Urban land use intensity assessment: The potential of spatio-temporal spectral traits with remote sensing

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Abstract

By adding attributes of space and time to the spectral traits (ST) concept we developed a completely new way of quantifying and assessing land use intensity and the hemeroby of urban landscapes. Calculating spectral traits variations (STV) from remote sensing data and regressing STV against hemeroby, we show how to estimate human land use intensity and the degree of hemeroby for large spatial areas with a dense temporal resolution for an urban case study. We found a linear statistical significant relationship (p=0.01) between the annual amplitude in spectral trait variations and the degree of hemeroby. It was thereof possible to separate the different types of land use cover according to their degree of hemeroby and land use intensity, respectively. Moreover, since the concept of plant traits is a functional framework in which each trait can be assigned to one or more ecosystem functions, the assessment of STV is a promising step towards assessing the diversity of spectral traits in an ecosystem as a proxy of functional diversity.

Key words

Spectral traits (ST), Spectral trait variations (STV), urban land-use-intensity (U-LUI), human-use-intensity, remote sensing, hemeroby, NDVI, GLCM

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Highlights

- This paper presents spatio-temporal spectral traits as indicators for urban land use intensity assessment.
- With spectral traits variations (STV) from remote-sensing (RS) data, we show how to estimate human land use intensity and the degree of hemeroby.
- We could separate different types of land use cover according to their degree of hemeroby.
- Each trait can be assigned to one or more ecosystem functions.
- The use of remote sensing (RS) data opens up the opportunity of spatially continuous comparisons of entire landscapes over longer periods of time.

Abstract

By adding attributes of space and time to the spectral traits (ST) concept we developed a completely new way of quantifying and assessing land use intensity and the hemeroby of urban landscapes. Calculating spectral traits variations (STV) from remote sensing data and regressing STV against hemeroby, we show how to estimate human land use intensity and the degree of hemeroby for large spatial areas with a dense temporal resolution for an urban case study. We found a linear statistical significant relationship ($p=0.01$) between the annual amplitude in spectral trait variations and the degree of hemeroby. It was thereof possible to separate the different types of land use cover according to their degree of hemeroby and land use intensity, respectively. Moreover, since the concept of plant traits is a functional framework in which each trait can be assigned to one or more ecosystem functions, the assessment of STV is a promising step towards assessing the diversity of spectral traits in an ecosystem as a proxy of functional diversity.

Key words: Spectral traits (ST), Spectral trait variations (STV), urban land-use-intensity, human-use-intensity, remote sensing, hemeroby, NDVI, GLCM

1. Introduction

The shape and surface of our cultural landscapes are driven by a multitude of factors and stressors, particularly urban areas representing a land use type with probably the highest density and intensity of multiple land uses (Elmqvist et al., 2013). Land use intensity is defined as the extent of land being used including the land used for growing crops, clearing land, planting trees, draining a wetland or sealing the surface (Haase, 2014). Land use intensity is also an indication of the amount and degree of development of the land in an area, and a reflection of the effects and environmental impacts generated by that development (Boone et al., 2014). Both land use intensity and population density can vary greatly over time and are not stable patterns (Haase and Schwarz, 2015). Depending on the economic and demographic development of a region (or a city) they can dynamically grow, decline or experience regrowth again, which is what the literature refers to as 'urban shrinkage' and regrowth after shrinkage (Wolff et al., 2016).

Urban land use intensity and population density as expressions of urbanization and land development processes have a considerable impact on the environment (e.g. Knapp et al., 2017). One consequence is that urban ecosystems largely vary in terms of naturalness (Haase, 2014; Kowarik, 2011). A measure describing the impact and the degree of all human interventions on ecosystems is the hemeroby index (Jalas, 1953, 1955) . It is an index that is associated with naturalness as a complementary term, with a high degree of hemeroby equating to a high human influence and thus low naturalness (Hill et al., 2002). The concept of hemeroby was used by Sukopp (1972) to describe the human influence on urban vegetation. The hemeroby index ranges from the ahemerobic degree (no anthropogenic impact on biocenosis) to the metahemerobic degree (biocenosis completely destroyed by e.g. 100% soil sealing; see e.g. Walz and Stein, 2014).

Kowarik (1988) used hemeroby to quantify the impact of human interventions on ecosystems. Later, hemeroby was used by e.g. Steinhardt et al. (1999), Walz and Stein (2014) and Lausch et al. (2015) for land use classifications and the assessment of the impact of land use on the biosphere (mainly on vegetation). Walz and Stein (2014) impressively documented this hemeroby classification of land use intensity using a range of GIS vector data (ATKIS). However, since large land classifications such as ATKIS (for Germany), Corine Land Cover or Urban Atlas (both with European coverage) just to name a few, only represent one specific moment in time (e.g. Corine Land Cover is provided by the EEA for 1990, 2000, 2006 and

2012 and ATKIS for cities in 2005 and 2014), they are limited in their scope and not very appropriate for monitoring the variability of vegetation over a growing season.

Therefore, new approaches based on temporal high-resolution remote sensing data are required. Remote sensing is effective in monitoring short-and long-term processes, patterns and thus also the consequences of human use on land and particularly on vegetation – e.g. plant species decline – and on soil, namely soil compaction or waterlogging (Lausch et al., 2013(2); Rocchini et al., 2010) . Because the analysis of land use intensity has received much less attention than the analysis of land use conversion, only a handful of studies have used remote sensing data for land use intensity (Erb et al., 2013; Kuemmerle et al., 2013) and grassland-use intensity (Gómez Giménez et al., 2017). In the recent study by Estel et al. (2016) land use intensity was assessed based on categorical remote sensing Data (CORINE) and economic input/output statistics for the whole of Europe except cities. To our knowledge, studies investigating and quantifying land use intensity and thus hemeroby change to the terrestrial land surface in its spatio-temporal short-term change neither exists for open landscapes nor for urban areas.

As a foundation for the remote sensing based analysis of land use intensity we use the indicators spectral traits (ST) and spectral traits variations (STV) by Lausch et al. (2016(2), p. 8): "ST are anatomical, morphological, biochemical, biophysical, physiological, structural, phenological or functional, etc. characteristics of plants, populations and communities that […] can be directly or indirectly recorded using remote-sensing techniques in space. […] STV are changes to Spectral Traits (ST) in terms of physiology, senescence and phenology, but also caused by stress, disturbances and the resource limitations of plants, populations and communities […]". Cabrera-Bosquet et al. (2011) use ST to derive biomass, nitrogen content as well as growth parameters from isolated plants. Variation (STV) in remotely-sensed biochemical traits (e.g. the content of nitrogen, lignin or cellulose) has successively been used to assess forest canopy functioning, including water stress, pressure from pests/ infestations, and canopy fluxes in nutrients and carbon (McManus et al., 2016). Other studies show that both ST and STV can be analysed with remote sensing indices (e.g. Normalized Difference Vegetation Index; NDVI) in order to determine the plant's nitrogen status, to differentiate between different ecosystem functional types or to determine an ecosystem's net exchange of CO_2 (Alcaraz et al., 2006; Morgan et al., 2016; Wang et al., 2012). This is also true for disturbance events. Lu et al. (2011) conclude "that [the] NDVI can be used as a secondary trait for large-scale drought resistance screening". The spectral traits approach is thus a powerful interface linking spectral remote sensing data with important ecosystem characteristics like stress, disturbances or resource limitations (Lausch et al., 2016 (1)& (2)).

The traits of a species impact its fitness, and thus its potential to grow, reproduce and survive (Violle et al., 2007). Consequently, traits enable an assessment of the reasons behind spatial and temporal changes in individual plants, communities, ecosystems and beyond (Garnier et al., 2016). A reduction in the number of traits represented in a species community (which can accompany the loss of species) has been shown to reduce the stability of ecosystems and the efficiency of ecosystem functioning (e.g. nutrient cycling) (Cardinale et al., 2012).As a consequence, the provision of those ecosystem services that are the product of ecosystem functions (e.g. soil formation) can be reduced (Lavorel, 2013). Traits and their diversity ('functional diversity') are dependent on numerous interactions and different drivers or stressors, meaning that "a particular disturbance regime – comprising disturbance type, intensity, frequency and severity – will lead to a specific plant assemblage with traits pre-adapted to this disturbance regime" (Bernhardt-Römermann et al., 2011, p. 778). This also applies to human-induced stressors. For example, Garnier et al. (2007) established a direct link between the spatial variation in plant traits and human land-use regimes in agricultural and pastoral systems. Other reasons for a variation of traits in the spatial dimension include different soil or topography patterns and biotic interactions (e.g. intra- and interspecific competition) (Garnier et al., 2007; - Lausch et al., 2013(1)). Temporal variations in plant traits can be attributed among other things to their reaction to anthropogenic stressors, seasonal biorhythms (Lausch et al., 2015), natural stressors such as pests (Fassnacht et al., 2014; Lausch et al., 2013(1)) or resource limitations such as soil moisture stress on plants (Lausch et al., 2013(2)). Traits thereby react to both short-term and long-term processes and provide a proxy to the variation of processes occurring in the landscape (Lausch et al., 2016(2)).

