International Journal of Digital Earth

ISSN: 1753-8947 (Print) 1753-8955 (Online) Journal homepage: http://www.tandfonline.com/loi/tjde20

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INTERNATIONAL JOURNAL OF DIGITAL EARTH, 2017
VOL. 10, NO. 1, 85–102
http://dx.doi.org/10.1080/17538947.2016.1250829

Remote sensing heritage in a petabyte-scale: satellite data and heritage Earth Engine© applications

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ABSTRACT

This paper aims to demonstrate results and considerations regarding the use of remote sensing big data for archaeological and Cultural Heritage management large scale applications. For this purpose, the Earth Engine© developed by Google© was exploited. Earth Engine© provides a robust and expandable cloud platform where several freely distributed remote sensing big data, such as Landsat, can be accessed, analysed and visualized. Two different applications are presented here as follows: the first one is based on the evaluation of multi-temporal Landsat series datasets for the detection of buried Neolithic tells ('magoules') in the area of Thessaly, in Greece using linear orthogonal equations. The second case exploits European scale multi-temporal DMSP-OLS Night-time Lights Time Series to visualize the impact of urban sprawl in the vicinity of UNESCO World Heritage sites and monuments. Both applications highlight the considerable opportunities that big data can offer to the fields of archaeology and Cultural Heritage, while the studies also demonstrate the great challenges that still are needed to be overcome in order to make the exploitation of big data process manageable and fruitful for future applications.

ARTICLE HISTORY
Received 30 July 2016
Accepted 10 October 2016

KEYWORDS
Big data; remote sensing; archaeology; cultural heritage; Earth Engine; orthogonal equations; urban sprawl

1. Introduction

Remote sensing archaeological research has been motivated during the last decades and especially after the launch of the first high-resolution satellite sensor IKONOS in 1999, for the systematic exploitation of earth observation data. Recent studies (Agapiou and Lysandrou 2015; Tapete and Cigna, forthcoming) reported a constant increase of applications in the literature oriented towards the exploitation of earth observation data, either by optical or active space sensors. Traditional remote sensing applications in archaeology and cultural heritage involved the exploitation of satellite data or products for the detection of buried archaeological remains (Bjoern et al. 2012; Agapiou et al. 2014; Chen et al. 2015; Reinhold, Belinskiy, and Korobov 2016); for the study of the temporal evolution and changes of the archaeolandscape (Alexakis et al. 2011; Min 2012); for the prediction modelling or automatic recognition of archaeological sites using spatial analysis and statistics from satellite datasets and products (Jahjah and Ulivieri 2010); for the monitoring of archaeological sites and monuments against natural and anthropogenic hazards (Lasaponara, Danese, and Masini 2012; Agapiou et al. 2015a), as well as other targeted applications for supporting archaeological

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questions in specific areas of interest (De Laet, Paulissen, and Waelkens 2007). In addition, new potentials from the exploitation of space-borne synthetic aperture radar (SAR) sensors have been also presented in the literature (Cigna et al. 2013; Stewart, Lasaponara, and Schiavon 2014; Chen et al. 2015; Tapete, Cigna, and Donoghue 2016), while the use of Persistent Scatterer Interferometry has been efficiency used for multispatial/temporal hazard assessment of cultural heritage sites and historical centres (Stramondo et al. 2008; Gigli et al. 2012; Tapete and Cigna 2012).

However, new developments in Big Data and mining are expected to impact the up-to now traditional and novel methodologies applied in the scientific field of 'remote sensing archaeology', since they offer an extensive quantity of data, characterized by a certain complexity and growing data (Sharma 2016) generated by many distinct sources (Wang et al. 2016). Big Data can be defined as 'Large, diverse, complex, longitudinal, and/or distributed data sets generated from instruments, sensors, Internet transactions, emails, videos, click streams, and/or all other digital sources available today and in the future' (National Science Foundation 2012, 2). In addition, as Gobble (2013, 64) states, 'big data can also include data which are either moving too fast, or even because these are not -yet- structured in a usable way'. Actually, Gil and Song (2016) argue that the term 'Big data' is very broad, and the single attention to the 'Big' word should be avoided, and recommends to focus also on the difficulty of dealing with such data in different dimensions. The actual pattern and nature of such Big Data is indistinct, but it is certainly large, complex, heterogeneous, structured and unstructured at the same time (Sharma 2016).

Currently, Big Data applications are playing a critical role in terms of decision-making and forecasting domains such as business analysis, product development, loyalty, healthcare, clinicians, tourism marketing, transportation, etc. (Wang et al. 2016). Therefore, Big Data is rising as a new solution to common problems found when processing large amounts of data, such as remote sensing datasets (Merino et al. 2016).

Remote sensing is a rapidly advancing technology, mainly driven by imaging sensor developments (Toth and Jóźków 2016). In the last years, a variety of new sensors have been launched providing additional information to end uses. For this reason, Ma et al. (2015b, 48) argued in their recent study that 'with the exponential growth of data amount and increasing degree of diversity and complexity, the remotely sensed data can be viewed as 'Big Data''. The new generation of space-borne sensors is generating nearly continuous streams of massive remote sensing imageries sending several Terabytes of information every day to the satellite data centres (Ma et al. 2015a). Free and open access remote sensing data including Landsat series, Sentinel datasets, MODIS images or DMSP-OLS Night-time Lights Time Series enabled researchers to exploit the benefits of Earth Observation. Since 1972, Landsat satellites are continuously acquiring space-based images of the Earth's land surface, providing valuable data. Currently, Landsat 8 LDSM and Landsat 7 ETM+ are acquiring over 1200 new images per day (USGS, Landsat Missions 2015). Compare to Envisat satellite which was providing 0.3 terabyte (TB) per day (before their failure in 2012), the daily volume of Sentinel-3A and Sentinel-1A/1B data are expected to be increased to 1.6 TB (DLR 2016). In addition, the Sentinels-2A and -2B series are collecting more than 400 TB per year.

A number of remote sensing applications have been already applied in regional and global scale for monitoring forested areas (Hansen et al. 2013; Sexton et al. 2013), deceases (Liu et al. 2015; Kazansky, Wood, and Sutherlun 2016) or even for global emergencies (Voigt et al. 2016a), based on Big Data information. Nevertheless, many challenges still occur when using such big data (Voigt et al. 2016b). As Wang et al. (2016) state, the application of remote sensing, generally follows a complex multi-stage processing chain, which consists of several independent processing steps. In addition, the use of large scale data with conventional algorithms can be very time and space (memory) consuming (Zheng et al. 2016). Moreover, data quality and usage, for remote sensing big data applications, need to be re-examined since the traditional methods have shown to be inadequate for properly describing data quality and potential use of these data (Liu et al. 2016). Therefore, novel methodologies and strategies are needed to be developed, tested and improved so as to extract useful information from huge multi-temporal datasets. In this new framework, the archaeological community and other researchers interested in the protection and further exploitation of earth observation data for tangible cultural heritage, need to work closely together to meliorate and finally maximize the impact of big earth observation data in these scientific fields.

With the recent availability of space sensors, new ways of collecting geospatial data have been emerged, leading to completely new data sources and data types of geographical nature (Li et al. 2016). Indeed, time series analysis of a large numbers of SAR images which has been recently presented in the literature – especially after the recent advanced mapping capabilities at high-resolution offered by COSMO-SkyMed and German TerraSAR-X sensors – (Lasaponara and Masini 2013; Linck et al. 2013; Cigna et al. 2013), have provided new types of data sources and products for archaeological research.

This paper aims to demonstrate some of the first attempts of how big data and big data platforms such as the Earth Engine© can be used for supporting archaeological research and Cultural Heritage management. Two examples are provided, in the first case study Landsat multi-temporal series have been used for the detection of buried archaeological remains, while in the second case study DMSP-OLS Night-time Lights Time Series have been used for the systematic monitoring of UNESCO World Heritage sites in Europe against urban sprawl for a long period (1992–2013). The analyses performed exploited a huge amount of the freely remote sensing datasets, covering extensive geographical areas. Such an approach would have been considered in the near past as inapplicable mainly due to the personal computers capabilities.

The paper is structured as follows: in Section 2 the Earth Engine© and some of the products that are currently supported by the specific platform are presented. The methodological approach followed in the present paper, alongside the cases studies and the data used are described in Section 3, followed by their applications within the Earth Engine© platform. Discussion about considerations and opportunities raised by the case study applications is presented in Section 4 and the paper ends with the conclusions exposed in Section 5.

2. Earth Engine© and products

Earth Engine© (Google Earth Engine Team 2015) has been recently released by Google© as 'a platform for petabyte-scale scientific analysis and visualization of geospatial datasets'. The Google Earth Engine© actually is a computing platform which can be used to run several applications of geospatial analysis using Google's infrastructure. The Earth Engine© enables researchers to access a tremendous petabyte of satellite information for global and large scale remote sensing applications. The data, already organized in the platform include historical images, which could be of great importance for archaeological and cultural heritage applications. The online platform can be expanded and modified by the user even for customized applications. The platform can be accessed by the users – upon approval by Google – either by the so call Core Editor or the Explorer. The latter is an easy web access point to the platform – with no need of programming skills – where the user may add remote sensing datasets as well as to apply some standard image analysis techniques (e.g. algebra between bands, image filters, etc.). The Core Editor is suitable for rendering the development of complex geospatial workflows fast and easy. Though, knowledge of programming (JavaScript) is needed, several remote sensing algorithms are already catalogued and can be directly used or customized. This approach makes easiest the advance use of the Core Editor interface even for researchers without any special programming skills.

