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A Methodological Proposal for Implementing Dark Infrastructure Within the Ecological Network of an Urban Forest

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Abstract

Ecological continuity cannot be limited to spatial surfaces and corridors without consideration of the day–night cycle. This integration is achieved through the implementation of dark infrastructure, a field that remains comparatively understudied. The present article proposes a methodological approach for implementing dark infrastructure within an urban forest near Liège (Belgium), where the ecological network has recently been characterised, but nocturnal landscape-specificities are not included. Several sources of information were combined, including satellite imagery, a point-light map and the existing ecological network. The research seeks to illustrate conflicts between ecological requirements and human activities, with particular emphasis on public, and private lighting. In the discussion, the paper identifies methodological limitations, characterises the nature of light pollution, and lists planning issues for the cohabitation of human activities and nocturnal species' habitats.

Keywords: dark infrastructure; ecological network; urban forest; planning; day-night cycle; artificial light at night (ALAN)

1. Introduction

Biodiversity conservation can no longer be addressed independently of human influences. Increasing levels of anthropisation have generated numerous obstacles to species movement [1–3], necessitating measures to protect and restore habitats that underpin biodiversity. One strategy involves establishing ecological networks, partially underpinned by the principles of island biogeography outlined by MacArthur and Wilson [4]. According to this theory, species richness within a given territory depends on available area, degree of isolation, and interspecific competition. Consequently, it is feasible to estimate a dynamic equilibrium influenced by the extinction rate, which is correlated with habitat area, and the immigration rate, which is dependent on isolation [5]. As a result, natural habitat fragmentation is widely incorporated into biodiversity conservation strategies and should be systematically integrated into urban planning and land-use management. The significance of this approach is further reinforced by metapopulation theory [6], which posits that population dynamics are governed on the one hand the ability to recolonise vacant habitat patches and on the other hand local extinction rates. The ecological network concept thus represents a conservation strategy designed to maintain a coherent spatial structure conducive to species movement at the landscape scale [7].

An ecological network is structured into thematic sub-networks to facilitate the management of groups of habitats with shared characteristics. The goal is to ensure ecological continuity between biodiversity reservoirs via appropriate corridors [8]. Both urban and rural landscapes are linked to ecological networks based on infrastructural logic, connecting

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natural, semi-natural, and anthropogenic environments [9]. This strategy enables the integration of ecosystem service provision into conservation objectives. The best-known forms are green and blue infrastructure, corresponding to terrestrial and aquatic environments, respectively. These aim to secure ecological continuity by drawing upon principles from landscape ecology [10]. Additional infrastructure types are also described in the literature: Tiwary and Kumar [11] define grey infrastructure as artificial structures shaping the urban environment, while others highlight soil connectivity through brown infrastructure [12].

However, ecological continuity cannot be limited to spatial surfaces and corridors without consideration of the day–night cycle. The nocturnal landscape is subject to additional disturbances at night that are not apparent during the day. It is therefore essential to integrate this temporal dimension and the disruptions resulting from artificial lighting into conventional green or blue infrastructure frameworks. This integration is achieved through the implementation of dark infrastructure, a field that remains comparatively understudied. Nearly 30% of vertebrates and more than 60% of invertebrates are nocturnal, highlighting the need to address light pollution [13]. The present article proposes a methodological approach for implementing dark infrastructure within an urban forest, where the ecological network has recently been characterised, but nocturnal landscape-specificities are not included. The research seeks to illustrate conflicts between ecological requirements and human activities, with particular emphasis on public and private lighting.

To this end, a brief review of relevant literature regarding light pollution and dark infrastructure precedes the presentation of the Sart-Tilman site context and the relevant datasets. In light of this case study, the objectives are to delineate the spatial extent of light pollution, identify areas of conflict between the ecological network and artificial light at night (ALAN), and evaluate the appropriateness of implementing dark infrastructure within the study area.

2. Literature Review

The concept of light pollution first appeared in the 1970s [14]. Research interest in this topic has grown [15], especially in highly urbanised countries such as the United States, China, and the United Kingdom. On a global scale, the loss of ecosystem services from light pollution is estimated at 3.4 trillion US dollars per year [16].

The designation of artificial light as pollution is predicated on its capacity to cause lasting disruptions to ecosystems when present or excessive in naturally dark environments [17–19]. If darkness at night is recognised as a form of natural capital, its degradation results in habitat impoverishment, notably through disturbances to movement patterns and foraging behaviour. As a result, measures such as reducing or adapting artificial lighting sources, as well as interventions such as reintroducing species into degraded environments, warrant consideration.

2.1. Biodiversity Challenges

Light pollution affects predation, reproduction, feeding, communication, migration, and competition [15,17,20–22]. Nocturnal species are more light-sensitive than humans and have different spectral sensitivities. This makes artificial light even more disruptive for them [17,20,23]. Most nocturnal activity depends on moonlight, a level of "biologically useful semidarkness" [23]. New artificial lights can mimic higher light intensities, leading species to stop performing essential survival activities.

Species generally display two distinct reactions to light: attraction or avoidance [17]. Nocturnal flying insects, for example, are attracted to light sources and may remain trapped near them until exhaustion [17,22], leading to shifts in population spatial distribution [20]. Some predators subsequently adapt their hunting behaviour to remain near illuminated

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areas. Species that rely on bioluminescence to locate mates also become less able to find one another, resulting in population declines [23].

These mechanisms lead to changes in activity patterns among nocturnal, diurnal, and crepuscular species. Artificial lighting allows diurnal and crepuscular species to extend their activity time, while nocturnal species reduce their activity and experience habitat degradation [17,23,24]. However, artificial light alone may not suffice for diurnal and crepuscular species to exploit nocturnal ecological niches, as lower nighttime temperatures can limit their activity [24]. Species inhabiting wetlands or aquatic environments are likewise affected in their movement and reproduction [22], with some becoming less selective in mate choice under increased light levels, a behaviour influenced by heightened predation risk and favouring rapid mate choice [17].

Bats are a key nocturnal group and are highly vulnerable, though vulnerability differs by species. Slow-flying, gleaning bats like *Myotis* and *Rhinolophus* spp. avoid light because they hunt by following prey until it stops [13,25]. Fast-flying hawkers such as *Pipistrellus* and *Nyctalus* spp. may use lit areas for foraging [13,25]. For light-averse bats, light worsens fragmentation and reduces prey [17,24,26]. Still, fast-flying species suffer too as reduced dark areas cut connectivity and suitable breeding sites [25].

2.2. Human Challenges

Humans are a diurnal species and, consequently, have sought to make darkness visible as soon as technology permitted it. Night-time lighting aims to provide protection by allowing individuals to see and be seen. Fear of darkness and its associated dangers have been a decisive factor in the development of lighting systems [27]. From the outset, illuminating the night has been linked to social needs and values [14] as well as to the idea of progress [28]. With the development of electric lighting, motorised transport, and the road network, the nocturnal landscape has undergone profound transformations at large spatial scales [17,20]. According to Falchi et al. [29], 83% of the world's population lives under a sky polluted by artificial light, defined as an increase of at least 8% above natural brightness levels, hindering the observation of stars and other celestial bodies. Globally, light pollution increases by an average of 6% per year [30]. The challenge, therefore, is to regulate the installation of lighting points, as their provision often exceeds actual needs [22].

