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A Framework for the Long-term Monitoring of Urban Green Volume Based on Multi-temporal and Multi-sensoral Remote Sensing Data

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Abstract

Green urban infrastructure is of key importance for many aspects of urban life and urban planning. Valid and comprehensive databases with very high spatial and temporal resolution are needed to monitor changes and to detect negative trends. This paper presents an approach to assess urban indicators such as green volume and soil sealing with very high accuracy and based on a wide range of different sensors (aerial stereo images, QuickBird, WorldView 2 and 3, Sentinel 2, HRSC, LIDAR). A framework using regression tree methods was developed and successfully applied in a case study (the city of Potsdam, Germany) resulting in a long time series dating back 25 years. The methodology offers the opportunity to analyze urban development in detail and to understand the functional relationships of urban planning processes. Demands for effective climate change adaptation, especially in terms of reducing heat stress, can thus be better defined.

Keywords Urban green volume · Remote sensing · Monitoring · Stereo matching

Introduction

By 2050, more than two thirds of the world population will live in urban areas; thus, one of the United Nations sustainable development goals (SDG 11) is dedicated to cities and their communities (UNDP 2019). To manage and monitor sustainable development, fine-scaled information on the city level is needed, such as maps of built-up areas, urban green infrastructure, and soil sealing. The availability of such data in a tight temporal update cycle is very important for the timely assessment of changes and trends. Green infrastructure and soil sealing play also a key role in achieving EU policy objectives. Creating and improving a valid and comprehensive knowledge base remains one of the strategic developments for the implementation of the EU Strategy on green infrastructure (EEA 2015).

A useful indicator to assess green urban infrastructure is the green volume per area unit (GVA). GVA comprises the above-ground volume of the urban green in m^3/m^2 (Schulze et al. 1984). It plays a major role for the quality of life and the environmental quality in cities and therefore for urban management. Urban green volume has strong positive effects on air quality (e.g., Roy et al. 2012; Maher et al. 2013) and has a massive impact on urban micro-climate, such as a cooling effect during heat waves (e.g., Susca et al. 2011). Green volume is of particular importance for recreation and the well-being of citizens.

Soil sealing describes the covering of natural soil with solid impervious materials such as concrete and tarmac. Soil sealing has various strong negative impacts on the urban environment. Increased runoff and higher surface temperatures (e.g., Fokaides et al. 2016) are only two of the unfavorable aspects. Soil sealing is often described as percentage of impervious area.

Both green volume and soil sealing are very useful indicators with regard to urban planning. They can be applied as an input for modeling (urban climate, water balance) as well as for evaluation processes (e.g., soil protection measures). A long time series of both indicators can reveal patterns of favorable/unfavorable urban development.

Federal and local authorities increasingly apply remote sensing for urban monitoring and change detection. Traditionally, urban remote sensing is based on very high–resolution (VHR) sensors. A large number of studies assessing urban green infrastructure or soil sealing are based on digital airborne ortho-images (e.g., Meinel and Netzband 1997; Eichberger and Sulzer 2004); VHR satellite sensors such as QuickBird,

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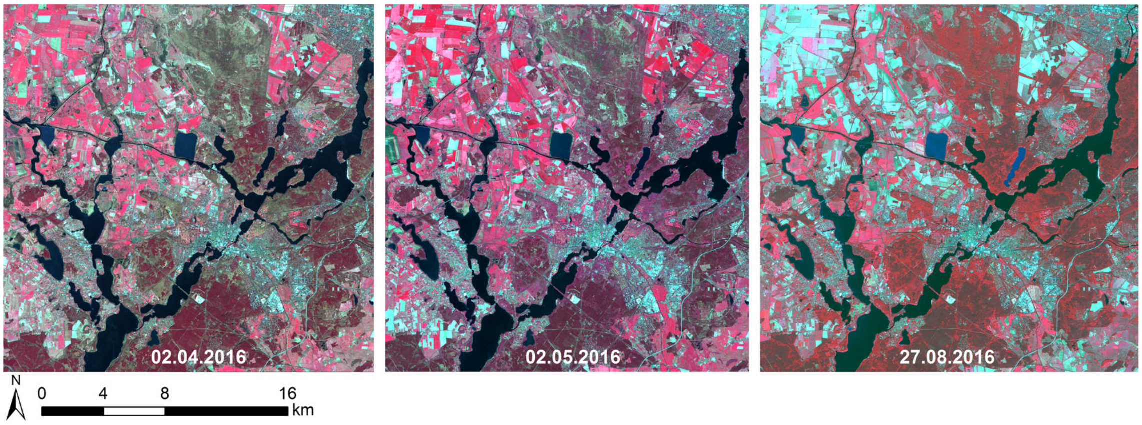

Fig. 1 Sentinel-2 scenes used for the environmental monitoring in Potsdam (RGB: Band 8, 4, 3)

WorldView, or GeoEye (e.g., Hofmann et al. 2011; Frick et al. 2007); or LIDAR data (e.g., Hodgson et al. 2003; Hecht et al. 2008). Drawbacks of those sensors are the small footprint, the high acquisition costs, and the scarcity of captures.

Stereo remote sensing plays a key role in environmental monitoring, as 3D information is essential for biotope type interpretation, the mapping of houses, and the assessment of green volume. LIDAR data are very popular for the creation of digital surface models (DSM). A very interesting approach is the application of voxels based on full waveform lidar or terrestrial lidar (Casalegno et al. 2017).

However, the time intervals of such surveys are often insufficient. Thus, the extraction of DSM from stereo remote sensing images has become more and more important. The development of powerful area-based matching algorithms (e.g., Hirschmüller 2008; Haala and Rothermel 2012) has promoted this tendency.

