7 Airborne and Spaceborne Remote Sensing and Digital Image Analysis in Archaeology

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Abstract

Remote sensing has a long and successful track record of detecting and mapping archaeological traces of human activity in the landscape. Since the early twentieth century, the tools and procedures of aerial archaeology evolved gradually, while earth observation remote sensing experienced major steps of technological and methodological advancements and innovation that today enable the monitoring of the earth's surface at unprecedented accuracy, resolution and complexity. Much of the remote sensing data acquired in this process potentially holds important information about the location and context of archaeological sites and objects. Archaeology has started to make use of this tremendous potential by developing new approaches for the detection and mapping of archaeological traces based on digital remote sensing data and the associated tools and procedures. This chapter reviews the history, tools, methods, procedures and products of archaeological remote sensing and digital image analysis, emphasising recent trends towards convergence of aerial archaeology and earth observation remote sensing.

Keywords

Remote sensing • Digital image analysis • Archaeological prospection • Object detection

7.1 Introduction

"*Remote sensing* is the science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area, or phenomenon under investigation" (Lillesand et al. 2015: 1; emphasis in original). This generic definition of remote sensing, a technique with many uses across a wide range of disciplines, is also valid in archaeology, where we commonly understand "device" as a sensor mounted on

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an airborne or spaceborne platform and "object, area, or phenomenon" as a portion of a landscape with its natural and cultural components. Geophysical prospection, which is a form of near-surface remote sensing and often subsumed under that term as well (Johnson 2006; Wiseman and El-Baz 2007), is not treated here following common terminology in Europe (see Chap. 14). Furthermore, this chapter focuses on image-based remote sensing, while range-based remote sensing is treated elsewhere (see Chap. 11).

The benefits of using remote sensing as a recording technique in archaeology are manifold. For example, one of the major advantages is that sensitive archaeological objects are not touched nor otherwise affected by remote sensing. This is in line with recent trends towards non-invasive methods of investigation that help to preserve the archaeological heritage (Corsi et al. 2013). In addition, the bird's eye perspective helps to observe and understand archaeological sites and objects in their landscape context that was formed by interwoven natural and anthropogenic processes (Musson et al. 2013). Furthermore, today remote sensing data is continuously being generated in the environmental sciences, in cartography and geodesy and in the military and commercial sectors, leading to an ever-increasing quantity and quality of data that potentially hold information about archaeological contexts. These data are available at a wide variety of scales and resolutions and often with a considerable time depth. They can thus contribute to a broad range of archaeological research questions.

In what follows, the history of remote sensing in archaeology and earth observation is summarised in Sect. 7.2. Section 7.3 provides a brief overview of platforms, sensors and data and their application to archaeology. Section 7.4 discusses the archaeological analysis of digital remote sensing data, focusing on recent trends and illustrating this with a case study from own research. This is then followed by an outlook in Sect. 7.5.

7.2 A Look Back

7.2.1 Aerial Archaeology

The first aerial images of archaeological sites were taken from military balloons around the turn of the nineteenth to the twentieth century (Trümpler 2005; Verhoeven et al. 2013; Campana 2017a). Shortly after, during World War I, aerial photographs taken for military reconnaissance from aeroplanes covered many archaeological sites and ruins in Europe and the Near East for the first time. In the 1920s, O.G.S. Crawford was the first archaeologist to systematically use crop marks, i.e. observable differences in plant growth caused by subsurface archaeological remains, for archaeological site detection and mapping. While crop marks and other proxies such as soil, shadow, snow and flood marks work well in the temperate climate regions of central Europe with their extended agricultural fields, they are less effective in dryer conditions and largely fail in woodlands. The introduction of infrared and later multispectral photography to aerial archaeology in the 1970s increased the visible range so that differences in soil moisture and vegetation growth could be used more effectively (Verhoeven 2008, 2012). However, inherent conceptual issues such as survey bias (Palmer 2005; Cowley 2016) could not be resolved through technological innovation.

In spite of these limitations, aerial archaeology has proven to be the single most effective method of archaeological site detection and mapping in Europe. The technique of taking oblique images with a handheld camera from a small aircraft has remained largely unchanged since the 1920s. Since then, systematic efforts such as English Heritage's National Mapping Programme (NMP; Horne 2009) and technological innovations such as digital cameras and positioning devices (e.g. GPS/INS) have increased the efficiency and effectiveness of the method (Leckebusch 2005; Doneus et al. 2016). As a result, today many European countries hold substantial collections of aerial images taken for the purpose of archaeological prospection. Important resources of archaeological information are also buried in the millions of vertical aerial photographs taken for purposes of military reconnaissance or cartography collected in major national archives (Cowley et al. 2010; Cowley and Stichelbaut 2012; Hanson and Oltean 2013). These historical images constitute a highly valuable resource, as many of them show sites and landscapes that have since been heavily altered, damaged or destroyed, e.g. through land consolidation, irrigation, urban sprawl, or armed conflict.

7.2.2 Earth Observation Remote Sensing

Like aerial archaeology, earth observation remote sensing grew out of military applications around the time of World War I. Systematic cartographic mapping based on aerial images began in the 1930s. Other early applications included land use studies, geology, hydrology and forestry (Lillesand et al. 2015). During World War II, millions of aerial photographs were taken for military reconnaissance, which brought about vastly improved methods of image capture, analysis and interpretation (Hanson and Oltean 2013). This time of conflict and the post-war years leading up to the Cold War also saw technological innovations such as colour and infrared photography that allowed new ways of studying land cover and vegetation. The basic remote sensing concept developed in those years, with aeroplanes serving as platforms for different sensors used for the systematic mapping of large areas, remains highly useful for earth observation until the present day. However, an important new branch developed in 1960 after the first satellites were launched into space. Photographs of the earth taken from manned spacecraft triggered the interest of the environmental sciences in spaceborne remote sensing, but the technological development was once again driven by military applications.