The Engine includes several remote sensing datasets, freely accessible and open data. Amongst others, through the Engine the users can access Landsat series datasets (from 1972) and Sentinel SAR 1 products (from 2014). For Landsat datasets, user can access through the Earth Engine© either in their raw form (Digital Numbers) or as top of atmosphere (TOA) corrected reflectance products. In addition, other ready-to-use computed products such as Normalized Difference Vegetation Index (NDVI) and enhanced vegetation index vegetation indices are also accessible. Other satellite datasets like Moderate Resolution Imaging Spectroradiometer and Defense Meteorological Satellite Program's

Operational Linescan System (DMSP-OLS) products are also available. The latest consist of a large imagery database of night-time lights at approximately 1-km resolution continuous since 1992.

3. Methodology and case studies

3.1. Case studies

3.1.1. Case study 1: Thessaly region, Greece

Thessaly is an extensive plain region located in Central Greece. According to Alexakis et al. (2009) in this area several Neolithic settlements called 'magoules' (tells) can be found. These Neolithic settlements are usually described as low hills of 1–5 m height and mean diameter of 300 m. Neolithic Thessaly has been studied for understanding human partitioning and territoriality of the landscape by non-hierarchical human groups. In this area, several remote sensing applications have been applied in the past (Alexakis et al. 2009, 2011; Agapiou, Hadjimitsis, and Alexakis 2012; Agapiou et al. 2012; Orengo et al. 2015).

For this case study Landsat TOA reflectance data have been used from 1999 to 2012. Since the early 1970s, the Landsat sensors have been widely used in archaeology for a variety of archaeological applications (Giardino 2011). The sun-synchronous orbit sensors are mounted on the various multispectral platforms covering from visible to infrared part of the spectrum providing systematic coverage from the seventies until today to several sites around the world. Currently Landsat 7 ETM+ and Landsat 8 LDCM are in orbit providing new acquisitions every 16 days. Using the Earth Engine©, a variety of multi-temporal analysis was performed in reasonable time (less than a minute). Figure 1 presents the annual reflectance TOA over the area of Thessaly. As it is demonstrated, 'magoules' are detected due to the variations of the spectral profile of the site compared to its surrounding cultivated area. However, visual interpretation is not always easy to perform since these variations – also known in the literature as crop marks – need to be enhanced using image analysis processing (Agapiou, Hadjimitsis, and Alexakis 2012).

In order to improve the interpretation of crop marks, linear orthogonal equations have been recently proposed in the literature (Agapiou et al. 2015b; Agapiou 2016). These equations are sensor sensitive and therefore for each satellite image a different equation should be used (Agapiou et al. 2013; Agapiou 2016). For instance, for Landsat ETM+ sensors the orthogonal equations are given below. These equations have been implemented in the Earth Engine© API and applied to the Landsat TOA reflectance data provided by the Google Engine.

$$\text{Crop mark}_{\text{Landsat 7 ETM+}} = -0.42\rho_{\text{blue}} - 0.69\rho_{\text{green}} + 0.21\rho_{\text{red}} - 0.55\rho_{\text{NIR}}, \quad (1)$$

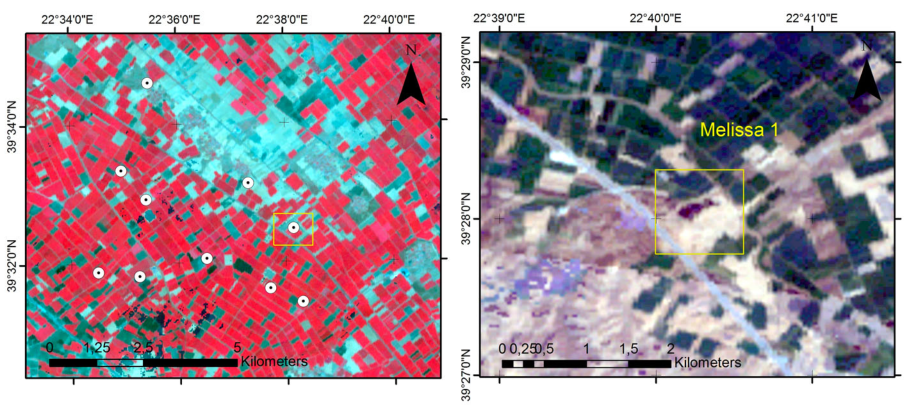

Figure 1. Annual Landsat reflectance TOA image over the Thessalian plain in the NIR-R-G pseudo colour composite (left). Known Neolithic tells are also indicated as points in this image. On the right the *Mellissa* 1 tell as seen in the true colour R-G-B.

$$\text{Vegetation}_{\text{Landsat 7 ETM+}} = -0.34\rho_{\text{blue}} - 0.41\rho_{\text{green}} - 0.65\rho_{-(\text{red})} + 0.53\rho_{\text{NIR}}, \quad (2)$$

$$\text{Soil}_{\text{Landsat 7 ETM+}} = 0.12\rho_{\text{blue}} + 0.22\rho_{\text{green}} - 0.73\rho_{\text{red}} - 0.64\rho_{\text{NIR}}. \quad (3)$$

3.1.2. Case study 2: UNESCO World Heritage sites

In the second case study, a larger scale application was performed, using the Earth Engine© capabilities. The purpose of this analysis was to estimate the changes in terms of urban expansion in the vicinity of Cultural Heritage sites in Europe, Middle East and North Africa regions. For this reason, all UNESCO World Heritage sites have been used (2015) as demonstrated in Figure 2. The list includes both natural and cultural heritage sites, as well as combination of the two.

Annual DMSP-OLS Night-time Lights Time Series Version 4 data for the period 1992 until 2013 have been used. As Hsu et al. (2015) discuss that night-time lights are unique among global remote sensing data products for their high correlation to human activities. These kinds of data (version 4) consist of cloud-free composites made by using all the available archived DMSP-OLS smooth resolution data. As it stated, by the Earth Engine©, in the cases where two satellites are collecting data – two composites are produced. From these sources the stable lights value has been mapped. Stable lights values refer mainly to the lights from cities, towns and other sites with persistent lighting, including gas flares. Ephemeral events such as fires have been discarded. The background noise was identified and replaced with values of zero (Google Earth Engine© 2015; see more at Imhoff et al. 1997).

The visible pixels of these images have relative values ranging from 0 to 63, rather than absolute values in Watts per m^2. Night lights are known to overestimate the spatial extent of development at the periphery of settlements and for this reason a low light threshold of 89% is proposed (Imhoff et al. 1997; Small et al. 2011). Doll (2008) argues that there is no single threshold that can be applied which would match the urban delimitation for all cities. However, despite these difficulties,

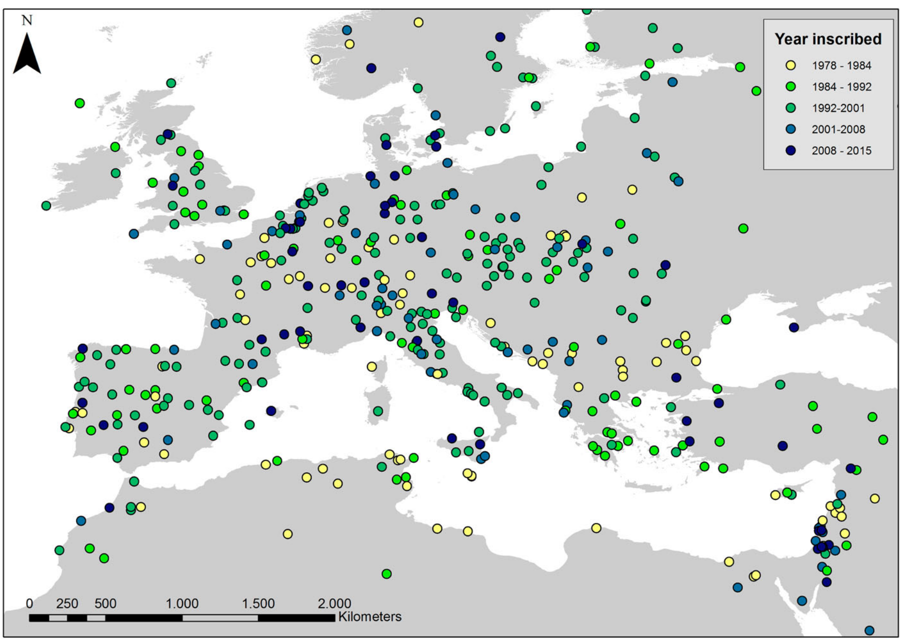

Figure 2. UNESCO World Heritage sites in the area of Europe, Middle East and North Africa regions per year of inscription (source UNESCO 2015).

DMSP-OLS Night-time Lights Time Series data are used in the literature as an information source to detect human settlements and to estimate the urban population (Amaral et al. 2006). Similar approach was also applied by Agapiou et al. (2015a) for monitoring urban expansion of Paphos district in Cyprus using both DMSP-OLS Night-time Lights and archive Landsat satellite datasets.

