Long-term trends of light pollution assessed from SQM measurements and an empirical atmospheric model★

Johannes Puschnig,1 † Stefan Wallner,2,3 Axel Schwöpe,4 Magnus Näslund5

1 Universität Bonn, Argelander-Institut für Astronomie, Auf dem Hügel 71, D-53121 Bonn, Germany
2 ICA, Slovak Academy of Sciences, Dubravska cesta 9, 84503 Bratislava, Slovak Republic
3 Universität Wien, Institut für Astrophysik, Türkenschanzstraße 17, A-1180 Wien, Austria
4 Leibniz-Institut für Astrophysik Potsdam (AIP), An der Sternwarte 16, 14482 Potsdam, Germany
5 Department of Astronomy, Stockholm University, AlbaNova University Centre, SE-10691 Stockholm, Sweden

ABSTRACT

We present long-term (4-10 years) trends of light pollution observed at 26 locations, covering rural, intermediate and urban sites, including the three major European metropolitan areas of Stockholm, Berlin and Vienna. Our analysis is based on i) night sky brightness (NSB) measurements obtained with Sky Quality Meters (SQMs) and ii) a rich set of atmospheric data products. We describe the SQM data reduction routine in which we filter for moon- and clear-sky data and correct for the SQM “aging” effect using an updated version of the twilight method of Puschnig et al. (2021). Our clear-sky, aging-corrected data reveals short- and long-term (seasonal) variations due to atmospheric changes. To assess long-term anthropogenic NSB trends, we establish an empirical atmospheric model via multi-variate penalized linear regression. Our modeling approach allows to quantitatively investigate the importance of different atmospheric parameters, revealing that surface albedo and vegetation have by far the largest impact on zenithal NSB. Additionally, the NSB is sensitive to black carbon and organic matter aerosols at urban and rural sites respectively. Snow depth was found to be important for some sites, while the total column of ozone leaves impact on some rural places. The average increase in light pollution at our 11 rural sites is 1.7% per year. At our nine urban sites we measure an increase of 1.8% per year and for the remaining six intermediate sites we find an average increase of 3.7% per year. These numbers correspond to doubling times of 41, 39 and 19 years. We estimate that our method is capable of detecting trend slopes shallower/steeper than ±1.5% per year.

Key words: light pollution – atmospheric effects – techniques: photometric

1 INTRODUCTION

During the last decade, an ever increasing number of studies found evidence that artificial light at night (ALAN) leads to negative consequences – not only for astronomy – but also for ecosystems (e.g. Longcore & Rich 2004; Perkin et al. 2011), biodiversity (e.g. Höller et al. 2010), animals (e.g. Eisenbeis 2006; Perkin et al. 2014; Matthews et al. 2015; Owens et al. 2020; Parkinson et al. 2020) and human beings (e.g. Chepessiu 2009; Haim & Portnov 2013; Cho et al. 2015; García-Saenz et al. 2018; Khodasevich et al. 2020; Menéndez-Velázquez et al. 2022). Therefore, monitoring night sky brightness (NSB) was soon recognized as being an inevitable effort in order to keep track of light pollution. Various organisations and individuals around the globe started to continuously measure the NSB using different methods and devices (Hänel et al. 2018). One of the probably most widely used devices is the so-called Sky Quality Meter (SQM). Operational SQM networks are found e.g. in Austria (Posch et al. 2018; Puschnig et al. 2020), Spain (Zamorano et al. 2015; Bará et al. 2019), Italy (Bertolo et al. 2019) and the Netherlands (Schmidt & Spoelstra 2020). Furthermore, several individuals have mounted SQMs at various sites on Earth (e.g. Puschnig et al. 2014a,b; Andreić et al. 2018). Kyba et al. (2015) have compiled many of these heterogeneous datasets to study the change of light pollution on a global scale.

Early light pollution studies based on SQM data revealed the strong impact of clouds (Kyba et al. 2011; Puschnig et al. 2014a; Jechow et al. 2019; Ścieżor et al. 2020) on the NSB. And more recently, the impact of several atmospheric parameters, in particular aerosol optical depth (AOD) and particulate matter (PM) were observed to show correlations with NSB (Ścieżor & Kubula 2014; Posch et al. 2018; Ścieżor & Czaplicka 2020; Kocifaj & Barentine 2021). Also, other seasonal parameters such as e.g. surface albedo or vegetation (Wallner & Kocifaj 2019; Puschnig et al. 2020) were previously discussed in the literature as potential factor causing changes in NSB.

More recently, Bará et al. (2021) and Puschnig et al. (2021) reported on the degradation of the SQM sensitivity (i.e. darkening) with time, when the devices are used outdoors. Using reference measurements from unused/unexposed SQMs at the beginning and end of a multi-year time series, Bará et al. (2021) find that readings from their SQMs, located in Galicia, need to be corrected by approximately...
0.06 mag$_{\text{SQM}}$ arcsec$^{-2}$yr$^{-1}$. Puschnig et al. (2021) have shown that twilight may serve as a source for their readings (Vienna, Berlin and Stockholm) need to be corrected by 0.03–0.05 mag$_{\text{SQM}}$ arcsec$^{-2}$yr$^{-1}$. A combined view on these results suggests that the “aging effect” depends on solar irradiance, that is a function of geographic latitude.

The assessment of long-term trends of light pollution at a given site is thus a complex problem that involves knowledge of atmospheric parameters as well as knowledge/derivation of the instrumental darkening of the SQM (or similar devices) with time. In this paper we aim to solve the problem via the combination of SQM data with atmospheric parameters obtained through the Copernicus Climate Change Service (C3S) and the Copernicus Atmosphere Monitoring Service (CAMS; Inness et al. 2019). We establish a simple empirical model to predict NSB variations due to changing atmospheric conditions. As a result, the purely ALAN-driven long-term change of NSB is assessed.

