

Contents lists available at ScienceDirect

## Journal of Quantitative Spectroscopy and Radiative Transfer

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



# Check for updates

### The reliability of satellite-based lighttrends for dark sky areas in Austria

Stefan Wallner a,b,\*, Johannes Puschnig c, Sarah Stidl a,b

- <sup>a</sup> ICA, Slovak Academy of Sciences, Dubravska cesta 9, Bratislava, 845 03, Slovakia
- <sup>b</sup> Department of Astrophysics, University of Vienna, Tuerkenschanzstrasse 17, Wien, 1180, Austria
- <sup>c</sup> Department of Physics and Astronomy, Division of Astronomy and Space Physics, Uppsala University, Box 515, Uppsala, 75120, Sweden

### ARTICLE INFO

Keywords: Light pollution Atmospheric effects Satellite observation

### ABSTRACT

Globally, light pollution is a phenomenon rising in its appearance and threatening human health and natural habitats for flora and fauna. Consequently, there is a great interest in interdisciplinary communities to keep an eye on its occurrence and development. One possibility to obtain meaningful data are satellite-based observations, coming mainly from the Visible Infrared Imaging Radiometer Suite (VIIRS) capturing top-of-theatmosphere radiance levels originating from Earth's surface. Tools designed to easily inspect monthly averaged data of this instrument are web applications. In this work, we focus on dark sky areas in Austria, namely 47 nature parks, and investigate collected data from such application and their reliability in making statements about the development of artificial light at night on the ground. Including atmospheric variations and other limitations, our results lead to a detection limit in radiance change by a minimum of  $\pm 10\%$ . Below this value, detected changes in surface brightness must not be traced back to changes of ground-based artificial light according to a specified statistical significance of three sigma. In total, 38 of 47 nature parks are examinable, showing an increase in radiance by ~42 percent over ten years in average, more than double compared to the entire national territory. As a conclusion, satellite data as analysed must be available for large periods, in order to decrease detection thresholds and make accurate statements about the development of light pollution. However, for detailed analytical research, it is highly recommended that especially dark areas globally establish ground-based light monitoring networks in their areas.

### 1. Introduction

For centuries, light at night has been used in order to ensure security for pedestrians and vehicles and to enhance important sites. The very first streetlights established in Europe were oil lanterns, installed in Paris in 1667 [1]. Only twenty years later, authorities in Austria's capital city, Vienna, adopted a new regulation stating that there is the liability of ensuring illumination of public streets at night [2]. In the 19th century, gas and electricity were exploited for lighting purposes and the number of such installations rose drastically. Over-illumination and misdirection of light emissions were the consequences of misuse, and artificial light was impacting natural dark skies. Johann Palisa (1848 – 1925), an astronomer at the University Observatory of Vienna, was one of the first to document this phenomenon called light pollution. During his observations at the University Observatory, around four kilometres away from the city centre, it stuck out that non-visible stars became visible to the naked eye if the electrical lighting was turned off daily at midnight. Consequently, stars which were up to six times fainter manifested, being proportional to a difference of around 2 astronomical magnitudes [3].

Today, light pollution became a global influencing factor resulting from anthropogenic activity. Besides of meteorological parameters, it is the central element in planning locations for observatory sites, and the main reason why, e.g., Northern America and Europe are no longer providing possibilities for such [4]. In astronomy, both photometric and spectroscopic observations are heavily affected, due to ground-based light sources emitting radiation directly to the upper hemisphere or via circuitous routes, being reflected on streets or walls. When analysing broader wavelength ranges, it is even possible to draw information, like identifying those sources, from the night sky or space [5,6]. However, not only the visibility of celestial objects, and therefore the daily astronomical work, is impaired, but major impacts are seen on human health, wildlife and the environment due to the disruption of the natural circadian rhythm [7].

Consequences like those discussed, but also many others, clearly demonstrate the danger light pollution evokes. Subsequently, it is of great importance to keep an eye on the influence of artificial light at night at individual locations as well as the long-term development of this phenomenon seen from a more global perspective. To achieve

<sup>\*</sup> Corresponding author at: ICA, Slovak Academy of Sciences, Dubravska cesta 9, Bratislava, 845 03, Slovakia. E-mail address: stefan.wallner@savba.sk (S. Wallner).

this, a variety of measurement instruments are available, starting from simple one-dimensional photometric and ground-based devices up to satellites [8–10]. In the former case, such instruments can be placed permanently at various locations, resulting in a measurement network like, e.g., existing in Austria [11]. However, it is challenging to use ground-based instruments to cover larger areas since they have to be numerous and peripheral influences like the instrumental decay must be taken into account when concluding longstanding data [12]. However, here it is essential to state that regardless of the approach chosen, devices' spectral sensitivity plays an important role when detecting artificial light since only its involvement enables inter-compare absolute values originating from various instruments.

In the light pollution research community, many studies are focusing on urban areas and direct sources of light emissions. In this paper, we decided to follow a different strategy and draw emphasis to areas mainly suffering from those with few or very low light emissions. This particularly applies to natural protected areas, already being very sensitive to influences by artificial light at night. As seen in, e.g., Lamphar et al. (2022) [13], the impact by the type of light emissions coming from surrounding areas solely, potentially reveals a substantial difference in the resulting night sky brightness. Logically, it is highly relevant for 'dark places' to keep track not only of the development of light emissions in their core area, but especially over the whole region up to their borders and beyond. Especially adjacent cities or towns are particularly worthy of mention.

### 2. Methods

### 2.1. Radiance data

To specify 'dark areas', 47 (of a total of 48) nature parks located in Austria were chosen (listed in Table 3). A nature park is a manmade cultural landscape that is suitable for recreation close to nature and for imparting knowledge about nature and culture. The award of a rural region with the title 'nature park' is carried out by the respective state government and poses challenges to the region like protection and development of the landscape, creation of recreational opportunities, ecological and cultural educational offers and promotion of sustainable regional development by creating jobs and sideline opportunities in tourism and agriculture. Even though there is a technical standard available, there are no national legal frameworks regarding the use of artificial light at night in Austria. Consequently, also areas like nature parks are not protected from potential influences caused by light pollution.