The first large-scale mapping of portions of the earth's surface from space was undertaken in the 1960s during the Cold War and for purposes of military espionage and reconnaissance. Consequently, the two main antagonists, the USA and UdSSR, mainly covered areas of geostrategic importance such as central Europe and the Near East (Fowler 2013). Images were captured by series of short-lived satellites, e.g. the American Corona and the Sowjet KOSMOS series, which initially produced black-and-white analogue images that were sent back to earth by parachute. Their recovery was complex and frequently failed (Day et al. 1998). The images had a spatial resolution of 1.2–12 m. In spite of great distortion due to their complex image geometry, they provide an invaluable data source for archaeology, for example, for the Near East prior to the time when mechanised agriculture, irrigation and urban sprawl destroyed many ancient sites and their surrounding landscapes (Goossens et al. 2006; Casana and Cothren 2008; Agapiou et al. 2016).

Beginning in the 1970s, government-run space agencies such as NASA initiated earth observation for scientific purposes. Landsat is NASA's most successful long-term programme with a series of seven satellites so far that capture multispectral images of large parts of the earth with a spatial resolution between 80 and 15 m (Lillesand et al. 2015). These images provide large-scale base data for applications, e.g. in geography, biology, climate and land use studies, urban planning, cartography, oceanography and numerous other disciplines. In spite of their low spatial resolution, they soon found first applications in archaeology (Sever 1990; Parcak 2009. For a recent overview of NASA's and ESA's activities related to archaeology, see Giardino 2011 and Stewart et al. 2015).

Technical developments in both platforms and sensors lead to a continuously increasing spatial resolution of spaceborne images. The best available spatial resolution from optical sensors mounted on earth observation satellites was 80 m in 1972, 30 m in 1982 and 5.8 m in 1995 (Lillesand et al. 2015). A paradigm shift occurred at the end of the last century when for the first time a commercial company launched a satellite into space with the sole purpose of selling the images to a wide range of clients (Ikonos 2, launched 1999). Consequently, commercial providers focused on very high spatial resolution (<1 m panchromatic) and up until today provide the highest available spatial resolution to private customers. However, recent satellites launched by government-run space agencies, while still featuring high spectral resolution, today reach spatial resolutions that come close to those of commercial satellites (Agapiou et al. 2015).

Table 7.1 lists selected satellites and sensors that have provided useful images for archaeological purposes in the past or have the potential of doing so in the future. This selection is necessarily subjective and incomplete. For additional data on satellites and sensors, see Remondino (2011) and Lillesand et al. (2015).

While spaceborne remote sensing blossomed, airborne remote sensing continued to be the workhorse for mapping and for environmental applications at smaller scales and has seen just as many technological innovations in recent years. One of them is the introduction of digital cameras, either following the traditional frame format or using linear array sensors (Lemmens 2011; Remondino 2011). Some digital cameras acquire oblique imagery, e.g. for urban mapping (Remondino and Gehrke 2015). Most of these new sensors cover also the near-infrared light, which makes them once again highly valuable for archaeological prospection using vegetation marks. At the same time, aeroplanes are common platforms for truly multispectral and hyperspectral sensors for environmental monitoring, as their lower altitude above ground allows higher spatial resolution than spaceborne platforms. These sensors are useful for a wide range of archaeological applications (Donoghue et al. 2006; Traviglia 2007; Beck 2011; Agapiou et al. 2014; Doneus et al. 2014).

7.3 Platforms, Sensors and Data

7.3.1 High to Low Altitude Platforms

Contrary to popular usage of the term, satellites themselves do not acquire images. Rather, they are platforms on which one or several sensors can be mounted which in turn capture images (Table 7.1). However, certain parameters of the platforms have an effect on image characteristics, among them orbit and altitude. For example, earth observation satellites carrying passive optical sensors, as well as many commercial satellites, circle the earth in sun-synchronous orbits roughly perpendicular to the equator to remain within the zone of sunlight at all times. Such a configuration entails that certain places on the surface of the earth are always visited at the same time of day. Another important parameter is altitude, which affects swath width and spatial resolution.

Table 7.1 Selected satellites and sensors ordered by ground resolution (pan, panchromatic; VIS, visible light; NIR, near infrared; MIR, mid infrared; TIR, thermal infrared)

Satellite	Sensor	Launched	Altitude (km)	Swath width (km)	Channels	Ground resolution (m)
Landsat 7	ETM+	1999	705	185	8 (pan, VIS, NIR, MIR, TIR)	15 (pan)
Landsat 8	OLI	2013	705	185	9 (pan, VIS, NIR, MIR)	15 (pan)
Terra	ASTER	1999	705	60	14 (VIS, NIR, MIR, TIR)	15 (VIS, NIR)
SPOT 5	HRG	2002	832	117	6 (pan, VIS, NIR, MIR)	5.0 (pan)
SPOT 6/7	NAOMI	2012/2014	694	60	5 (pan, VIS, NIR)	1.5 (pan)
Ikonos 2		1999	680	11	5 (pan, VIS, NIR)	1.0 (pan)
Quickbird 2		2001	450	16	5 (pan, VIS, NIR)	0.61 (pan)
Worldview 2		2009	770	16	9 (pan, VIS, NIR)	0.46 (pan)
Geoeye 1		2008	684	15	5 (pan, VIS, NIR)	0.41 (pan)
Worldview 3		2014	617	13	29 (pan, VIS, NIR, MIR)	0.31 (pan)
Worldview 4		2016	617	13	5 (pan, VIS, NIR)	0.31 (pan)

Typical orbits of satellites carrying optical sensors are 700–900 km above ground.

Aeroplanes operate in much lower ranges within the earth's troposphere, between several hundred metres (light aircraft) and 10–12 km (airliners). While earth observation remote sensing, depending on the purpose, may take advantage of this whole range, the flying height is usually closer to the lower end the higher the spectral resolution of the carried sensors is. This is to ensure a good trade-off between spectral and spatial resolution. While satellites operate on a global scale and follow a fixed schedule, aeroplanes operate on a regional scale and can be employed more flexible.

Low-altitude platforms on a local scale have seen a number of important innovations in recent years, especially in archaeological applications. While balloons, blimps and kites have been used for quite some time (Verhoeven 2009), unmanned aerial vehicles (UAVs) provide an unprecedented level of flexibility with regard to data acquisition ever since their first application in archaeology in 2004, especially with the introduction of autonomous navigation (Lambers et al. 2007; Gutiérrez and Searcy 2016; Campana 2017b. For more detail, see Chap. 10).