The paper is organised as follows. In Section 2 we give an overview of our SQM sites and the atmospheric parameters that are used in this study. In Section 3 we describe the data reduction routine that we apply to the SQM data to select for moonless, clear sky measurements. The section also contains the description of the empirical atmospheric model to predict NSB variations. The derived long-term trends for our sites are presented in Section 4. Finally, we discuss the results and summarize the paper in Sections 5 and 6.

2 MEASUREMENTS AND DATA PRODUCTS

2.1 Night Sky Brightness Measurements in Stockholm, Berlin, Vienna and 23 more sites in Austria

This study is based on long-term zenithal NSB measurements obtained with Sky Quality Meters (SQMs) located at various sites (see Table 1), including metropolitan areas of Stockholm, Berlin and Vienna. In previous studies, we already used parts of the data that is also included in this work, e.g. Puschnig et al. (2014b) and Puschnig et al. (2014a) studied the influence of the Moon, clouds and other environmental effects on the night sky brightness over Potsdam and Vienna using the first 1–2 years of SQM data. A detailed description and quantification of the light pollution level at the Upper Austrian sites is found in Posch et al. (2018), who examined data obtained during the years of 2015 and 2016.

We cover very remote locations such as Krippenstein on the Dachstein plateau (∼2000 m above sea level) as well as large metropolitan areas such as Stockholm (STO), Vienna (IFA) or Potsdam-Babelsberg (BA1), located ∼23 km to the southwest of the center of Berlin.

The measurements are taken in an automated way, with LAN-attached SQM devices (model SQM-LE) located in weather-proof housings. The SQMs situated in Upper Austria are run by the provincial government of Upper Austria. They take NSB measurements every minute. Most other SQMs (STO, IFA, FOA, GRA) provide a reading every 7 seconds which corresponds to a frequency of 0.143 Hz and BA1 even takes a measurement every ∼2 seconds.

2.2 Atmospheric data products

We make use of open access climate variables from ERA5 (Hersbach et al. 2018), the fifth major global reanalysis data produced by the European Centre for Medium-Range Weather Forecasts (ECMWF). ERA5 is developed through the Copernicus Climate Change Service (C3S). The data are based on a reanalysis of a large set of ground-, air- and satellite-based measurements. Data are available with hourly validity time at a spatial resolution of 0.28° x 0.28° in latitude and longitude, corresponding to ∼30 km x 30 km.

Using the python package cdasapi provided by the Atmosphere Data Store¹, we downloaded for all our sites and dates more than 70 available atmospheric parameters. From those we initially identified quantities that may have impact on zenithal NSB measurements. This pre-selection is mainly driven by our understanding of how the environment and the atmosphere impact the NSB, i.e. we chose parameters that may alter the NSB via scattering of light (e.g. aerosols and particles) as well as parameters that may enhance the fraction of upward light (e.g. albedo, snow cover) or enhance the fraction of light that is reflected back to the ground (e.g. cloud cover). An overview of the selected parameters is found in Table 2.

We note that aerosol optical depths and particulate matter are not available from ERA, but are provided through CAMS (Inness et al. 2019), the Copernicus Atmosphere Monitoring Service global reanalysis. Daily Data products are available in steps of six hours. Due to a bug that caused AOD and PM to not be computed for analysis time², we had to use the 3-hour forecasts with a validity time of 3 am UTC. CAMS native spatial resolution is 0.8° before 21 June 2016, and 0.4° henceforth, corresponding to ∼80 km x 80 km and ∼40 km x 40 km.

2.2.1 Description of selected atmospheric parameters

An overview of our initial set of parameters used for statistical analysis is given in Table 2. In the following we briefly describe the physical underpinning of the most relevant parameters.

Albedo (aluvd) is defined as the fraction of incident radiation that is reflected by a surface. Its numerical value thus ranges from 0 (no reflection) to 1 (all incident radiation is reflected). It varies with the type of surface (e.g. its roughness) and wavelength. For example, the broad-band albedo of grassland is a few percent only (Briegleb & Ramanathan 1982; Briegleb et al. 1986; Coakley 2003), with twice as much reflection in the near infrared than in the visible spectral range. On the other side, surfaces covered with snow may reflect more than 90 percent of the incident radiation, with snow albedo being significantly higher in the visible range than in the near infrared (Roesch et al. 2002). In this study, we make use of the UV-optical albedo for diffuse radiation (aluvd), that is measured within a range of 300 to 700 nm and thus matches the SQM band very well. It is thus expected that variations in surface albedo positively correlate with the night sky brightness.

Leaf Area Index (lai) is defined as the one-sided green leaf area per unit ground area (Boussetta et al. 2011). It is thus a dimensionless number (m² m⁻²). In ERA5, the leaf area index is split into high (lai$_{\text{hv}}$) and low vegetation (lai$_{\text{lv}}$). High vegetation consists of evergreen trees, deciduous trees, mixed forest/woodland, and interrupted forest and low vegetation covers grass, shrubs as well as water and land mixtures. For our study we use the sum of both available quantities. High vegetation impacts the NSB via blocking of upward light, while low vegetation has an impact on the reflection of downward light. We expect a negative correlation between NSB and the leaf area index.

Both, the leaf area index and albedo are based on observations with

¹ https://ads.atmosphere.copernicus.eu
² https://confluence.ecmwf.int/pages/viewpage.action?pageId=153393473
Impact of environment and atmosphere on light pollution

Table 1. Basic information about our SQM measurement sites, categorized into urban, intermediate and rural ones.

