Global Environmental Change 55 (2019) 97–104

Contents lists available at ScienceDirect

Global Environmental Change

journal homepage: www.elsevier.com/locate/gloenvcha

# World Heritage in danger: Big data and remote sensing can help protect sites in conflict zones

Noam Levin[a,b,*], Saleem Ali[c,d], David Crandall[e], Salit Kark[f]

[a] The Remote Sensing Lab, Department of Geography, Hebrew University of Jerusalem, Mount Scopus Campus, Jerusalem 91905, Israel
[b] School of Earth and Environmental Sciences and Center of Excellence for Environmental Decisions, University of Queensland, Brisbane, Queensland 4072, Australia
[c] Department of Geography, University of Delaware, Newark, DE 19716, USA
[d] Global Change Institute, University of Queensland, Brisbane, 4070, Australia
[e] School of Informatics, Computing and Engineering, Indiana University, Bloomington, IN 47405, USA
[f] The Biodiversity Research Group, School of Biological Sciences, Center of Excellence for Environmental Decisions, University of Queensland, Brisbane, Queensland 4072, Australia

ARTICLE INFO

*Keywords:*
World Heritage Sites
Big data
Remote sensing
Armed conflicts
Arab countries
Middle East
GDELT
Night lights
Flickr

ABSTRACT

World Heritage sites provide a key mechanism for protecting areas of universal importance. However, fifty-four UNESCO sites are currently listed as "*In Danger*", with 40% of these located in the Middle East. Since 2010 alone, thirty new sites were identified as under risk globally. We combined big-data and remote sensing to examine whether they can effectively be used to identify danger to World Heritage in near real-time. We found that armed-conflicts substantially threaten both natural- and cultural-heritage listed sites. Other major risks include poor management and development (globally), poaching (Africa mostly) and deforestation (tropics), yet conflict is the most prominent threat. We show that news-mining of big-data on conflicts and remote sensing of nights-lights enabled us to identify conflict afflicted areas in near real-time. These findings provide a crucial avenue for developing a global transparent early-warning system before irreversible damage to world heritage takes place.

## 1. Introduction

Remote sensing and big data are transforming our ability to monitor our world's natural ecosystems and a wide variety of human activities such as those related to transport, tourism, resource extraction and conflicts, enabling near real-time monitoring of events as they evolve. However, existing institutional mechanisms have yet to incorporate the advances offered by geoinformatics in the 21st century. UNESCO's World Heritage Site (WHS) designation has become a widely acclaimed and accepted trademark globally, aiming to conserve sites of outstanding cultural or natural heritage ("*sites must be of outstanding universal value and meet at least one out of ten selection criteria*"; https://whc.unesco.org/en/criteria/) for future generations (Rössler, 2006; Ryan and Silvanto, 2009). While substantial efforts are being made to declare new World Heritage Sites, after their declaration, these global priority areas may face substantial risk. Just as the designation of a protected area does not guarantee its protection (Jones et al., 2018), the inscription of a WHS does not safeguard its preservation for future generations. To address the long-term persistence of WHS, the Convention of World Heritage decided on creating a "List of World Heritage *in Danger*" threatened by serious and specific dangers, to encourage remedial action (Ryan and Silvanto, 2009). Examples of ascertained and potential dangers include accelerated deterioration, large-scale or rapid urban and/or tourist development projects, archeological looting (Brodie and Renfrew, 2005), natural disasters, collapse, fire, and armed conflict. Attacks on cultural heritage during conflicts can be due to various motives, such as the conflict goals, military-strategic attacks, low risk attacks signaling the aggressors commitment, or economic incentives (Brosché et al., 2017). Organizations such as the Global Heritage Fund (Kessler, 2011; https://globalheritagefund.org/) are therefore interested in developing early warning systems for monitoring threats to WHS.

World Heritage sites (WHS) "*In Danger*" are unevenly distributed across the Planet, and little is known about their threats, current status and their changes over time. In 2006 for example, Africa held 43% of the global "World Heritage *in Danger*" sites, and the majority of WHS in Africa were threatened (Breen, 2007). If identified threats have severely damaged a WHS, sites can lose their WHS designation, with or without the consent of the country where the WHS is located (see full discussion on the delisting procedure in Albrecht and Gaillard, 2015). Two WHS

* Corresponding author at: The Remote Sensing Lab, Department of Geography, Hebrew University of Jerusalem, Mount Scopus Campus, Jerusalem 91905, Israel.
*E-mail address:* noamlevin@mail.huji.ac.il (N. Levin).

https://doi.org/10.1016/j.gloenvcha.2019.02.001
Received 13 September 2018; Received in revised form 9 January 2019; Accepted 4 February 2019

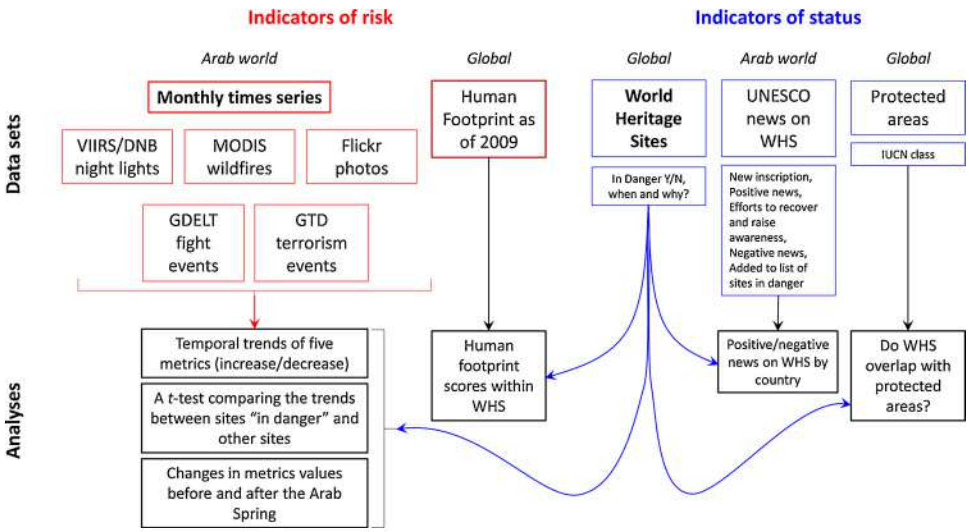


**Fig. 1.** Flow chart showing the overall methodology, data sources and analysis used in the study. Colors represent indicators of risk (in red), indicators of status (in blue), and the analyses performed (in black) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

have already lost their designation (Albrecht and Gaillard, 2015): The Arabian Oryx Sanctuary in Oman was de-listed in 2007 due to poaching, habitat degradation and oil exploration, and the Dresden Elbe Valley in Germany was delisted in 2009 due to the construction of a new bridge.

