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benefits of using high-resolution remote sensing**

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## **Abstract**

Cities of tomorrow strive for sustainability, resilience, low emissions and better living conditions. In this context, the concept of urban ecosystem services has gained attention for assessing and better integrating nature-based solutions. However, cities have been challenged due to rapid urbanization, heterogeneous and fragmented environments, climate change, financial constraints and political inertia. This is likely to induce a prevalent lack of up-to-date localized environmental information, which is important for science and professional practitioners to have in order for them to better implement urban ecosystem services. This lack of essential environmental information could be partially addressed using recent innovative technologies, such as remote sensing. This applies in particular to consistent and area-wide information that allows comparisons, but also to an increased precision of individual objects and their temporal changes. Therefore, this work shows recent options for implementing high resolution remote sensing in assessing urban forests in Berlin, Germany. State-of-the-art methodological approaches like machine learning and individual tree detection proved to be highly advantageous for analyzing details of urban ecosystem services within a heterogeneous urban environment. Recent remote sensing of high temporal resolution offers new options for more precisely addressing urban forest dynamics. This successfully shows that tree species could be identified from seasonal changes of remotely sensed imagery, though this has not yet been applied across cities. Furthermore, these tree species results could be combined with remotely sensed individual tree dimensions. This newly generated data can be suggested to update spatially explicit information on related urban ecosystem services. For example, this could reduce the uncertainties of such estimates as urban forest carbon storage, and also address the present lack of spatially explicit three-dimensional information on urban forests. However, few studies have considered the local scale of urban forests to effectively evaluate their potential long-term carbon offset. The lack of precise, consistent and up-to-date forest details is challenging within the scope of life cycle assessments. This can cause high uncertainties in urban forest carbon offset. Although, recent progress in high resolution remote sensing is promising to reduce these uncertainties. For this purpose, remote sensing options are extensively reviewed and briefly discussed using an example of life cycle assessment for Berlin, which allow more precise long-term prognoses of urban forest carbon offset. It can be concluded that this work exemplifies recent technological progress in high resolution remote sensing for an improved area-wide consistent assessment of spatially explicit information, and for monitoring urban biodiversity and urban forest carbon estimates in particular. This should be extended towards more robust automated processing and support a systematic application for long-term urban ecological research and improved environmental decision-making.

## **Zusammenfassung**

Städte von morgen zielen auf Nachhaltigkeit, Resilienz, geringe Emissionen und bessere Lebensverhältnisse. Diesbezüglich ist das Konzept urbaner Ökosystemdienstleistungen hervorzuheben, um auch naturnahe Lösungen zu bewerten und besser zu integrieren. Demgegenüber stehen allerdings eine zunehmende Urbanisierung, heterogene und zerteilte Lebensräume, der Klimawandel, Finanzierungsschwierigkeiten und träge politische Entscheidungsfindungen. Dies dürfte zu einem häufigen Mangel an aktuellen und lokalen Umweltinformationen führen. Für Wissenschaftler und Fachleute sind diese Informationen jedoch von hoher Bedeutung hinsichtlich einer verbesserten Umsetzung des Konzepts urbaner Ökosystemdienstleistungen. Dieser Informationsmangel könnte durch eine innovative Technologie wie die Fernerkundung reduziert werden. Das gilt insbesondere für konsistente und flächendeckende Informationen, die Vergleiche zulassen, aber auch für eine erhöhte Präzision einzelner Objekte und deren zeitliche Veränderungen. Vorliegende Arbeit zeigt daher die jüngsten Möglichkeiten hochauflösender Fernerkundung am Beispiel von Stadtwäldern in Berlin, Deutschland. Es wurden neuste methodische Ansätze eingesetzt, wie beispielsweise maschinelles Lernen und individuelle Baumdetektion. Sie erwiesen sich von großem Vorteil für die detaillierte Analyse urbaner Ökosystemdienstleistungen in einer heterogenen Umwelt. Neueste Fernerkundung von hoher zeitlicher Auflösung hat Möglichkeiten gezeigt, Veränderungen des Stadtwaldes präziser zu untersuchen. Diesbezüglich konnten Baumspesies klassifiziert werden auf Grundlage saisonaler Veränderungen, die mittels Fernerkundungsdaten aufgenommen wurden. Dies ist für den urbanen Bereich einmalig und über große Flächen noch nicht durchgeführt worden. Darüber hinaus haben diese Baumarten einzelnen Bäumen zugeordnet werden können, deren Abmessung fernerkundlich erfasst worden ist. Diese neu erzeugten Umweltinformationen einzelner Bäume können damit verbundene urbane Ökosystemdienstleistungen präzise aktualisieren. Zum Beispiel haben so Unsicherheiten in der Schätzung zur Kohlenstoffspeicherung städtischer Wälder reduziert werden können. Es ist zudem von Vorteil gewesen, den gegenwärtigen Mangel an räumlich expliziten dreidimensionalen Informationen über Stadtwälder anzusprechen. Allerdings ist die Rolle städtischer Wälder, das Treibhausgas CO<sub>2</sub> langfristig auszugleichen, immer noch wenig untersucht. Gerade der Mangel an präzisen, konsistenten und aktuellen Details führt zu großen Unsicherheiten im Rahmen von Lebenszyklus-Analysen. Auf Grund des aktuellen Fortschritts in hochauflösender Fernerkundung könnten diese Unsicherheiten reduziert werden. Dazu werden Möglichkeiten ausgiebig kritisch bewertet und anhand einer Lebenszyklus-Analyse am Beispiel Berlin andiskutiert, inwieweit sie präzisere langfristige Prognosen zum Stadtwald als Kohlenstoffspeicher liefern. Diese Arbeit zum technologischen Fortschritt hochauflösender Fernerkundung legt verbesserte Bewertungsmöglichkeiten urbaner Ökosysteme in Bezug auf Flächenweite, Konsistenz und Detailreichtum dar. Sie verdeutlicht zudem eine Optimierung beim Monitoring wie beispielsweise der urbanen Biodiversität oder der Kohlenstoffspeicherung von Stadtwäldern. Hier sollte eine solide automatisierte Verarbeitung angestrebt werden. Eine systematische Anwendung ist empfohlen für langfristige stadökologische Studien und für Entscheidungsprozesse, um ökologische Belange besser zu berücksichtigen.