| Code | Name | Latitude N | Longitude E | Elevation [m] (above sea level) | data operating | operating time in yrs. |
|------|------|------------|-------------|--------------------------------|----------------|-----------------------|
| urban |       |            |             |                                |                |                       |
| STO  | Stockholm (AlbaNova University Center) | N 59 21 12 | E 18 3 28 | 30 | Dec. 2014 – Dec. 2021 | 7.1 |
| IFA  | Vienna (Institute for Astronomy) | N 48 13 54 | E 16 20 3 | 250 | Apr. 2012 – Dec. 2021 | 9.75 |
| BA1  | Potsdam – Babelsberg | N 52 22 48 | E 13 6 22 | 90 | Jan. 2011 – Feb. 2021 | 10.2 |
| GRA  | Graz – Lustbuehel | N 48 18 19 | E 14 14 58 | 287 | Aug. 2014 – Dec. 2021 | 7.4 |
| LGO  | Linz, Göthestraße | N 48 18 19 | E 14 18 30 | 259 | Jan. 2014 – Dec. 2021 | 8.0 |
| STY  | Steyr | N 48 2 57 | E 13 6 22 | 307 | Aug. 2014 – Dec. 2021 | 7.4 |
| TRA  | Traun | N 48 14 8 | E 14 15 11 | 269 | Jan. 2015 – Dec. 2021 | 7.0 |
| WEL  | Wels, Rathaus | N 48 9 23 | E 14 1 29 | 317 | Aug. 2014 – Dec. 2021 | 7.4 |
| intermediate | | | | | |
| BRA  | Braunau | N 48 15 40 | E 13 2 41 | 351 | Jan. 2016 – Dec. 2021 | 6.0 |
| GRI  | Grieskirchen | N 48 14 4 | E 13 49 33 | 336 | Jan. 2016 – Dec. 2021 | 6.0 |
| FRE  | Freistadt | N 48 30 33 | E 14 30 7 | 512 | Jan. 2016 – Dec. 2021 | 6.0 |
| MAT  | Mattighofen | N 48 5 50 | E 13 9 6 | 454 | Jan. 2016 – Dec. 2021 | 6.0 |
| PAS  | Pasching | N 48 15 31 | E 14 12 36 | 292 | Jan. 2015 – Dec. 2021 | 7.0 |
| VOE  | Vöcklabruck | N 48 0 21 | E 13 38 43 | 434 | Jan. 2016 – Dec. 2021 | 6.0 |
| rural | | | | | |
| FOA  | Mitterschöpfl | N 15 55 24 | E 48 5 3 | 880 | Jan. 2013 – Jul. 2019 | 6.6 |
| BOD  | Nationalpark Bodinggraben | N 47 47 31 | E 14 23 38 | 641 | Jul. 2016 – Dec. 2021 | 5.5 |
| FEU  | Feuerkogel | N 47 48 57 | E 13 43 15 | 1628 | Jan. 2016 – Dec. 2021 | 6.0 |
| GIS  | Giselawarte | N 48 23 3 | E 14 15 11 | 902 | Jan. 2016 – Dec. 2019 | 4.0 |
| GRU  | Grünbach | N 48 31 50 | E 14 34 30 | 918 | Jan. 2016 – Dec. 2021 | 6.0 |
| KID  | Kirchschlag – Davidschlag | N 48 26 31 | E 14 16 26 | 813 | Jan. 2016 – Dec. 2021 | 6.0 |
| KRI  | Krippenstein | N 47 31 23 | E 13 41 36 | 2067 | Jan. 2016 – Dec. 2021 | 6.0 |
| LOS  | Losenstein, Hohe Dirn | N 47 54 22 | E 14 24 40 | 982 | Jan. 2016 – Dec. 2021 | 6.0 |
| MUN  | Müinzirkchen | N 48 28 45 | E 13 33 29 | 486 | Jan. 2016 – Dec. 2021 | 6.0 |
| ULI  | Ulrichsberg, Schöneben | N 48 42 20 | E 13 56 44 | 935 | Jan. 2016 – Dec. 2021 | 6.0 |
| ZOE  | Nationalpark Zöbloden | N 47 50 18 | E 14 26 28 | 899 | Jan. 2016 – Dec. 2021 | 6.0 |

Table 2. Overview of atmospheric parameters, i.e the features in the model

| Parameter | Description |
|-----------|-------------|
| aluvd     | UV-optical albedo for diffuse radiation |
| lai       | leaf area index |
| bcaod550  | black carbon aerosol optical depth |
| duaod550  | dust aerosol optical depth |
| ssaoad550 | sea salt aerosol optical depth |
| omaod550 | organic matter aerosol optical depth |
| pm10      | particulate matter 10μm |
| pm2p5     | particulate matter 2.5μm |
| pm1       | particulate matter 1μm |
| tcwv      | total column water vapour |
| taw       | total column water |
| wind      | wind 10m |
| tco3      | total column ozone |
| tcc       | total cloud cover |
| sd        | snow depth |

3 METHODS

3.1 Atmospheric model

We aim to find a set of atmospheric parameters that most directly impact (zenithal) NSB measurements. In particular, we attempt to separate fundamental correlations between the NSB and the atmosphere from those that are indirect consequences of covariance among atmospheric metrics. We distinguish these underlying relations through variable selection: For each NSB data (as a target variable), we compose an empirical predictive model using a set of atmospheric parameters (feature variables) that carry most predictive power. This is an effective way to collapse a high-dimensional data set into a concise model.

The basis of this analysis is a multi-variable penalized linear regression. That is, we restrict the model functional forms to simple linear combinations of variables (including an intercept term). The regression is done independently for each NSB measurement/chunk (Δskyobs) as a target variable, using all the atmospheric parameters plus time (to account for temporal trends) as available features. With this regression setup, we perform a lasso model fit (Tibshirani 1996) and use the Bayesian Information Criterion (BIC; Schwarz 1978) for automated feature/model selection. This is implemented with the LassoLarsIC function in the scikit-learn Python package. In detail, for a linear predictive model with the form \[ \hat{y}_i = \beta_0 + \sum_{j=1}^{m} \beta_j x_{ij}, \]
the lasso regression minimizes the following function:

$$\frac{1}{2n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 + \alpha \sum_{j=1}^{m} |\beta_j|.$$  \hfill (1)

The indices i and j run through the NSB data and the atmospheric features respectively. The parameter $\alpha$ is a hyper-parameter, so that the second term in the equation adds a penalty for the use of any non-zero slope in the fitted model. This particular “regularization” term is the reason that the lasso as a regression method can also be used for variable selection. The lasso regression yields a best-fit model that minimizes the equation for each choice of the $\alpha$ parameter.