New and outstanding opportunities arise with the Copernicus program of the European Union. The Sentinel satellites (especially Sentinel 1 and 2) provide free and spatially high-resolution data in tight repeat cycles and with wide swaths, thus representing a great potential especially for the monitoring of green urban infrastructure. Several recent studies demonstrate the vast spectrum of applications; Kopecká et al. (2017) successfully classified urban green spaces and their ecosystem services in several Slovakian cities with Sentinel 2 data. Krüger et al. (2018) derived urban vegetation structure with Sentinel 2 data. Haas and Ban (2018) investigated changes in urban land cover and ecosystem services using Sentinel 2 and Landsat TM data, though Landsat data have a lower spatial resolution which can result in lower classification accuracy compared with Sentinel 2 (Labib and Harris 2018).

The main challenge in the development of processes to monitor urban green volume or soil sealing is that the error rate of these assessments must be extremely low. The annual change in land cover often accounts for only a small proportion of the total area, so that overall accuracies of 85% usually rated as "very good" are insufficient. The high temporal and spatial resolution of Sentinel 2 data and the integration of multi-sensor approaches including VHR data and 3D information represent a great potential for achieving these very low error rates (e.g., Matikainen and Karila 2011).

Numerous exemplary studies demonstrate the capability of multi-temporal and multi-sensor approaches for urban monitoring; Haas and Ban (2017) successfully applied

Table 1 Remote sensing data used for the modeling of urban green volume and soil sealing in the city of Potsdam

Year	Spatial resolution in m	Sensor
1992	0.25	Scanned stereoscopic aerial images (CIR)
1998	5.8 (pan) and 23 (ms)	IRS-LISS III satellite images
	0.25	Scanned stereoscopic aerial images (CIR)
2004	0.6 (pan) and 3.7 (ms)	QuickBird satellite images
2006	0.5	High Resolution Stereo Camera (HRSC) aerial images
2010	0.5 (pan) and 2.4 (ms)	WorldView-2 satellite images
	3 points per m^2	LIDAR data
2015	0.2	Stereoscopic aerial images (Vexcel)
2016	0.5 (pan) and 2.4 (ms)	Stereoscopic WorldView-3 satellite images
	20	Sentinel-2 NDVI (April, May, August)

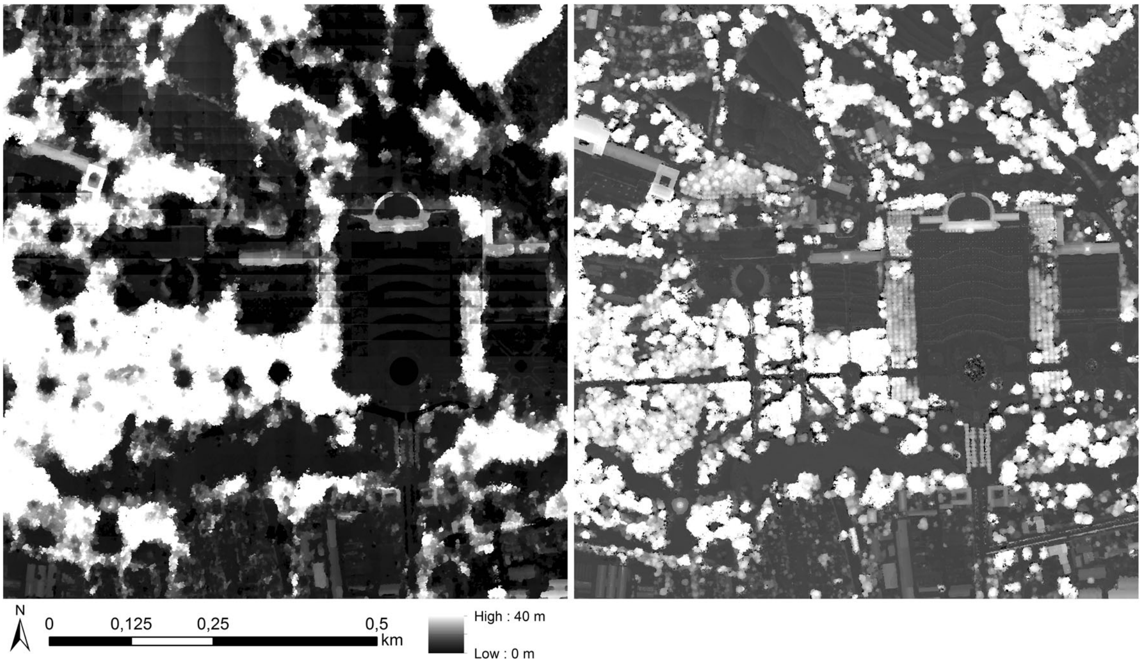

Fig. 2 Detail showing Sanssouci castle, left: DSM from Stereo-WorldView-3 2016; right: DSM from Stereo-aerial images 2015 (source: LUP)

Sentinel 1 and 2 data for the mapping of ecologically important urban areas and Griffiths et al. (2010) combined Landsat and ERS-1/ASAR data to map the development of megacities. The combination of deep learning algorithms (e.g., Audebert et al. 2017), symbolic machine learning (Pesaresi et al. 2016, 2018), and model-driven approaches for the automated classification of complex data (parametric and non-parametric) is a suitable tool to process those large amounts of data with high accuracies.

