Mapping and Monitoring of the Land Use/Cover Changes in the Wider Area of ltanos, Crete, Using Very High Resolution EO Imagery With Specific Interest in Archaeological Sites

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ABSTRACT

Archaeological site mapping is important for both understanding the history as well as protecting them from excavation during the developmental activities. As archaeological sites generally spread over a large area, use of high spatial resolution remote sensing imagery is becoming increasingly applicable in the world. The main objective of this study was to map the land cover of the Itanos area of Crete and of its changes, with specific focus on the detection of the landscape's archaeological features. Six satellite images were acquired from the Pleiades and WorldView-2 satellites over a period of 3 years. In addition, digital photography of two known archaeological sites was used for validation. An Object Based Image Analysis (OBIA) classification was subsequently developed using the five acquired satellite images. Two rule-sets were created, one using the standard four bands which both satellites have and another for the two WorldView-2 images their four extra bands included. Validation of the thematic maps produced from the classification scenarios confirmed a difference in accuracy amongst the five images. Comparing the results of a 4-band rule-set versus the 8-band showed a slight increase in classification accuracy using extra bands. The resultant classifications showed a good level of accuracy exceeding 70%. Yet, separating the archaeological sites from the open spaces with little or no vegetation proved challenging. This was mainly due to the high spectral similarity between rocks and the archaeological ruins. The satellite data spatial resolution allowed for the accuracy in defining larger archaeological sites, but still was a difficulty in distinguishing smaller areas of interest. The digital photography data provided a very good 3D representation for the archaeological sites, assisting as well in validating the satellite-derived classification maps. All in all, our study provided further evidence that use of high resolution imagery may allow for archaeological sites to be located, but only where they are of a suitable size archaeological features.

Keywords: *3D Modeling, Archaeology, Land Cover Mopping, OBIA, Remote Sensing, GIS*

1. Introduction

Urban landscape planning has many benefits in terms of the environment. Urban landscape planning means making decisions about the future situation of urban land (Kaya et al., 2018). In this case, it is necessary to predict how the land has changed over time and the effects of natural factors and human activities on the land. In this way, successful and sustainable landscape planning studies can be achieved (Cetin et al., 2016). Determination of land cover and green area change related to urban area and its immediate surroundings: Land use change is due to human activities and natural factors. Land cover is one of the most important data used to demonstrate the effects of land use changes, especially human activities. By using land cover maps, the changes in urban development and green areas over time have been evaluated Cetin et al., (2015).

Indeed, Earth Observation (EO) has seen an exponential growth in recent decades and its applications have also led to improvements in uses which were previously unavailable or not even thought of (Brown et al., 2018). Aerial platforms with sensors attached have a major advantage in being able to select the area covered and allowed for sensor choice, usually with high specifications and in short interval of time. The advantage of aerial imagery has lessened since the development of technology with the ability to launch satellites into orbit with capabilities to obtain imagery of the Earth (Markogianni et al., 2018). Similarly, it can be used for mapping of archaeological sites. Study of archaeological sites is important for historical research and has the potential to provide new information for understanding the human civilization (Banerjee and Srivastava 2013, 2014). Archaeology is similar to EO in the sense that it is multidisciplinary; it takes influence from history, geography, international politics and more (Brutto et al., 2012). The more techniques that have been invented and discovered, the more information has been able to be garnered from a site.

Parcak (2009) reviewed the use of EO in archaeology research. He concluded that, whilst progression has been occurring at an exponential rate, there are still a number of issues and unknowns. One of the main influences that EO has had in archaeology is the quick access to sites all around the world with many different sensor types which can be used in locating, analysing and monitoring areas (Fowler, 2004). The location of new archaeological sites may be speeded up using large swaths of EO data, as long as it is superficial and not sub-surface (Masini et al., 2009). There are advantages that EO methods have introduced into the study of archaeology: increasing spectral/spatial resolutions revealing more information of complex archaeological sites, the ability to alter angles and scales allows for greater understanding. Digital Elevation Model (DEM) creation has also been utilised to identify archaeological features, monitoring sites using time series data in case of hazards, both sub-surface and supra-surface analysis available (Lasaponara and Masini, 2012; Banerjee et al., 2018).

Archaeological sites can be found all around the globe, from many civilisations dating back centuries. Many of these sites have been investigated and analysed both in the field and using remote sensing datasets. One of the most common practical methods in archaeological study includes the use of field surveys and measurements, including excavation techniques. These were recognised as accurate techniques that became the staple methods for archaeological analysis. There are positives and negatives to this style of investigation. It allows for an in-depth analysis of a site, ensuring that nothing has been missed, and it acquires the most information available from the site (Barker, 1996). This does require a certain level of expertise in archaeological field practice and can require a significant length of time. It also introduces the possibility of damaging the site when using an invasive technique such as excavation (Tite,

2002) and raises questions about how proper it is to remove possible objects of significant cultural heritage (Schneider, 1982).