Protecting WHS from destruction due to human or natural causes is of utmost importance, and developing approaches for alerting about risks before they materialize are key. Previous work on natural world heritage (Allan et al., 2017) has proposed that studying changes in the global human footprint and in forest cover are useful approaches for investigating threats to natural WHS. Yet only 19% of the global 1073 WHS (as of May 2018) are defined as "Natural WHS" while 78% of all sites (n = 832), are defined as "Cultural WHS". Thus it is essential to identify the key factors threatening all WHS, and especially those "*In Danger*".

The Middle East is a region of major world heritage importance due to its historical and archeological significance, as one of the centers of the agricultural revolution, of animal and plant domestication, invention of writing, the first alphabet, and the origin of monotheistic religions (Diamond, 1997). Within Middle Eastern countries there are 128 WHS overall (92% of which are cultural WHS), and 79 of them found in Arab countries. However, this area has experienced many armed conflicts in recent decades, including those following the onset of the Arab Spring in 2010, which resulted in new threats to many of the region's WHS. These WHS require urgent global attention to prevent major destruction. In some cases inscribed or proposed WHS are the focus of conflict between countries, as in the case of Preah Vihear of Thailand (Silverman, 2011), and as WHS has been known in recent years to be the focus of attack by extremist groups such as the Taliban (Ashworth and van der Aa, 2002), better ways should be developed to safeguard WHS from such adversities (Di Lernia, 2015).

With limited accessibility of managers and visitors to sites at times of armed conflict, on-ground data collection is often very limited, thus hindering assessment of their status and its changes over time. Remote sensing and big data tools offer a window of opportunity to monitor and identify threats to WHS, and changes within WHS, thus enhancing the ability of the World's community to fulfill its obligations (O'Keefe, 2004) to protect the world's cultural and natural heritage. We set out to examine the potential of remote sensing of night-lights and big data to fill this key gap to identify conflict-related threats to WHS and to track changes in WHS over space and time. To this end, we identified the factors shaping the state of all "*In Danger*" World Heritage Sites globally, based on UNESCO reports and news. We then used monthly time series of remote sensing and spatial Big Data variables between 2000 and 2017 to examine whether an early warning system could be devised to safeguard WHS, focusing on the area and period in which armed conflict was a key threat to WHS – the Middle East following the Arab Spring.

## 2. Methods

### 2.1. Datasets

The full list of World Heritage Sites (WHS) was downloaded from https://whc.unesco.org/en/list/ (n = 1073, as of May 14th, 2018), and the List of World Heritage sites in Danger was downloaded from https://whc.unesco.org/en/danger/ (n = 54, as of May 4th, 2018). We analyzed UNESCO World Heritage sites located in all Arab countries (n = 18, including the Palestinian Authority) bounded by Morocco to the west, Sudan to the south, Syria to the north, Iraq to the east, and the entire Arab Peninsula. To understand some of the work of UNESCO on World Heritage Sites in the Arab World, we examined all of the news items published by UNESCO (which refer to Arab countries) between January 2000 and July 2017 in https://en.unesco.org/news (as of July 10th, 2017), and classified them according to five categories: New inscription, Positive news, Efforts to recover and raise awareness, Negative news, and Added to list of sites in danger. We identified for each WHS the various threats which led to its inclusion in the danger list, including the following factors (note that some of the sites were included for multiple reasons): armed conflicts, poor management, development, poaching, deforestation, mining, grazing, collapse (physical collapse of structures) and fire.

Several datasets were used in this study as explanatory variables for assessing the state of world heritage sites (Fig. 1):

- VIIRS monthly night lights at a spatial resolution of 742 m (Miller et al., 2012; Elvidge et al., 2017; available from https://www.ngdc.noaa.gov/eog/download.html), as the decrease in night-lights has been associated with destruction of infrastructure by armed conflicts (Li and Li, 2014; Levin et al., 2018).
- Wildfire centroids detected by MODIS (Giglio et al., 2003; available from https://firms.modaps.eosdis.nasa.gov/download/), as military conflicts can lead to large fires intentionally (Darques, 2015) or unintentionally. This fire detection algorithm uses a variety of spectral bands at a spatial resolution of 1 km, and can detect most fires larger than 1000 $m^3$ (Giglio et al., 2003).
- Flickr photos (Crandall et al., 2009), which serve as an indicator for visitation (Wood et al., 2013; Levin et al., 2015;). We chose Flickr so as to emphasize peace-time activities such as tourism related photographic exchange (Yang et al., 2017). We analyzed the numbers of

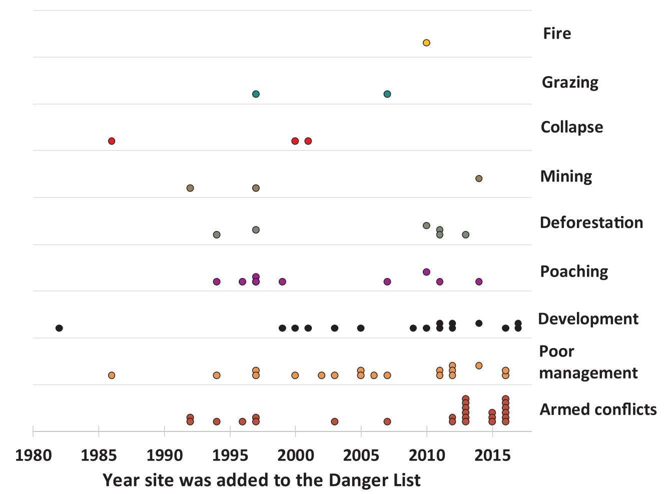


**Fig. 2.** UNESCO World Heritage Sites *"In Danger"* list (as of 2017), the year in which they were added to the list, and the threats which led to the inclusion of the sites in the list as listed by UNESCO (note that some of the sites were included for multiple reasons).

georeferenced Flickr photos at a grid cell resolution of 0.01° (equivalent to about 1 km).