Urban areas differ from other land-use types (such as forests or agricultural land-use types) with respect to the dominant environmental conditions. Urban landscapes are usually more heterogeneous (Niemela, 1999), with many of them being warmer than the surrounding landscapes due to the urban heat island effect (Oke, 1982), with drier soils, the isolation of green spaces from sealed structures and frequent disturbances acting as environmental and anthropogenic stressors (Kowarik, 2011). Consequently, urban and non-urban vegetation differ in the presence and abundance of certain traits (Knapp et al., 2008). One example is the photosynthetic pathway of plant species (C3- vs. C4- vs. CAM-photosynthesis), with higher frequencies of C4-species in urban compared to non-urban areas, as a reaction to urban heat and drought. These changes in the representation of traits across different land-use types together with the rich variety in different land use regimes make urban areas important regions for testing the ST/STV approach.

We understand urban land use intensity as a driver that homogenizes vegetation diversity by controlling the environmental boundary conditions and thus the diversity of traits that can persist in intensively used urban habitats. We therefore expect land use regimes that are associated with a higher use intensity to show less diversity in spectral traits in the urban biosphere (Fig. 1).

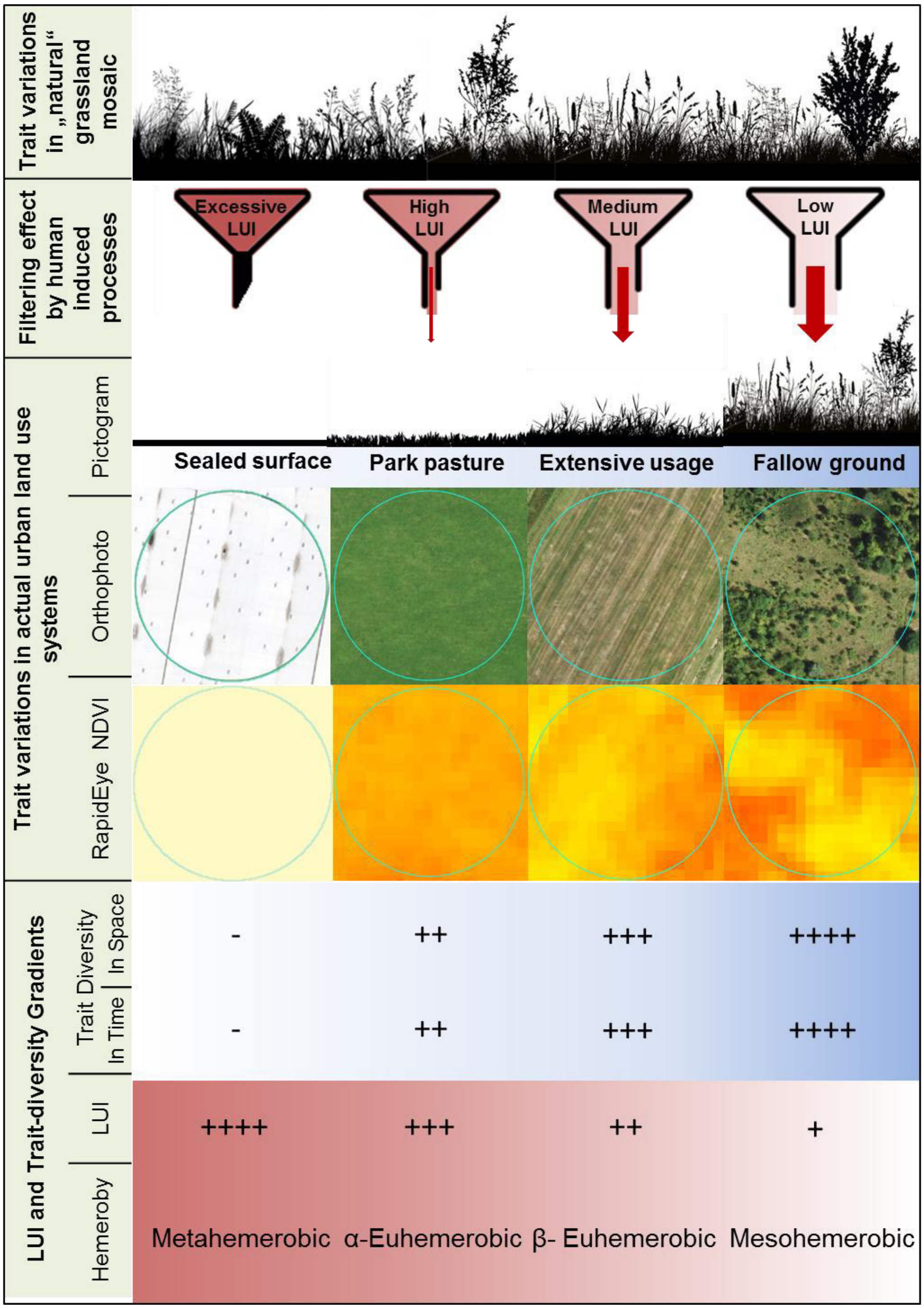

Fig. 1 Conceptual diagram showing the filtering effect of urban land use intensity (LUI) on traits in different urban land use classes, represented by an orthophoto and the complementary RapidEye normalized difference vegetation index (NDVI) values, set in relation to spectral trait variations (STV) and hemeroby.

When aiming to better understand coupled human environment systems in the city, a temporally and spatially explicit picture is necessary for well-informed management approaches. Since there is no procedure for the spatially and temporally explicit assessment of urban land use intensity, the goals of this paper are:

- to develop an approach for the analysis of urban land use intensity and the degree of hemeroby by using remote sensing techniques that work independently of categorical land use data and fixed boundaries and time frames.
- to develop the respective indicators that will be able to identify and quantify ST and STV over space and time.
- to reveal gaps and limitations of this approach and the newly developed indicators using the case study urban region of Leipzig, Germany.

2. Study area

The study region is the city of Leipzig, Germany, and its immediate surrounding landscape (51°20' N, 12°22' E, Fig.2). The city area is divided into four dominating landform configurations; built-up structures, alluvial forest, cropland, and former mining landscapes that have been transformed into lakes. In between those dominating landform configurations, Leipzig exhibits diverse patterns with small-scale variation (Haase and Nuissl, 2007). Over the last century, various contrasting trends in urban construction formed the city of Leipzig. These trends range from urban shrinkage & growth, suburbanization & re-urbanization and deindustrialisation & reindustrialization. In the early 1930s, Leipzig was home to over 700,000 inhabitants. Due to an economic downturn in the industrial sector, Leipzig's population went down to 530,000 by the fall of the Berlin Wall in 1989. This period of shrinkage was characterized by high vacancy rates in the old housing districts and in the city centre, because those buildings that had been damaged by the war were not rebuilt and instead prefabricated high-rise buildings emerged in districts on the outskirts of the city. In the years following German reunification, the outflow of people grew. The negative population balance was accompanied by further suburbanization processes in the form of townhouse complexes and large-scale infrastructure and production facilities, leaving even larger areas of the centre empty. Since the early 2000s, these processes have been turned into reurbanisation. Housing and places for work have returned to the city centre and the inner city districts that were formerly fallow grounds with vacant buildings. Residential spaces are faced with infill development and densification (Wolff et al., 2016; Nuissl and Rink, 2005).

The interaction of the manifold building trends has created a highly diverse cityscape, in which naturalness and thus hemeroby vary considerably between adjacent areas. In Leipzig, it often only takes a few steps to move from a place with an entirely destroyed biocenosis to reach the shores of semi-natural ecosystems. Situated right next to the city centre for instance is the alluvial floodplain forest ("*Auwald*"), which is dominated by ash-, oak-, beech-, lime- and sycamore trees and protected under the flora-fauna-habitat-directive (FFH). Furthermore, patches of fallow land are spread across the city. Both ecosystems are subject to very low management intensity and consequently feature a comparably natural character. In addition, the old housing districts feature old-grown vegetation, which is comparably rich in species diversity. This illustrates that in Leipzig the typical urban to rural gradient is often overlaid by sharp small-scale variation.