Numerous studies have now made use of satellites. These include the newest series, which are some of the highest resolution, for a range of different subjects. Archaeological studies have been utilising the high spatial capabilities to gain information (Laet et al. 2007; Lasaponara & Masini 2006; Banerjee et al., 2018). With these newer satellites having a spatial resolution averaging less than two metres, this allows for accurate mapping of sites that previously may have appeared as amorphous blobs of pixels (Whyte et al., 2018; Markogianni et al., 2018). This can have major implications for small sites or those with high levels of details, where it makes a significant difference as to what may, or may not, be captured in the imagery. The orientation of the imagery can also be an issue; an archaeological site is likely to be a 3D subject whether that is upon the Earth's surface or embedded in it. Satellite systems, such as Pleiades, formed of a constellation of sensors can acquire multiple angles of the site and allow for DEM extraction (Bernard et al.,, 2012; Jacobsen & Topan, 2015). This requires more images to be captured (Lafarge et al. 2006; Lafarge et al. 2008) which, in turn, means higher expenses; the greater processing power required may also become a problem.

Even more recently, everything changed with developments in unmanned aerial vehicles (UAVs). The capture of images using aerial technology had been occurring long before satellites. However, satellites were introduced and this became an effective method of gaining data anywhere in the world without travel. Nowadays, just as newer satellites have developed, so too have aerial means and drones become a new economical option for acquiring images from a height. There is still an issue with having to perform the data collection in person, but more studies have started to take advantage of this form of data collection (Hong et al., 2008). Non-invasive techniques have been developed over time to gain knowledge of the sub- surface without causing damage (Lasaponara et al., 2013). Several methods fit into this category and have been utilised in archaeological study. The most widely-used method is ground penetrating radar (GPR) which uses the radar wavelength frequency of the electromagnetic section to visualise underground areas. Many studies have used it for the sole reason that they do not have to disturb the site to gain understanding of what is beneath them (Eppelbaum et al. 2010; Colis & Colis, 2013).

Studies have employed these methods in archaeological studies before and each has used a different classification system (Siart et al., 2008; Alexakis et al., 2009; Bassani et al., 2009). They employed a style of hybrid system which used both use and cover classes. There was also use of binary systems which classified archaeology versus everything else; this is a useful style for defining the sites but not which classes may be being mistaken for one another due to spectral homogeneity. Three-dimensional (3D) modeling uses reference images to produce, firstly, a point cloud and then a triangular mesh that a texture can be layered upon (Remondino & EI-Hakim, 2006). This is a process-heavy method though and has only become feasible within the last decade on cheaper and simpler computer systems. There have been cases of this method being applied to archaeological studies. It has mainly been employed at sites where there has already been thorough examination and it is used for documenting important aspects, as well as creating an accurate representation for those who may not have visited the site. There are a few examples of papers using 3D modeling to portray archaeological objects (Brutto & Meli, 2012; Kersten & Lindstaedt, 2012).

This study aim is to explore the changes in the land/use cover in a Mediterranean site using very high resolution EO datasets with specific focus on the detection of the landscape's archaeological features. As a study site is selected the area of ltanos, Crete, where several known archaeological sites and remains exist. To achieve the study aim, three objectives were created, as follows: 1) to obtain a thematic mapping of Itanos with interest in the archaeological sites, 2) to quantify land changes with focus on archaeological sites, and, 3) to develop a 3D modelling of the known archaeological sites of Itanos and explore its use in mapping archaeological features using EO data.

2. Study Site

Crete is generally a Mediterranean-arid environment and this applies equally to the wider ltanos area (Karydas et al. 2009). It is a coastal region which is largely rural; there are no major settlements. The history of Itanos is one of importance to Cretan history, having been a site where both the Minoans and the ancient Greeks settled (Pendlebury, 1969). A number of studies have investigated the archaeological area of Itanos, mostly for mapping the expanse both surface and sub-surface (Vafidis et al., 2003; 2005). These were generally investigating both the surface and sub-surface remnants of the past civilisations of the area, mapping their extent rather than linking them to the historical knowledge.

Itanos was chosen to be used in this study through a number of defining factors, including its cultural importance. In addition, the availability of the satellite imagery played an influence in the size of the study site, ensuring that there was equal comparison between images but a small enough area to decrease processing times. The final extent decided upon is shown by **Figure 1** together with the three known archaeological sites, where the sites are highlighted, with their approximate extents outlined by red boxes.

[**Figure 1.** Extent of study site at ltanos, Crete, including the studied archeological sites in the area]

The three known archaeological sites are all within a relatively short distance near the middle of the eastern coast for the study site. Site 1 is an excavated area and is clearly a well-managed area. Site 2 is a small paved area that has no clear signs of management. Site 3, the southernmost of the three, is the largest and is a known basilica.

