Worldwide increase in Artificial Light At Night around protected areas and within biodiversity hotspots

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A R T I C L E   I N F O

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A B S T R A C T

Artificial Light At Night (ALAN) has several adverse impacts on biodiversity, and it has been recently used as a proxy to monitor human encroachment on landscapes at large spatial scales. The extent to which ALAN affects protected areas (PAs) and biodiversity hotspots (BHs) remains however untested at large spatial scales. We used this proxy to assess the spatial and temporal trends in the anthropization at a global scale within and around PAs and BHs. We found that ALAN is low and stable over time within PAs, but is the highest in a first outer belt (< 25 km) around PAs, and tends to increase in a second outer belt (25–75 km). In the meantime, ALAN is higher within BHs than outside, and is even the highest and increasing over time in an inner belt, close to their periphery. Our results suggest that although PAs are creating safety zones in terms of ALAN, they tend to be more and more isolated from each other by a concentric human encroachment. In contrast, BHs are submitted to an increasing human pressure, especially in their inner periphery. Overall, we suggest integrating ALAN in large-scale conservation policies.

1. Introduction

Artificial Light At Night (ALAN) is a pervasive phenomenon leading to an increasing light pollution across the globe (Hölker et al., 2010), and its study has become a major concern in conservation biology for two reasons.

First, because the adverse impacts of ALAN on biodiversity are now more and more documented. It impacts several taxa, including mammals, birds, reptiles, amphibians, fish, invertebrates and plants, both in terrestrial and aquatic ecosystems (see Gaston et al., 2014; Gaston and Bennie, 2014; Longcore and Rich, 2004 for detailed reviews). ALAN has for example significant impacts on individual movements (e.g. Polak et al., 2011; Stone et al., 2009), phenology (e.g. Bennie et al., 2016), and may lead to dramatic changes in interspecific interactions (e.g. Underwood et al., 2017), in community structures (e.g. Meyer and Sullivan, 2013), and in essential ecological processes such as pollination (Knop et al., 2017).

The second point of conservation interest is that ALAN can be used as a relevant proxy to monitor human encroachment at large (e.g. regional, national, or global) spatial scales. Since the 1990s, the monitoring of ALAN has received a large attention thanks to satellite data from the Defense Meteorological Satellite Program - Operational Linescan System (DMSP-OLS) observations (Elvidge et al., 1997) and more recently from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) (see Falchi et al., 2016; Kyba et al., 2017). Between 1992 and 2013, no fewer than 144 articles using nightlight data were published in 61 different journals (Huang et al., 2014). In addition to several methodological studies dealing with the way to use such data (e.g. Hsu et al., 2015; Li et al., 2013), different regional (e.g. Bennie et al., 2014; de Freitas et al., 2017; Liu et al., 2012), continental (e.g. Bennie et al., 2014; Small and Elvidge, 2011) and global (e.g. Bennie et al., 2015; Davies et al., 2016; Falchi et al., 2016) maps of ALAN have been generated. It thus rapidly became a proxy of urban extent (see the review of Li and Zhou, 2017), human demography, urban land dynamics and socioeconomic parameters (30, 28 and 27 publications, respectively, reviewed by Huang et al., 2014 for these applications). Recently, ALAN was also used as a component of the human footprint (Venter et al., 2016) because it can both be monitored at a global scale and at a fine temporal and spatial scale, whereas many other components of global human pressure are only available at either low spatial or low temporal resolutions, and are spatially heterogeneous (Geldmann et al., 2014).

However, the literature explicitly linking the spatial distribution of ALAN with areas of special importance for biodiversity remains scarce.

