BIODIVERSITY ENHANCEMENT

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9 Recommended Indicators of Biodiversity Enhancement

9.1 Structural and functional connectivity of urban green and blue spaces

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Connectivity of urban green and blue spaces (structural and functional) (Applied & EO/RS combined)		Biodiversity
Description and justification	One of the major impacts of urbanization is the *fragmentation of open spaces* into smaller and more isolated patches. Increased fragmentation of green in urbanized areas can reduce intra- and inter-species connectivity and lead to a loss of biodiversity (Kettunen *et al.*, 2007). Fragmentation of green areas and distance between habitat patches is thus an important factor in determining biodiversity. A *Green Infrastructure* approach, linking parks and other green spaces, is therefore considered essential for the preservation of biodiversity and to counter further habitat fragmentation and increase connectivity (Sylwester, 2009). Connectivity of landscapes can be evaluated in terms of:	

	• Structural connectivity – relating to the spatial configuration of patches, without considering the movement of individual organisms among these patches (Ioja et al. 2014) and • Functional connectivity – relating to the ability of organisms to move among patches (Tischendorf and Fahrig 2000). Both types of connectivity can be quantified using metrics that span different ranges of scale and complexity. Evaluation of blue-green space structural and functional connectivity can be used to: • Underpin green infrastructure and biodiversity spatial planning; • Prioritise sites for interventions; • Assess that impacts of NBS projects on pre-existing green networks; • Promote active transport initiatives.
Definition	Measuring the potential for green or blue areas to amplify the connectivity and multifunctionality of other urban green/blue areas.
Strengths and weaknesses	**Applied methods**: Robustness of evidence for structural connectivity tends to be based on the methodology used to identify and characterise urban greenspace, the scale of resolution of the data, and the age of the data in relation to current state. If up-to-date data from reliable sources is used, calculation of distances using GIS mapping provides solid evidence. For functional connectivity, the robustness of data tends to be correlated with the level of understanding in relation to the spatial dynamics of the target group or activity, and the suitability of habitat. **Earth observation/Remote sensing methods**: The potential for satellite remote sensing to provide key data has been highlighted by many researchers, offering repeatable, standardized and verifiable information on long-term trends in biodiversity indicators and characteristics of connectivity and fragmentation. As concluded by a variety of research (listed in the references), remote sensing permits one to address questions on scales inaccessible to ground-based methods alone, facilitating the development of an integrated approach to natural resource management, where biodiversity, pressures to biodiversity and consequences of management decisions can all be monitored. Remote sensing (RS)—taking images or other measurements of Earth from above—provides a unique perspective on what is happening within the urban landscape and thus plays a special role in green infrastructure analysis, environmental monitoring as well as biodiversity and conservation

	applications. The periodic repeat coverage of satellite-based RS is particularly useful for monitoring change and so is essential for understanding trends, and also provides key input into assessments of vegetation, connectivity and conservation management.
Measurement procedure and tool	A variety of methods exist from applied/public participation techniques through to earth observation/remote sensing approaches. *Applied/public participation metrics review*: Connectivity of landscapes can be evaluated in terms of: • Structural connectivity – relating to the spatial configuration of patches, without considering the movement of individual organisms among these patches (Ioja et al. 2014) and • Functional connectivity – relating to the ability of organisms to move among patches (Tischendorf and Fahrig 2000). Both types of connectivity can be quantified using metrics that span different ranges of scale and complexity. Structural connectivity is measured by the proximity of blue-green spaces and the infrastructure matrix that these form across a city. These are typically measured through a blue-green space mapping exercise that orientates and measures distribution and proximity on a city or regional level (Zhang et al. 2019). Typically, such mapping is done using the interrogation of satellite imagery and or land use maps. Examples of methodologies for such mapping include STURLA (Hamstead et al 2016) and FRAGSTATS (Saura and Torné 2009). The outputs from such exercises are usually represented through green infrastructure network maps that provide a planning tool for protecting existing blue-green spaces and opportunity maps for identifying priority areas for enhancing structural connectivity (Carlsen et al. 2011; Zhang et al. 2019). Participatory processes are also possible using internet-based public participation GIS (PPGIS) surveys to map functional aspects of urban blue-green space (Kahila-Tani et al. 2016; Brown et al 2018a; Brown et al. 2018b) and map underused/unmapped microspaces (Crowe et al. 2016). Functional connectivity is measured in relation to the ability of the landscape to support the movement of organisms through it (Peer et al. 2011). There has been a particular focus on functional connectivity in relation to urban biodiversity (Hess and Fischer 2001; Opdam 2006; Ahern 2007) because of the impact that fragmentation and the reduction in the number and area of natural habitats has on the ability of many species to persist (Fletcher et al. 2018).