Leipzig was chosen as a case study region, both because of the availability of data and the profound expert knowledge in interpreting ST and STV patterns.

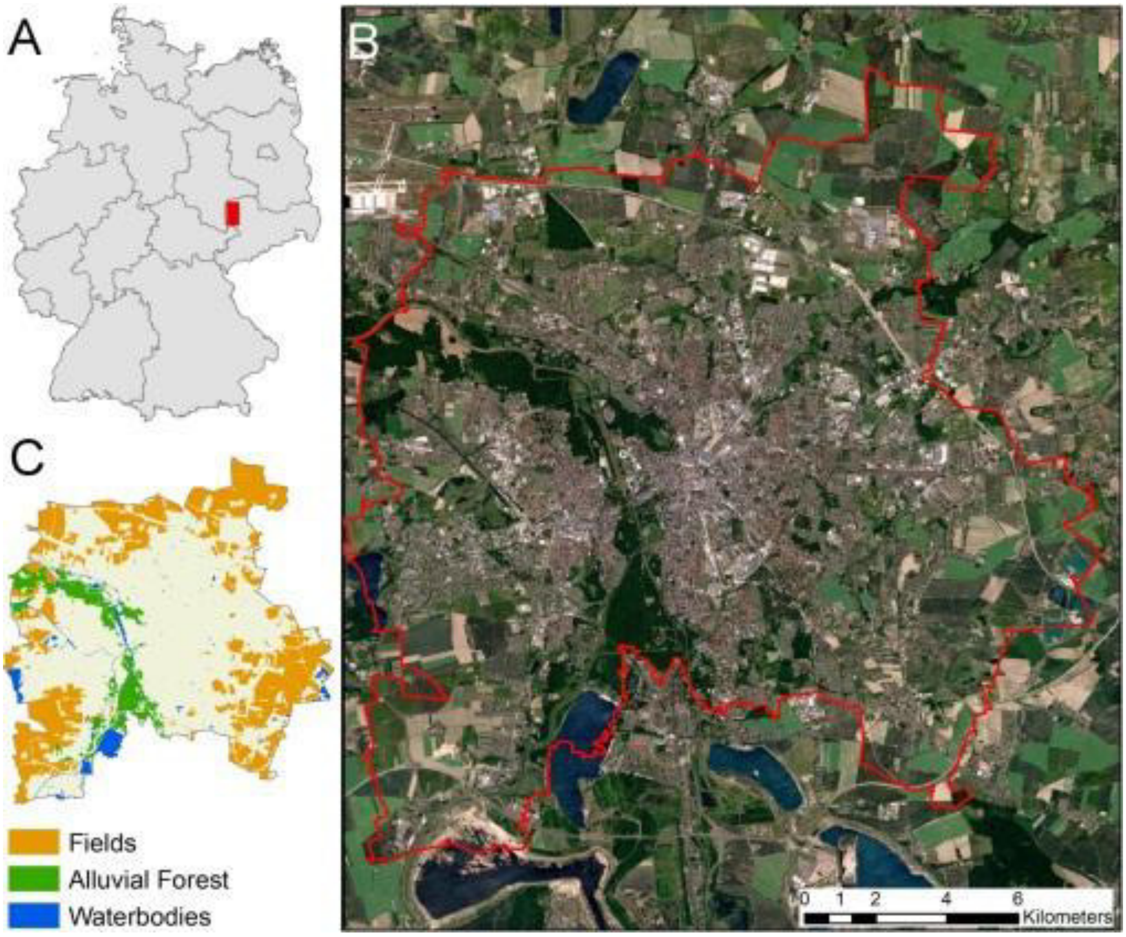

Fig. 2. (A) Location of the study region Leipzig in Germany, (B) RapidEye image of Leipzig showing the city borders, (C) and an overview of the main land use classes that are embeddeed in the urban land use matrix of Leipzig

3. Data and methods

3.1 Overview of the methodological approach

This study analyses STV to determine land use intensity and the degree of hemeroby of urban surfaces with remote sensing data and a biotope map as a reference scheme (Fig. 3). To determine STV, firstly the STs in every pixel cell of the satellite images (RapidEye) were calculated. For this purpose we used statistical indices (different principal components from a PCA carried out on the spectral RapidEye bands) and a range of normalized difference vegetation indices (NDVI, gNDVI, reNDVI). The vegetation indices can be used indicatively for the traits photosynthesis rate, chlorophyll content or phenological characteristics (Cabrera-Bosquet et al., 2011; Gamon et al., 2016, 1995; Gitelson and Merzlyak, 1997; Reed et al., 1994). This pixel-based information was extracted for every pixel of the regions of interest, whose location was derived from a biotope map (Frietsch, 1997). In every region of interest the STV were calculated for the 12 DOY (day of years) with 12 statistical measures assessing different aspects of the (un)equal distribution of the ST inside the region of interest. The information from the STV was then aggregated for each of the land use classes for every time step and plotted for the entire annual course.

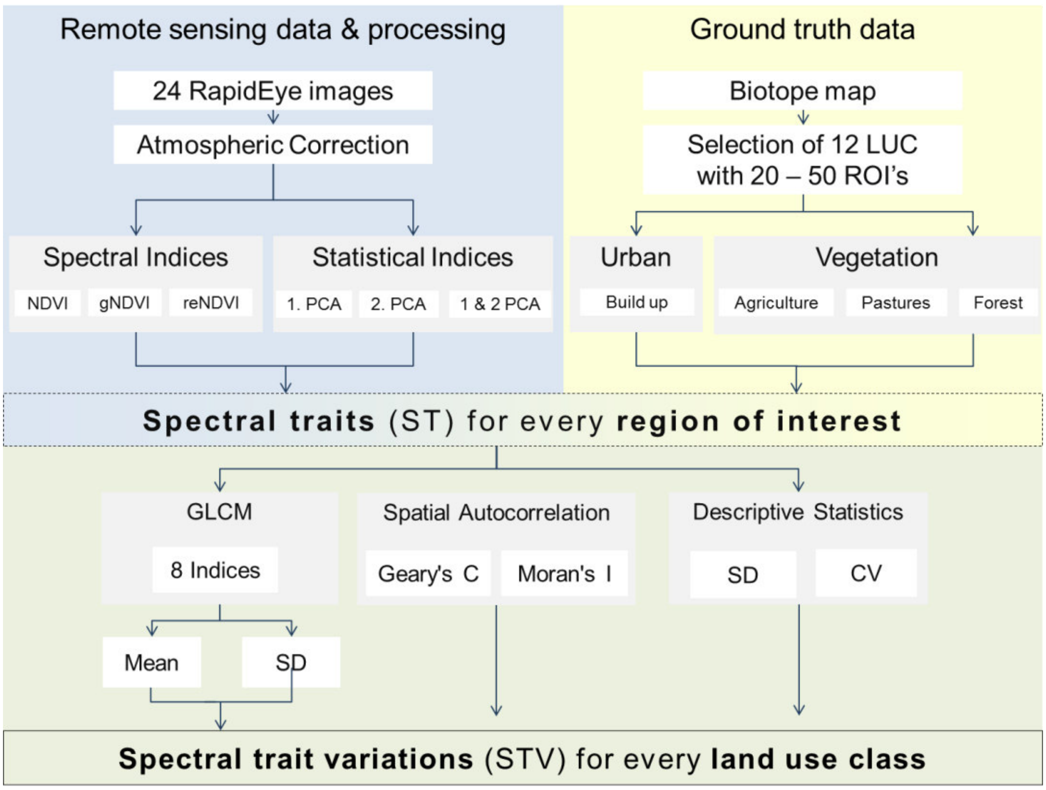

Fig. 3. Flowchart of the methodical approach for the quantification of urban-land use intensity and hemeroby on the basis of spectral trait variations (STV). Spectral traits were

calculated separately with each of the six different remote-sensing indices (three different normalized difference vegetation indices (NDVI) and three different combinations of principal components from a principal component analysis (PCA)) for the regions of interest (ROI) of the regarded land use classes (LUC). Inside the regions of interest spectral trait variations were then calculated with each of the twelve different indicators. We then identified the best performing combination of remote sensing and statistical indicator based on expected spectral trait variation behavior and used only these for further analysis.

