Haase, D., Jänicke, C., Wellmann, T. (2019):
Front and back yard green analysis with subpixel vegetation fractions from earth observation data in a city
Landsc. Urban Plan. **182** , 44 - 54

Research Paper

Front and back yard green analysis with subpixel vegetation fractions from earth observation data in a city

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This is the accepted manuscript.

For the published original paper see; DOI: https://doi.org/10.1016/j.landurbplan.2018.10.010

Highlights

- This paper introduces a novel approach to thus-far mostly neglected urban front and backyard green space in cities.
- We calculated subpixel vegetation fractions from RapidEye remote-sensing data for the entire city with a spectral unmixing technique.
- We applied a novel 'house-attached front and backyard green derivation algorithm' to the city of Leipzig with accuracy of 96%.
- Key findings include that the total amount of front and backyard green space is almost 2000 ha or 40% of the amount of public green.
- In 15 out of the 63 total districts, we found more house-attached front and backyard than public green space.

Abstract

This paper introduces a novel approach to green space availability in cities that includes the thus-far mostly neglected urban front and back yard green space around residential buildings on privately owned ground. To quantify the full spatial scope of urban green space, we calculated subpixel vegetation fractions from RapidEye remote-sensing data for the entire city with a spectral unmixing technique that enabled us to model the extent of urban vegetation with a high degree of confidence (MAE 7%, R^2 0.92). We then applied a novel 'urban front and back yard green space derivation algorithm', namely, a masking of the fractional vegetation data using GIS vector data of land cover, in order to delineate the front and backyard greenspace of residential houses in a city with an accuracy of 96%. Combining these two approaches, we can calculate the area of urban front and back yard green space for the entire city (including different residential structure types) and compare this data to the area of public (parks, urban forests) and semi-public (allotment gardens) green spaces that have been used for prevailing per capita green space availability analyses. The new method is exemplified at the city of Leipzig, Germany, which provides different residential structures concerning house types and the surrounding green that are characteristic of many European cities. Key findings include that the total amount of urban front and back yard green space is almost 2000 ha, which is ~40% of the amount of public green space (4768 ha). In 15 out of the 63 total districts, there is more private house than public green space, which highlights the importance of these urban front and back yard green space for the analysis of urban livelihoods and a tool for detailed ecosystem services-oriented urban planning.

Keywords

Front and back yard green, remote sensing, RapidEye, delineation, urban green space availability, spectral unmixing, sub-pixel mapping, urban planning

1 Introduction

Until now, the literature on green space availability in cities has mainly referred to public (parks, forests; Voigt et al., 2014) and different types of gardens when either mapping (Dennis et al., 2018) or calculating accessibility and availability (Comber et al., 2008; Fuller & Gaston, 2009; Kabisch & Haase, 2012; Kabisch et al., 2014; Kabisch et al., 2016; Larondelle & Haase, 2017). Urban front and back yard green space is the only major type of urban green space that has rarely been analysed in its full and differentiated quantitative scope, even more sporadically on a citywide level (for a promising approach see Dennis et al., 2018). Residential green space refers to the vegetation that surrounds residential buildings, directly attached to it in form of flower beds, lawns with or without trees in the front and backyard, or between houses in the case of a block location. Residential green space is also related to different forms of property rights and ownership constellations in the city and, therefore, this type of green space can hardly be derived from official land-use data. This is the research gap that we intend to fill with this study.

In general, urban green spaces can be subdivided into three groups of ownership: firstly, public green space including parks, cemeteries and urban forests; secondly, semi-public allotment garden areas and sport facilities, and thirdly, private-house and backyard green with limited (physical or jurisdictional) access for the tenants (Fischer et al., 2016). We define urban front and back yard green space as that which directly surrounds the residential houses, including front and backyard green space and what is most probably private and not public.

Numerous qualitative studies have shown the importance of house and backyard green space on public health (Bosch and Sang, 2017), happiness, life satisfaction and for urban biodiversity (Taylor and Taylor Lovell, 2014; Strohbach et al., 2009). There are areas in a city in which the major allotment of green space can be found around privately owned houses and backyards. Even though only a limited share of urban dwellers, namely the residents of the respective houses, have direct access to these areas, they are important for climate regulation, air cooling, local recreation, and human well-being to list a few important ecosystem services. With regard to an increasing number of elderly and aged residents in our European cities, local recreational amenities have gained in importance in enabling healthier lifestyles among older people (Brookfield et al., 2015).

Regardless of its importance for the city, the literature widely overlooks front and back yard green space front and back yard green as an important form of urban vegetation (Coolen and Meesters, 2012), mainly due to limited data availability and data access (Breuste et al., 2016). To overcome this lack of assessment of urban front and back yard green space, we provide a straightforward blueprint for how to generate such a dataset using remote sensing imagery and a limited number of vector layers.

With the use of remote sensing data, we achieve a spatially continuous analysis and open up the potential for long-term trend analysis. In order to quantify the amount of green space, we use a subpixel mapping approach with Random Forest Regression, a relatively new approach that is regularly applied to different fields in generating classifications of urban land cover. Random Forest Regression is widely used across disciplines and, as in the case for multispectral remote sensing data, is effective in handling multidimensional data with a high degree of collinearity. This is achieved in training the model with a multitude of decision trees. The entire methodology used in this study will soon be available in the open-source EnMapBos QGis Plugin (van der Linden, 2015) – an in-house development that facilitates techniques of analysis based on advanced remote sensing.

With this research paper we therefore introduce a GIS- and regression-tree-based scheme for the creation of a city-wide urban front and back yard green space delineation in the form of a spatial data set. In addition, we perform an analysis of this urban front and back yard green space type that includes a quantitative comparison with public and semi-public green spaces in order to search for complementarities and synergies.

2 Study Area

Leipzig is a fast growing, compact city (580,000 inhabitants) located in the eastern part of Germany and featuring a wide variety of building types and a wide variety of public, private and semi-public (with opening times) green spaces across its 63 districts. The provision with green space in the city is below mid-European and also German average. While the distribution of public and semi-public green spaces has already been analysed in previous studies (e.g. Haase and Nuissl, 2010; Haase and Gläser, 2009), front and back yard green space is, as in the case of all other cities, beyond the scope of the current research. The largest body of public green space in Leipzig – the Weiße-Elster-Pleiße floodplains – is arranged along a north south gradient to the west of the city centre (Haase & Gläser, 2009). Semi-public allotment gardens are relatively equally distributed across the city, particularly within the wetlands of the floodplains and along major roads and railways. The major residential types in the city are Wilhelminian-period perimeter development blocks, alignment blocks built in the 1950s and 1960s, prefabricated high-rise buildings from the socialist period (dating back to the 1970ies and 1980ies of the 20th century), late 19th and early 20th century villa districts, perimeter block estates of the 1950s and 19 60s, single-house colonies in the peripheral districts and, after 1990, townhouses built to fill vacant lots in the inner city (Haase and Nuissl, 2010). Between these major urban built structures, privately owned residential green space is distributed very unevenly. Its share ranges from almost zero to considerable green coverage around the houses, with larger absolute amounts of front and back yard green space in the townhouse and villa areas in comparison to the denser inner-city Wilhelminian perimeter-block quarters.