7.3.2 Active vs. Passive Sensors

There are two types of sensors mounted on airborne and spaceborne platforms: active and passive (Lillesand et al. 2015). Active sensors such as radar and lidar—not treated in this chapter but important to mention—use their own energy source to send a signal to the surface of the earth, from which it is partially reflected and then captured again by the sensor. Since the energy, a form of electromagnetic radiation, travels at the speed of light, the distance between the sensor and the surface can be calculated from the time interval between the emission and the return of the signal. This is called the time-of-flight (ToF) principle of range-based measurement. While radar uses radio/microwaves in different wavelengths, lidar uses visible or infrared light. Travelling between sensor and surface, the signal interacts with the atmosphere, with objects on the surface such as vegetation and with the surface itself in multiple and complex ways that need to be taken into account when reconstructing the surface geometry from the signal. An advantage of active sensing is its independence of sunlight and good weather: both methods work under cloudy/rainy conditions and by night. For accurate range measurements, the position and tilt or skew of the sensor needs to be determined with high accuracy, too. This is usually achieved with global navigation satellite system (GNSS) and inertial navigation system (INS) units.

Passive sensors do not have their own energy source but instead capture radiation emitted from or reflected by the earth's surface, the main source of which is the sun. They are often collectively called optical sensors, although many of them capture radiation outside the range visible to the human eye. Sensors for cartography, mapping and commercial purposes usually generate images with high spatial and limited spectral resolution, e.g. in the visible and near-infrared light (VNIR) range. On the other hand, sensors for earth observation often provide lower spatial yet higher spectral resolution, especially in the infrared range where atmospheric permeability is high and many relevant environmental parameters can be measured. Sensors that capture a limited number of—often disjoint—spectral bands produce multispectral images. Sensors that capture a high number of continuous narrow bands produce hyperspectral images. Since the total energy captured by a given sensor is limited, there is usually a trade-off between spectral and spatial resolution. Other relevant resolutions are the radiometric resolution, which expresses the range of digital numbers available to visualise an image (e.g. 8 bit: $2^8 = 256$ digital numbers), and the temporal resolution, which in the case of satellite images denotes the revisit time of the sensor over a given location on earth. As with radar and lidar data, passive sensing needs to take into account multiple atmospheric and other conditions that have an impact on image formation. Most importantly, passive imaging requires daylight and, in the case of satellite images, as little cloud cover as possible.

7.3.3 Analogue vs. Digital Images

While most optical images are today taken with digital sensors, there are huge archives from the era of analogue photography that contain a wealth of potentially useful information for archaeological purposes (Cowley et al. 2010; Cowley and Stichelbaut 2012; Hanson and Oltean 2013). Analogue photographs, be they negatives or positives, suffer from physical and chemical degradation and thus require measurements for their preservation and/or digitisation.

Aerial photographs for aerial archaeology are often taken with uncalibrated handheld cameras without registration of the exact position and tilt of the camera (Leckebusch 2005; Palmer 2005). Most of these images are oblique, showing the horizon (high) or not (low), in order to optimally capture crop, soil, shadow and other marks. Their acquisition depends on decisions of the operator. For all these reasons, their georeferencing is often difficult and depends on contextual information ideally provided by the operator.

In contrast, aerial photographs for cartography and military reconnaissance are usually taken with metric cameras from a near-vertical perspective in a systematic fashion that aims at the complete coverage of a given target area. Very often, there is a considerable overlap between consecutive images to enable stereoscopic analysis (Mikhail et al. 2001). Georeferencing is facilitated through positioning data collected along the flight path and ground control. In spite of these advantages, vertical aerial photographs are not always useful for archaeological purposes as they are often taken during unfavourable times of the year, e.g. in winter when there are no leafs on the trees, and of the day, e.g. around noon when shadows are minimal, when usual archaeological proxies such as crop marks do not show.

While analogue aerial cameras continue in use, most airborne and all spaceborne remote sensing today operates on digital sensors (Richards and Jia 2006; Lillesand et al. 2015).

Digital frame cameras, like analogue cameras, are pin-hole cameras that capture one individual scene at a time and produce rectangular images from it. Linear-array cameras, on the other hand, capture many narrow strips of a scene corresponding to one line of pixels in the digital image, one after the other. The lines of pixels are then being combined into a continuous image.

Both frame and linear array cameras may produce multispectral images or stacks of images with each layer corresponding to one spectral channel, or band. Many airborne and spaceborne sensors are furthermore operated such that they produce stereoscopic images that can be used for 3D analysis. While overlap between consecutive image scenes ensures this for frame cameras, linear array cameras capture imagery in forward-, nadir- and backward-looking mode, such that multiple perspectives on each portion of the terrain are available from the captured imagery.

7.4 Archaeological Analysis of Remote Sensing Data

The best practice of analysing traditional remote sensing data such as aerial photographs for archaeological purposes has been described elsewhere (Brophy and Cowley 2005; Musson et al. 2013). We here focus on the archaeological analysis of digital remote sensing data using computational tools.

7.4.1 Recent Trends

In geodesy, cartography and earth observation, the complexity of digital remote sensing data has led to the development of a wide range of quantitative and computational tools for image processing and analysis since the 1970s (Richards and Jia 2006; Lasaponara and Masini 2012; Abrams and Comer 2013; Lillesand et al. 2015). While processing usually encompasses image correction, enhancement, transformation and registration, analysis often entails some level of classification of the image contents that assist in their interpretation. Furthermore, overlapping images may be analysed in 3D for the extraction of geometric information (Mikhail et al. 2001).

These techniques are usually systematically applied to whole images, or series of images, and, thus, to entire landscapes that they cover.