Still, most studies concentrate on one aspect of urban monitoring; the assessment of several important indicators such as soil sealing and green volume within one operational workflow and with very high spatial and temporal resolution is rare. Following these findings, the research objectives of our study were to:

1. Develop a methodological framework for the assessment of urban indicators (green volume and soil sealing) that results in very high accuracies
2. Investigate a long time series dating back 25 years and apply a wide range of different sensors to accurately map changes

Methods

Study Area

The study area is the city of Potsdam (comprising 180 km^2) located in Germany very close to Berlin. It is classified as a forest city according to the city typology of EEA (2019). This city type is characterized by a high proportion of urban forests, a high to very high proportion of green urban areas, and low soil sealing degrees. Nevertheless, Potsdam is a growing city with thousands of new inhabitants commuting to Berlin, thus increasing the land consumption for new housing sites. Reacting to this pressure, Potsdam established an environmental monitoring system based on remote sensing. Indicators such as biotope type, degree of surface sealing, green volume, and biotope quality are updated comprehensively in a repeated cycle (Tervooren and Frick 2010). These indicators are used to document urban development every 6 years, so far for 1992, 1998, 2004, 2010, and 2016. They also serve as input for further modeling (e.g., urban climate, water balance) as well as for evaluation processes (e.g., soil protection, development trends).

Table 2 Additional information used for validation

In situ data and additional information	Source
Surface sealing assessment for waste water billing (2002)	Water supply company Potsdam
Surface sealing and sealing type recorded for the road register (2007)	City administration of Potsdam
German automated land register (various years)	State Agency for land survey and geo-information
Digital terrain model (2010)	State Agency for land survey and geo-information

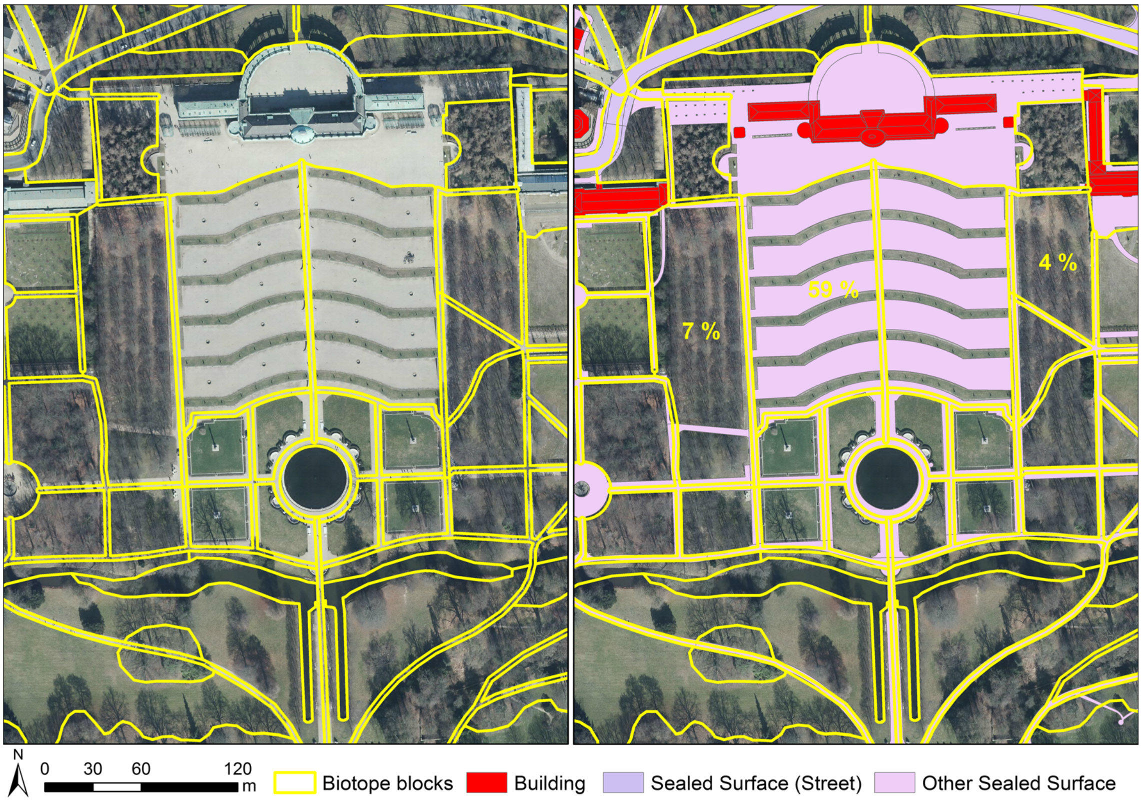

Fig. 3 Detail showing Sanssouci castle. Left: biotope blocks (background: Orthofoto 2015); right: biotope blocks and surface sealing assessment based on waste water billing and road register. The summarized surface sealing percentage is shown in yellow for three example blocks (source: LUP)

The monitoring is based on high- or very high–resolution optical aerial and satellite imagery. For the 2016 evaluation cycle, multi-temporal Sentinel-2 data was used for the first time (Fig. 1).

Remote Sensing Data

Remote sensing data sources for the urban monitoring in Potsdam changed with every monitoring cycle (see Table 1). All satellite scenes were pre-processed following the same standards for atmospheric correction and geo-coding. RMSE values for geo-coding stayed below one pixel (referring to the panchromatic resolution in case of multi-spectral sensors).

Clouds and cloud shadows were masked. All aerial and satellite image data were then used to derive various first- and second-order texture measures, ratios, and indices in order to be applied as parameters for regression tree models (see Table 3).