In practice, we produce 16 different predictive atmospheric models. Starting with a model based on all 15 atmospheric and ground features plus time, we expect to find the best agreement between observed NSB variations and the models. However, we also aim to quantify the impact of each parameter. Hence, we iteratively remove input features and re-calculate the models. This will allow us to use the residual after subtracting the model from the data as a measure of the importance of individual input features for the NSB modeling.

Note that due to the “regularization” term not all input features may survive the lasso method and only those parameters that have most direct impact on the NSB will be included in the final model.

### 3.2 Correcting SQM readings for degrading sensitivity with time using the twilight method

We apply an updated version of the “twilight” calibration as described in Puschnig et al. (2021) in order to correct our multi-year lasting SQM measurements for potential temporal changes in detector sensitivity. This is the “aging effect”, which is probably caused by changing transmission of the SQM housing window due to UV light exposure over several years. In brief, we utilize SQM observations of the zenithal NSB and compare the measurements to the twilight model of Patat et al. (2006). Moon and Sun altitudes are calculated using the Python ephem package, which provides an accuracy of approximately 1 arcsec. Note that one could also use an inter-comparison of SQM data obtained during twilight when the sun was at the same altitude. Assuming that the twilight sky brightness is not affected by ALAN and remains constant, one can reveal any underlying temporal sensitivity change of the measurement system. In addition to this procedure, we now also account for atmospheric changes that may impact the twilight observations. Thus, we utilize the same atmospheric model as described in Section 3.1. Any linear temporal trend obtained from the modeling procedure is then attributed to the “aging effect”.

Since we recognized at some stations (e.g. IFA) remaining non-linear trends, we additionally fit polynomials up to 3rd order to the residuals. If the subtraction of a polynomial further reduces the scatter (by more than 0.5 percent), we proceed and use also the polynomial as a correction function, accounting for non-linear effects.

A quantification of the degradation of SQM sensitivity with time is seen in Figure 1 for Potsdam-Babelsberg near Berlin and a rural site in Austria (Bodinggraben). Note the strong seasonal variation of NSB during twilight and how accurate the atmospheric model is able to predict them for both the urban site and the rural site. The histogram in Figure 2 shows the distribution of linear aging slopes found for all our 26 SQM stations. We find a relatively large variation between individual SQM sites with aging slopes ranging from zero to $-0.075 \text{mag}_{\text{arcsec}}^{-2} \text{yr}^{-1}$. On average, the aging effect leads to a darkening of $-0.031 \pm 0.020 \text{mag}_{\text{arcsec}}^{-2} \text{yr}^{-1}$.

### 3.3 Extraction of moonless, clear sky SQM measurements

We are interested in the anthropogenic contribution to the NSB. Thus, we compare our SQM measurements to a modeled zenithal NSB calculated from sky spectra available through the SKYCALC sky model (Noll et al. 2012; Jones et al. 2013). The whole procedure of how we extracted SQM magnitudes from the model spectra is described in the Appendix A. From this point on, we proceed with the difference between the sky model (sky) and the observed NSB (obs): $(\Delta \text{sky-obs})$. Note that – given our model constraints – the SKYCALC sky models lead to yearly peak and valley zenithal NSBs (due to changing starlight-zodiacal light) of 21.63 and 21.87 mag$_{\text{arcsec}}^{-2}$ for our sites. Comparing our yearly peak-to-valley difference of 0.24 mag$_{\text{arcsec}}^{-2}$ to the “GAIA map of the brightness of the natural sky” (Masana et al. 2022), shows that this is a relatively low value. Figure 3 of Masana et al. (2022) suggests a maximum yearly V-band variations of approx. 0.6 mag$_{\text{arcsec}}^{-2}$. This discrepancy arises due to several facts. First, we evaluate the SKYCALC models using (for the sake of simplicity) constraints such as a fixed precipitable water vapor value of 5 mm rather than a time-dependet value. This has an impact on the scattering of light in the atmosphere and will lead to lower NSB variations over the year. Second, our sites are located at geographic latitudes between 50 and 60 degrees. This is higher than the example shown in Figure 3 of Masana et al. Thus the contribution of zodiacal light to the zenithal NSB becomes lower at our sites (Masana et al. 2020, see Figure 10), further reducing the overall yearly zenithal NSB variation.

Our data reduction routine starts with splitting the SQM data into chunks of 45 minute length. We have chosen this time span to be short enough to allow for multiple sampling points each night (even during summer, except for Stockholm) and to be long/large enough to avoid stochasticity. For each of these time chunks we calculate the mean NSB and the standard deviation. Also a linear fit is performed and the maximum deviation from the fit line is determined. For the mean time of each chunk we further lookup the moon altitude. That way, we are prepared to downselect for observations obtained during moonless and clear sky conditions. We only keep chunks that fulfill the following constraints: i) the Moon is below the horizon, ii) the maximum deviation from the linear fit line of any single measurement is lower than 0.04 mag$_{\text{arcsec}}^{-2}$, iii) the standard deviation of the measurements within the chunk is less than 0.02 mag$_{\text{arcsec}}^{-2}$ for SQMs with a high sampling rate (BA1, IFA, STO, FOA) and 0.06 mag$_{\text{arcsec}}^{-2}$ for SQMs with a sampling frequency of only 1/minute, iv) the slope of the linear fit is shallower than 0.13 mag$_{\text{arcsec}}^{-2}$ per hour.

This procedure basically reduces the SQM data to chunks of 45 minute length within which the NSB remains almost constant. This is the case only when no clouds are present in zenith. Note that – given our model constraints – the SKYCALC sky model (sky) and the observed NSB (obs): $(\Delta \text{sky-obs})$. Finally, we lookup meteorological parameters for each of the data chunks and reject data chunks where i) the large-scale total cloud cover was larger than 50 percent and ii) the snow depth was larger than 5 cm (avoiding SQM readings when the sensor was potentially covered with snow).