Radiance data for discussed areas were collected using the lig httrend.lightpollutionmap¹ web application. Here, monthly averaged radiance data from the Visible Infrared Imaging Radiometer Suite (VIIRS), in more detail, its Day and Night Band (DNB), can be collected. They are already reduced to moonless and cloud-free conditions, being available since September 2012. Furthermore, it is necessary to use a zero-point correction, because compared to brightly lit infrastructure like large cities where the amount of artificial light is much larger compared to the natural sky background, nature parks and reservoirs tend to have lower values of artificial light radiation and data is therefore impacted more strongly by airglow. The correction is discussed in Coesfeld et al. (2020) [14] and has considerably affected the analysis of, e.g., International Dark Sky Places [15].

For this study, we collected available VIIRS data from September 2012 to March 2022. During summer months, the satellite cannot capture radiance measurements in astronomical night times. Therefore, only monthly data from September to March are available for all years. For the 47 nature parks, polygon lines were drawn corresponding to the nature park areas located in Austria. The nature parks Nagelfluhkette, Geschriebenstein-Írittkö, Raab-Őrseg-Goričko are partly placed in Germany, Hungary, and Slovenia, these parts are not included. The monthly mean radiance was fitted over time.

### 2.2. Statistical analysis

Aiming to focus on the statistical development of collected data rather than comparing absolute values, a polynomial trendline of 2nd order was derived for each dataset, i.e., nature park, via

$$y = a_2 * x^2 + a_1 * x + b, (1)$$

with x being the date, y the monthly mean radiance over the specified area and  $a_n$  and  $b_n$  calculated parameters of the function. In order to easily track the level of change over the defined ten years, trendline data were normalised to its first data point (corresponding to the trendline value of September 2012). The factorial change is then easily identifiable considering the last derived trendline data point (corresponding to March 2022).

# 2.3. Constraining the capabilities of VIIRS monthly averages for long-term trend analysis

VIIRS monthly averages are nowadays easily accessible and may serve as an additional tool to study temporal changes of light pollution. However, caution needs to be taken when interpreting time-series of photometric measurements, regardless whether they are space- or ground-based because several factors strongly impact individual radiance measurements. For example, strong seasonal variations of the night sky brightness may be present [e.g.16–18] and more recently, it became clear that local and short-term changes of the atmosphere (e.g. vegetation, dust, aerosols) further hamper the interpretation of time-series of photometric night sky brightness measurement [e.g.18–20].

In order to quantify the amplitude of long-term (seasonal) and short-term variations, we have inspected ground-based photometric (SQM) measurements carried out at various rural sites in Austria over several years. After filtering for clear and moonless sky data in the same manner as done by [18], we find that the seasonal variation may be well described/fitted by a triangular periodic function. and an additional (short-term) Gaussian-like scatter (as a result of short-term atmospheric variations). Fig. 1 demonstrates for a single rural location in Austria (Nationalpark Bodinggraben) the presence of such seasonal variation. The triangular model fit (black line) to the observed data (blue points) is shown in the top panel. In this case, the amplitude is  $\sim 0.4\,\mathrm{mag\,arcsec^{-2}}$ . The bottom panel shows the resulting residual after subtracting the model from the data. Fitting a Gaussian to the histogram of residuals, its width ( $\sigma_{\rm atm}$ ) describes the natural scatter due to (short-term) changing atmospheric conditions (e.g. composition) and environment (e.g. albedo). For the site shown in Fig. 1, we find  $\sigma_{atm} = 0.13 \, mag \, arcsec^{-2}$ . We repeat the same procedure for another set of three dark sites in Austria (Nationalpark Zöblboden, Krippenstein, Feuerkogel) for which we find  $\sigma_{atm}$  of 0.17, 0.20 and 0.18 mag arcsec<sup>-2</sup>. The average atmospheric short-term scatter for typical Austrian sites is thus 0.17 mag arcsec<sup>-2</sup>. Future analysis of this variation by selecting ground-based data solely at times according to satellite overflights could result in a decrease. However, this goes beyond the scope of this work and could be an interesting idea for further research.

To constrain the capabilities of VIIRS monthly averages for long-term trend analysis, we proceed as follows. We simulate a site with a seasonal luminance variation as explained above, i.e a triangular function as implemented in scipy.signal.sawtooth [21] with an amplitude of 0.4 mag arcsec<sup>-2</sup>. However, on long timescales, the luminance level remains constant. In the next step, we sample the continuous model function in a way that resembles the VIIRS data length (ten years) and data availability. For Austrian sites we only find monthly averages between September and March, because in summer the satellite does not cover times of astronomical night. For the remaining months, we examined VIIRS data products of three consecutive years between 2014 and 2017 and tabulated the number of nightly measurement points from which monthly averages are calculated (see

https://lighttrends.lightpollutionmap.info

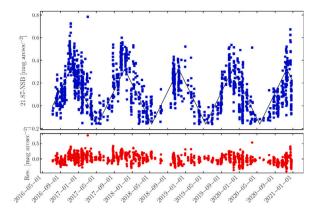


Fig. 1. Radiance measurements obtained between 2016 and 2020 with a Sky Quality Meter in Austria (Nationalpark Bodinggraben). After filtering for clear and moonless sky, a strong seasonal variation is revealed (blue points). The variation is well fitted with a triangular function (black solid line). After subtracting the model from the data (red points in bottom panel) a Gaussian-like scatter with  $\sigma_{\rm atm} \sim 0.13\,{\rm mag\,arcsec^{-2}}$  remains (bottom panel). We attribute the scatter to short-term atmospheric variations.

Table 1
Overview of the number of nightly measurements from which the VIIRS monthly averages are calculated. The two rightmost columns show the average number of measurements as well as the standard deviation for each month.

