The continuous built-up area extracted from ISS night-time lights to compare the amount of urban green areas across European cities

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ABSTRACT
The presence of urban green areas significantly impacts urban inhabitants’ well-being. However, comparative studies across European cities are constraint by urban administrative boundaries, which commonly do not match the continuous built-up urban area. This makes comparative research on environmental indicators very problematic, as administrative boundaries are not usually appropriate to define the urban human environment. Therefore, this study aims to explore the use of night-time light (NTL) images of the International Space Station (ISS) to delineate the continuous built-up area (CBA) of selected European cities to calculate the urban green area share per alternatively derived city extent. The result of the CBA shows that NTL images provide a robust data source to make the urban extent of European cities comparable. By comparing results of different datasets on green areas, we discuss the limitations of existing indicators and opportunities for new ones. Results show that green areas are rarely in close proximity to human living environment, even though the share of urban green areas within the CBA might be larger, as in comparison to the administrative boundary. We conclude that ISS NTL imagery is very suitable for mapping the CBA when aiming at comparability of environmental indicators across cities.

Introduction
The environmental quality of urban areas is an important concern at the local, but also the European scale (Council of the European Union, European Parliament, 2013). Green areas have an important contribution to the environmental quality of European cities and their inhabitants’ well-being (Douglas, Lennon, & Scott, 2017). For inhabitants, the benefits of close access to the green infrastructure range from physical, psychological health, increased social interactions to biodiversity conservation. At a European environmental policy scale, a sufficient amount of green areas is found essential to reduce air pollution (de Ridder et al., 2004; Jordan & Adelle, 2012; Yow, 2007). They also help to reduce other negative aspects of living in cities, like the urban heat island phenomenon (Koc, Osmond, & Peters, 2018) and improve the air quality (Chenoweth et al., 2018). However, the urban green area coverage differs enormously across Europe and individual cities. Furthermore, urban growth (expansion and densification) is reducing urban green spaces. Usually, each municipality/city makes use of different indicators when assessing its urban green areas (Kabisch, Strohbach, Haase, & Kronenberg, 2016), such as per capita coverage or the share of these areas in the overall city’s area, yet such indicators take the administrative boundary into account, and not the extent of the actual built-up area.

Administrative areas of cities often do not match the extent of the continuous built-up area (CBA) or the functional urban areas (FUA: as defined across Europe, refers to the densely inhabited cities and a less populated commuting zones, whose labour market is highly integrated with given city) (OECD, 2013). In some cases, the administrative boundary of cities is much larger than the built-up area, while for many cities the CBA is going far beyond the administrative boundary. This makes comparative studies using environmental indicators based on administrative boundaries, that might be inappropriate, very problematic. To improve the comparability, day-time optical and SAR images have been employed for urban area delineations or in general built-up area mapping (Esch et al., 2012; Pesaresi et al., 2013). However, mapping results show limitations in precisely delineating urban CBA with optical data, for example the spectral separability of built-up and bare areas remains to be a challenge in LC/LU (Land Use/Land Cover) mapping (Pesaresi, Gerhardinger, & Kayitakire, 2008; Sliuzas, Kuffer, & Masser, 2010); or might exclude lower density built-up areas with large green coverage from the CBA (Bagan & Yamagata, 2015). Night-time light images (NTL) have the advantage to show the presence of human activities (Small & Elvidge, 2013; Zhang et al.,...
2017), as well as indicating the difference between urban green areas (e.g. urban parks with street lights – being part of the CBA) and natural areas in the surrounding of cities (e.g. forest areas). However, much of these studies have employed low spatial resolution NTL images, that is the time series of DMSP/OLS (1992–2013) with a resolution of 1 km, and more recently VIIRS images with a resolution of 0.5 km (acquired at 0.75 km) for urban mapping (Kuffer et al., 2018; Román et al., 2018). Both datasets can be accessed via: https://ngdc.noaa.gov/eog/download.html. The spatial resolution of such imagery is not suitable to support an exact delineation of urban areas, while NTL images of the International Space Station (ISS) can reach resolutions up to 10 m.

Therefore, this study explores the use of NTL images to delineate the CBA of several European cities employing machine learning, and open source LC/LU data (OSM – Open Street Map and UA – Urban Atlas) to retrieve information about urban green areas. This allows calculating the urban green areas share per alternatively derived city extent (administrative boundary vs. NTL derived), to make environmental statistics comparable.