To our knowledge, there is for example no studies linking ALAN distribution with biodiversity hotspots (BHs), and only three studies linked ALAN distribution with the location of Protected Areas (PAs).
instance, Geldmann et al. (2014) used nightlight data together with human population density and land transformation to compute a Temporal Human Pressure Index (THPI), which was compared between the different IUCN protected area categories. However, as they reported, for several technical reasons (particularly the need for homogeneity between the different datasets used), this first and promising study used rather low spatial resolution data (10 km²), only took into account the largest protected areas (> 200 km²), did not compare artificial nighttime levels within and outside PAs, and only used a difference in artificial nightlight level between the two extreme dates of the dataset (1995 and 2010). Gaston et al. (2015), using two decades of ALAN recording data, compared the mean ALAN and its temporal trend in and out of the PAs at a global scale. They found that PAs tended to be darker at night than non-protected areas. The third study was conducted by Davies et al. (2016). Following the methods of Gaston et al. (2015), they focused on marine PAs and found that artificial light is widespread and increasing in a large percentage of marine PAs.

However, as for any human perturbation, ALAN not only has a direct influence at the exact place where it is located, but may also lead to the spatial fragmentation of “dark areas” (i.e. the areas which are not submitted to ALAN). Both PAs and BHs cannot be viewed as isolated islands, but rather as patches included in a larger landscape matrix. Therefore, it is crucial to assess whether ALAN is increasing not only in but also around (along a continuous spatial gradient) PAs and BHs. Indeed, beyond the situation within a particular zone, the continuous spatial distribution of a given pressure is highly informative in conservation biogeography (Whitaker et al., 2005). A given amount of ALAN can lead to very contrasted spatial dynamics depending on the fragmentation of impacted patches.

The aim of our study is to analyze the spatial distribution and the temporal trend in ALAN according to the spatial distribution of PAs and BHs. More precisely, we address the two following objectives:

(i) to draw a global map of the mean ALAN and its temporal trend between 1993 and 2012.

(ii) to analyse the spatial distribution of the mean ALAN and its temporal trend along a continuous spatial gradient from the core of the PAs and the BHs to their peripheries.

Protected areas are meant to protect biodiversity from major human pressures. We thus expect them to prevent any increase in ALAN or, at least, to be located where ALAN is the lowest. Biodiversity hotspots (BHs) are considered to be areas hosting the highest biological diversity, which have to be conserved first. However, they are also among the most densely populated areas (Williams, 2013), and we expect them to be located where ALAN is both high and increasing.

2. Material and methods

2.1. Nightlight data

The Defense Meteorological Satellite Program - Operational Linescan System (DMSP-OLS) Night-Time Light (NTL) archive is one of the most comprehensive datasets for monitoring, characterizing an understanding global human activities at a global scale and with such a long time lag. Although noise removal and other corrective processing are applied to the NTL imagery by the National Oceanic and Atmospheric Administration (NOAA), the time series cannot be directly used for quantitative change analysis because of the presence of systematic biases (Elvidge et al., 2014). One of the key issues is the lack of inter- and intra-annual calibration between satellites. Few models have been developed to improve the consistency of the data at global scale (e.g. Elvidge et al., 2014; Hsu et al., 2015; Zhang et al., 2016).

In this study, we used the freely available global inter-calibrated nighttime lights series (hereafter “NTL”) from Zhang et al. (2016) (http://urban.yale.edu/data). The dataset is a calibrated version using the “Ridgeline Sampling and Regression” method, generated from the stable DMSP-OLS NTL annual composite cloud-free product (version 4). At country and regional scales and among the different calibration methods, the systematic bias minimization of Zhang et al. (2016) appears to be superior (Pandey et al., 2017). The dataset includes the data from six satellites: F10, F12, F14, F15, F16, and F18 spanning over 20 years from 1993 to 2012 and quantifies the yearly average of stable light, ranging in brightness Digital Number (hereafter “DN”) from 0 (no artificial light) to 63 (value at which sensors saturate). Areas contaminated by sunlight, moonlight, fires and other ephemeral lights were removed (see Baugh et al., 2010) for a description of the methodology used to develop the Stable Light Product. In this study, we used the data acquired by the most recent satellite when several data were available the same year.

The final products have a spatial resolution of 30 arc sec (i.e. 1-km spatial resolution at the equator), spanning —180 to 180 degrees longitude and — 65 to 75 degrees latitude. For this study, all the raster data were projected using the Mollweide equal area projection, which accurate representation of areas takes precedence over the shape and angles.

