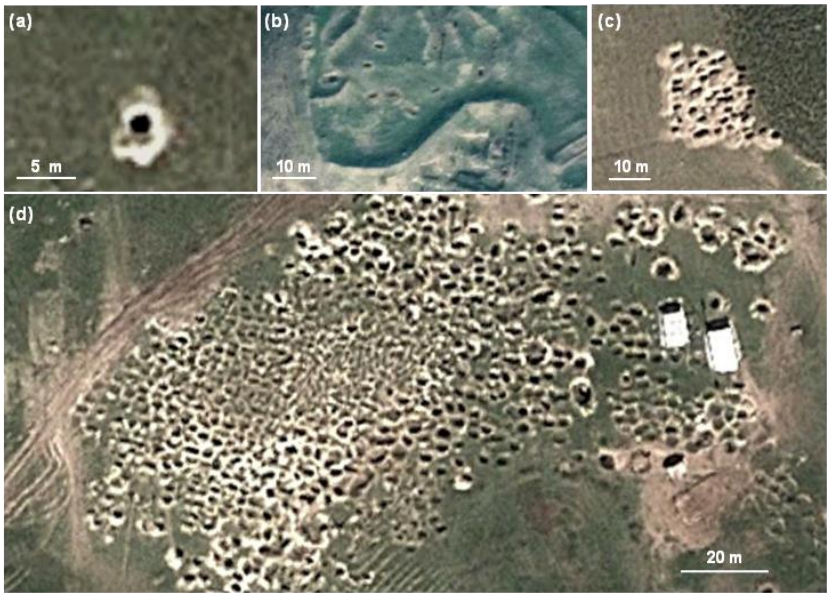

Figure 7. Examples of typical looting features in satellite VHR optical images covering vegetated sites: (**a**) single, isolated, circular looting pit; (**b**) low density cluster of looting pits; (**c**) high density cluster of looting pits; (**d**) extended looted areas with coalescence of looting pits. Google Earth images © 2019 Maxar Technologies.

Conceptually, a single looting pit marks a new incident of looting. Section 4.4 provides a detailed discussion about the meaning that a looting mark seen from space can assume depending on the archaeological context where it is dug in. Typically, areas where scattered isolated pits are dug are those that looters have started scouting to check whether they are advantageous places to dig. Depending on the digging method and the success in finding goods, looted areas can quickly manifest as dense clusters of looting pits. Extensive looting, such as that found in Apamea and Dura Europos in Syria, can cover entire sectors of archaeological sites and pockmark the whole landscape.

The examples above are not exhaustive of all the possible morphologies with which looting can manifest. In desert sites, it is also common that the areas dug by looters appear as wide concave holes, with nearly circular shape, that in time may erode and change their morphology to more bathtub-like depression in the ground ([4]; see Section 4.3). Figure 8 shows an example in the Roman/early Islamic site of Sergiopolis, Resafa (Syria), by comparing a VHR optical image from Google Earth, a VHR COSMO-SkyMed Spotlight image and a photograph taken during a field visit. Differently from the cases showed in Figure 6, there is not much contrast between the dark hole in the center and the surrounding soil. The looting feature is instead enhanced by its circular shape. Similar situations are found in other sites in the Middle East (e.g., Umm el Abar esh Sherquiye, Jordan [36]) and other continents (e.g., Cahuachi, southern Peru, [44,45]). Further morphologies include excavation trenches, that are commonly dug with the help of machinery. An example observed in Apamea is reported later in Section 3.2.2.

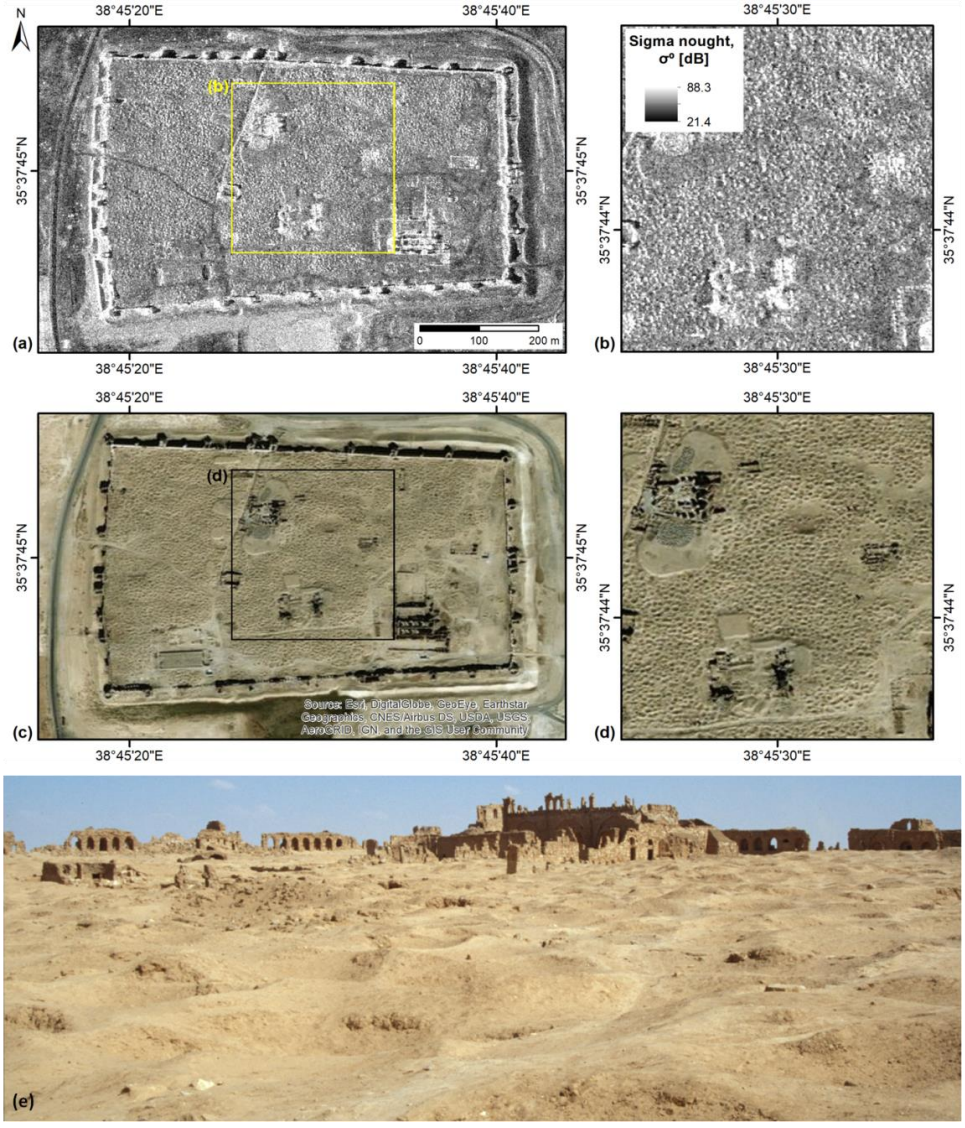

Figure 8. (**a**) Multi-temporal average of 9 COSMO-SkyMed Enhanced Spotlight images acquired between 31/08/2018 and 13/02/2019 at 1-m resolution in ascending mode over the archaeological site of Sergiopolis, Resafa (Syria), showing the extensive looting that took place prior to the Syrian civil war. (**b**) Zoomed view of the central area highlighting the density and circular concave shape of looting features, which match with evidence from (**c**,**d**) ArcGIS basemap image 05/10/2014 and (**e**) ground-truth photograph taken on 06/05/2000 (credit/courtesy: M.C.C. and M.C.). COSMO-SkyMed® Products ©ASI—Italian Space Agency—2018–2019. All Rights Reserved.

3.2.1. Optical Remote Sensing

In a satellite optical image displayed according to a true color composition in the visible wavelength range (i.e., where the Red-Green-Blue RGB channels are associated with the red, green, blue bands, respectively), a single isolated looting pit typically appears as a black/dark hole. This is often recognized due to the sharp color contrast with the surrounding grassland or light-colored ground in desert regions and dry soils (see Figures 6 and 7). Such contrast is frequently sufficient to allow for a full visibility of the looting pit, thus facilitating visual detection, manual digitization and quite accurate counting of the number of pits detected. For example, ref. [18] used this method in both arid and vegetated environments in Egypt, by manually drawing an individual polygon over the black hole in the center of each looting pit, thus excluding the surrounding crown formed by the accumulation of the brighter debris removed to excavate the pit. In those case studies, the looted areas mostly consisted in extended looting clusters. This is common situation to most of looted sites that were investigated with optical satellite images in the literature. As discussed in more detailed in Section 3.4, in presence of dense looting clusters, the digitization of a unique polygon enclosing the whole cluster is technically more manageable and less time-consuming, and allows for an estimate of the total surface extent affected by looting, thus overcoming the constraints due to the different visibility of each looting pit therein.

Visibility of looting features is indeed a crucial aspect that several scholars reported across different geographic locations (see Section 4.3) and can hamper the assessment, although the spectral information in the visible bands is provided at the highest spatial resolution possible.

In the literature, there is scarce evidence that authors explored NIR and Short-Wave Infra-Red (SWIR) channels to enhance looting features. This is somehow surprising, because looting pits and clusters are surface disturbance with distinctive spectral signatures compared to the surrounding un-looted virgin soil, depending on local mineralogical composition, moisture content and vegetation cover. This is specifically observed in vegetated sites. For demonstration purposes, Figure 9a shows the archaeological looting in Apamea as captured by a VHR WorldView-2 image that was collected on 3 April 2017 (i.e., when the unexcavated ground was green and covered with grassland) and later pansharpened using the Gram–Schmidt algorithm. Figure 10a shows the matching false colored infrared composite (R: Band 4—NIR1; G: Band 3—red; B: Band 2—green). The spectral signature in the two visible bands (red and green) vs. the NIR distinctively marks the extent of looted areas and even isolated pits. Stronger signal is found over fresher looting areas (i.e., areas more recently looted or where looting activities were rejuvenated) compared to older looting features (Figure 10b).

Similar result can be achieved with a nearly coeval Sentinel-2 imagery acquired on 21 April 2017 (Figure 9c) and the matching false colored infrared (R: Band 8—NIR; G: Band 4—red; B: Band 3—green; Figure 11a). Because of the lower spatial resolution (10 m in both visible and NIR bands), the detection and delineation of the most extended looting areas is comparable at looting cluster level only, and some of the older looting clusters appear more faint. However, even the visual comparison highlights that Sentinel-2 and WordView-2 images are highly comparable in case of extensive looting over a vegetated site.

Further corroboration is gathered from the spectral analysis of pixel samples selected in areas of the site that have been differently affected by looting, from null to fully looted (Figure 12a–f). Spectral profiles extracted from the Sentinel-2 image in the VIS and NIR (from Band 2—B2 to Band 8A—B8A; Figure 12g) show that fresh looting can be markedly distinguished from old looting owing to the higher reflectance in the visible bands (B2: 496.6 nm; B3: 560 nm; and B4: 664.5 nm) and short wavelength red edge band (B5: 703.9 nm). Whereas, spectra of old and fresh looting look similar from B6 to B8A, i.e., from 740.2 to 864.8 nm. This is the wavelength region where un-looted soil has a stronger NIR and long wavelength red edge response due to vegetation coverage.

Consequentially, in both VHR World-View-2 and HR Sentinel-2 images, commonly used spectral indices such as the Normalized Difference Vegetation Index (NDVI) allow the identification of looting as a "non-green negative mask" (Figure 10c,d and Figure 11c,d). In this regard, there are no studies where looting was specifically mapped by using the NIR, SWIR and/or combinations of these bands

with the visible ones. Therefore, the demonstration reported in this paper with regard to extensive looting in a vegetated site is the first example of this kind.

However, depending on the typology of looting features and the environmental context where this phenomenon is documented, traditional indices such as NDVI, Enhanced Vegetation Index (EVI) or Leaf Area Index (LAI) may not perform well. Ref. [46] conducted some experimental research to test a wide variety of spectral indices to identify looting imprints in a rocky and partially vegetated site, and found that "non-ordinary" indices for archaeological purposes (e.g., WorldView Built-Up Index) were more suited, given the particular context and type of looting.