Urban green areas

The urban landscape differs substantially from the rural one in many instances: development density, the quality of the environment, surface roughness, etc. Not only is the development much denser, but the access to green and recreational areas is more restricted. Urban residents on average can use parks, urban forests, residential gardens and other open spaces for the recreational purposes. Yet, their spatial distribution might prevent some part of inhabitants from using them on a daily basis due to too long distances needed to reach them. Urban green areas and their role for a healthy function of the environment are well understood and documented in the literature (Mishra et al., 2019). According to Sandström, Angelstam, and Khakee (2006) and Kabisch et al. (2016) they:

- play a crucial role in restoring health and providing recreational areas;
- stimulate the thermal environment on their surrounding areas;
- are essential in sustaining biodiversity and enriching city’s environmental ecosystem;
- play an important role in improving the air quality by reducing the pollutants concentration;
- are important in identifying the cultural heritage of the city and might help in addressing some technical problems in cities (e.g. sewage treatment, flood regulation).

Their lack or presence have an influence on real estate prices in the neighbourhood (Morano, 2003). Not only the absolute amount of green spaces is important for their positive impact on the urban environment, but also their spatial distribution across the urban area. Close physical access (i.e. being reachable within walking distance) and the quality of the green spaces are important factors that determine whether inhabitants use them.

However, the accessibility of urban green areas is measured differently across various studies. The great majority uses network analysis to assess the accessibility to urban green areas, yet accessibility does not necessarily mean usability. Nevertheless, many studies have shown, that distance is an important indicator for frequent usage of green spaces (Wendel, Downs, & Mihelcic, 2011). For example Nutsford, Pearson, and Kingham (2013), measured access via the road network between artificially created population centroids and the nearest urban green spaces, defining a threshold of 300 m as walkable distance. Barbosa et al. (2007) used an Integrated Transport Network to calculate the distance between a geolocated address and the nearest green space entrance on 10,000 sampled addresses across Sheffield, also referring to 300 m accessibility distance as stated by the UK government agency. Wendel et al. (2011) employed service and minimum distance analysis from green spaces using a 400 m threshold. Comber, Brunsdon, and Green (2008) measured the accessibility to urban green areas for different ethnic and religious groups within 300 m from homes also using network analysis. Yet, the European Environmental Agency (EEA) recommends to have urban green area access within a 15-minute walk (Barbosa et al., 2007), which corresponds to approximately 750 m (for a healthy adult), and the World Health Organisation (WHO) extends it even to 1000 m. Due to various approaches and distances used in numerous studies, we decided to calculate the share of urban green areas within the city’s boundary, to make statistics across cities more comparable.

Night time lights imagery to derive continuously built-up areas

Low-resolution NTL images (like DMSP-OLS or VIIRS) have been used in many studies to explore urban dynamics (Kotarba & Aleksandrowicz, 2016; Ma, Yin, & Zhou, 2018). Due to their coarse resolution (500 and 1000 m), they are suitable for large regions but show limitations for (intra) city level analysis. The publicly available archive of NTL images taken by astronauts on board of the ISS offers a much high spatial resolution. However, ISS NTL images have not been much explored for urban mapping. Main reason for the absence of studies is that images are taken with different camera systems, including different focal length (f) (e.g. f of NTL images of cities are commonly ranging from 50 to
800 mm) resulting in large variations of spatial details visible in images (Figure 1).

Furthermore, images are not collected systematic for all cities, some cities have a large collection of available data, while for other cities no or very few data are available, thus limiting the temporal analysis. Moreover, data access is not simple; it is difficult to get a quick overview of spatiotemporal data availability (the collection can be accessed via https://eol.jsc.nasa.gov/SearchPhotos/). The images can be downloaded in the native format NEF and converted to TIFF (e.g. using Photoshop). However, before using NTL images, they need to be georeferenced. It is not a trivial task, as many GCPs are required, and are often difficult to define, due to the nature of NTL images (blooming effect and buildings commonly appearing in dark tones). To fit models that can deal with the geometric distortions of these images, the few available studies commonly use third-order polynomial transformations (Kuffer et al., 2018; Kyba et al., 2014). A final limitation of ISS NTL images is their complex radiometry and the unavailability of correction procedures. For example, images are impacted by moonlight (Elvidge, Baugh, Zhizhin, Hsu, & Ghosh, 2017; Kohiyama et al., 2004) and stray light, and for lighted areas, the blooming effect is causing that lighted areas appear larger than they are, this limits their comparability, a common problem of all NTL image documented in literature (e.g. (Ou, Liu, Li, Li, & Li, 2015) or (Wang, Wan, Guo, Hu, & Zhou, 2017)). However, the blooming effect is more pronounced in low-resolution NTL image (see an example of DMPS/OLS – Figure 2).