3.2 Ground truth

For the selection of regions of interests - we used a biotope map from 2005 (Frietsch, 1997), containing information about the current plant communities, abiotic factors and different forms of land use. From this map we derived the location of our regions of interest, grouped them according to the current land use regime and assigned the corresponding degree of hemeroby to the land use classes (Tab. 1). In this way we sampled for a total of 12 land use classes, 20 to 50 regions of interest per class based on the biotope map, local expert knowledge and an orthophoto. The sampling was carried out with a round sample buffer with a radius of 50m. The 12 classes were split up into six built-up land use classes with different building densities and forms, and six vegetation-dominated classes covering the most important ecosystems of Leipzig. The land use classes thereby served as a basis for the larger purpose of deriving the hemeroby of the respective land surfaces in future studies without the guidance of a categorical land use product.

Tab. 1 Classification of the individual land use classes according to their degree of hemeroby and their corresponding degree of naturalness and their human impact (modified after Lausch et al., 2015; Sukopp and Kunick, 1976)

Land use class types	Land use classes	Degree of hemeroby	Degree of naturalness	Human impact
Built-up urban land	Inner city business district	7. Metahemerobic	Artificial	Excessive
	Crafts and industry	7. Metahemerobic	Artificial	Excessive
	High-rise buildings	6. Polyhemerobic	Close to artificial	Very strong
	Perimeter development	6. Polyhemerobic	Close to artificial	Very strong
	Townhouses	6. Polyhemerobic	Close to artificial	Very strong
	Allotment gardens	5. α-Euhemerobic	Far from natural	Strong
Vegetation – Pasture lands	Park pastures	5. α-Euhemerobic	Far from natural	Strong
	Extensively managed pastures	4. β- Euhemerobic	Far from natural	Moderate/Strong
	Fallow ground	3. Mesohemerobic	Semi-natural	Moderate
Vegetation – Agriculture	Agricultural Fields	5. α-Euhemerobic	Far from natural	Strong

	Fields fallow in winter	5. α-Euhemerobic	Far from natural	Strong
Vegetation – Forest	Alluvial hardwood forest	3. Mesohemerobic	Semi-natural	Moderate

3.3 Remote sensing data

The RapidEye satellite fleet offers high temporal- and spatial resolution imagery. The sensor acquires data in five spectral bands (R,G,B, red-edge & near infra-red) with a ground resolution of 6.5 meters at nadir, making it very capable of tracking the spatio-temporal pattern of small-scale urban environments (Tigges et al., 2013).

For our study, we acquired 24 cloud-free RapidEye images from the years 2010 to 2012 (Tab.2) and stacked those images according to the day of year (DOY). This way we generated an intra-annual time series with 12 images per tile, portraying the annual variability of the urban ecosystem.

Tab. 2. Image acquisition dates of the RapidEye remote-sensing data.

Month	DOY	Acquisition dates Leipzig south	Acquisition dates Leipzig north
January	26	26.01.2012	26.01.2012
March	60	01.03.2011	01.03.2011
	81	22.03.2011	22.03.2011
April	111	21.04.2011	21.04.2011
May	135	14.05.2012	20.05.2011
June	154	03.06.2011	03.06.2011
	178	27.06.2011	27.06.2011
July	206	24.07.2012	26.07.2011
August	232	20.08.2011	20.08.2011
September	265	22.09.2010	25.09.2011
October	305	31.10.2012	29.10.2011
November	326	21.11.2012	21.11.2012

3.3.1 Remote Sensing data processing

For the atmospheric correction of the acquired satellite data we deployed the widely used tool ATCOR 2 (Richter, 2011; Scatozza, 2013). From the pre-processed data we then calculated six indices combining multiple RapidEye bands into one single band file, to avoid constraints caused by multidimensionality (Tab. 3). We tested 3 variations of normalized difference vegetation indices and the first 3 components from a principal component analysis (PCA) in terms of their suitability to depict spectral traits variations. In our study the NDVI proved to be the most robust index and was therefore chosen to calculate the STV indicators. Overall, the NDVI was comparable to gNDVI and reNDVI with the advantages that it offered a greater contrast between the classes, while the principal components from the PCA did not foster any meaningful results.

Tab. 3. Remote-sensing indices calculated for the RapidEye data in the urban study region of Leipzig.

Type of Index	Index Name	Abbreviation	Reference
Vegetation Indices	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)
Statistical Indices	Principal component analysis	1^{st} component 2^{nd} component 1^{st} and 2^{nd} component	(Jolliffe, 2002)

3.3.2 Spectral trait-based indicators for urban land use intensity with remote sensing

For the analysis of spectral trait variations, we used 12 statistical indices of 3 different types. The first type of indices is computed on a grey level co-occurrence matrix (GLCM), the second group are measures of spatial autocorrelation and the third group consists of a set of descriptive statistics (see Fig. 4, Table 4).

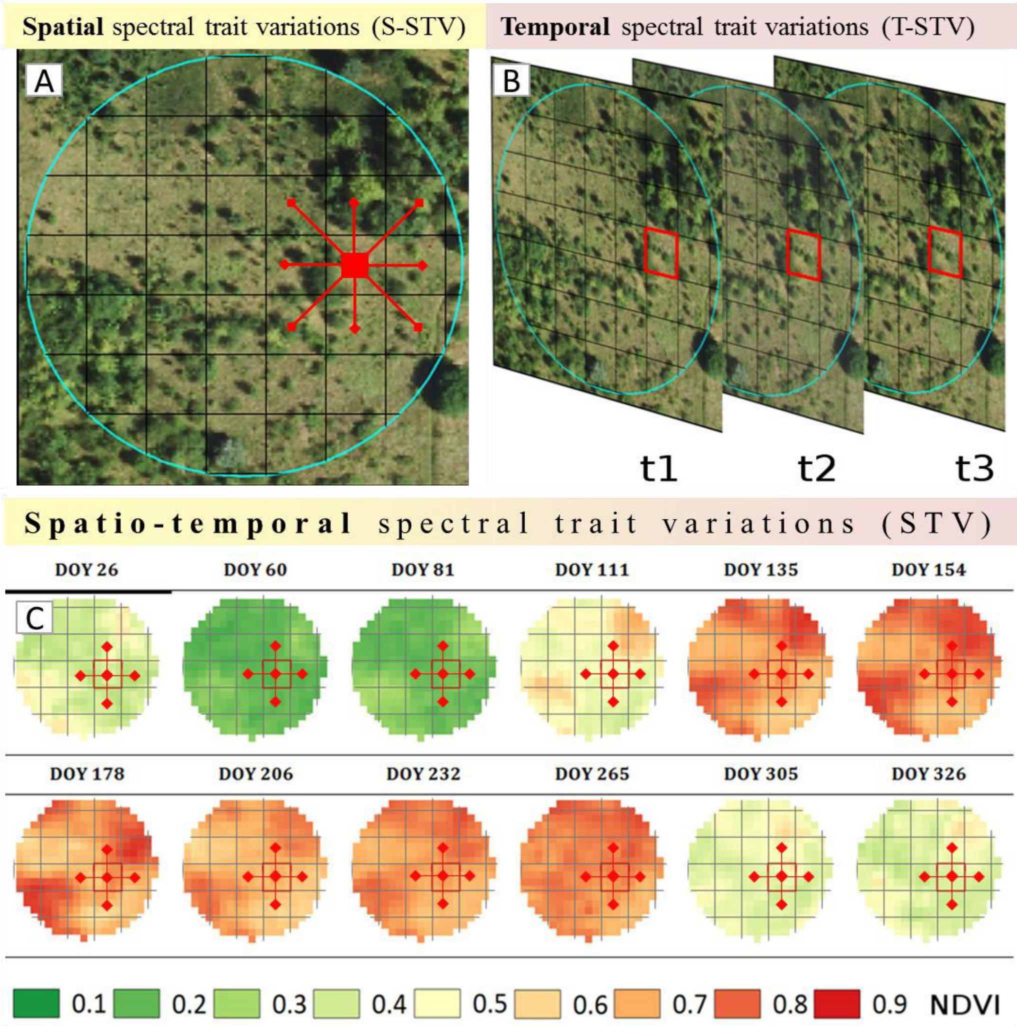

Fig. 4. Schematic explanation of the quantification of human use intensity using statistical indicators, (A) on monotemporal RapidEye remote-sensing data, analysing the spatial variability inside a region of interest, (B) on multitemporal RapidEye imagery, assessing the temporal aspect of variability and (C) an integrated scheme, where both temporal and spatial spectral trait variations (STV) are analysed over the course of a year (cf. DOY – day of year) based on RapidEye derived NDVI images to assess the degree of hemeroby and urban land use intensity.

