An urbanization monitoring dataset for world cultural heritage in the Belt and Road region

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\textbf{ABSTRACT}

World cultural heritage refers to properties recognized as having historical, social, and anthropological value. Global urbanization has changed the land cover, land use, transportation, landscape, and local environment in cities, and thus exposed World Heritage sites to risks induced by direct or indirect damaging factors. In this paper, an urbanization intensity index (UII) was developed to quantitatively measure urban dynamics in the vicinity of World Heritage sites. This index is based on three global Earth observation datasets, including a global human settlement layer, a global population grid product, and a global nighttime light imagery. Large UII values represent high urbanization levels and intensive human activities in the study area and vice versa. The assessment results show that the mean UII value at 79 world cultural heritage sites in the Belt and Road region increased from 0.26 in 2000 to 0.29 in 2015. The heritage sites were then classified into four types based on the change rates of UIIs. A total of seven heritage sites were identified as exposed to risks due to urban sprawl and infrastructure expansion. The UII dataset can be combined with UNESCO’s periodic reports and site-specific data to provide valuable information for international communities to develop heritage preservation policies. The dataset is available at http://www.dx.doi.org/10.11922/sciedb.980.

\textbf{1. Introduction}

World Heritage refers to properties globally recognized as having outstanding universal value. There are three types of world heritage, including cultural heritage (e.g., buildings and relics), natural heritage (e.g., landscapes and ecosystems), and mixed heritage (e.g., combined elements of nature and culture). In 1972, the United Nations Educational, Scientific and Cultural Organization (UNESCO) advanced the Convention Concerning the Protection of World Cultural and Natural Heritage, or the World Heritage Convention. This is an international agreement through which nations act jointly to conserve a collection of the world’s heritage (United Nations Educational, Scientific, and Cultural Organization (UNESCO), 1972). The World
Heritage Convention is the only international legal instrument for the protection of both cultural and natural heritage sites and encourages cooperation among nations for safeguarding their heritage. In 1978, the World Heritage List inscribed 12 sites spread across seven countries to its inaugural roster. As of July 2019, there have been 1,121 World Heritage sites from 167 countries inscribed on the World Heritage List, including 869 cultural sites, 213 natural sites, and 39 mixed sites (UNESCO World Heritage Convention, 2019). China and Italy have the largest number of heritage sites (55 each), followed by Spain, Germany, France, and India.

World Heritage is considered a critical enabler of sustainable development (Xiao et al., 2018). In September 2015, the United Nations Sustainable Development Summit in New York adopted Transforming Our World: The 2030 Agenda for Sustainable Development, which announced 17 sustainable development goals (SDGs) with 169 associated targets (United Nations, 2015). Among them, SDG 11 was created to make cities and human settlements inclusive, safe, resilient, and sustainable. Within this goal, Target 11.4 aims to strengthen efforts to protect and safeguard the world’s cultural and natural heritage.

The process of urbanization describes a shift in a population from one that is dispersed across small rural settlements where agriculture is the dominant economic activity to dense urban settlements that are characterized by industrial and service activities. According to the United Nations (UN DESA, 2018), the proportion of the global urban population increased from less than 30% in 1950 to 55% in 2018. It is predicted that the proportion will reach 68% by 2050, and nearly 90% of urban population growth will be concentrated in Asia and Africa. These global urbanization trends are closely related to sustainable development. The process of urbanization at the global scale has had significant negative impacts on the environment, biodiversity, ecological processes and regional sustainable development (Grimm et al., 2008; K C, Güneralp, & Hutyra, 2012). The density of population in urban dwellings can promote economic and social development when under appropriate planning and management. However, rapid and unplanned urban development without the construction of necessary infrastructure is a threat to sustainable development.