**Study areas**

Four European cities have been selected for a case study. They were chosen based on their location and the type of urbanised areas they represent: Warsaw – a dynamic central – eastern metropolitan city with visible influences of post-communism in the urban canopy; Dublin – the capital and largest city in Ireland situated at the mouth of the River Liffey, which enters the Irish Sea representing a harbour city; Rome – the capital of Italy and the biggest study area, located in the central-western proportion of the Italian Peninsula, representing antique south-European city rich in cultural heritage; and Frankfurt – the fifth biggest city in Germany, lying in the centre of Frankfurt Rhein-Main Metropolitan Region serving as a well-developed, western type of city which at the same time is a melting pot of commerce, culture, education

![Figure 1](image1.png)  
**Figure 1.** NTL ISS imagery available for London with different focal lengths, upper left: 50 mm, upper right 180 mm, lower left 400 mm and lower right 800 mm.

![Figure 2](image2.png)  
**Figure 2.** Comparing the different NTL products available for Dublin, left DMPS/OLS (1 km), centre VIIRS (500 m), ISS NTL (15 m).
and transportation. Each of the study areas differs in size, climate, and origin, and might well represent other cities located in Europe.

**Warsaw**

The first area of study covers the administrative boundaries of Warsaw (52° 13′ N, 21° 2′ O), which is approx. 517 km². It is located in east-central Poland, on the Masovian Plain with an average elevation of 100 m above sea level (Urząd Miasta Stołecznego Warszawy, 2006). The biggest river in Poland, Vistula, runs through Warsaw and thus divides the city into two parts, west and east bank. Due to the Vistula rivers’ different terraces, Warsaw’s Escarpment emerged over the centuries, making it the biggest relief significance within Warsaw varying from 25 to 10 m (Urząd Miasta Stołecznego Warszawy, 2006). As of 31 November 2015, Warsaw was inhabited by almost 1,775,000 people, which gives a mean density of 3,337 inh./km². It is the capital of Poland and at the same time the biggest city in Poland. It is ranked the ninth largest city in EU, and together with the metropolitan area, more than 3 million people live and work there (Rada m.st. Warszawy, 2010).

According to Rada m.st. Warszawy (2010) approximately 28% of the city’s area is covered by urban green areas (forests, parks, allotments and cemetery green areas). The structural overview reveals spatial disproportion of these areas – as seen in Figure 3 (more than 70%
of them is located only in 6 out of 16 Warsaw’s districts). The biggest share is attributed to the forest, while surprisingly parks occupy less area than allotments.

**Dublin**

The second study area is Dublin, the largest city in Ireland, and its capital. The city covers 128 km² (including the harbour water). The city is located in east-central Ireland and as of 2016, had a population of 1,173,179 inhabitants, whereas the Greater Dublin area is a home for almost 2 million people. Dublin represents a harbour city located on the isles, which is typical for this region. The River Liffey divides the city into north (working to middle class) and south-side (middle to upper class). The city is densely populated, and many industrial areas are to be seen across the urban canopy (Figure 4).

In comparison to the other study areas, Dublin has less urban green areas. It is a result of the historic development, climate and location. The Phoenix Park, clearly visible in the city’s structure makes it the biggest (7 km²) green area in Dublin, but at the same time, it might be inaccessible to the inhabitants of the north-central part of the city. According to the Dublin City Development Plan 2016-2022 (2016), some new parks and open spaces have been developed over the last few years, and the Dublin City Council is dedicated to delivering more areas of green infrastructure for their citizens.

![Figure 4. Urban Atlas land use classes in Dublin.](image-url)
**Rome**

The capital of Italy is the biggest study area covering 1300 km² and being inhabited by almost 3 million people. Located in the central-western part of Italy, Rome represents a city with ancient roots visible in the urban canopy. Rome is probably the root of public urban green spaces (i.e. the Forum, many villas across the cities). It is also the hottest (regarding climate and weather) study area, which undoubtedly determines the limited amount of green areas available in the city centre. The original urban settlement (The Rome of the Kings) was built on seven hills, and due to its long history, the urban limits were considered to be within the city’s walls (which were rebuilt and enlarged throughout the history). A clear division by Grande Raccordo Anulare (GRA – an orbital motorway that encircles the main settlement area) is visible in the urban structure and makes the distinction of the CBA easier (Figure 5).