Night-time lighting particularly impacts the circadian cycle [15,22,31], as melatonin production is stimulated by darkness. The presence of artificial light, especially blue-rich light, suppresses melatonin synthesis [23,32] and disrupts sleep [19,21]. Some studies also associate exposure to artificial light with diabetes and some cancers [33]. However, impacts on human health and on biodiversity more broadly remain insufficiently quantified [15]. Figure 1 summarises the main causes and consequences of ALAN.

2.3. Observation of ALAN Using Remote-Sensing Imagery

Current approaches to observing ALAN remain constrained by several methodological limitations. Although the spatial resolution of nocturnal observations has progressively improved, from DMSP/OLS in 1976 with resolutions of 2.7 km and later 1 km [21,31] to the Suomi-NPP VIIRS sensor, which provides a spatial resolution of 750 m for the panchromatic DNB band [21,31], this resolution remains too coarse for local-scale analyses. Since the early 2000s, the emergence of commercial satellites has further refined the spatial resolution of nocturnal imagery. EROS-B was the first commercial satellite to provide imagery with a spatial resolution below 1 m using a panchromatic sensor. Subsequently, in 2017 and 2018, the Jilin1-03 and Luojia-1 satellites were launched, offering spatial resolutions of 1 m and 130 m, respectively. Unlike EROS-B, these nocturnal images are multispectral [21], allowing the calculation of indices based on the red, green, and blue (RGB) bands, such as the melatonin suppression index or the potential of a light source to induce photosynthesis through the induced photosynthesis index [34].

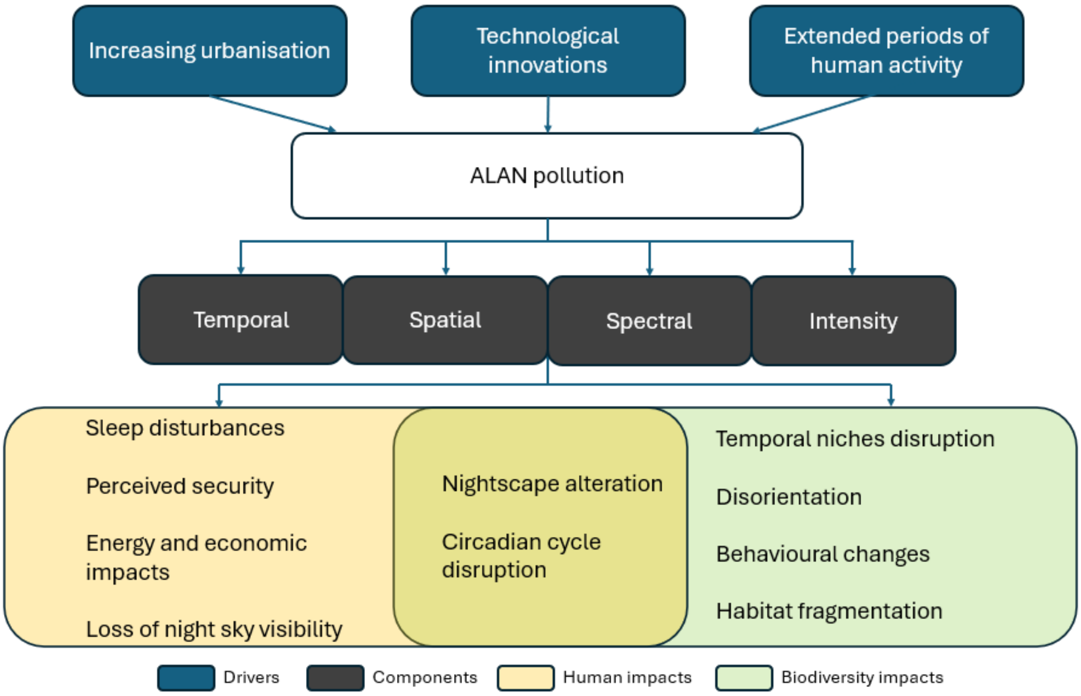

Figure 1. Schematic overview showing the general causes and impacts of ALAN pollution. Impacts shared by biodiversity and humans are presented in the central box of the impacts section.

Nevertheless, numerous challenges specific to satellite-based observation of nocturnal light pollution remain. First, observed scenes combine natural sources with very low radiance values and artificial sources that vary widely in intensity, orientation, and spectral signature. As a result, sensors must strike a balance between sufficiently broad spectral resolution and the finest possible spatial resolution. This challenge has become even more pronounced with the global transition towards LED lighting. The spectral output of LED lamps is broader than that of sodium lamps, for example, and, as mentioned above, the blue component is not captured by certain nocturnal satellite sensors. According to Bará et al. [35], the VIIRS sensor may even record a decrease in emissions in the DNB band while ground-based observations indicate the opposite trend. A comparison between Jilin1 imagery and drone-based measurements confirms this tendency [36], with the weakest correlation observed in the blue band compared to the red bands. In addition, the viewing angle strongly influences observations due to shading effects from buildings or vegetation, as well as emissions from façades or windows. Finally, temporal variability must also be considered. The Suomi-NPP and DMSP satellites are polar-orbiting and therefore operate at fixed overpass times, preventing the observation of nocturnal lighting dynamics throughout the night. This variability is partly driven by policy decisions that reduce or partially switch off lighting infrastructures. At the seasonal scale, snow also influences the captured luminance values [21].

2.4. Designing a Dark Infrastructure

The growing interest in light pollution has highlighted its importance for biodiversity and circadian rhythms. Consequently, implementing dark infrastructure requires preserving and restoring biodiversity reservoirs, as well as corridors that provide sufficient darkness [37]. Reflecting upon and establishing dark infrastructure is a new challenge for spatial planning, particularly within and around urban areas.

Several approaches have been proposed in the literature for constructing a dark infrastructure [8,37]. The first is a general and operational approach based on identifying conflict zones between artificial lighting and areas of high biodiversity value. It acts as a decision-support tool for prioritising restoration actions or reducing light pollution, without truly designing a complete network. The second method builds a dark infrastructure by relying on an existing map of the ecological network. This deductive approach overlays a map of light pollution with a map of the existing network to highlight areas that offer sufficient darkness and fall within the ecological network. The third approach treats light pollution as a direct source of habitat fragmentation for each thematic subnetwork of the ecological network. Specific reservoirs are identified using indicator species and the light pollution map. Corridors are then defined by modelling optimal paths that incorporate darkness as a factor in ecological permeability. The different corridors and reservoirs are subsequently aggregated for each thematic subnetwork. This approach, described as integrative, follows the classical procedure for constructing an ecological network while incorporating the day-night cycle into its structuring elements [8,37]. However, this method may overlook important areas for diurnal biodiversity if they are excessively illuminated. The result may therefore be an ecological network that is potentially more restricted than a daytime network.

3. Materials and Methods

3.1. Study Area

The study site covers 14 km^2. It is located in Sart-Tilman, in the Province of Liège, Belgium, and hosts the main campus of the University of Liège (Figure 2). The site was selected as it lends itself well to the study of the impact of ALAN on the ecological network. University facilities and the university hospital (CHU) have expanded close to forest and heathland areas considered to be of high biological value, 240 ha of which are designated as an approved nature reserve. The site is currently structured by its road network and is mainly accessible by car and bus.