	2014	2015	2016	2017	avg.	unc.
Jan	-	8	8.3	15.4	10.6	4.2
Feb	-	11.4	6.7	8.3	8.8	2.4
Mar	_	12.1	5.3	13.4	10.3	4.4
Apr-Aug	0	0	0	0	0	0
Sep	9.6	10.9	14.4	_	11.6	2.5
Oct	9.0	6.5	9.7	_	8.4	1.7
Nov	9.3	8.5	11.2	_	9.7	1.4
Dec	10.2	12.7	16.6	_	13.2	3.2

Table 1). Based on this, we randomly draw sampling points for each month with an additional uncertainty of  $\pm 3$  measurements per month, as suggested by the standard deviation given in the rightmost column of Table 1. After the sampling in time, we add to the model luminances (at the sampling points) random Gaussian noise, containing two sources of uncertainties: (i) impact of short-term atmospheric changes with  $\sigma_{\rm atm}$  =  $0.17\,\mathrm{mag\,arcsec^{-2}}$  and (ii) an estimated scatter of approximately  $\pm 25\%$ (0.25 mag arcsec<sup>-2</sup>) due to the dependence of VIIRS measurements on the viewing angle [see e.g.22]. The simulated monthly average luminances are then calculated from these noisy nightly measurements. Next, we further apply a random (Gaussian) shift in time (up to  $\pm 15$ days) in order to account for the fact that the VIIRS monthly averages do not provide (to our knowledge) information about the time validity, i.e., the exact points in time of individual observations. In the last step, we fit a linear trend through the simulated monthly averages, save the linear trend slope and convert units from mag arcsec<sup>-2</sup> to mcdm<sup>-2</sup> using the standard conversion as explained e.g. by [23]. We repeat the whole procedure of random sampling and linear fitting 20000 times. Fig. 2 shows the simulated VIIRS monthly averages (filled squares) for one of the iterations, as well as the range of slopes found from all iterations (green area). After fitting a Gaussian to the distribution of slopes (see Fig. 3), we find that the VIIRS monthly averages allow to assess trends of  $\sim \pm 1.0$  percent per year with 3-sigma significance (99.7 percent) for our rural sites in Austria. Over the course of ten years, this corresponds to  $\pm 10$  percent.

Additionally, we performed such simulations for a range of time series lengths. The results are summarised in Table 2, demonstrating

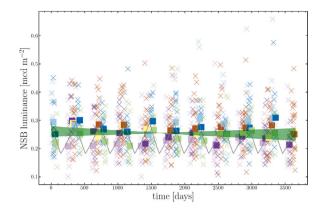
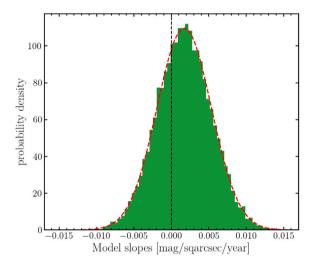


Fig. 2. The gray triangular periodic function is our NSB model with seasonal variations over ten years. The coloured crosses (one colour per month) show an example of the noise-added random sampling of this periodic function, i.e. hypothetical nightly VIIRS measurements that were first randomly drawn from a typical Austrian VIIRS monthly data sampling distribution (e.g. no single data is available for months April to August) and then randomly shifted along the y- and x-axis to reflect typical short-term changes due to atmospheric variations (valid for Austria) and the uncertainty of the time-validity of the VIIRS monthly averages. The filled coloured squares are thus simulated monthly VIIRS averages. In order to assess the range of possible linear trend slopes, we repeatedly perform linear fits through such randomly drawn datasets. The green area denotes the range of possible slopes after 20000 repetitions. We find that for our rural sites in Austria the VIIRS monthly averages allow to assess trends of  $\pm 1.0$  percent per year.



**Fig. 3.** The distribution of trend slopes inferred from 20000 model iterations (same as highlighted by the green area in Fig. 2). Since the underlying model has a true slope of zero, one would expect to see a Gaussian around the zero mean. However, an offset (or bias) towards positive slopes is observed. The bias must originate from the limited number (amount) of satellite observations and their inhomogeneous distribution along the time axis. Most likely the bias is driven by the edges of the data (due to strong seasonal variations).

that long time series are needed to reduce the systematic uncertainties that are inherent in VIIRS monthly means. For example, to enable the detection of a (continuous) yearly change of three percent, at least five years of data are needed.

Furthermore, we find that the 3-sigma (99.7 percent) significance threshold of any change between two consecutive VIIRS monthly means is 10 percent. Hence, only when the observed difference in the VIIRS

Table 2 Simulated uncertainties for long-term trends derived from VIIRS monthly means as a function of length (column 1) of the time series, taking into account the inhomogeneous and coarse sampling of VIIRS data for our sites in Austria (i.e. no data between April and August). The 3-sigma slopes (slope<sub>3a</sub>) in column 2 are used as an estimate of uncertainties on time-dependent trends derived from VIIRS data. Column 3 is the average yearly relative change over the given period expressed in percent per year. In column 4 we present the minimum and maximum slopes in units of mag arcsec<sup>-2</sup> yr<sup>-1</sup> that we find in our 20000 simulations.