The commune area, which expands as far as 20 km beyond the GRA, covers the area almost three times bigger as the settlement within it. The vast nature reserve areas located at the boundary of the municipality (Figure 5) contribute to the overall amount of urban green areas on the one hand, but on the other hand, they are inaccessible to most of the inhabitants. However, the large number of villas (most of them publicly accessible) and landscaped gardens found throughout the city provide some access to urban green areas.

*Figure 5. Urban Atlas land use classes in Rome.*
Frankfurt

Frankfurt, similarly to Warsaw, lies on both sides of the river – here the Main. It is located in the central-western part of Germany and is the largest city in the state of Hesse. Being the centre of the Rhein-Main Metropolitan Region (second biggest metropolitan region after the Rhine – Ruhr) makes Frankfurt a centre for commerce, culture, education, tourism and transportation. The city area sums up to 249 km\(^2\) and extends south-east of the Taunus mountain range. Frankfurt itself does not have many inhabitants (just above 0.7 million), but almost 2.5 million people are living in the actual urban area. This makes it the fifth largest city in Germany. The smallest city district – Altstadt – is Frankfurt’s historic centre dating back to the seventh century and lies on the opposite side of the Main riverbank to Sachsenhausen – the biggest and the greenest city district.

The Frankfurt City Forest, numerous parks, botanical gardens and well-maintained Main river banks make the city being perceived as green. According to the city’s environmental agency (Umweltamt Frankfurt, 2018), almost 50% of the city area is considered green. The Frankfurt City Forest, located almost exclusively in Sachsenhausen, is the biggest city’s forest in Germany and a part of the green belt in Frankfurt (established in 1991) (Umweltamt Frankfurt, 2018). However, as seen in Figure 6, the land use data provided by Urban Atlas does not recognize all of those supposedly green areas and marks them rather as arable land.

Figure 6. Urban Atlas land use classes in Frankfurt.
Methodology

Data

For this study, ISS NTL imageries of four selected European cities were retrieved, to derive the CBA, as seen in Table 1. The selection of cities was guided by the availability of cloud-free images acquired with a comparable camera system. For each city, the central part is covered by an NTL image of 400 mm focal length ($f$). For the cases, when the built-up area continued beyond the extent of the NTL image, an additional image was acquired, which covered the missing areas. For the second image, the first choice was an image of the same focal length and close acquisition date, if such an image was not available the second choice was the use of an image of 200 mm focal length. The images of $f$ 200 mm provide less spatial detail but allowed to cover the outskirts of the city (as seen in Figure 7).

To derive urban green areas, open data was used, that is land cover data freely available across Europe. Two common datasets were chosen: OpenStreetMap (OSM) (Geofabrik, 2018) data and Urban Atlas (UA) (EEA, 2018). Following classes have been extracted from the OSM dataset:

- forest, park, meadow, nature reserve, recreation ground, scrub, grass, national park.

The UA offers a smaller number of classes, which is why only three classes have been extracted:

- forests, green urban areas, sport and leisure activities.

Image analysis and post-processing

The downloaded NTL images have been used to extract in several steps the CBA. CBAs, defined according to the EU, are built-up areas that have a gap of not more than 200 m (EEA, 2011). Figure 8 provides an overview of the methodology to extract CBAs from NTL images. The first step was the conversion of the image from NEF to TIFF format (using Photoshop). Within the second step, the images were georeferenced, with at least 50 GCP (e.g. Figure 9) that had to be well distributed across the images using the third-order polynomial transformations (Kuffer et al., 2018; Kyba et al., 2014) to deal with the geometric distortions of these images. The third step included the generation of 150 training points (random samples, yet stratified and well distributed over the scene to ensure a robust classification), split into built-up (lighted) and non-built-up (dark) areas. These training points were used to classify the image into a binary output, that is built-up and non-built-up. To increase the number of the training samples, the points were buffered (20 m) – this enabled a greater collection of the spectral information. For the classification (producing a binary map), a popular machine learning algorithm, random forest (RF) – was chosen. RF was selected as a computationally efficient algorithm (Goldblatt, You, Hanson, & Khandelwal, 2016), which also showed in other urban studies high