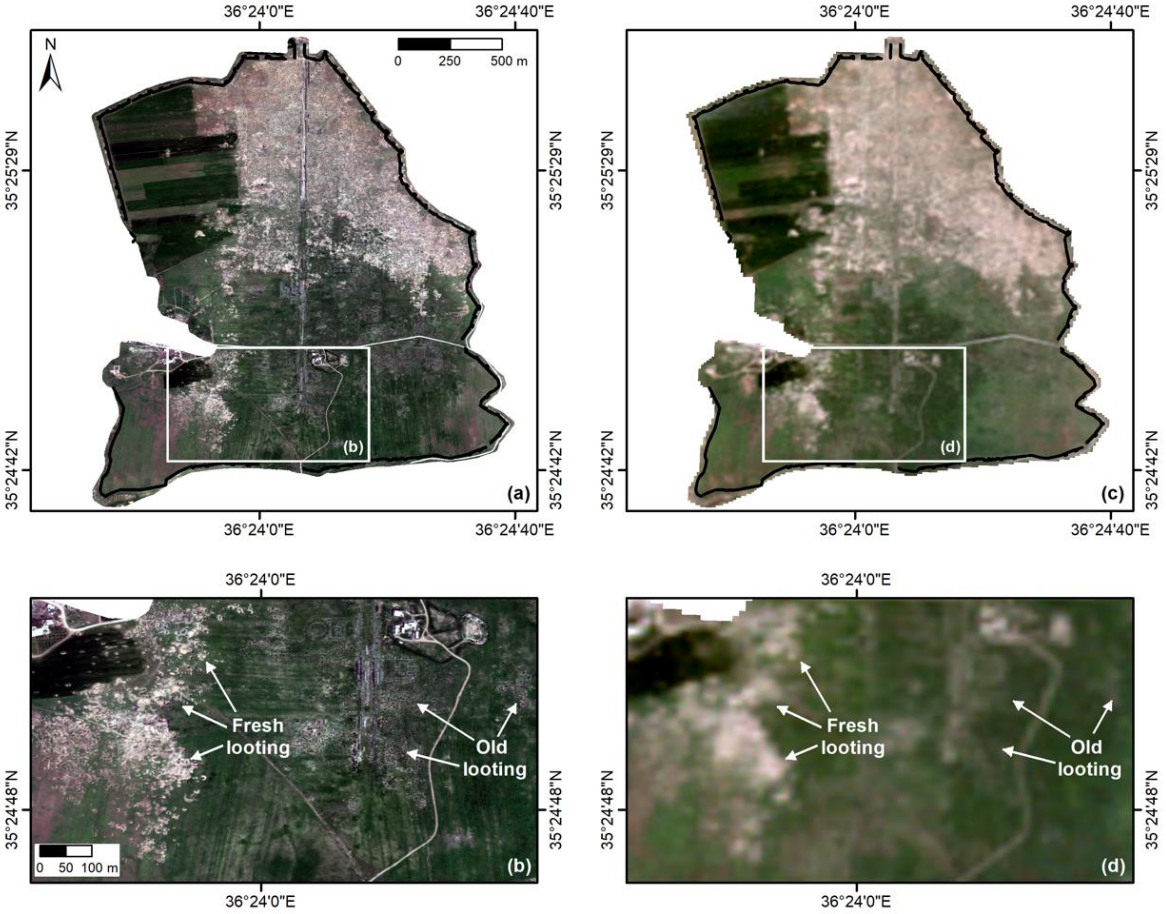

Figure 9. Archaeological looting at Apamea (Syria) captured with: (**a**) pansharpened 30-cm WorldView-2 image (03/04/2017) and (**c**) 10-m Sentinel-2 image (21/04/2017), displayed as true-color images (R: Band 3—red; G: Band 2—green; B: Band 1—blue, and R: Band 4—red; G: Band 3—green; B: Band 2—blue, respectively). Zoomed views (**b**,**d**) highlight areas of fresh vs. old looting features. WorldView-2 product © 2018 DigitalGlobe, Inc. Distributed by e-GEOS S.p.A. Contains Copernicus Sentinel-2 data 2017.

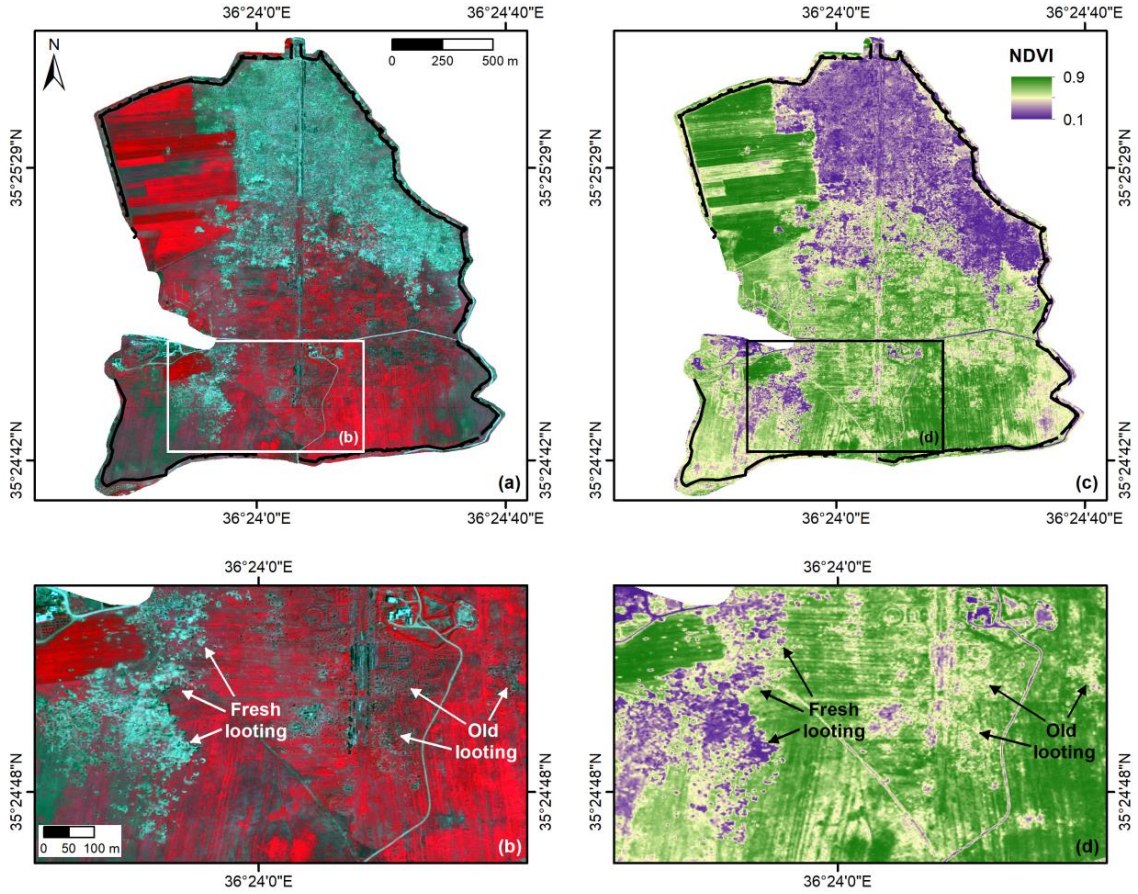

Figure 10. Archaeological looting at Apamea (Syria) captured with pansharpened 30-cm WorldView-2 image (03/04/2017) displayed as: (**a**,**b**) false-colored infrared (R: Band 4—NIR1; G: Band 3—red; B: Band 2—green) and (**c**,**d**) Normalized Difference Vegetation Index (NDVI). Zoomed views (**b**,**d**) highlight the marked difference in spectral signature of fresh vs. old looting features. WorldView-2 product © 2018 DigitalGlobe, Inc. Distributed by e-GEOS S.p.A.

Limitations of this multi-spectral approach may come from the availability of multi-spectral images providing the appropriate spatial resolution in the visible, NIR and SWIR bands. When available, the cost associated to access all these bands can be a constraint in the case of purchase of commercial VHR resolution. In general, the addition of NIR and SWIR channels to RGB channels may increase the purchase cost significantly.

The other constraint is, of course, the lack of spectral diversity between the looting features and the rest of the scene. In this regard, some authors reported different situations suggesting that each site has its own properties and the same approach may not perform equally. In Cahuachi, a desert archaeological site located in southern Peru, through a comparative visual inspection [44,45] found that the panchromatic images were more suitable than the pansharpened spectral bands to emphasize both the pitting holes and archaeological features (shallow to outcropping walls). Given the absence of significant spectral variations in the four bands of the QuickBird images, panchromatic scenes were used in that case to assess looting. Differently, in Cafetal and Arenal (Lambayeque, northern Peru), the same authors found that the red pansharpened band was more significant to detect the circular holes compared to the other spectral bands, including the panchromatic [16]. On the contrary, in Afghanistan [15] found that individual pits and disturbances were clearly visible on panchromatic WorldView-2 images, especially after pansharpening that incorporated the multispectral information.

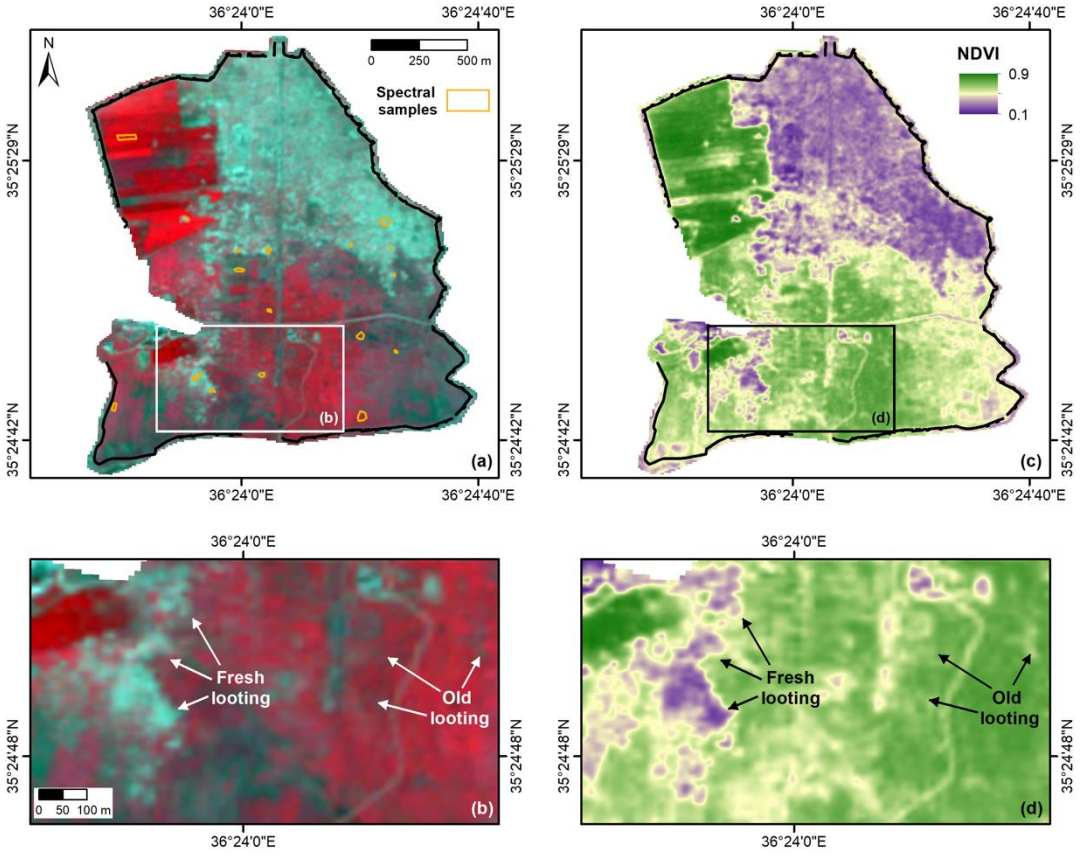

Figure 11. Archaeological looting at Apamea (Syria) captured with 10-m Sentinel-2 image (21/04/2017, i.e., nearly coeval with WorldView-2 image in Figure 10) displayed as: (**a**,**b**) false-colored infrared (R: Band 8—NIR; G: Band 4—red; B: Band 3—green) and (**c**,**d**) Normalized Difference Vegetation Index (NDVI). Zoomed views (**b**,**d**) highlight the marked difference in spectral signature of fresh vs. old looting features. Spectral samples reported in (**a**) were used to extract the spectral profiles showed in Figure 12. Contains modified Copernicus Sentinel-2 data 2017.

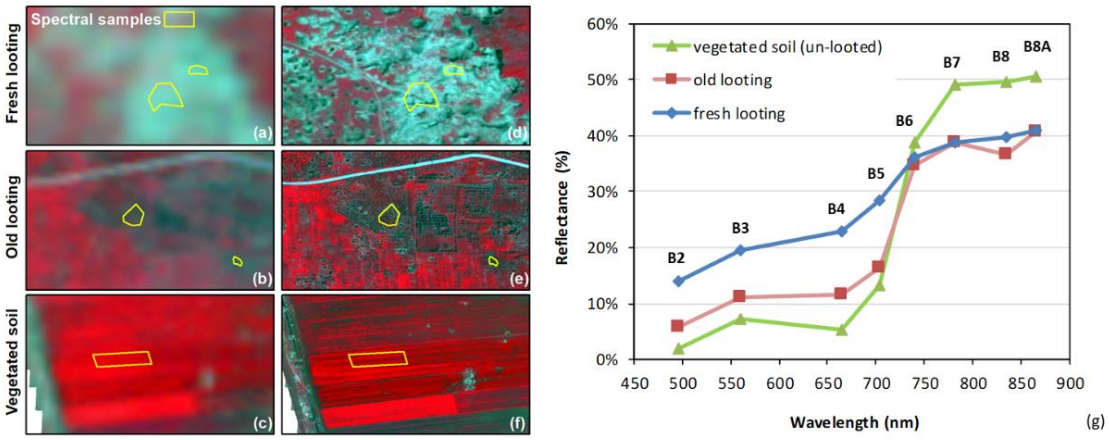

Figure 12. Spectral analysis of samples of: (**a**) fresh looting, (**b**) old looting, and (**c**) vegetated soil (un-looted) identified on 10-m false-colored infrared Sentinel-2 image (21/04/2017; R: Band 8—NIR; G: Band 4—red; B: Band 3—green; see Figure 11a) and (**d**–**f**) nearly coeval false-colored infrared WorldView-2 image (03/04/2017; R: Band 4—NIR1; G: Band 3—red; B: Band 2—green; see Figure 10a). (**g**) Extracted spectral profiles of surface reflectance in Sentinel-2 VIS and NIR bands (Band 2 to Band 8A). Contains modified Copernicus Sentinel-2 data 2017. WorldView-2 product © 2018 DigitalGlobe, Inc. Distributed by e-GEOS S.p.A.