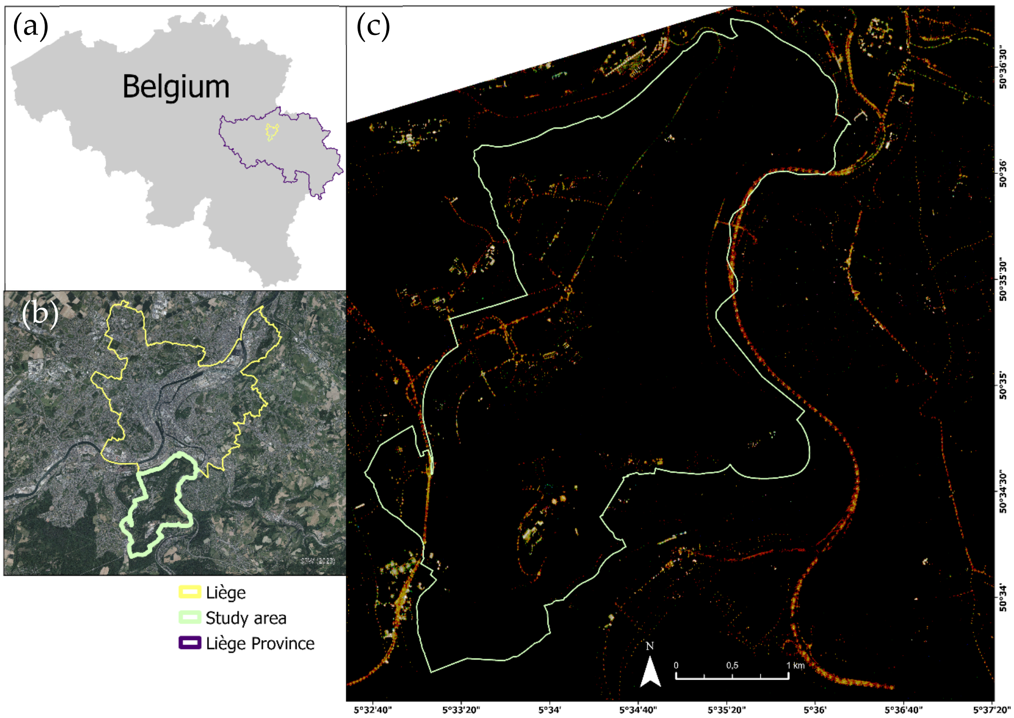

Figure 2. Location of the study area in Belgium (**a**) and within the city of Liège (**b**). JL1-7B image (**c**).

This site is of particular interest because it combines predominantly daytime human activities with extensive species-rich areas near an urban agglomeration of 500,000 inhabitants. In addition, it was recently the subject of ecological infrastructure mapping, though this prior work did not account for the site's nocturnal characteristics.

3.2. Data

To analyse the potential development of dark infrastructure at Sart-Tilman, several sources of information were combined, including satellite imagery, a point-light map, and the existing ecological network. Field surveys were also conducted to identify methodological limitations and characterise the nature of the light pollution.

3.2.1. Satellite Data

The primary data source is the commercial Chinese satellite Jilin-1 7B, operated by Chang-guang Satellite Technology Co., Ltd. (Changchun, China). Its multispectral sensor provides RGB imagery with a spatial resolution of 1.2 m and a radiometric resolution of 16 bits. The satellite is sensitive to low-level light emissions, which enables fine-scale analyses of the nocturnal landscape compared with NASA's Black Marble product derived from VIIRS/NPP data. The satellite flew over the study area on 25 March 2020 at 22:02 local time. The selected image has a signal-to-noise ratio (SNR) of 73 for the red band and 25 for both the green and blue bands. This indicates limited separation between the useful signal and noise in the green and blue bands, partly due to low nocturnal irradiance, which limits the amount of information captured. Moreover, shorter wavelengths, such as blue, are more strongly scattered by the atmosphere, further reducing the amount of light reaching the sensor. The use of a drone was considered but quickly ruled out due to the high risks associated with nocturnal navigation over a relatively large area that includes the hospital heliport.

3.2.2. Nighttime Photography

Field photographs were taken across the study site to document the visual impact of ground-level lighting and to compare it with the satellite-derived data. The photographs were captured between 23:00 and 00:30.

3.2.3. Light Points

The various light points within the site were obtained from the Real Estate Resources Administration of the University of Liège. These data were cross-checked with the regional road lighting network to obtain a more comprehensive dataset.

3.2.4. Land Cover

The land cover data used in this study are publicly available through a federal website (WalOnMap). The land cover layer is based on 2020 orthophotos and a Digital Elevation Model (DEM). Its original spatial resolution is 1 m. The raster was resampled (nearest neighbour method) to match the spatial resolution of the satellite data. Roads were categorised into three classes according to their relative importance within the road network. The final classification includes ten classes, which will be presented in the Section 4.

3.2.5. Ecological Network Mapping

The ecological network used in this study corresponds to the operational network. This network is derived from the functional ecological network, which represents the spatio-temporal dynamics of species within each thematic infrastructure [38]. At Sart-Tilman, the ecological network is divided into four thematic subnetworks [38]:

- Broadleaved forests, comprising habitats with at least 75% native species. They are divided into two subnetworks. The first includes broadleaved forests adapted to intermediate moisture levels, known as mesophilic forests. The model species for this infrastructure is the stag beetle (*Lucanus cervus*). The second consists of wet forests, which must include streams; the model species here is the fire salamander (*Salamandra salamandra*).
- Dry open habitats, which include dry grasslands and heathlands. The model species is the blue-winged grasshopper (*Oedipoda caerulescens*).
- Grasslands, which are also open habitats but are mesophilic, with richer soils supporting denser herbaceous vegetation.
- Forest edges, forming a transition zone between forested areas and open habitats.

It should be noted that the stag beetle exhibits both diurnal and crepuscular activity. During the day, individuals walk and rest, while the crepuscular period is used for flight and dispersal over longer distances [39]. The fire salamander, by contrast, is a nocturnal species [40], whereas the blue-winged grasshopper is predominantly diurnal [41]. Consequently, assessing the impact of ALAN on the thematic infrastructures, and especially on the forest infrastructure, is highly relevant. In addition, several bat species are present within the study area.

3.3. Methodology

3.3.1. Satellite Image Preprocessing

The raw image was projected into the Belgian Lambert 2008 coordinate system. To preserve the original reflectance values, the nearest neighbour resampling method was selected. Once georeferencing was completed, a median filter was applied using a 3-by-3-pixel window around each pixel. A 3-by-3 window provides slight smoothing while preserving edges. The median value is preferred because it is less affected by extreme values than the mean. Using the gain and offset coefficients included in the metadata, the image underwent radiometric calibration. This processing converts Digital Numbers (DNs) ranging from 0 to 65,535 into spectral radiance values expressed in $W \cdot m^{-2} \cdot sr^{-1} \cdot \mu m^{-1}$. However, this processing merges the three bands, preventing an RGB visualisation of the post-processed image. The mathematical relationship used is the following:

$$L\lambda = Gain \times DN + Offset$$

where $L\lambda$ represents the spectral radiance. The gain and offset values for the three wavelengths are provided in Table 1.

Table 1. Gain and offset coefficients for the red, green, and blue bands of the Jilin1-7B satellite image.

