

1 Colour remote sensing of the impact of artificial light at
2 night (I): the potential of the International Space
3 Station and other DSLR-based platforms

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20 **Abstract**

Sensors on remote sensing satellites have provided useful tools for evaluation of the environmental impacts of nighttime artificial light pollution. However, due to their panchromatic nature, the data available from these sensors (VI-IRS/DNB and DMSP/OLS) has a limited capacity accurately to assess this impact. Moreover, in some cases, recorded variations can be misleading. Until new satellite platforms and sensors are available, only nighttime images taken with DSLR cameras from the International Space Station (ISS), airplanes, balloons or other such platforms can provide the required information. Here we describe a theoretical approach using colour-colour diagrams to analyse images taken by astronauts on the ISS to estimate spatial and temporal variation in the spectrum of artificial lighting emissions. We then evaluate how this information can be used to determine effects on some key environmental indices: photopic vision, the Melatonin Suppression Index, the Star Light Index, the Induced Photosynthesis Index, production of NO_2 - NO radicals, energy efficiency and

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CO_2 emissions, and Correlated Colour Temperature. Finally, we use the city of Milan as a worked example of the approach.

21 *Keywords:* artificial lighting, light pollution, night, remote sensing, urban

22 **1. Introduction**

23 Artificial nighttime lighting, from streetlights and other sources, has diverse
24 and problematic environmental impacts. These include effects on the physi-
25 ology, behaviour and phenology of organisms (Dominoni et al., 2013; Dwyer
26 et al., 2013; Altermatt and Ebert, 2016; Bennie et al., 2016), the abundance
27 and distribution of species (Gaston and Bennie, 2014), their ecological interac-
28 tions (Davies et al., 2013), the composition of communities (Davies et al., 2017),
29 and ecosystem processes and services (Hölker et al., 2015). The severity of all of
30 these impacts depends critically on the spectrum of the lighting (Gaston et al.,
31 2014; Schroer and Hölker, 2016), and thus to map the associated patterns of
32 risk and how these are changing it is essential to have spatial and time series
33 data on the spectral composition of light pollution.

34 Unfortunately, obtaining information about the spectra of the emissions of
35 outdoor artificial light sources on large spatial scales has been challenging. The
36 main sources of remote-sensed nighttime lighting data have been colourblind
37 (i.e. single broad band; Elvidge et al. 1999; Liao et al. 2013; Levin et al. 2014;
38 Kyba et al. 2014), and hyperspectral and multispectral data have only been
39 available for a few specific locations photographed as a part of research cam-
40 paigns (Birmingham - Hale et al. 2013, Berlin - Kuechly et al. 2012; Sánchez
41 de Miguel 2015, Madrid - Sánchez de Miguel 2015, Catalonia - Tardà et al.
42 2011, Las Vegas - Metcalf 2012, Upper Austria - Ruhtz et al. 2015). There
43 are some new cubesat missions currently exploring the possibilities of nocturnal
44 remote sensing (Walczak et al., 2017; Zheng et al., 2018), in the future there
45 is likely to be access to hyperspectral data from satellites like TEMPO (Carr
46 et al., 2017) and potentially also from Sentinel 4 or 5b, and there have been calls
47 for a dedicated nightsat satellite (Elvidge et al., 2007, 2010). But multispec-

48 tral data are already urgently required. This is particularly the case because
49 rapid changes in the spectra of artificial nighttime lighting are currently taking
50 place (Kyba et al., 2014, 2017). For several decades outdoor lighting has mainly
51 made use of High Pressure Sodium (HPS), Low Pressure Sodium (LPS), metal
52 halide (MH) and fluorescent lamps. However, there are now widespread shifts
53 to 'white' light-emitting diode (LED) lamps, that are projected soon to become
54 the dominant source, and emissions from which have repeatedly been found to
55 have more severe environmental impacts (Davies et al., 2014, 2017).

56 An alternative, and thus likely vitally important, source of remotely sensed
57 spatial and temporal data on the spectrum of artificial nighttime lighting is
58 photographs taken by astronauts on the International Space Station (ISS). Noc-
59 turnal images are available from 2003 to the present, although their temporal
60 and spatial distributions are variable. Between 2003 and 2010, a total of 35,995
61 nighttime images were taken, with a further 423,520 between 2011 and Novem-
62 ber 2014. Of these, at least 30,000 images are of cities at night (Sánchez de
63 Miguel et al., 2014; Sánchez de Miguel, 2015). In this paper, we first present a
64 method to classify outdoor lighting types from ISS imagery, using colour-colour
65 diagrams (which can also be used for similar images obtained from remote sens-
66 ing aerial or ground based platforms). We then determine the relations between
67 the spectral information that can be obtained from the imagery and some key
68 environmental indices (photopic vision, the Melatonin Suppression Index, the
69 Star Light Index, the Induced Photosynthesis Index, production of NO_2 -NO
70 radicals, energy efficiency and CO_2 emissions, and Correlated Colour Tempera-
71 ture). Finally, we provide an example of the application of this approach to ISS
72 imagery of the city of Milan.

73 Throughout, we concentrate on the underlying principles of the approach.
74 For practical application, calibration and instrument effects also need to be
75 considered, and these will be explained in a future paper. We focus here on
76 establishing the principles using Nikon DSLR cameras as the exemplar, because
77 these are the ones used on the ISS. A similar technique can be applied to any
78 other RGB camera. With the primary exception of astronomical CCD cameras

and some professional cameras, current digital cameras use a Bayer matrix filter to create the final colour image. The characteristics of these filters can change from one brand to another. One of the advantages of Nikon cameras is that recent models have been very consistent in their spectral response. Thus, whilst we will concentrate on the spectral response of the Nikon D3s (the most common camera used on the ISS), this response is virtually identical to that of others that have been used, such as the D3, D4 and D5 (Fig. 1).

2. Synthetic photometry

The first thing we need to know in order to use an ISS image to determine the colour of outdoor lighting of an area is to calculate the predicted response of the sensor in the camera to a certain light spectrum. We employ synthetic photometry, a mathematical technique that allows prediction of the spectral features of a light source under different conditions or instrument settings (Straizys, 1996)). This is widely used in astronomy (Fukugita et al., 1995), but can be applied to other photonics based research topics. In astronomy, the brightness of a source, measured in magnitudes, can be predicted based on its spectral energy distribution and that of a reference source as:

$$m_{AB} = -2.5 \log_{10} \frac{\int_0^{\infty} T(\lambda) \phi(\lambda) d\lambda}{\int_0^{\infty} T(\lambda) \phi_{ref}(\lambda) d\lambda}, \quad (1)$$

where $T(\lambda)$ is the spectral sensitivity of the observation band (including the detector response), $\phi(\lambda)$ is the spectrum of the source and $\phi_{ref}(\lambda)$ a reference spectrum which defines the magnitude system. In particular, for many decades astronomers have employed the spectral energy distribution of the star Vega as a reference. This has not been free from systematic errors due to uncertainties in the absolute flux calibration of this star. For that reason, the tendency at present is to use the so-called AB magnitude system (Oke, 1974), in which the reference spectrum $\phi(\lambda)_{ref} = \phi(\lambda)_{AB}$ does not depend on any particular star but

¹⁰⁴ is defined for a source of constant spectral density flux of 3631 Janskys across
¹⁰⁵ the spectral range of the band.