3. Datasets

Pleiades is a European system launched in 2011 by Airbus made up of two separate satellites: 1A and 1B. Pleiades imagery is accessible straight from Airbus or through the European Space Agency (ESA). The two satellites simultaneously orbit the Earth along the same path but at a time delay. This allows for multiple overlapping images of sites to be obtained which can be used in conjunction as stereo or tri-stereo analysis. The latter is allowing generating accurate high resolution Digital Elevation Models (DEM). This layer can be used subsequently to reveal hidden objects or steep sided slopes that might be non-existent or hard to identify in normal 2D images. The Pleiades system is a 4-band multispectral system of 2 metres spatial resolution but with an extra panchromatic band which is sub-2 metres. The latter characteristic enables modern studies to work on highly detailed, complex sites. In this study, four images were acquired from the Pleiades images archive (**Table 1**). These were the scenes with the least cloud cover, but the Pleiades scenes acquired ensured full coverage of the wider area of Itanos.

[**Table 1.** Pleiades scene information for the images used to study the wider ltanos area, Crete]

[**Table 2.** WoldView-2 scenes information for the images used in our study]

In addition, satellite imagery from the WorldView-2 (WV-2) was acquired to facilitate the study objetives. WorldView series represents one of the highest spatial resolution systems that they have developed so far. WV-2 is an 8-band multispectral system with a panchromatic band that has a spatial resolution of sub-2 metres. Two WV-2 images from the satellite archive were obtained, showing the Itanos area of Crete; these were cloud-free and dated approximately a year apart (**Table 2**). This meant that the resolution of the images was 0.41m panchromatic and 1.84m multispectral with the four standard bands of blue, green, red and near infrared 1, and also an extra four bands of coastal, yellow, red-edge and near infrared 2. As a result of its high resolution and increased band selection, WV-2 data has been identified as applicable to many situations and study types, including archaeology (Ghosh & Joshi, 2013). In addition to the above datasets, digital photographs were acquired onsite at the three archaeological areas within the study site during a field visit that took place in the summer of 2016. They were obtained using a lumix FZ45 digital camera and were of the standard RGB colour composite using the highest resolution available with the camera (14 megapixels).

4. Methodology

4.1. Pre-processing

The acquired WV-2 data had already been corrected geometrically and radiometrically, so no pre-processing corrections had to be performed. On the other, Pleiades, had two different options when requesting the data: Primary and Ortho. Primary is as close to raw data as it is possible to get, with only simple radiometric corrections having been used to correct sensor errors; this may be useful for pure photogrammetric studies set up to test different correction methods or apply extra processes before correction has occurred. Ortho already has a number of pre-processing techniques applied and is more commonly utilised by those wanting to get straight to GIS analysis. Ortho imagery from Pleiades has been geometrically corrected, including the application of orthorectification with a relief model. Ortho has the simple radiometric corrections used for primary data, but with colour balancing and pixel sampling as well. For the purposes of our study, atmospheric correction was performed to the Pleiades images acquired using the Fast line-of-sight Atmospheric Analysis of Hypercubes (FLAASH), available in ENVI (v 5.1) software.

The next step involved ensuring that any cloud within the scene is masked out. This is to make certain that there is no interference when performing other techniques, such as thematic mapping. All the satellite images in this study bar one have no cloud, so this did not apply to them. The image with cloud, Pleiades 1B March 2014, contained 1.2% cloud cover but, when clipped to study site extent, the cloud all resides in one area. A decision was made to exclude this image because it would be biased when compared to the other scenes and one of the other Pleiades images was from May of the same year.

Panchromatic sharpening (PS) is the process of using a high spatial resolution image to increase the spatial resolution of a high spectral resolution image (Laben & Brower, 2000). This permits more information to be garnered from the image, and from any resultant images, after other methods and techniques have been applied. The two satellite platforms being exploited, Pleiades and WV-2, both have a panchromatic band available and can, therefore, create a high spatial and spectral resolution product. The WV-2 data is provided as two separate scenes: a high spatial resolution single panchromatic band image and a low spatial resolution multispectral 8-band image. A decision was necessary as to which PS technique would be used. One of the newer PS techniques, 'Ehler's Fusion', has been gaining academic recognition for its ability to combine more than 3 spectral bands with the panchromatic band (Kionus & Ehlers, 2007; Ehlers et al., 2010), which, for imagery like the 8-band WV-2, can be very useful. This technique was implemented in our study using ERDAS IMAGINE software. An example of the Wolrdview image pansharpening effect is shown in **Figure 2** below:

Figure 2. Example of pan-sharpening a multispectral WorldView-2image (middle), using its panchromatic band (top) and using modified HIS method (bottom)

Subsequently, the normalised difference vegetation index (NDVI) was computed in each scene. NDVI is a spectral index that focuses on photosynthesis and chlorophyll abundance (Tucker et al., 2005). NDVI is computed from the red (R) and near infrared (NIR) spectral bands of an image enabling easy identification of 'healthy' vegetation. The index was created using ENVI for all of the satellite imagery because both Pleiades and WV-2 have the necessary bands. Once the NDVI was created for all five scenes, they were added as an additional layer into e-Cognition Developer with their respective images.