	Red	**Green**	**Blue**
Gain	0.000574	0.000644	0.000895
Offset	0.009202	0.009854	0.011851

The radiance values were combined into a single band by converting them to greyscale using the method developed by Grundland and Dodgson [42], as applied in the studies of Zheng et al. [43] and Xue et al. [44], which used satellite data from JL1 3 B. This technique preserves the correspondence between greyscale levels and radiance values while providing rapid visual understanding by maintaining contrast. Thus, pixels displaying the same colour in the original image display the same shade of grey. The equation of the Grundland and Dodgson [42] method is the following:

$$Brightness = 0.2989 \times Red + 0.587 \times Green + 0.114 \times Blue$$

where the luminance represents the resulting greyscale value, and red, green and blue correspond to spectral radiance values.

The minimum value obtained after conversion was 85 nW·cm^{-2}·sr^{-1}, which is similar to the values reported by Zheng et al. [43] and Xue et al. [44]. This value is treated as background, and pixels with higher values are considered illuminated. After processing, the image still contained several outlier pixels, and an additional filtering step was performed to remove them. Values exceeding 5000 nW·cm^{-2}·sr^{-1} were considered abnormally high, based on the maximum values reported in Zheng et al. [43] and Xue et al. [44]. As their studies focused on urban districts, values of 5000–9500 nW·cm^{-2}·sr^{-1} within the study area were deemed unrealistically elevated. For each pixel, the median of the neighbouring pixel values within a 5-by-5 window was calculated. This approach was preferred because the median reduces the influence of neighbouring outliers, and a 5-by-5 neighbourhood allows the removal of larger clusters while remaining within a range of high brightness values.

3.3.2. Spatial Description of the Illuminated Area

The land cover classes were differentiated using statistical analysis to identify those most affected by the observed ALAN footprint. For each land cover class, the mean, median, standard deviation and coefficient of variation (CV) of brightness were calculated, as well as a skewness index defined as follows:

$$\frac{1}{n}\sum_{i=1}^{n}\left(\frac{x_i - \overline{x}}{SD}\right)$$

where n represents the number of pixels in the land cover class, x_i represents the brightness value of a pixel, $\overline{x}$ is the mean brightness of the class, and SD represents the standard deviation.

The nocturnal photographs then enabled visualisation of the illuminated surfaces from a ground-level perspective. To ensure systematic tracking of the photographs, the QGIS extension QField 4.9.0 was used. The satellite-observed luminosity footprint was imported to visualise the results of satellite image processing. The photographs were taken with a Canon EOS 550D without a flash.

The images were also processed in GIMP 3.0.4 software. To enhance the distinction of illuminated areas within the photographs, the image colours were converted to grey-scale while preserving the human eye's perception of brightness. This step follows a logic similar to that used in processing the satellite image. GIMP performs this conversion using a different formula:

$$Luminance = (0.22 \times R) + (0.72 \times G) + (0.06 \times B)$$

where R, G and B correspond respectively to the pixel values in the red, green and blue channels of the original image. The luminance values were then inverted to transform bright areas into dark areas.

3.3.3. Light Infrastructure

The approach selected to assess the impact of light pollution is a deductive one, partially inspired by the work of Sordello [8] and Sordello et al. [10]. The observed spatial structure of light pollution is integrated into the ecological network to identify potential conflict areas involving light infrastructure, which represents barriers to species movement. The brightness threshold considered corresponds to the minimum value obtained from the satellite image preprocessing. In the scientific literature, researchers agree that no normative minimum value exists to distinguish light-polluted areas. Thresholds depend on the sensor and the objectives of the study [8,24,29,33,37,45,46]. Consequently, any detected artificial light is considered to directly impact biodiversity in this study.

The dark infrastructure is constructed from the light infrastructure to highlight potential conflict areas with the ecological network described by Gillet et al. [38]. The light infrastructure is built on the footprint of observed brightness extracted from the satellite image, complemented by a set of light points available to us that are not all detected or detectable in the satellite image. Although purely theoretical, some light points present in the territory may not have been detected by the satellite for various reasons. This may occur if a lamp post has a device that reduces upward light emission, if the light intensity is too low to be detected, or if the light point is out of service. This extension was produced by intersecting the observed brightness with a fifteen-meter buffer around each lighting point. The buffer allows the intersection to be performed while mitigating positional biases caused by georeferencing and lighting-point positions, and is inspired by Angerand's [47] observations. Once the intersection was completed, a reverse selection was applied to retain lighting points that are not located near illuminated surfaces. A seven-meter buffer was then applied around these points, and the layer was rasterised.

The choice of these buffer values is based on measurements of light footprint conducted by Angerand [47] on standard road lighting systems in Wallonia. Ground level illumination values were observed beyond 15 m for both LED and sodium lamps. Regarding the 7 m raster, this value was selected based on the width of municipal roads as well as on field observations and photographic documentation collected on site. Furthermore, the final point raster constructed from the 7 m buffer represents a theoretical footprint, as the individual characteristics of each light source are not known.

3.3.4. Conflict Areas

The light infrastructure is then superimposed on the areas of the different thematic infrastructures of the ecological network to highlight and assess potential conflict zones. The same process is repeated on the existing corridors.

4. Results

4.1. Spatial Description of the Light Footprint

In the case of Sart-Tilman, the observed light pollution is mainly concentrated along road traffic axes and artificial surfaces, as shown in Figure 3. Although the intensity gradient is wide, ranging from 85 to 4956, most values fall near the lower end of this range. An inspection of the pixel histogram (Figure 4) shows that more than 35% of the pixels have a brightness value between 85 and 100 $nW \cdot cm^{-2} \cdot sr^{-1}$.

The land cover analysis refines the spatial description. The Table 2 presents all results by land cover class. While all land cover classes display a minimum value close to 85, which is also the minimum detectable brightness threshold, maximum values vary considerably. Built-up areas show the highest value (4956), followed by municipal roads (4897) and forests (4781). The maximum value of the forest class originates from a few targeted points located near human activity areas, including the vicinity of a golf club building. The classes bare soil, grove and water body present much lower maximum values but also represent a small proportion of the illuminated surface.

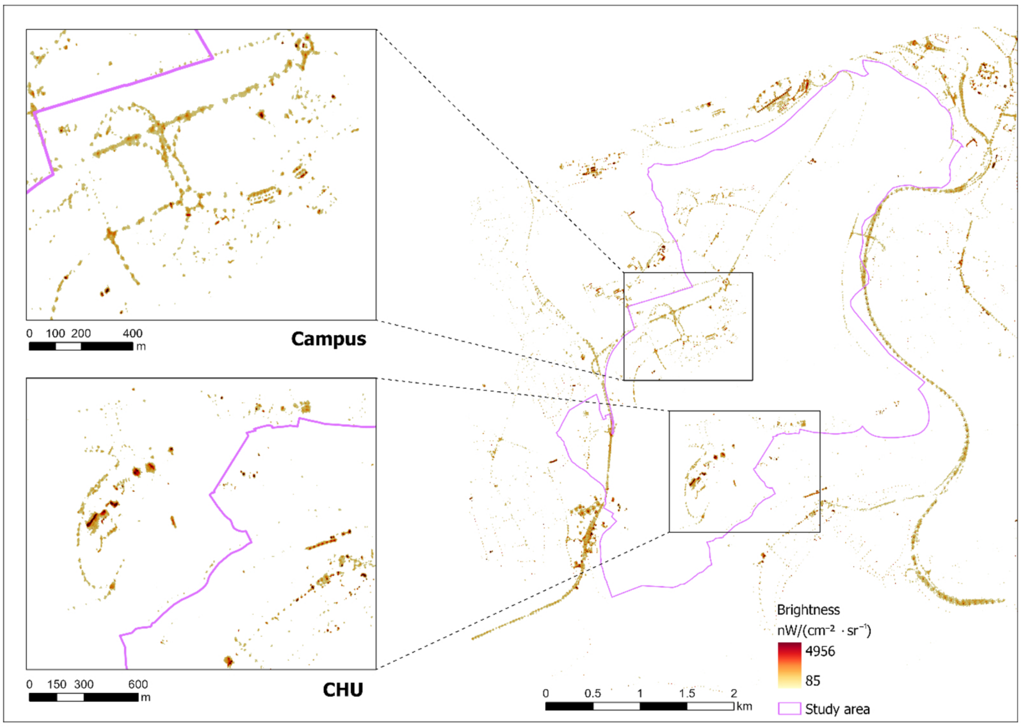

Figure 3. Cartographic representation of pixel brightness within the study site. Two detailed views are provided, focusing on the Sart-Tilman campus and the CHU, respectively.