3.2.2. SAR Remote Sensing

Individual looting pits can be seen distinctively in VHR SAR from 1 m resolution and below. Figure 13 provides an example of one of the thousands of looting holes as imaged in Apamea by COSMO-SkyMed Spotlight mode and a WorldView-2 image including both panchromatic and multi-spectral bands (see Figures 9a and 10).

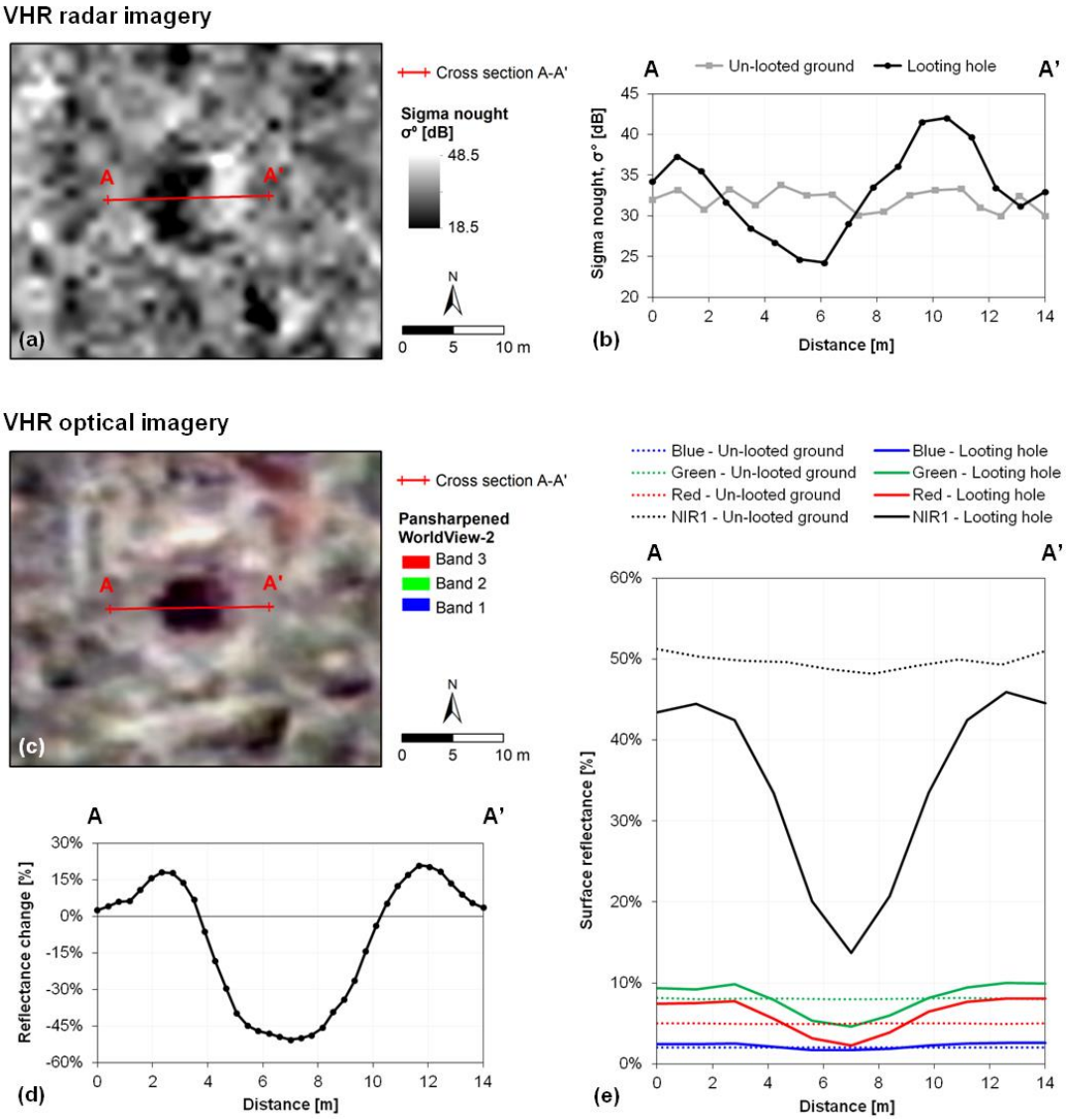

Figure 13. Spectral analysis of a looting hole in Apamea (Syria), compared with un-looted ground: (**a**) COSMO-SkyMed Enhanced Spotlight HH polarized image with 1-m ground resolution acquired in ascending mode, with 41° incidence angle; (**b**) sigma nought (σ^0) profile A-A' across the looting pit; (**c**) WorldView-2 image pansharpened with Gram-Schimdt algorithm (R: Band 3—red; G: Band 2—green; B: Band 1—blue), (**d**) surface reflectance change in the panchromatic band with respect to un-looted ground, and (**e**) spectral profiles A-A' across the looting pit. COSMO-SkyMed® Products ©ASI—Italian Space Agency—2018–2019. All Rights Reserved. WorldView-2 product © 2018 DigitalGlobe, Inc. Distributed by e-GEOS S.p.A.

As discussed in [7], the peculiar side-looking geometry of observation along the line of sight (LOS) of the SAR sensors causes the looting pit to be imaged as a combined pattern of radar shadow and layover (the so-called "looting mark"; Figure 13a). Therefore, the looting pit can be recognized thanks to the geometric distortions that are caused by its morphology and its illumination by the active sensor.

Compared to un-looted ground, the radar backscattering (sigma nought, σ^0) profile of the looting hole is characterized by an evident decrease of radar backscattering (e.g., by 8–10 dB with respect to un-looted ground) due to the radar shadow component of the looting mark, followed by a pronounced increase of the radar backscatter due to layover (Figure 13b). In the spectral profile of the same looting pit extracted from the WorldView-2 image (Figure 13c), a marked decrease of surface reflectance is found across the extent of the dark hole within the looting pit, compared to the un-looted ground nearby (Figure 13d). The surface reflectance drop is much more pronounced in the NIR1 (from ~50% reflectance of un-looted ground to 15% at the center of the pit), red and green bands (Figure 13e). On the other hand, a clear surface reflectance increase can be distinguished at the margins of the pit in the panchromatic, VIS and NIR bands, due to the accumulation of debris around the opening of the hole (Figure 13d,e).

To handle processed SAR images in the GIS environment, the images need to be re-projected on the ground range geometry. This is usually undertaken with a simple re-projection under the assumption of a flat-Earth model and absence of the hole. As a consequence, the extent of the looting mark exceeds the real boundaries of the looting hole (see Figure 13a,c) and the length of the radar shadow and layover components re-projected on the ground range (GR_S and GR_L, respectively) can be measured according to the following formulas [7]:

$$GR_S = \frac{h}{\sin\theta\cos\theta} \tag{1}$$

$$GR_L = \frac{h}{\tan\theta} \tag{2}$$

where h is the depth of the hole and θ is the incidence angle, i.e., the angle between the incident radar beam (i.e., the slant-range) and the local vertical to the intercepting surface on the ground.

Ref. [7] simulated layover and shadow for different sets of looting holes with variable dimensions, orientation and shape. At equal looking geometry of the satellite (i.e., orbit, incidence angle), the shape and extent of looting mark changes according to the dimensions, orientation and shape of the pit, although the mark still consists in the combination of radar shadow and layer.

This proves that morphology (and consequently the amount of radar backscatter) is the key property determining how a looting pit is imaged in SAR images compared to the surrounding flat ground. Un-looted land usually appears as a relatively homogeneous set of greyish pixels, with the typical salt-and-pepper effect due to radar speckle (Figure 13a).

Looting pits in SAR images represent alterations of surface roughness. This results in a distinctive image texture that can be extracted, for example, using the formula [7]:

$$Texture_{\sigma^0}(i) = \log\left[\frac{1}{m^2}\sum_{j=1}^{m^2} w_j\sigma^0(j)\right] - \frac{1}{m^2}\sum_{j=1}^{m^2} w_j\{\log[\sigma^0(j)]\} \tag{3}$$

where texture values at each location i are derived through a moving kernel of m by m pixels centered at pixel i, and by computing the difference between the logarithm of the average radar backscatter and the average of the logarithms of the backscatter of the m^2 pixels j within the kernel. σ^0 is the normalized radar backscatter expressed in dB, and w_j are the weighting coefficients used within the kernel.

Texture maps are usually more effective than the original σ^0 images, in the way that they enhance the separation between un-looted and looted areas. Examples over Apamea are provided using TerraSAR-X Staring Spotlight by [7] and COSMO-SkyMed Spotlight by [8]. Figure 14 shows the extent of looting pits extracted as polygons from the SAR texture map generated by processing the COSMO-SkyMed Spotlight image acquired over Dura Europos on 11 January 2019. This output provides a clear delineation of the extensive and dense looting. The spatial distribution of looting features is consistent, in the overlapping areas, with the published maps obtained in 2014 based on visual identification and manual mapping on VHR optical images [47], and it shows further

expansion of looting since then. Owing to VHR of COSMO-SkyMed Spotlight imaging mode, the level of destruction within the walls is evident. The town is fully pockmarked by pits. However, as reported by [47], looting within the walls is so extensive that it constrains the discrimination of single features from non-damaged areas, even at VHR. So this is a limit case that could have been better addressed if images (either optical or SAR) had been regularly collected since the onset of looting, to gradually monitor looting spread across the site.

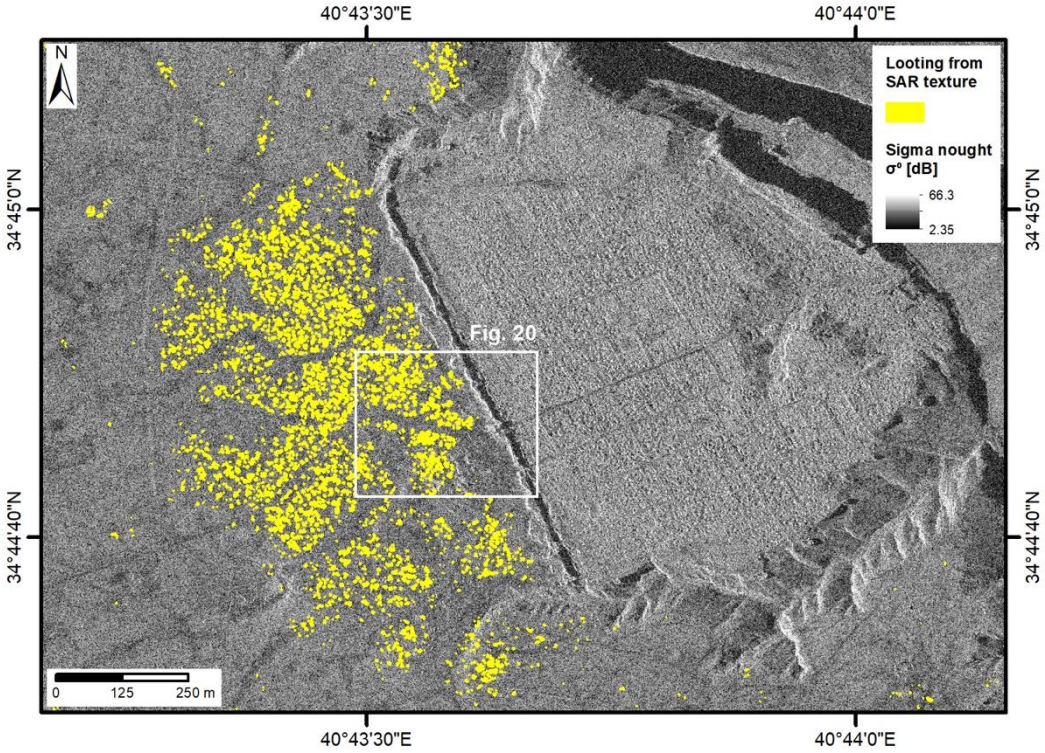

Figure 14. Polygons of extensive and dense looting beyond the walls of Dura Europos (Syria) extracted from the SAR texture map of the COSMO-SkyMed Enhanced Spotlight (~1 m ground resolution) image acquired in ascending mode on 11/01/2019, that is displayed on the background (COSMO-SkyMed® Product ©ASI—Italian Space Agency—2019. All Rights Reserved). The inset shows the location of Figure 20.

In this regard, ref. [7] already demonstrated how to generate supervised classification maps from consecutive SAR texture maps to monitor the evolution of looting extent. This second approach is definitely cost-effective and allows for a rather rapid mapping of looted areas. A limitation, though, can be represented by the presence of other objects not related to looting (e.g., urban and anthropogenic features), whose texture values can be confused with those of the looted areas, thus resulting in an overestimation of the looting extent. This constraint, however, can be at least reduced by applying a mask that allows the pre-existing un-related features (known as part of the background data of the studied site) to be removed and not be counted.