| City      | Date       | Camera tilt in degrees | RSME in m | Resolution in m | Altitude in km | $f$ in mm | Time GMT | Clouds according to Metro |
|-----------|------------|------------------------|-----------|-----------------|----------------|-----------|----------|--------------------------|
| Dublin    | 2013.04.07 | 49                     | 9.35      | 15.50           | 398            | 400       | 00:10:24 | Clear                    |
| Dublin    | 2013.04.07 | 46                     | 10.38     | 15.01           | 398            | 400       | 00:10:28 | Clear                    |
| Warsaw    | 2012.04.05 | 44                     | 9.67      | 11.15           | 391            | 400       | 23:54:13 | Clear                    |
| Warsaw    | 2011.04.21 | 49                     | 19.46     | 25.59           | 339            | 200       | 20:31:48 | Clear                    |
| Rome      | 2012.03.31 | 32                     | 15.95     | 16.41           | 391            | 400       | 23:47:52 | Clear                    |
| Rome      | 2011.02.10 | 16                     | 21.82     | 25.53           | 346            | 200       | 22:48:00 | Clear                    |
| Frankfurt | 2012.08.04 | 22                     | 9.23      | 11.03           | 394            | 400       | 00:02:40 | Clear                    |
| Frankfurt | 2010.05.01 | 41                     | 13.41     | 17.67           | 348            | 200       | 23:11:14 | Clear                    |
mapping accuracies (Breiman, 2001; Kuffer et al., 2018). Although training samples were iteratively reviewed to obtain most spectrally separable classes, the classified maps contained noise, for example non-built pixels containing stray lights, caused by the noise in the NTL images. In general, the classified data can often result in salt and pepper appearance because of the inherent spectral variability of the training areas in pixel-based approach. In such case, it is often beneficial to “smooth” the classified image to show only the dominant (presumably correct) class (Lillesand, Kiefer, & Chipman, 2014). Therefore, in the fourth step, a 3 by 3 majority filter was used to reduce the noise. To validate the classification results (classification after performing the majority filter), 10,000 random points were generated for each study area using as reference the Urban Atlas, combining all built-up classes and all non-built-up classes of the Urban Atlas into a binary reference map. This allowed to calculate the overall classification accuracy. However, the limitation of this assessment was that not all built-up areas are lighted, street lights commonly surrounds buildings with dark roofs. For the further processing, the validated classification results were converted to polygons. The fifth step used a region growing algorithm that groups neighbouring patches of built-up areas together forming a large continuously built-up patch depending on a user-specified (grouping) distance, starting at the centre of all built-up patches. Thus built-up patches that were closer than the grouping distance were forming the CBA. This allowed to combine all built-up areas that were not more than 200 m apart (defined as Urban Morphological Zones by the European Environmental Agency (EEA, 2011)). The result was a vector layer (one polygon) that represents the CBA. However, this layer still contained internal holes, for example water bodies and green areas without NTL. Thus, the sixth step employed a clean-up procedure to fill up all these internal holes (surrounded by built-up areas) for producing the final CBA layer of the NTL image with f400 mm. As in all cities, some parts of the outskirts of the CBA were not covered by the NTL image with f400 mm, a second image was used to cover the outskirts. Thus in the seventh step, the two images were combined, where the lower resolution images were
only used for the missing parts of the outskirts. The eight step was the comparison of the green area coverage at CBA and administrative city extents. This procedure encompassed extracting the urban green areas originating from different sources (OSM and UA) per city and per alternative extent. This allowed to conclude on the difference of green area share within the morphological city (CBA extent) compared to official statistics at the administrative city extent.

Results

The mapping results of the four cities provide a clear delineation of the CBA (Figure 10), depicting well the
Urban morphology. For validation, the maps of lighted (built-up) areas are used taking the built-up classes of the Urban Atlas as reference. The mapping accuracies of built-up (lighted) areas show variations between cities (Table 2). The differences relate to variations in the relations between built-up and street lights (e.g. in the outskirts of Rome this relationship is very complex due to scattered development patterns). Furthermore, a built-up pixel (e.g. a roof area of a larger building) is not necessarily having NTL; these differences are causing classification accuracies of around 80%. However, the omission of internal built-up areas is not problematic as this omission will be included into the CBA (using the region growing algorithm).

For the urban green areas analysis, previously described classes from OSM and UA were extracted from the datasets for each set of boundaries – administrative and derived from the NTL (CBA). The spatial variability of urban green areas recognised in OSM in each of the study areas can be seen in Figure 10 and respectively for UA in Figure 11. Table 3 shows the summarized distribution of each class in OSM and UA respectively, as well as the general share within the city area. Some study areas differ greatly in share of green areas depending on the extracted source, while some are fairly stable. One of the biggest differences in each case is the biggest share of prevailing urban green area type, but the single tendency remains unchanged – the urban green areas share within newly derived boundaries (CBA) is always substantially lower in comparison to the same share within the administrative boundaries. On average, the UA delivers less green areas and therefore lower share – probably due to the lower number of extracted classes and the level of generalization used.