Stereo matching

Digital surface models can be extracted from stereoscopic aerial or satellite images through automated matching. For the environmental monitoring in Potsdam, a semi-global algorithm was used (Hirschmüller 2008). The image quality is of great importance. Due to large patches of haze on

Table 3 Settings used for the calculation of green volume in the training and validation blocks

Supervised class		Vegetation height (m)	Green volume (m^3)
1	Water	0.00	Pixel size × vegetation height
2	Sealed/open soil	0.00	Pixel size × vegetation height
3	Grassland	0.50	Pixel size × vegetation height
4	Reed	1.50	Pixel size × vegetation height
5	Arable land	1.00	Pixel size × vegetation height
6	Shrubs < 5 m	nDSM	Pixel size × nDSM
7	Shrubs and trees 5–9 m	nDSM	Pixel size × nDSM − 10%
8	Trees > 9 m	nDSM	Pixel size × nDSM − 25%

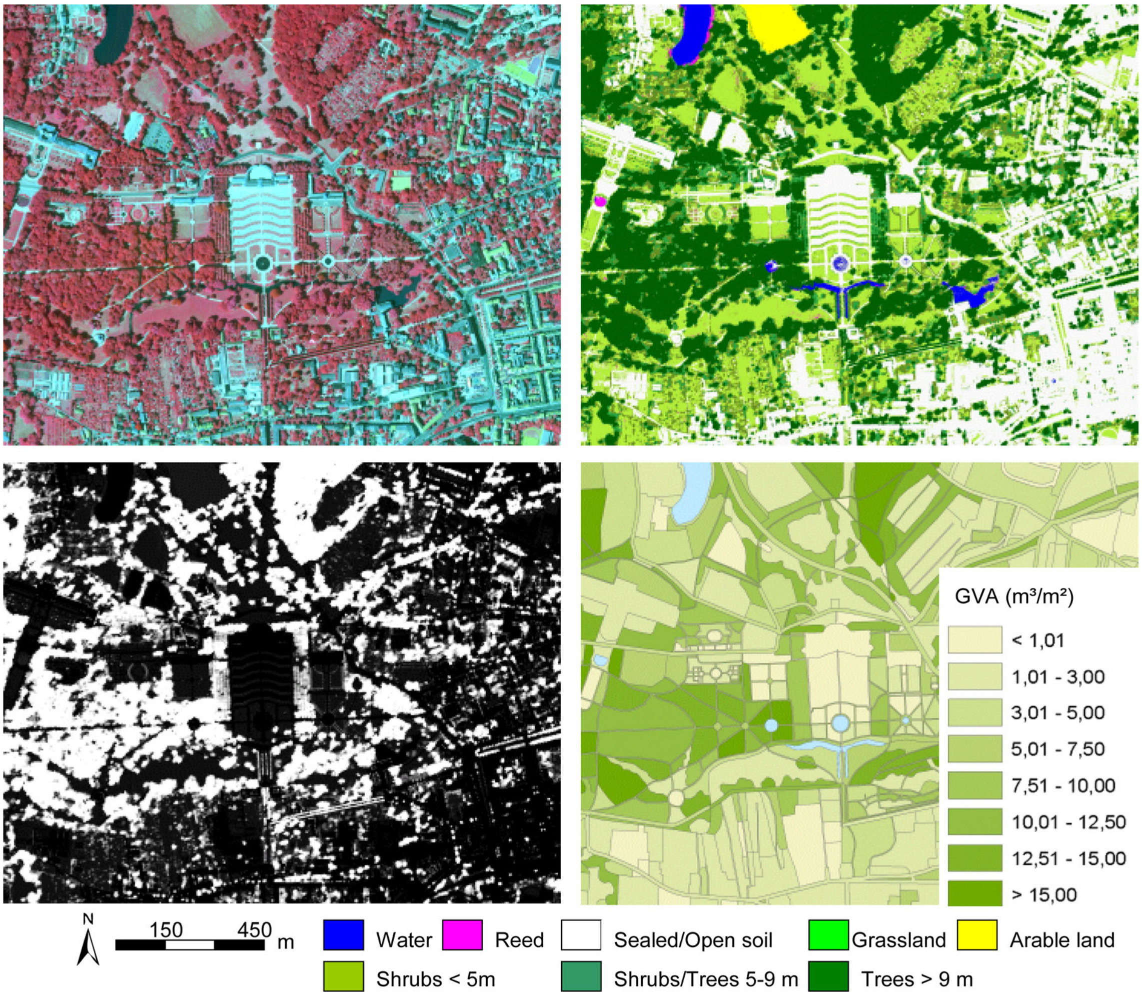

Fig. 4 Detail showing Sanssouci castle. Left above: WorldView 2010; right above: supervised classification result; left below: nDSM from LIDAR 2010; right below: final green volume per area unit for a subset of the training and validation blocks (source: LUP)

the WorldView-3 satellite imagery of 2016, the matching result was patchy and unsatisfactory (Fig. 2 left), so that, in addition, a matching of the stereo aerial images from 2015 was performed (Fig. 2, right).

The digital surface model based on LIDAR data (2010) was created through a linear interpolation of the classified point cloud. The final normalized digital surface models (nDSM) were created by substracting the ground from all objects through a simple difference calculation:

$$\mathrm{nDSM} = \mathrm{DSM–Digital\ Terrain\ Model(DTM)} \quad (1)$$

Training and Validation Data

In situ data were recorded for every monitoring cycle. Additionally, various external data sources were employed for accuracy assessment (see Table 2). For every monitoring cycle, at least 1000 biotope blocks were prepared as training and validation data for surface sealing: every block was visually checked for changes, and if no change was obvious, the accurate surface sealing percentage was calculated from the waste water billing and road register datasets (see Fig. 3). All surface sealing materials were summarized according to their sealing potential (e.g., tarmac seals to 100% whereas rubble only seals to 75%).