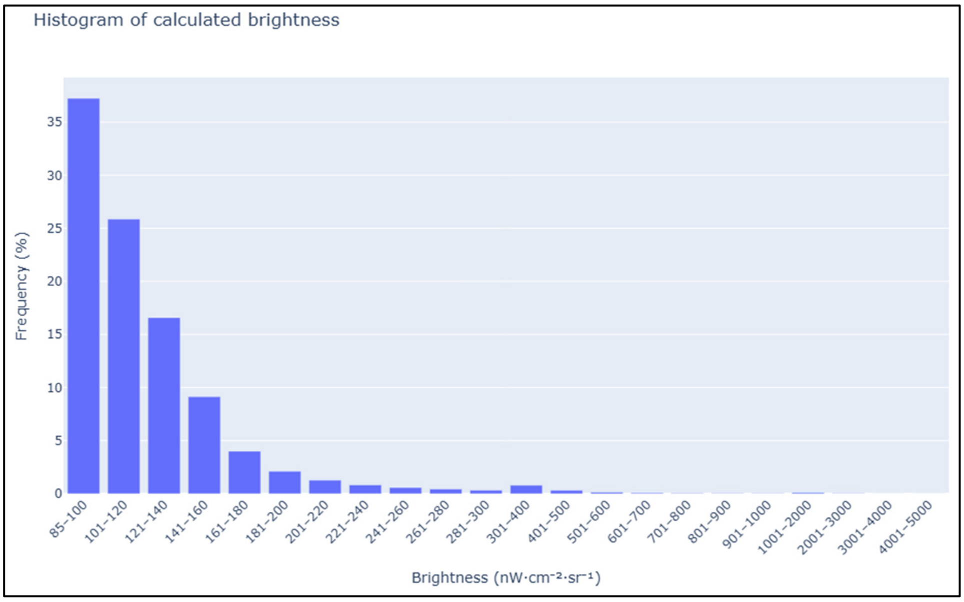

Figure 4. Histogram of the calculated brightness. The X-axis represents the different brightness values obtained. These values are grouped into classes of variable width based on the number of observations within each class. The Y-axis represents the number of pixels per brightness class as a frequency.

The standard deviation varies significantly across land cover classes. The classes built-up (144), forest (116), herbaceous cover (102) and municipal road (103) indicate high variability, whereas the classes path (40) and main road (48) show values clustered around the mean and are more homogeneous. The classes main road (42.5%) and municipal road (25.5%) represent a very large share of the total illuminated surface. Built-up areas (10.4%) and herbaceous cover (9.1%) are also significant.

Table 2. Distribution of observed brightness over the study site. The Min, Max, Mean, and Median columns respectively represent the minimum, maximum, mean, and median brightness values, expressed in $nW \cdot cm^{-2} \cdot sr^{-1}$, for each land cover class. The percentage of illuminated surface corresponds to the proportion of the illuminated surface area of each land cover class relative to the total illuminated surface area.

Land Cover Classes	Min	Max	Mean	Median	SD	CV	Skewness	Surface (%)
Bare soil	86	254	132	118	43	0.33	1.1	0.1
Forest	85	4781	119	100	115.5	0.97	20.3	7
Grove	85	1078	121	106	58	0.48	8.2	1
Railway	85	817	137	121	62.6	0.46	3.6	3.9
Primary road	85	4371	118	106	48.2	0.41	21.8	42.5
Communal road	85	4897	133	112	103	0.78	17.4	25.5
Path	86	471	112	100	40	0.36	4.7	0.2
Water body	85	547	121	104	48.5	0.40	3.8	0.3
Herbaceous cover	85	3799	128	104	102.1	0.80	15.3	9.1
Built-up	85	4956	143	113	144.1	1.01	14.9	10.4

Already considered as an obstacle during the day, the road network also constitutes the main driver of fragmentation at night, creating discontinuities in nocturnal ecological continuity. Roads, therefore, act as barriers structuring the nightscape, complemented by built-up areas whose brightness is higher but more variable. Indeed, within the built-up area, the character of the light sources is more diverse, oscillating between decorative lighting and functional illumination. The design of the lighting directly influences the amount of light perceived, as illustrated in Figure 5, with the original photographs provided in the Appendix B.

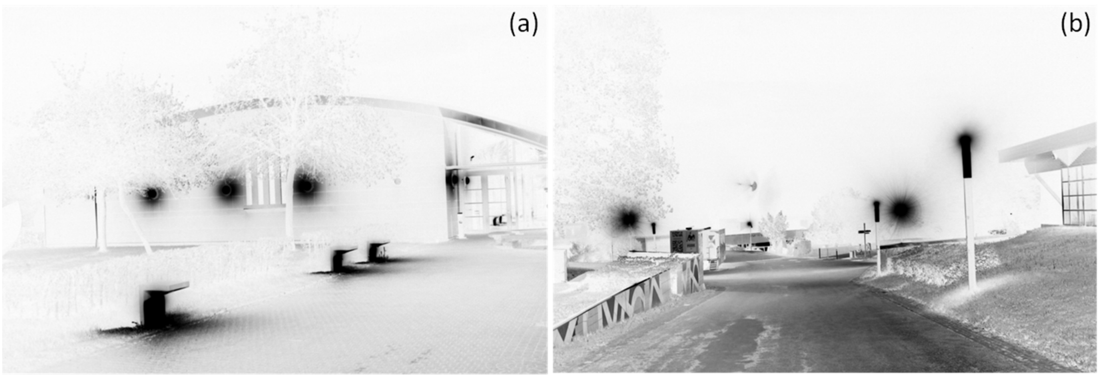

Figure 5. (**a**) photograph of a university building façade; (**b**) photograph of a campus pathway. The images were edited using the GIMP software, with white areas corresponding to dark zones and vice versa.

4.2. Light Infrastructure

The identified light infrastructure shown in Figure 6 corresponds to the light captured by the satellite, as referenced in Figure 3. The potential infrastructure includes lighting for secondary roads adjacent to the main road network and the surroundings of campus buildings. The Blanc Gravier sports centre, which combines parking and stadium lighting, appears to be a critical location which, although not illuminated throughout the night, may disturb certain species in its vicinity. The issue of hospital lighting, which is highly visible, is more problematic given the need for nighttime activity. Lastly, the mapping highlights several municipal public lighting points that could be considered unnecessarily disruptive to nocturnal species.