The same authors also developed a method for multi-temporal tracking of looting marks by ratioing the radar backscatter (σ^0) between consecutive SAR scenes, which allows for quantification of the magnitude, spatial distribution, and rates of looting activities [7]. As an example, Figure 15 compares the extent of new looted areas detected in the eastern sector of Apamea, by combining multi-sensor satellite time series, i.e., Sentinel-2, VHR Google Earth and COSMO-SkyMed Spotlight images. By April 2017 no new looting occurred in this sector (Figure 15a; see also [6]). Exactly one year after, severe looting affected the ruins of the House of Consoles, House of the Pilasters, the Eastern Cathedral and the surroundings (Figure 15b,c). The SAR change detection map produced by ratioing the COSMO-SkyMed Spotlight image acquired in ascending mode on 14 March 2019 with the first

available Spotlight image collected with the same parameters on 16 July 2018, confirms the extent of the large footprint of the looted areas (Figure 15d). The whole area is characterized by a general increase of radar backscatter, compared to the rest of the land where no new looting is observed. Tens of looting marks are found, with the σ^0 ratio profile according to the typical pattern of a looting mark, i.e., σ^0 decrease and increase (Figure 16a). The predominant irregular morphology of looting marks and shape of σ^0 patterns (Figure 16b) match with the evidence found in the VHR Google Earth image, i.e., looting manifesting as dense contiguous clusters and excavation trenches (Figure 15c). The new excavations also sealed old looting holes that were visible in earlier VHR images [7]. This further demonstrates that, in addition to new looting, satellite-based assessments need to account for reworked looting and back-filled holes. According to the reverse process by which a new looting hole appears in a SAR image, the "filling mark" (i.e., a filled-in looting pit) appears in the σ^0 image as a nearly homogeneous set of greyish pixels, and in the σ^0 ratio map as a combination of layover and shadow with opposite order with respect to a looting mark.

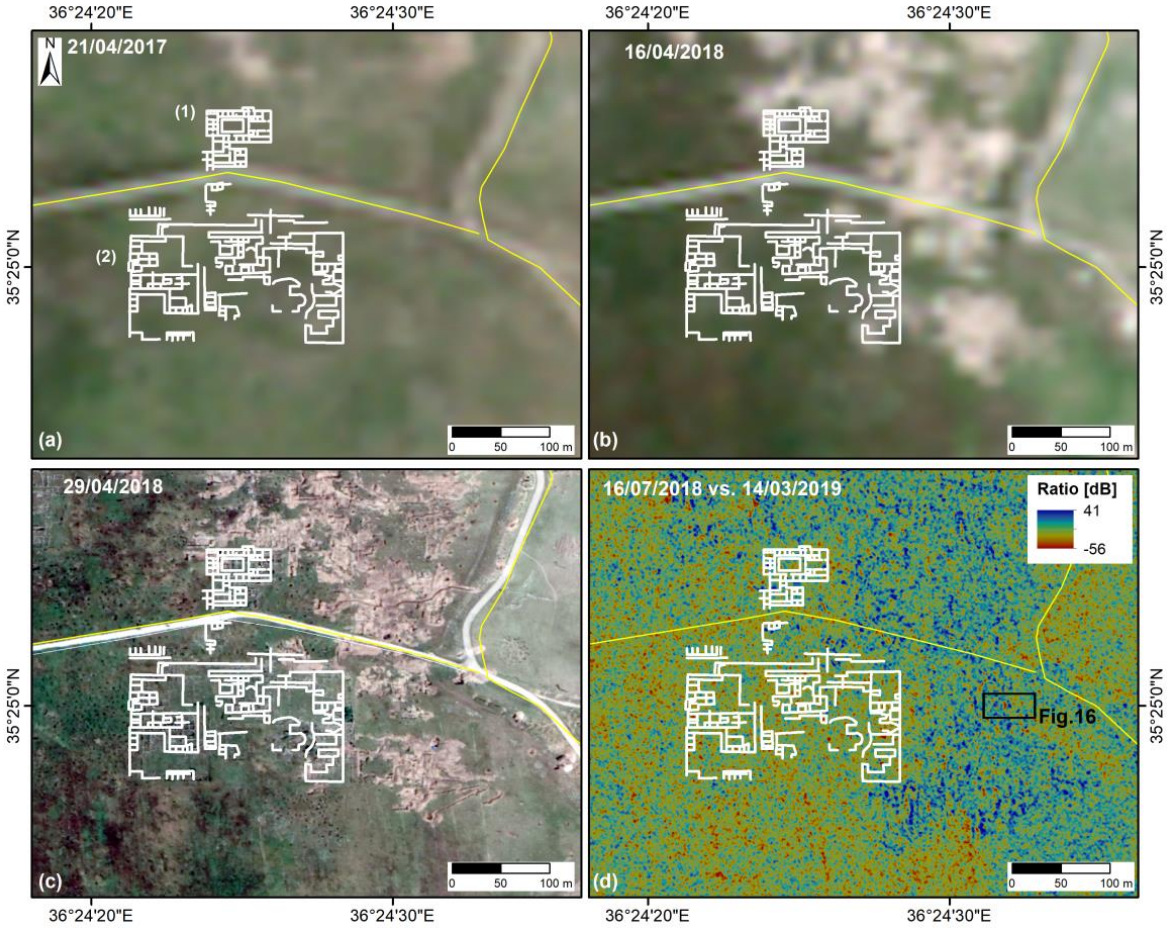

Figure 15. Multi-temporal evolution of looting from April 2017 to March 2019 near the ruins of (1) the House of Consoles and House of the Pilasters and (2) the Eastern Cathedral, along the Decumanus Maximus of Apamea (Syria), as captured in: 10-m resolution Sentinel-2 images acquired on (**a**) 21/04/2017 and (**b**) 16/04/2018 (contains Copernicus Sentinel-2 data 2017–2018), (**c**) VHR resolution Google Earth image 29/04/2018 (Image © 2019 Maxar Technologies), and (**d**) SAR amplitude change detection map from a pair of COSMO-SkyMed Spotlight Enhanced (~1 m ground resolution) scenes acquired in ascending mode on 16/07/2018 and 14/03/2019 (COSMO-SkyMed® Products ©ASI—Italian Space Agency—2018–2019. All Rights Reserved).

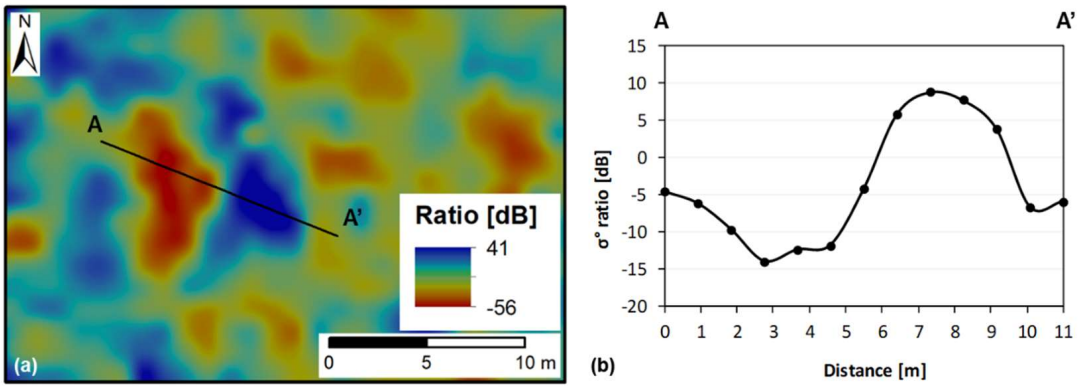

Figure 16. (**a**) Looting mark from the COSMO-SkyMed SAR amplitude change detection map in Figure 15d and (**b**) σ^0 ratio profile A-A'. COSMO-SkyMed® Products ©ASI—Italian Space Agency—2018–2019. All Rights Reserved.

From a spatial resolution point of view, in the case of extensive looting across a site, even SAR images acquired in Stripmap mode (ground resolution of ~3 m) can be used to detect looting at cluster level. Conversely, ScanSAR imaging modes (ground resolution ~15 m or above) are really too coarse to obtain an accurate delineation of the disturbed areas [43].

All the above image processing approaches are based on the amplitude information, i.e., the amount of radar backscatter, collected in a single polarization (e.g., horizontal transmit—horizontal receive; HH). No studies have investigated the possible use and potential performance of dual or quad-polarized data. Yet interferometric coherence has been used so far to map looting, although this derived product based on SAR images is commonly used for damage and condition assessment (e.g., [48,49]).

3.3. Sensor Selection vs. Size and Scale of Looting

The plot in Figure 17 clarifies the criteria and trade-off that an image analyst, either remote sensing expert or practitioner, should take into account to select satellite images, either optical or SAR, with regard to: size of looting features to detect; spatial scale of looting; temporal and spatial resolution of looting mapping. In particular, the plot is built to account for the satellite solutions for looting observation that have been used so far in the literature and those that could be considered for further implementation (although it is acknowledged that other solutions may be available). The plot therefore shows observation solutions allowing for repeated acquisitions collected with consistent parameters according to a given satellite geometry of observation. The site revisit time relates to the best temporal resolution achievable by each satellite system, or the one that is typically offered by image providers.

In brief, satellites such as Sentinel-2 and Landsat-8 are more indicated for wide-area/regional studies and cases of extensive looting spreading across a whole site, where the looting unit to identify is a cluster or a large area (see Figures 9 and 11). With 5 to 16 days of revisit time, the analyses can be undertaken on a monthly to intra-monthly basis. While the limit due to the high to medium spatial resolution is obvious, these satellite solutions are sufficient to observe significant variations over time, especially in hotspot areas and sites of known susceptibility to looting (see Figure 15a,b). As demonstrated by [6], this satellite-based assessment at HR can serve as a screening step to plan subsequent targeted observations at VHR, thus optimizing the costs for image purchasing.

VHR SAR and optical images are equally useful for looting assessment at the level of single pit, but with the drawback of the potential limitation due to discontinuous site revisit. While in theory these satellite images can be collected even every 1-day, such high frequency of observation strongly depends on ad hoc ordering and available resources for accessing these data.

Imaging modes with spatial resolution less than 5 m (e.g., COSMO-SkyMed and TerraSAR-X Stripmap modes) could be an acceptable trade-off. Not only these data provide wider spatial coverage that could help to make observations over multiple sites within a region at the same time, but also

archive images are more likely to be available in the satellite mission catalogues. Stripmap is, indeed, the most common SAR imaging mode of acquisition preferred by space agencies to populate their catalogues by means of low-priority background missions/observation scenarios. For example, this is the case of the background mission of the COSMO-SkyMed constellation which includes, among others, UNESCO World Heritage sites [8].

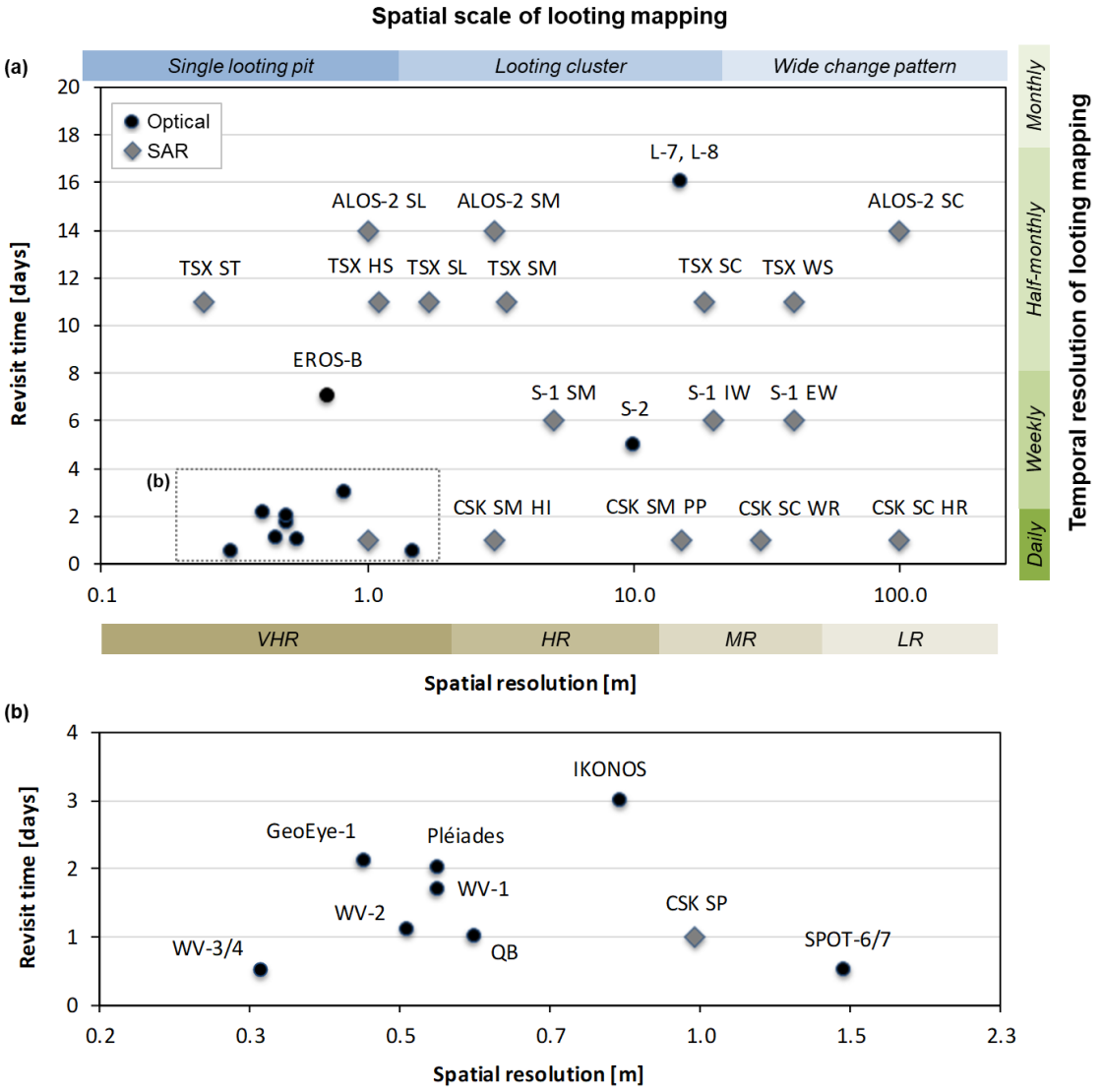

Figure 17. (**a**) Examples of optical and radar satellite solutions for looting observation by crossing spatial resolution and revisit time of satellite images with the spatial scale and temporal resolution of looting mapping. (**b**) Close-up showing the imaging modes with spatial resolution less than 2 m and very short revisit time. Spatial resolution for optical satellites is the ground sample distance (GSD) in the panchromatic channel. Notation: MR, HR and VHR—medium, high and very high resolution, respectively; satellites: CSK—COSMO-SkyMed; L—Landsat; TSX—TerraSAR-X; QB—QuickBird; S-1—Sentinel-1; S-2—Sentinel-2; WV—WorldView; acquisition modes: HI—Himage; HS—High Resolution Spotlight; IW—Interferometric Wide swath; PP—PingPong; SC—ScanSAR; SC WR—ScanSAR Wide Region; SC HR—ScanSAR Huge Region; SL—Spotlight; SM—Stripmap; ST—Staring Spotlight; WS—Wide ScanSAR.