## Contents

Acknowledgments	v
Abstract	vii
Zusammenfassung	viii
Contents	ix
List of Figures	xi
List of Tables	xii

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### **I: Introduction** **1**

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1	Cities, Environment and Ecosystem Services	2
2	From a Different Perspective – Remote Sensing	4
2.1	Urban Remote Sensing	4
2.2	High Resolution to Advance Urban Environmental Studies	5
3	Conceptual Framework	7
3.1	Motivation – Looking Beyond Green Vegetation	7
3.2	Study Area Berlin, Germany – A Heterogeneous Urban Forest	7
3.3	Objectives – Remote Sensing Benefits from a Temporal Point of View	9
3.4	Structure	11

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### **II: Urban Vegetation Classification: Benefits of Multitemporal RapidEye Satellite Data** **13**

---

	Abstract	14
1	Introduction	15
2	Material and Methods	18
2.1	Study Area	18
2.2	Data and Preprocessing	18
2.3	Reference Data	22
2.4	Classification Approach	24
3	Results	26
3.1	Classification Output	26
3.2	Automatic Feature Selection	29
4	Discussion	31
5	Conclusion	36
	Acknowledgments	37

---

### **III: Modeling Above-ground Carbon Storage: A Remote Sensing Approach to Derive Individual Tree species Information in Urban Settings** **39**

---

	Abstract	40
1	Introduction	41
2	Material and Methods	44
2.1	Study Area	44
2.2	Data	45
2.3	Modeling Above-ground Carbon Storage Estimates	46
3	Results	51
4	Discussion	56

5 Conclusion	62
Acknowledgments	63
<hr/>	
<b>IV: Progress in High Resolution Remote Sensing to Advance</b>	
<b>Life Cycle Assessments of Urban Forest Carbon Offset</b>	<b>65</b>
<hr/>	
Abstract	66
1 Background	67
2 Urban Forest Carbon Offset—Status Quo and Future Prognoses	68
2.1 LCA Inventory—Remotely Sensed Updates	73
2.2 The Berlin Case—Simplified LCA of Urban Forest Carbon Offset	79
2.3 Improvements—Remotely Sensed Changes over Time	90
2.4 At Different Scales—From Local to Global	93
3 Conclusion and Outlook	95
<hr/>	
<b>V: Synthesis</b>	<b>99</b>
<hr/>	
1 Findings, Plausibility and Transferability	100
2 Main Conclusion	107
3 Outlook	107
<hr/>	
<b>References</b>	<b>111</b>
<hr/>	
Eidesstattliche Erklärung	132