Warsaw’s and Dublin’s boundaries differ significantly, in both cases, the area of the CBA is larger than the administrative area – by 37% and 217% respectively. In both examples we can see, that the CBA encompasses most of the satellite towns located along the commuting routes – Legionowo, Pruszków, Piaseczno or Otwock (Figure 10(a)) in Warsaw’s case, and in Dublin (Figure 10(b)) in the north, the CBA was enlarged to Swords, in the west to Blanchardstown, Lucan up to Celbridge, and in the south down the coast up to Bray, covering in great part Greater Dublin area. Although these two cities differ greatly in terms of origin, architecture style and urban design, similar tendencies can be observed, when examining the data in detail. In both cases, the OSM urban green areas within the CBA decrease their share by approx. 30%. These tendencies can be also observed when single land use classes are investigated. In Warsaw, the biggest share in both, OSM and UA data, is attributed to the class “forest”. It occupies an area ranging from 21% of the city (OSM administrative) to 11% (UA CBA). Its spatial variability is almost evenly distributed around the edges of the administrative boundaries (apart from the western part). However, investigating the CBA boundary, we can see that in many cases, forests and other urban green areas are not easily accessible as they lie outside of the main settlement. In Dublin however, the biggest share in both datasets is allocated to parks (OSM) and green urban areas (UA) and oscillates around 11% in administrative boundary and below 10% for the CBA boundary. The spatial distribution of this class is relatively even throughout the city. However, when we investigated these areas more closely, it was discovered, that more than 60% of all parks (in the OSM dataset) were made up of green areas lower than 1 ha. It gives relatively small possibilities to use them as relaxation and recovery areas, especially, when some of them are located in the direct vicinity of industrial zones. Within the OSM administrative dataset, the nature reserve also bears a significant share – these areas are located with the administrative boundaries in these two cities. In case of Dublin, it is North Bull Island Special Protection Area, part of Natura2000 protected European areas network and is located at the most eastern part of the city, directly at the shore. For Warsaw, such areas can be found at the Vistula’s shore (Zawadowskie Islands reserve). These areas were not detected from the ISS imagery analysis, as they are completely uninhabited and therefore dark during the night time. We can clearly see, that the administrative areas of Warsaw and Dublin are much better supplied with all types green areas, whereas this is not the case in most of the outskirts included into the CBA boundary. Surprisingly, the urban green areas detected within the administrative boundary in the OSM data sum up to 42% and 29% of the city – much higher than what is declared in the official plans (Dublin City Development Plan 2016–2022, 2016; Rada m.st. Warszawy, 2010). Thus, it is clearly visible, that inhabitants located in the outskirts, along the commuting routes are deprived of the access to the urban green areas.

(Rada m.st. Warszawy, 2010) In contrast to Warsaw and Dublin, the CBA of Rome and Frankfurt is smaller in comparison to the administrative area – by 70% (1400 to 430 km²) and 30% (250 to 170 km²) respectively. This is caused in by landscape restriction in both cases. In Rome, the orbital motorway (GRA) and in Frankfurt the forest located south of the Main River restricted the development the most. Here, the CBA derived boundary does not

| Table 2. Overall classification accuracy of built-up classification using random forest. |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|
| Rome                           | Warsaw          | Frankfurt       | Dublin          |
| Overall accuracy                | 0.762           | 0.808           | 0.801           | 0.854           |
include arable lands between Eckenheim and Bonames and most of the northern part of the city. However, the CBA stretches in the western (including areas of Bad Soden) and eastern direction (joining Offenbach). Naturally, that resulted in the most significant drop in the biggest green areas – nature reserves in Rome and forest in Frankfurt, when comparing the administrative share and the CBA boundary. When investigating Rome’s urban green areas (Figures 10 and 11), we can see that the areas located outside the CBA are made up of arable land, marsh and vast areas of nature preservation parks. The latter represent more than 30% of the area within the administrative boundary, but the vast majority is

Figure 11. OSM urban green areas in: (a) Warsaw, (b) Dublin, (c) Rome and (d) Frankfurt.
located at the outskirts, beyond the CBA. This makes them less accessible for the inhabitants. A similar tendency can be seen in Frankfurt. The biggest contribution to the overall green areas has the Frankfurt City Forest. It is located south of the Main River and can be easily recognised in either of the datasets (Figures 10 and 11) or in the NTL imagery as a wide strip south of the city centre. Due to such significant land cover, that directly affects the image processing, the whole area of the Frankfurt Airport has been disjoined from the CBA. However, a positive trend in urban green areas, parks and sport areas can be seen for both datasets. In Rome, as in Frankfurt, the share of other urban green areas is higher in the newly derived boundary (CBA) in both (UA and OSM) datasets. It means that parks, leisure facilities or allotments are better accessible for the inhabitants (e.g. as compared to forest areas or nature reserves), as they are located rather in close vicinity to the urban settlement.