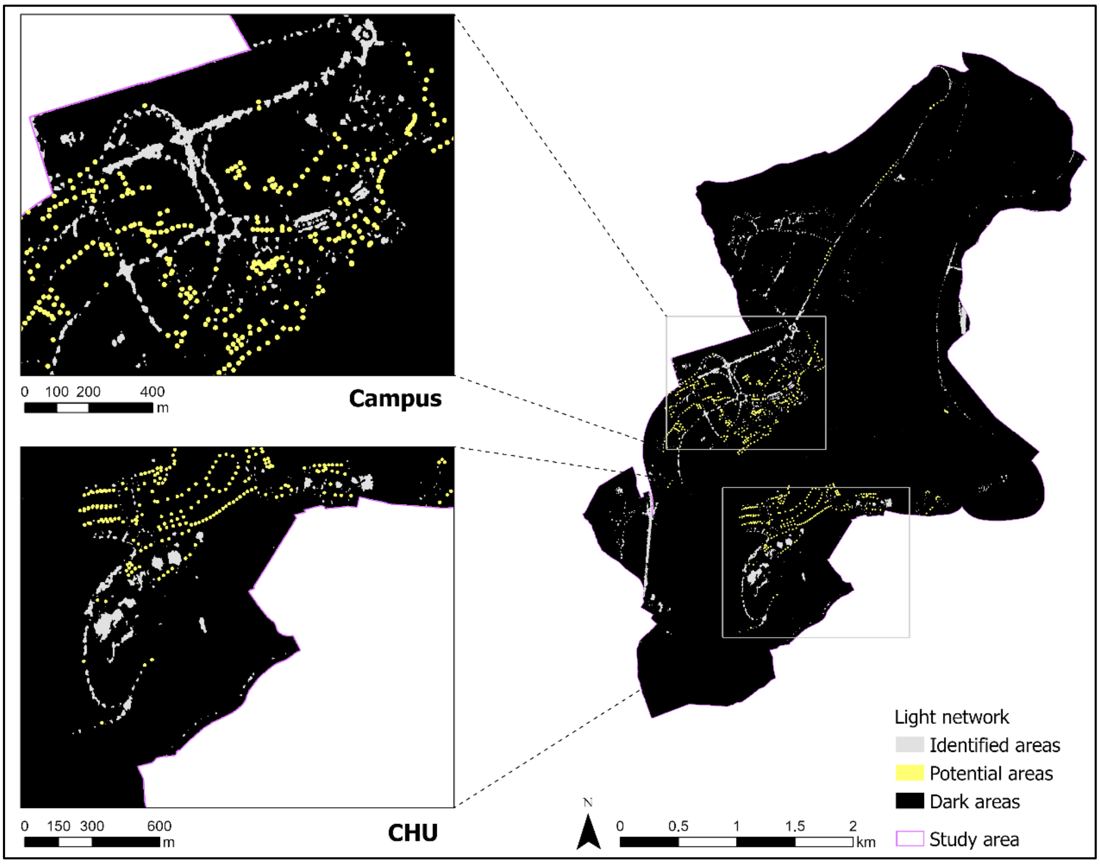

Figure 6. Cartographic representation of the identified light network and the potential light network on the Sart-Tilman site. The dark areas represent surfaces considered unlit according to the data used. Two detailed views are presented: one focusing on the Sart-Tilman campus and the other on the CHU and the Blanc-Gravier neighbourhood.

4.3. Conflict Zones

The results of the intersections between the light infrastructure and the different areas of the ecological network infrastructures (Figures 7 and 8) show that the impact is almost entirely located along the outer boundaries of the sites of core areas. The definitions of the ecological network components (core area, development area, and corridor) are provided in the appendices. The dry, open-habitat infrastructure is not affected because the sites are located in the very core of the nature reserve. Within the broadleaved forest infrastructure, light pollution identified in humid broadleaved forests primarily affects the core areas in direct contact with roads. Potential brightness affects mainly the development areas. The most important corridor zones are only slightly impacted. The mesophilic broadleaved forest sub-infrastructure is more strongly affected by the light infrastructure, particularly in corridor areas, some of which cross the campus and are directly fragmented by it. This is partly explained by the higher connectivity within the mesophilic forest sub-infrastructure. The forest-edge infrastructure covers limited areas but is affected at numerous locations directly adjacent to roads and university facilities. Finally, the grasslands infrastructure is the most affected by ALAN. Many areas of the operational network intersect the light infrastructure around the road network and within pedestrian zones on the campus. The impact is substantial because these areas have rectilinear and irregular shapes, which increases the contact surfaces.

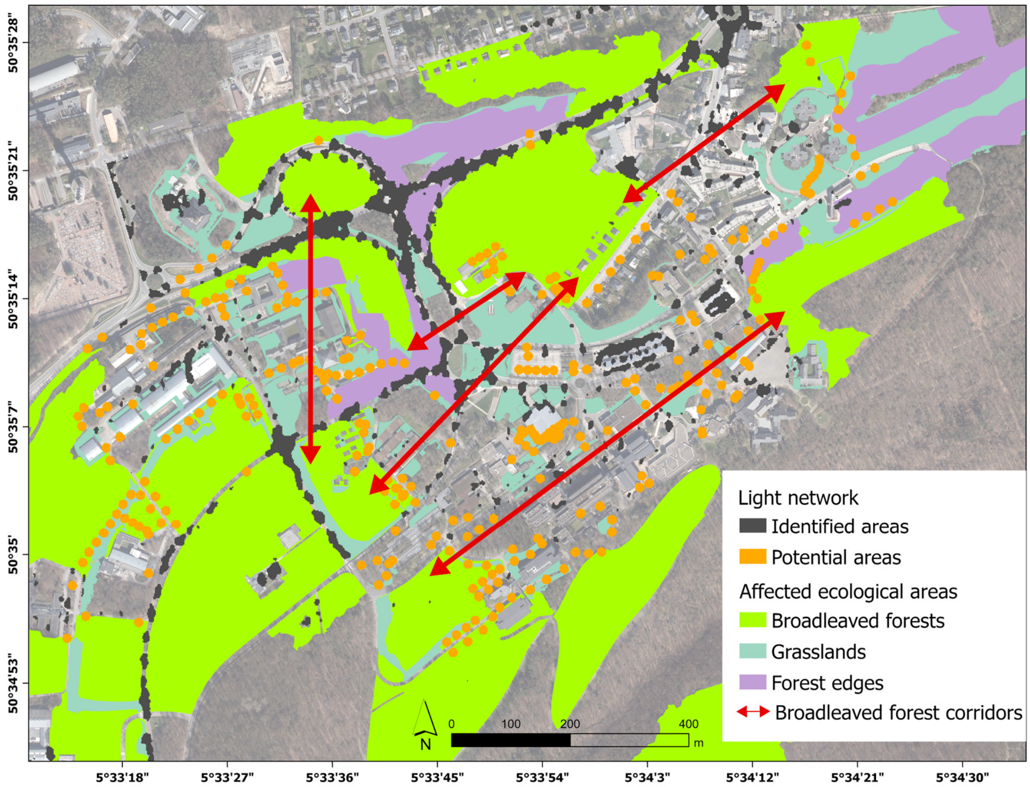

Figure 7. Cartographic representation of the light network's impact on the ecological network areas present on the campus (see detailed view in Figure 6). Only the affected surfaces are represented. The red arrows schematically represent the corridors of the broadleaved forest subnetwork.