Based on these annual datasets and the coordinates of the UNESCO World heritage sites, stable light values for each site was created in a GIS environment (ArcGIS v10.2). Then, the diachronically evolution of urban sprawl as this is recorded by the stable lights was plotted.

3.2. Applications

3.2.1. Case study 1: Thessaly region, Greece

In the first case study, at Thessalian plain, Landsat 7 ETM+ images (TOA calibrated images), available from Earth Engine© were used. In the beginning, the reflectance values over the detected 'magoules' (i.e. tells) have been extracted from the Earth Engine©. As it was found these reflectance values of the tells can be very close to the surrounding cultivated area of the Thessalian plain. In Figure 3, Landsat images acquired between the period of 1 January 2000 and 1 January 2010 have been processed using the Earth Engine© API (in total 370 satellite images). The NDVI for two sites has been extracted from the Earth Engine© in csv format and then processed in spreadsheets. The first site refers to the *Melia 1* Neolithic tell (coordinates: 22.590065°, 39.548588° World Geodetic System (WGS) coordinate system), while the second site is from the surrounding cultivated area (coordinates: 22.586832°, 39.545672° WGS coordinate system). As it is shown in Figure 3, in several images the absolute NDVI difference of these two sites is in between the pre-calibration radiometric accuracies and limits of the Landsat sensors (i.e. 5%) (Trishchenko, Cihlar, and Zhanqing 2002; Agapiou, Alexakis, and Hadjimitsis 2014), and therefore not a statistical bias conclusion can be carried out. In addition, it is clearly demonstrated that in some cases the difference recorded can be maximized over and above of 20% which should be associate with the different phenological stage of the crops between the two sites (i.e. full growth and beginning of the phenological cycle).

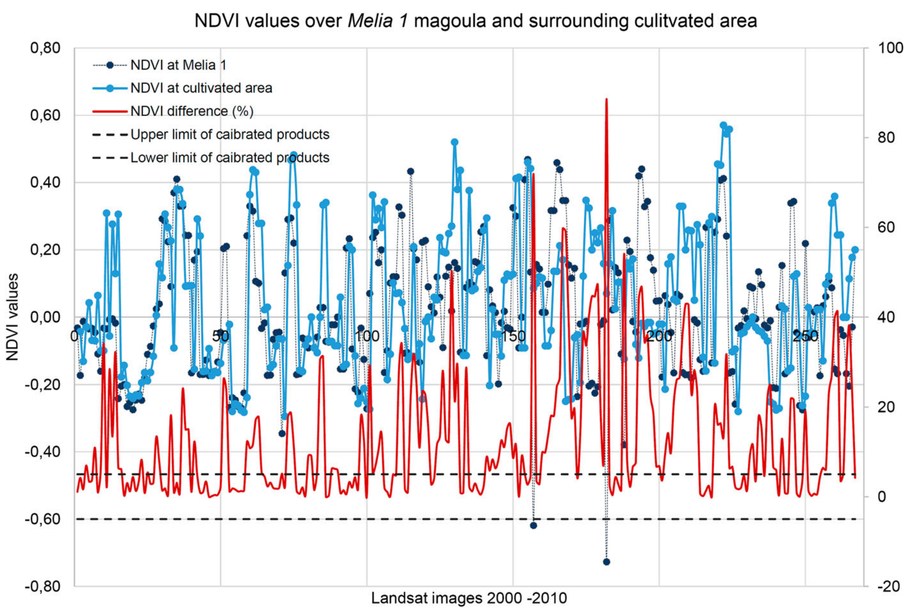

Figure 3. NDVI values calculated for the period 2000–2010 for two case studies: Melia 1 Neolithic tell and a cultivated site in the surrounding area. The absolute difference (in %) between the two sites is presented in red colour. Radiometric limits (errors) of the Landsat sensor are also shown.

In addition, within the Earth Engine© online platform, the orthogonal equations (see above Equation (1–3)) have been applied for the images between 1999 and 2002, and then the new products (i.e. 3 bands: crop component, vegetation component and soil component) have been downloaded. This period was selected due to the Scan Line Corrector (SLC) error (see more in USGS, SLC-off products 2015) observed in Landsat 7 ETM+ data since 2003. This dataset (i.e. 2003–2016) are discussed in Section 4. Figure 4 shows the results after the application of the crop component (Equation (1)). Red squares indicate all the up today known Neolithic tells of the area under examination. The size of the area is approximately 15 km length and 12 km width for a total area of approximately 180 km^2. A detail of a tell (Melissa 1, highlighted with yellow square) is indicated in the top right part of the figure. The figure evidences that the various tells are found in a relatively close proximity between them, while a gap of information (i.e. north-east area) is detected. The Neolithic tells are seen in Figure 4 as pixels with spectral difference from the surrounding cultivated area. Medium pixel resolution of the Landsat series (i.e. 30-m pixel resolution) is sometimes problematic for such investigations, however, the used datasets allowed the study and visualization of the landscape under examination before any major modem alteration of the environment occurred (e.g. urban expansion; intensive agriculture; adequate infrastructures in the area such as Karla Lake etc.). Neolithic tells identified from visual inspection and interpretation from this dataset are indicated in the same figure as green squares. These tells are recognized based on the different spectral behaviour compare to its surrounding cultivate areas and with their size and shape properties (i.e. 2–4 pixels' dimensions and almost circular shape). Crop component was able to maximize – for most of the tells – the spectral distance between the areas of interest (i.e. tells) and the surrounding cultivated areas. Since, Figure 4 indicates the average results of the whole Landsat dataset for the period 1999–2002, this improve the hypothesis that this multi-temporal spectral difference observed in the recognized tells (i.e. with green square) is not a noise. Tells with no clear spectral indication (i.e. nit indicated with green square) are

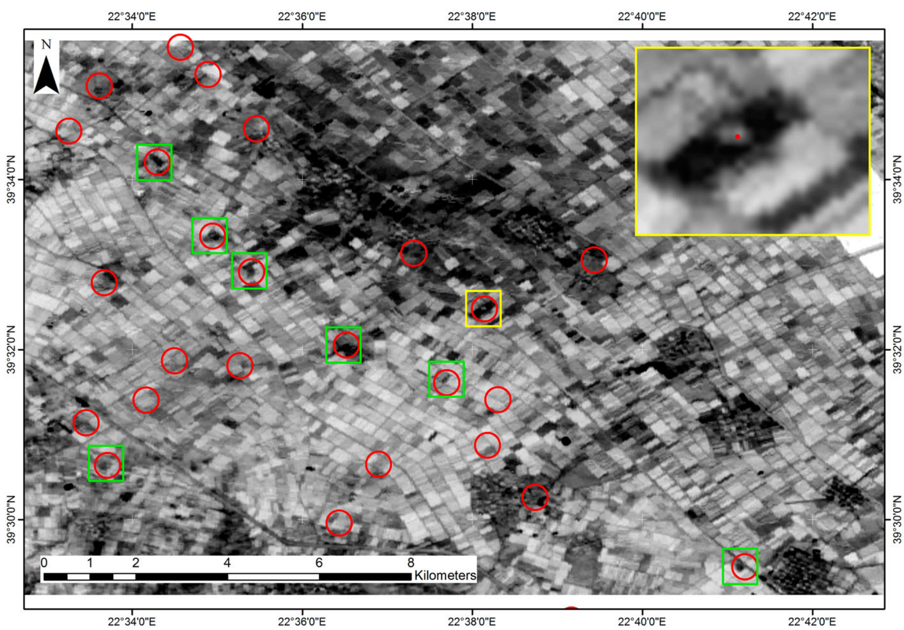

Figure 4. Results from the crop component band applied in the Landsat 7 ETM+ series for the period 1999–2003. Red squares indicate all the known Neolithic tells of the area (approximately 180 km^2). Green squares show tells identified from visual inspection and interpretation of the Landsat images. A known tell, Melissa 1, is highlighted with yellow square and indicated in the top right part of the figure.

probably already flatten areas, used for agricultural purposes and therefore no significant signal can be recorded.

A similar approach was followed for the other two bands derived from the orthogonal equations: (a) the vegetation component demonstrated in Figure 5 and (b) the soil component presented in Figure 6. Again, Neolithic tells recognized by visual interpretation are highlighted in these two figures in green squares. While the majority of the sites can be only seen in a single component band, other sites might be also visible in more than one component. As it is shown from Figures 4–6, almost 33% of the tells (eight tells in total) are recognized in one of the components, while 15% are spotted in two components (four tells in total) and only 10% can be identified in all components (two tells in total).

The overall results from this extensive dataset (Landsat 7 ETM+ images from 1999 to 2002) are shown in Figure 7. From the total application analysis, it was found that more than 50% of the known Neolithic tells were identifiable from visual interpretation of the crop, vegetation and soil components. Given the medium resolution used in this example, as well as the capabilities of the Earth Engine© to explore additional data from different periods, the success rate of the results is very promising.