Previous studies have reported that World Heritage sites suffer from both anthropogenic and natural threats (Agapiou et al., 2015; Luo et al., 2019). Possible natural and environmental threats include soil erosion, landslides, floods, and sea level rise. Human activities such as war and tourism may also cause the degradation and destruction of heritage sites. In particular, the urbanization process has changed the land cover, land use, transportation, landscape, and environment in cities, which has directly or indirectly impacted the character of heritage sites. Heritage sites that are threatened by urbanization, armed conflicts, natural disasters, or other causes can be added to the endangered list administrated by the World Heritage Committee for their urgent protection (World Heritage Centre (WHC), 2020). Almost half of the cultural heritage properties, sites, or groups of buildings or monuments inscribed on the World Heritage List are situated in an urban context. Thus, they are vulnerable to the pressures and threats associated with urbanization processes (WHC, 2010). However, UNESCO has developed an international standard-setting instrument for safeguarding historic urban landscapes. Therefore, up-to-date and accurate information on urban sprawl and development in the neighborhood of World Heritage sites can facilitate local governors and planners to design timely policies and measures to preserve and safeguard these properties.
Remote sensing data has been widely used to monitor the dynamics of urban land use (Weng, 2012). The nighttime light (NTL) time-series data obtained by the Defense Meteorological Satellite Program’s Operational Linescan System (DMSP-OLS) has been used to visualize the impact of urban sprawl in the vicinity of UNESCO World Heritage Sites and monuments in Europe (Agapiou, 2017). Multi-temporal Sentinel-2 data were used to track the spatial patterns of urban sprawl across the cultural landscape of the World Heritage site in Cyrene, Libya, and the ancient coastal Greek sites of Tocra, Ptolemais, and Apollonia in Cyrenaica (Tapete & Cigna, 2018). The availability of global Earth Observation datasets and products has made dynamic urban mapping and monitoring at large spatial scales possible in recent years (Lu, Guo, Corbanel, & Li, 2019a). For heritage sites which are facing the environmental and social risks of rapid urbanization, the spatiotemporal dynamics of measurable indicators can be used to track the progress towards achieving the SDGs and can help countries and international organizations identify hotspot regions for targeted policy action (Xu et al., 2020). In this study, an Urbanization Intensity Index (UII) based on multi-source remote sensing data and products was proposed as a novel indicator for monitoring the urban dynamics surrounding cultural heritage sites.

2. Methods

2.1. Data source

The intensity of urbanization can be measured by the extent to which human land use develops, utilizes, and transforms the natural cover of the land surface. In this study, the built-up area, population density, and nighttime light imagery were used conjunctively to reflect the intensity of human activities associated with the urbanization process in the areas surrounding cultural heritage sites. Specifically, the datasets consisted of DMSP-OLS nighttime light data, the built-up area data from the global human settlement layer, and gridded population data. The geographic location data for World Heritage sites was obtained from the official World Heritage list (UNESCO World Heritage Convention, 2019).

The JRC Global Human Settlement Layer (GHS-L) product maps human presence on the planet through the analysis of satellite data, census data, and volunteered geographic information (Pesaresi et al., 2013). The dataset is available at https://ghslysys.jrc.ec.europa.eu/. The GHS-Built data contains a multitemporal information layer, and a symbolic machine learning (SML) methodology is used to examine the built-up presence in four epochs. These periods were extracted from Landsat image collections (GLS1975, GLS1990, GLS2000) and Landsat 8 imagery (2013/2014). The SML can provide better outputs than several state-of-the-art supervised classification methods with less computational cost. This study used the global built-up area dataset from the GHS-Built products obtained in 2000 and 2014. The dataset features a 1 km resolution and the World Mollweide projection (EPSG:54009).

The nighttime lights data obtained by DMSP-OLS has served as a proxy for a variety of socio-economic variables, such as population, power consumption, and gross domestic product (Lu, Weng, Xie, Guo, & Li, 2019b). In this study, the DMSP-OLS version 4 stable nighttime lights annual composite from 1992 to 2013 was obtained from the National Oceanic and Atmospheric Administration’s National Geophysical Data Center (NGDC, 2010). The dataset is available at https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html. The DMSP-OLS product provides light intensity data as raster layers with near global coverage.
between the latitudes of 75°N and 65°S with a spatial resolution of 30 arc-seconds (about 1 km at the equator). The stable composite product captures lights from cities, towns, and other sites with persistent lighting. Ephemeral events such as wildfires and vehicles are discarded. The digital numbers in the DMSP-OLS data can range from 0 to 63. The NTL data from 2000 and 2013 were used in this study. Inter-calibration of data from different OLS instruments was carried out using the invariant region-based method (Li, Lu, Weng, Xie, & Guo, 2016). This was necessary due to the lack of an onboard calibration system and long-term sensor degradation.

The gridded population dataset from the WorldPop Project was produced using a combined machine learning and dasymetric modeling approach (Worldpop & CIESIN, 2018). The dataset is available at https://www.worldpop.org/. Several geospatial covariates were standardized and harmonized as input to a random forest model to create a population density layer (Stevens, Gaughan, Linard, Tatem, & Amaral, 2015). The population density layer was then used to disaggregate the administrative unit-based population counts to 100 m spatial resolution grids. The WorldPop population dataset represents residential population counts effectively since it relies on census data to inform the modelling process. The global population data for 2000 and 2015 were acquired in this study. The 100 m gridded population datasets were spatially aggregated by summing the population per grid cell to match the 1 km spatial resolution of NTL and GHSL data.