3.4. Image Processing and Methods for Looting Assessment

Space-based assessment of looting can typically consist of the following steps: (1) detection of looting incidents through the identification of surface features that can be recognized as caused by looters; (2) mapping of the detected features to derive spatial information on their distribution and extent; (3) counting of features to quantify the damage extent and/or estimate the rate of looting; (4) if the analysis is repeated in time, multi-temporal monitoring of looting is achieved.

Methodologies for looting assessment that have been developed and published in the literature so far differ essentially with regard to how the detection is made, how looting features are mapped, and the scale at which the analysis is conducted.

The first major distinction is whether the features are detected and identified visually by the operator, or with the aid of image processing. The literature review highlights that since 2006 visual methods were predominant and applied chiefly to VHR satellite optical images (Figure 18). A clear explanation of this evidence can be found in the more intuitive understanding of looting features in the visible domain of the electromagnetic spectrum, as well as the accessibility of large volumes of freely accessible data through online visualization platforms such as Google Earth and BingMaps (see Sections 3.1 and 3.2).

Because they require image interpretation and ability to discern features, these methodologies are frequently questioned for their subjectivity, time-consumption and lack of repeatability and replication. However, the increasing tendency in the literature to a negative over-emphasis of the inherent weaknesses of visual identification (e.g., the review by [17]) does not give justice to the fact that practitioners adopting these methodologies are well conscious of the drawbacks and sources of error of these methods, and implement measures to manage the subjectivity, skills gap, lack of standardization and uncertainty. For example, the initiative EAMENA has developed workflows to guide analysts through the decision-making process, including the comparison with existing digitized datasets that are used as reference data to make interpretation of new features, as well as training programs to ease skill sharing and standardization [41]. Section 4.3 provides further discussion about the most common sources of error and uncertainties in visual identification of looting features.

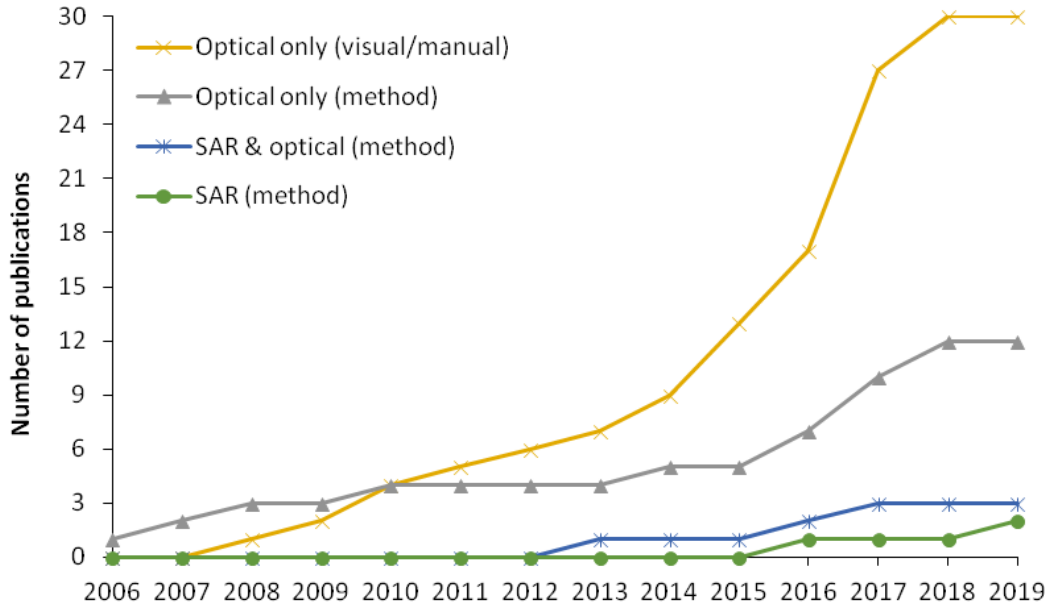

Figure 18. Peer-reviewed publications indexed in Scopus as of June 2019, distinguished based on type of satellite images used (either optical or synthetic aperture radar, SAR) and the mapping approach adopted: visual and manual, or assisted by an image processing-based method.

When looting features are identified through visual inspection of satellite imagery, often they are then mapped manually. The literature review confirms this association (Figure 18). Section 3.2.1 already recalled that some authors prefer to draw an individual polygon over each looting pit. Alternatively, a larger polygon can be drawn to enclose dense looting clusters, or to bound areas affected by different types of encroachment. Ref. [26,36] used this second method, because the spatial resolution of the images was generally not adequate to allow the counting of individual pits, and thus the retrieval of direct estimates of pit number and density. To assess extremely heavy looting in Dura Europos (see Figure 14), ref. [47] found that inside the ancient city wall individual looting pits overlapped so much each other that their counting was impractical. Therefore, the image analysts opted to identify all areas that were not visibly affected by looting (although this classification could not imply that these features were free of damage).

GIS shapefiles of either individual pits or affected areas are then used to calculate looted areas in square meters per site [26,36], as well as the extent of looting and encroachment in square meters [18]. The same authors employed inverse distance weighting (IDW) to create thematic maps illustrating the density of the areas worst affected by looting. In case of regional studies where looting was documented in different sites, this can be an effective geospatial method to highlight known hotspots and predict approximate weights for the unknown areas within the extents of the known points [18].

Section 1 recalled the current shift of the practitioner community from single site-focused or event substantiation to regional-scale mapping exercises [34], and the perceived need to employ automated methods to identify looting, record changes and speed up mapping, and thus mitigate the bottleneck created by the quantity of available imagery in relation to the number of analysts and associated costs [28]. The development and implementation of such algorithms and image processing routines is likely to represent the arena where the archaeological and cultural heritage community may connect with the remote sensing scientists more than happened so far.

The plot in Figure 18 shows unequivocally that methods of image processing other than visual inspection of satellite images and subsequent manual mapping of observed looting features, are increasingly being developed and published in the specialist literature.

As of June 2019, there has been a steady rate of publication of papers wherein authors present workflows to process optical imagery and extract looting features. A sharp increase doubling the total number of papers is recorded from 2015 to 2018. This trend associates (but not necessarily correlates) with the occurrence of warfare events in the MENA region (see Figure 2 and Section 3.1.1). It cannot be excluded that the growing number of initiatives documenting damages to heritage, and the increased flow of information and media attention about looting and site destruction contributed to raise this topic higher in the scientific research agendas, thus stimulating scholars and research groups to undertake further research in addition to that already ongoing.

Table 3 lists the image processing-based methods for looting assessment published as of June 2019, by: satellite data used; type of algorithm; parameter associated to a specific property of looting feature that is used as a proxy to identify and extract the looting feature; methodology for validation of results. It is outside the scope of this paper to analyze each of these methods in detail. The focus is rather on the commonalities and differences that interestingly come out when all these methods are looked at with a synoptic view.

With regard to input data, authors have developed their methods using a wide variety of satellite images, although VHR optical and, secondarily, VHR SAR (the latter, from X-band TerraSAR-X and COSMO-SkyMed missions) largely predominate. Google Earth images were mostly used for validation, while only in three cases [17,46,50] they were processed through specific workflows to assess looting. As already commented in Section 3.1.2, HR and MR data, either optical or SAR, are under-used. With regard to optical and SAR data combination, refs. [51,52] were the first studies where both VHR optical and SAR data were collected over looted sites, but the published results only refer to looting observed in VHR optical data. Ref. [53] were the first to combine MR SAR and optical images for looting assessment. Ref. [54] developed a method for automatic detection of larger grave mound

structures in optical and SAR data, in the Altai Mountains where incidents of looting are reported. However, the two datasets were processed separately (although using the same type of object detection algorithm), and no examples specifically referring to looted grave mounds were presented. Therefore, optical and SAR data combination appears to be still at its early stages and yet to be explored.

The predominance of VHR data is mainly due to the parameters used as proxies to identify looting features. Most of the processing methods rely on identification of morphological properties (e.g., shape, circularity, roundness, roughness) that VHR data only can allow the analysts to observe at the scale of single looting pit. The other most commonly used properties are the spectral signature and peculiar brightness/reflectance in the optical images, and radar backscatter in the case of SAR data.

The majority of the image processing methods are run using commercial software, such as ENVI, ERDAS Imagine, eCognition, ArcGIS/ArcMap/ArcView, GAMMA SAR and Interferometry software. The developed workflows commonly include earlier steps aiming to enhance the looting features, so to make their identification and extraction easier during the later steps of classification and segmentation.

For example, ref. [46] applied linear (linear percent stretch) or non-linear histogram stretches (histogram equalization) to enhance the spectral properties of the soil disturbance (i.e., the proxy for looted tombs) and spatially improved the WordView-2 images by means of Gram–Schmidt and NNDiffuse pansharpening algorithms. The same authors calculated vegetation indices and implemented a suppression algorithm to highlight un-vegetated spots matching with looted areas.

Table 3. Summary of image processing-based methods for looting assessment (published as of June 2019). Notation: MS—multispectral; P—panchromatic; PS—pansharpened; RGB—Red Green Blue true composite.

Authors	Satellite Image Type	Method/Algorithm	Looting Feature	Looting Feature Property and Associated Parameter	Validation
Agapiou et al., 2017 [46]	VHR optical (WorldView-2, Google Earth) MS, P, PS	Histogram and image enhancement (Google Earth), pansharpening (WorldView-2); vegetation indices, Principal Component Analysis (PCA), color transformations (HSL and HSV), object-oriented classification and segmentation	Looting mark-ensemble	Spectral signature, texture, spatial attributes (area), shape (roundness)	Ground truthing
Balz et al., 2017 [54]	VHR optical (IKONOS, WorldView-2) VHR SAR (TerraSAR-X)	Object detection through Hough Forests (archaeological mounds); looting mark detection: n/a	Sensitive areas (potentially looted mounds)	Shape	Ground truthing
Bowen et al., 2017 [55]	VHR optical (EROS-B1) P	Hierarchical categorization and localization (HCAL) algorithm; unsupervised identification of repeated featural motifs, localization of candidate feature sets, unsupervised image categorization based on similarity; checking for mismatching (supervised) labels; unsupervised hierarchically category splitting	Looting pits	Normalized luminance, repeated featural motifs, similarity	Visual inspection of optical satellite images, manual mapping and cross-checking of looting features by multiple trained operators
Cerra et al., 2016 [50]	VHR optical (WorldView-2, GeoEye-1, Google Earth) MS	Co-registration of (multi-sensor) images; Gabor texture features; Robust Differences (RD) based on brightness levels (recommended for same-sensor images only)	Sensitive / changed areas	Texture, robust differences of brightness (minimum value of the absolute difference)	Satellite-based incident reports
Cigna and Tapete 2016 [56]	MR SAR (ENVISAT)	SAR amplitude change detection	Changed areas (looted sectors of the site)	SAR backscatter ratio	Literature, ground-truth knowledge
Hernandez et al., 2008; Schreier et al., 2007 [51,52]	VHR optical (IKONOS) P VHR SAR (TerraSAR-X)	Optical: Method by Van Ess et al. (2006) [57]; SAR: n/a	Looting pits, Looting clusters (optical)	Brightness, contrast, size, shape and density	Aerial images, ground truthing
Lasaponara et al., 2010, 2012 [44,45]	VHR optical (QuickBird-2, WorldView-1) MS, P, PS	Local indices of spatial autocorrelation (LISA): Local Moran's I, Geary's C and Getis-Ord Local Gi index (on P images)	Looting pits (circular)	Spatial autocorrelation statistics (degree of spatial dependency, similarity, level of interdependence)	Ground truthing
Lasaponara et al., 2014 [16]	VHR optical (GeoEye-1, Google Earth) MS, P, PS	LISA (on MS images); convolution filtering (High Gaussian high pass); automatic unsupervised classification (K-means) of red-P band and LISA indices	Looting pits (circular)	Spatial autocorrelation statistics (degree of spatial dependency, similarity, level of interdependence)	Ground truthing