4.2. Classification

The aim of this study was to map the Itanos area with a focus on the three known archaeological sites, yet, one of these sites was later discarded from the analysis because of cloud coverage. To ensure that the features of interest were defined, the properties of the site were considered. One of the key advantages of remote sensing is the spectral information available. For archaeological sites this would be important as a means of distinguishing the remains of buildings from other classes, such as water, trees and even bare rock. Another aspect which is commonly noted is the shape of objects. An archaeological site may be expected to have a uniform, building-related shape, and this element was also included in our hypothesis for the present study. This would help emphasise differences from classes such as bare rock or scrubland, likely to be an irregular shape and not consistent. In order to take advantage of the above features that we assumed archaeological sites should have, an object based image analysis (OBIA) method was selected.

OBIA is a process that divides an image into small areas pixels or 'objects' and then the objects can be classified (Blaschke, 2010; Whyte et al., 2018;; Petropoulos et al., 2013). OBIA is based on dividing an image into numerous objects. 'compactness' - which designates the overall shaping of the final object. The other preparation for this process was deciding which layers had the most influence on the process. For the 4-band method, there are five layers: Blue, Green, Red, NIR and NDVI. It was thought that NIR would have a more defined threshold between pixels and therefore be a greater influence, so its weighting was doubled. The 8-band classification had the four extra bands, for which a weighting also had to be designated. It was decided to leave all four as standard, in order to keep a close comparison to the 4-band method.

A second segmentation process was used after the multi-resolution technique as it was not easy to detect the land cover beneath the objects and test classification became difficult when nearly all the objects were hard to group under specific rules. The second method employed was the spectral difference segmentation; this was used on the results of the first process to merge objects with spectral homogeneity within a defined band, signified by 'maximum spectral difference'. Once the segmentation had taken place, classifying the objects was the next step. Two decisions had to be made which would direct the classification: the classification system to be used and the selection of the classification technique.

The system adapted for this study is the CORINE classification system. This is a three-tier hierarchical system which has features that could be construed as a hybrid class composition in the lower tiers. A class for 'archaeological site' was added to create the new system. The selected classes were chosen to represent known classes within the study site; in general, the second-tier choices were taken so as to produce a classification with an appropriate level of detail and the class 'Archaeological Site' was added.

Having decided on segmentation of the images and on which of the classes to use, the next step was to select an appropriate method to perform the classification. Standard methods include: unsupervised, supervised, random-tree, support machine vectors, rule-based. The choice made was to use rule-based because it integrates well with OBIA, allowing the user to include the geometric properties with ease. It also grants the greatest control to the user to ensure specific areas are mapped correctly. The first rule-set outline was for the 4-band classification method. This outlines the order in which the classes were created and which properties were applied to do so. There are no definitive numbers in any of the rules as tweaking had to be performed on the rule-set to fit each individual scene. The second rule-set outline created used the 4-band method as its basis but integrated the other available bands of the WV-2 sensor when necessary. It was found that either replacing rules with the new bands, or using them as well, produced better classification results.

4.3. Accuracy Assessment

Validating land use/cover classifications can be done in different ways, the most common being the production of an error matrix which can give an overall accuracy and kappa coefficient (Congalton, 1991). This was achieved by performing an accuracy assessment for each of the classification products. The classifications were exported from eCognition Developer into Arcmap 10.3 where 640 random points were formed using the tool 'Create Random Points'; these were then equally distributed between the eight different classes to ensure equal assessment of each class. The points were then 'ground truthed' using Google Earth imagery of the same year to label each point with its real class. Since the images were from a specific period of time, the function to view old images was used in Google Earth, enabling the use of the closest image possible to the satellite capture times for a more accurate validation. These points were then overlaid on the classifications and their class as designated by each classification was noted. These were then formed into tables to compare the known class for each point with the classification representation for them. While many studies utilise the confusion matrix validation methods, an alternative is the McNemar test. This is a parametric method which is thought to be easy to implement (Manandhar et al., 2009; Petropoulos et al., 2012). Equation 1 shows how the test is performed:

$$x^2 = \frac{(f_{12} - f_{21})^2}{f_{12} + f_{21}} \qquad (1)$$

Where: x' (chi square value},fu (cases both wrongly classified by map 1 but correctly by map 2},f,, (cases correctly classified by map 1 but nat map 2}, fu (cases correctly classified by both maps).

Using the paired results from two different confusion matrices, it allows comparison of classifiers. This test was carried out to compare the different classifications produced from the different years as well as testing the 4-band against the 8-band methods.

4.4. Land Change Detection Mapping

To assess whether the land cover maps showed change, specifically focusing on the archaeological sites, with the use of Arcmap, the five 4-band classification products were compared to see if there was any change in archaeological site according to the different maps. This was achieved by comparing only the same sensor results (so Pleiades versus Pleiades, WV-2 versus WV-2) as there are differences in the sensors that cannot be accounted for in the study. The other test was to compare the 4-band and 8-band results of the WV-2 to get an idea of which classifications were improved by having four extra bands. Three more land cover changes were produced to compare the two 8-band products and then the 8-band results against their 4-band counterparts.