2.2. Estimating the urbanization intensity index

The built-up area, nighttime light, and population density data were used as factors to document the proximity of urban land expansion and anthropogenic activities to cultural heritage sites. Before performing the UII calculation workflow, the remote sensing products were preprocessed by calibration and re-projection to ensure that they are in the same coordinate system. The workflow for estimating the urbanization intensity index (UII) using remote sensing data is illustrated in Figure 1. The workflow mainly consists of three steps: (1) data normalization, (2) UII calculation, and (3) spatial averaging.

First, six buffer zones with a distance of 500 m, 1,000 m, 1,500 m, 2,000 m, 2,500 m, and 3,000 m were delineated with the geographic location of the World Heritage sites as the center. The average value of the three datasets – population density, built-up area, and nighttime lights – was derived in each of the buffer zones surrounding the heritage sites. The average value was then normalized to the range of 0 ~ 1 using the maximum value of each factor.

The UII of the world cultural heritage sites in urban areas was calculated as the geometric average of the three factors using the following formula (Lu, Weng, Guo, Feng, & Li, 2019c):

\[
UII = \sqrt[\Delta]{BU_{nor} \times NTL_{nor} \times POP_{nor}}
\]

where \(BU_{nor}\), \(NTL_{nor}\), and \(POP_{nor}\) represent the urban built-up area, nighttime lights, and population data after normalization, respectively.

Finally, the UII values of each buffer zone were averaged to obtain the mean UII value at a specific cultural heritage site. Large UII values indicated the occurrence of high levels of urbanization and intense human activities, and vice versa. The risks induced by urban
sprawl at cultural heritage sites were then identified and evaluated based on the spatial pattern and temporal changes in UII values.

3. Data records

The spatial domain of the dataset covers the majority of the Belt and Road region, spanning from 12°S to 66°N and 18°W to 148°E. The Belt and Road Initiative, also known as the Silk Road Economic Belt and 21st Century Maritime Silk Road, is a foreign policy initiative that was first launched by the Chinese government in 2013 (National Development and Reform Commission (NDRC), Ministry of Foreign Affairs (MFA), and Ministry of Commerce of the People’s Republic of China (MOC), 2017). The initiative encourages regional connectivity and economic integration between China and other Asian, European, and African countries (Guo, 2018). The Belt and Road region includes 66 countries that are in Asia, Europe, and North Africa with a total population of 4.73 billion. Asia and Africa experienced rapid urbanization from 1990 to 2014 (UN DESA, 2018), and the urban population in Asia increased from 32.3% in 1990 to 47.5% in 2014. China, India, Indonesia, Pakistan, and Bangladesh are the most populous countries in the Belt and Road region. Among them, the population of China reached 1.4 billion in 2014 with 54% of the population living in cities. The population of India reached 1.3 billion in 2014 with 32% of the population living
in urban areas. Singapore, Qatar, Kuwait, and Israel were found to have high urbanization levels (above 90%), while Sri Lanka, Nepal, Cambodia, Afghanistan, and Tajikistan were observed to have low urbanization levels (e.g., below 30%). The forthcoming urbanization process will lead to possible impacts to world cultural heritage sites in countries with low urbanization levels.

The UII dataset was produced at an annual scale and saved in xlsx format. Each table in the xlsx file contained the UII values for cultural heritage sites located in countries in the Belt and Road region. The UII values were derived from cultural heritage sites located in city and town settlements. A total of 79 heritage sites were selected and the urban dynamics in their surrounding areas were measured with UIIs obtained in 2000 and 2015. The first page of the shared xlsx file presents a list of cultural heritage sites in each country. The cultural heritage sites in each country are grouped into a separate page. Data for each site includes the three data values used, the calculated UII values, and a graph showing the UII changes. The columns of the table represent buffer distances and the rows represent years. Using this data, the changes of UII values with time and space can be clearly revealed at each cultural heritage site.

4. Technical validation

The UII values in 2000 and 2015 were used to derive the UII rates for each heritage site. The rates of UII in all heritage sites ranged from 351.64% to −3.53%. Three heritage sites were selected with high UII rates in China to validate urban growth trends. High-resolution satellite images that covered the heritage sites from 2000 to 2015 were collected using Google Earth Pro software (Cao et al., 2018). The growth rates for UII values in the Classical Gardens of Suzhou, the Historic Monuments of Dengfeng, and the Mausoleum of the First Qin Emperor were 136.57%, 93.56%, and 90.06%, respectively. The high-resolution satellite images of the three sites are shown in the left column (2000) and right column (2015) in Figure 2. During this period, croplands were observed to change to a newly built settlement near the Classical Gardens of Suzhou (Figure 2(a)). Moreover, transportation infrastructure such as highway networks were further developed in accordance with economic growth. The previously small and scattered settlements near the Dengfeng Historic Monuments were transformed to large and continuous built-up areas over time (Figure 2(b)). The sprawl of built-up areas was also observed in the areas surrounding the Mausoleum of the First Qin Emperor (Figure 2(c)). Overall, the extent and area of human settlements increased significantly from 2000 to 2015. The expansion of built-up areas and infrastructure observed from high-resolution satellite images agreed with the increasing trend in UII values.