¹⁰⁶ In remote sensing, where the AB magnitude system of units is not used, the
¹⁰⁷ brightness of a source is quantified as radiance, that can be measured using the
¹⁰⁸ much simpler expression:

$$R = \frac{\int_0^{\infty} T(\lambda) \phi(\lambda) d\lambda}{\int_0^{\infty} T(\lambda) \phi_{AB}(\lambda) d\lambda}. \quad (2)$$

¹⁰⁹ Conversion from m_{AB} , AB magnitudes, to radiance R can be done using
¹¹⁰ (Sánchez de Miguel et al., 2017):

$$m_{AB} = -2.5 \log_{10}(R) - 5 \log_{10}\bar{\lambda} - 2.41, \quad (3)$$

¹¹¹ where R is expressed in $\text{erg s}^{-1} \text{ cm}^{-2} \text{ \AA}^{-1}$, and $\bar{\lambda}$ is the average wavelength of
¹¹² the band defined by

$$\bar{\lambda} = \frac{\int_0^{\infty} \lambda T(\lambda) d\lambda}{\int_0^{\infty} T(\lambda) d\lambda}. \quad (4)$$

¹¹³ Synthetic photometry measurements can be obtained for any combination
¹¹⁴ of spectral source and wavelength range using equations 1 and 3. In astronomy
¹¹⁵ one can employ the spectrum of many stars for calibration purposes. This is
¹¹⁶ much cheaper, precise and accessible than using absolute calibrated radiometric
¹¹⁷ lamps. In this paper we use radiance ratios of the form:

$$\frac{R}{R'} = \frac{\int_0^{\infty} T(\lambda) \phi(\lambda) d\lambda}{\int_0^{\infty} T'(\lambda) \phi(\lambda) d\lambda} \frac{\int_0^{\infty} T'(\lambda) \phi(\lambda)_{AB} d\lambda}{\int_0^{\infty} T(\lambda) \phi(\lambda)_{AB} d\lambda} \equiv C_{T,T'} \frac{\int_0^{\infty} T(\lambda) \phi(\lambda) d\lambda}{\int_0^{\infty} T'(\lambda) \phi(\lambda) d\lambda}, \quad (5)$$

¹¹⁸ where R is the radiance in one filter/instrument system, R' is the radiance of
¹¹⁹ the same source using a different filter/instrument system, T and T' are the
¹²⁰ spectral transmittance of the respective filter/instrument systems, and $C_{T,T'}$
¹²¹ can be considered as a constant after setting the two filter/instrument systems

122 in use. These radiance ratios are called colours in astrophysics and we will use
123 the terms colour and ratio interchangeably.

124 *2.1. Spectral libraries used*

125 In order to predict the colours that will appear on the sensors or the synthetic
126 bands that will be discussed later, it is necessary to have high resolution spectra
127 of the light sources. For this work we have used two different spectral libraries,
128 the LSPDD database and the LICA UCM database. The LSPDD database
129 mainly comprises spectra measured in the laboratory. It includes 254 lamp
130 spectra (with information also about energy efficiency), in ASCII text format
131 (273 nm to 900 nm every 0.5 nm; Sánchez de Miguel et al. 2017). By contrast,
132 the LICA UCM database comprises spectra obtained mainly from measurements
133 made in the field (Tapia et al., 2017). Here we use 50 spectra from this database,
134 mainly for the more common forms of lamps used for street lighting. The two
135 databases complement each other for our purposes since in a laboratory it is
136 difficult to get a real representation of how street light lamps actually perform
137 outside (depending on factors such as changes in spectra due to aging of lamps,
138 frequency of maintenance and cleaning etc.), whilst in the field it is difficult to
139 obtain information on energy efficiency. In this paper we use the classification of
140 illumination technology (kinds of lamps) employed by the LSPDD database. We
141 focus on lamps typical of the street lights of the European Union and Canada,
142 although the industry is constantly creating new kinds of street lights.

143 **3. Lamp classification using RGB DSLR colours**

144 The colourcolour (or two colour) technique has long been used widely in as-
145 trophysics to discriminate different light sources based on their predicted phys-
146 ical properties (Öhman, 1949; Dixon, 1965). However, it has not previously
147 been used in the context of nocturnal remote sensing. The technique compares
148 two ratios each of two different bands in a bidimensional space. Each ratio is
149 named as a colour. These colours can be calculated analytically or observed.

150 The large potential of this technique comes from the ease of comparing analytical
151 or theoretical predictions with observations. In our case, we have computed
152 analytically the expected colours (radiance ratios) detected by the camera sensor
153 of a Nikon D3s for the different lamps in the LSPDD and LICA databases
154 using the synthetic photometry technique (see above). DSLR cameras use a
155 Bayer filter in front of the sensor, which comprises microfilters of three different
156 colours, Blue (B), Green (G) and Red (R). With this structure it is possible to
157 obtain for a given field of view four images of three colours simultaneously, one
158 red, one blue and two green images that are identical but from slightly different
159 perspectives. These images do not correspond precisely to the same viewpoint,
160 therefore an interpolation procedure is usually used to obtain a higher resolution
161 image. For the colourcolour technique we use ratios between the colours
162 to obtain a distribution of values on the plane B/G vs G/R. In daylight remote
163 sensing similar techniques have been used for the calculation of the Normalised
164 Difference Vegetation Index (NDVI) since the late 1970s (Rouse Jr et al., 1974;
165 Tucker, 1979; Tucker et al., 2005), although NDVI is a spatial transformation
166 of two bands of a spectral ratio (NIR/VIS), and we propose the use of three
167 bands. For present purposes we assume direct line-of-sight to the light source.
168 In practice, atmospheric corrections may need to be considered when the observation
169 is made from space, or reflectance corrections if the light does not take
170 a direct path to the sensor. We also treat the detector as ideal, so it is not
171 affected by differences in the sensitivity of the camera to different wavelengths
172 or linearity issues. In practice, the RAW image data would also need to be
173 corrected for these effects.

174 It is important to note that the RAW image is the least processed that
175 a DSLR camera can produce, but whilst in theory this should be completely
176 unprocessed this is usually not the case. Such images do not have corrections
177 for color balance, linearity corrections, gamma corrections etc. The JPG format
178 is more common and widespread but this is not the native format and can have
179 several issues. Most JPG images use lossy compression, so a large part of
180 the information is lost. They do not use the full dynamic range of the data

181 and a gamma correction (Poynton, 1998) is used to make them more human
182 vision friendly, destroying the linearity of the original data. The JPG format
183 is not recommended for quantitative analysis unless all these issues have been
184 addressed first.

185 Different lamp types do not completely separate out in B/G vs G/R space
186 using the spectral information from the databases (Fig. 2). This said, the likeli-
187 hood of particular types giving rise to emissions in different regions of this space
188 can be markedly narrowed down. The area framed by B/G [0-0.05] and G/R
189 [0-0.36] can be assigned to Low Pressure Sodium (LPS) and pure amber LEDs;
190 the area B/G [0.05-0.25] and G/R [0-0.36] to High Pressure Sodium (HPS) light
191 sources; the area B/G [0-0.25] and G/R [0.36-0.55] has a combination of HPS,
192 LED phosphor converted (PC) amber, some warm light fluorescents, incandes-
193 cent lamps and other warm LEDs; the area B/G [0.25-0.45] and G/R [0-0.55]
194 is where neutral white lamps like LED 3000k and many fluorescents lie; the
195 area B/G [0-0.36] and G/R > 0.55 is where we find lamps with high mercury
196 content, and some LEDs many of which have a greenish colour as a result of
197 degradation from their original specification; the area B/G > 0.36 and G/R >
198 0.55 has the more bluish lamps like LEDs of 4000k and 5000k, and metal halide
199 lamps. There are also some "forbidden" areas, like the region G/R [0-0.55] and
200 B/G > 0.45, which can only be populated by mixtures of extremely warm lights
201 with extremely cold lights or if there are problems with signal to noise ratios in
202 image data.