3.2.2. Case study 2: UNESCO World Heritage sites

For the second case study, UNESCO World Heritage sites at a European, Middle East and North Africa regions level have been examined. DMSP-OLS Night-time Lights Time Series Version 4 data for the period 1992 until 2013 have been downloaded from the Earth Engine© platform and inserted into the ArcGIS v10.2 software for further analysis. Stable lights for this period –with a 4-year interval (i.e. 1992–1996, 2000–2004 and 2008–2012) – were visualized and shown in Figure 8. Red colour in Figure 8 indicates areas with higher value of stable lights, a parameter which is linked to the presence of urban areas. Therefore, multi-temporal analysis of this dataset is suitable as a

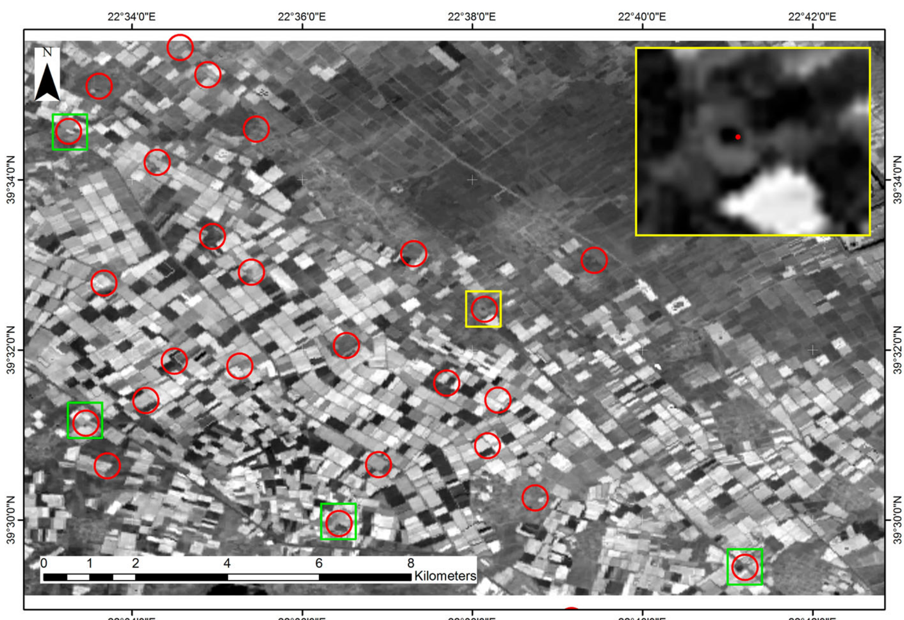

Figure 5. Results from the vegetation component band applied in the Landsat 7 ETM+ series for the period 1999–2003. Red squares indicate all the known Neolithic tells of the area (approximately 180 km^2). Green squares show tells identified from visual inspection and interpretation of the Landsat images. A known tell, Melissa 1, is highlighted with yellow square and indicated in the top right part of the figure.

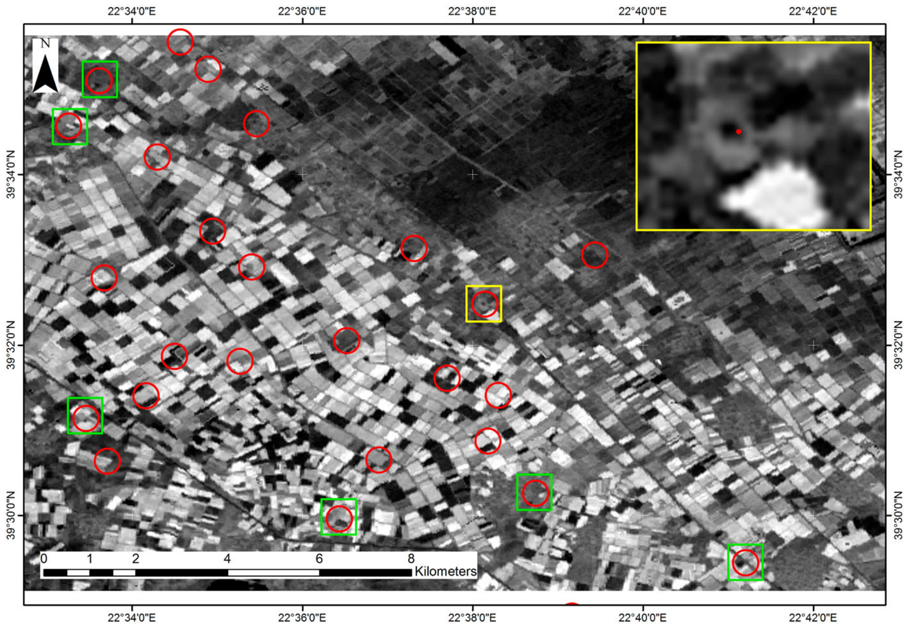

Figure 6. Results from the soil component band applied in the Landsat 7 ETM+ series for the period 1999–2003. Red squares indicate all the known Neolithic tells of the area (approximately 180 km^2). Green squares show tells identified from visual inspection and interpretation of the Landsat images. A known tell, Melissa 1, is highlighted with yellow square and indicated in the top right part of the figure.

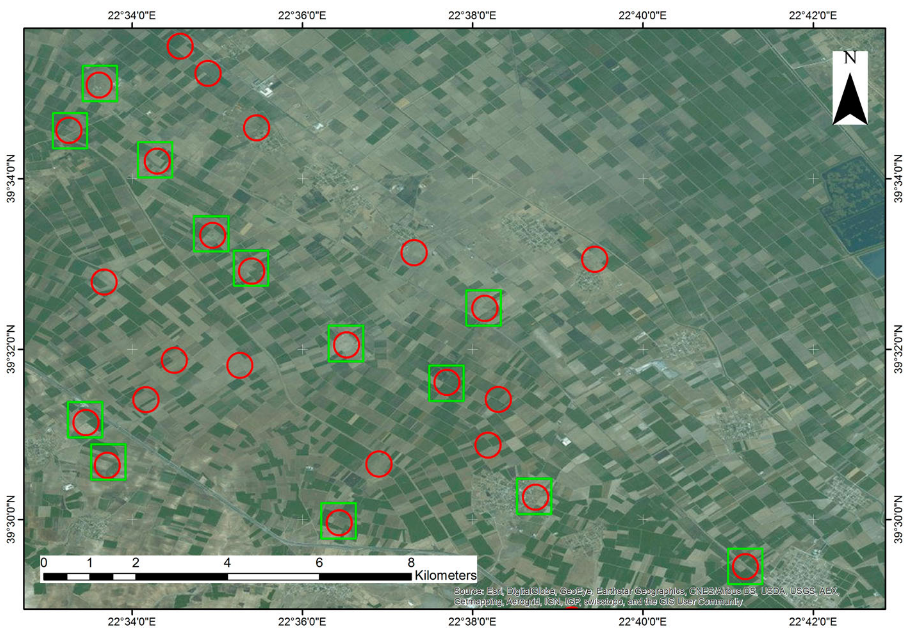

Figure 7. Overall success results after the application of the orthogonal equations for Landsat 7 ETM+ series for the period 1999–2003. Red squares indicate all the known Neolithic tells of the area (approximately 180 km^2). Green squares are the Neolithic tells identified from visual inspection and interpretation.