For the green volume per area unit, at least 8000 biotope blocks per monitoring cycle were prepared as training and validation data. In situ data for the height of trees and shrubs were collected either through field measurements or through 3D stereo information (e.g., normalized digital surface models nDSM). The final green volume per biotope block was then calculated based on a supervised regression tree classification of the remote sensing datasets (see Table 3 and Fig. 4). For shrubs and trees smaller than 9 m, 10% was substracted to account for the woody parts. Green volume for trees bigger than 9 m was decreased by 25% to account for tree trunks.

The training and validation datasets were then split randomly into training and testing subsets (70% training, 30% testing).

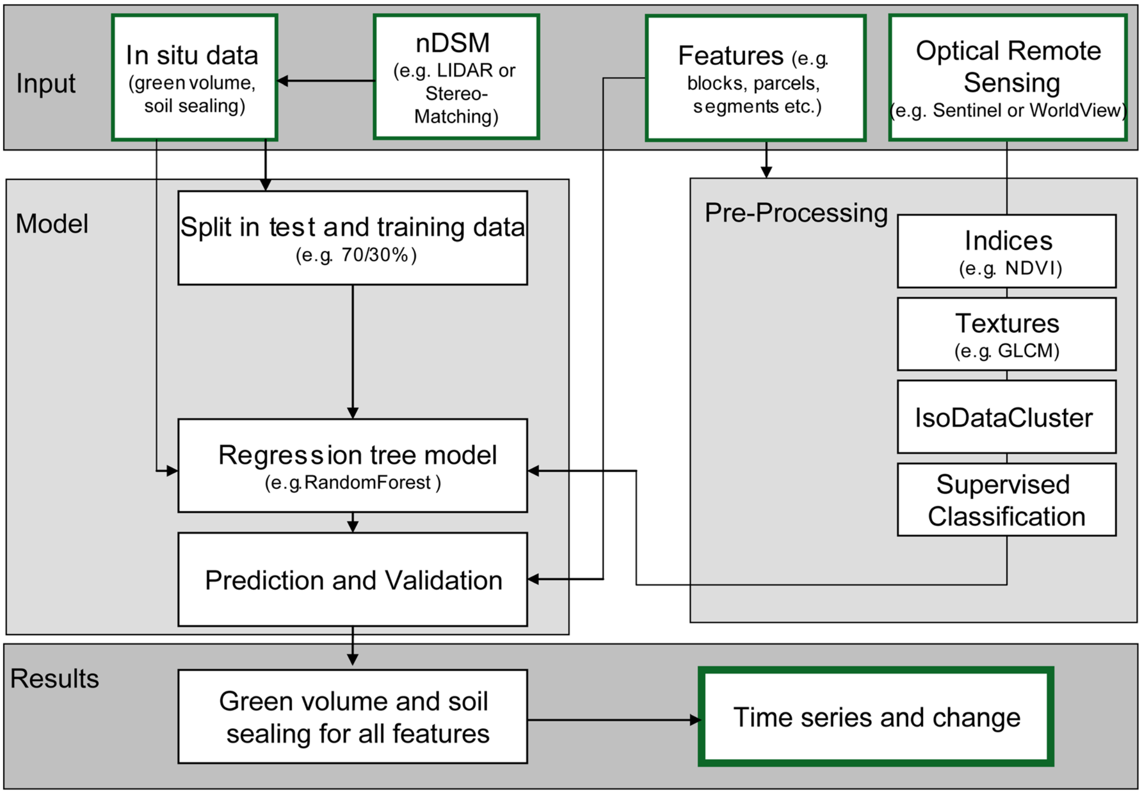

Fig. 5 Framework for the model setup

Methodological Framework

Since the spatial and spectral properties of remote sensing data can change dramatically with the years, the choice of methods is very important in order to achieve comparable results at all times. To guarantee high-quality analytical outcomes and to take into account different data characteristics, robust processing methods and standards are required to guarantee consistency. Non-parametric regression tree models are a good choice to handle very different data sources. Regression trees such as RandomForest (Breimann 2001) or Cubist (Quinlan 1993) are widely used for remote sensing applications (Belgiu and Drăguț 2016). Regression tree classifiers are less sensitive than other classifiers to the quality of training samples and to overfitting; this is mainly due to the large number of decision trees produced by randomly selecting a subset of training samples and a subset of variables for splitting at each tree node (Belgiu and Drăguț 2016). Thus, it was our choice to use a regression tree classification approach in order to derive stable results.

Figure 5 depicts the general framework for the model setup. To achieve comparability over a long time span, the geometrical base for analytical assessment is of utmost importance. For urban monitoring, the use of land parcels, biotopes, or blocks is the most promising approach, since management and urban planning refer to such features. Every single feature (more than 20,000 biotope blocks) for the whole city is filled with various parameters derived from optical remote sensing data for every time step. The parameters used for modeling

Table 4 Parameters used for modeling calculated for every feature for every single optical band

Parameter	Description	Reference/tools
Zonal statistics	Variance, standard deviation, mean, maximum, minimum	Zonal operator/Erdas Imagine
2nd-order texture in a 5 × 5 window, distance 1 pixel, 8 directions	Homogeneity, entropy, correlation, second moment, contrast, dissimilarity, mean, variance	Haralick et al. 1973
NDVI	Normalized vegetation index	Rouse et al. 1973
Simple ratios for every band combination	Depending on the spectral resolution of the sensor	Band Math/Erdas Imagine
Zonal statistics for every classification (supervised and unsupervised)	Majority, majority fraction, variety	Zonal operator/Erdas Imagine
Feature information	Area, perimeter, biotope type	ArcGIS

Table 5 Model results for green volume per area unit for the 30% test data

Year	R^2	Standard error
1992	0.89	1.89
2004	0.90	1.68
2010	0.91	0.34
2016	0.99	0.42

were first- and second-order textures, spectral indices calculated from all remote sensing data, and additional information like biotope type and classification results (see Table 4).