In contrast, archaeological image analysis originally focused on certain portions of images that were of archaeological interest, namely, traces of human activity in the landscape (Brophy and Cowley 2005). Consequently, the intensity of landscape coverage varied greatly. Site detection and mapping is still one of the most important goals in archaeological image analysis. However, in recent years, the theoretical turn towards landscapes as frames of reference for an archaeological enquiry has facilitated the adoption of full coverage remote sensing data originally not acquired and analytical tools originally not developed for archaeological purposes (Doneus 2013). This adoption of data and methods from earth observation remote sensing requires innovation and change in the practice of archaeological prospection (Cowley 2012; Verhoeven and Sevara 2016). For example, the thorough screening of individual aerial images by a human observer as in aerial archaeology is not scalable to the quantity and complexity of, e.g. multi-/hyperspectral images. On the other hand, existing analytical tools for object detection associated with digital remote sensing data, e.g. for road or building detection in cartography and mapping, usually fail when targeting faint, elusive archaeological traces.

Therefore, since the early 2000s, archaeologists, in close collaboration with experts from the earth sciences and computer science, have attempted to partly automate the archaeological analysis of remote sensing data, using digital image processing and analysis to detect and map archaeological traces (e.g. De Laet et al. 2007, 2009). Such attempts initially met with considerable scepticism (e.g. Hanson 2010) due to the unclear role that computer algorithms should play in the process of observing, analysing and interpreting archaeological traces in the landscape (Cowley 2012; Bennett et al. 2014). In the meantime, however, a number of projects have demonstrated the feasibility of such an approach (Traviglia et al. 2016). An interesting aspect here is that some automated approaches can be applied to both image data and range data. For example, algorithms have been developed to reliably detect burial mounds (Trier et al. 2009, 2015; Caspari et al. 2014; Sevara et al. 2016; Cerrillo-Cuenca 2017), stone tombs (Schuetter et al. 2013), charcoal kilns (Schneider et al. 2015), animal traps (Trier and Pilø 2012), trails (Vletter 2014) and tells (Menze and Ur 2012) in digital elevation models, high-resolution panchromatic images, or multispectral images. All of these handcrafted algorithms target well-known, clearly defined categories of recurrent, typical archaeological objects. They are thus designed to assist archaeological prospection and provide base data, not to replace fieldwork and archaeological interpretation. To illustrate this field of research more clearly, the following describes a case study from our own research.

7.4.2 Case Study: Archaeological Object Detection in the Silvretta Alps

The Silvretta Archaeological Project, directed by Thomas Reitmaier and conducted from 2009 to 2016 in the Silvretta mountains on the border between Switzerland and Austria, served as a case study to develop methods for a semi-automated archaeological analysis of optical remote sensing images. The main goal of the project was to investigate Holocene human-environment interaction and resource use in the alpine zone above the tree line, with a special focus on the prehistoric origins and further development of alpine pastoralism (Dietre et al. 2014, 2017; Kothieringer et al. 2015). An important category of archaeological sites relevant for this topic was ruins of livestock enclosures (LSEs) used for the management of sheep, goats and cattle during the annual grazing period in the short summer (Fig. 7.1). About 30 LSEs were registered during archaeological fieldwork from 2009 to 2016, dating from the Bronze and Iron Ages to the Modern Period. These known LSEs served as target objects for the development of an algorithm for archaeological object detection.

Fig. 7.1 Well-preserved livestock enclosure (LSE) in Val Urschai, Lower Engadine, Switzerland (photo: K. Lambers). About 30 LSEs were recorded in the Silvretta region, most of them older and less well preserved than this one

While the results have been described in detail elsewhere (Zingman 2016; Zingman et al. 2014, 2016), the following is a brief overview with a focus on the general idea behind the workflow.

Images captured in 2011 by the commercial satellite Geoeye 1 served as primary data source (cp. Table 7.1). They feature four bands in the VNIR spectrum and a spatial resolution of 0.5 m in the panchromatic band, downsampled from the original 45 cm due to legal restrictions. These images were chosen for two reasons. Firstly, they provided the only consistent, up-to-date data source for the entire study area of ca 500 km^2. Secondly, images of this type are a useful starting point for archaeological research in areas where other types of remote sensing data are not available or difficult to acquire or where access on the ground is difficult, as is the case in many remote or contested parts of the world. For the same reason, one aim of the project was to achieve as much as possible in terms of object detection based on the satellite images alone, without making use of contextual information, which in other cases might not be available. For reference, an orthoimage with 0.5 m resolution based on aerial images provided by SWISSTOPO was used as secondary data source.

The goal of the case study was to develop a workflow that would allow the quick and reliable detection of LSEs in optical remote sensing images of 0.5 m resolution. In order to be useful, the workflow needed to be robust to illumination changes and quick and enable a high detection rate combined with a manageable number of false detections. It should furthermore indicate the probability of the presence of a target object rather than yielding a binary yes/no classification, as the workflow was envisioned as an assisting step prior to archaeological fieldwork that would facilitate the ground truthing of its results.

The design of the workflow was determined by the nature of the target objects. While the LSEs show a wide variety of shapes, sizes, states of preservation and contexts (e.g. associated vegetation), they can all be described as roughly rectangular, though often incomplete objects. Furthermore, they are all located in open grassland. These features determined the detection approach.

Their location in open grassland meant that other portions of the study area—mainly forests, rocky/ice-covered areas and settlements—would have led to many false detections. Thus, in a first step, the images were segmented based on texture contrast such that open grasslands were distinguished from all other portions of the landscape. For this purpose, and based on mathematical morphology, two complementary operators were developed. The first, called morphological texture contrast (MTC), filters out high texture contrast regions. The second, called morphological feature contrast (MFC), highlights individual features in the remaining image portions, since those might be part of the target objects. The result is a binary image showing individual features in open areas. By filtering out irrelevant areas, computation time for all subsequent steps is reduced considerably.