3 Data & Methods

With the exception of sealed surfaces, urban front and back yard green space – including the front and backyard green space of residential houses that are predominantly on private individual property or that of private housing companies – are all green spaces as defined above. We thereby calculate the fractional amount of vegetation of each of the pixels situated in the privately owned areas around the houses in order to calculate the actual amount of green space. We exclude bare soil since, in the moment of analysis, it is not vegetated. However, this can rapidly change and is therefore often incorporated in green space definitions. Our analysis only incorporates ground-based front and back yard green space as defined above, rooftop green space as well as wall green remains excluded in order to keep the delineation algorithm simple and to minimize miss-classifications.

From our dataset we can derive multiple indicators, comparable in different (spatial) reference units (e.g. land-use type, urban districts, per capita etc.) and between entire cities. Thereby, both the total area values (m^2) and the relative values (%) can be obtained. To derive sub-pixel fractions of vegetation, we used a Random Forest Regression combined with ensemble learning and synthetically mixed training data, an approach successfully applied to map urban land cover (Okujeni et al. 2013, Okujeni et al. 2017, Rosentreter et al. 2017). The underlying assumption of this method is that spectral reflection changes with land-cover composition. Pure spectra of trees show different spectral characteristics than pure spectra of soils or impervious surfaces such as streets or pavements. Due to the high degree of heterogeneity in the urban environment however, most pixels do not contain pure spectral information but are rather a mixture between different land-cover classes. The spectral signature depends on the environmental heterogeneity resulting in different fractional abundance of each land-cover class in different pixels.

The relationship between the covered area and the signal change can be described by a linear function (Keshava & Mustard, 2002). Important in regard to the high degree of urban heterogeneity is that the training data needs to cover as many as possible combinations of different land cover compositions and spectral signals to train the model. In this study we overcome this challenge by generating training data that features pure spectral information in order to calculate synthetic mixtures between the spectra of pure land-cover classes. This approach simplifies the training data collection greatly because only pure spectra need to be sampled.

3.1 Data

Our quantitative assessment of house and backyard green space makes use of the capability of RapidEye satellite data sensor, which acquires data in five spectral bands (R,G,B, red-edge & near infra-red) with a ground resolution of 6.5meters resampled to 5 m. For our study, we acquired two cloud-free RapidEye images of Leipzig and its surroundings from the year 2012 (14.05.2012) and corrected for atmospheric influences with ATCOR (Richter, 2011). For the validation of our regression model we compiled a validation dataset based on very high-resolution (VHR) satellite imagery from Google Earth. The dataset encompasses 141 validation sites and spatially explicit mapping of vegetated areas, thus enabling us to calculate the fraction of green space in each of the polygons. For the purpose of deriving the exact location of three regarded forms of urban green space, a set of spatial vector data is used (Table 1). Most prominently in this regard are the biotope map and ATKIS (Amtliche Topographisch-Kartographische Informationssystem Deutschland) land-use database, which allow the detection of a variety of urban infrastructure.

Table 1. Vector datasets used in this study with date, source and a detailed description

Datasets	**Masked out areas**	**Date**	**Source**
City border	Rural surrounding	2014	Free State of Saxony
Biotope map	Public green and blue infrastructure	2014	Free State of Saxony
	Semi-public green infrastructure	2014	Free State of Saxony
	Agricultural areas	2014	Free State of Saxony
	Railway corridors	2012	Free State of Saxony
	Industrial and commercial sites	2014	Free State of Saxony
Roads	Road surfaces	2014	City of Leipzig
ATKIS	Building footprints	2014	Free State of Saxony
Public trees	Canopies of public trees	2012	City of Leipzig and UFZ

3.2 Methods

3.2.1 Estimation of subpixel vegetation fractions

For the estimation of subpixel vegetation fractions, we used spectral unmixing with Random Forest Regression trained with synthetic mixtures of pure land cover signals. Vegetation fractions are derived from a RapidEye scene. The Random Forest Regression models are embedded in an ensemble learning system to reduce the calculation time and to improve the subsequent generalization of the unmixing results (Figure 1; Breiman, 1996). Resulting maps are validated with a reference dataset created by visual interpretation of high-resolution imagery as described above (see section 3.1).