203 **4. Evaluation of relationships between environmental measures and**
204 **RGB colours**

205 Whilst the distribution of lamp types across B/G vs G/R space may not be
206 simple, it may still be the case that one or other of these ratios may show useful
207 relationships with measures of the environmental impact of artificial nighttime
208 lighting. If this were to be the case, then it would be possible to re-express RGB
209 images taken from the ISS in terms of these measures. Here we evaluate this

210 potential for a varied selection of such measures, namely photopic vision, the
211 Melatonin Suppression Index, the Star Light Index, the Induced Photosynthesis
212 Index, production of NO_2 - NO radicals, energy efficiency and CO_2 emissions,
213 and Correlated Colour Temperature.

214 In each case, we determine the relationships between the measure and the
215 G/R and B/G ratios. The fits reported are statistical approximations. Linear
216 fits were calculated with Robust linear model estimation RANSAC (Pedregosa
217 et al., 2011), in order to reduce the effect of outliers without removing them.
218 Polynomial fits were calculated using the `polyfit` function of Walt et al. (2011).
219 The errors of the fits have been calculated using the bootstrap technique with
220 1000 iterations and considering one sigma error, so the central value is the
221 median, and data points falling outside the error bars $\pm 1\sigma$. The selection of
222 the order of the polynomials reported has been decided manually due to the
223 statistical peculiarities of the sample. In particular, whilst some lamp types
224 have an industrial standard single spectrum (and therefore effectively no error
225 in the measurement; e.g. LPS) others have multiple spectra and have been
226 'field sampled' (with associated error; e.g. LEDs). The reported polynomial fits
227 are those that are judged to give the highest explained variance whilst also not
228 unduly punishing fit to the LPS data because of its representation by only one
229 point.

230 *4.1. Photopic vision*

231 Photopic vision (aka $V(\lambda)$ or luminance) is that which humans use when
232 illumination levels are higher than $\sim 0.7cd/m^2$ (Eloholma and Halonen, 2006).
233 There is a strong relationship between the ratio G/R and the $V(\lambda)/G$ ratio
234 derived from the sensitivity curve for this vision (Smith and Guild, 1931) (Table
235 1, Fig. 3). The relationship is not linear, such that errors in the determination
236 of lower values of the G/R ratio will lead to larger errors in the $V(\lambda)/G$ ratio.
237 This relationship can nonetheless be very useful to convert images taken by
238 DSLRs to units of Lux or Candelas that are used in most regulations concerning
239 artificial lighting. Assuming that radiation is monochromatic, radiometric units

240 of Watts per steradian can be converted to Candelas by dividing by 683 (Zong,
 241 However, we do not recommend use of this conversion in remote sensing
 242 applications if the spatial resolution of the image is less than 1m/pixel. If the
 243 resolution of the image is higher than 1m/pixel, this can be used for a reliable
 244 measure of illumination, that can have legal implications. This is because these
 245 units are usually used to measure illumination for regulatory purposes. Values
 246 measured at low spatial resolution will be misleading because they will include
 247 illuminance from a mixture of surfaces, including the roofs of buildings. In
 248 order for the end result to represent photopic intensity we need to multiply the
 249 intensity of the green channel $V(\lambda)/G$ ratio (eq. 6) (this paper):

$$V(\lambda) = V(\lambda)/G \cdot G \quad (6)$$

250 This equation gives us the possibility of measuring luminance using DSLR
 251 cameras, by getting an estimate of the $V(\lambda)/G$ ratio from B/G or G/R ratio
 252 images and the intensity on the G channel.

253 *4.2. Melatonin Suppression Index and Melatonin Suppression band*

254 Melatonin is one of the key drivers of biological rhythms in a wide array of
 255 organisms, and its production is highly responsive to light spectra. The Mela-
 256 tonin Suppression Index was defined by Aubé et al. (2013) using the melanopsin
 257 response function (aka msas) published by Thapan et al. (2001) and Brainard
 258 et al. (2001). The MSI values are weighted by photopic intensity and constitute
 259 a measure of the potential suppression of melatonin production by a light source
 260 compared to the solar spectrum:

$$MSI = \frac{\int_{380nm}^{730nm} \phi_n(lamp)(r, \lambda) M(\lambda) d\lambda}{\int_{380nm}^{730nm} \phi_n(D65))(r, \lambda) M(\lambda) d\lambda} \quad (7)$$

261 There is a linear relationship between MSI and the G/R ratio (Table 1, Fig.
 262 4). The dispersion of values is greater for bluer lamp sources. However, for
 263 most lamps this relationship is sufficient for an estimate of MSI of better than
 264 ± 0.2 , data points falling outside the error bars, that allow us to estimate the

265 MSI of the sources with a typical precision of 75%. There is a tighter linear
266 relationship between MSI and the B/G ratio (Table 1, Fig. 4), although it is
267 much more difficult to get a good signal to noise ratio on the blue channel of
268 DSLRs than on the green and red. Using both relationships, we can obtain a
269 more reliable estimate of the real MSI value. MSI is weighted by the human
270 vision response, so that we can measure with the $V(\lambda)/G$ relationship we can
271 calculate the real impact by the next equation (this paper):

$$\text{MSI Impact} = \text{MSI}(B/G \text{ or } G/R) \cdot \left[\frac{V(\lambda)}{G} (B/G \text{ or } G/R) \right] \cdot G \quad (8)$$

272 Sometimes we might want to skip the step of the estimation of luminance
273 (aka $V(\lambda)$) and go directly to estimate the energy emitted across the melatonin
274 suppression band (msas). Indeed, this variable shows less scattered relationships
275 with G/R and B/G ratios, but it is not weighted by the human vision response
276 (Fig. 5).

$$\text{msas intensity} = \text{msas}/G (B/G \text{ or } G/R) \cdot G \quad (9)$$

277 If we want to know the total intensity emitted in the melatonin suppression
278 band we need to apply equation 9 (this paper). Doing so allows the intensive
279 function of msas/G and extensive values of a G image to be combined. As
280 msas/G ratio is a function of B/G or G/R spectral values it is possible to create
281 images that represent msas/G by using B/G or G/R images.

282 The potential application of this or derived indicators can be appreciated
283 from recent publication of the finding of a statistically significant correlation
284 between MSI and the risks of breast and prostate cancer (Garcia-Saenz et al.,
285 2018).

286 *4.3. Star Light Index and Scotopic vision*

287 The loss of visibility of stars as a consequence of artificial nighttime lighting
288 is a particular concern to astronomers, but may have wider impacts in terms
289 of limiting human experiences of the natural world (Kyba, 2018) and nocturnal

290 orientation by other species (Bird and Parker, 2014; Wallraff, 1960; Warrant and
 291 Dacke, 2011). The Star Light Index (SLI) was defined by Aubé et al. (2013)
 292 using human scotopic vision (CIE 1951; Wyszecki and Stiles (1982)) aka $V'(\lambda)$,
 293 as a measure of the visibility of stars to people:

$$SLI = \frac{\int_{380nm}^{730nm} \phi_n(lamp)(r, \lambda)S(\lambda)d\lambda}{\int_{380nm}^{730nm} \phi_n(D65))(r, \lambda)S(\lambda)d\lambda} \quad (10)$$

294 There is a polynomial relationship between SLI and the G/R ratio (Table
 295 1, Fig. 6). Similar to MSI, the blueish light sources are more dispersed than
 296 the warm light sources. In addition, the plot shows a good fit concerning the
 297 predicted SLI values derived from the spectra using the B/G ratio (Table 1).
 298 This SLI(B/G)relationship is less scattered than the SLI(G/R) ratio, although
 299 the level of accuracy will depend on the signal to noise ratio. Usually, the
 300 blue channel has a lower signal to noise ratio. Therefore, the G/R relationship
 301 will often be more accurate. Similar to how we obtained the actual photopic
 302 intensity, in order for us to obtain the scotopic intensity we also calculated the
 303 $V'(\lambda)/G$ using the B/G and G/R ratios and the G channel. In other words,
 304 the equation used for obtaining the photopic intensity can also be applied to
 305 obtain the scotopic intensity simply by replacing the $V(\lambda)/G$ function with the
 306 $V'(\lambda)/G$ function. In addition, by joining these two functions we are also able to
 307 estimate the scotopic-photopic (SP) ratio. The SP ratio is useful for determining
 308 the impact on star visibility. It should be noted that, contrary to the belief of
 309 some researchers, the SP ratio is not useful for establishing suitable illumination
 310 intensity levels since scotopic vision starts at 0.5 lux. This means that scotopic
 311 vision is used only when illumination intensity levels are extremely low. Much
 312 lower than the average lit street.