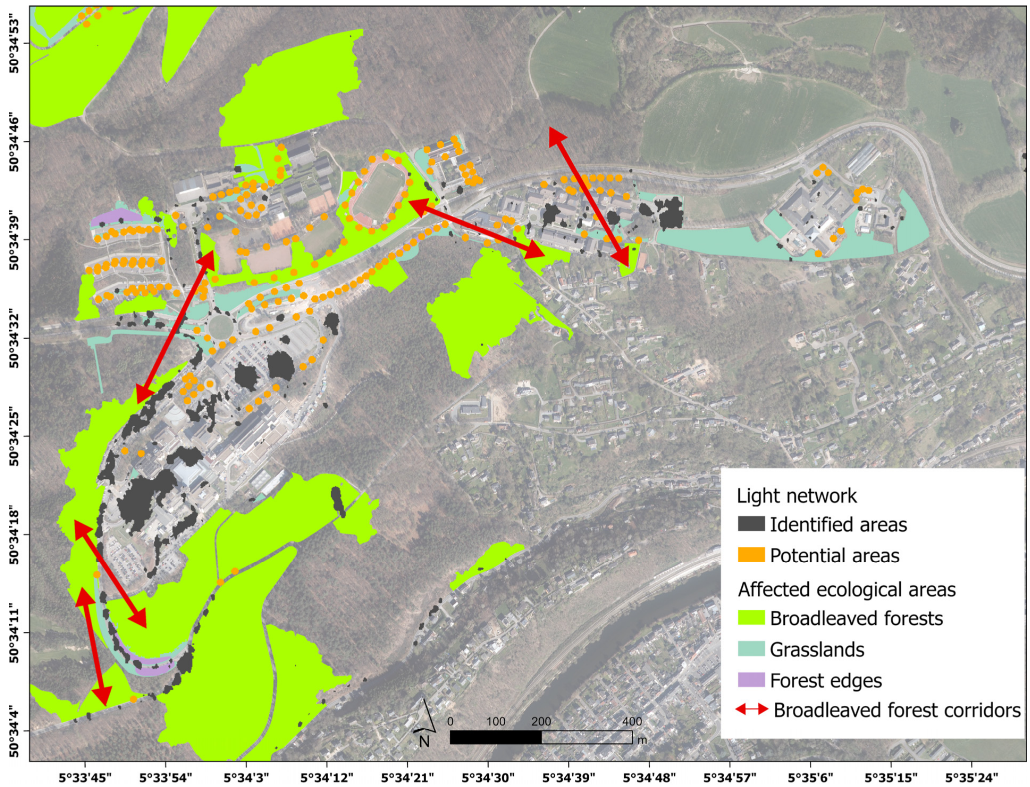

Figure 8. Cartographic representation of the light network's impact on the ecological network areas present on the CHU and Blanc Gravier (see detailed view in Figure 6). Only the affected surfaces are represented. The red arrows schematically represent the corridors of the broadleaved forest subnetwork.

On campus, some zones are isolated from the rest of the system due to the lighting footprint. Examples can be observed in Figure 7 along the road network and each ecological infrastructure is affected. The corridor zones of broadleaved forests crossing the campus are all impacted by the light infrastructure. Around the university hospital and the Blanc Gravier sports complex (Figure 8), contacts are less numerous but occur within core areas. The Blanc Gravier site is almost exclusively associated with the potential light infrastructure, whereas the hospital site is well integrated within the identified light infrastructure.

5. Discussion

5.1. The Footprint of ALAN on the Sart-Tilman

The spatial analysis of luminance data revealed the distribution of light pollution across the study area. The road network, which is the main barrier to the ecological network during daytime, strongly structures the nocturnal landscape, with more than 60% of illuminated pixels concentrated along primary and municipal roads. Roadside areas are also illuminated to varying degrees depending on the type of lighting. The overall lighting infrastructure forms an almost continuous luminous barrier, contributing to the fragmentation of corridor zones and wildlife habitat areas. Built-up areas are also illuminated. Quantitatively, the values are generally homogeneous, with more than 75% of illuminated pixels ranging between 85 and 140 $nW \cdot cm^{-2} \cdot sr^{-1}$, including 35% between 85 and 100 $nW \cdot cm^{-2} \cdot sr^{-1}$. However, the mean levels of light intensity per land cover class show that, despite locally high maxima, illuminated environments are mostly moderately bright. Variability indices (standard deviation, coefficient of variation and skewness) show that built-up areas and some municipal roads exhibit high heterogeneity in their values, whereas the main roads provide more homogeneous and sustained lighting. Still, some parts of the territory show higher light intensities than expected given their socio-economic context, suggesting oversized or poorly adapted lighting systems. Built-up areas exhibit the highest light intensities and greater variability than the road network. Conversely, forest zones are relatively dark, with most illumination observed near forest edges. High values within forests are very localised and related to human activities.

5.2. Relevance of Integrating a Dark Infrastructure

A dark infrastructure can be understood as an ecological network adapted to nocturnal conditions. This spatial framework is designed to preserve ecological continuity at night by explicitly integrating the characteristics of nocturnal space, including levels of darkness, unlit corridor zones, and the spectral and temporal properties of artificial lighting, in complement to existing diurnal infrastructures. Accordingly, dark infrastructure aims to identify and restore priority areas where artificial lighting fragments the nocturnal landscape by cross-referencing fine-scale mapping of the lightscape with ecological sub-infrastructures to target operational measures that maintain nocturnal ecological continuity and the coherence of the nocturnal landscape.

Within this conceptual framework, the Sart-Tilman territory appears particularly relevant. The study area is mostly forested, dominated by mesophilic broadleaved forest subinfrastructure (58%), followed by humid broadleaved forests (41%). These surfaces largely overlap and provide ecological continuity around the nature reserve, which serves as a core area for both forest sub-infrastructures. Forest edges, dry open habitats, and grassland infrastructure are less represented, often fragmented, poorly connected, and composed largely of restorable areas. Yet these infrastructures play an essential complementary role for overall biodiversity, especially since Sart-Tilman is a key node of the ecological network at the scale of the urban agglomeration, hosting many biologically important sites.

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Including the potential pressure of nocturnal lighting in the assessment of the ecological network, therefore, appears relevant.

However, the intersections between the light infrastructure and the ecological network elements nuance the importance of integrating a dark infrastructure at the scale of the Sart-Tilman. On the one hand, the overall surface area affected by light is relatively limited, suggesting that a site-wide dark infrastructure is not strictly necessary. On the other hand, the spatial distribution of impacts reveals intersections with key elements of the operational ecological network, particularly within the mesophilic broadleaved forest sub-infrastructure, where corridor zones of medium and high centrality are strongly affected. Corridor zones crossing the campus, the Blanc Gravier sports complex, and the hospital surroundings are impacted, reducing movement capacity for certain species and diminishing connectivity among core areas across the ecological infrastructure. For the humid broadleaved forest sub-infrastructure, impacts appear to be limited compared to those in the mesophilic forest. However, the influence of light pollution on corridor zones is reduced by the road network's dominant weight in corridor modelling. When defining the ecological network, the movement cost assigned to urbanised and road surfaces was sufficiently high to force corridor zones to avoid illuminated areas. Protected areas, such as the nature reserve, also contributed to reducing the potential footprint of artificial light. The species used to model the broadleaved forest sub-infrastructures are nocturnal or crepuscular, making light pollution a critical factor in designing a functional network. Several bat species inhabit forest habitats and use forest edges as foraging ecotones, requiring special attention regarding ALAN. According to Azam et al. [25], artificial light at night has a greater negative impact on movement capacity than impermeable surfaces. Although individual light points may offer local foraging opportunities, they negatively affect bat activity at the landscape scale.