### 3.4 Error estimation

In order to estimate the error of our final trend slopes expressed in mag$_{\text{arcsec}}^{-2} \text{yr}^{-1}$ we take into account uncertainties due to the aging correction and the trend fitting. Both errors are estimated through examination of linear fits through the residuals, e.g. bottom panels in Figures 1 and 3. We calculate the linear regression un-
Impact of environment and atmosphere on light pollution

4 RESULTS

4.1 Long-term trends

After selecting aging-corrected SQM data chunks as explained in Section 3, one can easily see in the top panel of Figure 3 that even under clear and moonless conditions individual SQM measurements are prone to large variations with peak-to-valley differences up to $-1.0$ mag$_{SQM}$ arcsec$^{-2}$ yr$^{-1}$ corresponding to a factor of 2.5. At rural sites such as e.g. BOD, the scatter is dominated by a seasonal variation, caused by variations of albedo (e.g. enhancing NSB during winters due to snow cover) and vegetation (darkening during summers due to vegetation). The uncertainties resulting from the linear trend analysis vary between 0.001 and 0.008 mag$_{SQM}$ arcsec$^{-2}$ yr$^{-1}$ with a mean uncertainty of 0.0045 mag$_{SQM}$ arcsec$^{-2}$ yr$^{-1}$. Using a conservative approach, we finally calculate the absolute maximum 1-sigma error for our routine simply via addition: $0.0035 + 0.0045 = 0.0080$ mag$_{SQM}$ arcsec$^{-2}$ yr$^{-1}$. We thus conclude that our method is capable of detecting trends that are shallower/steeper than $0.016$ mag$_{SQM}$ arcsec$^{-2}$ yr$^{-1}$, corresponding to the $\pm2$-sigma level. Expressed on a linear scale, our trend detection limit is thus $\pm1.5$ percent per year.
to blocking of light on leaves). In urban areas (e.g. BA1) such seasonal effects are typically weaker and other parameters seem to gain importance, e.g. atmospheric aerosols or particulate matter.

Pronounced variations and the scattering of data points hamper the assessment of long-term trends. For example, non-uniform, stochastic sampling of a periodic function (seasonal variations) may introduce a bias that leads to a spurious trend when performing a linear regression. For that reason, we aim to model and remove the impact of the atmosphere. To do so, we use atmospheric products freely available from the Copernicus Earth observation program. Our empirical atmospheric model is then found from a penalized linear regression method (lasso) as explained in Section 3.

The middle panel in Figure 3 makes evident that our model is capable of predicting the bulk of the seasonal NSB variations solely from the atmospheric data. The long-term linear trends we find for Potsdam-Babelsberg (BA1) and Bodinggraben (BOD) are 45±16 and 27±16 mmag$_{SQM}$ arcsec$^{-2}$ yr$^{-1}$, respectively. This corresponds to an increase of $\sim$4±1.5% and 2±1.5% per year.

The average increase in light pollution at our 11 rural sites is 1.7±1.5% per year. At our nine urban sites we measure an increase of 1.8±1.5% per year and for the remaining six intermediate sites we find an average increase of 3.7±1.5% per year. These numbers correspond to doubling times of 41, 39 and 19 years. Results for all 26 stations are found in Table 3.

4.2 Impact of the atmosphere

As explained in Section 3, we perform a multi-variate penalized linear regression to identify the importance of individual atmospheric parameters. In detail, we calculate models with increasing complexity, i.e. with an increasing number of atmospheric input features. Starting with a model based on only a single variable (time), any potential long-term linear trend is revealed. Then, we consecutively add single atmospheric features (those listed in Table 2) to the model in order to study the relative importance of each parameter. That is, we compare the scatter (standard deviation) of the residuals after subtracting the model from the data. As shown in Figure 4, additional features reduce the residual scatter. In particular, the Figure shows that at all our sites, the leaf area index ($lai$) and surface albedo ($aluvd$) are the most important model input parameters that reduce the final scatter by a large fraction. Snow depth ($sd$) in principle may firmly enhance the NSB. However, we did not expect that $sd$ has a strong impact on our models, since for the bulk of our locations $sd$ is typically zero most of the time. Moreover, we rejected data points when the snow cover was more than 5 cm (to avoid observations when the SQM sensor was covered with snow). Yet, we do see a decreasing residual scatter due to $sd$ for some rural sites (BOD, FEU, KRI, ZOE) and we observe that snow depth even has a strong effect in Stockholm (STO). Variations of albedo mostly impact our rural sites, while urban and intermediate sites are less affected. In contrast to that, the leaf area index ($lai$) helps in reducing the scatter of all sites by a large degree, be it rural, intermediate or urban.
Table 3. For each SQM station in column 1, the linear slope of the aging effect given in mmagSQM arcsec⁻² year⁻¹ is shown in column 2. Column 3 contains the order of the polynomial used to account for non-linear sensitivity changes of the SQM. The long-term linear trend slope in mmagSQM arcsec⁻² year⁻¹ is found in column 4. All features that survived the lasso regression are listed in column 5 and the total number of data chunks are given in column 6. The last column contains the Pearson R correlation coefficient for the full model (using 16 features). The best fits with R>0.8 are BOD, FEU, KRI, STO.