313 4.4. Induced Photosynthesis Index and Photosynthetic band

314 The Induced Photosynthesis Index (IPI) has been defined by Aubé et al.
 315 (2013) using Germany: Deutsches Institut Fur Normung EV (German National
 316 Standard) (2000), and represents the potential of a source of illumination to
 317 enable plant photosynthesis.

$$IPI = \frac{\int_{380nm}^{730nm} \phi_n(lamp)(r, \lambda) I(\lambda) d\lambda}{\int_{380nm}^{730nm} \phi_n(lamp)(r, \lambda) I(\lambda) d\lambda} \quad (11)$$

318 There is no relationship between the IPI and the G/R ratio (see in sup-
 319 plementary materials) or the B/G ratio (Table 2). We conclude that as the
 320 spectral sensitivity of photosynthesis is so broad, any lamp spectrum, no mat-
 321 ter the dominant wavelengths, can produce a photosynthetic response. The
 322 highest response is to lamps that have emissions similar to a black body (this is
 323 logical as plants are adapted to respond to sunlight that is effectively emission
 324 from a black body). There is not a significant correlation between the IPI and
 325 the ratio G/R, and more careful analysis is needed to exclude the black bodies
 326 (Fig. 8).

327 *4.5. Production of NO₂-NO radicals*

328 Stark et al. (2011) observed that emissions from city lights can interact
 329 with the chemistry of the atmospheric production of NO₂ and NO radicals and
 330 thus change levels of air pollution, with different types of lamps influencing this
 331 interaction differently.

$$\frac{j(NO_3)}{Luminance} = \frac{\int \phi_n(lamp)(r, \lambda) \sigma_{NO_3}(\lambda) \cdot [\phi_{NO_3 \rightarrow NO_2}(\lambda) + \phi_{NO_3 \rightarrow NO}(\lambda)] d\lambda}{\int \phi_n(lamp)(r, \lambda) V(\lambda) d\lambda} \quad (12)$$

332 Because of the complicated absorption spectrum of NO₃ (aka *jNO₃*), the
 333 main precursor of NO₂ and NO, it does not show a good relationship with the
 334 G/R ratio (Fig. 9, Table 2) nor with the B/G ratio (Table 2). However, LPS
 335 lamps are associated with much higher levels of yields of NO₃ than are other
 336 lamps. Equation 12 is the formula used to create fig. 9, more details in Stark
 337 et al. (2011).

338 *4.6. Energy efficiency - CO₂ production*

339 There is much interest in estimating the energy efficiency of lighting - which
 340 has obvious implications for its wider environmental impacts - and how this is

³⁴¹ changing, at landscape scales and above (e.g. nationally). However, there is
³⁴² no relationship between luminous efficacy measures of lamps from the LSPDD
³⁴³ database or from Wikipedia contributors (2018) and either the G/R ratio or
³⁴⁴ the B/G ratio when considering all the lighting technologies (Table 2). Some
³⁴⁵ authors have argued that there is a correlation at higher levels of Correlated
³⁴⁶ Colour Temperature (for definition see below) (Donatello et al., 2017). However,
³⁴⁷ we found no marked relationship amongst just the white light technologies. In
³⁴⁸ short, there is no way to determine energy efficiency using only the colour of
³⁴⁹ lights without knowledge of the technology that is producing this specific colour,
³⁵⁰ and even in that case for some technologies, such as LEDs, a wide range of energy
³⁵¹ efficiencies is possible.

³⁵² *4.7. Correlated Colour Temperature*

³⁵³ Correlated Colour Temperature (CCT) is a measure of the human sensation
³⁵⁴ of colour compared with black bodies of a certain temperature (McCamy, 1992).
³⁵⁵ This parameter is widely used by the lighting industry and in photography to
³⁵⁶ give an approximate sense of the colour of light, although it poorly captures the
³⁵⁷ blue content of light sources, which is a significant issue with regard to many
³⁵⁸ "white" LEDs (Galadí-Enríquez, 2018). CCT and the G/R ratio are related in
³⁵⁹ an approximately linear fashion (Fig. 10), but the best fit is a polynomial one.
³⁶⁰ The scatter is much greater for bluer lamps. CCT has been criticized because
³⁶¹ it does not represent the environmental impact of the light, even though it has
³⁶² been used in several regulations that are intended to do so (Kinney et al., 2017).

³⁶³ **5. Milan an example application**

³⁶⁴ Probably the best known recent conversion of a streetlight system has been in
³⁶⁵ 2015 in the city of Milan during which high pressure sodium lamps were replaced
³⁶⁶ with LEDs. In this section we use nighttime images from the ISS taken before
³⁶⁷ and after this conversion as an example of the application of the methodology
³⁶⁸ described in this paper. The images used are ISS032-e-012145(2012) and ISS043-

369 e-093509(2015) taken from Sánchez de Miguel et al. (2015) and downloaded from
370 NASA’s Gateway to Astronaut Photography of Earth (<https://eol.jsc.nasa.gov/>).

371 To apply the statistical relationships between the RGB values and the en-
372 vironmental variables it is necessary to make several corrections to the raw
373 image data of the city since this does not represent the real intensity of the
374 RGB channels. Neither does the raw data show the real ratios between the
375 different channels. In order to resolve these discrepancies we applied standard
376 procedures of decodification of the raw data, linearity correction of the sensor
377 and vignetting correction of the lens(Sánchez de Miguel, 2015). Furthermore,
378 corrections of the relative intensity between channels have been applied. For
379 accuracy, calibrations used the same lens and camera models used by the astro-
380 nauts to take the images. Because, we are using the images for a comparative
381 analysis only, we did not need to apply atmospheric corrections or ISS window
382 transmission corrections.

383 We focus on two of the environmental measures, photopic intensity and MSI.
384 There was no measurable change in photopic intensity, estimated using equation
385 6, across Milan between the two time periods (Fig. 11; measured variation was
386 0% 5%). This makes sense because the streetlight conversion was designed to
387 produce the same luminance level as did the original streetlights. By contrast,
388 there was an increase in values of MSI, estimated using equation 7, of 37% in
389 Milan (Fig. 11). Weighting MSI by photopic vision, using equation 8, shows an
390 increase of 23% (Fig. 13).

391 6. Discussion

392 Images of the Earth taken using DSLR cameras from the ISS, and poten-
393 tially other platforms, can provide valuable data on the colour of nighttime
394 artificial lighting. As reported here, we have determined an approach to ex-
395 tracting these data through the use of colour-colour diagrams. In turn, this
396 enables the association to be determined with a variety of measures of environ-
397 mental impacts (Table 1 and 2). In some cases these relationships are strong

398 (e.g. Photopic vision, Melatonin Suppression Index), providing a basis for cre-
399 ating spatial maps of potential risks of artificial lighting and also how those
400 risks are changing through time. In other cases these relationships are poor or
401 non-existent (e.g. Induced Photosynthesis Index, energy efficiency), meaning
402 that such maps cannot be created.