4.4. 3D Modelling

One of the key study objectives was to see if 3D modelling of archaeological sites could be of use and, if so, how accurate it could be. This was achieved using the photographs obtained through fieldwork. The first option was to use a UAV to collect the imagery as this could then be used for thematic mapping data source as well to compare another sensor platform. This option proved unavailable though, as a result of restraints on work to be carried out over archaeological sites in Crete set in place by the country's Ministry of Culture and Sport. However, as an alternative, the decision was made to simulate the effects of a UAV by collecting the photographs using a camera monopod. Photographs were collected from chest height, head height and finally elevated approximately a metre above head height with the camera angle slightly down. The method was used systematically to photograph the three known archaeological sites, around the edges of each site pointing inwards and- in the case of Site 3- both around the edge and throughout as it was the largest and most complex area.

With the photographs collected, the next step of the process involved the production of a point cloud and then a 3D model representation for all 3 sites. The software used to do this was Agisoft PhotoScan Professional, and this was used to produce the three different models. The results of this were exported into Meshlab, allowing the final product to be exported in a manner that represented the sites most closely. Next, these models were used for validation of the archaeological sites; the site class was laid over the models to see how closely the two resembled each other and whether one had a distinct advantage.

5. Results

5.1. Land Cover Classification using 4 Bands

The 4-band classifications follow the method outlined above, but are slightly different for each image. In WV-2 2013 March image (the earliest acquisition date image available) the sea, which dominates the right-hand half of the image, has been classified as such. The two classes that are widespread are the open spaces and the vegetation classes; these are the dominant classes on land. A large arable field has been identified at the centre of the image with a number of industry buildings to the south of it. The urban fabric class is mainly identifying the roads but has struggled with the industrial class, intermingling with the previously mentioned industrial buildings. The other issue for the urban layer is the amorphous shape in the centre of the study site which looks neither road nor building shaped. It is actually a bare land area by the roadside that should have been classified as open space. There is difficulty in distinguishing urban and open space in coastal areas. In sea and ocean areas, beach is not uniformly classified.

The three known archaeological sites are then compared to the visible images of the PS resultant satellite images (**Figure 3).** This is to give a visual inspection of how accurately the known sites were defined. Site 1 is a rectangular shaped site focused in one spot, where the classification has roughly depicted its boundaries but the shaping is more irregular than it should be; there are also areas of 'archaeological site' classified around the known site which are likely to be bare rock or ground. The second site has been overclassified - it is a very small site (3 metres) and it was expected to be converted into three pixel-sized objects but has spread slightly southward, once again getting confused with bare land. The final known site, both the largest and most complex, has been represented well; the east-west running walls have been identified and it is the rough extent of the site as well. The issues arise within the site, where bare land gets confused with the site detail and the curved wall does not keep its shape during classification. The validation of the site follows the methodology using a confusion matrix to calculate the accuracy of classification of elements within the sites. The end result was not inaccurate (over 70% correct), but there was a great division between the separate classes, some being much better than others (Overall accuracy: 73.44%, Archaeological Site Accuracy: 51.25%, Kappa Coefficient: 0.644, SE of kappa: 0.020).

[**Figure 3.** 4-band rule-set OBIA classification of three known archaeological sites at ltanos using War/dView-2, March 2013]

The Pleiades 2013 July image was classified using the 4-band rule-set guidelines. The archaeological sites (**Figure 4**) have changed from the first classification. Site 1 has become entrenched by urban classified areas, but the known section is still classified. Site 2 shows real improvement with the individual pixel being a good representation. The disappointment arises with Site 3; it has lost almost all of its outside walls and its north side has been classified as open space. Once again, the confusion matrix shows the validation and there has been a slight decline compared to the first image; slight improvement in the archaeological site classified as such being correct but now it has become under-represented in the scene. There has been a slight accuracy reduction for all the classes (Overall Accuracy: 71.17%, Archaeological Site Accuracy: 62.50%, Kappa Coefficient: 0.682, SE of kappa: 0.020).

[**Figure 4.** 4-band rule-set OBIA classification of three known archaeological sites at ltanos area using Pleiades,July2013]

In Pleiades 2014-May image Classification (a year on from the second image but in May, so mid-way between the seasons of the previous two images) there is a large improvement of archaeological Sites 1 and 3 (**Figure 5**); they have become more representative whilst limiting encroaching classes such as urban. Site 2 however has disappeared completely - small areas to the south of it have been classified but they are mostly bare ground and are too far from the coast to be Site 3. Accuracy has improved from both the previous images. Even though the known archaeological sites seem better represented than the 2013 Pleiades, there has been a decrease in the figures (Overall Accuracy: 76.88%, Archaeological Site Accuracy: 56.25%, Kappa Coefficient: 0.732, SE of kappa: 0.019).

[**Figure 5.** 4-band rule-set 08/A classification of three known archaeological sites at ltanas area using Pleiades, May 2014]

In WV-2 2014 August image Classification (4-band method still in use but back to the WV-2 sensor, now in 2014 towards the end of summer) the archaeological sites have changed once more; now it is 1and 2 that have been poorly defined due to interfering classes of urban, arable and industrial. Site 3 has been the most successful this time and looks very similar to the Pleiades 2014 image of it (**Figure 6**). Even though the classifications look poor in a number of areas, the accuracy is high in comparison to the previous images. The difference is that, while not many classes are outstanding, overall they are of a reasonable level of accuracy (Overall Accuracy: 77.19%, Archaeological Site Accuracy: 60.00%, Kappa Coefficient: 0.739, SE of kappa: 0.019).