The supervised classification is based on a simple land cover model (see Fig. 4). The unsupervised classification is built with 10 maximum iterations and a 10% threshold. The final model is created with a regression tree approach using the training data and validated with the testing data. The next step is the prediction for all features, all indicators, and all time steps.

Results and Validation

The framework was applied to all time steps for Potsdam (1992, 1998, 2004, 2010, and 2016). It resulted in a long time series showing the change in soil sealing and green volume for every feature.

In Table 5, all validation results for the models to predict green volume per area unit (GVA) are listed.

With the years, the spatial, spectral, and temporal resolution improves, leading to a constant rise in accuracy. The integration of multi-temporal Sentinel 2 NDVI data resulted in a substantial refinement (see Table 6 and Fig. 6). A regression tree model based only on multi-temporal zonal statistics from Sentinel 2 NDVI data explained more than 85% of the variance in green volume. A regression tree model based only on the very high–spatial resolution WorldView-3 parameters (zonal statistics for all bands as well as texture measures) explains 91% of the variance in green volume. The best model fit with R^2 0.93, and the lowest standard error is obtained by an integration of both sensors.

The modeling results show in detail important developments in the city (see Figs. 7 and 8). The development of GVA shows a slight decrease since 1992 until 2016. A more pronounced decrease is evident when the development is related only to the built-up areas (see Table 7). The phase of lesser dynamics until 2004 and 2010 (see Fig. 7) even produced a slight increase in green volume values, which was interrupted between 2010 and 2016. As a result, the fairly balanced development changed after 2010.

The mean soil sealing in the built-up areas increases from 38.5 to 51.2% from 1992 to 2016 in total, which is a rise based on the 1992 values of 33%, with high dynamics from 1992 to 1998 and 2010 to 2016 (see Fig. 6).

Discussion

The developed framework was successfully applied to various remote sensing sensors. A long time series dating back 25 years was realized that enables the accurate mapping of changes. The geometric focus on biotope features was a valuable base to achieve consistent results. With the regression tree approach, it was possible to use such different image data as scanned aerial photographs and multispectral satellite sensors. Crucial for the whole process is the availability of 3D stereo information for the derivation of training data to predict urban green volume. The stereo matching of optical images proved to be a very good way to retrieve such information. One limitation is the necessity for images captured in the growing season for green volume assessment whereas soil sealing is best estimated with leafless images. The integration of multi-temporal Sentinel 2 data can help overcome this problem. Still, VHR imagery and 3D information are needed to satisfy the request for very high accuracy as has also been shown by other studies (e.g., Matikainen and Karila 2011; Huang et al. 2013). Multi-temporal Sentinel 2 NDVI data alone do not achieve the necessary precision on biotope level, the integration of all spectral bands should be further investigated. Another limitation is the need for cloud-free images. Even the occurrence of haze can be of great impact on assessment accuracy. Stereo matching with hazy WorldView 3 data did not lead to useful results. As with

Table 6 Difference in model results for green volume per area unit 2016

Model	R^2	Standard error
Only Sentinel NDVI parameters (zonal statistics: variance, standard deviation, mean, maximum, minimum)	0.85	2.11
Only WorldView-3 parameters ((1) Zonal statistics for every band and NDVI: variance, standard deviation, mean, maximum, minimum; (2) 2nd-order texture in a 5 × 5 window, distance 1 pixel, 8 directions for every band: homogeneity, entropy, correlation, second moment, contrast, dissimilarity, mean, variance; (3) Simple ratios for every band combination)	0.91	1.60
Combination of Sentinel NDVI and WorldView-3	0.93	1.41

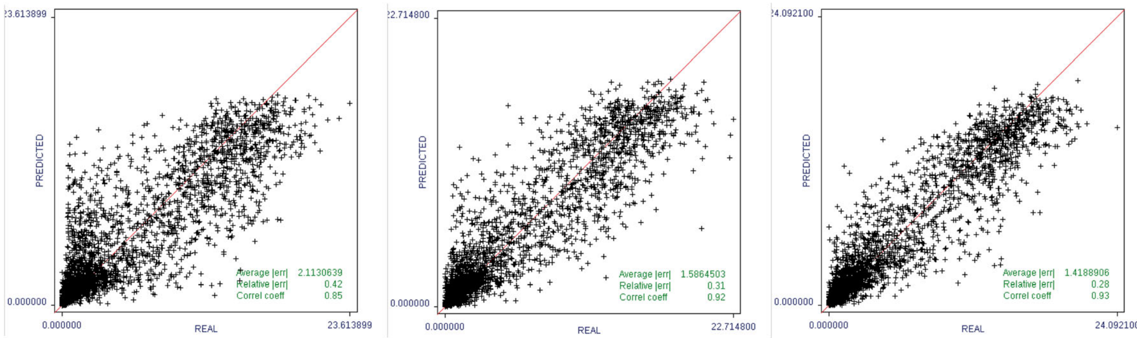

Fig. 6 Left: only Sentinel NDVI parameters; middle: only WorldView-3 parameters; right: combination of both

most remote sensing–based evaluations, the quality and quantity of training data are crucial. The presented framework largely depends on very accurate and representative in situ information; thus, the amount of visual interpretation and manual work is very high.