2.2. Protected areas (PAs)

We used the World Database on Protected Areas (WDPA) of December 2016. All the PAs smaller than the spatial resolution of the nightlight data (1 km²), marine PAs as well as PAs created after 1993 were removed from our analyses. Thus, 40,701 protected areas were analyzed from a total of 211,723 which covered 10,733,883 km².

2.3. Biodiversity hotspots (BHs)

We used the freely available Biodiversity Hotspots database version 2016.1 from the Critical Ecosystem Partnership Fund, (http://www.cepf.net/resources/hotspots/Pages/default.aspx). We removed non-terrestrial hotspots. Our analyses include 36 different biodiversity hotspots (listed in Appendix 1).

2.4. Biogeographical regions

Because both ALAN on the one hand and PAs and BHs on the other are unevenly distributed across the globe (in terms of number and coverage), we also disentangle our results according to the 6 main biogeographical realms following the typology of Olson et al. (2001): Paleartic (PA), Neotropic (NT), Indo-Malay (IM), Nearctic (NA), Australasian (AA), and Afrotrropic (AT). The Antarctic biogeographical realm was not considered because of the poor coverage of nightlight data in this area. All the results by biogeographical realms are given in Appendix 2.

2.5. Distance from PAs and BHs borders

To study the spatial distribution of ALAN according to PAs and BHs, two distance maps from (i) PAs and (ii) BHs borders were generated.
We used the “Euclidean distance” tool of ArcGis 10.4 which calculates for each cell, the minimum straight-line distance to a border. The result is 2 global maps of a 1 km resolution which represent the distance from PAs and BHs borders, along a continuous spatial gradient. Values are given in negative kilometers for the areas located within PAs and within BHs, and in positive kilometers for the areas outside of PAs and BHs. For example a value of −10 means that the pixel is located within a PA or a BH, at 10 km from its border; conversely a value of +10 means that the pixel is located out of a PA or a BH, at a distance of 10 km from its border.

2.6. Mapping the mean ALAN and its temporal trends

All the calculation of mean ALAN or temporal trends in ALAN were based on the Digital Number (DN) values available in the Night-Time Light (NTL) series. A workflow chart of the following method is proposed in the Appendix 3. The stable light product (DMSP-OLS NTL) suffers from poor geolocation accuracy (Baugh et al., 2010).

To calculate the mean ALAN values and their temporal trends throughout the NTL series, we used the GRASS™ module “r.series” (GRASS™ SIG 7.2.0) which makes each output cell value a function of the values assigned to the corresponding cells in the input raster map layers. The module creates an output raster map of a function calculated on the NTL series. To map the mean DN values (i.e. the mean ALAN), we calculated the average and the standard deviation of the DN values in each pixel and throughout the 20 years. The result was two maps: one of the mean DN values, the other of the standard deviation in the DN values. To map the temporal trends in the DN values (i.e. temporal trends in ALAN), we computed a simple linear regression on the 20 raster maps, with the dependent variable being the DN values, the independent variable being the years, and the statistical individuals being each pixel. This resulted in two additional maps, one corresponding to the mean slope value of the regression (representing the linear temporal trend in ALAN), and the other corresponding to the coefficient of determination of the regression. The maps of the standard deviation around the mean and the map of the coefficient of determination of the linear regression are given as supplementary information in Appendix 4.

2.7. Calculation of ALAN along a continuous gradient of distance from the core to the peripheries of the PAs and the BHs

All the pixels every 5 km² were considered as statistical sample. In a table, the mean ALAN, the trend in ALAN and the distance from PAs and BHs border were merged. We kept the sampling effort (n = 20,347,848) constant among discrete distance classes. Thus, all the individuals were ordered along the distance gradient and then divided into 20 classes of the same areas (equal number of pixels). For each class, the mean and the standard deviation were calculated for the mean ALAN, the trend in ALAN, the distance from PAs and BHs.