- News items related to conflicts based on Global Data on Events, Location and Tone (GDELT), a Conflict and Mediation Event Observations (CAMEO) coded data set which contains hundreds of millions of geolocated events based on global news coverage from 1979 onwards (Gerner et al., 2009; Leetaru and Schrodt, 2013). Within the GDELT dataset (https://www.gdeltproject.org/), events are hierarchically coded based on event classes. We counted frequency of events belonging to code 19 (fight) on a monthly basis, as events belonging to this code were highly correlated with actual deaths from fighting (Levin et al., 2018).
- Real-world dataset of terrorist acts from the Global Terrorism Database (GTD; START, 2017; http://www.start.umd.edu/gtd). The major differences between the GTD and the GDELT datasets, are that the GTD dataset is solely devoted to terrorism events and is essentially based on expert interpretation of news items (after relevant news items have been selected using various machine learning techniques), whereas the GDELT database covers various event types, and is fully based on automated coding (Jensen, 2013; Gavshon and Gorur, 2018).
- Protected areas data. Data on protected area location and boundary, and year of inscription were obtained from the 2018 World Database on Protected Areas (WDPA, 2018; accessed May 22nd, 2018). We included only protected areas represented as polygons in the database. A lot of the protected areas overlapped spatially, containing different IUCN categories. We assigned each WHS to the strictest IUCN category of all protected areas in that location, following Jones et al. (2018).
- The Human Footprint map, which measures the cumulative impact of direct anthropogenic pressures on nature, based on the following inputs: the extent of built areas, crop and pasture lands, population density, night-time lights, railways, roads, and navigable waterways. We used the revised human footprint mapping (Venter et al., 2016a, b) to estimate human pressure within WHS. The revised human footprint map is a globally-standardized estimate of cumulative human pressures on the terrestrial environment at a spatial resolution of 1 $km^2$. The cumulative score of human pressure ranges from between 0 and 50 for each 1 $km^2$ cell. Following Jones et al. (2018) a human footprint score below four indicates low pressure, whereas a Human Footprint value of 4 or more was used as a threshold criterion for a human dominated landscape (following Allan et al., 2017). We calculated the average human footprint score within a moving window of 5 × 5 km around each WHS.

### 2.2. Statistical analysis

All datasets were spatially explicit, either as points with longitude and latitude, or as raster layers (in the case of the remotely sensed night lights), and we analyzed them as monthly time series, within a radius of 5 km surrounding the locations of UNESCO World Heritage sites. To examine the possible impact of events following the "Arab Spring" (which began with the Tunisian Revolution on 17 December 2010) and its aftermath, we compared two periods: Jan 2007 – Nov 2010, and Dec 2010 – present. We calculated Spearman's rank correlations for each variable to examine its changes during these two time periods, as well as over the entire time frame. The Spearman correlation coefficient is defined as the Pearson correlation coefficient between two ranked variables, and has the advantage of being a non-parametric test, i.e. it is not assuming a normal distribution, and it is not sensitive to outliers (Spearman, 1904). Differences in the temporal trends of each variable were tested with a two-way *t*-test, comparing the average trends for WHS declared as being in danger and those which were not included in the danger list.

## 3. Results

### 3.1. Global distribution of World Heritage Sites in danger

As of May 2018, 54 sites were included in the global List of World Heritage "*In Danger*", most of them being cultural WHS (38 out of 54). When examining the portion of sites "*In Danger*" out of all WHS globally, we found that 4.6% of all cultural WHS were listed as "*In Danger*" and 7.8% of all natural WHS were listed as "*In Danger*". In recent years there has been an alarming upsurge in sites identified as "*In Danger*" globally, with 30 new sites added to the WHS "*In Danger*" list since 2010 alone (Fig. 2). An analysis of the major drivers of this listing show the leading threats to WHS of cultural heritage being armed conflicts (19 sites), poor management (14 sites) and development (11 sites), whereas the three leading threats to WHS of natural heritage were poaching (10 sites), deforestation (6 sites) and armed conflicts (6 sites) (Fig. 2). Armed conflicts were the key threat listed as threatening both cultural and natural sites of world heritage importance.

Whereas one-third of global protected areas are under intense human pressure (Jones et al., 2018), WHS are mostly located in areas of even higher human pressures. We found that 95% of all cultural WHS (average human footprint score of 24.3) and 50% of all natural WHS (average human footprint score of 5.2) were in areas of high human pressures. Out of the 1073 WHS, only 348 were located within protected areas included in the 2018 World Database of Protected Areas. Of the 135 WHS located in strict biodiversity conservation areas, 22 were found within strict nature reserves (IUCN class Ia) with an average human footprint score of 4.3, 8 were found in wilderness areas (IUCN class Ib) with an average human footprint score of 1.4, and 105 WHS were found in national parks (IUCN class II) with an average human footprint score of 5.9. High human pressures (as quantified by the human footprint score) were found in 95% of the cultural WHS located in IUCN class II protected areas. The human footprint score was almost the same in cultural WHS "*In Danger*" (average score of 23.9), and those not "*In Danger*" (average score of 24.3), indicating that this metric was not useful for alerting of threats to cultural WHS.