Table 3. *Cont.*

Authors	Satellite Image Type	Method/Algorithm	Looting Feature	Looting Feature Property and Associated Parameter	Validation
Lasaponara and Masini 2016 [58]	VHR optical (Pléiades) MS, P, PS	Lasaponara et al. (2014) [16] + vegetation filtering and segmentation	Looting pits (circular)	Spatial autocorrelation statistics (degree of spatial dependency, similarity, level of interdependence)	Ground truthing, aerial images, visual inspection of optical satellite images
Lasaponara and Masini 2018 [17]	VHR optical (Google Earth) RGB	Lasaponara et al. (2014) [16] + vegetation filtering and segmentation	Looting pits (circular)	Spatial autocorrelation statistics (degree of spatial dependency, similarity, level of interdependence)	Ground truthing, visual inspection of the same optical satellite images
Lauricella et al., 2017 [15]	VHR optical (WorldView-2) MS, P, PS	Principal component analysis (PCA; on MS images); false positive removal based on empirically established geometric properties of looting pits	Looting pits	Spectral signature from training sampling; size and shape (index of circularity)	Visual inspection of the same optical satellite images, manual mapping of looting features (to establish geometric properties)
Tapete et al., 2013 [53]	MR SAR (ENVISAT)	SAR amplitude change detection	Changed areas (looted sectors of the site)	SAR backscatter ratio	Literature, aerial images, ground-truth knowledge
Tapete et al., 2016 [7]	VHR SAR (TerraSAR-X)	SAR backscattering modelling; texture extraction; SAR amplitude change detection	Looting pits, looting mark-ensemble, filling mark	Surface roughness (SAR signal, layover and shadow), texture, SAR backscatter ratio	Literature, satellite-based incident reports, visual inspection of optical satellite images and manual mapping of looting features on them
Tapete and Cigna 2018 [6]	HR optical (Sentinel-2) MS, RGB	Change detection; feature extraction	Looting clusters, changed areas	Reflectance (Bottom Of Atmosphere; L2 product), texture	Literature, satellite-based incident reports
Tapete and Cigna 2019 [8]	VHR SAR (COSMO-SkyMed)	SAR backscattering modelling; texture extraction; SAR amplitude change detection	Looting pits, looting mark-ensemble, filling mark	Surface roughness (SAR signal, layover and shadow), texture, SAR backscatter ratio	Literature, satellite-based incident reports, visual inspection of optical satellite images and manual mapping of looting features on them
Van Ess et al., 2006 [57]	VHR optical (IKONOS) MS, P, PS	Object oriented knowledge-based software for feature detection and extraction (Definiens Developer, Cognition Network Language)	Looting clusters (> 60 single looted pits)	Brightness, contrast, size, shape and density	Aerial images, ground truthing

Similarly, refs. [17,58] applied vegetation filtering prior to the extraction of Local Indices of Spatial Autocorrelation (LISA) among the processing steps of their Automatic method for archaeological Looting Feature Extraction Approach (ALFEA). In this regard, it is worth noting that ALFEA presented as a new method in [17] is actually the latest version of the image processing workflow that the authors refined and improved, starting from the original LISA-based method first published in [44]. To the LISA core step, the authors added convolution filtering (High Gaussian high pass) and automatic unsupervised classification (K-means) [16], and subsequently steps of vegetation filtering and segmentation [58]. Therefore, the entries in Table 3 [16,17,44,45,58] are meant to acknowledge the evolution of the same method rather than the development of separate distinct methods.

In the SAR domain, refs. [7,8] developed and applied, respectively, an image processing workflow to extract the texture of looting features from VHR SAR data stacks and use this parameter to map the extent of looted areas (see also Section 3.2.2).

All the above methods are effective in the way they exploit a specific property or combination of indices to improve the visibility and discernibility of looting features. This rationale for looting feature detection is also a commonality between some visual and manual methodologies. Ref. [36] exported images from Google Earth Pro and adjusted contrast, brightness and color balance in Corel Photo-Paint, where necessary. Ref. [39] exported GeoTiff files of satellite images from ArcMap and enhanced them by applying Contour and Emboss routines in Adobe Photoshop. The "raised" effect after embossing allowed better visual identification of individual features, while contouring made the boundary outline of individual depressions more evident. The results of such image enhancement were then imported back into ArcMap, and overlaid onto the original imagery to improve the visual identification of looting features. Similar image processing can be run directly in ArcGIS or QGIS using surface analysis routines (e.g., slope, hillshade).

The methods listed in Table 3 have different suitability depending on the type and scale of looting. Some methods allow identification of individual looting pit, some others are better suited in situations where looting pits manifest as circular or nearly circular holes. In other circumstances, the observation allows for the whole ensemble of pit and its surrounding debris to be identified and mapped (i.e., the whole feature called 'looting mark') [7].

While the methods in Table 3 are designed to identify looting features, not all of them are presented and applied to multi-temporal time series. It is evident that the methods that are best suited to provide spatial and quantitative information to track whether and at what extent looting is spreading across a site are those based on change detection approaches (e.g., [6–8,50,53]) and/or iteration of the same image processing workflow onto satellite data acquired in different years (e.g., [16,44,45]). As such, these methods can support tasks of monitoring and multi-temporal damage assessment.

4. Discussion

4.1. Automation in Looting Assessment

Focusing on the image processing-based methods discussed in the previous section, it frequently happens to notice that the authors themselves declare in their publications whether their methods are automatic or semi-automatic. For example, ref. [15] described their method as "semi-automated". Ref. [55] referred to their method as "automated image processing mechanism". Ref. [17] named their method ALFEA, with first letter of the acronym standing for "automatic". Ref. [50] did not label their method. Instead, the authors explicitly proposed their change detection algorithm with the perspective to go toward the automatic production of maps highlighting the areas suspected of having been damaged.

Reading carefully how the image processing is done, it becomes clear that the degree of automation of all these methods lies on the reduction of the steps requiring human intervention. These steps typically consist of visual checks, adjustments of thresholds, setting up of algorithmic parameters. So, it happens that some of the steps in the above workflows are not fully automated, even if the

whole method is presented as "automatic". For example, ref. [58] stated that the step of K-means unsupervised classification to classify the LISA indices needs parameter setting by the operator. Vice versa, methods that are not presented as "automatic" may actually include steps that are fully "automated". For example, ref. [50] refined the co-registration of satellite images by automatically deriving 1000 Ground Control Points by matching of Scale Invariant Feature Transform features between the two images, and by warping the image acquired at time t_1 using the image acquired at time t_2 as reference.

To now contextualize the above image processing-based methods in the wider panorama of methodologies based on visual identification and manual mapping, some general definitions can be drawn.

Identification of looting features in satellite images can be defined as "visual", if the process of feature recognition is purely done by direct observation by naked eye, without the aid of any image processing other than a mere enhancement of the image per se, for example by stretching the image histogram (i.e., adjusting the brightness and contrast of the image) or, in the case of SAR data, by adapting the visualization symbology of radar backscatter or converting it to the dB scale.

Different is the case when the identification of looting features is made based on products that were generated by processing the original satellite image, extracting features and/or calculating/deriving a specific parameter (e.g., LISA from optical images; texture and backscatter ratio from SAR data stacks). Regardless the degree of automation of each separate step in the image analysis workflow, these methods cannot be classified as "visual" or "manual" as a whole.

The discussion about automation in looting assessment is quite topical, since the evidence gathered in the survey presented in this work is that image processing-based methods are increasingly being developed (Figure 18). This trend also matches with the need to automate the change detection analysis, as expressed by the stakeholder community (e.g., [28]; see Section 1). In this context, warning is necessary about the risk due to the current tendency in the literature to label methods as either visual/manual vs. automatic, and over-emphasize the intrinsic limitations of visual methods (see Section 3.4). Such approach can lead to an incorrect representation of the published methods. For example, in the state-of-the-art published in [17], the methods by [7] and [46] are mistakenly cited among those of visual identification, in the same context of the methods of manual mapping employed by [59] and [36]. From what presented above (see Section 3.4 and Table 3), in [17] these citations are wrongly reported under the category of visual methods.

Therefore, the present paper adopts the terminology "visual/manual" on one side and "image processing-based" on the other, and intentionally does not label the methods with regard to automation. To prevent confusion and misrepresentation, and allow an unequivocal understanding of the methods, the proposal (and hope) of best practice is that in future publications authors would clarify the degree of automation of each step of their methodologies, instead of providing a generic labelling of their methods as a whole, which may be misleading. This approach appears more sensible, given that satellite-based looting assessment does anyway require, upstream, parameter settings informed by operator's expert knowledge of looting features (and, more generally, of local archaeological specifics) and, downstream, a certain amount of interpretation to use the outputs from the image processing.

4.2. Practices in Image Processing and Data Interpretation

Except for some commonalities, the different groups working on image processing chain development for space-based looting assessment exploited different techniques and did not come out, as a community, to shared practices yet.

This is particularly evident in the optical domain, where methods are applied to different input satellite images (either multispectral, panchromatic or RGB) and different levels of pre-processing (e.g., pansharpened). Some authors work on panchromatic images (e.g., [55]), others pansharpen images before further analysis. Sometimes this choice seems to be site-specific and dependent on the peculiar characteristics of the satellite data used. For example, refs. [44,45] focused on panchromatic

Quickbird and WordView-1 images only, as the comparative visual inspection of the images highlighted that the panchromatic were more suitable than the pansharpened spectral bands to emphasize both the pitting holes and archaeological features (shallow to outcropping walls), and there were no significant spectral variations in the looted areas in the four bands of Quickbird imagery. Conversely, in another study area, ref. [16] pansharpened GeoEye-1 images by means of Gram-Schmidt method in ENVI, and selected the red pansharpened band for the detection of the circular holes with respect to the other spectral bands, including the panchromatic.

The same Gram-Schmidt and NNDiffuse algorithms were used by [46] to pansharpen multispectral WorldView-2 image over Politiko (Cyprus). Instead, over Ai Khanoum (Afghanistan), ref. [15] pansharpened WorldView-2 images by means of the Hyperspherical Color Transform preset in the ERDAS Imagine software, and found that individual pits and disturbances were clearly visible. Interestingly, the authors observed that, despite the visibility on all bands and components, the looting pit features were particularly well contrasted from their surroundings in the fourth principal component raster of the WorldView-2 [15]. This component appeared well suited to large mounded sites lacking significant foliage cover, thus suggesting that it may fit many sites in the Near East. However, the authors rightly acknowledged that other landscapes may be better described by different components.

More standardization on the pre-processing of the satellite images is found in the radar domain, where all the studies use Single Look Complex (SLC) data and the methods are developed to exploit the amplitude information (e.g., [7,54]).

With regard to the use of multi-sensor images (i.e., images collected by different satellite sensors), a large part of the studies present results obtained using images from the same sensor. When multi-sensor images are used, these are mostly processed separately and the respective results are then combined (e.g., [16,44,45]). However, the feasibility for data fusion has not been yet investigated. Some methods are developed with the purpose of a broader applicability across different sensors. This is the case of the method by [55]. In the SAR domain, refs. [7,8] already proved that SAR amplitude change detection and feature extraction apply equally to TerraSAR-X and COSMO-SkyMed images collected in the same range of spatial resolution.

There are of course some limitations in the use of multi-sensor data. In studies where different types of images were visually interpreted, spatial resolution was claimed to be the principal cause of the different performance in looting assessment. Ref. [60] used WorldView-2, IKONOS and Google Earth images to assess looting-related destruction of Early Iron Age burial mounds, and found that not all data types perform equally. While the assessment was fairly consistent over the different data types for large burial mounds, it resulted much more variable as the smaller size of burial mounds decreased their visibility and detectability, up to the point that it became pointless to even attempt to assess the condition of the mound given that the visual interpretation was totally hampered.

Multi-sensor data can also pose some difficulties to apply image processing-based methods. For example, ref. [50] warned that the use of the Robust Differences (RD) method should be restricted to images acquired by the same sensor, since it is based on the calculation of absolute brightness values differences. The same authors found some difficulties to analyze comparatively a GeoEye-1 image and a WorldView-2 one over Nimrud (Iraq) using the Gabor features method. They needed to spatially downsample the high-resolution image to match the low-resolution one, prior to co-registration.

These technical challenges also relate to the long-debated challenge of accessing satellite images to repeat the observation over time and update the condition assessment accordingly. As discussed in Section 3.3, the obvious best practice is to select types of data that provide a temporal revisit commensurate with the characteristics of (known, expected or supposed) looting incidents and their spatial and temporal dynamics (see Figure 17). Although several studies and assessment reports in the grey literature relied on discontinuous data or one-shot observations, there is an increasing consensus in the community about the value of those space missions, either optical or SAR, that allow for temporal regularity and technical consistency of image acquisition parameters as the keys to retrieve reliable

and comparable estimates of looting rates. Ref. [6,7] specifically demonstrated the benefits of long, consistent and frequent HR optical and VHR SAR satellite time series, respectively.