[**Figure 6.** 4-band rule-set 08/A classification of three known archaeological sites at Itanos area using Wor/dView-2, August 2014]

In Pleiades 2016-May image classification (the final 4-band based classification is much more modern, but is in the same month as the Pleiades image of 2014) the archaeological sites (**Figure 7**) can once again be compared visually. The issue that occurred with Site 1 previously has happened again, an urban object has been identified nearly overlapping the site. Site 3 which has been the most consistent in previous images, has been classified once again but it is less elegant than those classifications. Instead of individual segments comprising the structure, one larger object has formed of the eastern site of the site and, though it defines the outer boundaries, it loses a lot of information. Site 2 has been ephemeral; some have classified it, others have completely missed it. This time it had been classified; it may have been slightly to the west of the site but this is open to interpretation. The archaeological sites have once again been one of the least accurate classes. The overall accuracy for this classification is not the best but is ahead of some of the early images (Overall Accuracy: 76.09%, Archaeological Site Accuracy: 60.00%, Kappa Coefficient: O.725, SE of kappa: 0.019).

[**Figure 7.** 4-band rule-set 08/A classification of three known archaea/agical sites at ltanas area using Pleiades, May 2016]

5.4 8 Land Cover Classification *using the 8 Bands*

In WV-2 2013 -March image classification (the first image from the 8-band method but this time with an altered rule-set) the use of the 8-band method has also been tested on the available imagery. The result looks almost plain in comparison to the 4-band method results. There are similarities in the ocean appearing on the right side and the open space and vegetation classes being widespread. The arable and industrial objects at the centre are once again classified but with precision, leading to no random offshoots. The main issue is with the urban fabric not being classified for the road leading north-west and classifying the southern coastal area instead. Archaeological sites have altered slightly as a result of the rule-set change. **Figure 8** shows them once again but there seems to be numerous smaller 'archaeological sites'. Site 1 demonstrates this very issue- while the site has been defined, so it has a lot of small random areas surrounding it. Site 2 is very similar to the 4-band version with some classification to the south of the site but not quite recognising the actual area. Site 3 looks very similar but has more breaks between the objects, possibly reflecting the likelihood of wear-and-tear expected in an archaeological site. The bare ground area to the west of the site has been wrongly included.

[**Figure 8.** 8-band rule-set 08/A classification of three known archaeological sites at Itanos area using WorldView-2, March 2013]

There is an improvement on the results of the 4-band methodology. It almost reaches 80% accuracy which for many studies is a reasonable statistical outcome. The archaeological site class has improved on the whole, as have vegetation and permanent crops. The main issue is with the urban fabric class (Overall Accuracy: 79.69%, Archaeological Site Accuracy: 61.25%, Kappa Coefficient: 0.768, SE of kappa: 0.018). In WV-2 2014-August image Classification (the 8-band version of the second WV-2 image in late summer) the final comparison to the RGB image can be made. The same issue has occurred with Site 1, on a smaller scale but an urban object appeared within the archaeological site. There are fewer false sites surrounding it though. Site 2 is probably defined as well as it has been previously; there is a definite archaeological site presence and it would be evident to anyone looking. Finally, Site 3 has been defined well again, the thin objects running west to east have been classified and there are no errant objects interfering apart from that bare ground patch to the west (which has shrunk). The archaeological class accuracy is the highest it has been of all seven classifications. The overall accuracy has been able to exceed the 80% mark. All of the classes have improved apart from issues apparent in the arable class (Overall Accuracy: 83.44%, Archaeological Site Accuracy: 76.25%, Kappa Coefficient: 0.811, SE of kappa: 0.017).

5.5 McNemar Tests

As explained in the methodology, the McNemar tests analyse data to see what the likelihood is that pixels were classified correctly by chance. The McNemar test results (**Table 3**) are formatted in chi-square, which are interpreted using a critical table of values. To do this a confidence level was chosen and the degree of freedom calculated. The degree of freedom for each test is 49 as there are 8 classes in both the row and the column of the confusion matrices, and the result is calculated by taking one away from each and multiplying them together (i.e. 7x7). Therefore for a 90% (0.01) confidence that the classifications are definitively different the value must exceed 1.4267 (Gordon et al. 1952). The figures show that only one of the map pairs may be related (and not by chance); these are the Pleiades 2014 and Pleiades 2016.