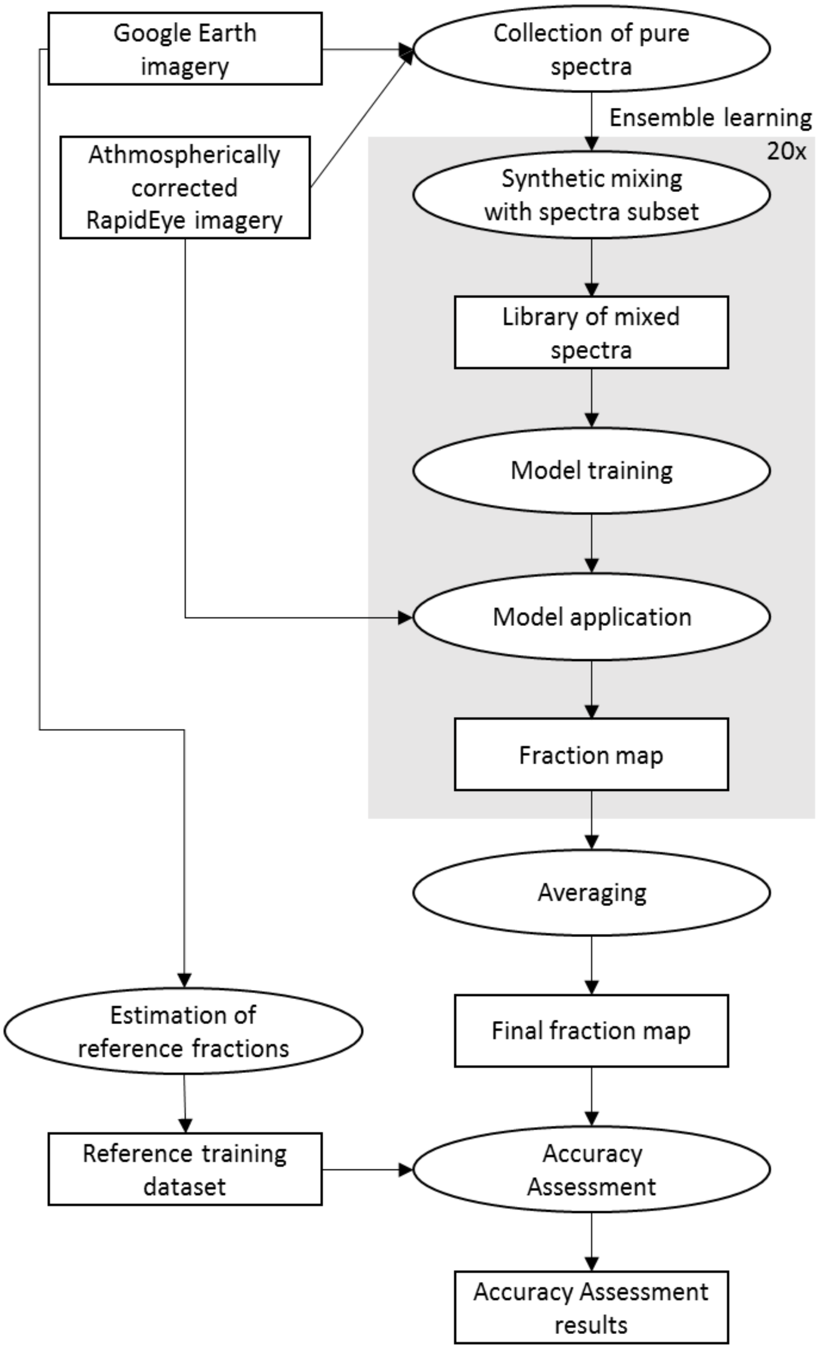

Figure 1. Flowchart of the applied subpixel vegetation modelling approach using spectral unmixing with a RapidEye imagery library.

3.2.1.1 Training data generation

We collected pure spectra of different urban land-covers present in the remote sensing data using Google Earth imagery. They were either belonging to the vegetation class or the non-vegetation class. With the help of the higher-resolution imagery from Google Earth, larger areas of homogenous land cover could be identified more accurately. Then, the spectral signal was obtained from the RapidEye imagery. We captured the original spectral variability in the scene by including as many different land-surface materials as possible – e.g. different rooftops, ground layers and tree, shrub and grass species. Overall, our library of pure spectra contains 39 spectra of the vegetation class and 62 spectra of the non-vegetation class.

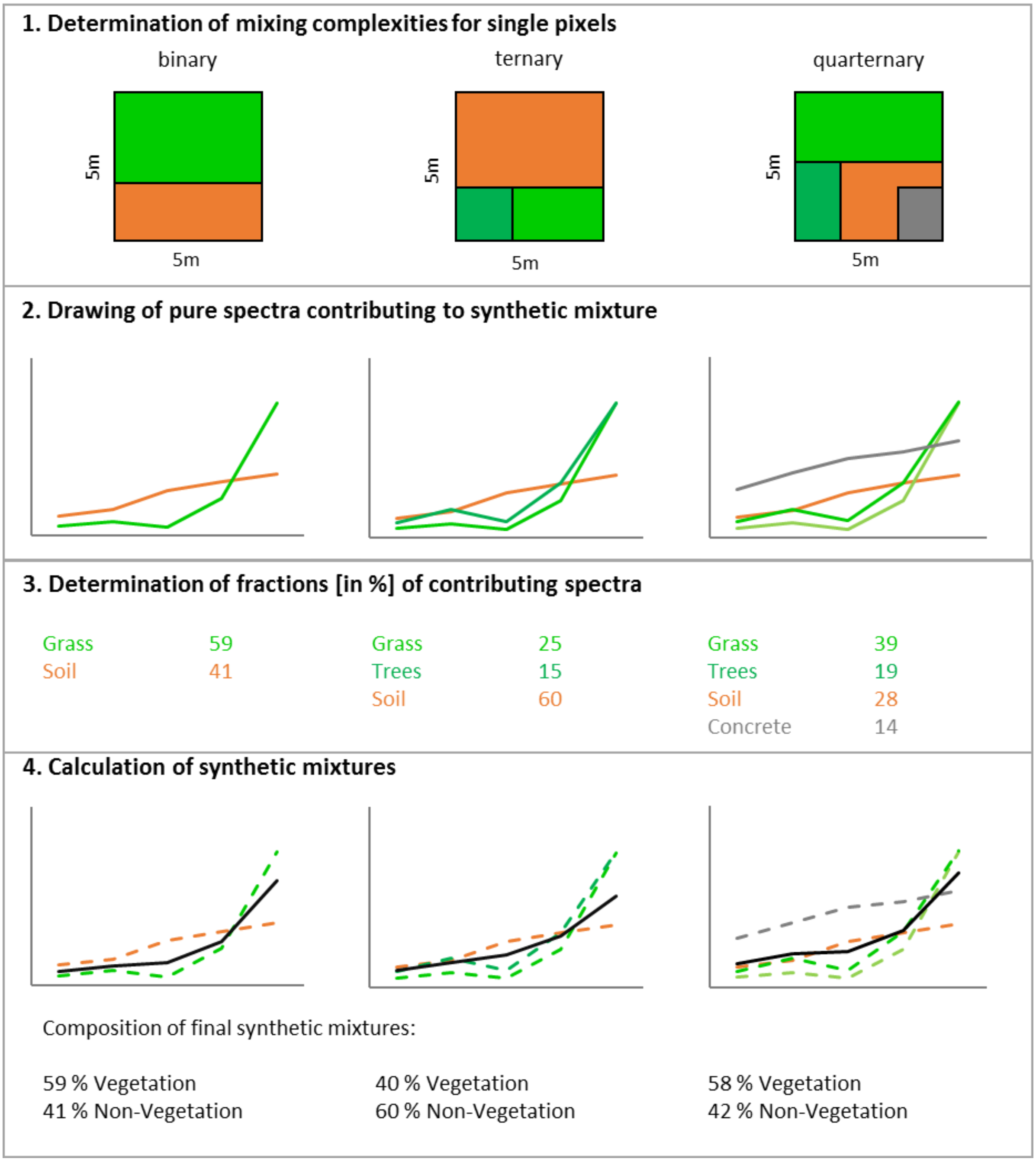

Figure 2. The concept of synthetic spectral mixing shown in four iterative steps. Firstly, a mixing complexity needs to be determined; secondly, pure spectra are drawn and thirdly, their respective share of their contribution is determined. Thereof synthetic mixtures are finally calculated.