### 3.2. Spatial distribution of World Heritage Sites in Danger

The spatial distribution of WHS "*In Danger*" and their threats substantially varied globally. While WHS "*In Danger*" were located on all continents, most of them (91% of the 54) were located in developing regions and non-OECD countries (Fig. 3). Deforestation and poaching were a threat to WHS "*In Danger*" in equatorial regions (mostly in

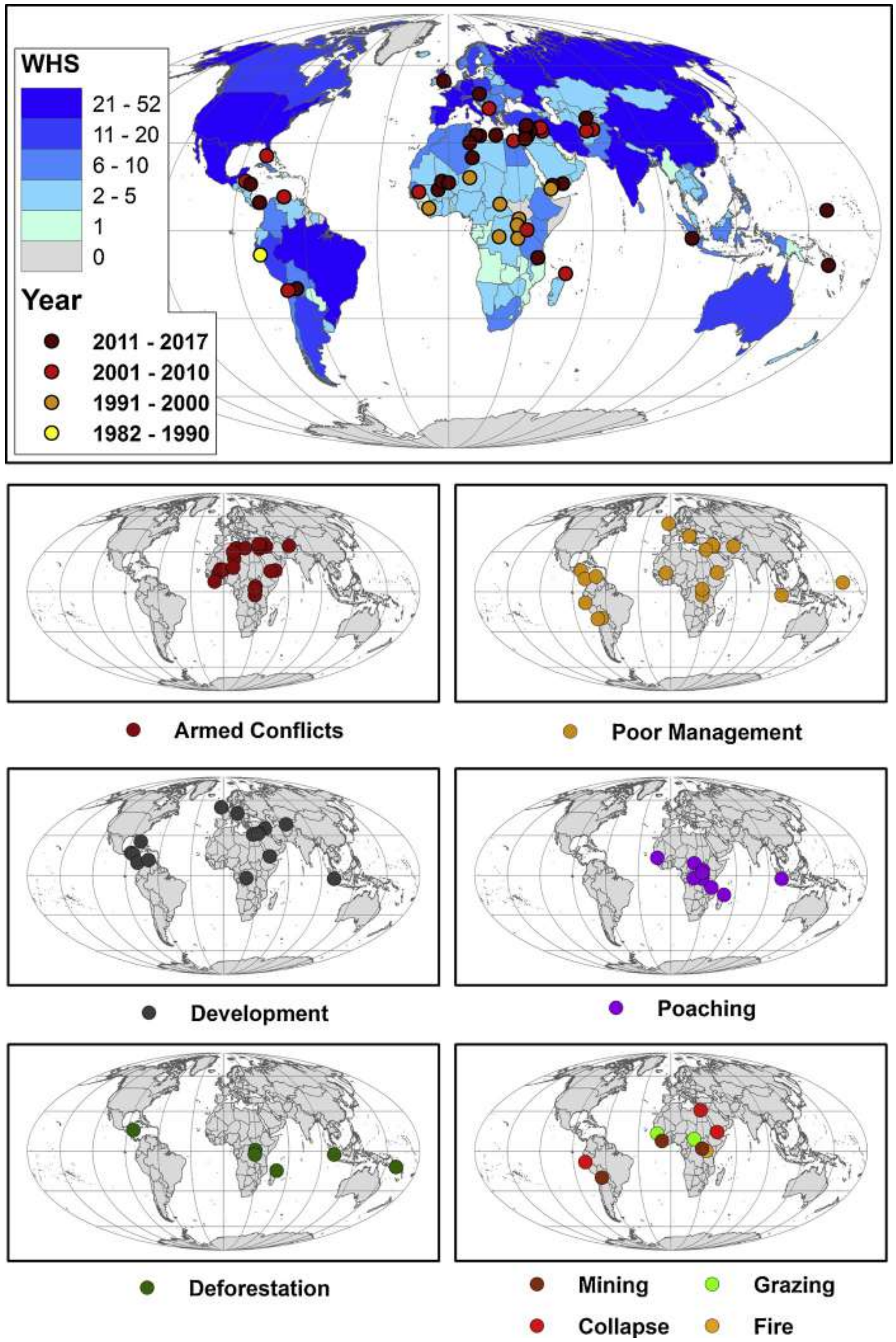


**Fig. 3.** UNESCO World Heritage Sites included in the danger list as of 2017. The upper panel shows the number of World Heritage Sites in each country (trans-boundary World Heritage Sites were counted in all of the countries where they are found), and the year in which World Heritage Sites were added to the danger list. The lower maps show the major threats for which World Heritage Sites were included in the danger list (note that some of the sites were included for multiple reasons).

Africa), and armed conflicts were described as a threat to WHS only in Africa and the Middle East. (Fig. 3).

Over a third (39%) of all sites defined as being "*In Danger*" globally were located in the Middle East in 18 Arab countries. We found an increase over time in the number of conflict-related UNESCO news items related to Arab countries, especially in Iraq, Libya, Syria and Yemen (Fig. S1). Of the 79 WHS sites in the Middle East's Arab countries, 21 (26%) were defined as being "*In Danger*", with 17 new sites being listed as "*In Danger*" since the 2010 onset of the Arab Spring and related armed conflict events (Figs. S1, 4). These 17 sites designated as being "*In Danger*" since 2010 were located in the Syria (six as of 2013), Libya (five since 2016), Yemen (two as of 2015), and Iraq (one since 2015) (Fig. 4), with armed conflicts being the major threat leading to their inclusion in the "*In Danger*" list. Three additional sites were designated as "*In Danger*" in the Palestinian Authority in 2012, 2014 and 2017, due to development pressures and poor management.

### *3.3. Estimating threats to WHS using remote sensing and big data*

In order to study the potential use of remote sensing and big data to identify threats to WHS, we examined the temporal trends in numbers of Flickr photos, VIIRS night time brightness, fires, GDELT fight events and events registered in the Global Terrorism Database (GTD), within a radius of 5 km of all WHS, comparing sites which were defined as being