To understand whether looting at a site is spreading or not, the incidents observed from space need to be referred to the temporal scale when the observations are made. The interpretation of looting timing based on satellite observations is affected by the temporal sampling, and thus by the presence of temporal gaps and shifts between the datasets used. The major risk when the assessment is made based on discontinuous or multi-sensor data acquired at different times is that an increase in the number of looting pits or incidents of damage, or of the total extent of looted areas, is interpreted as a sign of acceleration and intensification of looting (e.g., [60]).

To account for the inherent temporal uncertainty driven by imagery availability, ref. [34] developed a method to determine the time-range in which each looting incident could have occurred. In particular, for a given site, they calculated the average probability that an episode of looting occurred in any individual month across the entire timeframe of the satellite observations covering that site. Therefore, each site was given a cumulative looting severity score instead of each individual looting episode, and this enabled the authors not to give greater weight to those sites that were covered by a higher number of images.

Among the image processing-based methods, the SAR change detection approach by [7] is one of the few that has been used to estimate rates of looting as the number of 'looting marks' per month. This estimate is possible only if regular and consistent SAR image acquisitions are made, and this is typically achieved with tailored image acquisition tasking. Unfortunately, due to the highly variable imagery coverage of individual sites, there are not so many sites in the Middle East or other regions for which regular image stacks can be accessed to run these calculations and make comparative assessments across sites.

Comparison between published studies is sometimes difficult and not straightforward, since the different authors reported their satellite-based observations in different ways. The most common include, but are not limited to: (i) maps showing looting incident locations; (ii) maps of looting severity; (ii) maps showing the extent of affected areas; (iii) maps of density of worst affected areas; (iv) tables with looting hole counts and/or total looted area; (v) total number and associated percentage of looted sites (when multiple sites are surveyed).

4.3. Limitations and Uncertainties in Feature Detection

An obvious limitation common to all satellite-based methods for looting assessment is the lack of visibility of the looting features. Looting in obscured areas, covered by accumulated sediment [33], within structures and buildings (e.g., situations found in Bosra (Syria) by [30]), or dug as tunnels and holes along slopes, are unlikely to be visible in satellite images. So, not all forms of looting can be recognized using satellite data [33].

Figure 19 shows the case of Tell Hizareen (Syria), where extensive illegal excavations in the form of holes dug along the slopes occurred presumably during 2014, and were later reported by [61,62]. The post-looting satellite image (Figure 19b) highlights very well that the inclined position along the slope with regard to the nadir view of the optical satellite sensor, the poor contrast with the surrounding brown-colored ground, the similar shape, roundness and color as the local bushes and soil stains, make the looting holes not easily and unequivocally detectable from above. Without the knowledge from ground surveys, some of them would not be distinguished from natural features that were visible in the pre-looting image (Figure 19a). If the assessment is made visually, the operator needs high skills in feature recognition, as well as knowledge of local archaeological specifics [41]. It is envisaged that, for the same reasons, an image processing-based method would struggle to identify accurately all these looting features without false positives.

Confusion of looting with natural features has been repeatedly reported in the literature as a common case of misidentification, in different geographical locations and environments. Ref. [18] pointed out that their count of looting pits in Egypt was the lowest possible, to take into consideration the

ambiguity of smaller pits being confused with vegetation patches. In the Altai Mountains, ref. [60] found that dark bushes growing in the middle of a burial mound could sometimes resemble looting pits, so these could influence the condition assessment of the burial. Ground truthing allowed [36] to discard records of looted sites, including one case where piles of back-dirt were mistaken for pitting.

Other sources of uncertainties and interference that are known in the literature but, interestingly, were not investigated extensively are: (i) aging of looting features; and (ii) repeated looting (i.e., looting onto already looted grounds).

Weathering of older looting holes can cause their erosion, with consequent morphological change. Ref. [4] referred to bathtub-like depression in the ground. From a spectral point of view, older holes may appear discolored and resemble like stains in the soil, thus making their identification more difficult.

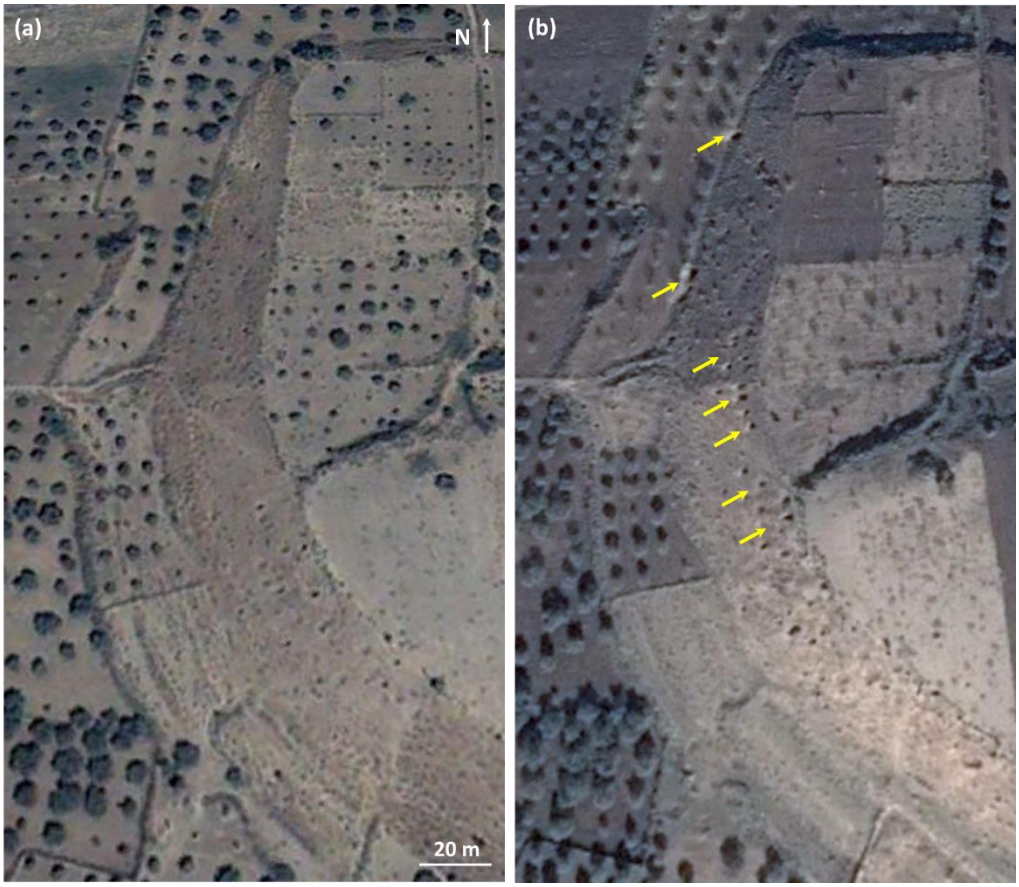

Figure 19. Western slope of Tell Hizareen (Syria), (**a**) before (Google Earth image 06/09/2012 © 2019 Maxar Technologies), and (**b**) after looting excavations (Google Earth image 03/12/2015 © 2019 CNES/Airbus). Yellow arrows indicate looting holes, most of which are barely distinguishable from rocks and soil, given the limited visibility and spectral contrast.

Figure 20 shows an example of progressive aging of looting features in the archaeological site of Dura Europos (Syria). This phenomenon is particularly visible in the looted areas beyond the town walls and was first commented by [4] using a couple of WorldView-2 images taken on 4 August 2011 (Figure 20b) and 11 April 2015 (Figure 20c). In August 2011, looting features located both north and south of the access road to the Palmyrene Gate appeared eroded and faint, with those north of the road in particular resembling differently colored stains in the desert soil (Figure 20b). Four years later, in April 2015, several new looting pits appeared to have been dug in proximity to and onto the old looting pits, and were easily recognizable owing to the very dark shadow marks formed thanks to sun illumination from the south-east (Figure 20c).

Visual identification of looting based on a longer time series of Digital Globe images covering the site since 12 December 2007 and made available in Google Earth, allowed the refinement of the above interpretation of looting timing. A GeoEye-1 image taken over the southern part only of the study area on 7 April 2011 (i.e., only 4 months earlier than the WorldView-2 image of 4 August 2011; Figure 20b) shows the looting pits located south of the road with sharper edges owing to the shadow inside the holes (see lower portion of Figure 20a). A QuickBird image acquired in December 2007 highlights that north of the road there were already some pits interspersed with stain-resembling rounded features (see upper portion of Figure 20a), matching with those visible on 4 August 2011 (Figure 20b). Therefore, what appeared as old looting on 4 August 2011 was actually a combination of looting features likely dug in different epochs. The zenithal lighting of the August 2011 WorldView-2 image (sun elevation 67.4°; Figure 20b) caused a homogenization effect that made all the looting features appear as equally aged and old. The role that lighting in satellite optical images can play to influence the morphological interpretation of looting features (either visual, or with the aid of image processing) is proved by a later GeoEye-1 image acquired on 23 January 2017 with a more raking light (sun elevation 32.6°; Figure 20d), from south-east, that enhanced the three-dimension and morphology of looting pits and natural relieves. Some of the stain-like features north of the road are visible, while others are not, with consequent variable impact on the identification and interpretation of the different types of looting features.

Figure 20. Multi-temporal comparison of (**a**) QuickBird (12 December 2007, upper part) and GeoEye-1 (7 April 2011, lower part), (**b**) WorldView-2 (4 August 2011), (**c**) WorldView-2 (11 April 2015) and (**d**) GeoEye-1 (23 January 2017) images over the looted areas beyond the walls of Dura Europos (Syria) highlights the effect of temporal granularity of VHR optical satellite images, lighting and visibility of looting features on interpretation of looting timing (i.e., old and new looting). Precise location is reported in Figure 14. Google Earth images © 2019 Maxar Technologies.

In this regard, ref. [15] observed that their method is less likely to detect shallow pits and suppose that older pits may have a higher chance of not being detected. However, this observation is made by processing a single image, while the same analysis may capture these features and improve the performance if it is run on a series of images acquired in different epochs. In this regard, ref. [6] discussed an example in Apamea and proved the benefit of analyzing a regular satellite time series. The high temporal frequency offered by Sentinel-2 allowed the authors to capture looting features when they were still fresh and visible, and account for them during the analysis of subsequent images where the same features were already aged and less visible.

Local geomorphology and erosion may be further factors of interference. Ref. [44,45] achieved a lower rate of success in those test areas in Cahuachi that were located on mounds and/or were affected by wind erosion. Similarly, ref. [15] acknowledged that their method could be less effective in detecting pits located on the slopes between the different levels of the Ai Khanoum site.

Areas of repeated looting or reworked looting pose the question about how image processing-based methods for looting assessment and quantification can account for these incidents and avoid underestimation of looted areas. In this regard, the approach developed with VHR SAR images by [7] is the only one that was specifically tested in this situation. The output from the SAR change detection map is the spatial distribution of looting marks, either new holes or filled holes, occurred in a given time interval, even within areas that were already looted.

4.4. Validation and Accuracy Assessment

To deal with the uncertainty in looting feature identification and mapping from space, nearly all the scholars agree on the importance of validation. This is typically undertaken through ground truthing (e.g., through field checks and in-situ observations), where and when allowed.

Across the archaeological community, there is general consensus that ground truthing is essential to get the thorough picture to complement satellite observations [36,63]. In-situ checks were used not only to confirm the identification but also to better understand what looting features observed from space are proxies for. For example, ref. [63] inspected Early Bronze Age mortuary sites on the east bank of the Dead Sea in Jordan and found that each hole visible on Google Earth did not equal a robbed tomb. The blank holes were located in areas where looters started to dig but, because they did not find a tomb with objects to plunder, they left and moved to another location. Therefore, even if such holes have similar characteristics and appearance in satellite images, they do not all necessarily provide the same type of information to understand patterns of archaeological looting. Consequently, the assumption that the number of looting pits coincides with the number of looted sites is not always correct. It is instead much more robust to estimate the total area of the site that was disturbed, or to use the count of looting pits to estimate rates of looting, i.e., the velocity and frequency at which holes were excavated.

Different is the situation when looting holes identified on images match with disturbed monuments and archaeological records. For example, during in-situ visits in looted sites in Egypt, at every pit they examined, ref. [18] found evidence of broken coffins, pottery and human bone, indicating the presence of recently disturbed tombs. Based on this outcome, the authors attempted to determine site damage by archaeological period, and noted which type and period of antiquities were more represented in their statistics of looting.

Cross-checking and validation are also key steps in the robust operational methodologies developed in the framework of archaeologists-led initiatives and projects documenting archaeological sites and the threats posed to them, in databases and inventories.

Ref. [41] provided an example of EAMENA field-based validation strategy. In particular, the authors discussed the results achieved with the comparison of a sample of ground- and image-based interpretations that was made by getting an analyst not familiar with the areas concerned, but trained in the EAMENA methods, to identify sites and damage threats in two sample areas for which ground data were available. The exercise showed that recording archaeological sites and their condition using

imagery can be difficult even for trained analysts. The authors concluded that knowledge of local archaeological specifics is clearly as important as technical skills, since looting assessment based on visual inspection always requires a process of interpretation (see Section 4.1). In this regard, ref. [33] warned that, with incomplete knowledge of the archaeological potential at a given site, satellite-based approaches would be very limited.