The predominance of grey infrastructure in urban areas can represent a physical barrier to the movement of many species. These barriers can occur to the extent that urban development can exclude many species (McKinney 2006). Similarly to biodiversity, lack of blue-green space connectivity can also present a barrier to the movement of humans through urban areas (Ioja et al. 2014), particularly in relation to the use of active transport (Giles-Corti et al. 2010) and physical activity (Davison and Lawson 2006).

Thresholds for connectivity differ between different species/groups. For some, connectivity must represent linear physical connections, for other species, 'stepping stones' of suitable habitat over appropriate spatial scale represent sufficient functional connectivity (Vergnes et al. 2012). Similar patterns are also reported for human activities associated with blue-green space (Wineman et al. 2014; Peschardt et al. 2012). This means that, for both biodiversity and human functional connectivity, it is vital to have an understanding of the spatial dynamics of connectivity of relevance to your target group and activity (e.g., for humans - active transport; for biodiversity – foraging, colonisation, etc) in order to set threshold values.

Methods for measuring connectivity are therefore based on the spatial thresholds for the group and activity of interest. The most basic method to achieve this is to use Geographical Information Systems (GIS) to apply buffer areas to mapped blue-green spaces that are known to be suitable for the target group and activity.

A more complex, but potentially more realistic approach is to combine distance data with data on the spatially heterogeneous impedance of the landscape matrix (i.e., a measure recognising that some non-target landuse types might be more permeable than others) (Hargrove et al. 2004). By adopting such an approach, it is possible to measure potential connectivity corridors using least-cost path tools using GIS software combined with gravity models and graph theory (Kong et al. 2010).

Conefor software in ArcMap can be used to calculate the integral index of connectivity (IIC). This represents a method for combining the distance between patches with the threshold dispersal distance of a certain species (Saura and Torné, 2009). Such a tool enables evaluation of functional connectivity and provides a suitable metric for landscape conservation planning (Pascual-Hortal and Saura, 2006). Another example of a method for capturing functional connectivity is the use of habitat suitability models (HSM) utilising remote sensed vegetation data to map landcover composition and species distributions across cities (Bellamy et al. 2017).

In general, the biggest barrier to the delivery of such mapping tends to be a lack of understanding of the spatial dynamics (in relation to what constitutes functional connectivity) for the target groups (LaPoint et al. 2015). Applied methods to study the spatial dynamics of target groups, and to assess the permeability of different habitat types by direct observation, can strengthen the validity of mapped data.

Evaluation of blue-green space structural and functional connectivity can be used to:

- Underpin green infrastructure and biodiversity spatial planning;
- Prioritise sites for interventions;
- Assess that impacts of NBS projects on pre-existing green networks;
- Promote active transport initiatives.

Earth observation/remote sensing metric review:

One of the major impacts of urbanization is the fragmentation of open spaces into smaller and more isolated patches. Increased fragmentation of green in urbanized areas can reduce intra- and inter-species connectivity and lead to a loss of biodiversity (Kettunen et al., 2007). Fragmentation of green areas and distance between habitat patches is thus an important factor in determining biodiversity. A Green Infrastructure approach, linking parks and other green spaces, is therefore considered essential for the preservation of biodiversity and to counter further habitat fragmentation (EEA, 2010). Fragmentation and isolation of urban green spaces can be described by means of spatial metrics, i.e., quantitative measures of spatial pattern that were originally developed by landscape ecologists to examine the link between the spatial patterning of ecosystem types in natural landscapes and ecological processes (Turner, 1989, 1990). Many metrics have been developed for characterizing patterns in landscapes and were later implemented in the spatial analysis program FRAGSTATS by McGarigal and Marks (1995), which today is a commonly used quantitative tool in the field of landscape ecology.

For instance, in the study of Van de Voorde et al. (2010) various spatial metrics available in FRAGSTATS were calculated to describe fragmentation and isolation of open and dense vegetation patches in the Brussels Capital Region, mapped from high resolution Quickbird data. Fragmentation can be described by the total number of patches and by summary statistics characterizing the frequency distribution of patch size (expressed in hectares), including mean patch size, median patch size, standard deviation of patch size and coefficient of variation. Isolation of open and dense patches can be described by two indicators: the Euclidean nearest neighbor distance of a patch to other patches of the same type, and the proximity index.