5. Dataset value

This section outlines the potential applications and usefulness of the UII dataset in supporting the protection of World Heritage from anthropogenic threats.

5.1. Spatial pattern of UII values

The UII values of cultural heritage sites were obtained for each buffer zone, which revealed different spatial gradients in UII values. The increasing gradient of UII values in
Figure 3(a) indicated that anthropogenic influences surrounding these sites became more intense as they moved farther away from the center. Both sites in Figure 3(a) were located in growing cities on the plains of northern China. Yin Xu, the capital of the late Shang Dynasty, was located at the northwest of the nationally famous historic and cultural city of Anyang. The heritage sites in Figure 3(b) were observed to have decreasing UII gradients. The urban development intensity was observed to decrease when moving farther away from the property. The Potala Palace, the winter palace of the Dalai Lama, was built on Red Mountain in the center of Lhasa Valley at an altitude of 3,700 m. For the heritage sites in Figure 3(c), the UII values fluctuated in different buffer zones, implying that the landscape patterns were heterogenous near the heritage sites. This may have been caused by varying topography or diverse land cover types. For instance, the temples of various architectural styles and imperial gardens were situated in lakes, pastureland, and forests in Chengde Mountain Resort.

A comparison of the UII values in different time periods revealed that the UIIs increased significantly from 2000 to 2015 across the buffer zones in the Classical Gardens of Suzhou. Suzhou inhabits the center of the Yangtze River Delta and is a major transportation hub city in the Yangtze River Economic Circle, which is the largest Economical Circle in China. Since 2000, continued economic development has enabled the infrastructure to be gradually improved and urban and rural areas have become comprehensively connected. There were slight changes or even decreases in UII values for different distance buffers from 2000 to 2015 near the Temple and Cemetery of Confucius and the Kong Family Mansion in Qufu. The site is mainly located in urban areas, where land use, population density, and infrastructure were relatively stable during the study period.
5.2. Temporal changes in UII values

The UII values for all buffer zones were averaged to obtain the UII value at each heritage site. The mean UII value for 79 world cultural heritage sites in the Belt and Road region increased from 0.26 in 2000 to 0.29 in 2015. The UII values for 15 cultural heritage sites in China are shown in Figure 4. The UII values for the heritage sites in the metropolitan areas of large cities such as at the Temple of Heaven and Summer Palace in Beijing were observed to be higher than at other sites. The heritage sites in small cities or suburban areas such as in Kulangsu, the Mausoleum of the First Qin Emperor, and Potala Palace featured lower UII values.

The growth rate of UII was derived for each heritage site to analyze the changes in values from 2000 to 2015 (Figure 5). The changing UII rates for cultural heritage sites in
China exhibited a large increasing rate at sites such as Kulangsu, the Classical Gardens of Suzhou, the Historic Monuments of Dengfeng, and the Mausoleum of the First Qin Emperor. As seen in Figure 2, the neighborhoods of these sites all experienced tremendous built-up area sprawl and the construction of new infrastructure. In contrast, the UII growth rates for the Temple of Heaven and the Summer Palace in Beijing were lower in comparison. Previous studies using land cover maps classified from Landsat imagery reported that urban sprawl mainly occurred in suburban and rural areas in Beijing since 2000 (Haas & Ban, 2014; Lu, Guo, Wang, Martino, & Daniele, 2014). This coincides with the relatively stable UIIs observed in this study and implies that slight urban changes have occurred near heritage sites.

5.3. Classification of cultural heritage sites using UII

The UII values can represent possible anthropogenic risks directly or indirectly induced by the urban development process. The 79 heritage sites were classified using the natural breaks method based on the change rates of UII values from 2000 to 2015 (Figure 6). The heritage sites were divided into four types, including: very low change (< 0.14), low change (0.14–0.39), medium change (0.39–1.37), and high change (> 1.37). A total of seven heritage sites, including five in China, one in Nepal, and one in India were identified as having high and medium changes in UII values. Since the 1990s, China has experienced unprecedented urban expansion and rapid socioeconomic development (Bai, Shi, & Liu, 2014). The buffer zones surrounding Kulangsu, the Classical Gardens of Suzhou, the Historic Monuments of Dengfeng, the Mausoleum of the First Qin Emperor, and the Old Town of Lijiang in China have all had large changes in UII values. During the study period, these sites experienced the expansion of built-up areas and an increased population density.