The next, and crucial, step in the workflow was to determine which linear features in the binary images belonged to the target objects. Based on the geometric properties of LSEs, two constraints were defined: (1) a convexity constraint, requiring that linear features form a nearly convex hull, and (2) a rectangularity constraint, requiring that they meet at roughly right angles. First, candidate points in the images were determined which were surrounded by linear features in certain distances and configurations and were thus potential centre points of target objects. Second, from these candidates, the location and configuration of the linear features surrounding them were tested against the abovementioned constraints in a graph-based search. That way, most naturally occurring configurations such as random alignments of stones, streams or trails were rejected. Third, the remaining configurations were assessed based on how well they fulfilled the constraints, for which a rectangularity measure was introduced and assigned to the candidate points. Colour coding this quantitative measure results in a heat map in which red indicates a high probability of the presence of a target object, yellow a low probability and no colour a zero probability (Fig. 7.2). This heat map can serve as starting point for fieldwork, as it indicates the most likely locations where target objects can be detected.

Applying the above described workflow to large images results in a huge number of false detections. Therefore, the geometric properties of the known LSEs were used for filtering the results. Mapping their sizes against their rectangularity measures resulted in a clear distribution of the known LSEs towards one end of the overall distribution, such that a linear classifier could be defined that discarded the majority of the false detections. This classifier can be used in other contexts as well.

Testing the workflow on the original dataset showed that all known LSEs were reliably detected. In addition, a low number of hitherto unrecorded LSEs were detected, too. Applying the workflow to a similar dataset from the Bernese Alps also yielded promising results, which have yet to be validated in the field.

The Silvretta case study shows how computational tools can extract meaningful archaeological information from complex remote sensing data, thereby assisting archaeological fieldwork and enquiry. As in other disciplines, the combination of domain knowledge with methodological expertise from remote sensing and computer science is the key to tapping the full potential of remote sensing data.

7.5 A Look Ahead

For a long time, and in spite of their shared origins, aerial archaeology and earth observation remote sensing have followed own trajectories that overlapped only occasionally. In recent

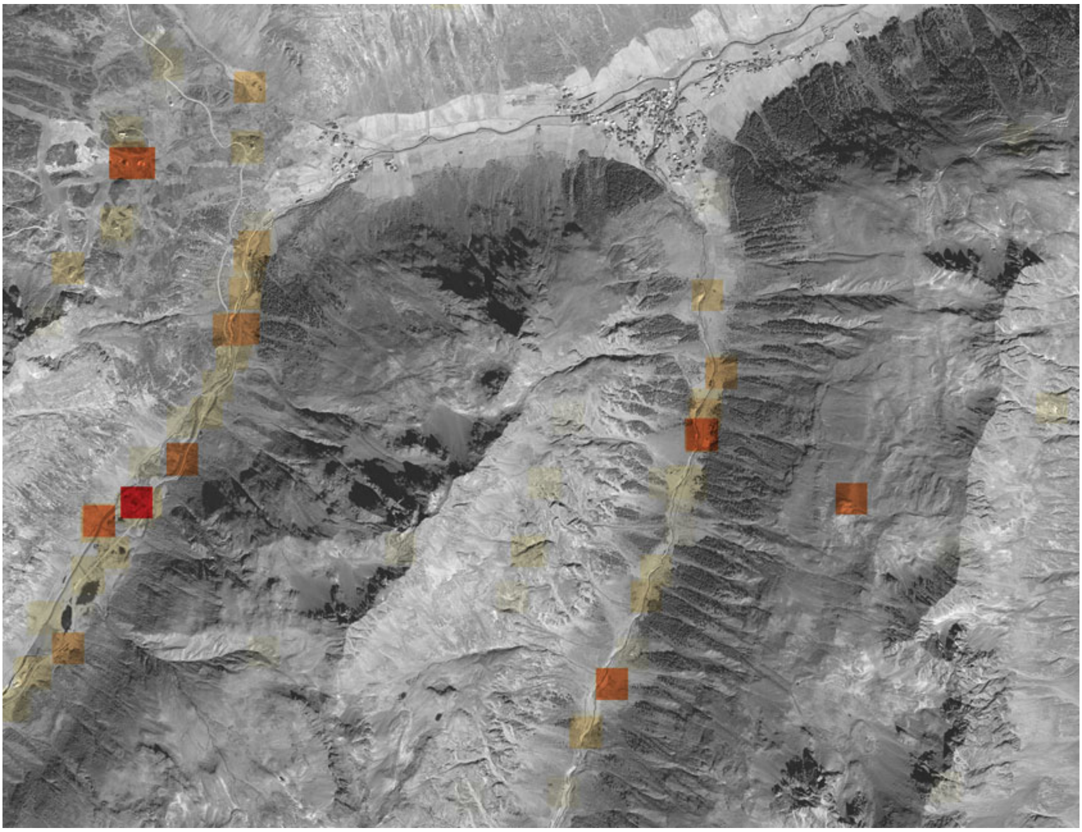

Fig. 7.2 Geoeye 1 satellite image (panchromatic channel) of the Jam and Larein valleys above Galtür, Tyrol, Austria, with superimposed colour code indicating low (*yellow*) to high (*red*) probability of the presence of LSEs (image: I. Zingman, using copyrighted material of DigitalGlobe, Inc., All Rights Reserved). This heat map serves as starting point for ground-based archaeological survey

years, however, there is a clear and irreversible, highly promising trend towards convergence. Aerial archaeology has an enormous potential to adapt to new requirements (Verhoeven and Sevara 2016). At the same time, the continuously increasing use of data, tools and methods derived from earth observation remote sensing for archaeological purposes leads to exciting new opportunities and challenges. Airborne laser scanning, the first effective technique for large-scale archaeological prospection in woodlands, is just the most striking example (Crutchley and Crow 2009). At the same time, it is a good example of the data explosion (Bennett et al. 2014) or deluge (Bevan 2015) that archaeology now faces. Multidimensional, multi-resolution, multi-sensor remote sensing data are much more complex than traditional aerial photographs, and this requires new conceptual approaches to data processing, analysis and interpretation. While crowdsourcing is one way to address this problem (Casana 2014; Lin et al. 2014), computational approaches is another (Gattiglia 2015; Grosman 2016). Archaeology as a discipline has started to develop computational approaches in close collaboration with the earth and environmental sciences, engineering and computer science, as recent successful attempts towards automation in archaeological object detection show.