Length [yr]	Slope <sub><math>3\sigma</math></sub> [mag arcsec <sup>-2</sup> yr <sup>-1</sup> ]	<rel. change="" p.a.=""> [percent p.a.]</rel.>	slope <sub>minmax</sub> [mag arcsec <sup>-2</sup> yr <sup>-1</sup> ]
1	0.2734	28.64	0.770
2	0.1137	11.04	0.285
3	0.0644	6.11	0.191
5	0.0302	2.82	0.074
7	0.0185	1.72	0.048
9	0.0127	1.18	0.033
11	0.0094	0.87	0.023
13	0.0073	0.67	0.021
15	0.0059	0.54	0.016
17	0.0049	0.45	0.013
19	0.0041	0.38	0.012
21	0.0035	0.32	0.011

Table 3 Results of statistical analysis of each nature park investigated, indicating the long-term development of radiance. AAD = Averaged annual development, AVP = averaged pixel value over 10 years in [nW/cm²sr]. Red-coloured cells display areas with changes below the threshold of  $\pm 10\%$  over ten years and being below the capabilities of VIIRS monthly averaged data for such. In brackets, the Austrian province the nature park is situated in is named; BGLD = Burgenland, KTN = Kärnten (Styria), NOE = Niederösterreich (Lower Austria), OOE = Oberösterreich (Upper Austria), SALZ = Salzburg, TIR = Tirol (Tyrol), VOR = Vorarlberg.

(Tyrol), VOR = Vorarlberg.			l =2	
Nature Park (Province)	AAD	Development over 10 years	R <sup>2</sup>	AVP
Purkersdorf (NOE)	+1.39%	+14.78%	0.037	3.325100
Neusielder See - Leithagebirge (BGLD)	+2.61%	+29.44%	0.149	1.745928
Ybbstal (NOE)	-1.43%	-15.27%	0.131	1.614979
Blockheide (NOE)	+3.92%	+46.86 %	0.1078	1.371790
Föhrenberg (NOE)	+0.51%	+5.25%	0.013	1.215033
Rosalia-Kogelberg (BGLD)	+2.65%	+29.88%	0.150	1.146520
Eichenhain (NOE)	+1.05%	+11.00%	0.054	1.028544
Sparbach (NOE)	-0.45%	-4.57%	0.010	1.002320
Dobratsch (KTN)	+9.82%	+155.10%	0.033	0.736385
Dobersberg (NOE)	+21.93%	+626.41%	0.324	0.621586
Leiser Berge (NOE)	+3.73%	+44.24%	0.143	0.585891
Falkenstein (NOE)	-2.50%	-28.12%	0.199	0.560040
Wüste Mannersdorf (NOE)	+7.42%	+104.65%	0.070	0.459525
Tiroler Lech (TIR)	+0.16%	+1.59%	0.014	0.433247
Kamptal-Schönberg (NOE)	+1.09%	+11.45%	0.014	0.388467
Südsteiermark (KTN)	+0.60%	+6.17%	0.002	0.358343
Karwendel (TIR)	+0.75%	+7.78%	0.007	0.331425
Heidenreichsteiner Moor (NOE)	+7.43%	+104.67%	0.095	0.285640
Geschriebenstein-Írittkö (BGLD)	+2.80%	+31.81%	0.085	0.272076
Sierningtal-Flatzer Wand (NOE)	-0.88%	-9.14%	0.010	0.269335
Raab-Őrseg-Goričko (BGLD)	-1.8%	-19.57%	0.068	0.230551
Obst-Hügel-Land (OOE)	-2.33%	-25.86%	0.017	0.208156
Hochmoor Schrems (NOE)	+10.13%	+162.41%	0.224	0.194118
Jauerling-Wachau (NOE)	+3.39%	+39.59%	0.027	0.185746
Kaunergrat (TIR)	+3.28%	+38.12%	0.054	0.184886
Nagelfluhkette (VOR)	-0.27%	-2.78%	0.020	0.144018
Buchberg (SALZ)	+0.32%	+3.28%	0.018	0.138623
Landseer Berge (BGLD)	+3.06%	+35.15%	0.033	0.123420
Weinidylle (BGLD)	+7.06%	+97.85%	0.184	0.118084
Nordwald (NOE)	+5.59%	+72.32%	0.060	0.117372
Almenland (KTN)	+4.63%	+57.24%	0.075	0.110875
Pollauer Tal (KTN)	+2.11%	+23.22%	0.018	0.101359
Hohe Wand (NOE)	+2.00%	+21.87%	0.023	0.097691
Geras (NOE)	-1.88%	-20.46%	0.004	0.094432
Ötztal (TIR)	+3.46%	+40.45%	0.072	0.086757
Mühlviertel (OOE)	+4.05%	+48.81%	0.022	0.083209
Zirbenkogel-Grebenzen (KTN)	+1.01%	+10.57%	0.137	0.066295
Attersee-Traunsee (OOE)	+1.78%	+19.30%	0.014	0.047286
Zillertaler Alpen (TIR)	-3.4%	-39.74%	0.025	0.032623
Mürzer Oberland (KTN)	+31.49%	+1444.68%	0.066	0.031892
Ötscher-Tormauer (NOE)	+0.22%	+2.18%	0.020	0.031420
Riedingtal (SALZ)	-4.67%	-57.78%	0.045	0.023554
Weissensee (KTN)	+10.96%	+182.85%	0.051	0.010997
Weißbach (SALZ)	undefinable	undefinable	undefinable	undefinable
Steirische Eisenwurzen (KTN)	-11.05%	-185.30%	0.041	0.000196
Sölktäler (KTN)	undefinable	undefinable	undefinable	undefinable
NÖ Eisenwurzen (NOE)	-7.79%	-111.82%	0.101	-0.033967
	11	1		•

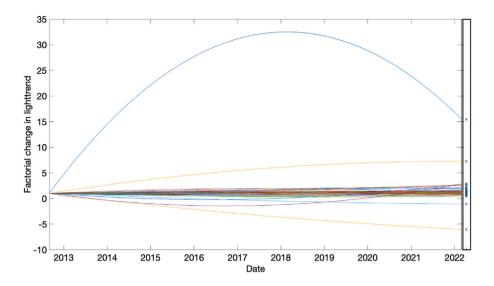


Fig. 4. Illustration containing plots of all trendlines statistically analysed from 47 nature parks.

luminance data from one month to another is larger than 10 percent, the observation can be ascribed to a physical change in ground-based emissions with specified three-sigma confidence.