The library of pure spectra was used to calculate the synthetic mixtures, i.e. the number of training data sets that were later used to train the Random Forest Regression. In order to generate a single synthetic mixture, several parameters and components need to be set including the mixing complexity, the actual spectra contributing to the mixture and the respective fractions of the contributing spectra. Subsequent parameterization was carried out in a randomized and automatic manner. The entire process consists of four steps (see Figure 2):

a. First, the mixing complexity was determined. It specified how many different spectra were contributing to the synthetic mixture (Figure 2, part 1). We considered binary, ternary and quaternary complexities that varied randomly per mixture.
b. In a second step, the actual spectra contributing to the mixture were randomly drawn (Figure 2, part 2). For binary complexities, two pure spectra were used and for ternary and quaternary complexities, three and four pure spectra were used. We allowed for intra and interclass mixtures.
c. After the pure spectra were determined, the fractions that each spectrum contributed needed to be specified (Figure 2, part 3). The fractions defined the extent to which each spectrum contributed to the mixture. We therefore used a randomized method under the condition that all fractions sum up to 100%.
d. Finally, the synthetic mixing could be applied (Figure 2, part 4). In our analysis, we calculated that there were 1000 spectral mixtures for each model in the ensemble learning (see section 3.2.1.2).

3.2.1.2 Random forest regression ensemble

Random Forest Regression is a classification procedure based on the process of ensemble learning. In this study, the Random Forest Regression was itself embedded in an ensemble learning system (Breiman, 1996). An ensemble learning approach consists of a specified number of Random Forest Regression models that are trained with a subset of the training data. Each of the resulting models is then applied separately to the RapidEye image. The resulting fraction-maps of the different model runs are subsequently combined by averaging. The approach of using training sample subsets for the development of models is called bootstrap-aggregation (bootstrapping, bagging) and was first introduced by Breiman (1996). In our approach, we trained 20 Random Forest Regression models with sample subsets consisting of 1000 random synthetic mixtures (see section 3.2.1.1).

3.2.1.3 Validation

We validated the final subpixel vegetation fraction map with reference to the aforementioned dataset (section 3.2.1.2). As a performance measure, we used the Mean Absolute Error (MAE)

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} \quad (1)$$

with y_i being the fraction of the reference polygons, x_i the average estimated fraction inside the reference polygons, and n the number of reference polygons. The model fit was assessed by the coefficient of determination R^2.

3.2.2 Calculation of the extent of parks and forests, gardens and front and back yard green

Since the full extent of urban front and back yard green space is unknown, we iteratively masked out every urban structure that did not represent urban-front and back yard green space from our vegetation fraction map. Public and semi-public blue and green infrastructure, agricultural areas, railway corridors, and industrial and commercial sites were masked out using a biotope map. Thereof, and according to the mean statistics of the vector data we have for the city, we defined buffers around roads (16m) and public trees (r = 5m) and clipped these from our imagery. Public trees were excluded, because in this paragraph the creation of the private front and back yard green layer is explained. Finally, buildings whose location was derived from the ATKIS dataset were masked out. The remainder of the satellite image is front and backyard green space.

For the delineation of public green space, the land-use classes of forests, parks, graveyards and grasslands, that are located in the forest or show early signs of shrub/tree encroachment as indicators of not entirely pure agricultural usage, were extracted from the biotope map. As semi-public green space, we defined allotment gardens and sport facilities as in the biotope map. By masking the remote sensing data iteratively using these datasets, we were able to determine the amount of total house-attached front and back yard green, allotment and community gardens, as well as public parks and forests at city level. Thereof, we calculated nine relative indicators: front and back yard green, gardens, parks and forests respectively per urban district, per capita and per land-use type (cf. Figure 3 in the Results section).

We validated the urban front and back yard green space dataset by randomly distributing 50 sampling points across the regarded dataset. Through visual interpretation, we were able to validate that 96% of the sampling points were correctly classified as urban front and back yard green space. The visual interpretation was carried out by a visiting of the randomly selected sites and an assessment of the authors whether the site belongs to most probably private house-attached or to public green. Of great help were fences and other visible delineations which indicate private properties or that a green lot belongs to a house. Since the other datasets are directly derived from a single, well-established GIS source, there is no need for validation.

4 Results

4.1 Subpixel vegetation fractions

The final vegetation map portrays the fractions of vegetation for the entire city with a high degree of certainty and allows us to distinguish between house-attached, public and semi-public green space. The map shows a clustering of public green space along a north–south gradient to the west of the city centre, which is a large remnant of alluvial forest situated on the floodplains. Allotment and community gardens are distributed relatively equally across Leipzig's districts with a lower abundance in the central districts. Urban front and back yard green space can be found in all of the districts and is especially abundant in the outer districts where residential quarters were constructed after 1990.