## List of Figures

Figure I - 1: Mono-temporal (left, vegetation colored red) and intra-annual (right) RapidEye satellite image, Berlin. ....	8
Figure II - 1: Left: Summertime, false color composite (near-infrared, red, green) RapidEye and LiDAR data coverage inside the administrative boundaries of Berlin. ....	20
Figure II - 2: a) RapidEye single date (July 27th 2009), false color composite (near-infrared, red, green). b) Vegetation mask (white). c) Tree mask (white) combining a 3 m LiDAR nDSM height threshold and the RapidEye vegetation mask. ....	21
Figure II - 3: Classification accuracy and allocation and quantity disagreement of tested scenarios (Table 2).....	27
Figure II - 4: Variability of SVM class probability values for each reference class of Scenario 4.2. The classes are: a) Acer, b) Populus, c), Platanus, d) Fagus, e) Tilia, f) Quercus, g) Aesculus, h) Pinus.....	28
Figure III - 1: a Tree canopy inside the administrative boundaries of Berlin. "Unclassified" refers to areas where either RapidEye or LiDAR data were not available for classification. ....	46
Figure III - 2: Estimated average carbon density (tC/ha) per unit of land cover for urban trees in Berlin. ....	53
Figure III - 3: Spatial distribution of tree carbon density (tC/ha) per unit of land cover in a densely built part of Berlin (red dot, Fig. 2).....	54
Figure III - 4: Differences in carbon storage density (tC/ha) per unit of land cover within the city of Berlin for methods listed in Table 2.....	54
Figure III - 5: a Spatial distribution of the average tree density (#/ha) per unit of land cover. b Spatial distribution of the average tree diameter at breast height (dbh in cm) across the study area.....	55
Figure III - 6: a Spatial distribution of the average tree diameter at breast height (dbh in cm) of a densely built area.....	56

Figure IV - 1: LCA inventory of remotely sensed trees in Berlin, Germany. Spatial distribution of (a) dominant tree species and (b) tree density per unit of land cover (Tigges et al. 2017). .....	81
Figure IV - 2: LCA of 60 years on urban forest carbon offset in Berlin. The carbon weight for alive and accumulated dead biomass is presented in kilotons (ktC) for our land use classes (streets, mixed, parks).....	85
Figure IV - 3: Potential tree planting initiative of 100,000 trees. Calculations of alive biomass were based on a mixture of dominant tree species in Berlin (Class mix, Table 1) with a 70-year growth period.....	87

### List of Tables

Table II - 1: 2009 RapidEye satellite imagery (5 bands: RGB, near-infrared, red-edge). Available phenological information for the region of Berlin is related to each date. ....	19
Table II - 2: Spectral and temporal classification scenarios. ....	22
Table II - 3: Classification accuracy (F1-measure) of urban tree genera (Scenario 4.2, all available imagery of this case study).....	27
Table II - 4: Ranking of multitemporal RapidEye imagery from 2009. Total kappa is listed for cumulated ranks. ....	30
Table III - 1: Most dominant tree species in the study area are listed as classes 1–10. Classes 1–8 are classified using RapidEye satellite data.....	48
Table III - 2: Methods used to estimate biomass using different levels of tree species information. ....	49
Table III - 3: City-wide average of carbon estimates of trees in Berlin obtained using different levels of input detail (Table 2).....	52
Table IV - 1: Most dominant tree species for biomass and growth calculations.....	83
Table IV - 2: Temporal development of urban forest carbon estimates in Berlin.....	86

**I: Introduction**

### **1 Cities, Environment and Ecosystem Services**

The majority of the world's population is living in cities. Cities being the nodes of global economic expansion have faced rapid population growth, which is not likely to end (Seto 2009). The increasing share of megacity dwellers and attached informal settlements are further blurring the lines of administrative boundaries (Kraas 2007). Despite the existence of shrinking cities like Detroit, which was a particular example due to socio-economic development in the 1980s, urban space continues to be a point of spatial attraction. However, a lack of economic opportunities, political intentions and global impacts, such as tertiarisation, suburbanization, deindustrialization, aging and international migration, have also led to the prioritization of certain cities while others continuously decline, a major disparity in today's world. (Martinez-Fernandez et al. 2016)