403 This method is analytical, and uses calculations of the light spectra to deter-
404 mine the lamp colours. The important advantage of this approach is that it is
405 device independent. And therefore, the cameras should be calibrated to fit the
406 predicted colours. This means that success or failure "only" depends on the sig-
407 nal to noise ratio as well as the accurate characterisation of the DSLR cameras,
408 the completeness of the spectral databases and other environmental corrections.
409 The only limitation of this method is that, although the data concerning pre-
410 dicted colours is fully reliable, some field study is needed in order to set initial
411 accurate boundaries for the clusters of predicted colours. This additional data
412 will allow for precise fine tuning devices used in studies. We propose that the
413 radiance calibrated G/R and B/G ratios be termed the Normalized Ratio Light
414 Index (NRLI) Warm and Cold respectively, that is NRLIw and NRLIc, to dis-
415 tinguish them from non-radiance calibrated G/R and B/G ratios used by other
416 authors (Hale et al., 2013).

417 While our focus is on the potential for using the method documented here to
418 measure the environmental impacts of artificial nighttime lighting using images
419 taken from the ISS, the approach is applicable to DSLR camera images from
420 other platforms. Terrestrial-based and airborne images of cities at night could
421 be useful tools to assess the environmental impacts of artificial light, particularly
422 in assessing historical changes where new measurements are not possible. Field
423 ecological studies on the impacts of artificial light on ecosystems often lack a
424 spectral characterisation of light sources due to the cost of spectrophotometers,
425 despite the importance of emission spectra for the ecological responses (Bennie
426 et al., 2016; Davies et al., 2017); the routine use of DSLR images could help to
427 fill this gap.

428 A recent conservative approach, that is limited because of the spectral range

429 of the VIIRS satellite sensor (Hillger et al., 2013; Miller et al., 2012), has es-
430 timated that both the extent and intensity of artificial nighttime lighting are
431 growing globally at a rate of about 2 percent per annum (Kyba et al., 2017).
432 Perhaps more significantly, the rate of increase is similar across regions that,
433 over the time period analysed (2012-2016), began with very different levels of
434 artificial lighting. Thus the environmental pressures that result from the in-
435 troduction of lighting (see section 1) are both being introduced into areas in
436 which previously they have not been experienced, and are being exacerbated
437 in regions in which they may already have been quite acute. Given that these
438 pressures are sensitive to the spectrum of lighting, having tools to track the
439 spatial pattern and change in this spectrum will be vital.

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Relationship	Factors ($p_n \cdot x^n + \dots + p_0 \cdot x^0$)	Valid area(x)	R^2	p value
Photopic				
$V(\lambda)/G = f(G/R)$	$-4.0 + 9.8 - 8.2 + 3.60$	[0.1,1.1]	0.97	< 0.001
$-\delta$	$-0.5 - 0.6 - 0.5 - 0.06$			
$+\delta$	$+0.4 + 0.9 + 0.3 + 0.09$			
$V(\lambda)/G = f(B/G)$	$-2.4 + 4.9 - 3.6 + 2.15$	[0.0,1.0]	0.72	< 0.001
$-\delta$	$-1.2 - 1.8 - 0.8 - 0.13$			
$+\delta$	$+1.1 + 1.8 + 0.8 + 0.12$			
Melatonin Suppression Index				
$MSI = f(B/G)$	$+1.09 - 0.053$	[0.15,1.0]	0.87	< 0.001
$-\delta$	$-0.05 - 0.019$			
$+\delta$	$+0.05 + 0.019$			
$MSI = f(G/R)$	$0.97 - 0.19$	[0.0,1.0]	0.68	< 0.001
$-\delta$	$-0.12 - 0.06$			
$+\delta$	$+0.12 + 0.06$			
$msas/G = f(B/G)$	$+0.75 + 0.03$	[0.0,0.8]	0.88	< 0.001
$-\delta$	$-0.02 - 0.01$			
$+\delta$	$+0.03 + 0.01$			
$msas/G = f(G/R)$	$+0.57 - 0.02$	[0.18,1.0]	0.54	< 0.001
$-\delta$	$-0.06 - 0.04$			
$+\delta$	$+0.08 + 0.03$			
Stellar Light Index				
$SLI = f(G/R)$	$+0.84 + 0.07$	[0.18,1.0]	0.64	< 0.001
$-\delta$	$-0.18 - 0.09$			
$+\delta$	$+0.18 + 0.09$			
$SLI = f(B/G)$	$+0.59 + 0.14$	[0.0,0.8]	0.84	< 0.001
$-\delta$	$-0.04 - 0.08$			
$+\delta$	$+0.03 + 0.12$			

Table 1: Relationships between different environmental indices and the G/R or B/G ratios obtained from imagery from a DSLR. In all cases the number of spectra used is 206. $f(x)$ indicates the function where x is equal to B/G or G/R. Factors represent the p_n values of the polynomial fit. Uncertainties in the coefficients are given as $\pm\delta$. Valid area represent the X range where the fit is accurate.

Relationship	Factors ($p_n \cdot x^n + \dots + p_0 \cdot x^0$)	Valid area(x)	R^2	p value
Scotopic vision				
$V'(\lambda)/G = f(G/R)$	$-27 + 81 - 91 + 47 - 9 + 0.9$	[0.18,0.9]	0.66	< 0.001
$-\delta$	$-18 - 65 - 80 - 37 - 15 - 0.8$			
$+\delta$	$+22 + 63 + 72 + 50 + 9 + 1.8$			
$V'(\lambda)/G = f(B/G)$	$-15 + 33 - 25 + 6 + 0.7 + 0.23$	[0.0,1.0]	0.90	< 0.001
$-\delta$	$-15 - 26 - 25 - 7 - 1.1 - 0.05$			
$+\delta$	$+12 + 32 + 21 + 8 + 1.1 + 0.05$			
Induced Photosynthesis Index				
IPI= $f(B/G)$ no fit	NO		NO	NO
IPI= $f(G/R)$ no fit	NO		NO	NO
Correlated Color Temperature				
$CCT = 10^4 \cdot f(G/R)$	$-3.0 + 5.8 - 3.2 + 1.0 + 0.06$	[0.2, 1.]	0.91	< 0.001
$-\delta$	$-1.5 - 4.3 - 3.5 - 1.2 - 0.14$			
$+\delta$	$+1.5 + 3.8 + 3.5 + 1.1 + 0.14$			
$CCT = 10^4 \cdot f(B/G)$	$-3.6 + 6.0 - 1.6 + 0.4 + 0.18$	[0,1]	0.82	< 0.001
$-\delta$	$-4.0 - 4.6 - 3.3 - 0.5 - 0.03$			
$+\delta$	$+2.6 + 6.2 + 2.6 + 0.6 + 0.03$			
Yields NO_3				
jNO3/V(λ)= $f(B/G)$ no fit	NO		0.38	NO
jNO3/V(λ)= $f(G/R)$ no fit	NO		0.008	NO
Luminosity efficiency				
Lum. eff.= $f(G/R)$ no fit	NO		NO	NO
Lum. eff.= $f(B/G)$ no fit	NO		NO	NO

Table 2: Relationships between different environmental indices and the G/R or B/G ratios obtained from imagery from a DSLR. In all cases the number of spectra used is 206. $f(X)$ indicates the function where x is equal to B/G or G/R. Factors represent the p_n values of the polynomial fit. Uncertainties in the coefficients are given as $\pm\delta$. Valid area represent the X range where the fit is accurate.