Satellite imagery is the fastest method for data collection for urban planning. Since the first development of satellite imagery, many studies have investigated extracting various types of vegetation information. Johansen & Phinn (2006) combined IKONOS and Landsat ETM+ data in order to map structural parameters and the species composition of vegetation. Dennison et al. (2010) used GeoEye-1 high spatial resolution satellite data to map canopy mortality caused by a pine beetle outbreak. Gašparović et al. (2018) used WorldView-2, RapidEye, and PlanetScope data to detect urban vegetation based on land cover classification. Kranjčić et al. (2018, 2019) used Sentinel-2 data to visualize bark-beetle-damaged forests in Croatia, and Wessel et al. (2018) tested object-based and pixel-based methods on Sentinel-2 imagery for two forest sites in Germany. They stated that Sentinel-2 data had high potential for applied forestry and vegetation analysis. Friedel et al. (2017) used unsupervised machine learning to map landscape soils and vegetation components from satellite imagery. Tsai et al. (2018) used machine learning classification in order to map vegetation and land use types. As seen from the abovementioned literature, a lot of work has been done with remote sensing and machine learning to extract vegetation information and measure the potential for green or blue areas to amplify the connectivity and multifunctionality of other urban green/blue areas.

Many studies highlighted landscape fragmentation which was caused by rapid urbanization and has resulted in an immense amount of damage to the ecological system. Taking city districts as study areas, Guo et al. (2018) distinguished the vital patches and corridors for landscape connectivity maintenance through morphological spatial pattern analysis (MSPA), the probability of connectivity (PC), and the least-cost path analysis. These methods are mostly adopted and combined from the existing research about landscape modeling and can be divided into two parameters: the resistance value and the distance threshold. In order to get a species-specific result, some focal species should be selected whose biological characteristics and habitat types are assumed to represent most of the habitats in the city being studied (umbrella species). The result of such studying can show the different habitats and corridors for such species.

Then, the results of simulated scenarios can be used to obtain the final landscape pattern. Based on this study, one can propose a paradigm of ecological network identification of multiple species, which may contribute to landscape modeling and greenspace planning.

Landscape connectivity, the opposite of landscape fragmentation, describes the facilitating or impeding effect of the landscape on the dispersal of species among habitats. It is used to evaluate the ecological service function of a certain landscape by quantifying landscape patterns from a macro point of view. In recent decades, an interdisciplinary field called landscape ecology has proposed new methods to understand how landscape patterns influence ecological processes, for instance, biodiversity and the warmer microclimate-heat island effect.

The high-resolution remote sensing images (RS-images) can be used to extract land cover information. Image processing should be performed using ENVI (Harris Geospatial, Boulder, CO, USA) and eCognition (Trimble, Westminster, CA, USA), which can extract meaningful information from remote sensing image. Before classification, images have to be segmented. The scale parameter refers to the threshold of the heterogeneity variation allowed in the segmentation process (Dekavalla & Argialas, 2018). Scale parameter will affect the accuracy and efficiency of the extraction process. Multiscale segmentation was used to fix this problem. It is the foundation procedure of object-based image analysis (OBIA) to convert discrete pixels of RS-images into a homogeneous image object. Depending on the required land-cover categories (green space, agriculture land, built-up area, transportation area, and water), the segmentation scale parameter and the hierarchical relationship were identified according to their characteristics after several attempts to obtain a satisfactory result.

Difficulties in pixel-based classification caused by increasing satellite resolution led to the development of OBIA (Blaschke 2010). By identifying spectral and spatial information (the normalized difference vegetation index, geometry, brightness, texture, neighborhood attributes), adjacent pixels are grouped into multipixel objects (Aplin et al. 1999). For this reason, the K-nearest neighbor method can be adopted in order to obtain the land-cover categories by creating the following spectral characteristics: normalized difference vegetation index, standard deviation, maximum difference, brightness, length/width, roundness, and aspect ratio.

Landscape metrics, for example, the L-Z complexity method (Li et al. 2009) and mean patch shape fragmentation index can be developed to quantify landscape fragmentation. Landscape fragmentation processes can be classified into perforation, subdivision, shrinkage, and attribution, which can also be measured. However, these studies evaluate the overall landscape fragmentation without locating where fragmentation is taking place. According to the definition of landscape fragmentation, fragmentation will bring two results: one is the decrease in patch area, and the other is the increase in patch number. In other words, the mean patch area will decrease. Therefore, the mean patch area can be used to quantify the fragmentation. The RS-image can be clipped into grids (size = 1 km × 1 km) using the Fishnet tool in ArcGIS. The area and number of patches in each grid can be summarized, then the mean patch area can be calculated to indicate its landscape fragmentation.