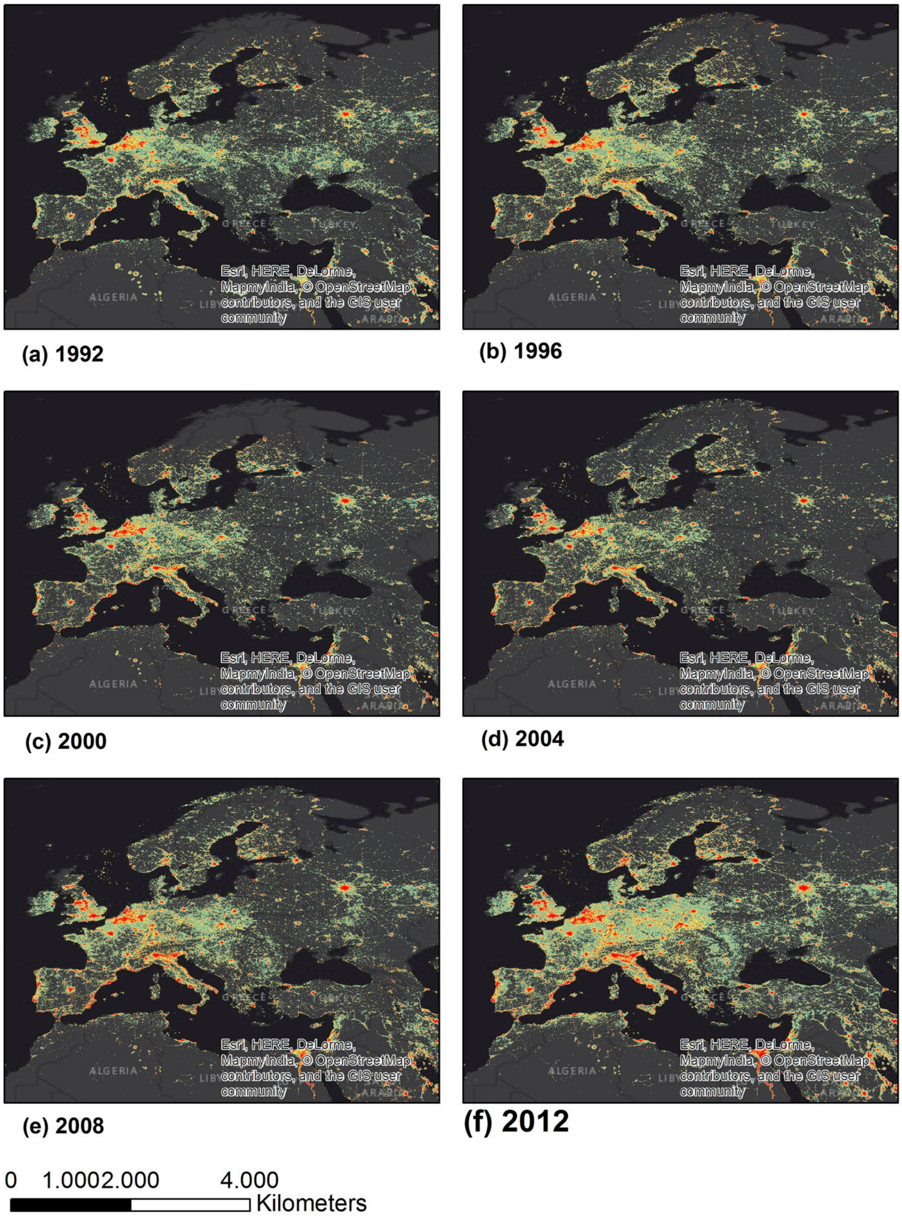

Figure 8. DMSP-OLS Night-time Lights Time Series Version 4 data over Europe, Middle East and North Africa regions from 1992–2012 (with 4-year interval). Red colour indicates higher stable lights values, a value used for the estimation of urban expansion. (Data generated from Google Earth Engine(c). Background Source Maps: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community).

proxy of the phenomenon of urban sprawl in this area. As it is demonstrated, new large urban centres have been developed in the last 20 years in several parts of Europe, Middle East and North Africa regions. In addition, large cities have been grown larger. The central and north-west parts of Europe, as well as cities in the eastern part of Europe, are the areas with the greatest change in terms of urban sprawl. Major cities are mainly found in the western part of Europe while exceptions are also noticed such as Moscow, Cairo, Athens, etc. During the period between 2008 and 2012, the largest rate of expansion was recorded mainly in the central part of Europe as well in the western part of Africa.

Based on this information differences between two DMSP-OLS Night-time Lights Time Series Version 4 data for the years 2012 and 1992 have been calculated for each site. Figure 9, presents the UNESCO sites grouped into eight major categories according to the differences recorded from the images of 2012 and 1992 (expressed in percentage). The background image is a pseudo colour composite of the DMSP-OLS data for the years 2012, 2002 and 1992. The red colour of the image stands for areas with large Digital Numbers of stable light values for the year 2012, while blue lights for areas with large Digital Numbers of stable light values in 1992. Similar for green colour which indicates areas that have recorded large Digital Numbers of stable light values in 2002. As demonstrated the urban expansion in relation to the UNESCO monuments is quite heterogeneous over the area of interest. Positive night lights difference values between the 2012 dataset and the 1992 images has been recorded for the whole sites under UNESCO Heritage list. Some sites mainly in the central and western part of Europe have the largest difference. Of course we have to keep in mind the spatial resolution of the dataset used here (1-km pixel size) which can be only used as an indicator and not as final conclusions. Even if processes of urban densification are ongoing in some UNESCO city centres, the 1-km resolution data will not be sensitive enough to show this impact.

In an attempt to analyse further the data collected from the DMSP-OLS Night-time Lights Time Series, a hot and cold spot analysis was carried out based on the Getis-Ord *Gi** statistic (Figure 10). The Getis-Ord *Gi** statistic for each monument is calculated based on the Equations (4–6) given below:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}x_i - \bar{X}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}}, \tag{4}$$

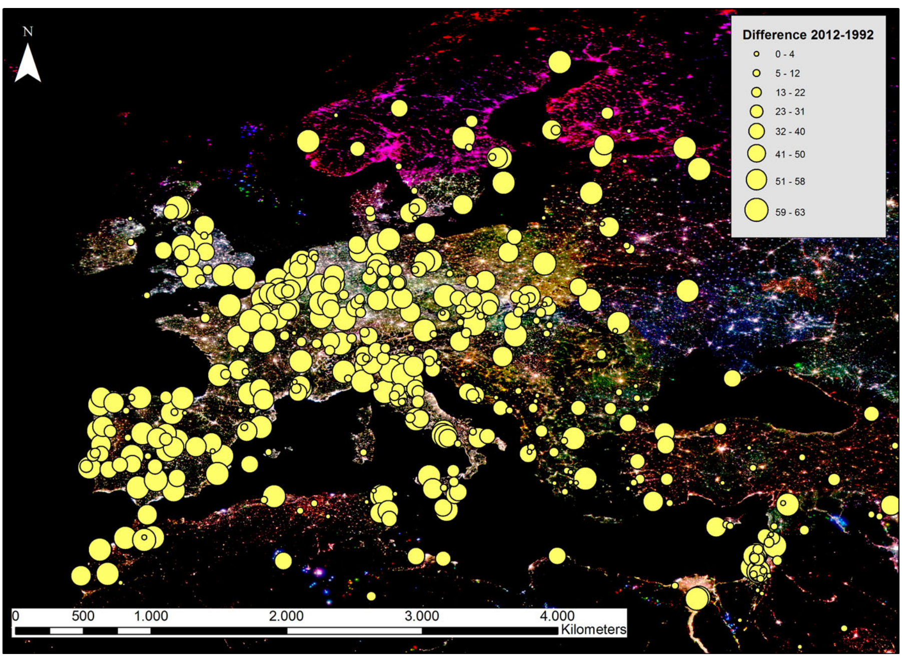

Figure 9. Difference between DMSP-OLS Night-time Lights Time Series Version 4 data over Europe, Middle East and North Africa regions for the period 1992–2012. The background image is a pseudo colour composite of the DMSP-OLS data for the years 2012–2002–1992. (Data generated from Google Earth Engine(c). Background Source Maps: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community).

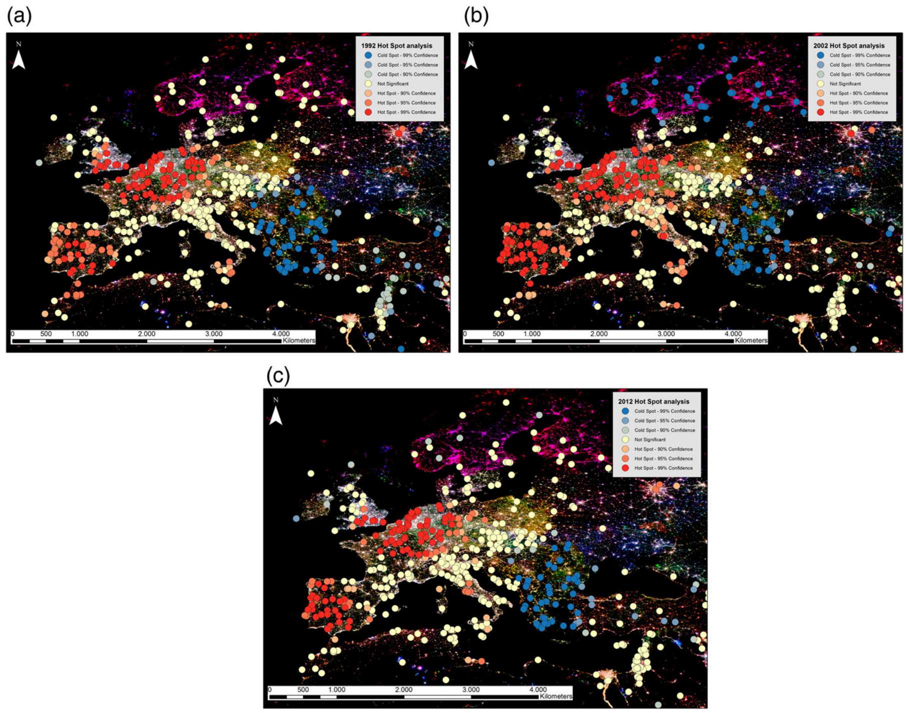

Figure 10. Hot spot analysis based on the Getis-Ord Gi* statistic for the years 1992–2002 and 2012 (10-years interval, a,b,c, respectively). The background image is a pseudo colour composite of the DMSP-OLS data for the years 2012–2002–1992. (Data generated from Google Earth Engine(c). Background Source Maps: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community).

where x_j is the night light value for each monument, $w_{i,j}$ is the spatial weight between two monuments i and j, n is equal to the total number of monuments (here $n = 512$) and

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n}, \tag{5}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2}. \tag{6}$$

The results from this analysis identify if UNESCO monuments may have (hot) or not (cold) high or low values cluster spatially within the context of neighbouring features. Therefore, monuments indicated with red colour in Figure 10 which corresponds to hot spot areas are monuments that have high value (i.e. night light value which is linked to the presence of urban areas) but are also surrounded by other monuments with high values as well. Cold spot areas, indicated with blue colour in Figure 10, are monuments that have relative low night values (i.e. low dense urban areas) but also surrounded with other monuments with low values. The overall analysis takes into considerations the whole sample, and it was performed for the years 1992, 2002 and 2012. As indicated in this figure, monuments in the eastern and southern part of Europe (i.e. Balkans area) are ranked as cold spot areas for the whole period, compared to the central and western part of Europe (i.e. Germany, France, UK, Spain, etc.). Other regions, such as the northern part of Africa seem to have no significant difference.