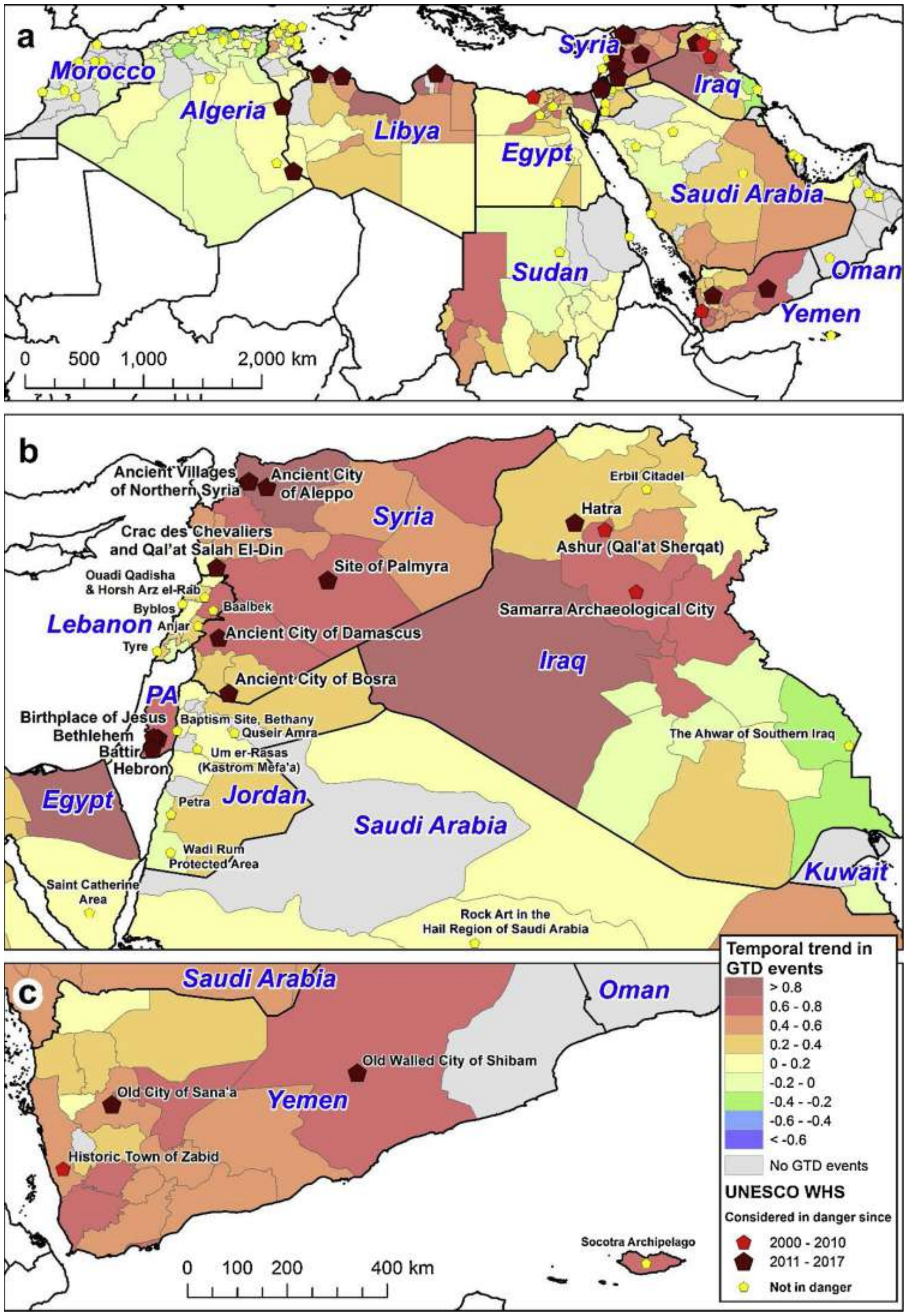


**Fig. 4.** UNESCO World Heritage sites in all Arab countries. The sites are colored based on the time when they were listed as being In Danger by UNESCO. Administrative regions are colored according to temporal trends (Spearman's correlation coefficient) in the number of terrorist events (between the years 2000 and 2016), as registered by the global terrorism database (GTD).

"*In Danger*" since 2010 to all other sites. On average, WHS sites that were added to the danger list since 2010 became darker (loss of night-time lights; Fig. 5a), and experienced both more fighting (Fig. 5b) and more terrorism events (Fig. 5c). However, on average, the monthly trends in Flickr photos and fire events did not differ much between WHS sites which were defined as being "*In Danger*" since 2010 and those which were not defined as such (Fig. 5d and e). We found that sites which were defined by UNESCO as being "*In Danger*" since 2010 had a greater decrease in night-time brightness (t-test $p = 0.001$; Fig. S2). There was no statistically significant difference in the temporal trends of fires or in the fire radiative power of fires between WHS defined as being "*In Danger*" and those not "*In Danger*".

Focusing on the three variables that showed the most difference between WHS added to the danger list and those which were not on the list (Fig. 5a–c), we visualized changes in GDELT fight events, VIIRS night-time brightness and GTD (terrorism) events, within a radius of 5 km from UNESCO World Heritage Sites which were added to the danger list, as a function of the time when they were added (based on UNESCO news) (Fig. S4). In five of the six sites shown on Fig. S4, there was a decrease in night time brightness and an increase in GTD events and in GDELT fight events before the sites were included in the list of being "*In Danger*", in some cases several months or even more than a