A GLCM is a reliable way of spatial texture evaluation for remote sensing data (Guo, 2004; Marceau et al., 1990), e.g. the evaluation of remote sensing measured NDVI. The procedure assesses the texture of an image by calculating the number of occurrences of specific value combinations between adjacent pixels, evaluating the distribution of remote sensing measured NDVI values in every region of interest. Based on this frequency matrix we calculated eight indicators, introduced by Haralick et al. (1973) (Tab. 4).

The descriptive statistics that we calculated included the median, standard deviation, and the Shannon index of NDVI values and two measures of spatial autocorrelation (Geary's C and Moran's I) (Tab. 4). The last two indices describe the degree of relation that the values of a variable feature based on their location (Geary, 1954; Moran, 1950).

Tab. 4 Statistical indicators that have been tested in this study for the quantification of spectral trait variations.

Type	Name	Formula	Reference
GLCM *Stats group*	GLCM mean	$\mu_i = \sum_{i,j=0}^{N-1} i\left(P_{i,j}\right)$	(Haralick et al., 1973)
	GLCM variance	$\sigma_i^2 = \sum_{i,j=0}^{N-1} P_{i,j}\left(i-\mu_i\right)^2$	(Haralick et al., 1973)
	GLCM correlation	$\sum_{i,j=0}^{N-1} P_{i,j}\left[\frac{\left(i-\mu_i\right)\left(j-\mu_j\right)}{\sqrt{\left(\sigma_i^2\right)\left(\sigma_j^2\right)}}\right]$	(Haralick et al., 1973)
GLCM *Contrast group*	GLCM homogeneity	$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+\left(i-j\right)^2}$	(Haralick et al., 1973)
	GLCM contrast	$\sum_{i,j=0}^{N-1} P_{i,j}\left(i-j\right)^2$	(Haralick et al., 1973)
	GLCM dissimilarity	$\sum_{i,j=0}^{N-1} P_{i,j}\left\|i-j\right\|$	(Haralick et al., 1973)
GLCM *Orderliness group*	GLCM entropy	$\sum_{i,j=0}^{N-1} P_{i,j}\left(-\ln P_{i,j}\right)$	(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)

All the indicators mentioned in table 4 above have been tested if they could reproduce anticipated STV behavior of the test sites. This was done for every of the above mentioned indicators with all remote sensing indices, making 72 different testing combinations. Out of these combinations we chose GLCM Variance and Correlation as final indicators for the calculation of STV.

3.4 Relating spectral trait variations (STV) with hemeroby

To derive meaningful information from our analysis of spatio temporal variability we calculated a first indicator, the annual amplitude in STV. For each of the hemeroby classes featured in this study (Tab. 1) we derived the mean annual amplitude in STV of every land use class exhibiting the regarded degree of hemeroby. This was done by subtracting the lowest from the highest GLCM Variance or Correlation value. Fallow ground, forest, extensively managed- and park pastures were measured with GLCM Correlation, the others in GLCM Variance (for normalization, the value range for the GLCM Correlation indicators was fitted by a factor of 1000). Based on these figures we fitted a linear model (1). As the dependent variable we used the mean annual amplitude in STV and the degree of hemeroby as the independent variable

$$\text{A-STV}_i = \alpha + \beta\ \text{H}_i + \varepsilon \qquad (1)$$

A-STV: Mean annual amplitude in STV

H: Degree of hemeroby

To test for statistical significance we used a one-sided analysis of variance (ANOVA) test with a significance level of 0.05%. The expert-based, empirically-tested biotope map of the city of Leipzig was used as the ground truth for the modeled degree of hemeroby.

In order to avoid misinterpretation, it is important to state that we looked at pure lawn spaces within a larger park and not at the entire park unit. Thus, we could exclude the effects of designed structural diversity and complex configuration of different types of green in such parks. Second, we are looking at the spectral diversity of the land surface and not at species diversity.

4. Results

4.1 Quantification of urban land use intensity by remote sensing for all land use classes

The framework outlined above is able to detect STV in the urban environment to a degree where we can draw conclusions about the degree of hemeroby of the ecosystem in question directly from the remote-sensing data. With this we can show that higher urban land use intensity, meaning more human use related pressure causes a reduction in the variety of spectral plant traits both in the spatial and in the temporal dimension.

From the linear model, we can deduct, that for a difference of 38 in annual STV amplitude (measured in GLCM Variance), there is a reduction of 1 degree of hemeroby (Fig. 5). We found the relation to be statistically significant with a p value of 0.01.

$$\boldsymbol{A\text{-}STV = 285 - 38.5 * H + \varepsilon} \qquad (2)$$

A-STV = Annual amplitude in spectral trait variation

H = Degree of Hemeroby

ε = Error term

We achieved this relation by using the NDVI as an indicator for the spectral traits' photosynthesis rate, chlorophyll content, greenness content or phenological status. Thereof we calculated the spectral trait variations (STV). For this we successfully deployed two indicators, namely GLCM Variance and GLCM Correlation. While GLCM Variance proved to be best suited in built-up land use classes, GLCM Correlation was better for land use classes solely with vegetation.

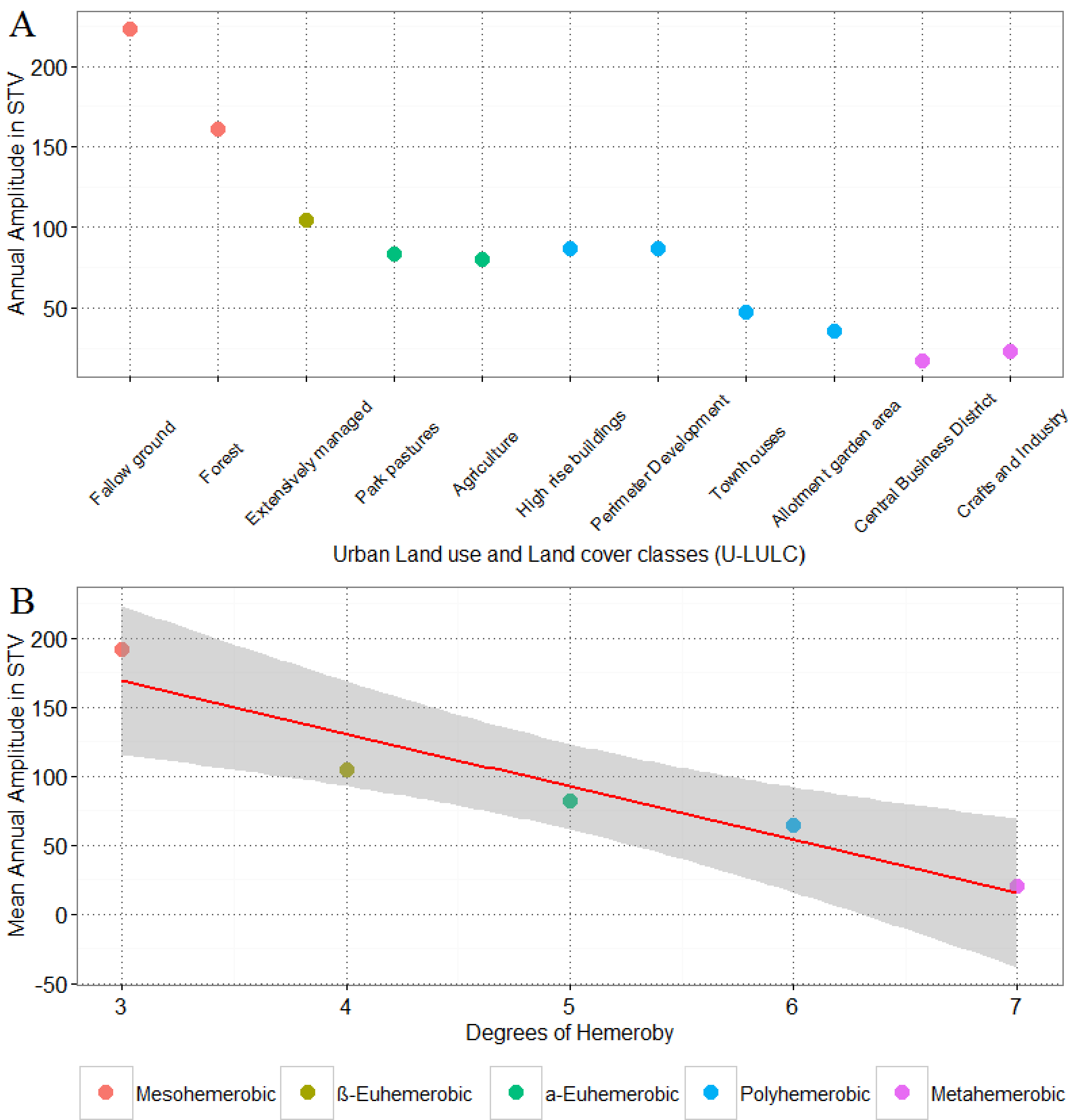

Fig. 5 (A) All analysed urban land use classes with their corresponding degree of hemeroby and their annual amplitude in spectral trait variations (STV) measured in GLCM Variance; fallow ground, forest, extensively managed- and park pastures were measured with GLCM Correlation. For normalization, the value range was fitted by a factor of 1000. (B) The mean annual amplitude of spectral trait variation (STV) in relation to the degree of hemeroby of the analysed urban areas, with a fitted linear model in red and the confidence interval in grey, showing that for every degree of hemeroby we measure 38.5 less in the annual amplitude in spectral trait variations (STV); the degree of hemeroby Metahemerobic and ß-Euhemerobic were measured in GLCM Correlation, the rest in GLCM Variance.