Therefore, even though the quantitative footprint of nocturnal lighting is limited, many authors have demonstrated the ecological disruptions caused by ALAN. The spatial distribution of lighting and its intersections with key corridor zones justify targeted actions to preserve ecological continuity. In least-cost path modelling, illuminated areas can be assigned a movement cost, just like any other land cover class. The cost can also be modulated according to light intensity, providing a flexible tool. Establishing a dark infrastructure, therefore, enables the integration of the temporal dimension of ecological processes into the design of a connected network of habitat cores and corridor zones.

5.3. Methodological Considerations

This study developed a method to identify light pollution on the site. Once the footprint was defined, the analysis profiled insights for the development of a dark infrastructure on Sart-Tilman. The work was based on satellite imagery and the existing ecological network mapping. The deductive method provides rapid results. However, light pollution is treated as a secondary criterion in the construction of the ecological network. This approach confines the dark infrastructure to the boundaries of the existing ecological network and may overlook other dark zones, making the results dependent on the initial ecological study.

Night-time satellite images capture only the upward light flux, i.e., the light passing through the atmosphere to reach the sensor. Viewing angle also greatly influences observations, as buildings and vegetation cast shadows. The presence of strong LEDs on the site adds complexity. Guk and Levin [36] showed that Jilin-1 images may detect reduced emissions even when ground measurements indicate the opposite, partly because the relatively low SNR of the green and blue bands reduces the amount of captured information. The images also offer only a single observation at a fixed time, preventing evaluation of nighttime variations in intensity or colour temperature. In this case, the image was taken early at night, reflecting the maximum expected intensity.

Thus, the entirety of artificial light perceived by wildlife is not represented, particularly for species on the ground, in flight or in aquatic environments. Nonetheless, the images allow direct visualisation of upward light flux from both public and private lighting.

The threshold value of 85 $nW \cdot cm^{-2} \cdot sr^{-1}$ was chosen to classify pixels as either illuminated or dark. This threshold corresponds to the lowest luminance observed, following Zheng et al. [43] and Xue et al. [44]. This implies that all illuminated pixels are considered, consistent with sensitivity thresholds for bat species present on the site, which are lower than 85 $nW \cdot cm^{-2} \cdot sr^{-1}$ [13]. Light points not captured by the satellite were integrated into a potential light infrastructure. This addition provides a more precise representation of the potentially affected area, distinguishes observed and unobserved sources, and supports prioritisation for dark corridor planning. However, this potential infrastructure remains theoretical, based on an arbitrary buffer distance that does not differentiate lighting types.

Although the existing ecological network had previously been the subject of a dedicated study to ensure its validity, the model produced in this article was visually verified at several locations across the study site using field photographs and nocturnal survey routes. Satellite imagery alone does not capture the full extent of ecologically relevant light pollution, a limitation corroborated by field photographs. The observed light infrastructure footprint was imported into QField to assess the results of satellite image processing directly in the field. This qualitative approach aimed to document the diversity of lighting types presents across the study site and the reliability of the measurements. The limited representation of certain areas that are nevertheless illuminated reinforced the decision to implement a potential dark infrastructure. This step also highlighted one of the main limitations of exploiting satellite data. The proposed model could be further validated by measuring, for example, changes in bat movement patterns before and after the implementation of a dark corridor within the study site.

5.4. Contributions and Perspectives

This work proposes a reproducible protocol for analysing the characteristics of dark infrastructures. Through the identification of the light infrastructure and hotspot mapping, affected operational network zones and corridor zones are highlighted, allowing light pollution to be explicitly integrated into the design of an ecological network that accounts for diurnal, crepuscular and nocturnal species.

The method enables the identification of conflict areas between artificial lighting and ecological continuities, which constitutes a key basis for developing targeted action plans. The visual outputs facilitate communication with local decision makers and stakeholders, while providing operational guidance for prioritising mitigation measures, such as dimming strategies, luminaire redesign or the removal of unnecessary lighting, particularly along low-traffic road segments and near corridor zones. More broadly, the results support the protection of dark refuges and the integration of nocturnal ecological criteria into urban planning, land-use regulation and public lighting policies.

Beyond the Sart-Tilman case, the protocol is designed to be transferable to other territories, provided that a mapped ecological network and nighttime imagery with sufficiently fine spatial resolution are available. While high-resolution satellite data remain costly, the workflow can be adapted using drone-based imagery or by estimating the spatial extent of artificial lighting through ground-based measurements. These conditions make the approach applicable to a wide range of contexts, including peri-urban natural parks or municipalities engaged in dark sky or biodiversity policies.

In the case of Sart-Tilman, although the core areas of the ecological network are relatively little affected by artificial lighting, the main challenges concern corridor zones and the overall connectivity of the network. Some road segments classified as low-traffic or low-risk for road safety could therefore be dimmed or switched off. Ecological areas that become isolated at night remain a major concern, particularly along primary roads that are not locally managed and remain heavily used during nocturnal periods. Azam et al. [26] recommend a minimum distance of 50 m between ecological corridors and light sources for bats.

In the longer term, the method could be improved by integrating time series of nighttime images, ground-based radiometric measurements and a more complete inventory of light points. Discriminating lighting types using indices based on RGB channels, such as that developed by Sánchez de Miguel et al. [34], would further enhance the ecological relevance of the analysis.

6. Conclusions

This work provides an analytical and operational framework for assessing the footprint of artificial light at night. The methodology, designed and applied, combines several elements: the acquisition and processing of a night-time satellite image, the production of light-intensity data, and the creation of a light infrastructure integrating both observed light and potential light generated by existing light points. These data were spatially cross-referenced with land cover and the existing ecological network to identify conflict areas and the issues related to light pollution.

The methodology developed is reproducible and usable by local managers, although several methodological limitations must be considered. The satellite image alone cannot capture the full extent of ecological light pollution, but it provides a first estimate, albeit one that underestimates reality. This work opens operational perspectives by enabling landscape connectivity modelling that incorporates light intensity as a movement cost while accounting for seasonal variations. The dark infrastructure thus appears as an operational tool for reconciling human activities with the requirements of nocturnal conservation, to be integrated into green and blue infrastructures.

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Abbreviations

The following abbreviations are used in this manuscript:

ALAN	Artificial Light at Night

Appendix A

Table A1. Glossary of landscape ecology and ecological network terminology.

Landscape matrix	The dominant land cover within which biodiversity nuclei (reservoirs) are embedded [6].
Core areas	Surfaces accommodating target species populations and biotopes within each thematic network. These sites require a protection status and are exclusively dedicated to nature conservation [38].
Development areas	Areas where socio-economic activities are permitted, provided they are compatible with the promotion of biodiversity development. Sites of known biodiversity interest but smaller than the minimum vital size required for the species are also considered development areas [38].
Corridors	Elements ensuring ecological continuity and connectivity between different biodiversity reservoirs within the landscape matrix. They correspond to the theoretical optimal paths that connect the reservoirs within the matrix.

Appendix B

Figure A1. Original photographs of Figure 5.

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