The cultural heritage of the Kathmandu Valley in Nepal consists of several groups of monuments and buildings which display the full range of historic and artistic achievements. The property was declared a protected monument zone in 1956, providing the highest level of national protection. Some monuments at Kathmandu were in danger and have since been reconstructed. The preservation of heritage structures has involved geocrowdsourcing and web-mapping to collect damage information such as location and the degree of damage, which has supported timely risk mitigation (Xiao et al., 2018). Since 2007, the property has been managed by the coordinated action of the central government, local government, and non-governmental organizations.
The Jantar Mantar is an astronomical observation site that was built in the early 18th century in Jaipur, India, and was inscribed on the UNESCO World Heritage List in 2010. The challenges for the property include the development of tourism and urban growth in the immediate vicinity of the site (UNESCO World Heritage Convention, 2019). The major projects to upgrade and modify the district and traffic may affect the landscape and environment of the property. Some measures have been suggested to protect the buffer zone of the property, which has been incorporated into the urban management of the municipality of Jaipur.

6. Usage notes

In the Operational Guidelines for the Implementation of the World Heritage Convention, the boundaries of heritage sites were required to be adequately delineated to incorporate all the attributes that convey the outstanding universal values (OUV) of inscribed properties (WHC, 2019). Legislative and regulatory measures should be implemented for the protection of inscribed properties from social, economic, and other pressures that might negatively impact the OUV such as human encroachment and resource use. A buffer zone that includes the immediate setting of the property, important views, and other areas that are functionally important was suggested to support the property and its protection (WHC, 2009). Complementary legal and/or customary restrictions should be imposed on the use and development of buffer zones on the inscribed properties. The updated information, changing circumstances, and conservation status of World Heritage properties (including buffer zones) were provided to UNESCO by state parties using a periodic reporting mechanism (UNESCO World Heritage Convention, 2019). In addition to periodic reports, the UII dataset can provide complementary information on the conditions of surrounding areas near World Heritage properties.
The construction of infrastructure and the frequent use of vehicles during the urban development process may cause vibrations and structural deficiencies in properties at heritage sites. Environmental deterioration caused by unmanaged urbanization may have an indirect impact on heritage. Archaeological research and excavations are usually long-term projects and the heritage sites should be protected from these damages (Agapiou et al., 2015). The UII dataset for cultural heritage sites in the Belt and Road region helps international communities identify archaeological heritage that may face the threat of human interference, especially for the remaining unexcavated archaeological features. The future expansion of urban areas in the vicinity of heritage sites can be predicted using simulation models based on the built-up area extracted from remote sensing data. Furthermore, these models can contribute to more archaeologically oriented urban planning strategies in developing areas (Agapiou et al., 2015). Additionally, satellite data can be used conjunctively with topographic and geological maps, digital elevation models, and air pollution measurements to explore the risks for cultural heritage within a GIS environment (Hadjimitsis, Agapiou, Alexakis, & Sarris, 2013).

The main limitation of the UII dataset is that the data is only available for 2000 and 2015 and the spatial resolution of source data is 1 km. However, UII values can be derived with enhanced temporal and spatial resolution due to the availability of satellite data with improved characteristics such as Sentinel 1/2 satellite data and Visible Infrared Imaging Radiometer Suite (VIIRS) nighttime light data. Furthermore, the UII values were only validated with high-resolution satellite images in this study. However, field observations and statistical data can also be used to evaluate the results. In addition to the factors that were considered, there are other factors that can reflect the intensity of human activity and urbanization, such as transportation network density, energy consumption, carbon emissions, and atmospheric pollutants. More factors should be considered for the improvement and development of UII in future studies. The factors negatively affecting cultural properties can include local conditions, natural disasters, climate change, infrastructure development, resource use, unfavorable human activities, tourism, and pollution (UNESCO, 2012). The factors leading to changes in UII values and conservation status may vary due to the historical, ecological, geological, climatic, and social diversity in World Heritage properties. Site-specific data should be obtained for in-depth analysis of the cause of changes in UII values at heritage sites to provide practical value for planners and the broader World Heritage system.

**Data availability statement**

The dataset is openly available in Science Data Bank at [http://www.dx.doi.org/10.11922/sciencedb.980](http://www.dx.doi.org/10.11922/sciencedb.980).

**Disclosure statement**

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