Main Trends in Urban Development

The results for every biotope feature in the city were subsequently examined to create trend classes for urban development. Four main types were identified:

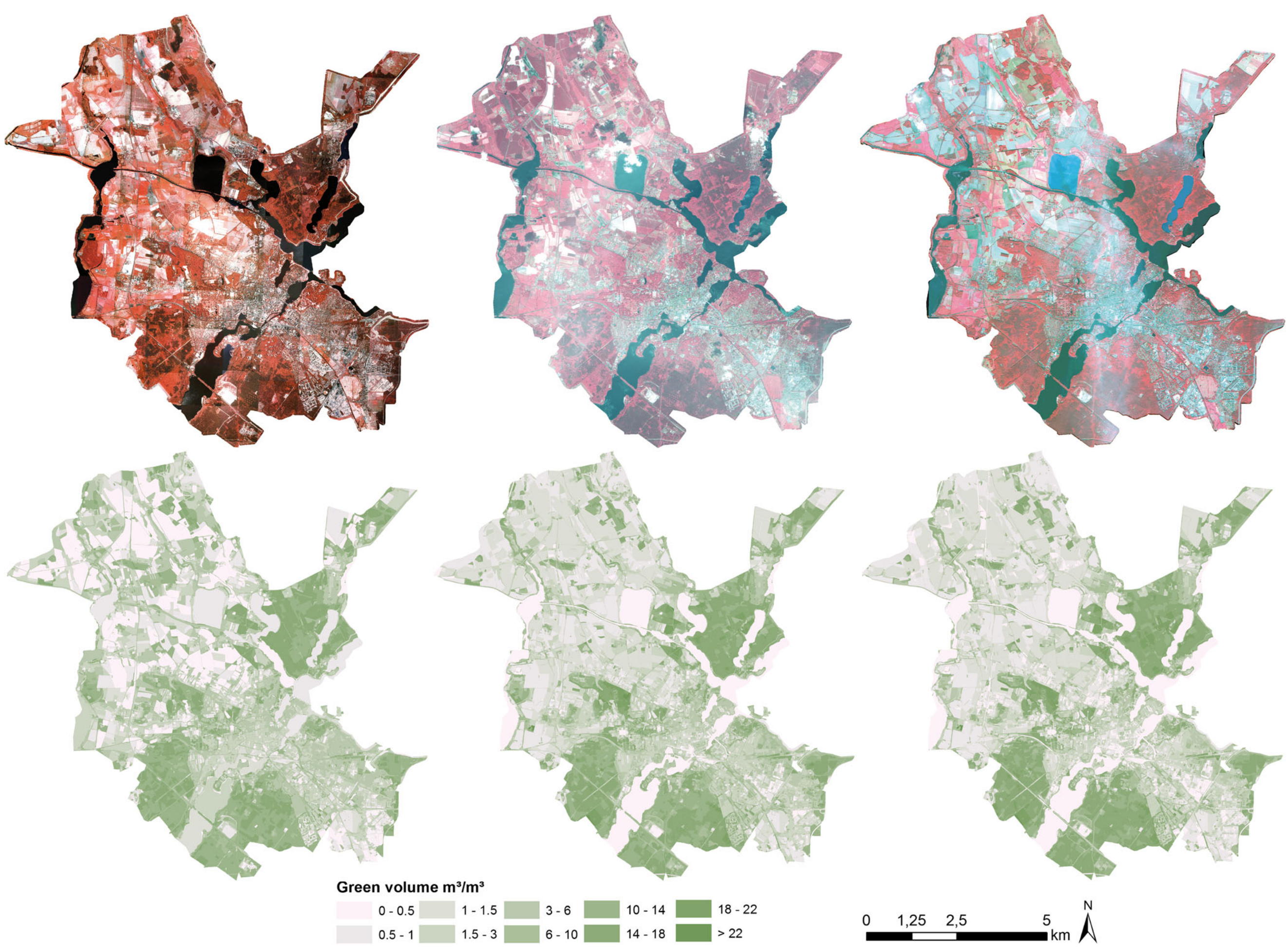

Fig. 7 From left to right: aerial images 1992, WorldView-2 2010, WorldView-3 2016, and respective green volume results