Cross-checking is part of ASOR CHI workflow too [28]. The protocol of damage assessment includes cross-checking the incident reported by the geospatial team analyzing satellite images against data being generated by the non-geospatial reporting team. This step can also foresee the engagement of local in-country sources to visit the affected site. Traditional sources for ground verification were coupled with different types of information, by critically compiling and analyzing the sheer volumes of user-generated internet content and digital/traditional media coverage [62]. Ground-based observations and media reports were useful to corroborate the satellite-based assessment and, at the same time, to develop initial reports that the subsequent analysis of available satellite imagery could confirm, refine or refute [28]. Thus, depending on circumstances of data availability and reliability, the workflow of validation could be reversed.

However, as highlighted by ref. [28], such new sources of information have the well-known limitations to be often near-instantaneous, inaccurate, propagandistic, or even to contain deliberately falsified information. Ref. [64] provided an interesting discussion of the inconvenience from the use of online sources of transient nature, or inaccurate online reporting (e.g., picturing an allegedly damaged monument or site with non-pertinent images depicting different sites). Furthermore, social media reports, by definition, are concise and tend to omit details perceived as non-essential by who writes the report, but that instead would be useful for the image analyst during the assessment and validation process.

Moving to image processing-based methods, from Table 3 it is clear that validation was made by means of ground truthing every time the authors had direct access to the test site(s), or collaborated with archaeologists working at site, and local stakeholders who could provide this type of information [16,17,44–46,51–54,57,58]. This happened in 11 out of 18 publications. In the remainder cases, the inaccessibility to the study site(s) was overcome by comparing the image processing results with published incident reports (written either based on ground surveys or through space observations; [7,50]), coeval satellite images (e.g., VHR optical to complement VHR SAR [7]; VHR optical to complement HR optical [6]), polygons digitized manually [15] or targets identified visually [17] on the original images prior to processing. Ref. [55] employed human experts to identify initial sets of disrupted burial sites for training and validation manually, with cross-checking by multiple trained participants.

In particular, ref. [17] assessed the rate of success achieved with ALFEA, through the calculation of the normalized false alarm index (N_{FA}), given by the formula N_{FA} = FA/(FA+TD), where FA is the number of false alarms that they found based on visual inspection of looting holes on the original image, and TD is the number of looting pits detected with ALFEA.

Ref. [15] instead developed a procedure to remove the false positives produced by the principal component analysis (PCA) and supervised classification of their workflow, based on thresholds of geometric properties (size and shape) common to most looters' pits. These thresholds were determined by compiling a sample of looting features observed in VHR satellite images covering different geographic locations, landscapes and periods across the world, and investigating pit size and the characteristics of these intrusions. As part of this process, false positives too small or too large to correspond to a pit dug by hand were easily removed. An index of circularity equal to 4π*area/perimeter^2 was used to filter out particularly long, linear features such as ditches or canals.

With a similar approach, ref. [7] applied a matrix of interpretation keys of the patterns of layover and shadow found in the SAR change detection maps, to identify looting marks, filling marks and unchanged holes. In particular, the authors developed a conceptual model showing how looting holes look like in SAR imagery and appear in a change detection map, depending on their dimension

(diameter, width and depth), orientation and shape, at a given observation geometry (orbit and incidence angle) of the satellite SAR sensor.

4.5. Dissemination and User Uptake

The results of the survey presented in Sections 3.1 and 3.4 and Figure 18 highlight that over the years there has been some evolution in the use of satellite images. From the earliest studies where images were simply used to observe looting incidents, the archaeological community has refined their observation approaches, achieved very robust methodologies and workflows, and increasingly disseminated them across the user and stakeholder communities to provide a common ground of expertise and facilitate operators' skilling. EAMENA, in this regard, is one of the best examples owing to its efforts of dissemination and training across the MENA region. Furthermore, it is worth mentioning that there have also been initiatives of dissemination of the visual and manual methodologies, for example to academic audience [65] and wider public [66], up to citizen science through crowd-sourcing portals (e.g., [67]). Given the type of information that can be extracted from satellite imagery, these platforms (as well as scientific articles) pay attention when publishing information that is potentially sensitive, such as the location of places that are looted. This prevents that these data can be used for more looting [68].

Not the same can be said for the image processing-based methods (Table 3). Reading the publications and analyzing the citations in the research catalogues is clear that this domain is still focusing on development of methods. Technological push, release of new satellite image acquisition modes at higher resolution, increased accessibility to data, and availability of software facilities to process the signal and extract features, are the main triggers for research groups to advance with new methods or improve existing ones. Yet these methods are to be shared among the remote sensing community. The evidence from the literature is that these methods are used by their developers, and currently there are no studies comparing the different methods.

To provide more insights into the connections between the interested research communities and users engagement, for each of the publications reviewed in this paper, the research domains of the authors were extracted according to the bibliographic metadata (see Table 1) and were then cross-checked with the content of the publication. The following three major categories of expertise were identified:

1. "Remote Sensing";
2. "Other", including archaeology, anthropology, cultural heritage, geography;
3. "Multidisciplinary", whenever authors came from diverse disciplines including "Remote Sensing".

Figure 21 plots, for each paper, the expertise of the authors vs. the use or development of an image-processing based method. The latter has been labelled "SAR-based" or "optical-based", depending on the type of satellite data used. In those cases where both SAR and optical data were used, the label highlighting the predominant source of information was assigned, given that none of these papers relied on SAR-optical data fusion or processing of both types of data to assess looting.

Except for [15], image processing-based methods always associate with research groups with dominant remote sensing expertise or multidisciplinary expertise co-authorship (Figure 21). Authors coming from a non-predominant remote sensing background mostly tend to use visual and manual methodologies to assess looting. When they partner with remote sensing experts, they mostly work on optical data. As expected, the greater assortment of approaches is observed with regard to multidisciplinary expertise, from very simple visual/manual methodologies to more complex processing with SAR images (although the latter are still less common than optical-based image processing methods).

These figures also match with archaeologists' statements reported in the earliest literature [36]. Image processing-based methods were frequently perceived as more sophisticated approaches to identify looted areas, and thus appropriable only by specialists.

The question that arises then is about the feasibility of the user uptake of such image processing-based methods, and the barriers for these methods to generate real impact on heritage management practices. Some considerations that were recently made by [69] with regard to the possibility that automated feature detection can support applications of detection of cultural features for documentation or verification, could well apply to the current situation in the discipline of satellite-based looting assessment. Probably, it is also a matter of perception and awareness, i.e., the users are given the opportunity to access these methods and can understand how to use them and what for, so they can assess whether these methods could significantly improve or contribute to heritage management practices. However, for those methods that were tested on areas in conflict, it is also true that the lack of direct networking with local heritage stakeholders and the logistic difficulties due to the conflict situations were objective barriers to establish a proper chain for data sharing and information flow from researchers and image analysts to end-users and stakeholders.

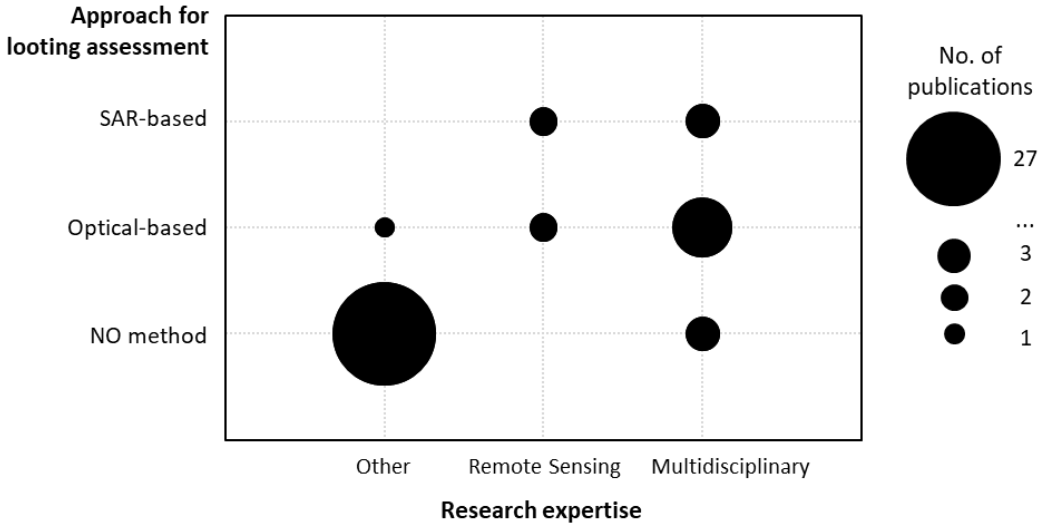

Figure 21. Comparison between the research expertise of authors using satellite images to assess looting (x axis) and the approach for looting assessment employed (y axis), i.e., an image processing-based method relying on either synthetic aperture radar (SAR) or optical data, or without the aid of any image processing (therefore, visual/manual methodologies).

5. Conclusions

Archaeological looting has been assessed from space by various scholars in different geographic areas across the globe, with highest concentration in the MENA region and South America. Spatial and temporal patterns of the publications confirm that looting is a much wider phenomenon, and does not happen in conflict and warfare areas only. However, the destruction of Iraqi and Syrian heritage (and more generally across the MENA region) abundantly reported by broadcast and social media, were facts and contexts that contributed to trigger academic-led exercises, as well as international initiatives that make large use of satellite images for condition and damage assessment.

Studies using satellite images were uninterruptedly published in the peer-reviewed and grey literature. On one side, archaeologists and heritage scientists have developed robust workflows for visual identification, manual mapping, incident recording, database creation and validation, and established standardized methodologies that they are now increasingly disseminating across users and practitioners through dedicated training programs. On the other side, studies presenting or relying on image processing-based methods increased since 2010, doubling the total number of papers from 2015 to 2018.

This proves that remote sensing experts and multidisciplinary teams are more engaged to develop and test image processing-based methods with variable degree of automation, aiming to mitigate the well-known intrinsic limitations of visual identification and manual mapping of looting features,

as well as the bottleneck created by the quantity of available imagery in relation to the number of analysts and associated costs for regional survey efforts. As such, this development represents the arena where the need for automation expressed by the archaeological community leading in this field can be addressed by the remote sensing experts.

Despite the differences in input satellite data and type of algorithms, there are some clear commonalities between the different image processing-based methods that suggest that the remote sensing community has a common methodological ground. Among all, the inclusion of steps in the processing chains aiming to enhance looting features so to ease their identification and extraction, the use of commercial software, and validation of processing outputs through ground truthing (where and when allowed) and cross-checking of looting features by trained operators. Most of the differences lie on the pre-processing of the data, and the specific parameters or properties of looting features that are used as the proxies for identification. However, morphological, textural and spectral-based proxies are all selected to exploit the fact that looting features are a surface alteration of un-looted ground.

The other side of the coin, though, is that image processing-based methods do not appear to be used outside the research groups that developed them, or to have been yet disseminated across the archaeological community and users. Furthermore, there seems to be a marked distinction between the preferred type of satellite data to use (optical vs. SAR), with very few studies integrating both or, even, attempting their fusion. Additionally, because the highest attention was given to identify looting features at the finest scale up to individual looting pit, there are very few studies that investigated the advantage of HR satellite data acquired with very short revisit time, such as Sentinel-2.

In this regard, the demonstration sites that are presented in this paper provide examples to critically discuss the advantage and limitations of Sentinel-2 data and the use of their multispectral information (i.e., NIR and SWIR in addition to VIS), as well as VHR SAR data and methods for texture extraction and multi-temporal change detection. This is coupled with selected examples in VHR optical images showing the major sources of interference and uncertainty in feature interpretation that are sparsely mentioned in the literature but were yet to be categorized.

In light of this state-of-the-art, satellite-based assessment of looting seems to have become a mature field of remote sensing. As a larger and multidisciplinary community, method developers and users could move toward sharing and harmonization of methodologies, as well as definition of best practices. To this aim, the authors' opinion is that this should happen at least at the following three levels:

1. Satellite data selection: the approach should be driven by a trade-off between size of looting features to detect, spatial scale of looting and assessment, temporal and spatial resolution of satellite observations, accessibility to the full range of spectral information, instead of a mere preference of a particular type of satellite image or according to consolidated routines.
2. Image processing methods: pre-processing of satellite images (e.g., pansharpening) may be standardized, although it is envisaged that different contexts may require some adaptations. This particularly applies to optical data. Future studies could focus on comparing different methods to understand how the combination of their strengths could mutually solve or mitigate their intrinsic limitations. This could lead to the development of feasible workflows based on multi-sensor data, favor a more integrated use of optical and SAR imagery, and a better sharing of the methods across the community. Automation is definitely key to move from research to more operational implementation. However, the overemphasis on automated against manual/visual methods should be left aside, and much more efforts should be made to find ways to feed the expert knowledge gathered through visual/manual exercises and image analysis practice into the training of the automated steps of image processing and feature extraction.
3. Outputs and dissemination of extracted information: currently there are various ways to present the outputs from satellite observations including, but not limited to: maps of looting incident locations, severity of looting, extent of affected areas, density of worst affected areas, tables with looting hole counts. These necessarily depend on the specific outputs provided by the given

method. However, toward comparability across sites and geographic contexts, the community should interrogate whether there would be some benefits in attempting a "standardization" of the outputs.

Further directions of this field of remote sensing would be, on one side, investing on training of non-experts to enlarge the user community of these data and methods and, on the other, moving from pure observations of looting incidents to more interpretation of looting as a local, regional or global phenomenon. These two directions match with considerations outlined by various scholars during recent conferences (e.g., [70]). In this regard, papers by [4,34,38] are good examples proving how satellite images and the evidence gathered from them can feed into studies that go beyond condition and damage assessment and make interpretations.

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