At the same time, these examples also reveal certain limitations. Handcrafted custom algorithms for object detection, while effective, have so far proven to be too specialised to be widely applied in cultural heritage management. They often target narrow object categories, sometimes require specific data, and are mostly not yet integrated into common working environments such as GIS. Clearly, more generic and user-friendly approaches are needed to make full use of computational power for the archaeological analysis of the rich content of remote sensing data. Currently, advanced machine learning techniques seem to offer the best solution for this problem. For example, deep learning based on convolutional neural networks has revolutionised computer vision in recent years, enabling considerable progress in such complex analytical problems as face recognition and image understanding. Whereas traditional methods of digital image analysis map and classify image contents, deep learning is capable of comprehensively analysing and describing them, e.g. in text (LeCun et al. 2015). This and related approaches thus seem to offer a great potential for a truly semantic analysis of remote sensing data for archaeological purposes. First archaeological case studies in this field (Zingman et al. 2016; Trier et al. 2017) show promising results.

References

Abrams MJ, Comer DC (2013) Multispectral and hyperspectral technology and archaeological applications. In: Comer DC, Harrower MJ (eds) Mapping archaeological landscapes from space. Springer, New York, pp 57–71. https://doi.org/10.1007/978-1-4614-6074-9_6

Agapiou A, Alexakis DD, Hadjimitsis DG (2014) Spectral sensitivity of ALOS, ASTER, IKONOS, LANDSAT and SPOT satellite imagery intended for the detection of archaeological crop marks. Int J Digital Earth 7:351–372. https://doi.org/10.1080/17538947.2012.674159

Agapiou A, Alexakis DD, Simon FX, Kalayci T, Papadopoulos N, Sarris A, Hadjimitsis D (2015) Extraction of archaeological information using high resolution FormoSAT-2 data. Int J Herit Digital Era 4:241–255. https://doi.org/10.1260/2047-4970.4.3-4.241

Agapiou A, Alexakis DD, Sarris A, Hadjimitsis DG (2016) Colour to greyscale pixels: re-seeing greyscale archived aerial photographs and declassified satellite CORONA images based on image fusion techniques. Archaeol Prospect 23:231–241. https://doi.org/10.1002/arp.1536

Beck A (2011) Archaeological applications of multi/hyper-spectral data – challenges and potential. In: Cowley DC (ed) Remote sensing for archaeological heritage management. Occasional Publication of the Aerial Archaeology Research Group No. 3. Europae Archaeologia Consilium, Brussels, pp 87–97

Bennett R, Cowley D, De Laet V (2014) The data explosion: tackling the taboo of automatic feature recognition in airborne survey data. Antiquity 88:896–905. https://doi.org/10.1017/S0003598X00050766

Bevan A (2015) The data deluge. Antiquity 89:1473–1484. https://doi.org/10.15184/aqy.2015.102.

Brophy K, Cowley D (eds) (2005) From the air: understanding aerial archaeology. Tempus, Stroud

Campana S (2017a) Remote sensing in archaeology. In: Gilbert AS (ed) Encyclopedia of geoarchaeology. Springer, Dordrecht, pp 703–725. https://doi.org/10.1007/978-1-4020-4409-0_122

Campana S (2017b) Drones in archaeology. State-of-the-art and future perspectives. Archaeol Prospect. doi: https://doi.org/10.1002/arp.1569

Casana J (2014) Regional-scale archaeological remote sensing in the age of Big Data. Adv Archaeol Pract 2:222–233. https://doi.org/10.7183/2326-3768.2.3.222

Casana J, Cothren J (2008) Stereo analysis, DEM extraction and orthorectification of CORONA satellite imagery: archaeological applications from the Near East. Antiquity 82:732–749. https://doi.org/10.1017/S0003598X00097349

Caspari G, Balz T, Gang L, Wang X, Liao M (2014) Application of Hough Forests for the detection of grave mounds in high-resolution satellite imagery. In: Proceedings of the 2014 IEEE geoscience and remote sensing symposium, pp 906–909. https://doi.org/10.1109/IGARSS.2014.6946572

Cerrillo-Cuenca E (2017) An approach to the automatic surveying of prehistoric barrows through LiDAR. Quat Int 435B:135–145. https://doi.org/10.1016/j.quaint.2015.12.099

Corsi C, Slapšak B, Vermeulen F (eds) (2013) Good practice in archaeological diagnostics: non-invasive survey of complex archaeological sites. Springer, Cham. https://doi.org/10.1007/978-3-319-01784-6

Cowley DC (2012) In with the new, out with the old? Auto-extraction for remote sensing archaeology. In: Bostater CR Jr, Mertikas SP, Neyt X, Nichol C, Cowley DC, Bruyant JP (eds) Remote sensing of the ocean, sea ice, coastal waters, and large water regions 853206. Proceedings of SPIE 8532. SPIE, Dresden. https://doi.org/10.1117/12.981758

Cowley DC (2016) What do the patterns mean? Archaeological distributions and bias in survey data. In: Forte M, Campana S (eds) Digital methods and remote sensing in archaeology. Springer, Cham, pp 147–170. https://doi.org/10.1007/978-3-319-40658-9_7

Cowley DC, Stichelbaut BB (2012) Historical aerial photographic archives for European archaeology. Eur J Archaeol 15:217–236. https://doi.org/10.1179/1461957112Y.0000000010

Cowley DC, Standring RA, Abicht MJ (eds) (2010) Landscapes through the lens: aerial photographs and historic environment. Occasional Publication of the Aerial Archaeology Research Group No. 2. Oxbow Books, Oxford

Crutchley S, Crow P (2009) The light fantastic: using airborne laser scanning in archaeological survey. English Heritage, Swindon

Day DA, Logsdon JM, Latell B (eds) (1998) Eye in the sky: the story of the CORONA spy satellites. Smithsonian Institution, Washington

De Laet V, Paulissen E, Waelkens M (2007) Methods for the extraction of archaeological features from very high-resolution Ikonos-2 remote sensing imagery, Hisar (southwest Turkey). J Archaeol Sci 34:830–841. https://doi.org/10.1016/j.jas.2006.09.013