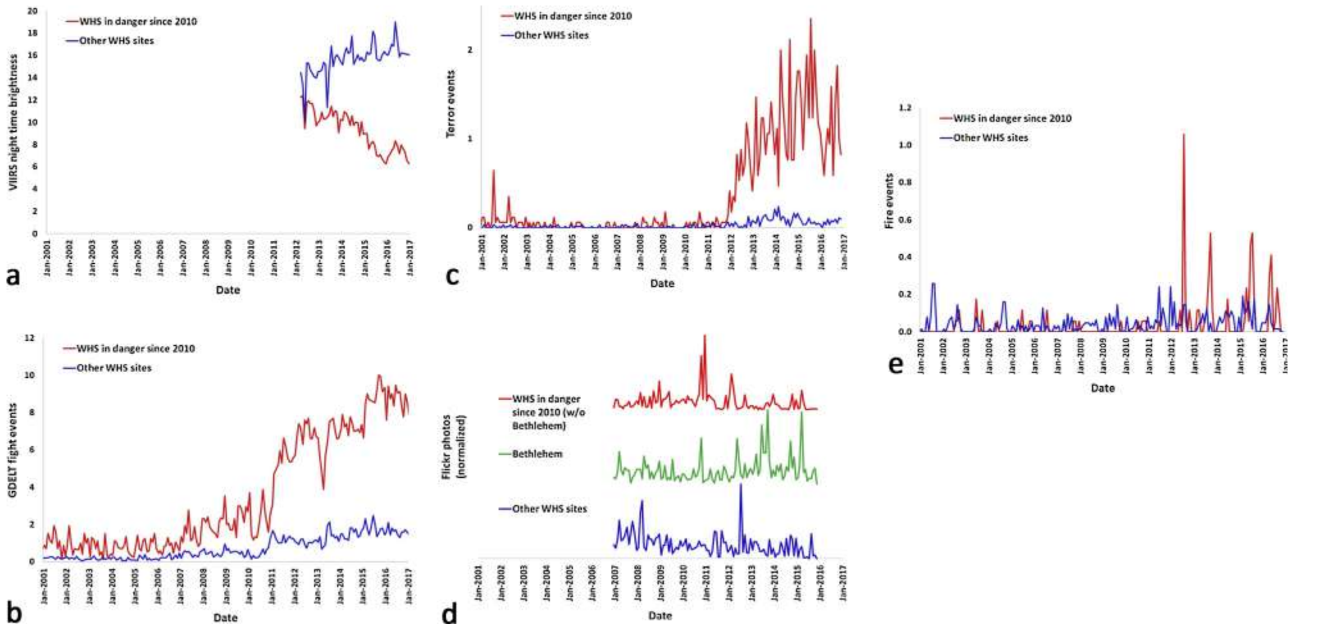


**Fig. 5.** Monthly trends, comparing world heritage sites (WHS) defined as being in danger since 2010 (n = 17) and other WHS (n = 62), covering all Arab countries in: (a) VIIRS night time brightness (data available since 2012); (b) GDELT fight events; (c) terrorism events; (d) Flickr photos (data available since 2007); (e) fires.

year before a site was included in this list. Of these six sites, only in Palmyra (Syria) did the major damages inflicted by armed conflict take place after the site was included on the UNESCO danger list.

## 4. Discussion

UNESCO's 1972 Convention on the Protection of the World Cultural and Natural Heritage is the major international instrument for safeguarding the world's heritage (Meskell, 2013). We have found that the human footprint score (Venter et al., 2016) is not a useful metric for identifying threats to WHS. This may be explained by the fact that (1) most WHS were designated based on their cultural values and not based on their natural values; (2) that the human footprint is mostly relevant to examine the impact of humans on natural ecosystems, and is thus less relevant to estimate the potential impact on cultural heritage; (3) that various indicators, e.g., threats related to armed conflicts, are not incorporated in the human footprint, and (4) that the human footprint has only been produced for two years (1993 and 2009), and is not generated (yet) on an annual or monthly basis.

While the designation of an area as a world heritage site is a useful branding tool that can help attract tourism and raise funding (Levin et al., 2015; Wuepper and Patry, 2017), it may also pose risks to sites, either due to excessive tourism pressures, or to them becoming high-profile targets by terrorists which will attract global media attention (Frey and Steiner, 2011; Brosché et al., 2017), such as in the notorious case of the city of Palmyra (Harmanşah, 2015; Campion, 2017). Our analysis demonstrates that Big Data and remote sensing methods can be used to identify risk to cultural assets due to the impacts of armed conflicts and terrorism. With armed conflicts being the leading threat for including WHS on the list of being "*In Danger*" (where risks to site's authenticity and integrity are anticipated; Alberts and Hazen, 2010), remote sensing and big data can be useful to provide timely forecasts whether WHS are "*In Danger*" or not. In addition to conflicts, remote sensing can be useful to identify additional threats to WHS, such as deforestation (Hansen et al., 2013) and wildfires (Davies et al., 2009; Rose et al., 2015).

A major limitation of the past and current process for adding sites to UNESCO's list of sites "*In Danger*" is that this process commonly takes place during the annual ordinary sessions of the World Heritage Committee (around June/July annually). Thus, the inclusion of sites in the danger list may come too late after substantial damage has already been caused. It should be noted, however, that the inclusion of sites in the danger list does not guarantee their protection without an internationally recognized real-time mechanism to address the risk. This was, for example, the case of Palmyra (Syria), which was added to the list of being "*In Danger*" (along with five other sites in Syria) in June 2013, yet its use for military purposes was reported in February 2014, and in summer 2015 several of the archeological sites within Palmyra were destroyed.

Remote sensing can offer tools for monitoring archeological sites and identifying looting (Parcak et al., 2016), and the planned launch of constellations of hundreds of "nano" Earth-observing satellites, offering daily high spatial resolution images (between 2.5 and 5 m) by companies such as PlanetLabs and AstroDigital (Butler, 2014; Hand, 2015; Strauss, 2017), with digital video from space planned by EarthNow (https://earthnow.com/) to be available in a few years, will enable the monitoring of ongoing conflicts and world heritage sites in unprecedented ways. Near real-time identification of crisis areas using abrupt decreases in night-time brightness will become a reality later on in 2019 with the planned release of NASA's new Black Marble product of daily calibrated and corrected night lights imagery (Román et al., 2018), while monitoring changes in agricultural productivity have also been utilized to examine broader impacts of conflicts from space (Eklund et al., 2017), amongst other approaches for remote sensing of conflicts (Witmer, 2015).

Complementary to remote sensing, big data geospatial technologies can provide a future reliable and effective way to track in real time the social and political state of societies, identifying periods and locations of crisis events as they develop. Better monitoring of World Heritage Sites globally can benefit from specially designed big data efforts focused on such sites, applying approaches developed for monitoring crisis areas (Castillo, 2016) and by using crowdsourcing to assist in humanitarian response (Meier, 2015), as in the Humanitarian OpenStreetMap Team (https://www.hotosm.org/; Palen et al., 2015). The Global Heritage Fund organization is using Google Earth imagery to examine and visualize the state of WHS (www.globalheritagefund.org/google/). Organizations such as Blue Shield International and the Blue Shield Network whose aim is to protect cultural sites from attacks in armed conflicts (Wegener, 2010) can take advantage of such real-time information and tools such as those proposed in this work. While we used the GDELT Project to explore georeferenced events, additional databases are becoming available to enable global monitoring of events, such as the Temporally Extended, Regular, Reproducible International Event Records (TERRIER; http://terrierdata.org/; Liang et al., 2018), or the Real Time Event Data / Phoenix (http://eventdata.utdallas.edu/), as machine coded data are found to be as valid as human coded data (Bagozzi et al., 2018).