All the analyses were conducted with R 3.3.2.

3. Results

3.1. Global picture of the mean ALAN and its temporal trend

From west to east, the areas which are the most submitted to ALAN were found in eastern North America, Europe, the Nile Delta, India, eastern China, South Korea, Japan, and Java in Indonesia (Fig. 1A). In South America, Africa and Australia, the hotspots of nighttime pollution were limited to the largest cities and their suburbs (Fig. 1A).

The map of the temporal trend in ALAN from 1993 to 2012 provided a different picture (Fig. 1B). While ALAN increased in some areas already deeply submitted to ALAN, including the Nile Delta, India, eastern China and Java, it was stable or even decreased in the other ALAN hotspots: eastern North America, the core of Europe (ALAN in Europe mainly increased in the periphery of the European Union: Ireland, Portugal, Poland; and in northern Italy) and Japan. The only large area where ALAN decreased was located in eastern Canada.

3.2. Spatial distribution of ALAN according to the distance from PA and BH borders

At a global scale, the mean ALAN differs along the 20 equal size classes of distance from PA borders (Fig. 2A-i) (Table 1). Mean ALAN is lower within PAs, higher in their close surrounding (0–25 km) and tended to decrease further from the periphery of the PA borders. The mean ALAN appears lower (< 50 DN value) and stable from 150 km from PA borders (Fig. 2A-i).

For comparison, the mean ALAN in the BHs and in their 500 km surrounding areas is higher (200.48 DN value in BHs; 159.53 DN values in PAs). The mean ALAN differs along the 20 equal size classes of distance from BH borders (Fig. 2. A-ii) (Table 2). Mean ALAN is higher within an inside belt of 50 km and drops immediately outside the BH border. From 100 km to the BH borders to 500 km, the mean ALAN falls under the general mean ALAN (= 200.48) (Fig. 2A-ii). The mean ALAN remains stable from 250 km to 500 km from the BH borders.

The temporal trend in ALAN differs according to the distance from PA borders (Fig. 2B-i) (Table 1). It follows a similar general pattern to the mean ALAN except that the peak is reached farther from the PA borders (25–75 km). The trend in ALAN is higher (between 2 and 3 DN value/year) within the buffer area at 25 to 100 km from PA borders, and the temporal trend is higher than the general mean (2.00/year).

The temporal trend in ALAN in the BHs and their 500 km surrounding is higher than for PAs (2.85 DN value/year in BHs; 2.00 DN value/year in PAs). The trend in ALAN differs along the 20 equal size classes of distance from BH borders (Fig. 2. B-ii) (Table 2) and follows a pattern similar to the mean ALAN. The trend in ALAN is also higher within an inside belt of 50 km (between 4 and 5 DN value/year) and falls immediately outside the BH border. From 100 km to 500 km from BH borders, the trend in ALAN is under the general mean (= 2.85).

4. Discussion

4.1. Protected areas are saved from ALAN but not their surroundings

The distribution of ALAN and its temporal trend are known to have different spatial and temporal patterns globally depending on the countries (Elvidge et al., 2014), what is also reflected by our global picture (Fig. 1) and confirmed by our analyses by biogeographic realms (Appendix 2). Less expected was the clear pattern of the spatial distribution of ALAN according to the distance to PAs.