Table 1. Remote-sensing based indices for the effectiveness and health of green (Wellmann et al., 2018)

Type of Index	Index Name	Abbreviation	Reference
Vegetation Indices	Vegetation fractions	Frac	(Haase et al., 2019)
	Normalized difference vegetation index	NDVI	(Tucker, 1979)
	Green NDVI	gNDVI	(Gitelson et al., 1996)
	Red edge normalized difference vegetation index	reNDVI	(Gitelson and Merzlyak, 1994)
	Vegetation health index	VHI	(Lausch et al., 2018)
			(Kogan, 1990, 1997)
	Vegetation condition index	VCI	(Kogan, 1995)
	Temperature condition index	TCI	(Singh et al. 2003)
Combination of methods	satellite remote sensing with on-the-ground observations	-	(Lotze-Campen and Lucht, 2001)
			(Haase et al., 2019)
Statistical Indices	Principal component analysis	1st component	(Jolliffe, 2002)
		2nd component	
		1st and 2nd component	

Note: No single approach is sufficient to monitor the complexity and multidimensionality of health of green and VH over the short to long term and on local to global scales (as stated by Haase et al., 2019; Lausch et al., 2018; Wellmann et al., 2017). Rather, every approach has its pros and cons, making it all the more necessary to link approaches. It is possible to realize within the frameworks proposed in the above mentioned publications and by reflecting crucial requirements for coupling approaches and integrating additional monitoring elements to form a multisource vegetation health monitoring network (MUSO-VH-MN) as suggested by Lausch et al. 2018. Thereby it is important to have in mind, that when it comes to linking the different approaches, data, information, models or platforms in a MUSO-VH-MN, big data with its complexity and syntactic and semantic heterogeneity and the lack of standardized approaches and VH protocols pose the greatest challenge. Therefore, Data Science with the elements of (a) digitalization, (b) semantification, (c) ontologization, (d) standardization, (e) Open Science, as well as (f) open and easy analyzing tools for assessing VH are important requirements for monitoring, linking, analyzing, and forecasting complex and multidimensional changes in health of green and VH.

Table 2. Statistical indicators that have been tested for the quantification of spectral plant trait variations (Wellmann et al., 2017).

Type	Name	Formula	Reference
GLCM *Stats group*	GLCM mean	$\mu_i = \sum_{i,j=0}^{N-1} i(P_{i,j})$	(Haralick et al., 1973)
	GLCM variance	$\sigma_i^2 = \sum_{i,j=0}^{N-1} P_{i,j}(i-\mu_i)^2$	(Haralick et al., 1973)
	GLCM correlation	$\sum_{i,j=0}^{N-1} P_{i,j}\left[\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}}\right]$	(Haralick et al., 1973)
GLCM *Contrast group*	GLCM homogeneity	$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2}$	(Haralick et al., 1973)
	GLCM contrast	$\sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2$	(Haralick et al., 1973)
	GLCM dissimilarity	$\sum_{i,j=0}^{N-1} P_{i,j}\lvert i-j\rvert$	(Haralick et al., 1973)
GLCM *Orderliness group*	GLCM entropy	$\sum_{i,j=0}^{N-1} P_{i,j}(-\ln P_{i,j})$	(Haralick et al., 1973)
	GLCM angular second moment	$\sum_{i,j=0}^{N-1} P_{i,j}^2$	(Haralick et al., 1973)
Spatial Autocorrelation	Geary's *C*	$C = \frac{n-1}{2*\left(\sum_i\sum_j w_{ij}\right)} * \frac{\sum_i\sum_j w_{ij}(x_i - x_j)^2}{\sum_i (x_i - \bar{x})^2}$	(Geary, 1954)
	Moran's *I*	$I = \frac{n*\sum_i\sum_j w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\left(\sum_i\sum_j w_{ij}\right)*\sum_i (x_i - x)^2}$	(Moran, 1950)
Descriptive Statistics	Standard Deviation	$\sigma = \sqrt{\frac{\sum(x-\overline{x})^2}{N}}$	
	Coefficient of Variation	$CV = \frac{\sigma}{\mu}$	(Datt, 1998)