Urbanization has required and stressed natural resources, along with increasing vulnerability concerning the access and availability of vital important resources, such as food, clean air and water (Vörösmarty et al. 2000; Fenger 2009; Badami and Ramankutty 2015). The consumption of natural resources is not limited exclusively to the urban scale, however. It has a wider regional and global influence on land use change, which seems to be necessary in order to satisfy the needs of a growing urban population. Recent debates and planning have aimed to better address those land use transformations, e.g., in the matter of energy use and material flows. Different methodologies have been applied to better understand those transformations using urban metabolism, ecological footprint, life cycle analysis, environmental assessment, influence on ecosystem functionality and more. (Yeh and Huang 2012; Lauf et al. 2014; Liu et al. 2014; Long et al. 2014)

Global climate change is another major challenge for cities, particularly regarding the vulnerability of an aging and more sensitive population. This is likely to be extended by continuous urbanization and the ongoing urban heat island effect due to the modification of more heat radiating surfaces. (Arnfield 2003; Kraas 2007; Seto 2009; UN 2011). Spatiotemporal variations of the urban heat island effect are not solely a city scale issue, as micro-scale impacts can also affect the energy demand of buildings, the social aspects of

## Introduction

living comfort, mortality and more (Mirzaei 2015). Additionally, impervious surfaces can be problematic during heavy rain, causing inundation and runoff problems that cities will be more exposed to due to expected climate change (IPCC 2013).

Urban citizens seek for social and economic achievements to improve their living conditions. This has also raised attention for the role of urban green infrastructure contributing to better living conditions. In most cases, green infrastructure refers to vegetation, which still holds an important share of urban areas. It offers multifunctional benefits like regulative, supportive, provisional and cultural services, as well as unwanted disservices, for instance, pollen can cause allergies or plants can damage buildings or block views. (Bolund and Hunhammar 1999; Lovasi et al. 2008; Honour et al. 2009; von Döhren and Haase 2015). Urban green infrastructure can decrease high temperature extremes and therefore reduce the physiologically equivalent (felt) temperature, which will increase human well-being (Sung 2013). More green living space strongly reduces heavy rainwater surface runoff and therefore damage and insurance costs (Zhang et al. 2012a). Urban forest and soil store a considerable amount of carbon (Churkina et al. 2010). Therefore, the multifunctional role of urban green infrastructure could gain importance as climate change impacts increase and make adaptation inevitable for cities.

In order for cities today to become livable, equitable and resilient, they need effective countermeasures for such challenges as, to name only a few of the most important: Rapid changes, population growth and needs, socio-economic and ecological disparities within cities, large area effects of continuous urbanization and densification, and uncertainty in the matter of climate change, which is a local responsibility that carries with it global consequences (Kahn and Walsh 2015). Different movements have risen for enhancing cities, such as the Garden City movement, sustainable development concepts, and the concepts of eco-cities and green communities, low carbon cities, smart cities, sharing cities and more. These movements have inspired a more integrative approach to dealing with environmental issues, wherein city stakeholders are assigned an important role in bearing responsibility for nature (Holt 2014). However, in the matter of nature-based solutions, city planning that holistically considers multifunctional urban green infrastructure is still rare among cities (Hansen et al. 2015).

## **2 From a Different Perspective – Remote Sensing**

### **2.1 Urban Remote Sensing**

Cities have long been places of heterogeneity. Comprising social, economic and environmental changes, city dynamics have caused specific land covers, land use changes and developments. Therefore, information about such urban dynamics is highly important for drawing implications for planning and governance of future cities and their environment. In this case, remote sensing can play an important role in retrieving the details needed for improved assessments using area-wide and up-to-date information (Netzband 2007).

Aside from the early beginnings of balloon rides and military airplane reconnaissance, Earth observation using satellite-based systems has initiated the acquisition of large geographical areas at a single point in time. The first modern Earth observation by the Landsat satellite in the 1970s offered a global patchwork of data coverage, which allowed the spatial expansion of urban areas to be classified on a globally comparable basis (Haas et al. 2015). Furthermore, consistent and reproducible satellite-derived information offered the first opportunities for detecting and tracking environmental change, such as the land cover dynamics and growth rates of cities like Beijing (Li et al. 2015b). Periodically updating satellite data could also be used for risk assessments, such as the automatic detection of damaged buildings following an earthquake hazard, which exemplifies the remote sensing benefits of rapid responses and time and cost savings for monitoring changes (Menderes et al. 2015). Remotely sensed data is also free of political or private boundaries, allowing it to be collected globally. For example, remote sensing data can help to identify and differentiate areas of informal settlements, which are difficult to access by field surveys and are not part of official administrative sources (Owen and Wong 2013). Different carrier systems have allowed for better access to the urban environment using satellites, aircrafts, mobile and terrestrial stations, or unmanned aerial vehicles (drones). The ongoing development and application of various sensors, advanced processing algorithms and techniques have further advanced the retrieval of components and their physical conditions, for example: using hyperspectral imagery to differentiate surface materials, thermal remote sensing to better analyze the urban heat island effect, LiDAR-based height information to classify urban