[**Table 3.** Results of McNemar tests]

5.6 Land/Use Change Detection

The land change detection is focused on the area of the known archaeological sites. There were three Pleiades images each producing one classification, so three change detections were performed: from the earliest image to the next; the middle to the most recent; and the earliest to the most recent. In May 2014 – May 2016 land change detection there is little change in the south. Change at archaeological Site 3 is apparent. Disappearance of a number of urban features is recognisable as well. The coast shows a small amount of shift on the horizontal plane. The archaeological class seems to decrease in the central northern zone around Site 1and vegetation starts to dominate. In July 2013 - May 2016 land change detection (**Figure 9**) there is very little change within the south of the images; the main differences occur in the central and northern portions. The main archaeological change that can be seen is Site 3, the largest most southerly site which seems to have swelled over the three years. The coastline also seems to have moved on an east-west plane. Site 1 is the next site to highlight, as there are definite differences between the two, a decrease in urban interference. The urban difference is very noticeable between the two images.

[**Figure 9.** Land change detection af the wider area af ltanos, using Pleiades from 2013-2016]

The land change detection of WV-2 images in March 2013 (4-band)- August 2014 (4-band) the largest visible changes are the arable and urban classes, the first increasing from 2013 to 2014 and the latter receding. The archaeological sites are relatively stable and there is not a significant amount of change, other than a slight shrinking at the known sites. In March 2013 (8-band) - August 2014 (8-band) the largest differences are in the urban areas; the road along the north thins out and the urban coastal zone in the south has disappeared. Vegetation distribution over the image changes especially in the south and the arable region appearing at the western edge. There is very little coastal shift and the archaeological sites do not change much. The main change in March 2013 (4-band) - March 2013 (8-band), is a decrease in urban area along the coast and from the western edge. Archaeological sites seem to shrink across the study region, especially site 3, but a few new areas appear near or on the road. There is little coastal change and a thinning of vegetation. In August 2014 (4-band) - August 2014 (8-band) the main changes are reductions in the number of errant arable and industrial patches across the image. Archaeological Sites 1 and 3 are relatively stable but Site 2 becomes visible thanks to the arable object being altered. It is mostly alterations of precision that occurred, such as objects slimming and errant zones becoming correct (**Figure 10**).

[**Figure 10.** Land change detection at the wider area at ltanos, using 4-band WV-2 tram 2013 versus 8-band WV-2 tram 2014]

5.7 3D Modelling Findings

The 3D modelling performed for each of the archaeological sites produced a single model. The models are shown from an aerial perspective for greatest comparison to the satellite imagery. The first site 1 (**Figure 11**) that was visited allowed for easy access due to previous work done to excavate and record structures that identified the objects of importance. Site 2 (**Figure 12**) was the smallest and -perhaps- the least important for useful archaeology. It does contribute, in an academic sense, to thinking on site size and complexity and how these affect mapping and modelling. The edges of the site are quite blurred as the photos taken were limited by its placement on a cliff path and a large shrub obscuring one side from easy access. A portion of sky has been modelled along the edge of the bush, which may cause the transfer of erroneous information by those who did not conduct this study. Site 3 (**Figure 13**) is the most complicated and largest site. The structures which can be found show that intricate and thoughtful architecture was implemented. The curved sections along the central portion of the site can be easily recognised and seen in proportion and relevance to the rest of the site. Once again, the edges have blurred slightly, mainly around the large shrub-like vegetation.

[**Figure 11.** 3D model of archaeological Site 1 in ltanos, Crete.]

[**Figure 12.** 3D model of archaeological Site 2 in Itanos, Crete.]

[**Figure 13.** 3D model of archaeological Site 3 in Itanos, Crete.]

6. Discussion

Thematic mapping of Itanos, with interest in the archaeological sites was achieved by using data from two different sensors and across a period of three years. Other studies had carried out similar works in the area but they had focused on sub-surface methods and hyperspectral aerial platforms for data (Rowlands & Sarris, 2007). This study attempted to use high resolution multispectral to perform a comparable role. The methodology used was a rule-based OBIA classification. It was thought that it would be one rule-set that would be applicable to all the images and would allow for direct comparison. This was not the case because of the difference in band data between the separate images. Instead, the outline was created: the class creation order - which bands needed to be used and then it was tweaked for each image.

The use of OBIA was vindicated when it was a combination of spectral and spatial properties that allowed for the classifying of the archaeological sites to a decent degree. There is no agreed criterion of a minimum size that objects should be for OBIA, but it can alter the results significantly (Kim et al., 2008). So, the option to make the objects small enough so that a few of them comprise a feature of interest, but not so small that they are single pixels, was decided upon. This is what led to the use of two segmentations, the first to break the image up and the second to ensure that their size fitted the focus -that is, the archaeological sites. The class which seemed to be mistaken for archaeology (and vice versa) was mainly open spaces, but there were also issues with urban and vegetation. These are likely to have been due to the spectra being close to homogeneous. The bunching of the spectra towards the red and NIR wavelengths made it difficult to classify separately.

The overall accuracy of each classification was of a reasonable standard, being greater than 70% which is a recognised threshold of good classifications (Petropoulos et al., 2012; Markogianni et al., 2018). An example of this is Thomlinson et al. (1999) who suggest that an overall accuracy exceeding 80% and all class accuracies over 70% indicate a good classification. This is, at best, a guideline and it is wholly dependent on what need the classification is satisfying. One of the ways that this classification may have been improved for the purpose of it was to only use two classes - archaeology and everything else. This would allow for the rules to be biased towards the archaeological site class and the remainder can be grouped together. This might allow for more accurate mapping of the class but would decrease understanding of which classes are most similar and which needs ought to be balanced.