### 3. Results

Taking into account the significant limitation of discussed capabilities of VIIRS monthly averages, results from polynomial trendlines are summarised in Table 3, comparing percentual changes of all nature parks, comparing first (2012) and last trendline datapoint (2022). In order to allow for a generalised statement about the predominant radiance levels, an averaged pixel value (AVP) over all lighttrend data points was calculated, showing nature parks with higher amount of lit areas at the top. Without surprise, since satellite data show large scattering over years which was expectable for dark areas with low signal, the coefficient of determination ( $\mathbb{R}^2$ ) is generally low and independent to the AVP in its strength.

Results indicate that from 47 analysed nature parks, 38 show changes in their radiance stronger than the  $\pm 10$  percent threshold over ten years. This means in effect that in those areas solely, the detected change in surface brightness can be traced back to changes of ground-based artificial light. All others, also those showing trends only slightly below the detected threshold, are also potentially showing physical changes in ground-based emissions, but with smaller degrees of confidence.

Fig. 4 illustrates the trendlines for all areas investigated. Especially here it becomes visible that one nature park, Mürzer Oberland, seems to suffer from an enormous increase in detected radiance. However, since we are analysing the factorial changes, such an extreme increase is easily conceivable if the general brightness level is shallow (e.g., first trendline point is only slightly above 0). In such a case, every little change in ground-based lighting leads to higher impacts in percentage. This is why the AVP shall always be considered when qualitative statements about light pollution developments are made. In the Appendix, data points and trends from all areas are illustrated individually in Figs. A.5–A.8.

Especially at areas with lower AVP, there also exist lighttrend radiance data containing negative values, underlining a higher scattering

and potentially caused by applied correction and satellite calibration. Since we are investigating the general tendency of radiance development, this generally comes with no problems for us. However, trends in two areas (Weißbach and Sölktäler) are undefinable since the trendline is shifting from negative or positive to positive or negative values, respectively.

Incorporating results from those 38 nature parks able to be analysed, some statements about their overall behaviour in light pollution development are possible. Checking the statistics from lightpollution-map.info, $^2$  the statewide territory of Austria shows an increase in radiance by  $\sim \! 18$  percent. However, exploitable nature parks (excluding the extreme value of Mürzer Oberland) display an even higher increase by an average of  $\sim \! 42$  percent over the whole time range of ten years. As discussed above, this comes with no surprise since minimal changes of ground-based lighting sources in dark areas potentially result in very high percentages. Nevertheless, this could result in major negative consequences, especially for the nocturnal biodiversity active in such regions.

### 4. Discussion

Lighttrend data are easily accessible and therefore frequently in use when discussing light pollution and its development in various areas globally. Furthermore, VIIRS data reach back a relatively high amount of time, being able to use them for long-term analyses. Lower resolution satellite data can be traced back even further, with data from Defense Meteorological Satellite Program (DMSP) up to 1996. Since the web application is also easy to handle, users can be tempted to use it not only for urban areas causing most of artificial light at night, but rural ones too in order to obtain an overview of the development of light pollution in their areas. However, it must be clearly stated at this point that satellite observations do suffer from unavoidable problems, making their use potentially troublesome for darker areas especially.

<sup>&</sup>lt;sup>2</sup> https://www.lightpollutionmap.info/LP\_Stats/

In general, Earth observations from space-borne instruments all share the same issue of not only detecting signals from the planet's surface, but the influence of the volatile atmosphere too. Even though VIIRS data are already reduced to moonless and cloudless conditions, detected radiance is known to be highly influenced by atmospheric parameters [24]. Such phenomena can be avoided when collecting a very high amount of data points throughout multiple years containing all possible conditions. This is the case in our work when collecting data over ten years and over the same months annually. However, the atmosphere is still capable of increasing the scattering behaviour of collected data points and therefore decreasing the coefficient of determination for applied trends. Another issue solved via data points of large quantity are varying observation angles and times of the satellite. As shown before in Table 1, each monthly averaged data point consists of multiple observations covering differing observation angles, potentially revealing disparate ground-based light emitting sources [25] and also times containing differing ground-based light levels by dimming or deactivation of sources.

In connection with the use of VIIRS Day and Night Band data, a nonneglectable limitation emerges, namely its spectral blindness at short wavelengths. Starting its observational range at 500 nm, the satellite potentially misses light sources emitting large amounts of radiation in wavelengths below. This applies specifically for neutral-white Light Emitting Diodes (LEDs). Such were continuously the foundation for large-scale lighting conversions in Austria over the past years. However, this implies that gradients from our statistical analyses can be either underestimated (for increasing lighttrends) or overestimated (for decreasing lighttrends), since past generation lamps mostly consisted out of high-pressure sodium lamps containing only small amounts of radiation in shorter wavelengths. If ground-based lighting sources are known in detail, it is possible to subtract reported systematic factors affecting the trends [26]. Furthermore, SQM devices too show limitations in their spectral sensitivity, here specifically in longer wavelengths [27]. Spectral weakness by both VIIRS and SQM are insuperable technical limitations influencing our study, posing challenges in determining if observed trends are consistent across the entire spectrum. Consequently, the average increase in radiance derived for Austria's nature parks can be seen as lower limit and potentially be higher with exact values named only if outdoor lighting inventories are known and included to the analysis. This is not only the case for dark sites like in our presented work, but valid for all observations provided by

As results can be summarised, the capability of VIIRS-based light-trend data is restricted and limited. A more detailed view on technical limitations for light pollution observations occurring by the satellite can be found in past studies [28,29]. In the case of rural sites in Austria, it has been found that changes of more than ~10 percent over the course of ten years are detectable solely (traced back to artificial light at night) when defining a three sigma confidence. With changes of this statistical significance, which is reasonable depending on application, this value is not generally fixed for all investigations regarding light pollution. Results indicate that correct analyses of long-term developments must include investigations of long- and short-term variations and statistical derivation of an existing number of observations, each depending on location. Only then, the detection limit of available data can be defined in order to make proper predictions of light pollution.