As a useful next step to operationalizing such early warning assessments, the Institute for Applied Systems Analysis (IIASA) could play an important role in developing an integrated evaluation model through data supplied by signatories to the World Heritage Convention. This can also be managed through existing institutions such as the World Conservation Monitoring Centre (WCMC) under the auspices of the United Nations. While the IUCN conducts regular assessments of the conservation status of all natural and mixed UNESCO WHS (Osipova et al., 2017), an equivalent evaluation of cultural WHS is still missing. The approach demonstrated here can contribute to this end, by enhancing on-the-ground information with remote sensing and big data sources, which can provide near real-time warnings. This can be achieved by designing algorithms to send warnings to relevant organizations and agencies in charge of managing WHS, when events which may threaten WHS, are drawing closer spatially, and are increasing in their intensity, whether it be wildfires, armed conflicts, terrorism events, or other relevant threats. To better predict the advancement of such threats, modelling and simulation approaches developed in other fields, e.g., in studies on the spread of wildfires (Sá et al., 2017) or in the spatial and temporal prediction of conflicts (Weidmann and Ward, 2010; O'Brien, 2013; Schutte, 2017) can be adapted.

## Declarations of interest

None.

## Acknowledgments

We thank Andrew Fairbairn for fruitful discussions. This research was supported by the Australian Research Council (ARC) Centre of Excellence for Environmental Decisions (CEED) (S.K. and N.L.). D.C. was supported in part by the U.S. National Science Foundation (CAREER IIS-1253549).

## Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.gloenvcha.2019.02.001.

## References

Alberts, H.C., Hazen, H.D., 2010. Maintaining authenticity and integrity at cultural world heritage sites. Geogr. Rev. 100 (1), 56–73.
Albrecht, E., Gaillard, B., 2015. Procedure for delisting a site from the world heritage list: is delisting with consent or against the wish of a state party possible? J. Tour. Hosp. Manag. 3 (1–2), 15–21.
Allan, J.R., Venter, O., Maxwell, S., Bertzky, B., Jones, K., Shi, Y., Watson, J.E., 2017. Recent increases in human pressure and forest loss threaten many Natural World Heritage Sites. Biol. Conserv. 206, 47–55.
Ashworth, G.J., van der Aa, B.J., 2002. Bamyan: whose heritage was it and what should we do about it? Curr. Issues Tour. 5 (5), 447–457.
Bagozzi, B.E., Brandt, P.T., Freeman, J.R., Holmes, J.S., Kim, A., Mendizabal, A.P., Potz-Nielsen, C., 2018. The prevalence and severity of underreporting bias in machine-and human-coded data. Political Sci. Res. Methods 1–9. https://doi.org/10.1017/psrm.2018.11.
Breen, C., 2007. Advocacy, international development and world heritage sites in sub-Saharan Africa. World Archaeol. 39 (3), 355–370.
Brodie, N., Renfrew, C., 2005. Looting and the world's archaeological heritage: the inadequate response. Annu. Rev. Anthropol. 34, 343–361.
Brosché, J., Legnér, M., Kreutz, J., Ijla, A., 2017. Heritage under attack: motives for targeting cultural property during armed conflict. Int. J. Herit. Stud. 23 (3), 248–260.
Butler, D., 2014. Many eyes on earth. Nature 505 (7482), 143–144.
Campion, K., 2017. Blast through the past: terrorist attacks on art and antiquities as a reconquest of the modern Jihadi identity. Perspect. Terror. 11 (1), 26–39.
Castillo, C., 2016. Big Crisis Data: Social Media in Disasters and Time-critical Situations. Cambridge University Press.
Crandall, D.J., Backstrom, L., Huttenlocher, D., Kleinberg, J., 2009. Mapping the world's photos. Proceedings of the 18th International Conference on World Wide Web 761–770.
Darques, R., 2015. Mediterranean cities under fire. A critical approach to the wild-land–urban interface. Appl. Geogr. 59, 10–21.
Davies, D.K., Ilavajhala, S., Wong, M.M., Justice, C.O., 2009. Fire information for resource management system: archiving and distributing MODIS active fire data. IEEE Trans. Geosci. Remote. Sens. 47 (1), 72–79.
Di Lernia, S., 2015. Save libyan archaeology. Nature 517 (7536), 547.
Diamond, J.M., 1997. Guns, Germs and Steel: a Short History of Everybody for the Last 13,000 Years. W.W. Norton & Co, New York.
Eklund, L., Degerald, M., Brandt, M., Prishchepov, A.V., Pilesjö, P., 2017. How conflict affects land use: agricultural activity in areas seized by the Islamic State. Environ. Res. Lett. 12 (5), 054004.
Elvidge, C.D., Baugh, K., Zhizhin, M., Hsu, F.C., Ghosh, T., 2017. VIIRS night-time lights. Int. J. Remote Sens. 38 (21), 5860–5879.
Frey, B.S., Steiner, L., 2011. World Heritage List: does it make sense? Int. J. Cult. Policy 17 (5), 555–573.
Gavshon, D., Gorur, E., 2018. Information overload: how technology can help convert raw data into rich information for transitional justice processes. Int. J. Transit. Justice. https://doi.org/10.1093/ijtj/ijy029.
Gerner, D.J., Schrodt, P.A., Yilmaz, O., 2009. Conflict and Mediation Event Observations (CAMEO) Codebook. http://eventdata.parusanalytics.com/data.dir/cameo.html.
Giglio, L., Descloitres, J., Justice, C.O., Kaufman, Y.J., 2003. An enhanced contextual fire detection algorithm for MODIS. Remote Sens. Environ. 87 (2-3), 273–282.
Hand, E., 2015. Startup liftoff. Science 348, 172–177.
Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A.A., Tyukavina, A., et al., 2013. High-resolution global maps of 21st-century forest cover change. Science 342 (6160), 850–853.
Harmanşah, Ö., 2015. ISIS, heritage, and the spectacles of destruction in the global media. Near East. Archaeol. 78 (3), 170–177.
Jensen, M., 2013. Discussion Point: the Benefits and Drawbacks of Methodological Advancements in Data Collection and Coding: Insights From the Global Terrorism Database (GTD). (Accessed 26 December 2018). https://www.start.umd.edu/news/discussion-point-benefits-and-drawbacks-methodological-advancements-data-collection-and-coding.
Jones, K.R., Venter, O., Fuller, R.A., Allan, J.R., Maxwell, S.L., Negret, P.J., Watson, J.E., 2018. One-third of global protected land is under intense human pressure. Science 360 (6390), 788–791.
Kessler, R., 2011. Group Launches Early-Warning System for Threats to Global Heritage Sites. Science. news posted on Mar, 16, 2011. (Accessed 26 December 2018). https://www.sciencemag.org/news/2011/03/group-launches-early-warning-system-threats-global-heritage-sites.
Leetaru, K., Schrodt, P.A., 2013. Gdelt: global data on events, location, and tone, 1979–2012. ISA Annual Convention Vol. 2, 1–49 No. 4.
Levin, N., Kark, S., Crandall, D., 2015. Where have all the people gone? Enhancing global conservation using night lights and social media. Ecol. Appl. 25 (8), 2153–2167.
Levin, N., Ali, S., Crandall, D., 2018. Utilizing remote sensing and big data to quantify conflict intensity: the Arab Spring as a case study. Appl. Geogr. 94, 1–17.
Li, X., Li, D., 2014. Can night-time light images play a role in evaluating the Syrian Crisis? Int. J. Remote Sens. 35 (18), 6648–6661.
Liang, Y., Jabr, K., Grant, C., Irvine, J., Halterman, A., 2018. New techniques for coding political events across languages. 2018 IEEE International Conference on Information Reuse and Integration (IRI) 88–93.
Meier, P., 2015. Digital Humanitarians: How Big Data is Changing the Face of Humanitarian Response. CRC Press.
Meskell, L., 2013. UNESCO's World Heritage Convention at 40: challenging the economic and political order of international heritage conservation. Curr. Anthropol. 54 (4), 483–494.
Miller, S.D., Mills, S.P., Elvidge, C.D., Lindsey, D.T., Lee, T.F., Hawkins, J.D., 2012. Suomi satellite brings to light a unique frontier of nighttime environmental sensing capabilities. Proc. Natl. Acad. Sci. 109 (39), 15706–15711.
O'Brien, S.P., 2013. A multi-method approach for near real time conflict and crisis early warning. Handbook of Computational Approaches to Counterterrorism. Springer, New York, NY, pp. 401–418.
O'Keefe, R., 2004. World cultural heritage: Obligations to the international community as a whole? Int. Comp. Law Q. 53 (1), 189–209.
Osipova, E., Shadie, P., Zwahlen, C., Osti, M., Shi, Y., Kormos, C., Bertzky, B., Murai, M., Van Merm, R., Badman, T., 2017. IUCN World Heritage Outlook 2: a Conservation Assessment of All Natural World Heritage Sites. IUCN, Gland, Switzerland, pp. 92.
Palen, L., Soden, R., Anderson, T.J., Barrenechea, M., 2015. Success & scale in a data-producing organization: the socio-technical evolution of OpenStreetMap in response to humanitarian events. Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems 4113–4122.
Parcak, S., Gathings, D., Childs, C., Mumford, G., Cline, E., 2016. Satellite evidence of archaeological site looting in Egypt: 2002–2013. Antiquity 90 (349), 188–205.
Román, M.O., Wang, Z., Sun, Q., Kalb, V., Miller, S.D., Molthan, A., et al., 2018. NASA's Black Marble nighttime lights product suite. Remote Sens. Environ. 210, 113–143.
Rose, R.A., Byler, D., Eastman, J.R., Fleishman, E., Geller, G., Goetz, S., et al., 2015. Ten ways remote sensing can contribute to conservation. Conserv. Biol. 29 (2), 350–359.
Rössler, M., 2006. World heritage cultural landscapes: a UNESCO flagship programme 1992–2006. Landsc. Res. 31 (4), 333–353.
Ryan, J., Silvanto, S., 2009. The World Heritage List: the making and management of a