For the regarded urban land use classes, we find that the STV contained in different land use classes varies substantially. This is true for their mean annual STV, the amplitude as well as the annual course of the STV. This is primarily due to the fact that land use management schemes systematically vary between different land use forms. The vegetation that is found between sealed surfaces, in rather densely-populated areas is thereby of pronounced importance because while it delivers vital ecosystem services it is subject to a wide variety of stressors. This underpins the fact that an integrated view of the city's ecosystems is necessary, that is not limited to the classical green infrastructure, but rather includes the dynamics of change across the entire city in a continuous temporal and spatial scope to draw conclusions about the nature of urban ecosystems.

4.2. Quantification of urban land use intensity by remote sensing for single land use classes

4.2.1 Urban built land

For the built land use classes (Fig. 6), STV between the different building- densities, shapes and sizes varies substantially, demonstrating that even in densely-populated and therefore intensely-used areas, different types of vegetated areas can exist in a relatively small space (Fig. 7). Figure 7 shows that land use classes with the same degree of hemeroby are discernibly clustered together. These two major groupings are high-rise buildings, perimeter development and townhouses on the one hand featuring polyhemerobic habitats, and industrial areas and the CBD on the other, featuring metahemerobic habitats with (almost) exclusively sealed surfaces and a completely damaged biocenosis. Both the mean and the annual amplitude follow the trend that lower values represent a higher degree of hemeroby. (The exception of the allotment gardens will be discussed in the course of this section and in section 5.)

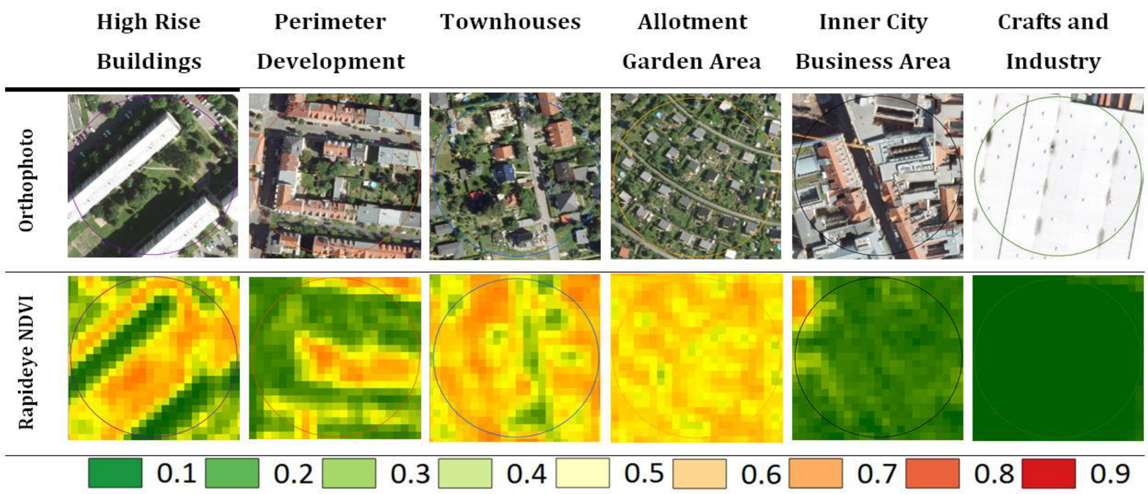

Fig. 6 Orthophoto and the corresponding NDVI values quantified by RapidEye data for urban built land use classes

The main determinants for the STV in built-up areas are the degree of surface sealing, defining the general available space for plants, and secondly the anthropogenic management techniques. This means that higher levels of unsealed surfaces or greenness do not directly translate into higher STV. For instance, even though they are subject to less surface sealing the newly build townhouse areas feature lower STV compared to the perimeter development areas. This is due to higher green space management intensity and the fact that these areas feature large sections of fastidiously cut lawn and not yet old but fast-growing tree species. Comparable management schemes between neighboring gardens lead to the situation that adjacent RapidEye pixels are spectrally very similar resulting in less spatial STV. This also holds true for the temporal STV dimension, since multiple phenology related traits are absent in the presence of management schemes such as cutting, weeding, watering, fertilization and the application of pesticides. In contrast to this the perimeter development areas, feature large old-growth trees with other green areas in their back yards, leading to a higher annual amplitude in STV. The higher share of deciduous trees in comparison to evergreen lawn can also be derived from the fact that the STV recorded in winter are higher for the areas with townhouses and lower for perimeter development areas.

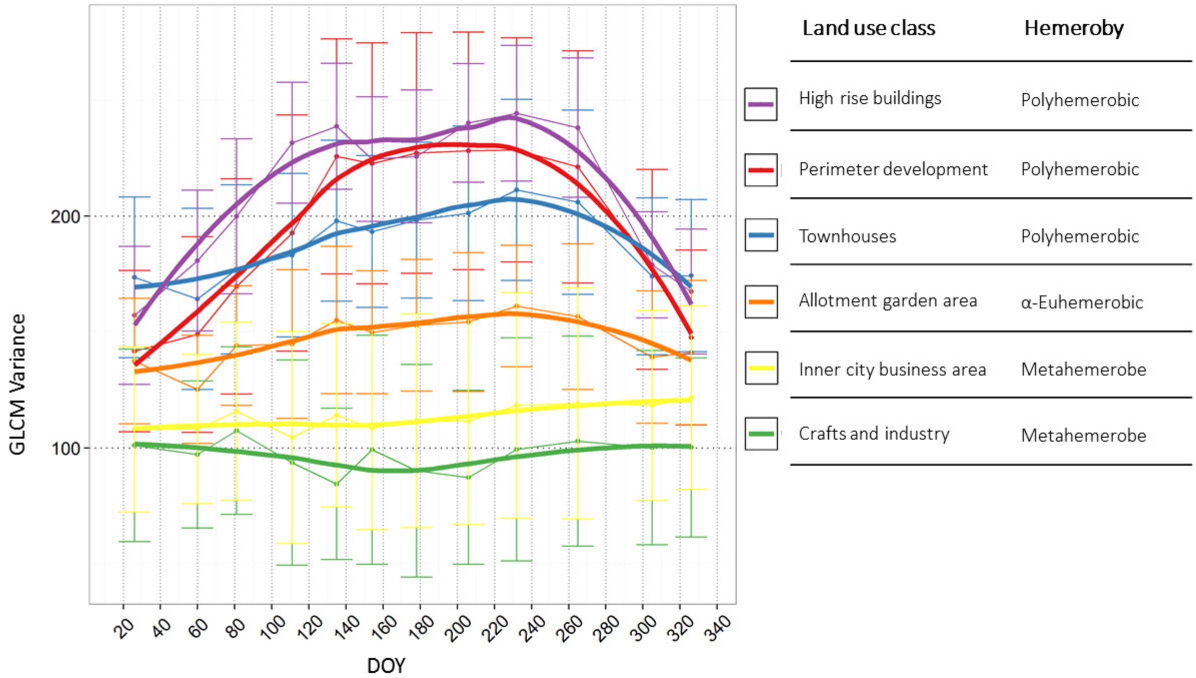

Fig. 7 Spectral trait variations (STV) of six urban built land use classes and their corresponding hemeroby values. The GLCM variance values are given over the course of a year (DOY = day of year).