De Laet V, Paulissen E, Meuleman K, Waelkens M (2009) Effects of image characteristics on the identification and extraction of archaeological features from Ikonos-2 and Quickbird-2 imagery: case study Sagalassos (southwest Turkey). Int J Remote Sens 30:5655–5668. https://doi.org/10.1080/01431160802705821

Dietre B, Walser C, Lambers K, Reitmaier T, Hajdas I, Haas JN (2014) Palaeoecological evidence for Mesolithic to Medieval climatic change and anthropogenic impact on the Alpine flora and vegetation of the Silvretta Massif (Switzerland/Austria). Quat Int 353:3–16. https://doi.org/10.1016/j.quaint.2014.05.001

Dietre B, Walser C, Kofler W, Kothieringer K, Hajdas I, Lambers K, Reitmaier T, Haas JN (2017) Neolithic to Bronze Age (4850–3450 cal. BP) fire management of the Alpine Lower Engadine landscape (Switzerland) to establish pastures and cereal fields. Holocene 27:181–196. https://doi.org/10.1177/0959683616658523

Doneus M (2013) Die hinterlassene Landschaft – Prospektion und Interpretation in der Landschaftsarchäologie. Mitteilungen der Prähistorischen Kommission 78. Austrian Academy of Sciences, Vienna

Doneus M, Verhoeven G, Atzberger C, Wess M, Rus M (2014) New ways to extract archaeological information from hyperspectral pixels. J Archaeol Sci 52:84–96. https://doi.org/10.1016/j.jas.2014.08.023

Doneus M, Wieser M, Verhoeven G, Karel W, Fera M, Pfeifer N (2016) Automated archiving of archaeological aerial mages. Remote Sens 8:209. https://doi.org/10.3390/rs8030209

Donoghue D, Beck A, Galiatsatos N, McManus K, Philips G (2006) The use of remote sensing data for visualising and interpreting archaeological landscapes. In: Baltsavias E, Gruen A, van Gool L, Pateraki M (eds) Recording, modeling and visualization of cultural heritage. Taylor & Francis, London, pp 317–326

Fowler MJF (2013) Declassified intelligence satellite photographs. In: Hanson WS, Oltean IA (eds) Archaeology from historical aerial and satellite archives. Springer, New York, pp 47–66. https://doi.org/10.1007/978-1-4614-4505-0_4

Gattiglia G (2015) Think big about data: archaeology and the Big Data challenge. Archäologische Informationen 38:113–124. https://doi.org/10.11588/ai.2015.1.26155

Giardino MJ (2011) A history of NASA remote sensing contributions to archaeology. J Archaeol Sci 38:2003–2009. https://doi.org/10.1016/j.jas.2010.09.017

Goossens R, De Wulf A, Bourgeois J, Gheyle W, Willems T (2006) Satellite imagery and archaeology: the example of CORONA in the Altai mountains. J Archaeol Sci 33:745–755. https://doi.org/10.1016/j.jas.2005.10.010

Grosman L (2016) Reaching the point of no return: the computational revolution in archaeology. Annu Rev Anthropol 45:129–145. https://doi.org/10.1146/annurev-anthro-102215-095946

Gutiérrez G, Searcy MT (eds) (2016) Special issue: Drones in archaeology. SAA Archaeol Rec 16

Hanson WS (2010) The future of aerial archaeology in Europe. Photo Interprétation. Eur J Appl Remote Sens 46:3–11

Hanson WS, Oltean IA (eds) (2013) Archaeology from historical aerial and satellite archives. Springer, New York. https://doi.org/10.1007/978-1-4614-4505-0

Horne PD (2009) A strategy for the national mapping programme. English Heritage, Swindon

Johnson JK (ed) (2006) Remote sensing in archaeology: an explicitly North American perspective. University of Alabama Press, Tuscaloosa

Kothieringer K, Walser C, Dietre B, Reitmaier T, Haas JN, Lambers K (2015) High impact: early pastoralism and environmental change during the Neolithic and Bronze Age in the Silvretta Alps (Switzerland/Austria) as evidenced by archaeological, palaeoecological and pedological proxies. Z Geomorphol 59(2):177–198. https://doi.org/10.1127/zfg_suppl/2015/S-59210

Lambers K, Eisenbeiss H, Sauerbier M, Kupferschmidt D, Gaisecker T, Sotoodeh S, Hanusch T (2007) Combining photogrammetry and laser scanning for the recording and modelling of the Late Intermediate Period site of Pinchango Alto, Palpa, Peru. J Archaeol Sci 34:1702–1712. https://doi.org/10.1016/j.jas.2006.12.008

Lasaponara R, Masini N (eds) (2012) Satellite remote sensing: a new tool for archaeology. Springer, Dordrecht. https://doi.org/10.1007/978-90-481-8801-7

Leckebusch J (2005) Aerial archaeology: a full digital workflow for aerial photography. Archaeol Prospect 12:235–244. https://doi.org/10.1002/arp.260

LeCun Y, Bengio Y, Hinton G (2015) Deep learning. Nature 521:436–444. https://doi.org/10.1038/nature14539

Lemmens M (2011) Digital aerial cameras. GIM Int 25 (4):18–25

Lillesand TM, Kiefer RW, Chipman JW (2015) Remote sensing and image interpretation, 7th edn. Wiley, New York

Lin AYM, Huynh A, Lanckriet G, Barrington L (2014) Crowdsourcing the unknown: the satellite search for Genghis Khan. PLoS One 9(12):e114046. https://doi.org/10.1371/journal.pone.0114046

Menze BH, Ur JA (2012) Mapping patterns of long-term settlement in Northern Mesopotamia at a large scale. PNAS 109(14):E778–E787. https://doi.org/10.1073/pnas.1115472109

Mikhail EM, Bethel JS, McClone JC (2001) Introduction to modern photogrammetry. Wiley, New York

Musson C, Palmer R, Campana S (2013) Flights into the past: aerial photography, photo interpretation and mapping for archaeology. Occasional Publication No. 4 of the Aerial Archaeology Research Group. http://archiv.ub.uni-heidelberg.de/propylaeumdok/volltexte/2013/2009. Accessed 3 Feb 2017.