Fig. 3 demonstrates that the inhomogeneous and coarse sampling of VIIRS monthly means for our sites, leads to a systematic bias towards positive trends, i.e. darkening with time. This selection bias is revealed by the non-zero, positive mean value of the Gaussian peak (0.002 mag arcsec $^{-2}$  yr $^{-1}$ ) in Fig. 3. This corresponds to a bias of  $\sim$ 0.2 percent per year. As this value is very small compared to the uncertainty, we do not perform a bias-correction of our measurements.

#### 5. Conclusions

This work aimed to quantify how precise easily-accessible lighttrend data based on VIIRS satellite observations are for rural sites. Considering 47 natural protected sites in Austria, a detection threshold for a specified statistical confidence of three sigma was found, indicating that for 38 of them, a trend of the long-term development of surface radiance data over ten years can be analysed. Limitations regarding satellite data in general could influence outcomes more significantly, which underlines that absolute values originating from lighttrend analyses must be a matter of careful investigation, especially for dark sites. Limitations occurring by satellite-based measurements cannot be bypassed and must be taken into consideration when analysing the (long-term) development of light pollution at the ground. Even though results are valid for the majority of nature parks investigated, we feel that there the need of ground-based measurements at rural locations in order to either be independent of satellite-based limitations (e.g. more measurements with clearly definable build-ups) and more accurately connect observations to peripheral influences like atmosphere or light emission behaviour. Exploitable nature parks have shown an increase in radiance by ~42 percent over ten years, more than double the amount compared to incorporating the whole national territory. Considering spectral shortcomings of the satellite, this result only poses a lower limit of its increase with its actual value being potentially higher and only derivable knowing types of outdoor lighting at the ground. This poses a general problem for VIIRS observations. This leads to the conclusion that dark areas need even greater protection from artificial light at night in the future. In order to draw more specific conclusions, it is highly recommended that natural protected sites globally establish ground-based light monitoring networks in their areas.

### **Declaration of competing interest**

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Stefan Wallner reports financial support was provided by European Union. Stefan Wallner reports article publishing charges was provided by University of Vienna.

### Data availability

All data used are available online, their availability is described in the text. Data Availability Statement is included in the manuscript

### Acknowledgements

This work is part of the project for which the financial means was funded by the European Union's Horizon 2020 Research and Innovation Programme on the basis of the Grant Agreement under the Marie Skłodowska-Curie funding mechanism No. 945478 - SASPRO 2. Open access funding was provided by the University of Vienna. This work was supported by the Slovak Research and Development Agency under Project No. APVV-22-0020.

### Appendix. All data

See Figs. A.5-A.8.

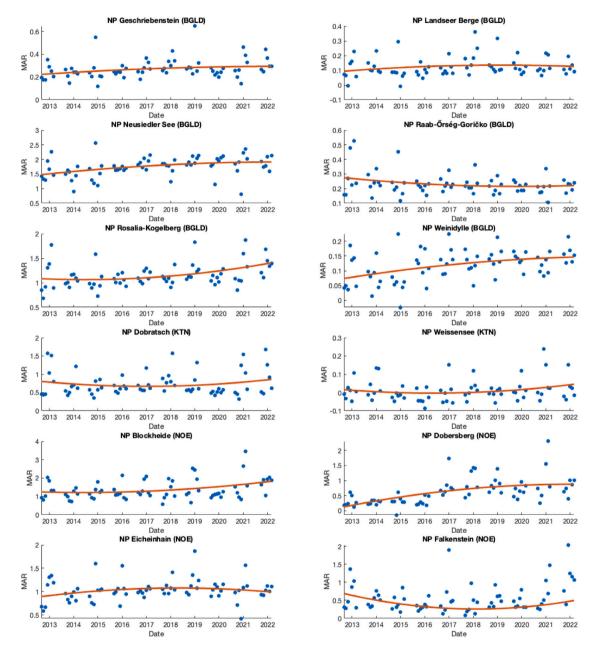


Fig. A.5. Lighttrend data of all nature parks investigated, illustrated individually for each area. MAR = monthly averaged radiance in  $[nW/cm^2sr]$ , the red line displays the non-normalised polynomial trendline.

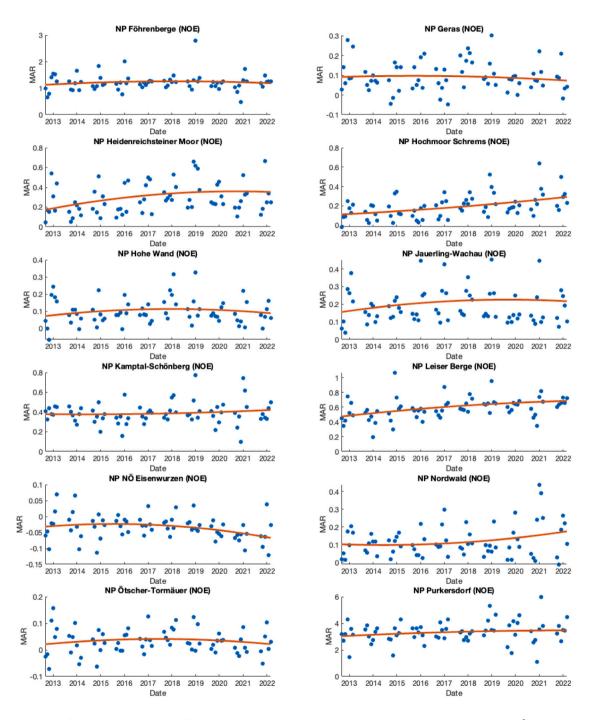


Fig. A.6. Lighttrend data of all nature parks investigated, illustrated individually for each area. MAR = monthly averaged radiance in  $[nW/cm^2sr]$ , the red line displays the non-normalised polynomial trendline.