Further details and hyperlinks on measurement tools and metrics, including those adopted by past and current EU research and innovation projects can be found in: [Connecting Nature Environmental Indicator Metrics Review Report]

Scale of measurement	**Applied methods**: Analysis is generally performed on a city-wide or regional scale. Local connectivity analysis is also possible. **Earth observation / Remote sensing methods**: Remotely sensed data are inherently suited to provide information on urban vegetation and land cover characteristics, and their change at various geographical scales. However, the higher resolution required, the more expensive would be the RS data needed. In some cases, it would be better to use images provided by drones, but in this case permissions for survey mapping will be required and depends on the local and national/government regulations.
Data source	
Required data	Required data will depend on selected methods, for further details see applied and earth observation/remote sensing metrics reviews in: Connecting Nature Environmental Indicator Metrics Review Report
Data input type	Data input types will depend on selected methods, for further details see applied or earth observation/remote sensing metrics reviews in: Connecting Nature Environmental Indicator Metrics Review Report
Data collection frequency	Data collection frequency will depend on selected methods, for further details see applied or earth observation/remote sensing metrics reviews in: Connecting Nature Environmental Indicator Metrics Review Report
Level of expertise required	**Applied methods**: Expertise in mapping and interrogation of data using GIS software is typically required. Level of expertise required is greater with increasing complexity of software processing. **Earth observation / Remote sensing methods**: The measure of the physical connectedness of the vegetation across a landscape, sometimes referred to as the 'structural vegetation connectivity' will typically be measured using remote sensing methods. It differs from 'ecological connectivity' which will usually be measured through on-ground observations and analysis. "Hyperspectral" sensors can have more than 200 bands and can provide a wealth of information to help, for example, identify specific species. Processing such datasets requires special expertise and satellite-based hyperspectral sensors are not yet common.
Synergies with other indicators	Remote sensing is generally most useful when combined with in situ observations, and these are usually required for calibration and for assessing RS accuracy. RS can provide excellent spatial and temporal coverage, for example, though its usefulness may be limited by pixel size which may be too coarse for some applications. On the other hand, in situ measurements are made at very fine spatial scales but tend to be sparse and infrequent, as well as difficult and relatively expensive to collect. Combining RS and in situ observations takes advantage of their complementary features. As such,

	synergies exist with other indicators that use greenspace mapping as a foundation for analysis
Connection with SDGs	Links with SDGs 3, 4, 8, to 11 and 13 to 17: Links to better accessibility; Links to environmental education; Job creation; More connected infrastructure; Social equality in relation to greenspace; Sustainable urban development; Climate change adaptation; Potential co-benefits related to more sustainable water management; Potential habitat creation/habitat connectivity; Environmental Justice in relation to high-quality greenspace; Opportunities for collaborative working.
Opportunities for participatory data collection	**Applied methods**: Opportunities are available for participation. This can be in the form of mapping greenspaces using internet-based public participation GIS (PPGIS), assessing habitat suitability for target species and activities, or surveying for presence/absence/movement of species. **Earth observation/Remote sensing methods**: Participatory processes can be used to support data analysis. For details see Applied above.
Additional information	
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9.1.1 *Structural connectivity of green space*

Project Name: UNaLab (Grant Agreement no. 730052)

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Structural connectivity	**Biodiversity**
Description and justification	Biodiversity is the measure of biological variety in the environment and it has an important role in functioning ecosystems services and health of environment and society. Biodiversity is an aspect of natural environment that is most directly affected by anthropogenic influence. City biodiversity is seen as an important aspect of sustainable and resilient urban development. The fragmentation of natural environments is a major threat to biodiversity as scattered and non-connected natural areas are much less efficient in preserving biodiversity than large and connected areas.
Definition	Degree of physical ("structural") connectivity between natural environments within a defined urban area
Strengths and weaknesses	+ Relatively easy to evaluate - Estimation about connections
Measurement procedure and tool	To estimate fragmentation, natural areas are defined and then an estimation is made about their connections. A mesh indicator value is calculated. Natural areas are categorized into separate interconnected patches. The area of each patch is summed, squared and these squares are summed and divided by the total area of natural areas. $$Mesh\ indicator = \left(\frac{A_1^2 + A_2^2 + \cdots + A_n^2}{A_1 + A_2 + \cdots A_n}\right)$$ This index (in hectares) is a metric - mesh indicator - used in the indicator value.
Scale of measurement	District to region scale
Data source	