The overall results demonstrated the potential use of such large datasets in large scale applications, while at the same time the complexity to map urban sprawl in the European, Middle East and North Africa regions level was evidenced. However, in some cases it is clear that within the last 20 years (i.e. 2012–1992) a great expansion of urban areas has been recorded in the vicinity of UNESCO World Heritage sites. This overview could be of major substance to local and regional stakeholders operating in the field of protection and monitoring of Cultural Heritage sites against natural and anthropogenic hazards. A step forward would be the exploitation of medium and high-resolution datasets in order to gather more detail results for specific areas of interested using again multi-temporal remote sensing datasets. Clustering analysis carried out, based on the night-time series data, revealed that five classes can be used so as to characterize the UENSCO monuments (Figure 11). Class 1, indicated with blue dots in Figure 11, represents monuments that from 1992 to 2012 have relative low night values (less than 10). However, monuments of this class have also a noticeable increase of night value from the value 5 to 10 between the period 2008 and 2012. The second class, represented with green colour in Figure 11, groups monuments that have light night values around 15 but again during this period (2008–2012) a significant increase has been recorded (from light value 18 during 2008 to light value 29 to 2012). The third class (indicated with yellow colour in Figure 11) has an average night light value of around 25 which then remain stable until 2006. Since then a dramatic increase has been recorded from the DMSP-OLS Night-time Lights Time Series Version 4 data (light values over 40 in 2012). Dots with orange colour in Figure 11 are the monuments that had high night values (over 40) from the beginning of the dataset (1992) and by the end of the 20 years' period, this value was over 50. Last, class five, shown with red colour in Figure 11, indicates monuments with the highest night values since 1992. This value remains almost stable at around 60 (top value is 63), and probably these class represent UNESCO monuments that are found the historical centres of Europe and Middle East with huge populations.

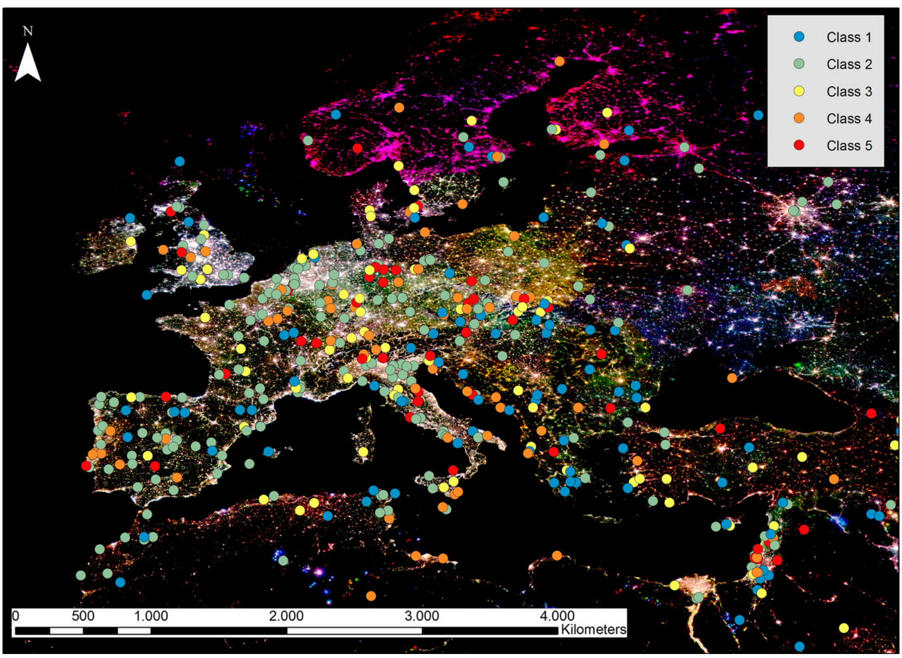

Figure 11. Group analysis of the monuments in the Europe, Middle East and North Africa regions for the period between 1992 and 2012. Classes refer to monuments with similar trends over the year based on the values from the DMSP-OLS Night-time Lights Time Series Version 4 data. The background image is a pseudo colour composite of the DMSP-OLS data for the years 2012–2002–1992. (Data generated from Google Earth Engine(c). Background Source Maps: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community).

4. Discussion: new challenges and new opportunities for remote sensing archaeology

As Gattiglia (2015, 117) has recently stated 'archaeological data are messy and difficult to structure by definition: archaeological data structures are arbitrary, and there is no question about the interpretative character of their nature'. However, Big Data and Big Data engines as the one used here are able to provide further insights for researchers working in the fields of cultural heritage and archaeology. Evaluating the applications and results presented in this study, the question emerging concerns the notion whether these methodological approach would be of interest and helpful for pure archaeological research and for cultural heritage management in general. Could all this information gathered from the several petabytes of datasets be really supportive to researchers and professionals working in the aforementioned fields? Answering this question from a 'top to bottom' approach the reply rather turns to be 'no' since several issues are needed to be addressed, such as the interpretation of the data and of the results, the level of accuracy, problems related to the georeference between the different datasets, the parameter of the different scale of observation, the variety of spectral and spatial resolutions, etc. For instance, in the case study of the Thessalian plain, the use of Landsat images for the periods 2003–2016 could result problematic due to the strip complications observed at the sensor after 2003 onwards. As shown in Figure 12, strip lines are observed in the whole image rendering difficult the interpretation and identification of the Neolithic tells (shown as green squares). Comparing the results of the crop component recognized for the periods 1999–2003 (Figure 4) and the ones for the periods 2003–2016 (Figure 12), is becoming evident that interpretation for the second sample of datasets, is problematic.

On the other hand, further to the challenges that both archaeological and remote sensing community need to address regarding the use of Big Data, approaching this new challenge from a 'bottom to top' perspective, future opportunities and potentialities are also observed. Indeed, complexities of Big Data need to be overcome in order to have the maximum benefits from using large scale datasets in archaeological research. The example of the UNESCO World Heritage sites

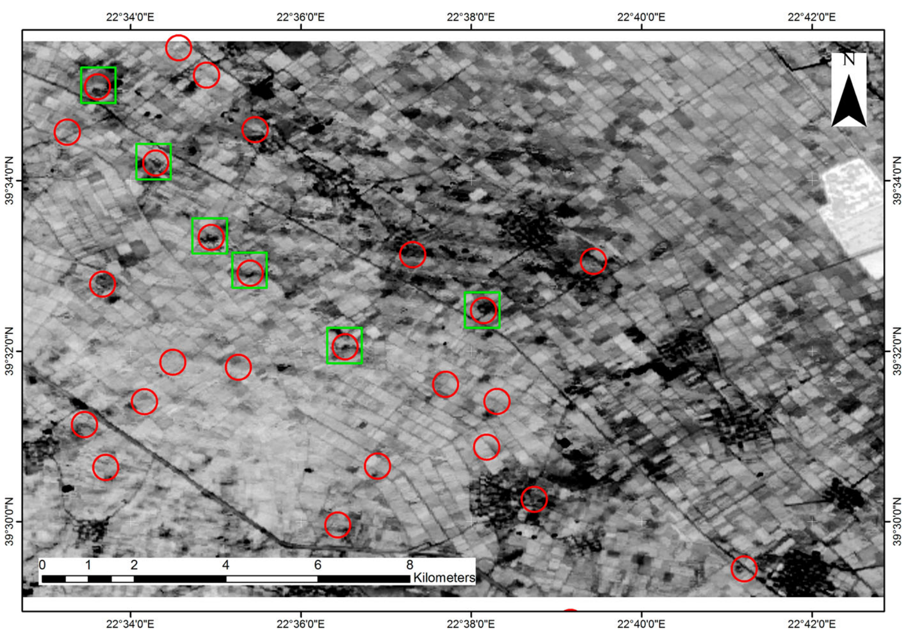

Figure 12. Results from the crop component band applied for Landsat 7 ETM+ series for the period 2013–2016. Red squares indicate all the known Neolithic tells of the area (approximately 180 km^2). Green squares are the Neolithic tells identified from visual inspection and interpretation. Strip problems are also observed in the image.

(case study 2), based on the multi-temporal analysis of the annual DMSP-OLS Night-time Lights Time Series Version 4 data, indicates that Big Data engines can support large applications for large spatial extent and for hundreds of monuments. The critical aspect is therefore shifted from the storage and manage of these huge datasets, to the analysis and interpretation of the results. Spatial statistics tools, as those applied in the second case study, show that further insights can be retrieved for the monuments from the multi-temporal analysis.

Despite the small number of archaeological studies that have been applied in the past based on Big Data, still their exploitation could be of great benefit to archaeologists in exploring large scales and multi-temporal datasets. Furthermore, the current capabilities of Big Data engines that provide a platform for manipulating and analysing the data can be seen as a computational turn in thought and research as well (Burkholder 1992). New and probably still unknown applications and tools might be built in the near future for the exploitation of the Big Data datasets in a useful and even more efficient and accurate manner. Therefore, the multidisciplinary of this approach imposes the close collaboration between scientists in order to overwhelm in a productive way the complications here acknowledged.