For the built-up land use classes in question we find a strong relationship between spatial and temporal STV. It is true that the higher the classes' annual STV mean, the higher the annual amplitude. The industrial class, on the one hand, is absent of vegetation and lacks an annual amplitude, because the measured variance solely originates from either the buildings, the background noise from the sensor or illumination effects. The polyhemerobic land use classes on the other hand, feature both a much higher mean and amplitude. The amplitude thereby particularly depends on the green space management intensity. This exemplifies how the connection between spatial and temporal variability is related to both the degree of sealing and green space management.

4.2.2 Pasture land

Our results for the pasture classes follow our hypothesis, that the higher the land use intensity and the degree of hemeroby, the lower the spectral trait variations. For the most intensively managed pasture type we measured the lowest variations in spectral traits (park pastures) and for the least intensively managed pastures we measured the highest variations (succession) (Fig 8).

The low STV for intensively managed pastures can predominantly be traced to the monoculture planting scheme and the high cutting frequency, which serve as important filters for many plant traits such as variation in growth height, different leaf forms or traits that are related to different stages of the phenological cycle. The extensively managed pastures feature lower levels of management intensity and higher spectral trait variations, especially in summer. This is primarily due to a lower cutting frequency, allowing plants to run through larger parts of their natural life cycle. In this respect, the phases of flowering and maturity are particularly important as it is during these phases that different plant species produce unique traits such as different flower colours and forms or different seed sizes. Spectral trait variation for the two classes under investigation is very similar in spring (DOY 60, 80 & 110) and during the autumn/winter time frames (DOY 220-320), which could be attributed to cutting taking place in both pasture types. This observation emphasizes just how great the need is for spectral trait diversity analysis to feature multi-temporal data that covers all major phenological stages and abrupt changes due to human influences.

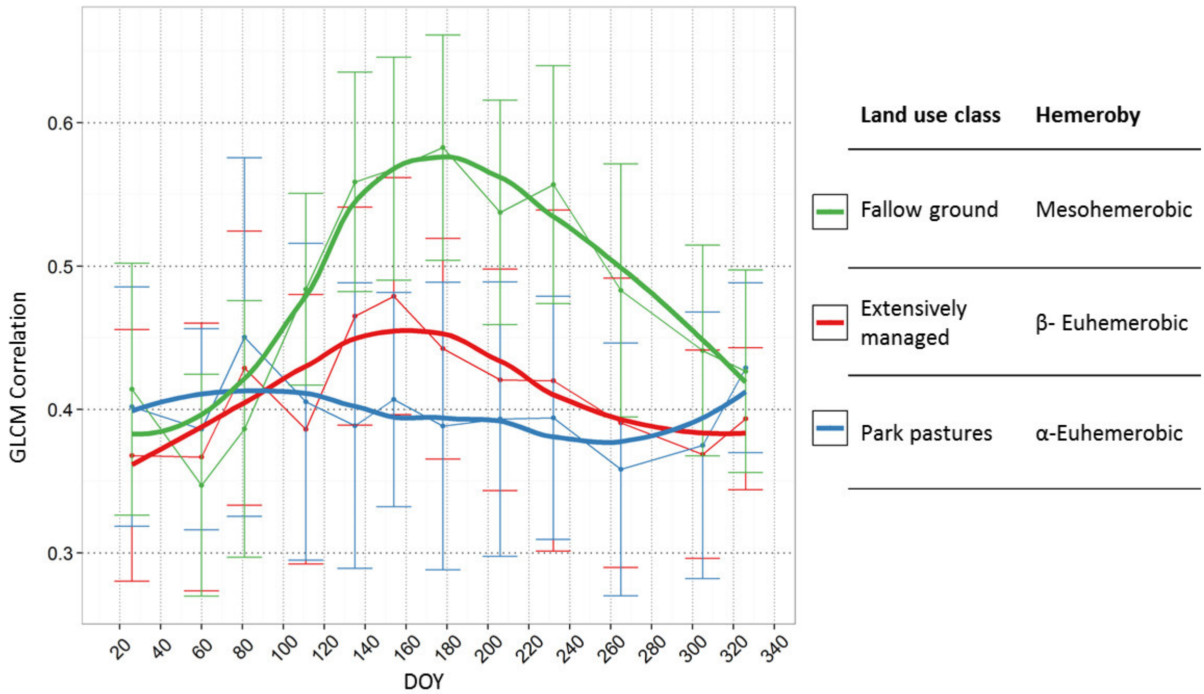

Fig. 8 Spectral trait variations (STV) of three urban pasture types and their corresponding degree of hemeroby. The GLCM correlation values over the course of a year are shown.

We measured the largest spectral trait variations on fallow land that has only been subjected to human actions in the past or is only affected by the surrounding urban landscape (e.g. soil sealing, contamination, eutrophication and the restriction of dispersal vectors). These systems are able to develop a wide variety of plant traits from a range of different plants that are part of the grassland mosaic. These include different forms of leaves – broad-leafed and coniferous species; different growth heights - from grass to shrubs or even trees; and different forms of flowering. This variety is then reduced in the summer months when deciduous plants also feature a large set of traits, and flowering plants exhibit the traits of flowering and their seeds.

4.2.3 Farmland

Mechanized agriculture can be thought of as an intense repetitive intra-annual land use intensity gradient that basically consists of ploughing, seeding and harvesting and produces different spectral traits over the course of the year. To account for different cultivation schemes, we subdivided our sampling areas into fields that show photosynthetically active vegetation in winter and those that do not. Due to crop rotation, it is very likely that the same plant grows on the field in successive years. Since we aggregated remote sensing data from two years, we suggest that the effect caused by different plants in terms of their STV is smaller than the general repetitive character of the system.

In spring, STV are higher in those fields with plant cover in winter compared to those fields without (Fig. 9) (DOY 26 is an exception that is likely to be caused by illumination effects). In late spring / early summer time frames, when the newly planted fields start to grow, both curves align with one another. Between DOY 180 and DOY 200 in late July and August, both index curves drop significantly (Fig. 9). This sharp drop relates to the main harvesting time, when most of the plants are eliminated. Subsequently, farmers mulch and plough under the crop residues, eliminating the vegetation and subsequently any remaining traits. Since this procedure is thought to greatly eliminate any crop pests, it is fair to assume prompt and rather consistent action of the farmers, showing that STV analysis from remote sensing data can trace specific human management intervention. The rise in GLCM Correlation for the winter recordings (DOY 305 & 326), is very likely to be caused by illumination effects due to the low sun angle.

Fig. 9 Spectral trait variations (STV) for fields, subdivided into fields that are cultivated in the winter and those that are not. The GLCM correlation values over the course of a year are shown.

4.2.4 Forest

The intra-annual changes observed in STV in Leipzig's urban forest can be attributed to natural phenomena, namely the phenological cycle. Spectral trait variations in the forest are highest in spring, with a slight increase in autumn (Fig. 10). In the winter and the summer months spectral trait variations in Leipzig's forest are comparably lower. In periods with high GLCM variance values there is a strong shift in various traits in terms of photosynthetic activity and general chemical leaf composition. While the spring phenophase is characterized by foliation, autumn is dominated by foliage discoloration and leaf fall. Since different plants have differently timed onsets for these changes, a heterogeneous cover unfolds in spring and autumn. In summer, when all trees feature a dense canopy and the photosynthesis capacity is consequently higher, the spectral trait variations between adjacent areas are lower. Since there is only one larger consistently managed forest in Leipzig with low land use intensity, it is not possible to draw conclusions about the effects of human land use on STV in a forest ecosystem.