| Code | aging slope | poly. order | trend slope | features that survived lasso | data count | R  |
|------|-------------|-------------|-------------|-----------------------------|------------|----|
| urban |             |             |             |                              |            |    |
| BA1  | -48         | 2           | 45          | time, lai, bcaod550, duao550, omaod550, ssaod550 | 1819       | 0.74 |
| GRA  | -73         | 3           | 49          | time, aluvd, lai, bcaod550, pm1, duao550, omaod550, ssaod550, pm2p5, tcwv, sd, wind10, tco3, tcc | 846        | 0.58 |
| IFA  | -68         | 2           | 35          | time, aluvd, lai, bcaod550, pm1, duao550, omaod550, pm10, pm2p5, tcwv, wind10, tco3, tcc | 1506       | 0.59 |
| LGO  | 6           | 3           | -12         | aluvd, lai, pm1, duao550 | 315        | 0.59 |
| LSM  | -35         | 3           | -16         | aluvd, lai, sd | 424        | 0.6  |
| STY  | -15         | 2           | 19          | time, aluvd, lai, bcaod550, duao550, omaod550, ssaod550, pm2p5, sd, wind10, tco3 | 1335       | 0.51 |
| TRA  | -37         | 3           | 29          | time, aluvd, lai, duao550, omaod550, ssaod550, wind10, tco3 | 410        | 0.53 |
| WEL  | -29         | 3           | -9          | time, aluvd, lai, pm1, duao550, omaod550, ssaod550, wind10 | 1101       | 0.64 |
| STO  | -43         | 0           | 37          | time, aluvd, lai, duao550, omaod550, tcwv, sd | 913        | 0.82 |
| intermediate |             |             |             |                              |            |    |
| BRA  | -45         | 3           | 31          | time, aluvd, lai, pm1, duao550, omaod550, ssaod550, tco3 | 970        | 0.58 |
| FRE  | -36         | 0           | 21          | time, aluvd, lai, bcaod550, duao550, omaod550, ssaod550, sd, tco3 | 960        | 0.61 |
| GRI  | -45         | 0           | 46          | time, aluvd, lai, bcaod550, pm1, ssaod550, pm10, pm2p5, tcwv, sd, wind10, tco3 | 893        | 0.67 |
| MAT  | -48         | 3           | 90          | time, aluvd, lai, bcaod550, duao550, ssaod550, tcwv, sd, wind10, tco3, tcc | 979        | 0.64 |
| PAS  | -29         | 3           | 7           | time, aluvd, lai, bcaod550, pm1, duao550, omaod550, pm10, pm2p5, tcwv, sd, wind10, tco3, tcc | 564        | 0.6  |
| VOE  | -50         | 0           | 50          | time, aluvd, lai, bcaod550, duao550, omaod550, ssaod550, pm10, tcwv, sd, wind10, tco3, tcc | 678        | 0.54 |
| rural |             |             |             |                              |            |    |
| FOA  | -28         | 3           | 7           | time, aluvd, lai, bcaod550, duao550, omaod505, ssaod550, pm10, tcwv, sd, wind10, tco3, tcc | 1122       | 0.65 |
| FEU  | -5          | 3           | 21          | aluvd, tco3 | 848        | 0.81 |
| GIS  | 0           | 2           | 62          | time, aluvd, lai, bcaod550, duao550, pm10, wind10, tco3, tcc | 343        | 0.59 |
| GRU  | -17         | 0           | 11          | aluvd, lai, bcaod550, duao550, omaod550, tcwv, sd, wind10, tco3, tcc | 1265       | 0.63 |
| KID  | -11         | 0           | -11         | time, aluvd, lai, bcaod550, duao550, omaod550, tcwv, sd, tco3, tcc | 1069       | 0.55 |
| KRI  | -24         | 3           | 22          | time, aluvd, lai, bcaod550, tco3 | 800        | 0.82 |
| LOS  | -51         | 0           | 1           | aluvd, lai, omaod550, ssaod550, tcwv, tco3 | 913        | 0.54 |
| MUN  | -58         | 3           | 61          | time, aluvd, lai, bcaod550, duao550, ssaod550, sd, tco3 | 860        | 0.72 |
| BOD  | -31         | 3           | 27          | time, aluvd, lai, bcaod550, duao550, omaod550, tco3 | 874        | 0.84 |
| ZOE  | -17         | 3           | 5           | aluvd, lai, duao550, omaod550, tco3 | 817        | 0.78 |
| ULI  | -1          | 3           | 3           | time, aluvd, lai, bcaod550, duao550, omaod550, pm10, tcw, sd, wind10, tco3, tcc | 908        | 0.68 |

Atmospheric black carbon (bcaod550) is an important ingredient for our models of urban and (in particular) intermediate sites, while it has almost no impact on rural sites. Interestingly, our coarsely spatially resolved atmospheric data, does not suggest any strong correlation between NSB and large particulate matter (pm10). However, for smaller grains, we do see that pm2p5 and pm1 reduce the residual scatter of the bulk of our urban and intermediate sites. Organic matter in the atmosphere (omaod550) plays mostly only a minor role at all rural sites, but at one station (GIS), omaod550 seems to be important for the modeling.

Ozone makes no difference for the modeling of our urban and intermediate sites. However, models that include ozone as a feature reduce the residual scatter of some rural sites such as ULI, GIS, GRU. Finally, we find that the 10-meter wind speed (wind10) improves the match between the models and NSB observations for some of our sites (GRA, GRI, GIS). The correlation between wind speed and NSB is a non-causal secondary effect, that may be the result of an increase in aerosol transport when wind speed increases. We reckon that due to the coarser temporal resolution of our AOD data (one measurement per six hours) compared to the wind data (hourly data), at sites where aerosol abundance correlates with wind speed, the wind parameter may serve as a proxy for AOD variations at shorter time scales.

For each of our models and sites we calculate the Pearson correlation coefficient R (see Table 3). While the correlation between the SQM data and a solely linear trend is weak (R ~ 0.3 on average), the correlation between the full atmospheric model and the SQM observations becomes strong (R ~ 0.7 on average). For some of the sites (BOD, FEU, KRI, STO) the Pearson correlation coefficient even increases to values greater than 0.8, indicative for a very strong correlation.

5 DISCUSSION

Our long-term analysis of zenithal NSB measurements reveal that it is not the urban regions that show the largest increase in light pollution, but rather the intermediate regions. This may be explained by the fact that the installation of additional lighting points in urban areas contributes relatively less to the NSB, as in urban areas the overall brightness level is already extremely high. On the other side, when intermediate areas develop, new or upgraded lights have a much larger impact on the NSB, as it is relatively darker than in urban areas. More so, in rural regions. There, even only few additional lights may have a recognizable impact. Having said that, Stockholm is probably an exception of that average rule, because it is our brightest site and still shows a very strong increase.