The good news is that PAs seem to be much less exposed to ALAN than non-protected areas, both at a global scale and in each of the six main biogeographic realms. With a different methodological approach, this fits with the conclusions of Gaston et al. (2015): ALAN is lower and its temporal increase is less important within PAs than outside. However, we also found that mean ALAN reaches a peak immediately in the PA surroundings (in the first 25 km), and that ALAN mostly increase in a second belt (25–75 km). PAs thus seem to play their role of defense against human encroachment, but human presence is dense at their close proximity, and tends to extend across a second belt. This agrees with other studies reporting an increasing urban growth at the periphery of PAs (McDonald et al., 2009; McDonald et al., 2008). However, this trend will probably continue in the future, as the distance between PAs and cities is predicted to decrease by 2030 (McDonald et al., 2008). However, the increase in human population at the borders of PAs has been the subject of much controversy. Our results fit with the study of Wittmer et al. (2008) who found in a set of 306 PAs in Africa and Latin America that human population growth rates were nearly double.
the average rural growth. But this result was challenged by Joppa et al. (2009), who argued that it was due to an artifact of the datasets used, and by Joppa et al. (2010), who considered the available global datasets insufficient to assess the so-called “global-park questions”. The three mechanisms at the origin of potential population growth at the periphery of PAs were summarized by Scholte and De Groot (2010): “frontier engulfment” (PAs established in a still-intact area are later engulfed by an extraction frontier and then by agriculture); “attraction model” (people are attracted to PAs for economic reasons); “incidental mechanisms” (PAs may become refuges for people living in countries subjected to conflicts or natural disasters).

Whatever the origin of this increase in ALAN around PAs, this phenomenon deserves a special interest in a conservation perspective for at least two reasons.

First, because it reveals a spatial isolation of PAs that tend to become more and more isolated “dark islands” surrounded by high ALAN. From a conservation biogeography perspective, these belts of high and increasing ALAN may weaken potential connectivity in the global PA network, and may play a role of ecological barriers for many species that prevent potential exchanges between PAs and their peripheries.

Second, if ALAN is high and increasing around PAs at a close distance, its effects may also impact the areas within PAs, because ALAN...
may have biological influence to a larger extent than lit areas by several mechanisms (Gaston et al., 2015). In particular, ALAN can be visible at many kilometers in the PAs while the lit area is located around the PA. Specific plants or animals with positive light attraction within PAs can thus be attracted out of PAs, and the belts surrounding PAs with high ALAN may thus act as ecological traps.

4.2. Biodiversity hotspots are impacted by ALAN, especially their inner periphery

Comparatively to PAs, BHs are exposed to an intense ALAN within their perimeter. At a global scale, the mean ALAN is greater within BHs than outside. We expected this result because BHs are defined as places where exceptional concentration of endemic species are undergoing exceptional loss of habitat (Myers et al., 2000). The temporal trend in ALAN appears also greater within BHs than in their surrounding areas, highlighting a greater increase in human pressure inside than outside. This fits with Williams (2013) who found that during 2000–2010, the number of people living in BHs increased in absolute numbers and as a fraction of the global population. A few years before, Cincotta et al. (2000) also reported that in 1995, 20% of the world’s population was living within the BHs, and that population growth rates in the hotspots from 1995 to 2000 were higher than that of the world.

Within BHs, we finally found a peak of both mean ALAN and temporal trend in ALAN at a 50 km inner periphery from BH borders. We suppose this result is mainly explained by the singularity of coastal zones included in the BHs. In a large proportion of BH borders, coastlines play the role of frontier and several studies have shown that coastal zones are associated with large and growing concentration of human population, settlements and socioeconomic activities (Small and Nicholls, 2003). Small and Nicholls (2003) found that in 1990s, lighted settlements were centered within 5 km of coastlines worldwide and the near-coastal population living within 100 km of the shoreline was in 2000 3 times higher than the global average density. More recently, Kummu et al. (2016) found that between 1990 and 2010, the population living closer than 200 km from the coast increased from 2.7 to 3.5 billion people and is projected to reach 4.2 billion by the year 2030. Within BHs, which are exposed to high level of ALAN, coastal areas included in BHs are probably experiencing even more human pressures.