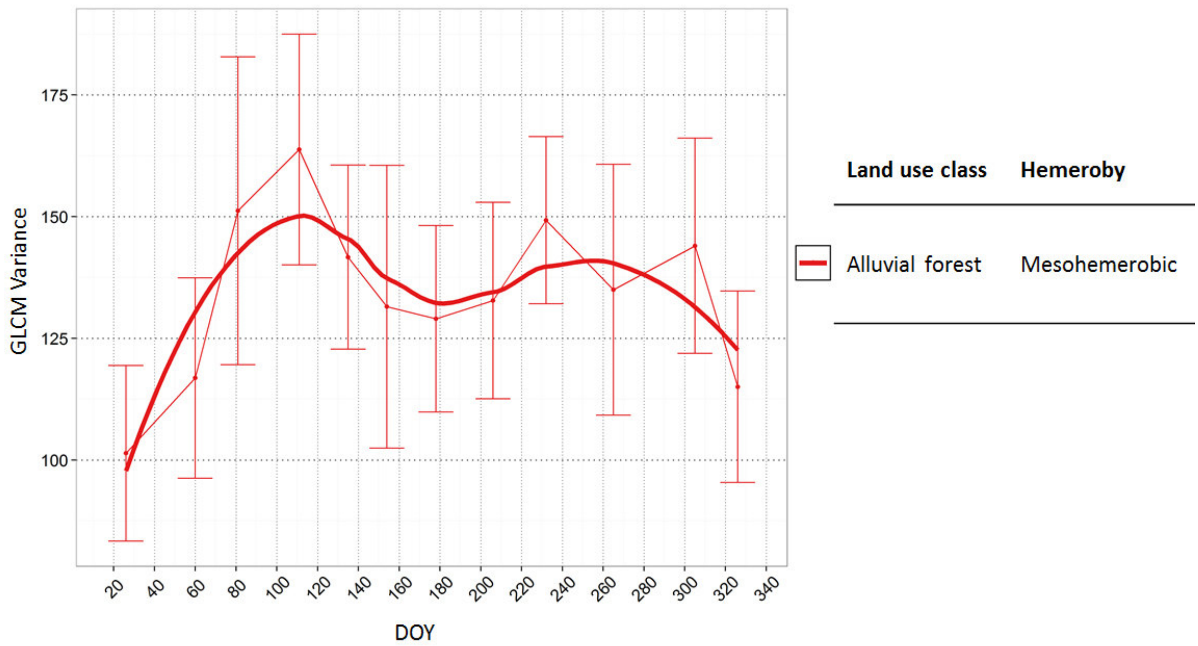

Fig. 10 Spectral trait variations (STV) for the urban forest of Leipzig over the course of a year, the GLCM variance values are shown.

5. Discussion

By adding the spatio-temporal component to the ST and STV concept, we developed a framework that analyses land use intensity and its effects on the degree of hemeroby irrespective of the categorical land use data. This is an important new reference point in the ecology of the urban landscape and land use intensity assessment. Since the concept of plant traits is a functional framework in which each trait can be assigned to one or more ecosystem functions, (Lausch et al., 2016(2); Violle et al., 2007) the assessment of STV is a promising step not only for assessing the functional diversity in an ecosystem (Diaz et al., 2004) but also for improving the interpretation of the effects of human activity on land and its specific place-based temporal/seasonal impacts on the affected ecosystems (Hill et al., 2002). The use of remotely sensed data thus opens up the opportunity of spatially continuous comparisons of entire landscapes over longer periods of time.

From the three vegetation remote-sensing indices (NDVI, NDVIre, gNDVI) and the three different combinations of principal components from a PCA, we found that the NDVI is superior to the other indices in representing spectral traits. The NDVI is a well-proven index that is sensitive towards a variety of key spectral traits: It correlates with photosynthetically active radiation (Gamon et al., 1995), allows for the differentiation between canopy structures and phenological characteristics (Gamon et al., 1995; Reed et al., 1994) and can differentiate between different ecosystem functional types or determine an ecosystem's net exchange of CO_2 (Alcaraz et al., 2006; Morgan et al., 2016; Wang et al., 2012).

To calculate the distribution of ST, we successfully used the indicators GLCM Correlation and GLCM Variance and were thus able to determine STV. The other indicators used in this study (table 4) allowed for no consistent and meaningful linkage between STV and hemeroby or did not provide as much contrast between the single classes. We found that GLCM Variance proved to be best in built-up land use classes, whereas GLCM Correlation was better for land use classes solely with vegetation. Geary's C and Moran's I produced results with tendencies that were very similar compared to GLCM correlation, but without offering as much contrast between individual classes. The similarity between GLCM correlation and the means of spatial autocorrelation is very promising and in accordance with the literature, especially as those measures are independent in their calculation (Van Der Sanden and Hoekman, 2005).

The STV featured in different types of urban vegetation varies strongly and depends on human land use intensity and specific management strategies over the season/year. Results generally follow the trend that the lower the human green space management intensity, the higher the STV. This is in accordance with the hemeroby classification of urban sites introduced at the beginning of the paper. Thus, our STV analysis is a proof-of-concept for deriving urban land intensity and hemeroby from remotely sensed data.

We thereby find that of emphasized importance is thereby the amplitude in STV. This is because heterogeneity caused by sealed land is stable over the course of the year. Only changes in vegetation due to stressors or phenology can cause intra annual change. While this provides for a god and effective starting point more sophisticated indicators could be calculated in upcoming studies.

What is also interesting is the large gradient in STV between the different types of built structures, implying that the ecological diversity between primarily sealed land can be very different. The high trait diversity in the late 19th century districts dating back to the Wilhelminian period with their large backyards with old mature trees is very much in accordance with recent literature, stating that both plants and birds can develop a high diversity in these areas, compared to other inner-urban areas (Müller, 2009; Strohbach et al., 2009). This highlights the need for urban landscape planning that focuses much more on the qualitative aspects of plant trait diversity, particularly in times of strong urban growth and the trend towards infill development (Schetke et al., 2012).

The classification of different types of pasture land using remote sensing is difficult and has so far only been partly solved (Schuster et al., 2015). This is also true for the differentiation between different land use management intensities (Franke et al., 2012). These shortcomings are largely due to the high spectral similarity of pastures and grasslands, the small size of objects to be measured, and the overall small spatial extent of such habitats (Schuster et al., 2015). With our approach, the diversity in grassland habitats could be analyzed. Moreover, promising results in the domains of agriculture and forests indicate that our study can be transferred into peri-urban and rural areas.

We conclude that in the urban context; less management or reduced land use intensity result in a higher diversity of spectral plant traits, i.e. higher functional diversity. As functional diversity supports a range of ecosystem services such as pollination or wood provision ((Lavorel, 2013) and references therein), the preservation of it should be a central goal of land management. We therefore see a tremendous need for strategies and programs that inform policy makers, land owners, planners and managers about the verified impacts which intensified management actions, such as mowing, irrigating, and the application of pesticides and fertilizers have on the diversity of life in cities and the services it provides for us. Hence, we strongly believe that it is important to get urban land owners and other stakeholders to become part of creating change towards a more diverse urban biosphere.

Uncertainties

Scaling is one of the key uncertainties in ecology when comparing patterns observed on different spatial scales. One example from our study is the comparison of town house and allotment garden areas, which both tend to exhibit a matrix of built-up and vegetated structures that consist of the same compartments, only that in the case of the allotment gardens everything is somewhat smaller. Therefore, the structures of the allotment garden areas are aggregated into mixed pixels, meaning that a comparative assessment between differently scaled biotopes is hard to achieve. What is true for the scaling of such patterns extends to the scaling of the data derived from these patterns. We therefore highlight the fact that this assessment is only comparable to studies featuring equally scaled data (6.5x6.5m). For the analysis of small-scale structures, finer resolution images are required.

We analysed all 12 land use intensity classes in separate groups, because of various issues regarding the scaling and as a consequence thereof, different levels of aggregation. The level of aggregation depends on the relational scaling between the sensor and the object and therefore changes when objects of different sizes are analyzed. While, for instance, the canopy of a single tree might well fill out an entire RapidEye pixel, the canopy of a grass stalk only fills out a very minute portion of one pixel. This results in the fact that grassland pixels are much more of an aggregation of an uncertain amount of stalks, possibly belonging to different species that exhibit different traits and other abiotic components compared to single trees. In contrast, the forest pixels will show much less aggregation of different individual plants, featuring varying traits and an abiotic background signal. While the different degrees of aggregation are already important for mere image classification, they are even more important when measuring the variance of image regions (Woodcock and Strahler, 1987).

6. Conclusions

With spectral trait variations from a dense remotely sensed time series we can estimate urban land use intensity and the degree of hemeroby for large spatial areas. Adding attributes of space and time to the spectral traits concept opens up the possibility of analysing these important indicators for urban and open land surfaces in a repeatable, comparable and cost effective manner.

By expanding the analysis of land use intensity and hemeroby in the urban environment beyond land cover maps we open up the opportunity of spatially continuous comparisons of entire landscapes over longer periods of time, irrespective of a classification procedure. Remotely sensed data still reflects the physio-chemical information of both the vegetation and the soil layers that were grabbed by the sensor. Only then properties of the living elements of the site/area can be analysed and interpreted such as the differentiation of lawns or forests in a city according to their fitness and greenness which would be not at all possible using land cover maps.

Upcoming studies should use the spatially continuous spectral data of remote sensing missions rather than analysing specific patches. For this purpose, the integration of the presented routine into remote sensing based classification tools would be desirable. At the same time, more ground truth measurements of traits are necessary to verify remote sensing data. If these obstacles are overcome, the presented procedure could become an important cornerstone in decision making processes.

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