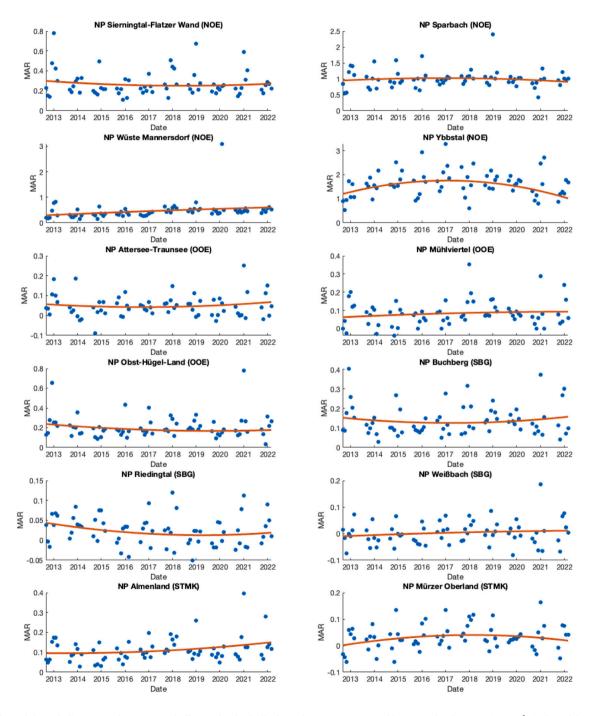


Fig. A.7. Lighttrend data of all nature parks investigated, illustrated individually for each area. MAR = monthly averaged radiance in  $[nW/cm^2sr]$ , the red line displays the non-normalised polynomial trendline.

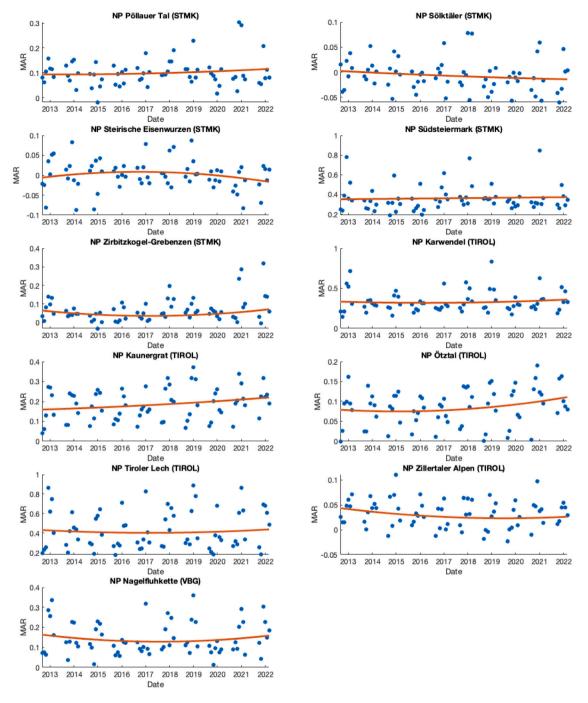


Fig. A.8. Lighttrend data of all nature parks investigated, illustrated individually for each area. MAR = monthly averaged radiance in [nW/cm²sr], the red line displays the non-normalised polynomial trendline.

### References

- [1] Nye DE. American illuminations Urban lighting 1800-1920. Massachusetts Institute of Technology; 2018, p. 11–33, Illuminations [chapter 4].
- [2] Altfahrt M, Fischer K. Illuminations-anfang der stadt wien (zur einführung der straßenbeleuchtung in wien im jahre 1687). Wiener Geschichtsblätter 1987;42:167–70.
- [3] Palisa J. Beobachtungen am 27-zölligen Refraktor. Astron Nachr 1924;222(11):161–72. http://dx.doi.org/10.1002/asna.19242221102.
- [4] Falchi F, Cinzano P, Duriscoe D, Kyba CCM, Elvidge CD, Baugh K, et al. The new world atlas of artificial night sky brightness. Sci Adv 2016;2(6):e1600377. http:// dx.doi.org/10.1126/sciadv.1600377, URL https://www.science.org/doi/abs/10. 1126/sciadv.1600377.
- [5] Rybnikova N, Sánchez de Miguel A, Rybnikov S, Brook A. A new approach to identify on-ground lamp types from night-time ISS images. Remote Sens

2021;13(21). http://dx.doi.org/10.3390/rs13214413, URL https://www.mdpi.com/2072-4292/13/21/4413.

- [6] Puschnig J, Posch T, Uttenthaler S. Night sky photometry and spectroscopy performed at the Vienna university observatory. J Quant Spectrosc Radiat Transfer 2014;139:64–75. http://dx.doi.org/10.1016/j.jqsrt.2013.08.019, Light pollution: Theory, modeling, and measurements. URL https://www.sciencedirect. com/science/article/pii/S002240731300352X.
- [7] Falchi F, Cinzano P, Elvidge CD, Keith DM, Haim A. Limiting the impact of light pollution on human health, environment and stellar visibility. J Environ Manag 2011;92:2714–22. http://dx.doi.org/10.1016/j.jenvman.2011.06.029.
- [8] Kocifaj M, Wallner S, Barentine JC. Measuring and monitoring light pollution: Current approaches and challenges. Science 2023;380(6650):1121–4. http://dx.doi.org/10.1126/science.adg0473, URL https://www.science.org/doi/abs/10.1126/science.adg0473.