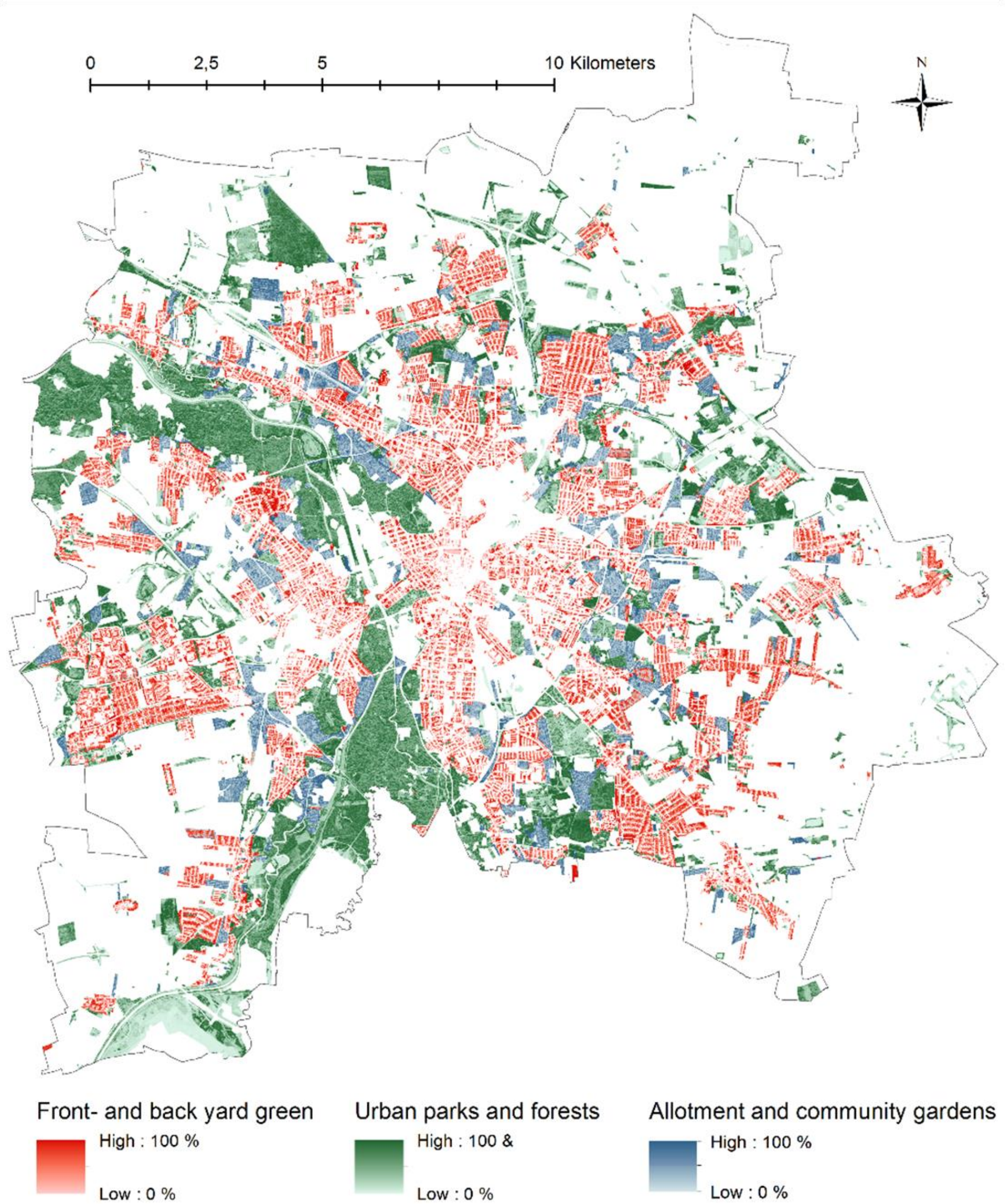

Figure 3. The extent of front and back yard green space, allotment and community gardens and urban parks and forests as important green space types in the city of Leipzig

An R^2 of 0.92 and an MAE of 7.4 % highlight a very robust overall model fit (figure 4). This is reinforced by the fact that the model data closely follows the diagonal, representing a hypothetical perfect fit. It can be derived from the formula that we are overestimating vegetation fractions in pixels featuring sparse vegetation as well as underestimating the amount of vegetation in areas of dense plant cover.

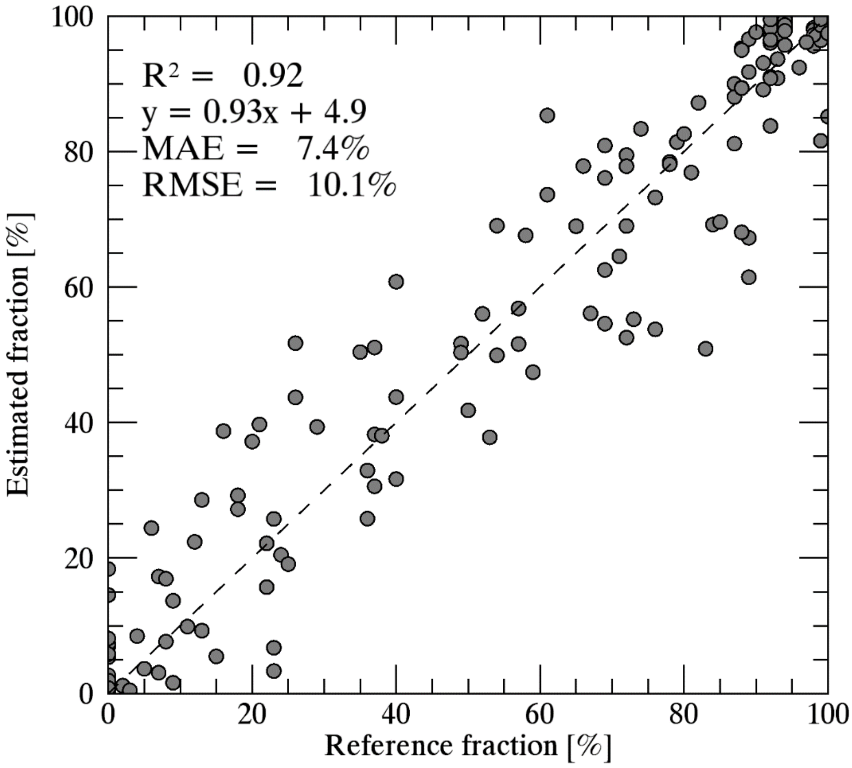

Figure 4. Validation plot showing the R^2, the mean absolute error (MAE) and the model formula of a fitted linear least squares regression between reference fraction and estimated fraction.

4.2 Extent of the different urban green space types

Analysing the new dataset of urban -front and back yard green space, we find a clear trade-off between public, semi-public and most probably private green spaces (Figure 5). Districts with high shares of public park and forest green space, namely the Leipzig floodplain forest or large parks, exhibit a lower share of house green space and vice versa. While the former group consists mostly of peripheral districts, including former village cores, are included, the latter group is mainly comprised of inner-city districts. Therefore, we can conclude that inner-city districts offer considerable availability of house green space compared to more peripheral districts which, surprisingly, have less backyard green space. Central parts of the so-called "Inner East" (centre-located reddish patches in Figure 5B), an under-privileged area with a high share of migrants and low-income families with many children, report both a comparatively low supply of house-attached and public green space, meaning that we also find clear inequalities in green space availability in the city and, indicating 'injustice' in terms of access to green space in Leipzig (Low, 2013; Kabisch et al., 2016; cf. again Figure 5).

The prefabricated socialist housing estates in the west of Leipzig, predominantly in the settlement of Grünau, show the highest supply of urban house green space by far, and thus, housing quality has potentially been underestimated if only analysed with previously existing public green space datasets (west-located reddish patches in Figure 5B). Houses in such prefabricated estates are often surrounded by larger lawns around the single blocks that are richly equipped with flower beds and some bushes or short trees. This type of green space is different from that in the old built-up perimeter blocks as the lawns are publicly accessible and, in most of the cases, not fenced in. However, the flower beds are under the care of the local residents of the blocks and thus this ‘lawn-green’ is dedicated to those families living in the large housing estates. Small signs also provide information as to which housing company the block and the lawns around belong to.