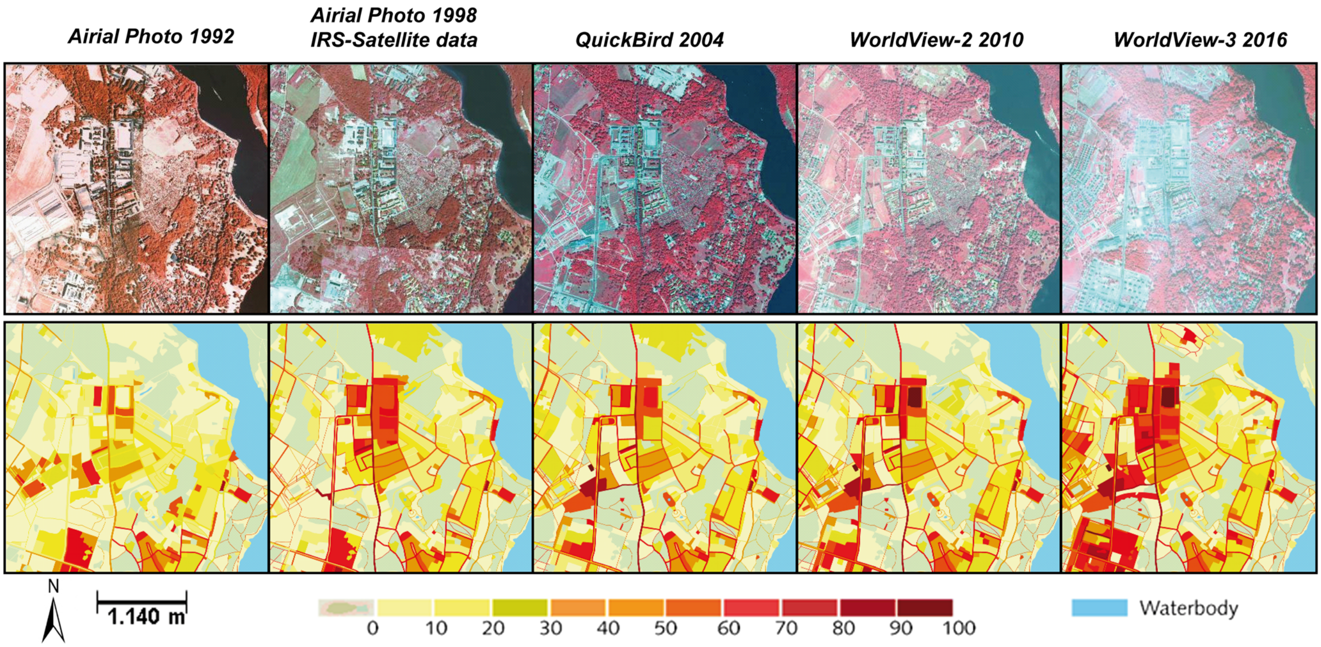

Fig. 8 Time series showing the soil sealing for a subset of the study area from 1992 to 2016

1. Type A: green volume increases, soil sealing decreases.

This type stands for ecological improvement of the living environment and active urban greening processes.

2. Type B1: green volume increases, soil sealing increases.

This type characterizes green urban development, considering sustainability aspects in urban planning processes.

3. Type B2: green volume decreases, soil sealing decreases.

This type characterizes active demolition and dismantling or change of land use.

4. Type C: green volume decreases, soil sealing increases.

Type C finally stands for "gray urban development", areas of urban development without/with limited consideration of environmental issues or with the lack of implementation of sustainability measures.

In Fig. 9, main trends in Potsdam are illustrated; after the Fall of the Wall, an intense urban development started (mainly type C) which attenuated between 2004 and 2010 due to a decrease in population and the reconsideration of sustainable urban development (mainly type B1). After 2010, the population trend reversed and a massive expansion and densification of built-up areas followed (mainly type C). In most of the cases, no compensation for the increase in surface sealing via green volume was made. The percentage of built-up areas with very low green volume and very high soil sealing increased from 7.2% in 1992 over 11.9% in 2004 and 2010 to over 16.5% in 2016.

Table 7 Change in GVA and soil sealing from 1992 to 2016

	1992	2004	2010	2016	1992–2016
Green volume per area unit (m^3/m^2)					
Mean for the whole city	5.12	4.98	5.18	5.04	− 0.08
Mean for the built-up areas	3.13	2.73	3.17	2.48	− 0.65
Soil sealing (%)					
Mean for the whole city	9.3	11.0	11.2	12.6	+ 3.3
Mean for the built-up areas	38.5	47.3	47.6	51.2	+ 12.7

Applications in Climate-Change Modeling

The environmental monitoring results for Potsdam were furthermore used to determine the potential of urban green and unsealing for climate change adaptation. The climate change postulated for Potsdam from 2.5 to 3.0 °C from 2013 to 2050 (Gerstengarbe et al. 2014) with pronounced heat events justifies the investigation of the effect of the two core indicators for urban monitoring. They provide information on the search for adaptation options and can act as parameters for the reduction of stress: green volume as a "positive indicator" for adjustment (cooling option) and sealing as a "negative indicator" (warming risk).

For the analysis, land surface temperatures determined on the basis of thermal Landsat data were linked with the parameters of the environmental monitoring (Tervooren 2015). In

Fig. 9 Change in green volume and soil sealing for built-up areas compared with 1992

addition to the development of temperature values, the decisive factor is their spatial distribution in the urban area. Thus, statements are possible as to whether certain areas can act as buffer zones for heat in the city center. The following guideline values were found suitable to address local conditions:

- 1 m^3 additional green volume per m^2 area leads to a temperature reduction of approx. 0.3 °C
- 1% additional sealing (e.g., 1 m^2/100 m^2) causes a temperature increase of about 0.03 °C (Tervooren 2015)

These values emphasize the importance of urban green volume and the need for the consideration of sustainable development in urban planning processes.

Conclusion

In this study, a methodological framework for the assessment of urban indicators (green volume and soil sealing) was developed. We investigated a long time series dating back 25 years and successfully applied a wide range of different sensors to accurately map changes. The coefficient of determination for the GVA models ranged from 0.86 to 0.99 with standard errors between 1.89 and 0.42. They were constantly improving with spatial, spectral, and temporal resolution of the input data.

In addition to the climate assessment, regular environmental monitoring data help to analyze the effect of small-scale structures in the development of settlement areas. The temporal documentation of the development, in Potsdam since 1992, enables the better understanding and steering of development processes. Green volume and soil sealing are increasingly easy to assess due to new air- and spaceborne sensors. The assessment methodology can be standardized for cross-regional use. The given indicators form a good base to discuss and qualify arguments addressing urban development, for administration, politicians, and citizens.

Limitations to acquire suitable data to establish a similar monitoring for other European cities can be at least partly overcome using recently available Sentinel 2 data. The use of all Sentinel 2 spectral bands should be further investigated since, especially, the red edge bands promise to be very valuable for the assessment of urban green. The integration of Sentinel 1 should further enhance and improve the model accuracy; several recent studies demonstrated the suitability for urban monitoring (e.g., Lehner et al. 2017). Future research should also focus on automated change detection methods to minimize visual and manual work in updating the training datasets.

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Compliance with Ethical Standards

We comply with ethical standards.

Conflict of Interest The authors declare that they have no conflict of interest.

Ethical Approval Our research did not involve human participants.

Informed Consent Our research did not involve human participants.

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