Palmer R (2005) If they used their own photographs they wouldn't take them like that. In: Brophy K, Cowley DC (eds) From the air: understanding aerial archaeology. Tempus, Stroud, pp 94–116

Parcak SH (2009) Satellite remote sensing for archaeology. Routledge, London

Remondino F (2011) Heritage recording and 3D modeling with photogrammetry and 3D scanning. Remote Sens 3:1104–1138. https://doi.org/10.3390/rs3061104

Remondino F, Gehrke M (2015) Oblique aerial imagery – a review. In: Fritsch D (ed) Photogrammetric week '15. Wichmann, Berlin, pp 75–84

Richards JA, Jia X (2006) Remote sensing digital image analysis: an introduction, 4th edn. Springer, Berlin

Schneider A, Takla M, Nicolay A, Raab A, Raab T (2015) A template-matching approach combining morphometric variables for automated mapping of charcoal kiln sites. Archaeol Prospect 22:45–62. https://doi.org/10.1002/arp.1497

Schuetter J, Goel P, McCorriston J, Park J, Senn M, Harrower M (2013) Autodetection of ancient Arabian tombs in high-resolution satellite imagery. Int J Remote Sens 34:6611–6635. https://doi.org/10.1080/01431161.2013.802054

Sevara C, Pregesbauer M, Doneus M, Verhoeven G, Trinks I (2016) Pixel versus object – a comparison of strategies for the semi-automated mapping of archaeological features using airborne laser scanning data. J Archaeol Sci Rep 5:485–498. https://doi.org/10.1016/j.jasrep.2015.12.023

Sever TL (1990) Remote sensing applications in archeological research: tracing prehistoric human impact upon the environment. PhD dissertation, University of Colorado. University Microfilms, Ann Arbor

Stewart C, Rast M, Sarti F, Arino O (2015) ESA activities in earth observation for cultural heritage applications. Int J Herit Digital Era 4:325–338. https://doi.org/10.1260/2047-4970.4.3-4.325

Traviglia A (2007) MIVIS hyperspectral sensors for the detection and GIS supported interpretation of subsoil archaeological sites. In: Clark JT, Hagemeister EM (eds) Digital discovery: exploring new frontiers in human heritage. CAA 2006 Fargo. Archaeolingua, Budapest, pp 287–299

Traviglia A, Cowley DC, Lambers K (2016) Finding common ground: human and computer vision in archaeological prospection. AARGnews 53:11–24. http://hdl.handle.net/1887/43751. Accessed 3 Feb 2017

Trier ØD, Pilø LH (2012) Automatic detection of pit structures in airborne laser scanning data. Archaeol Prospect 19:103–121. https://doi.org/10.1002/arp.1421

Trier ØD, Larsen SØ, Solberg R (2009) Automatic detection of circular structures in high-resolution satellite images of agricultural land. Archaeol Prospect 16:1–15. https://doi.org/10.1002/arp.339

Trier ØD, Zortea M, Tonning C (2015) Automatic detection of mound structures in airborne laser scanning data. J Archaeol Sci Rep 2:69–79. https://doi.org/10.1016/j.jasrep.2015.01.005

Trier ØD, Salberg AB, Pilø LH (2017) Semi-automatic mapping of charcoal kilns from airborne laser scanning data using deep learning. In: Uleberg E, Matsumoto M (eds) Proceedings of the 44th annual conference on computer applications and quantitative methods in archaeology (CAA 2016)

Trümpler C (2005) Aerial photography in archaeology and its pioneers. In: Trümpler C (ed) The past from above: photographs by Georg Gerster. Frances Lincoln, London, pp 9–23

Verhoeven G (2008) Imaging the invisible using modified digital still cameras for straightforward and low-cost archaeological near-infrared photography. J Archaeol Sci 35:3087–3100. https://doi.org/10.1016/j.jas.2008.06.012

Verhoeven G (2009) Providing an archaeological bird's eye view – an overall picture of ground-based means to execute low-altitude aerial photography (LAAP) in archaeology. Archaeol Prospect 16:233–249. https://doi.org/10.1002/arp.354

Verhoeven G (2012) Near-infrared crop mark archaeology: from its historical use to current digital implementations. J Archaeol Method Theory 19:132–160. https://doi.org/10.1007/s10816-011-9104-5

Verhoeven G, Sevara C (2016) Trying to break new ground in aerial archaeology. Remote Sens 8:918. https://doi.org/10.3390/rs8110918

Verhoeven G, Sevara C, Karel W, Ressl C, Doneus M, Briese C (2013) Undistorting the past: new techniques for orthorectification of archaeological aerial frame imagery. In: Corsi C, Slapšak B, Vermeulen F (eds) Good practice in archaeological diagnostics: non-invasive survey of complex archaeological sites. Springer, Cham, pp 31–67. https://doi.org/10.1007/978-3-319-01784-6_3

Vletter WF (2014) (Semi-)automatic extraction from Airborne Laser Scan data of roads and paths in forested areas. In: Hadjimitsis DG, Themistocleous K, Michaelides S, Papadavid G (eds) Second international conference on remote sensing and geoinformation of the environment (RSCy2014), Proceedings of SPIE 9229. SPIE, Paphos 92291D. https://doi.org/10.1117/12.2069709

Wiseman J, El-Baz F (eds) (2007) Remote sensing in archaeology. Springer, New York. https://doi.org/10.1007/0-387-44455-6

Zingman I (2016) Semi-automated detection of fragmented rectangular structures in high resolution remote sensing images with application in archaeology. PhD dissertation, University of Konstanz. http://nbn-resolving.de/urn:nbn:de:bsz:352-0-386546. Accessed 3 Feb 2017

Zingman I, Saupe D, Lambers K (2014) A morphological approach for distinguishing texture and individual features in images. Pattern Recogn Lett 47:129–138. https://doi.org/10.1016/j.patrec.2014.03.019

Zingman I, Saupe D, Penatti OAB, Lambers K (2016) Detection of fragmented rectangular enclosures in very high resolution remote sensing images. IEEE Trans Geosci Remote Sens 54:4580–4593. https://doi.org/10.1109/TGRS.2016.2545919