objects, RADAR imagery to acquire cloud-free data for change detection, and more (Melesse et al. 2007; Weng and Quattrochi 2007; Heiden et al. 2012; Okujeni et al. 2015; Yan et al. 2015). Therefore, recent developments and applications in urban remote sensing should be evaluated regarding how much more they can contribute to understanding the complexity of cities and their spatiotemporal dynamics in particular.

### **2.2 High Resolution to Advance Urban Environmental Studies**

Vegetation plays an important role in urban ecosystems. This has been addressed more frequently by urban remote sensing, as developments in technology and methodology advanced the analysis beyond mapping vegetation for assessing the degree of impervious surfaces (Yang 2011; Weng 2012).

Increasing resolution has enabled small-sized and fragmented vegetation analysis with high amounts of detail at multiple scales using satellite imagery like QuickBird (< 1 m pixel size), ultra-high resolution of airborne digital sensors (e.g., ADS40, < 10 cm pixel size) or recent developments and sensors attached to low-altitude unmanned aerial vehicles (Petrie and Walker 2007; Eurimage 2009; Feng et al. 2015). This has updated conventional moderate resolution remote sensing, which has been frequently applied using space-borne systems like Landsat (30 m pixel size) (Eurimage 2007). Integrating an increasing spectral resolution, such as hyperspectral imagery, has shown improvements in retrieving biophysical properties, patterns and processes concerning urban vegetation stresses (Zhuokun et al. 2010). LiDAR data or stereo imagery has extended the spatial dimension and added very high resolution height information, which has been successfully applied to improve delineating vegetation types or green volume estimates (Tooke et al. 2009; Huang et al. 2013). Such height information has a strong application in traditional forestry, but it has also gained importance for urban environmental studies, such as extracting individual tree information (Wei and Yuzhang 2013).

Urban remote sensing, which directly addresses vegetation dynamics, has become of increasing interest in recent years. This includes, for example, the spatiotemporal changes of vegetation coverage in regard to urbanization or land surface temperature (Amiri et al.

## Introduction

2009; Paul and Nagendra 2015). Details about temporal changes of urban vegetation are still difficult to acquire due to a lack of data availability across large areas. Oftentimes, large area remote sensing still consists of patchwork (mosaic) imagery acquired at different times, which creates additional costs, requires further processing and can be problematic concerning differences like seasonal changes. Additionally, analyzing such seasonal changes has rarely been addressed by remote sensing across cities, or even beyond their administrative boundaries. New satellite imagery—RapidEye, for example—could fill this gap by offering high spatial resolution data (6.5 m), as well as consistent large area coverage (a swath width of 77 km with continuous observation coverage up to 1500 km). High temporal resolution can provide additional important information for vegetation differentiation or add new insights into changes within ecosystem service provision. Hence, the additional benefits of high spatial resolution remote sensing and data comparability for area-wide urban vegetation analyses should be explored (Hostert et al. 2010).

Due to increasing remote sensing data availability, the combination of different data has shown further improvements in urban vegetation analysis. The selection of most relevant features can be evaluated to more precisely classify heterogeneous urban environments using, for instance, a combination of hyperspectral, color-infrared and LiDAR data (Forzieri et al. 2013). LiDAR point clouds have been successfully used to retrieve information on tree dimensions, different types of vegetation and tree species (Yan et al. 2015).

The integration of high spatial resolution (two-dimensional) and height information (three-dimensional), additional multitemporal time series (four-dimensional) and spectral data (multi-dimensional) offers a promising approach for advancing the assessment of urban environments across large areas. However, verifying the accuracy and precision of this approach will require further research on urban remote sensing and applications concerning the necessity, sufficiency and consistency of relevant remotely derived information. This will substantially support additional modeling and valuing approaches, which require urban vegetation details.