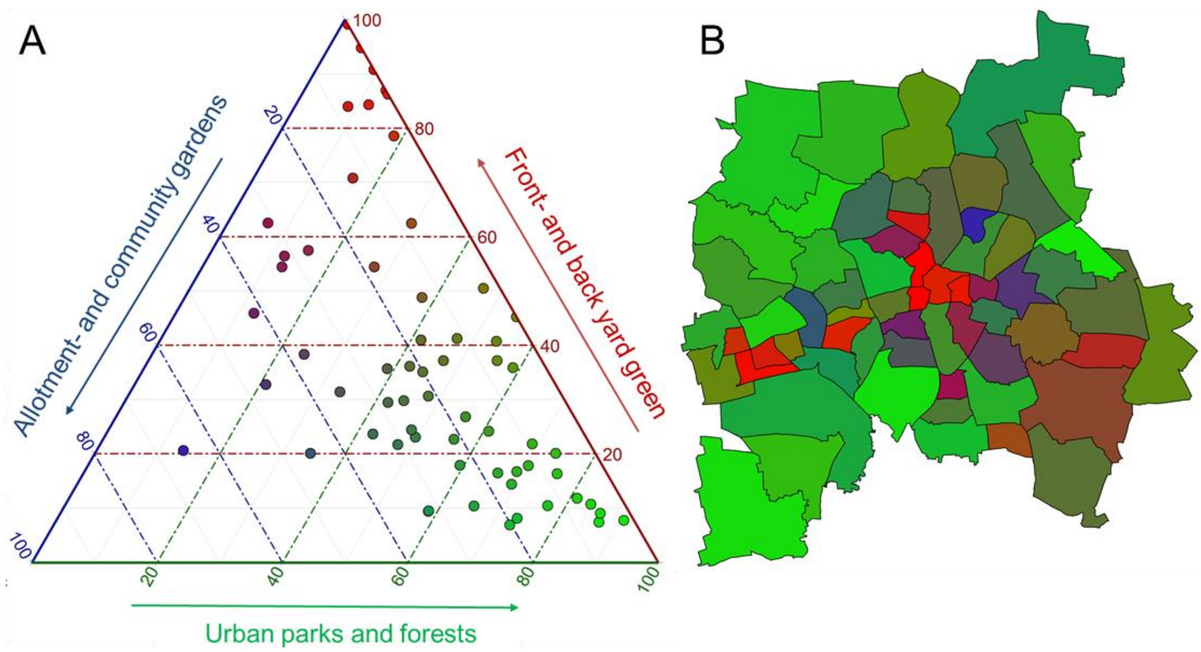

Figure 5. Ternary plot showing the relative amount of each type of green space in relation to the total amount (front and back yard green, gardens and parks and forests) for Leipzig’s 63 districts (A), whose locations are shown in (B).

Overall, in terms of absolute area (Table 2), public green spaces in the form of forest or parks make up almost half of Leipzig’s total green space. However, in terms of vegetated area, front and back yard green spaces cover an area of almost 2000 hectares compared to 4800 hectares of public green space. Due to the higher share of lawn vegetation, the vegetation density of urban front and back yard green spaces in Leipzig is lower compared to parks, forests and gardens (Table 2).

Table 2. Spatial extent of the three regarded green space types, their mean vegetation density and their share in the total city area

Green Space Type	Absolute area (ha)	Vegetated area (ha)	Vegetation density (%)	Share of the absolute total area in the city (%)	Share of the vegetated total area in the city (%)
Front and back yard green space	3518	1990	56	12	7
Allotment and community gardens	2166	1364	62	7	5
Parks and forests	5662	4768	84	19	16

In terms of the per capita supply, we find that all densely populated districts in Leipzig suffer from a significant undersupply of house-attached as well as parks, forests and gardens. Only a small number of districts (7) benefit from above-average house-attached and publicly accessible green space, while only 8 districts with dense population (according to Leipzig census data) contain above-mean front and back yard green space. For the garden-type green space, the picture is less segregated, with more people benefitting either from private or allotment garden green space; the number of people suffering from a double undersupply is lower compared to the chart showing the population number per public green space (Figure 6).

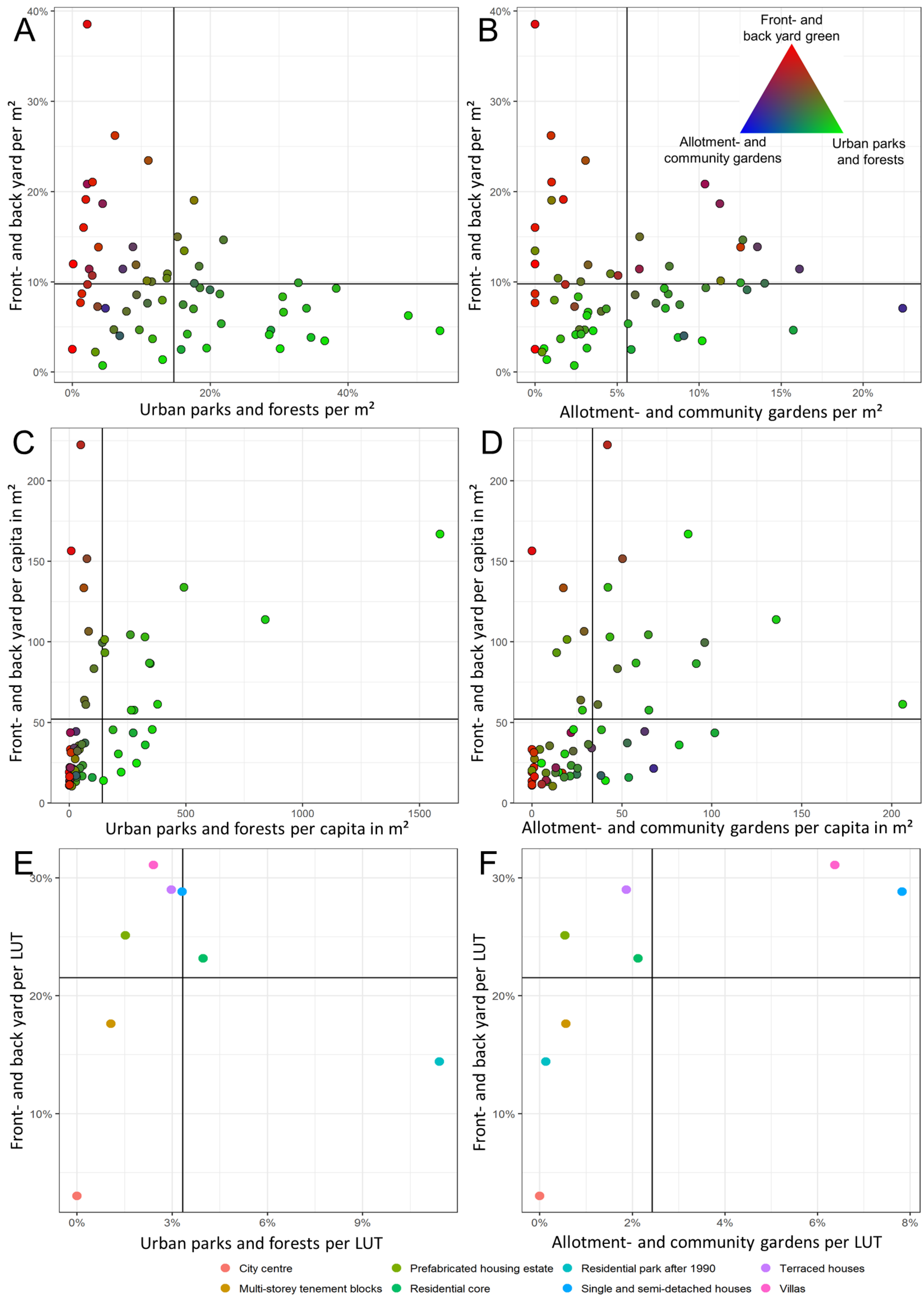

Figure 6. Share of parks and forests, gardens, and front and back yard green space relative to district area (A&B) and in m² per capita (C&D), for each of the 63 districts of Leipzig and per land-use type (LUT) (E&F) with indication for the mean value of the x- and y-axis, respectively.