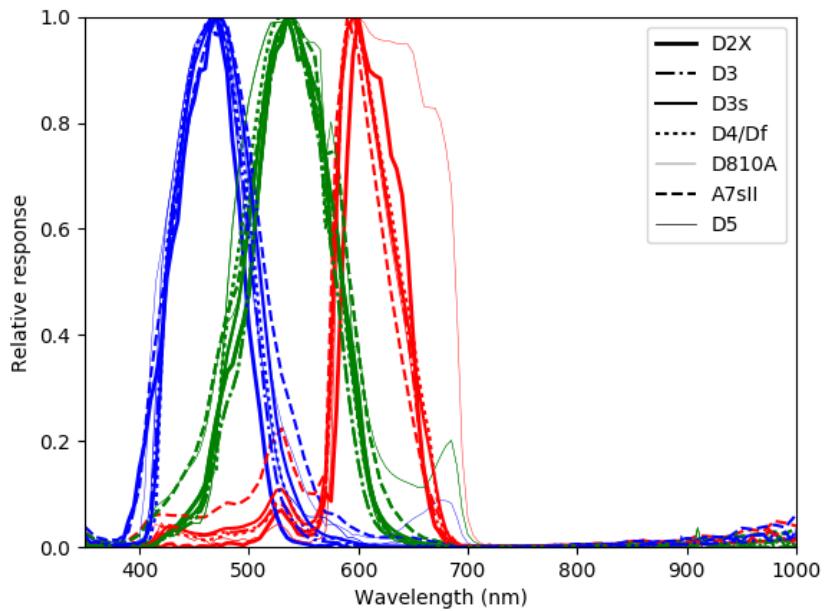


Figure 1: Spectral responses of recent models of DSLR cameras (Nikon D2X, D3, D3s, D4, D5, Sony A7SII(Sa7SII), Canon5D Mark II(C-5D) and the special astrophotography camera Nikon D810A). All of these cameras, except the D810A and the C-5D, are being (or have been) used on the ISS; the others have been included for comparison. These data were obtained by C. Tapia and A. Sánchez de Miguel at the LICA-UCM laboratory. To facilitate the comparison among responses they have been normalized to a maximum value of 1.

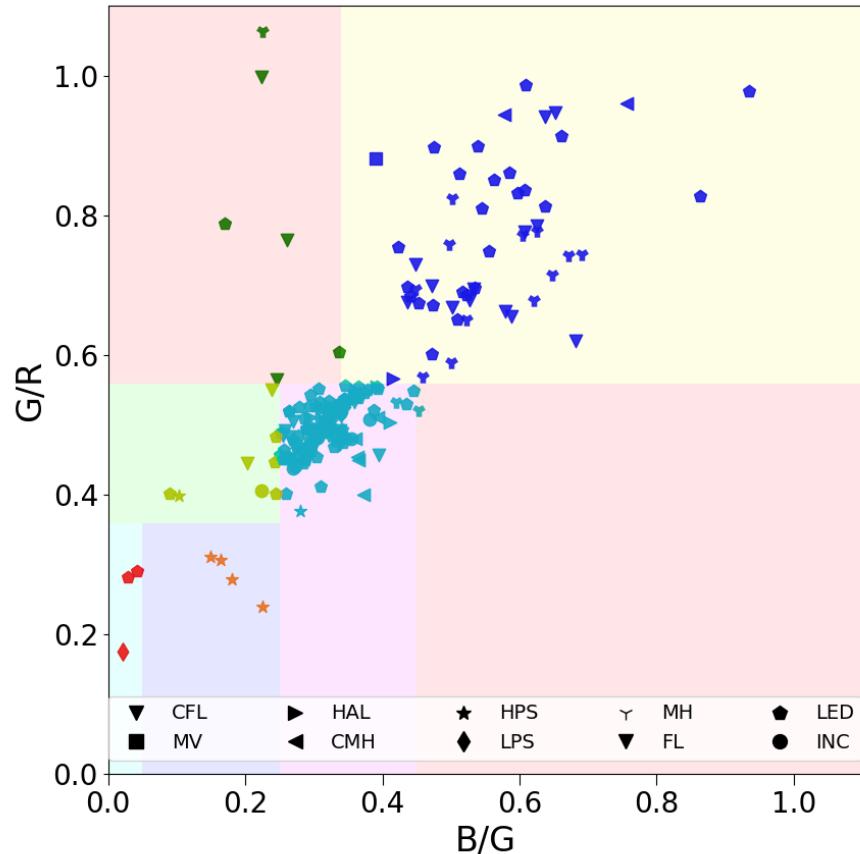


Figure 2: The distribution of emissions from different kinds of lamps with respect to B/G and G/R ratios. The coloured areas are described in the main text. The colour of the points mimics the colour tone of the lights, so the bluer lamps are coded in dark blue, the reddish in red, etc., with exception of cyan, which represents white lights. The technologies are indicated as HAL - Halogen, MH - Metal Halide, CMH - Ceramic Metal Halide, CFL - Compact Fluorescent, FL - Fluorescent, HPS - High Pressure Sodium, LPS - Low Pressure Sodium, and INC - Incandescent. The symbol used for CFL and FL is the same because they share the same spectral features.

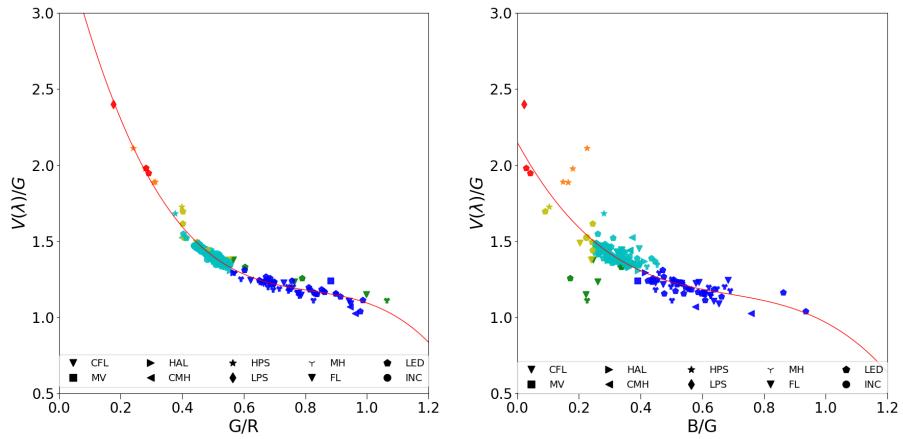


Figure 3: Relationship between photopic vision and (left) the G/R ratio and (right) the B/G ratio. Colours are the same as on fig 2.

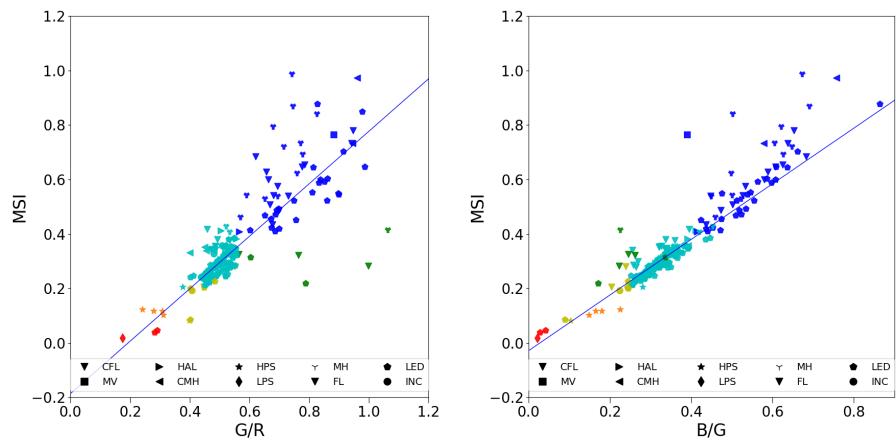


Figure 4: Relationship between the Melatonin Suppression Index (MSI) and (left) the G/R ratio and (right) the B/G ratio. Colours are the same as on fig 2.