### **3 Conceptual Framework**

#### **3.1 Motivation – Looking Beyond Green Vegetation**

The world population will continue to live in cities predominately. Additionally, urban population growth, land use dynamics and natural resource consumption continue to stress the urban environment. This requests measures that contribute to assess the urban environment concerning a sustainable and resilient urban living conditions. In this context, urban vegetation seems to currently be undervalued. Urban ecosystems offer multiple benefits, as well as climate change mitigation and adaptation options that can help with handling the uncertainty of future climate change effects. The availability of appropriate urban vegetation information and understanding would support better integration for recent and future cities. However, there is currently an ongoing information gap regarding city dynamics, heterogeneity and external influential factors. Urban remote sensing can significantly contribute to narrowing those knowledge gaps. It can improve the access to and availability of appropriate detailed information, as well as ensure that the data is consistent and up-to-date. Classification of urban vegetation that is derived from remote sensing has been addressed in many ways, but up until now, its application has often been limited to a few details. Spatially explicit assessments of ecosystem services lack up-to-date and area-wide information. However, recent developments in remote sensing technology offer increasing resolution and new access to information. Furthermore, advanced processing methods are available. Both should be used in the evaluations in order to further enhance the scientific understanding of urban green details across the city. Their incorporation into modeling and valuing approaches would advance applications of urban environmental decision-making, as well as provide access to scientifically sound information with its potential for visualization.

#### **3.2 Study Area Berlin, Germany – A Heterogeneous Urban Forest**

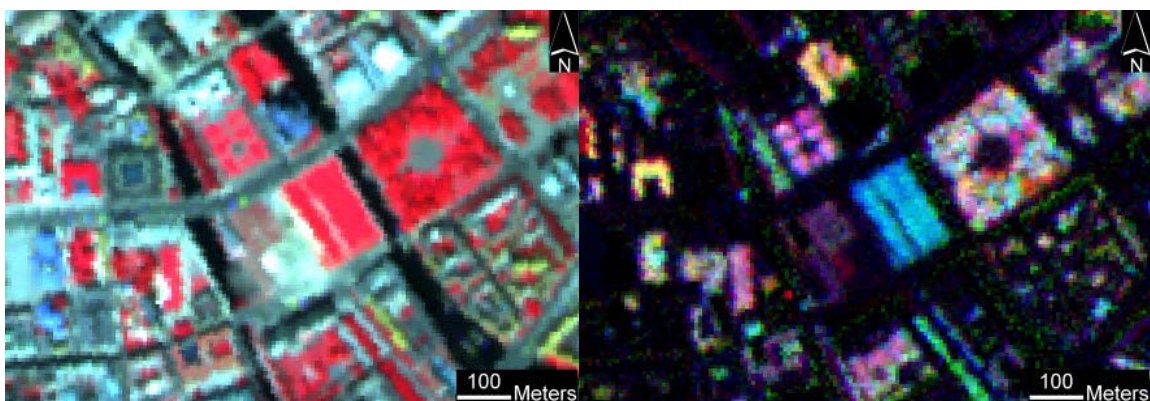
The chosen study area reflects a more consistent acquisition of heterogeneous forest structure using remotely sensed imagery. The imagery also underlines spatially explicit

## Introduction

information in high resolution in order to better reflect the recent lack of three-dimensional data and seasonal differences within urban forests.

The city of Berlin (52° 31' N, 13° 24' E) was chosen for this study's area of research. It is Germany's capital and largest city, with a population of approximately 3.4 million. It has a moderate climate and is characterized by a mostly flat topography. The administrative area is approximately 890 km<sup>2</sup>, 40% of which is covered by vegetation such as urban forests, parks, street trees and urban agriculture (Berlin Department of Urban Development 2010a). Urban forests take up more than 290 km<sup>2</sup> of Berlin, constituting the largest urban forest in Germany; by comparison, Berlin's public parks cover approximately 55 km<sup>2</sup> (Berlin Department of Urban Development 2010b). Berlin's built-up and vegetative green infrastructure is best used as an example for a diverse and heterogeneous urban environment.

High resolution multispectral RapidEye satellite imagery (6.5 m pixel resolution; 5 spectral bands) was acquired at five points in time within a single growing season in 2009. Very high resolution wintertime airborne LiDAR data (crown height model with a point density of 4 points/m<sup>2</sup>) from 2007/08 was used for additional height data information. Both data sets covered an overlapping area constituting approximately 80% of the total area of Berlin, which concluded most of the built-up area of Berlin. This allowed us to acquire new area-wide and detailed three-dimensional information on the urban environment and new options concerning intra-annual short-term dynamics across a highly urbanized area. This has not been applied in cities so far, which makes it valuable for science and additional applications.