**Discussion**

Analysing the availability of urban green areas, results show a diversified range for this indicator in selected European cities. On average, a low amount of tree and forest cover might be expected in the southern EU (e.g. Rome) as well as harbour cities (e.g. Dublin). Commonly, such cities tend to have a high degree of impervious cover and bedrock surfaces. According to Grove and Rackham (2003), it might have been caused by unsustainable land use developments, which led to deforestation (in southern EU cities) or by the compactness of urban development and industrial heritage (e.g. Dublin). Although it was expected, that in eastern EU cities, the values would be lower due to the lack of green space management policies after the entry to the new economic realities in 1990, Warsaw’s urban green areas share was the biggest across the four cities (for both UA and OSM) (Figure 12).

However, the derived boundaries quite often omitted big woodland complexes in close proximity to the CBA, due to the fact that they stay dark at night. One of the best examples was the Frankfurt’s City Forest, which was excluded completely from the CBA. On the one hand, it is located on the one side of town, therefore it might have a poor accessibility for inhabitants from the other side of the river Main, on the other hand, a significant number of Frankfurt’s Sachsenhausen population benefits from it daily. Therefore, our recommendation for the further study is to buffer the boundaries to the outside of the CBA, to include some adjacent areas. According to Kabisch et al. (2016), a 750–800 m distance corresponds roughly to a 15 min walk (for a healthy person), which in social studies is referred to as the distance a human is willing to walk to reach a relaxation site.

![Figure 12](image_url). Amount of urban green areas comparing the CBA (from ISS images) and the administrative city boundary in study areas.

| Area [km²] | Warsaw Admin. ISS | Dublin Admin. ISS | Rome Admin. ISS | Frankfurt Admin. ISS |
|------------|------------------|------------------|-----------------|----------------------|
| City       | 516.786          | 709.281          | 128.356         | 407.249              |
| OSM        | 218.313          | 192.385          | 30.042          | 80.293               |
| Allotments | 13.795           | 13.191           | 0.035           | 0.184                |
| Forest     | 106.935          | 97.811           | 1.697           | 8.677                |
| Grass      | 23.196           | 25.002           | 5.411           | 22.885               |
| Nature reserve | 44.402 | 26.973          | 13.252          | 4.369                |
| Orchard    | 0.344            | 0.841            | 0.000           | 0.008                |
| Park       | 14.873           | 15.851           | 16.034          | 33.886               |
| Recreation ground | 0.786 | 1.533           | 1.369           | 7.585                |
| Scrub      | 13.983           | 11.164           | 0.245           | 2.699                |
| UA         | 213.094          | 129.545          | 23.873          | 71.162               |
| Forests    | 92.809           | 76.867           | 0.1542          | 0.1369               |
| Green urban areas | 24.470 | 30.821       | 14.8574         | 39.069               |
| Sports and leisure facilities | 21.749 | 21.857         | 8.8610          | 28.353               |

Table 3. Summary statistics of OSM and UA urban green areas in administrative and ISS derived boundaries in four study areas.
However, this threshold cannot be strictly defined and depends on many geographical and socio-economic factors. Furthermore, such a threshold would not allow evaluating the real physical accessibility of green areas within the buffer, for example whether roads or footpaths are available or natural barriers exist. Therefore, we did not use a buffer, for our comparison of the amount of urban green areas across European cities. For a single case study, such a threshold could be easier defined.

What is more, the result of the analysis provides the share of urban green areas respectively to the investigated boundary. In comparison to other indicators (per-capita threshold values for urban green areas or the minimum distance to green spaces), it does not provide the information on how many people are affected or what is the spatial distribution of the urban green areas, what might be considered as a disadvantage. On the other hand, such indicator is much easier to obtain, as data are easily accessible and simple computation might propagate other comparative studies. A possible way to address limitations of this study would be to include the approach of Tsilimigkas, Stathakis, and Pafi (2016) where the downscaled Global Settlement Layer (GHSL) and a road network were used as population and network data respectively to measure how cities perform in providing accessible green spaces to city dwellers. However, the GHSL provides only the built-up and non-built areas and not the boundaries of the urban area. Some studies (e.g. Kabisch & Haase, 2014; van Herzele & Wiedemann, 2003), focused on the quantitative distribution of green space in relation to the associated population. Others, more on detailed socio-economic aspects (Germann-Chiari & Seeland, 2004) using spatial and regression analyses to analyse the distribution and spatial availability of urban green areas by social groups in three cities in Switzerland. These examples indicate that a more detailed judgement on the availability of urban green areas is possible, if one focuses on a case study and investigates others (not only spatial) factors. However, when aiming at comparative analysis across cities, the delineation of the urban area is crucial, where the CBA based on high-resolution NTL provides a solid base and does not require complex spatial data (e.g. as compared to the FUA).