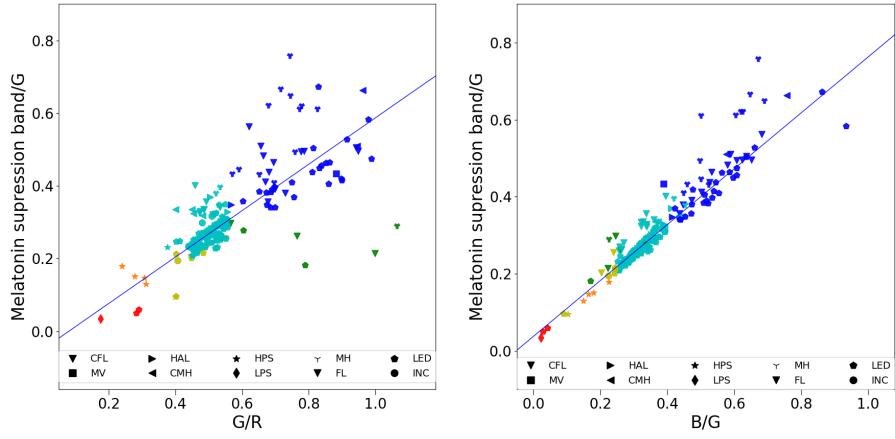


Figure 5: Relationship between the Melatonin suppression band and Green band ratio and (left) the B/G ratio and (right) the G/R ratio. Colours are the same as on fig 2.

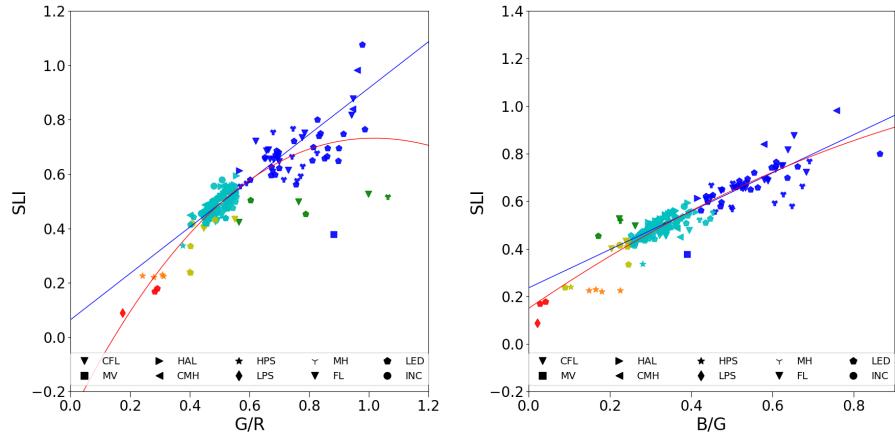


Figure 6: Relationship between the Stellar light Index and (left) the G/R ratio and (right) the B/G ratio, with linear (blue) and polynomial fits (red). Colours are the same as on fig 2.

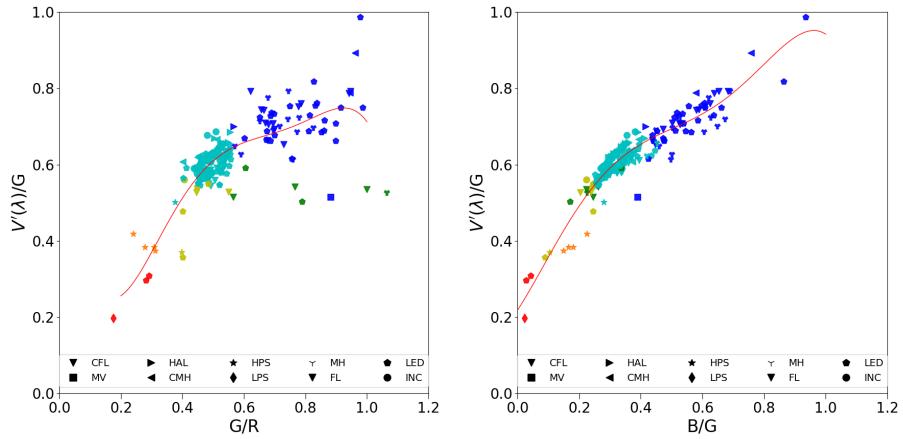


Figure 7: Relationship between Scotopic vision and G band ratio and (left) the G/R ratio and (right) the B/G ratio. Colours are the same as on fig 2.

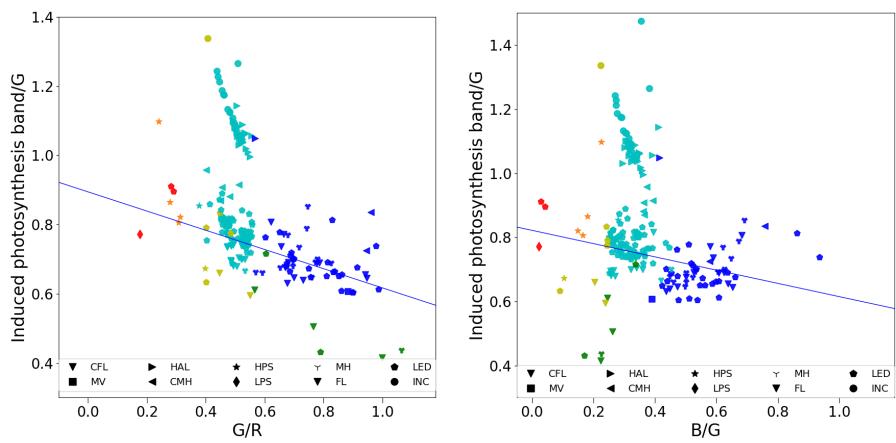


Figure 8: Relationship between the Induced Photosynthesis band and G ratio and (left) the G/R ratio and (right) the B/G ratio. Colours are the same as on fig 2.

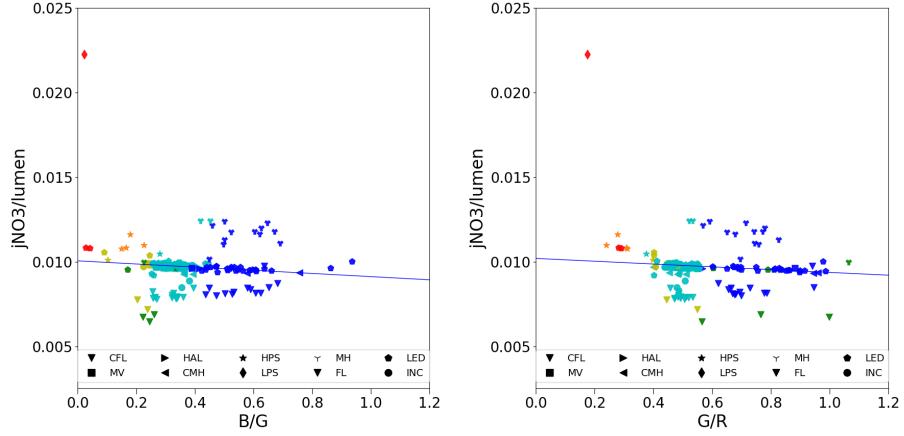


Figure 9: Relationship between NO_2+NO radical production and (left) the B/G ratio and (right) the G/R ratio. Colours are the same as on fig 2.