*Figure 1 - 1: Mono-temporal (left, vegetation colored red) and intra-annual (right) RapidEye satellite image, Berlin. The possible differentiation within the vegetation by a multitemporal, intra-annual dataset is made apparent by visual interpretation.*

### **3.3 Objectives – Remote Sensing Benefits from a Temporal Point of View**

Green cities bring about sustainability, resilience and better living conditions, such as by using the concept of urban ecosystem services. Still, such services are challenged by a general lack of relevant information, natural and anthropogenic disturbances like the influence of climate change, investment constraints and more. This could imply a lack of up-to-date environmental information, and such information is highly important for improved decision-making. This lack of essential environmental information can be narrowed using recent innovative technology, such as remote sensing. This is especially true in the matter of the consistency and comparability of area-wide information and the provision of more precise information on individual objects and their changes over time.

The object of this work is urban forests because they consist of a highly heterogeneous and dynamic structure. This work extends the possibilities of advanced high resolution remote sensing from a temporal point of view for better assessing related urban ecosystem services:

- (1) Past: Recent remote sensing of very high temporal resolution offers new options for more adequately addressing urban forest dynamics. It is meant to derive further details on vegetation from past events (seasonal changes), which has not yet been applied across cities.
- (2) Present: A combination of recent high resolution remote sensing imagery has the potential to provide improved spatially explicit information on urban forests. It can be used as a common baseline for related urban ecosystem services and will address the present lack of three-dimensional information on urban forests.
- (3) Future: Recent high resolution remote sensing options are intended to provide more precise environmental information, which can reduce uncertainties in future prognoses. This will be of the utmost importance for future cities that seek to adapt to climate change impacts or support and improve today's urban ecosystem services.

## Introduction

The following research questions are related to notes (1) through (3):

*1) Can we advance the classification of urban forest details by considering seasonal changes using recent technological options of RapidEye satellite imagery?*

We developed a strategy to extend the classification of urban tree species using advanced machine learning and a time-series of RapidEye satellite imagery related to vegetation phenology. We investigated five images taken in 2009 concerning their potential for combining high spatial (6.5 m pixel size) and spectral resolution (5 bands), multiple images within a single growing season (intra-annual) and large area coverage (a single image across the city). We also investigated a pre- and automatic selection of different temporal and spectral band combinations of 2009 RapidEye satellite imagery, specifically regarding their contribution to accurately classifying tree species.

*2) To what extent do details on additional remotely sensed tree species provide more precise estimates of urban forest carbon storage?*

We analyzed area-wide urban forest above-ground carbon estimates to determine the details of remotely sensed tree species information, including: no species information, dominant species, fractions of species and species information of each individual tree. The present carbon stock of the urban forest was based on information on individual tree species, which we derived from a combination of RapidEye satellite imagery (2009) and LiDAR height data (2007/2008). The results should improve spatially explicit and area-wide urban forest carbon estimates.

*3) How can recent progress in remote sensing advance life cycle assessments of urban forest carbon offset?*

It is important to consider changes in urban forest carbon offset in the matter of urban forest dynamics and future disturbances. We discussed a life cycle assessment regarding how advantageous a combination of recent developments in high resolution remote sensing can be for developing more precise prognoses for future decision-making. We complemented the review with a simplified case study of Berlin, Germany. The discussion puts a focus on the aspects of urban forest structure and growth because they have an extremely significant influence on life cycle assessments of urban forest carbon offset.

### 3.4 Structure

The main objectives of this dissertation are addressed in Chapters II–IV, which are to be published in international peer-reviewed journals.

Chapter II, *Urban Vegetation Classification: Benefits of Multitemporal RapidEye Satellite Data (published)*. In this chapter, a Support-Vector-Machine approach is applied for classifying tree species using a time series of RapidEye satellite imagery and ancillary LiDAR height data for orthorectification and improved tree masking.

Chapter III, *Modeling Above-Ground Carbon Storage: A Remote Sensing Approach for Deriving Individual Tree Species Information in Urban Settings (published)*. This chapter is based on the composition data for tree species (results of Chapter II) and an individual tree detection approach using a local maxima filter algorithm and LiDAR height data. Both are input for allometric biomass equations.

Chapter IV, *Progress in High Resolution Remote Sensing to Advance Life Cycle Assessments of Urban Forest Carbon Offset (submitted)*. This chapter examines remote sensing options in order to acquire more precise and consistent input for a life cycle assessment to reduce the uncertainty related to future prognoses of urban forest carbon offset.

Chapter V, *Synthesis*. This chapter concludes the major outcomes of this work and provides an outlook concerning the role of urban remote sensing in the context of future cities and their environment.