5. Conclusions

Two different applications have been presented in this study for the exploitation of remote sensing Big Data in the fields of archaeology and cultural heritage management. An online Big Data platform (Earth Engine©) has been used to retrieve both Landsat and DMSP-OLS Night-time Lights Time Series Version 4 data. The Earth Engine provided a robust platform in order to apply the orthogonal equations in the area of the Thessalian plain. The overall results from this approach were found to be very promising since more than half of the Neolithic sites in an area of more than 180 km^2 were identified. The success rate could be further increased upon the selection of the 'best' datasets (i.e. images taken during the boot stage of the crops) in an automatic way to minimize the computational time. For this task-specific algorithms are needed to be developed both for retrieving the 'best' datasets and for excluding the problematic ones.

Multi-temporal datasets for vast areas such as Europe, Middle East and North Africa regions can be also easily exploited within the platform. The DMSP-OLS Night-time Lights Time Series Version 4 data for a period of more than 20 years was downloaded in the second case study regarding the visualization of urban sprawl (based on the stable lights value) in the vicinity of UNESCO World Heritage sites of Europe, Middle East and North Africa regions.

Both examples provided a fruitful feedback of how Big Data can be used for archaeology and cultural heritage management, while at the same time evidenced both the challenges that are needed to be addressed and the several opportunities that could be raised in the future. The concluding perception relies in the essentiality of a close collaboration between archaeologists, remote sensing and IT experts. Analysis and interpretation of such large multi-temporal datasets will definitely require additional tools and algorithms to be developed so as to be able to fully take advantage of this new potential. The use of large datasets, especially for remote sensing application in archaeology, is essential so as to verify or not a hypothesis that is probably build upon only a single or few satellite images. Though, the any obstacles that may be still need to deal with, such as the use of medium or low spatial resolution satellite data (e.g. Landsat and DMSP-OLS Night-time Lights Time Series Version 4 data) will probably change in the near future with the use of new data with higher spatial resolution.

Acknowledgements

The present communication is under the 'ATHENA' project H2020-TWINN2015 of European Commission. Thanks are given to Dr Vasiliki Lysandrou for her valuable comments and suggestions. Special thanks to Dr Dimitrios Alexakis and Dr Apostolos Sarris for their support in the case study of the Thessalian plain. Thanks are given to Prof. Diofantos

G. Hadjimitsis and the Remote Sensing and Geo-Environment Laboratory, member of the Eratosthenes Research Centre.

Disclosure statement

No potential conflict of interest was reported by the author.

Funding

The present communication is under the "ATHENA" project H2020-TWINN2015 of European Commission. For communication activities: This project has received funding from the European Union's Horizon 2020 research and innovation programme under [grant agreement number 691936].

References

Agapiou, A. 2016. "Orthogonal Equations for the Detection of Archaeological Traces De-mystified." *Journal of Archaeological Science: Reports*. doi:10.1016/j.jasrep.2016.07.004.

Agapiou, A., D. D. Alexakis, and D. G. Hadjimitsis. 2014. "Spectral Sensitivity of ALOS, ASTER, IKONOS, LANDSAT and SPOT Satellite Imagery Intended for the Detection of Archaeological Crop Marks." *International Journal of Digital Earth* 7 (5): 351–372.

Agapiou, A., D. D. Alexakis, V. Lysandrou, A. Sarris, B. Cuca, K. Themistocleous, and D. G. Hadjimitsis. 2015a. "Impact of Urban Sprawl to Cultural Heritage Monuments: The Case Study of Paphos Area in Cyprus." *Journal of Cultural Heritage* 16 (5): 671–680. doi:10.1016/j.culher.2014.12.006.

Agapiou, A., D. D. Alexakis, A. Sarris, and D. G. Hadjimitsis. 2013. "Orthogonal Equations of Multi-spectral Satellite Imagery for the Identification of Un-excavated Archaeological Sites." *Remote Sensing* 5 (12): 6560–6586. doi:10.3390/rs5126560.

Agapiou, A., D. D. Alexakis, A. Sarris, and D. G. Hadjimitsis. 2014. "Evaluating the Potentials of Sentinel-2 for Archaeological Perspective." *Remote Sensing* 6 (3): 2176–2194.

Agapiou, A., D. D. Alexakis, A. Sarris, and D. G. Hadjimitsis. 2015b. "Linear 3-D Transformations of Landsat 5 TM Satellite Images for the Enhancement of Archaeological Signatures During the Phenological Cycle of Crops." *International Journal of Remote Sensing* 36 (1): 20–35. doi:10.1080/01431161.2014.990646.

Agapiou, A., D. G. Hadjimitsis, and D. D. Alexakis. 2012. "Evaluation of Broadband and Narrowband Vegetation Indices for the Identification of Archaeological Crop Marks." *Remote Sensing* 4: 3892–3919.

Agapiou, A., D. Hadjimitsis, D. Alexakis, and G. Papadavid. 2012. "Examining the Phenological Cycle of Barley (*Hordeum vulgare*) Using Satellite and *in situ* Spectroradiometer Measurements for the Detection of Buried Archaeological Remains." *GIScience and Remote Sensing* 49 (6): 854–872.

Agapiou, A., and V. Lysandrou. 2015. "Remote Sensing Archaeology: Tracking and Mapping Evolution in European Scientific Literature from 1999 to 2015." *Journal of Archaeological Science: Reports* 4: 192–200. doi:10.1016/j.jasrep.2015.09.010.

Alexakis, D., A. Sarris, T. Astaras, and K. Albanakis. 2009. Detection of Neolithic settlements in thessaly (Greece) through multispectral and hyperspectral satellite imagery. *Sensors* 9: 1167e1187.

Alexakis, A., A. Sarris, T. Astaras, and K. Albanakis. 2011. "Integrated GIS, Remote Sensing and Geomorphologic Approaches for the Reconstruction of the Landscape Habitation of Thessaly During the Neolithic Period." *Journal of Archaeological Science* 38 (1): 89–100. doi:10.1016/j.jas.2010.08.013.

Amaral, S., A. M. V. Monteiro, G. Camara, and J. A. Quintanilha. 2006. "DMSP/OLS Night-time Light Imagery for Urban Population Estimates in the Brazilian Amazon." *International Journal of Remote Sensing* 27 (5): 855–870. doi:10.1080/01431160500181861.

Bjoern, H. Menze, and A. Ur Jason. 2012. "Multi-temporal Classification of Multi-spectral Images for Settlement Survey in Northeastern Syria." In *Mapping Archaeological Landscapes from Space*, edited by C. D. Commer and J. M. Harrower, 219–228. New York: Springer.

Burkholder, L., ed. 1992. *Philosophy and the Computer*. Boulder: Westview Press.

Chen, F., N. Masini, R. Yang, P. Milillo, D. Feng, and R. Lasaponara. 2015. "A Space View of Radar Archaeological Marks: First Applications of COSMO-SkyMed X-band Data." *Remote Sensing* 7 (1): 24–50.

Cigna, F., D. Tapete, R. Lasaponara, and N. Masini. 2013. "Amplitude Change Detection with ENVISAT ASAR to Image the Cultural Landscape of the Nasca Region, Peru." *Archaeological Prospection* 20: 117–131. doi:10.1002/arp.1451.

De Laet, V., E. Paulissen, and M. Waelkens. 2007. "Methods for the Extraction of Archaeological Features from Very High-resolution Ikonos-2 Remote Sensing Imagery, Hisar (Southwest Turkey)." *Journal of Archaeological Science* 34 (5): 830–841.