- [9] Levin N, Kyba C, Zhang Q, Sanchez de Miguel A, Román M, Li X, et al. Remote sensing of night lights: A review and an outlook for the future. Remote Sens Environ 2020;237:111443. http://dx.doi.org/10.1016/j.rse.2019.111443.
- [10] Hänel A, Posch T, Ribas SJ, Aubé M, Duriscoe D, Jechow A, et al. Measuring night sky brightness: methods and challenges. J Quant Spectrosc Radiat Transfer 2018;205:278–90. http://dx.doi.org/10.1016/j.jqsrt.2017.09.008, URL https:// www.sciencedirect.com/science/article/pii/S0022407317304442.
- [11] Posch T, Binder F, Puschnig J. Systematic measurements of the night sky brightness at 26 locations in eastern Austria. J Quant Spectrosc Radiat Transfer 2018;211:144–65. http://dx.doi.org/10.1016/j.jqsrt.2018.03.010, URL https:// www.sciencedirect.com/science/article/pii/S0022407317308804.
- [12] Puschnig J, Näslund M, Schwope A, Wallner S. Correcting sky-quality-meter measurements for ageing effects using twilight as calibrator. Mon Not R Astron Soc 2021;502(1):1095–103. http://dx.doi.org/10.1093/mnras/staa4019.
- [13] Lamphar H, Wallner S, Kocifaj M. Modelled impacts of a potential light emitting diode lighting system conversion and the influence of an extremely polluted atmosphere in Mexico city. Environ Plan B Urban Anal City Sci 2022;49(2):501–18. http://dx.doi.org/10.1177/23998083211012702.
- [14] Coesfeld J, Kuester T, Kuechly HU, Kyba CCM. Reducing variability and removing natural light from nighttime satellite imagery: A case study using the VIIRS DNB. Sensors 2020;20(11). http://dx.doi.org/10.3390/s20113287, URL https://www.mdpi.com/1424-8220/20/11/3287.
- [15] Kyba CCM, Coesfeld J. Satellite observations show reductions in light emissions at international dark sky places during 2012–2020. Int J Sustain Light 2021. http://dx.doi.org/10.26607/jjsl.v23i2.111.
- [16] Bertolo A, Binotto R, Ortolani S, Sapienza S. Measurements of night sky brightness in the veneto region of Italy: Sky quality meter network results and differential photometry by digital single lens reflex. J Imaging 2019;5(5). http:// dx.doi.org/10.3390/jimaging5050056, URL https://www.mdpi.com/2313-433X/ 5/5/5/6
- [17] Puschnig J, Wallner S, Posch T. Circalunar variations of the night sky brightness - an FFT perspective on the impact of light pollution. Mon Not R Astron Soc 2020;492(2):2622–37. http://dx.doi.org/10.1093/mnras/stz3514.
- [18] Puschnig J, Wallner S, Schwope A, Näslund M. Long-term trends of light pollution assessed from SQM measurements and an empirical atmospheric model. Mon Not R Astron Soc 2023;518(3):4449–65. http://dx.doi.org/10.1093/mnras/ stac3003.
- [19] Wallner S, Kocifaj M. Impacts of surface albedo variations on the night sky brightness - A numerical and experimental analysis. J Quant Spectrosc Radiat Transfer 2019;239:106648. http://dx.doi.org/10.1016/j.jqsrt.2019.106648.

- [20] Ściężor T, Czaplicka A. The impact of atmospheric aerosol particles on the brightness of the night sky. J Quant Spectrosc Radiat Transfer 2020;254:107168. http://dx.doi.org/10.1016/j.jqsrt.2020.107168, URL https://www.sciencedirect. com/science/article/pii/S0022407319309203.
- [21] Virtanen P, Gommers R, Oliphant TE, Haberland M, Reddy T, Cournapeau D, et al. SciPy 1.0: Fundamental algorithms for scientific computing in python. Nature Methods 2020;17:261–72. http://dx.doi.org/10.1038/s41592-019-0686-2.
- [22] Li X, Ma R, Zhang Q, Li D, Liu S, He T, et al. Anisotropic characteristic of artificial light at night – Systematic investigation with VIIRS DNB multi-temporal observations. Remote Sens Environ 2019;233:111357. http: //dx.doi.org/10.1016/j.rse.2019.111357, URL https://www.sciencedirect.com/ science/article/pii/S0034425719303761.
- [23] Bará S, Aubé M, Barentine J, Zamorano J. Magnitude to luminance conversions and visual brightness of the night sky. Mon Not R Astron Soc 2020;493(2):2429–37. http://dx.doi.org/10.1093/mnras/staa323.
- [24] Kaufman YJ. Aerosol optical thickness and atmospheric path radiance. J Geophys Res: Atmos 1993;98(D2):2677–92. http://dx.doi.org/10.1029/92JD02427, URL https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/92JD02427.
- [25] Kyba CCM, Aubé M, Bará S, Bertolo A, Bouroussis CA, Cavazzani S, et al. Multiple angle observations would benefit visible band remote sensing using night lights. J Geophys Res: Atmos 2022;127(12):e2021JD036382. http://dx. doi.org/10.1029/2021JD036382, e2021JD036382 2021JD036382. URL https:// agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2021JD036382.
- [26] Bará S, Bao-Varela C, Lima RC. Quantitative evaluation of outdoor artificial light emissions using low earth orbit radiometers. J Quant Spectrosc Radiat Transfer 2023;295:108405. http://dx.doi.org/10.1016/j.jqsrt.2022.108405, URL https://www.sciencedirect.com/science/article/pii/S0022407322003405.
- [27] Sánchez de Miguel A, Aubé M, Zamorano J, Kocifaj M, Roby J, Tapia C. Sky quality meter measurements in a colour-changing world. Mon Not R Astron Soc 2017;467(3):2966–79. http://dx.doi.org/10.1093/mnras/stx145.
- [28] Sánchez de Miguel A, Bennie J, Rosenfeld E, Dzurjak S, Gaston KJ. First estimation of global trends in nocturnal power emissions reveals acceleration of light pollution. Remote Sens 2021;13(16). https://dx.doi.org/10.3390/ rs13163311 URL https://www.mdni.com/2072-4292/13/16/3311
- [29] de Miguel AS, Bennie J, Rosenfeld E, Dzurjak S, Gaston KJ. Environmental risks from artificial nighttime lighting widespread and increasing across europe. Sci Adv 2022;8(37):eabl6891. http://dx.doi.org/10.1126/sciadv.abl6891, URL https://www.science.org/doi/abs/10.1126/sciadv.abl6891.