For three of our stations (BA1, BOD, MAT) we utilize the “Radiance LightTrends” web application3, which provides monthly mean radiances measurements obtained with the “Day-Night Band” (DNB) of the “Visible Infrared Imaging Radiometer Suite” (VIIRS) aboard the Suomi-NPP satellite. The resulting long-term radiance trends are

3 https://lighttrends.lightpollutionmap.info
analysis, albedo has a strong impact on the NSB. Thus, data obtained which are more prone to large changes in albedo. As revealed by our VIIRS data contain only measurements of the winter half-year, of the observations and basically filters out seasonal trends. Thus, this may drastically reduce the dynamic range all, VIIRS data is only available for our sites between September and March, because only during these months the satellite passes during the clear and moonless sky, long-term trends of light pollution are "aging correction" to correct for changing detector sensitivity with time, i.e. the "aging effect". Using aging-corrected data obtained using the "twilight method" to correct for changing detector sensitivity. An example that provides evidence for the robustness of our method is the comparison of the results obtained at the stations LGO and LSM. These two SQMs are situated in the same city (Linz), and are thus only 1 km apart. While for one of the sites (LGO) the aging effect is even below the recognition limit, for the other one (LSM), an aging slope of ~35 mmag\text{arcsec}^{-2} \text{yr}^{-1} is found. While the correction slopes are quite different, the final trends are in good agreement. A comparison of several SQMs operating in parallel at different sites within a small area could potentially provide more insight into the aging effect in the future.

6 SUMMARY AND CONCLUSION

We analysed long-term (4–10 years) SQM measurements obtained at 26 different sites, of which 24 are located in Austria, one in Stockholm (Sweden) and one in Potsdam-Babelsberg (Germany). We utilize the "twilight method" to correct for changing detector sensitivity with time, i.e. the "aging effect". Using aging-corrected data obtained under clear and moonless sky, long-term trends of light pollution are derived for our sites. Categorizing our sites into rural, urban and intermediate ones, we find an average increase in light pollution of approximately 1.7, 1.8 and 3.7 percent per year respectively, with an estimated ±2-sigma uncertainty of ±1.5% per year. The corresponding doubling times are 41, 39 and 19 years.
Figure 5. Radiance trends for three of our sites obtained through the “Radiance Light Trends” web application. A radius of 10km around our SQM sites was chosen for summing up radiances. Each red point is a monthly average and the gray shaded area represents the uncertainty of a linear fit.

Furthermore, we establish an empirical atmospheric model which allows us to investigate the relative impact of 15 different atmospheric parameters on the night sky brightness. We find that surface albedo and vegetation have by far the largest impact on the zenithal night sky brightness. Additionally, black carbon and organic matter aerosols are important at urban and rural sites, respectively. Snow depth was found to be important for some sites, while the total column of ozone leaves impact on some rural places.

In the paper we have shown that large-scale (30–40 km resolution) atmospheric parameters obtained through the Copernicus Climate Change Service and the Copernicus Atmosphere Monitoring Service may serve as a basis of a predictive model to constrain the (zenithal) NSB. However, we also recognized that our empirical model correlates better with SQM observations obtained at rural sites, i.e. where albedo and vegetation have strongest impact, while aerosols and particulate matter play only a minor role. Obviously, at urban sites the situation is different. There, aerosols and particulate matter are typically more abundant, and vary on shorter times and scales. The weaker correlation between our model and the observations at urban sites the situation is different. There, aerosols and particulate matter play only a minor role. Obviously, at urban sites the situation is different. There, aerosols and particulate matter are typically more abundant, and vary on shorter times and scales.

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Part of this work has been generated using Copernicus Climate Change Service information (2022) This research made use of SciPy (Jones et al. 2001) and NumPy (Van Der Walt et al. 2011).

DATA AVAILABILITY

The SQM data underlying this article are available for download through repositories at https://www. land-oberoesterreich.gv.at/115999.htm and https://astro.univie.ac.at/en/science-communication/reading-material/light-pollution/. Our reduced SQM data can be made available upon reasonable request.

The third party meteorological data used in this article are available through the Climate Data Store Application Program Interface (CDS API) using Python (e.g. pip install cdsapi).

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In order to quantify anthropogenic light at night, knowledge of the natural night sky brightness is needed. An all-sky model that takes into account scattered moonlight, starlight, molecular emission of the lower atmosphere, emission lines in the upper atmosphere and airglow, was published by Noll et al. (2012) and Jones et al. (2013), as part of an Austrian in-kind contribution to the European Southern Observatory (ESO), e.g. ESO’s exposure time calculator is based on the model.

The main input parameters are zenith distance or airmass of the observation, precipitable water vapor and monthly averaged solar flux. For the moon radiance component, the separation of Sun and Moon as seen from Earth, the Moon-target separation, Moon altitude over horizon and the Moon-Earth distance are needed.

The result is a synthetic (cloud-free) night sky spectrum for the target location.

For our purpose, we multiply the so derived night sky spectrum with the SQM transmission curve and calculate a synthetic SQM magnitude via integration. We have decided to make some simplifications, allowing us to evaluate the model on a 2-dimensional parameter grid with vectors of (Sun-Moon-separation, Moon altitude) and (Moon-target separation, Moon altitude) only. This is reasonable in our case, because the measurement devices we are using, the Sky Quality Meters of type SQM-LE, are equipped with a front lens that narrows down the field of view to a roughly 20° wide cone, pointed towards zenith. Hence, we only need to consider zenithal night sky brightness. The two input parameters Moon-target separation and Moon altitude can thus be simplified to one parameter, with the former one being the Moon zenith distance.

We have further decided to evaluate the model for a fixed precipitable water vapor value of 5 mm, a monthly averaged solar flux of 130 sfu and for a fixed mean Moon-Earth distance. These simplifications have practically no influence on our results, since ALAN’s contribution to our SQM measurements is magnitudes larger than the natural variation caused by phenomena such as water vapor or solar flux. However, variations due to Moon phase and height are large enough to be important and are thus fully treated by our gridded model evaluation for the zenith.

Since the natural, cloudless sky brightness changes smoothly, a grid spacing of one degree in both parameters (Sun-Moon-separation, Moon altitude) was found to be sufficient.