Final issue to be discussed is the versatility and representativeness of the ISS NTL. When it comes to the image processing, the radiometric and photometric accuracy, as well as sensor’s stability needs to be considered. Here, these factors are challenging to control, as the light source might produce different DN (digital number) depending on: the exposure parameters (ISO, exposure time); optics (focal length and vignetting); and viewing angle (off-nadir). In case of ISS imagery, they might vary from image to image (Kotarba & Aleksandrowicz, 2016). Furthermore, there has been no systematic review of the quality of ISS NTL imagery archives for the remote sensing purposes. In addition, other NTL imagery (OLS or VIIRS) are operational services, unlike ISS. Their advantage is that they both are hosted by meteorological satellites that provide continuous, global scanning, which makes them suitable for continuous earth observation purposes. However, the introduction of auxiliary support systems (i.e. NightPod) (Castiglione et al., 2012) might lead to semi-operational NTL imagery acquisition. To upscale the delineation of CBAs to a European or even global scale, a more systematic and regular acquisition of ISS NTL would be important. Furthermore, access to ISS NTL images via an improved NASA Geo-portal, providing optimally geo-referenced images, would be of great value to facilitate the general use of the data. For example, this would ease the production of an atlas of CBAs, which would support comparative environmental assessment at continental or ultimately as global scale. Moreover, ISS NTL image have the potential of being used in other urban/environmental fields, for example they can serve as proxy of variations in socio-economic conditions within urban areas by indicating deprived areas (Kuffer et al., 2018). Further potential applications of ISS NTL images could relate, for example to analysing patterns of energy consumption across cities, light pollution, dynamics of urban expansion or combining such images with optical high-resolution data to improve land use/cover mapping.

**Conclusions**

The indicators derived in this study show the urban green area availability as a share of newly derived urban (continuously built-up area: CBA) boundaries. The publicly available archive of NTL images taken by astronauts on board of the ISS has been explored to serve as a possible source to derive comparative boundaries of urban settlements, as they reflect the extent of lit (inhabited) surfaces. These have been then investigated against chosen OSM and UA data, that provide information on the land use/cover. In general, urban green areas share within the CBA boundaries was always substantially lower in comparison to the same share within official administrative boundaries. This indicates that green spaces are not well distributed within the areas where people live. Moreover, we observed that on average UA detects less urban green areas than OSM. It might be connected to the fact, that in the UA dataset there were only three classes taken into consideration, whereas in the OSM eight. It is probably also connected with the mapping approach of the UA and Minimum Mapping Unit.
(MMU) varies for urban (0.25 ha) and rural (1 ha) land cover classes.

Our analysis delivered some vital information about the cites we studied. Warsaw’s and Dublin’s urbanized areas extend far beyond the administrative boundaries, to the adjacent satellite settlements. In Warsaw’s case inhabitants located in the outskirts have worse access to the green areas, in Dublin on the contrary – this is due to the historical differences in urbanisation processes. On the other hand, Rome’s and Frankfurt’s urbanised area proved to be smaller than officially stated. In addition, Rome has huge natural preservation parks located in the outskirts – and therefore are not easily accessible for most of the inhabitants (e.g. having a quick walk after work). Frankfurt’s City Forest is a similar matter, visible as a wide stripe on the southern part of the city, the area might not be available for some urban residents. However, we noticed, that in comparison to the analysis based on the administrative boundary, other urban green areas (parks, allotments) share have a higher share, so it might indicate, that these are better distributed among the urban canopy.

The urban green areas have received a lot of scientific attention in the field of urban biology and planning, yet comparable datasets at the regional level are not always available. Furthermore, the indicators provided by different studies often refer to the administrative boundary, which might not reflect the actual morphology of the urban settlement. Despite some limitations of the NTL images (e.g. temporal data availability), we conclude, that this repository might be used to derive reference areas for urban green areas studies.

Disclosure statement

No potential conflict of interest was reported by the authors.

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