We only find a small number of districts benefitting from both semi-public green space and front and back yard green space, as the supply with allotments is more limited than that with public parks and urban forests. Districts with high share of allotments are found along the floodplains in Leipzig, from south to north, and thus cover inner-city and peripheral locations (Figures 5 and 6). Interestingly, here we find almost all settings of residential areas that Leipzig has: privileged inner-city, poorer inner-city, prefabricated socialist inner-city and peripheral single/detached house areas (Figure 6).

In terms of per capita supply, the majority of the districts suffer from below average front and backyard green and park- and forest-type green space. There are only three districts with exceptionally high amounts of public and front and back yard green space.

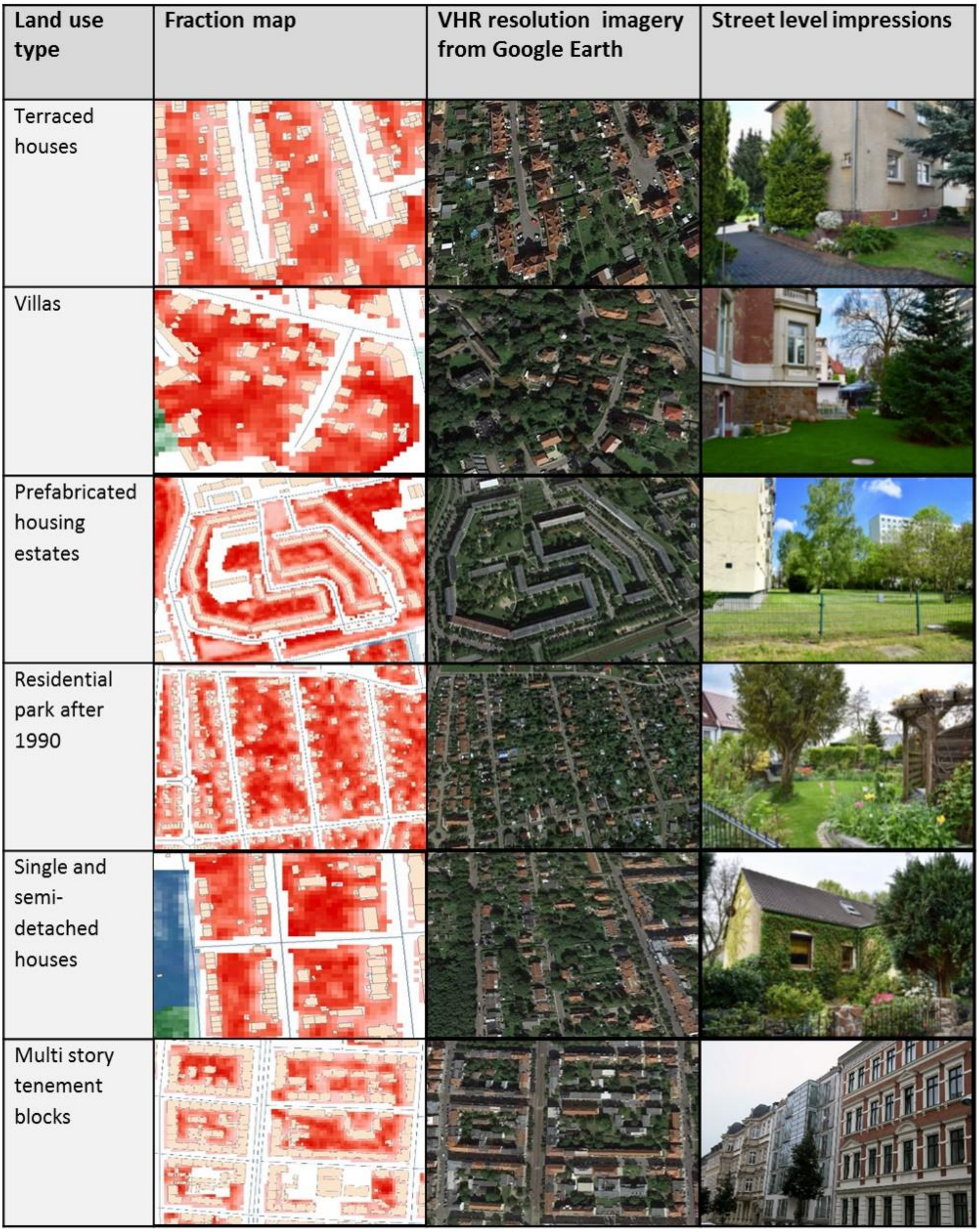

Figure 7. Overview of the most prominent urban land-use types in Leipzig, consisting of the fraction map, a very high-resolution (VHR) Google Earth satellite image and a characteristic image from the sites.

Concerning the urban residential structure types, the dense old built-up multi-storey perimeter block and tenement fabric shows in the city centre and the inner-city residential ring exhibit the highest undersupply with all types of green space: front and back yard green, gardens as well as parks and forests, although it is the most wanted in Leipzig at the moment. Exclusively the old residential cores including the city centre and the former village cores show both above average public and front and back yard green space. A hotspot with high supply of house-attached front and back yard green space are clearly the single house areas and the terraced houses spread across the whole outer city area as well as the urban villa areas close to the floodplains and allocated more in the inner parts of the town (cf. again Figure 7).