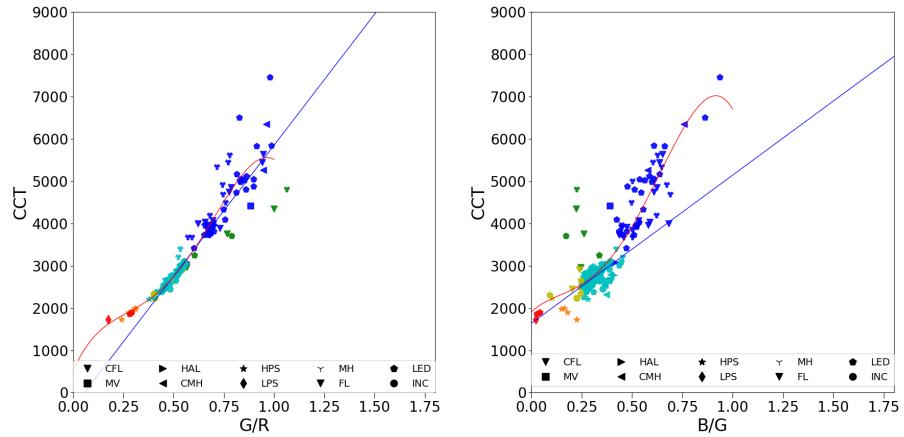


Figure 10: Relationship between Correlated Colour Temperature (CCT) and (left) the G/R ratio and (right) the B/G ratio, with linear (blue) and polynomial fits (red). Colours are the same as on fig 2.

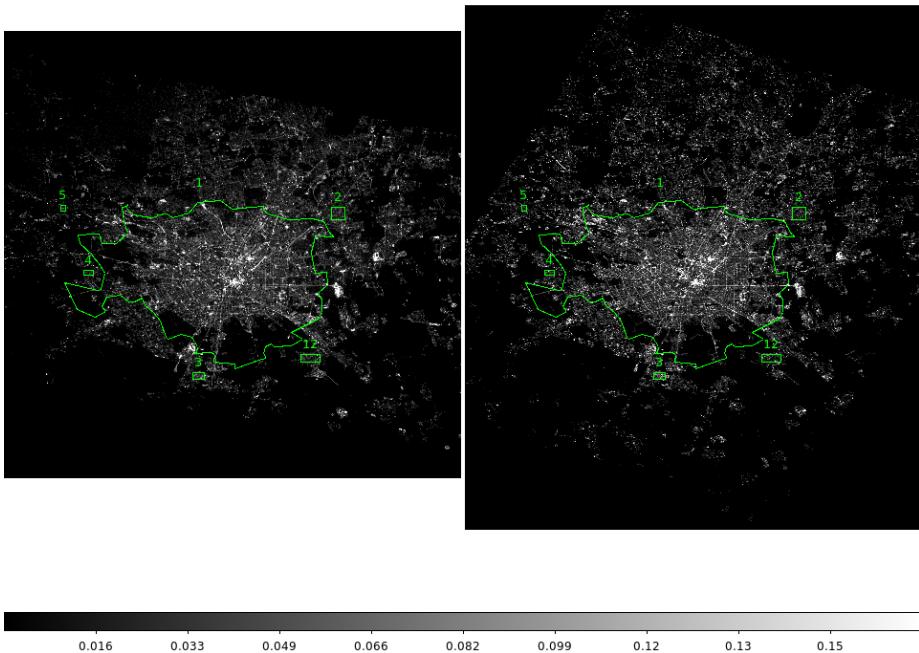


Figure 11: Images taken from the ISS corrected to represent photopic intensity (units proportional to lux). Milan in 2012 (left) and in 2015 (right). The green rectangles are the reference regions for the differential photometry, and the polygon represent the municipality of Milan.

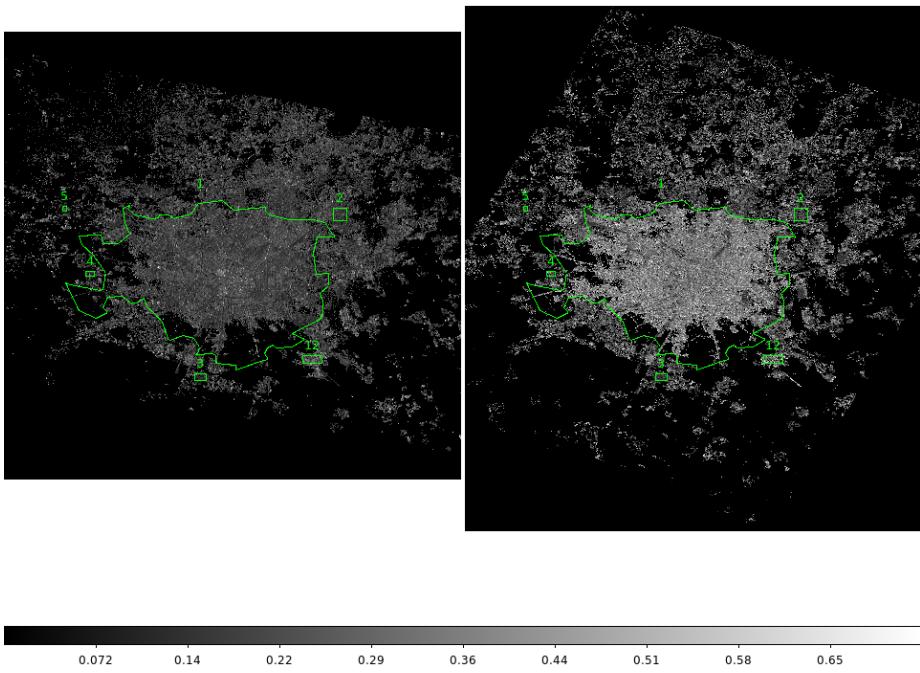


Figure 12: Images taken from the ISS corrected to represent MSI. Milan in 2012 (left) and in 2015 (right). Rectangles and polygon as in Figure 11.

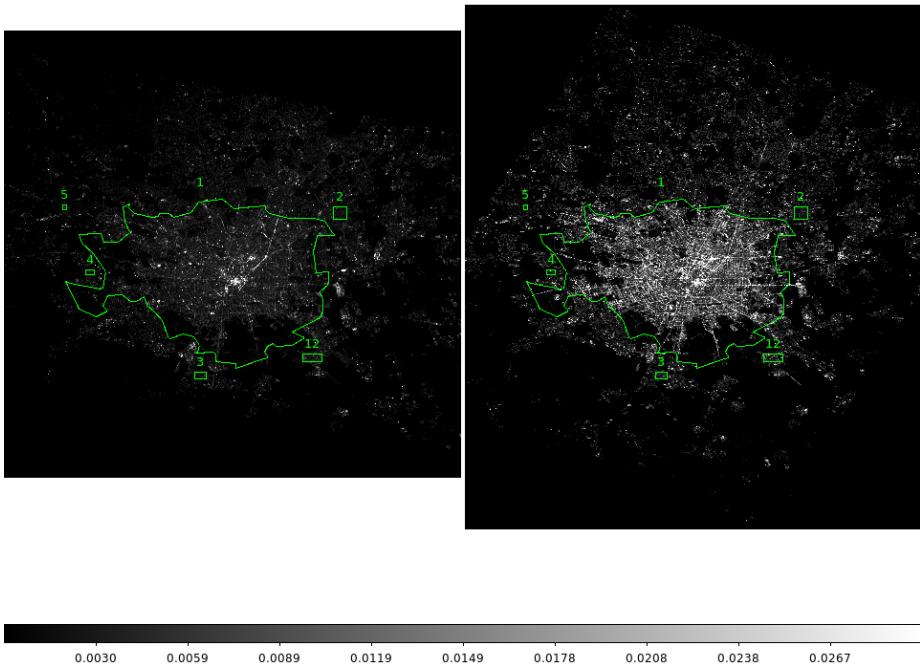


Figure 13: Images taken from the ISS corrected to represent the impact on MSI. It shows weighted MSI by photopic vision, using equation 8. Milan in 2012 (left) and in 2015 (right). Rectangles and polygon as in Figure 11.