The archaeological accuracies were not so high; on all of the images, a number of objects which were not the known archaeological sites were classified as such. Some of these extraneous objects were confirmed as 'archaeological sites' through the validation but others were not. This reiterates the problem that Parcak (2009) raised when questioning what makes an archaeological site; not just its physical attributes (spectra, location, geometry etc.) but the non-physical links to the past and information that it may hold on the past. This causes an over classification of archaeology because what is selected based on its physical properties could be rejected on the significance of the information it holds. This was the case here with the class accuracy being so low for all the images; this is an issue that will arise whenever a property like archaeology is being quantified by set rules or numbers. This is not purely negative either: it still has a use in identification, not just for definite sites but for those with high likelihoods of having matching characteristics.

The second purpose of this investigation (i.e. the land change detection with focus on archaeological sites.') was conducted multiple times to highlight the differences that such a wide variety of data could produce. Firstly, concentrating on the site itself by analysing the two different sensors along their time series, to see if there had been any change in the known archaeological sites. There were quite visible differences from 2013 to 2014 using both the Pleiades and the WV-2 and then to 2016 with just the Pleiades. The two Sites changing the most were 1 and 3, the third site enlarging reasonably significantly. This is of great interest as substantial change in an archaeological site is unexpected except for three reasons: excavation (Rinaudo et al., 2012), hazard (Grossiet al., 2007; Sdao & Simeone, 2007; Rodriguez-Pascua & Perez-Lopez, 2011) or vandalism (Matero et al., 2013). All three can be disastrous for a site if not prepared for or dealt with after the event. So the fact that the change detection revealed large differences between the years could indicate something further to investigate.

The land change detection became of most use when observing the differences between the two different rule-sets employed using the WV-2 data. The side-by-side comparison revealed a lot of information at a glance, where comparing confusion matrices would take time, effort and understanding. Once again, it is down to source material of the accuracies to be able to say definitively whether the results of this analysis were correct, but even so the use of this technique has developed from a simple time comparison. The land change detection would have been more effective on a higher temporal scale; the gap of a year is potentially too great to be of use for many cases as one event may have occurred and a second one changed it back.

The final objective which was a factor in the study (3D modeling of the known archaeological sites of ltanos') was achieved and was the greatest success of the three different objectives. It cannot be quantified in data, but a visual comparison of the satellite imagery with collecting the digital photographs in the field allows an insight into what each site looks like and the models do a very good job representing that. The use of the models was two-fold in this study. First, to assist validation of the classification, overlaying one onto the other allowed for the extent of the sites to be known, as well as the more central areas of the site - especially Site 3 which had many complexities. The second use of the models is to indicate how helpful this sort of methodology is; even if it is lacking the advantages of obtaining the image remotely, making field-work a necessity, it still achieves results that satellites so far have not yet achieved. If the 3D process was repeated on a regular basis, it could be viewed as a form of land change detection as well, but its use would be slowed by the time constraints that would be caused in the necessary data collection and heavy duty processing.

7. Conclusions

The main objective of this study was to map the land cover of the Itanos area of Crete, with specific focus on the detection of the landscape's archaeological features. The following main conclusions can be drawn upon the present study:

- Our study showed that very high resolution EO sensors allow for archaeological sites to be located to a reasonable degree of accuracy, but the detection accuracy is dependent of the EO instrument spatial and spectral properties and the features of the archaeological site itself that we look to identify/map in each case. Separation of the archaeological features from a spectrally similar background (e.g. rock types, dense vegetation). The results showed that having the additional four bands of information was an asset in detection accuracy but this was counterbalanced by the added tweaking of the system necessary to fit each scene.
- The land change detection worked to identify differences between the classifications. The issue with this is that the technique is reliant on the source data so, if the accuracies of the input images are low, then the resulting land change detection may not be a good representation. The greatest benefits revealed were the difference between the two different rule-sets and the visual impact those four extra bands can produce.
- The 3D modelling in this study, it once again proven itself to be of great uses and has a definite application in both field archaeology and modelling archaeological finds. The use it has been with relevance to the other two objectives has been a revelation; its use of validation and the idea of a land change detection method being developed with it have exceeded expectation. The studied archaeological sites were all modelled and the method used was successful, especially given that the process developed as a result of the practical issues encountered with UAV use in the area.

Future studies should utilise satellite imagery from the same sensor or UAV data at similar times each year, to make monitoring as accurate as possible. Other considerations will be to use the ever- increasing resolutions of satellites and to try to incorporate more shape-based ruling into identifying archaeological remains and develop accurate and 3D modelling structures of such sites. The results from such efforts remain to be seen in the coming years.

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Author Contributions

ARB conducted the research described in this study under the supervision and guidance of GPP and GPP together with LT and PKS and prepared this manuscript for submission to the journal.

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