5 Discussion

The mixed method of RapidEye imagery and GIS-data combined with random forest models appears to be an efficient, straightforward and 'safe' way to delineate different types of urban green spaces including planning-relevant public green spaces such as large parks and forests, partly fenced and opening-time restricted allotment gardens, but also, house-attached green space as a category which has not yet been quantified for a city such as Leipzig and, what is more, are so far neglected in a systematic and all-encompassing green space assessment by the city planners. The results are in excellent agreement with an estimate by Breuste (2016) that states that front and back yard green space has often been neglected in urban green space assessments "although private green can often constitute up to 10% of the total greenspace in a city (page 213)**". The spectral unmixing of these different types of green space also allows a city wide and district specific quantification and assessment of distribution over- and undersupplies with both public and – most probably – private front and back yard green, which is essential for a modern urban green planning in large cities (Buijs et al., 2016). In particular for ageing cities such as Leipzig, a good estimate and a spatial allocation of front and back yard green spaces provides a more complete picture for planners where people can relax from heat when discussing adaptation to hot days and tropical night temperatures, one of the major health concerns of the future (Schinasi et al., 2018).**

In addition, and of major interest for both urban planners and urban ecologists, green space type-specific analyses between different urban structural types, and using housing areas from different eras, becomes possible at a very detailed spatial level. The validation of the extent of private green space could be validated by randomly distributing 50 sampling points across the dataset. That the resulting 96% of the sampling points were correctly classified is an excellent result. Since the other datasets, namely of parks, forests and allotment garden colonies, are directly derived from a single well-established GIS data source, there is no need for validation (Haase and Nuissl, 2007).

We are convinced that the method and the models we have developed and presented in this article can be of great help to (a) identify different types of urban green spaces and (b) quantify the amount of green space using spectral unmixing with trained random forest regression models. This method can also: (c) identify urban front and back yard green space for the first time, which is rarely to be found in any other urban green space classification created from remote-sensing data but that is of enormous importance for less mobile population groups in our cities (elderly, young children, disabled or chronically ill persons to list the most important affected groups; Brookfield et al., 2015). And, finally, this method can (d) bring the different types of public, semi-public and house green space existing in a large city at the level of the local districts in mutual size and availability relation which is key for a sustainable and just urban planning (Haase et al., 2017; Kabisch et al., 2016). However, it is important to state that our novel method characterises the spatiality of the quantity of green space types and not the quality.

Such a classification which we presented in the paper is not doable using the classical Biotope map as it mixes and partly aggregates green space types which we want to have separated. Moreover, the regional as well as the urban Biotope maps for many cities – among them Leipzig – are far too old for a present-day analysis and assessment. But, this novel approach is also of interest from a purely methodological perspective using remote sensing data for urban planning purposes. Even though we combined RapidEye with comparatively high-resolution satellite data, the calculation of vegetation fractions also allows for the integration of sensors with lower spatial resolution like Sentinel and Landsat. Fractions greatly enhance the accuracy of estimation in heterogeneous landscapes by calculating the amount of green in every pixel and thus delivering the actual extent of vegetation. Remote sensing indicators like the NDVI (Normalized Difference Vegetation Index; Tucker, 1979) have the potential to lead to valuable insights about urban greenspaces, however, they do not allow for exact spatial quantification because the state of the vegetation is assessed by the chlorophyll content, in the case of the NDVI. The entire procedure described in the methods section of this paper will be implemented in the upcoming QGIS Plugin of the EnMap box (van der Linden, 2015), an in-house development of the Geographical Institute of the Humboldt University of Berlin, Germany. This will open up the potential of this fraction-mapping procedure to the wider urban ecologists and environmental planning community who are aiming for more real-

world, evidence-based implementation and monitoring of green infrastructure at the city and urban landscape levels (Buijs et al., 2016). A potential coupling with three-dimensional indicators, such as those recently introduced by Alavipanah et al. (2017), would lead to very valuable indicators, for example, in the ability to determine the volume of green space next to trees which is crucial to know for urban planners to determine the shade and air pollution fixation potential of the green they implement.

Moreover, basing green space classification on remote sensing data has considerable potential for using long-term series of imagery and respective long-term change detection (e.g. ~40 years with Landsat images; Wulder et al., 2012). Remote sensing and the functional indicators that can be derived from it as spatio-temporal traits and trait variations (Wellmann et al., 2018; Lausch et al., 2016a, b) also permit a gradual distinction and assessment of urban green space functionality, which is key to more accurately monitoring and developing a better understanding of ecological (bio-geo-chemical) processes in the vegetation layer of cities. Traits can be also used for a more qualitative assessment (gains and losses) of taxonomic and structural biodiversity in cities (Lausch et al., 2015, 2016a).

Uncertainties: As in every remote sensing study, our study is accompanied by certain margins of error. Transferability: Since our study is based on several GIS layers, the transferability of our study in a 1:1 scheme is only given if these data sources are present. Another limiting factor in terms of data availability might be the use of RapidEye remote sensing data since it is not normally provided free of charge; however, with the new Planet Labs academic data policy the download of RapidEye scenes got feasible. Trade-offs accompanied by the use of coarser satellite sensors, such as Landsat or Sentinel, and also benefits of finer sensors (Worldview) will be reviewed in upcoming studies in order to justify and enrich the results and statements achieved in this study.

6 Conclusions

In this study, we applied a novel ‘urban front and back yard green derivation algorithm,’ namely a masking of the fractional vegetation data using GIS vector data of land cover to delineate the front and backyard green space of residential houses in a city with an accuracy of 96%. Combining these two approaches, we can calculate the area of urban front and back yard green space for the entire city (including different types of residential structures) and compare this data to the area of public (parks, urban forests) and semi-public (allotment gardens) green spaces that have been used for the analysis of prevailing per capita green space availability. In combination with the remote sensing based spectral unmixing techniques, we are able to delineate house-attached, semi-public and public green spaces in a mid-density Central European city with a high degree of certainty (MAE 7%). For the city Leipzig – a case in point in terms of structural characteristics and growth-shrinkage dynamics in Europe – key findings include that the total amount of house green space is almost 2000 ha, which is ~40% of the amount of public green (4768ha) and about 10% of the total urban area. In a quarter of all 63 total districts, front and back yard green space is the major source of green, a finding that highlights the importance of this structure for urban green space analysis of livelihood but also for urban planning and ecosystem service assessments.

The delineation of property-attached green that is not part of green space classes in classical land-use maps is therefore of pronounced importance. Using the novel and more complete dataset of urban green space, we can add this data to that of public (parks, urban forests) and semi-public (allotment gardens) green spaces to create a more complete picture of green space (availability when compared to the population data) in cities and to classify ‘hot’ (well-supplied) and ‘cold’ (undersupplied) spots. As this new green space class relates to private ground, it cannot be ‘simply’ part of the overall per capita green space availability equation (Kabisch et al., 2016) but is also important as complementary proxy in approaching a real assessment of green space availability for urban residents, almost all of whom have access to the urban front and back yard green space of the property they live in. In addition, agricultural land – be it used or unused – has, so far, not been included in the public green space data as it is not clear how this land will develop in the sample city of Leipzig.

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