brand. Place Brand. Public Dipl. 5 (4), 290–300.
Sá, A.C., Benali, A., Fernandes, P.M., Pinto, R.M., Trigo, R.M., Salis, M., et al., 2017. Evaluating fire growth simulations using satellite active fire data. Remote Sens. Environ. 190, 302–317.
Schutte, S., 2017. Regions at risk: predicting conflict zones in african insurgencies. Political Sci. Res. Methods 5 (3), 447–465.
Silverman, H., 2011. Border wars: the ongoing temple dispute between Thailand and Cambodia and UNESCO's World Heritage List. Int. J. Herit. Stud. 17 (1), 1–21.
Spearman, C., 1904. The proof and measurement of association between two things. Am. J. Psychol. 15 (1), 72–101.
START, 2017. National Consortium for the Study of Terrorism and Responses to Terrorism (START). Global Terrorism Database [Data file]. Retrieved from. July 31st, 2017. http://www.start.umd.edu/gtd.
Strauss, M., 2017. Planet Earth to get a daily selfie. Science 355, 782–783.
Venter, O., Sanderson, E.W., Magrach, A., Allan, J.R., Beher, J., Jones, K.R., et al., 2016a. Sixteen years of change in the global terrestrial human footprint and implications for biodiversity conservation. Nat. Commun. 7, 12558.
Venter, O., Sanderson, E.W., Magrach, A., Allan, J.R., Beher, J., Jones, K.R., et al., 2016b. Global terrestrial Human Footprint maps for 1993 and 2009. Sci. Data 3, 160067.
WDPA, 2018. UN Environment World Conservation Monitoring Centre, International Union for Conservation of Nature, World Database on Protected Areas. www.protectedplanet.net.
Wegener, C., 2010. The 1954 Hague Convention and Preserving Cultural Heritage. AIA Site Preservation Program, 1-3. Archaeological Institute of America (Accessed 25 May 2018). https://www.archaeological.org/sites/default/files/files/Wegener%20v2.pdf.
Weidmann, N.B., Ward, M.D., 2010. Predicting conflict in space and time. J. Conflict Resolut. 54 (6), 883–901.
Witmer, F.D., 2015. Remote sensing of violent conflict: eyes from above. Int. J. Remote Sens. 36 (9), 2326–2352.
Wood, S.A., Guerry, A.D., Silver, J.M., Lacayo, M., 2013. Using social media to quantify nature-based tourism and recreation. Sci. Rep. 3, 2976.
Wuepper, D., Patry, M., 2017. The World Heritage list: which sites promote the brand? A big data spatial econometrics approach. J. Cult. Econ. 41 (1), 1–21.
Yang, L., Wu, L., Liu, Y., Kang, C., 2017. Quantifying tourist behavior patterns by travel motifs and geo-tagged photos from Flickr. ISPRS Int. J. Geoinf. 6 (11), 345.