Fig. 2. Plots of (A) mean Artificial Light at Night (ALAN) and (B) its temporal trend according to the distance (in km) from (i) Protected Area (PA) borders and (ii) Biodiversity Hotspot (BH) borders. Mean ALAN are given in Digital Numbers (DN * 100) from the Defense Meteorological Satellite Program - Operational Linescan System (DMSP-OLS) Night-Time Light (NTL) archive. Trend in ALAN are given in DN value *100/year and distances are given in km. X-axis corresponds to the mean values of (A) mean ALAN and (B) trend in classes of ALAN; Y-axis corresponds to the mean distance of the classes. Curves represent generalized additive model (GAMs) with a smoothed function (s) of the distance (Trend or Mean~s(distance)) and the colored shade represent the standard errors.
Although the calibrated time series from the DMSP-OLS Nighttime Light Data is the longest and one of the more accurate consistent nightlight time series, caution is required when interpreting results derived from this data. There are several biases inherent in the DMSP-OLS NTL series data listed by Zhang et al. (2016), especially the lack of onboard calibration, the lack of systematic recording of in-flight gain changes, a limited radiometric dynamic range, and signal saturation in dense urban centers. Atmospheric condition changes, satellite shifts, sensor degradation and different satellite overpassing times can also be considered biases. Although these are minimized by the calibration model developed by Zhang et al. (2016), inconsistencies, in the form of differences in pixel values from two satellites of the same region and year, still exist in NTL data despite the application of calibration methods (Pandey et al., 2017). Caution is also required in the interpretation of the temporal trends we calculated, as DN values are known to saturate at a DN value of 63 with the DMSP dataset (Elvidge et al., 2009). ALAN can thus increase in the brightest areas, such as urban centers, but we failed at detecting this trend and such areas appear with stable ALAN.

However, we think the overall results of the study are quite robust to these drawbacks because several methodological and statistics precautions have been taken.

Firstly, our analyses took into account large areas at both global and biogeographical realms scales, with a large number of PAs and large areas of BHs. Secondly, to study the ALAN distribution, we focused on means and temporal trends calculated on all the pixels of the 20 years data records, rather than year-to-year comparison that would have been less robust. Average and linear regression calculations are also controlled by a mapping of the standard error and the coefficient of determination. Moreover, the overall spatial patterns we found are robust because we took into account all the pixels every 5 km as statistical individuals contrary to others studies for which PAs and BHs are the statistical individuals (Gaston et al., 2015; Geldmann et al., 2014). Finally, although the data are not free from specific bias, these ones should be constant with respect to the question addressed in this paper. In other words, there is no reason that the pattern found within and around PA or BH borders can be attributed to a systematic and directional shift in data quality.

Nightlight data offer a promising way to monitor human pressures at a large spatial scale, at a fine spatial resolution, and from the early 1990s to today, as new satellite data are now available from 2012 onwards (derived from the new Visible Infrared Imaging Radiometer Suite (VIIRS)). The VIIRS offers the first-ever calibrated nighttime radiance measurement at a global scale, at a spatial resolution of near 750 m, in a spectral band of 500 to 900 nm (Kyba et al., 2017; Miller et al., 2013). This new dataset will be very useful to detect recent trends in ALAN.

Caution is however required when using such data (DMSP but also VIIRS data). While nightlight data can be considered a proxy of different human pressures, it must be acknowledged that this is an indirect and partial way of measuring such pressures, and even urban sprawl. Many countries are not entirely electrified (e.g. in Sahel), other anthropic elements generate ALAN (e.g. gas flaring, etc.), and high-latitude areas are not well covered.

These data are now more often used as one component of the human footprint or human pressure. However, there are advantages of using

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Table 1
Mean and standard deviation (sd) of distance from PAs, mean ALAN and its temporal trend by classes of distance of the same areas (6,398,350 km²) within and around PAs.

Table 2
Mean and standard deviation (sd) of distance from BHs, mean ALAN and its temporal trend by classes of distance of the same areas (3,491,525 km²) within and around BHs.
only nighttime data because human pressure indices are synthetic indicators, which give rise to several problems: the resulting maps are “cartographic monsters” (putting together very different things); there is always a need for a hierarchization between pressures to obtain real and direct conservation implications; and “none of the existing products include all possible sources of human pressure on nature, either because spatial products for the omitted components do not exist or because the study and global monitoring programs now provide data that could also be crossed with this kind of human pressure.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.bioclean.2018.04.018.

References