The Sky Quality Meters (SQMs) are produced by Unihedron. Several types are available, of which we are using those denoted by SQM-LE, indicating that they are equipped with a lens (L), and connected via ethernet (E). The lens narrows down the field of view to a half-width-half-maximum (HWHM) angular sensitivity of 10°, corresponding to a cone with an opening angle of 20°. 

APPENDIX A: A SYNTHETIC SKY MODEL FOR THE SQM BAND AS A REFERENCE

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The spectral sensitivity of the SQM is sometimes compared to the V-band, but as shown in Figure A1 it is much wider towards the blue end. Detailed technical specifications are found in Cinzano (2005).

All our SQMs are operated inside weather-proof housings, also produced by Unihedron. Our measurements are corrected for the loss of light due to the housing’s cover glass (via subtraction of 0.11 mag$_{\text{SQM}}$ arcsec$^{-2}$ from the reading).

We aim to compare our SQM measurements to natural (cloud-free) night sky brightness values derived through a sky model. From our gridded model implementation, spectra in physical flux units of photons s$^{-1}$ m$^{-2}$ μm$^{-1}$ arcsec$^{-2}$ are obtained, which we convert to erg s$^{-1}$ cm$^{-2}$ Å$^{-1}$ arcsec$^{-2}$. The spectra are then multiplied with the SQM transmission curve. Subsequently, the total flux is calculated via integration and the result is divided by the bandwidth, which finally gives again a flux density in erg s$^{-1}$ cm$^{-2}$ Å$^{-1}$ arcsec$^{-2}$. The transformation into a Vega-based SQM magnitude (that should be compared to our measurements), is done using the photometric zeropoint and the zero magnitude flux for the SQM. The latter two quantities were derived as explained in the following:

- A Vega spectrum was downloaded from the CALSPEC Calibration Database\(^5\). The flux density of the spectrum is given in units of erg s$^{-1}$ cm$^{-2}$ Å$^{-1}$. For Vega (A0V star) the V-band magnitude is 0.03 mag and its (B-V) color is 0.
- The Vega spectrum is multiplied with the SQM transmission curve, and for sanity checks also with B, V, R Bessel filter transmission curves using data from Bessell (1990).
- The bandwidths were calculated via integration of the filter curves along the wavelength axis (see Figure A1 for the transmission curves used). As seen in Table A1, our results agree on a 10-percent level with those published by Masana et al. (2022), who found 959, 909, 1634 and 2228 Å for B, V, R and the SQM band.
- The integrated flux of the product (Vega*Filter) is divided by the bandwidth. The resulting flux density (FD) is then given in units of erg s$^{-1}$ cm$^{-2}$ Å$^{-1}$. For B, V, R the zeropoints (ZP) are calculated via: 0.03 = −2.5log(FD) + ZP. Bessell (2005) published zeropoints for these filters. They are -20.45, -21.12 and -21.61 mag for B, V and R respectively. Our results agree at a level of 0.1 mag, which is better than the absolute photometric accuracy of the SQM.
- It is known that Unihedron’s in-house calibration of the SQM is performed using a green LED. This calibration leads to (SQM−V) = −0.35 (see Cinzano 2005, Figure 15). Thus, the SQM photometric zeropoint is calculated via: −0.32 = −2.5log(FD) + ZP. The SQM zeropoint is -21.18±0.1 mag. The zeropoint is defined as the magnitude of a source having unity flux.
- Finally, the zero magnitude flux (FD$_0$) can be calculated using the zeropoint from above and: 0 = −2.5log(FD$_0$) + ZP. For the SQM the zero magnitude flux is 3.38 × 10$^{-9}$ erg s$^{-1}$ cm$^{-2}$ Å$^{-1}$.

### APPENDIX B: LONG-TERM TRENDS

This paper has been typeset from a \TeX/\LaTeX file prepared by the author.

\footnote{https://archive.stsci.edu/hlsps/reference-atlases/cdbs/current_calspec/}

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**Table A1.** Filter (column 1), peak wavelength (column 2) and bandwidth (column 3). The zero point (ZP), defined as the magnitude of a source having a flux of 1 erg s$^{-1}$ cm$^{-2}$ Å$^{-1}$ (column 4), and the zero magnitude flux (column 5), were derived via multiplication with subsequent integration of a Vega spectrum with the corresponding filter transmission curve.

| Filter | \(\lambda_{\text{peak}}\) [Å] | BW [Å] | ZP [mag] | \(F \text{D}_0\) [10$^{-9}$ erg s$^{-1}$ cm$^{-2}$ Å$^{-1}$] |
|--------|-----------------|--------|----------|---------------------------------|
| B      | 4350            | 959    | -20.45   | 6.43                            |
| V      | 5437            | 893    | -21.08   | 3.69                            |
| R      | 6433            | 1591   | -21.64   | 2.21                            |
| SQM    | 5087            | 2008   | -21.18   | 3.38                            |

**Figure A1.** Bessel B, V, R and SQM transmission curves (solid curves) and Gaussian fit results (dashed curves) on top of the spectrum of Vega.
Figure B1. Long-term trend for STO and IFA. See caption Figure 3 for more details.

Figure B2. Long-term trend for GRA and FOA. See caption Figure 3 for more details.
Figure B3. Long-term trend for BRA and FEU. See caption Figure 3 for more details.

Figure B4. Long-term trend for FRE and GIS. See caption Figure 3 for more details.
Figure B5. Long-term trend for GRI and GRU. See caption Figure 3 for more details.

Figure B6. Long-term trend for KID and KRI. See caption Figure 3 for more details.
Figure B7. Long-term trend for LGO and LSM. See caption Figure 3 for more details.

Figure B8. Long-term trend for LOS and MAT. See caption Figure 3 for more details.
Figure B9. Long-term trend for MUN and PAS. See caption Figure 3 for more details.

Figure B10. Long-term trend for STY and TRA. See caption Figure 3 for more details.
Figure B11. Long-term trend for ULI and VOE. See caption Figure 3 for more details.

Figure B12. Long-term trend for WEL and ZOE. See caption Figure 3 for more details.