DLR. 2016. "DFD-PAC Operational for Sentinel-3A and Sentinel-1A/1B." Accessed September.
Doll, N. H. C. 2008. "CIESIN Thematic Guide to Night-time Light Remote Sensing and its Applications." Center for International Earth Science Information Network (CIESIN), Columbia University, Palisades, NY, USA.
Gattiglia, G. 2015. "Think Big about Data: Archaeology and the Big Data Challenge." *Archäologische Informationen* 38: 113–124.
Giardino, J. M. 2011. "A History of NASA Remote Sensing Contributions to Archaeology." *Journal of Archaeological Science* 38 (9): 2003–2009. doi:10.1016/j.jas.2010.09.017.
Gigli, G., W. Frodella, F. Mugnai, D. Tapete, F. Cigna, R. Fanti, E. Intrieri, and L. Lombardi. 2012. "Instability Mechanisms Affecting Cultural Heritage Sites in the Maltese Archipelago." *Natural Hazards and Earth System Science* 12: 1883–1903. doi:10.5194/nhess-12-1883-2012.
Gil, D., and Il-Y. Song. 2016. "Modeling and Management of Big Data: Challenges and Opportunities, Future Generation." *Computer Systems* 63: 96–99. doi:10.1016/j.future.2015.07.019.
Gobble, M. M. 2013. "Resources: Big Data: The Next Big Thing in Innovation." *Research-Technology Management* 56 (1): 64–67.
Google Earth Engine Team. 2015. "Google Earth Engine: A Planetary-scale Geospatial Analysis Platform." https://earthengine.google.com.
Hansen, M. C., P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, et al. 2013. "High-resolution Global Maps of 21st-century Forest Cover Change." *Science* 342: 850–853.
Hsu, F.-C., K. E. Baugh, T. Ghosh, M. Zhizhin, and C. D. Elvidge. 2015. "DMSP-OLS Radiance Calibrated Nighttime Lights Time Series with Intercalibration." *Remote Sensing* 7: 1855–1876.
Imhoff, M. L., W. T. Lawrence, D. C. Stutzer, and C. D. Elvidge. 1997. "A Technique for Using Composite DMSP/OLS 'City Lights' Satellite Data to Map Urban Area." *Remote Sensing of Environment* 61: 361–370.
Jahjah, M., and C. Ulivieri. 2010. "Automatic Archaeological Feature Extraction from Satellite VHR Images." *Acta Astronautica* 66 (9–10): 1302–1310. doi:10.1016/j.actaastro.2009.10.028.
Kazansky, Y., D. Wood, and J. Sutherlun. 2016. "The Current and Potential Role of Satellite Remote Sensing in the Campaign Against Malaria." *Acta Astronautica* 121: 292–305. doi:10.1016/j.actaastro.2015.09.021.
Lasaponara, R., M. Danese, and N. Masini. 2012. "Satellite-based Monitoring of Archaeological Looting in Peru." In *Satellite Remote Sensing*, edited by R. Lasaponara and N. Masini, 177–193. Amsterdam: Springer.
Lasaponara, R., and N. Masini. 2013. "Satellite Synthetic Aperture Radar in Archaeology and Cultural Landscape: An Overview." *Archaeological Prospection* 20: 71–78. doi:10.1002/arp.1452.
Li, S., S. Dragicevic, F. Antón Castro, M. Sester, S. Winter, A. Coltekin, C. Pettit, et al. 2016. "Geospatial big Data Handling Theory and Methods: A Review and Research Challenges." *ISPRS Journal of Photogrammetry and Remote Sensing* 115: 119–133. doi:10.1016/j.isprsjprs.2015.10.012.
Linck, R., T. Busche, S. Buckreuss, J. W. E. Fassbinder, and S. Seren. 2013. "Possibilities of Archaeological Prospection by High-resolution X-band Satellite Radar – A Case Study from Syria." *Archaeological Prospection* 20: 97–108. doi:10.1002/arp.1444.
Liu, Y., J. Hu, I. Snell-Feikema, S. M. VanBemmel, A. Lamsal, and C. M. Wimberly. 2015. "Software to Facilitate Remote Sensing Data Access for Disease Early Warning Systems." *Environmental Modelling & Software* 74: 247–257. doi:10.1016/j.envsoft.2015.07.006.
Liu, J., J. Li, W. Li, and J. Wu. 2016. "Rethinking Big Data: A Review on the Data Quality and Usage Issues." *ISPRS Journal of Photogrammetry and Remote Sensing* 115: 134–142.
Ma, Y., L. Wang, P. Liu, and R. Ranjan. 2015a. "Towards Building a Data-intensive Index for Big Data Computing – A Case Study of Remote Sensing Data Processing." *Information Sciences* 319: 171–188. doi:10.1016/j.ins.2014.10.006.
Ma, Y., H. Wu, L. Wang, B. Huang, R. Ranjan, A. Zomaya, and W. Jie. 2015b. "Remote Sensing Big Data Computing: Challenges and Opportunities." *Future Generation Computer Systems* 51: 47–60. doi:10.1016/j.future.2014.10.029.
Merino, J., I. Caballero, B. Rivas, M. Serrano, and M. Piattini. 2016. "A Data Quality in Use Model for Big Data." *Future Generation Computer Systems* 63: 123–130.
Min, L. 2012. "Archaeological Landscapes of China and the Application of Corona Images." In *Mapping Archaeological Landscapes from Space*, edited by C. D. Commer and J. M. Harrower, 45–54. New York: Springer.
National Science Foundation, Core techniques and technologies for advancing big data science and engineering (BIGDATA) 2012. Accessed July 2016. http://www.nsf.gov/publications/pub_summ.jsp?ods_key=nsf12499.
Orengo, H. A., A. Krahtopoulou, A. Garcia-Molsosa, K. Palaiochoritis, and A. Stamati. 2015. "Photogrammetric Re-discovery of the Hidden Long-term Landscapes of Western Thessaly, Central Greece." *Journal of Archaeological Science* 64: 100–109. doi:10.1016/j.jas.2015.10.008.
Reinhold, S., A. Belinskiy, and D. Korobov. 2016. "Caucasia Top-down: Remote Sensing Data for Survey in a High Altitude Mountain Landscape." *Quaternary International* 402: 46–60. doi:10.1016/j.quaint.2015.10.106.
Sexton, J. O., X.-P. Song, M. Feng, P. Noojipady, A. Anand, C. Huang, D.-H. Kim, et al. 2013. "Global, 30m Resolution Continuous Fields of Tree Cover: Landsat-based Rescaling of MODIS Vegetation Continuous Fields with Lidar-based Estimates of Error." *International Journal of Digital Earth* 6: 427–448.
Sharma, S. 2016. "Expanded Cloud Plumes Hiding Big Data Ecosystem, Future Generation." *Computer Systems* 59: 63–92. doi:10.1016/j.future.2016.01.003.

Small, C., D. C. Elvidge, D. Balk, and M. Montgomery. 2011. "Spatial Scaling of Stable Night Lights." *Remote Sensing of Environment* 115: 269–280.

Stewart, C., R. Lasaponara, and G. Schiavon. 2014. "Multi-frequency, Polarimetric SAR Analysis for Archaeological Prospection." *International Journal of Applied Earth Observation and Geoinformation* 28: 211–219. doi:10.1016/j.jag.2013.11.007.

Stramondo, S., F. Bozzano, F. Marra, U. Wegmuller, F. R. Cinti, M. Moro, and M. Saroli. 2008. "Subsidence Induced by Urbanisation in the City of Rome Detected by Advanced InSAR Technique and Geotechnical Investigations." *Remote Sensing of Environment* 112 (6): 3160–3172. doi:10.1016/j.rse.2008.03.008.

Tapete, D., and F. Cigna. 2012. Rapid Mapping and Deformation Analysis Over Cultural Heritage and Rural Sites Based on Persistent Scatterer Interferometry. *International Journal of Geophysics*, Article ID 618609. doi:10.1155/2012/618609.

Tapete, D., and F. Cigna. Forthcoming. Trends and Perspectives of SAR Remote Sensing for Landscape Archaeology and Cultural Heritage Applications. *Journal of Archaeological Science: Reports*. http://dx.doi.org/10.1016/j.jasrep.2016.07.017.

Tapete, D., F. Cigna, and N. M. D. Donoghue. 2016. "'Looting Marks' in Space-borne SAR Imagery: Measuring Rates of Archaeological Looting in Apamea (Syria) with TerraSAR-X Staring Spotlight." *Remote Sensing of Environment* 178: 42–58.

Toth, C., and G. Jóźków. 2016. "Remote Sensing Platforms and Sensors: A Survey." *ISPRS Journal of Photogrammetry and Remote Sensing* 115: 22–36. doi:10.1016/j.isprsjprs.2015.10.004.

Trishchenko, P. A., J. Cihlar, and L. Zhanqing. 2002. "Effects of Spectral Response Function on Surface Reflectance and NDVI Measured with Moderate Resolution Satellite Sensors." *Remote Sensing of Environment* 81 (1): 1–18. doi:10.1016/S0034-4257(01)00328-5.

UNECO World Heritage Sites. 2015. "Official World Heritage List." Accessed July 2016. http://whc.unesco.org/en/list/.

USGS, Landsat Missions. 2015. Accessed July 2016. http://landsat.usgs.gov/about_LU_Vol_9_Issue_7.php.

USGS, SLC-off products. 2015. Accessed July 2016. http://landsat.usgs.gov/products_slcoffbackground.php.

Voigt, S., F. Giulio-Tonolo, J. Lyons, J. Kučera, B. Jones, T. Schneiderhan, G. Platzeck, et al. 2016a. "Global Trends in Satellite-based Emergency Mapping." *Science* 353 (6296): 247–252. doi:10.1126/science.aad8728.

Voigt, S., F. Giulio-Tonolo, J. Lyons, J. Kučera, B. Jones, T. Schneiderhan, G. Platzeck, et al. 2016b. "Towards Felicitous Decision Making: An Overview on Challenges and Trends of Big Data." *Information Sciences* 367–368: 747–765. doi:10.1016/j.ins.2016.07.007.

Wang, L., Y. Ma, J. Yan, V. Chang, and Y. A. Zomaya. 2016. pipsCloud: High Performance Cloud Computing for Remote Sensing Big Data Management and Processing. *Future Generation Computer Systems*. doi:10.1016/j.future.2016.06.009.

Zheng, M., Y. Zhang, S. Zhou, J. Zhu, and X. Xiong. 2016. "Bundle Block Adjustment of Large-scale Remote Sensing Data with Block-based Sparse Matrix Compression Combined with Preconditioned Conjugate Gradient." *Computers & Geosciences* 92: 70–78. doi:10.1016/j.cageo.2016.04.006.