## Introduction



**II: Urban Vegetation Classification: Benefits of Multitemporal RapidEye Satellite Data**

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### **Abstract**

Global climate change and sustained urban growth have increased the necessity of assessing the role that urban vegetation plays in urban dwellers' lives, as well as in urban ecosystem services. Urban environmental studies, however, still lack methods to characterize urban vegetation with adequate detail and across large areas. To remedy this gap, we apply a Support-Vector-Machine approach to classify eight frequent tree genera in the capital city of Berlin, Germany. We investigate different spectral and temporal band combinations of five RapidEye images acquired during the 2009 phenological season, and use ancillary surface and terrain models for orthorectification and improved tree masking. Results show that intra-annual time-series of RapidEye data can be used for high-precision tree genera classification in an urban environment. Differences within RapidEye time-series correlate well with empirical phenological studies of different tree genera, and RapidEye's red-edge band supports class separability. Further assessment is needed on the individual tree level and mixed stands regarding the quality of mapping urban individual trees, as our sampling approach mainly focused on larger stands with only a single tree genus. Urban applications will benefit from multitemporal RapidEye data, which offers area-wide monitoring and allows in-depth vegetation analysis to augment existing assessments. Such information is indispensable for assessing differences in urban ecosystem services related to carbon storage, cooling or air filtering, all of which differ between tree species. Therefore, the importance of in-depth analyses of urban vegetation cannot be underestimated in today's context of climate change.

## 1 Introduction

Global climate change is a major burden for cities and is most likely to be potentiated by the ongoing urban heat island effect, an increasing number of urban dwellers, and often being augmented by an ageing and more sensitive population (Arnfield 2003; Kraas 2007; Seto 2009; UN 2011). Therefore, effective countermeasures like the role of urban vegetation as an ecosystem service should not be underestimated for mitigating climate change impacts (Cadenasso et al. 2006; Pickett et al. 2011).

Urban vegetation, particularly trees, serve a multitude of urban ecosystem functions (Bolund and Hunhammar 1999). Trees, for example, provide an important share of above-ground carbon storage in cities, which has largely been neglected until now (Davies et al. 2011). In-depth analysis of trees is necessary to account for differences in their contribution to ecosystem functions such as carbon storage, since uptake greatly varies among urban tree genera and species (McHale et al. 2009). Biophytomass, species-specific leaf structures and seasonal differences among tree species affect the filtering of air pollutants, as well as the cooling and retention of rainwater (Shashua-Bar et al. 2003; McDonald et al. 2007; Morin et al. 2009; Pandit and Laband 2010). Urban remote sensing offers opportunities to overcome the lack of reliable and reproducible information on urban vegetation across large areas for more accurate assessments of ecosystem functions (Melesse et al. 2007; Seto 2009; Churkina et al. 2010; Davies et al. 2011; Liu and Li 2012; Weng et al. 2012). At the same time, urban areas pose specific challenges for remote sensing-based approaches. These challenges are largely related to the spectrally and spatially heterogeneous urban structure and the pronounced 3D character of urban environments with shadowing and obscured urban objects, as well as rapid temporal changes. The variety of vegetation types and the dominance of single trees add to that complexity. Recently implemented high resolution remote sensors have opened up new possibilities to classify details, which is required to differentiate objects like tree species within heterogeneous urban environments (Weng et al. 2012).

Very high resolution multispectral satellite data was investigated by Pu and Landry (2012), who classified seven tree species using WorldView 2 data. These authors found that

## Urban Vegetation Classification: Benefits of Multitemporal RapidEye Satellite Data

classifications benefit from additional spectral information of an 8-band WorldView 2 springtime image compared to a 4-band IKONOS springtime image. The maximum overall accuracy of 63 percent was nevertheless too low to be useful. Immitzer et al. (2012) found similar classification results for European tree species using a summertime WorldView 2 image, but the benefits of additional spectral information were highly species-dependent.

High resolution airborne data most commonly uses spectral or structural information for tree species classification, whereas studies of traditional 4-band high resolution imagery was found too low for tree species classification and was affected by high variations (Zhang and Hu 2012). In contrast, very high spectral information of recent hyperspectral airborne data produced high accuracies for tree species classification in forests of southeast Britain, as well as urban settings of Tampa, USA (Pu and Liu 2011; Ghiyamat et al. 2013). Airborne LiDAR data has become an important source for the 3-dimensional analysis of trees with a focus on carbon estimates (Omasa et al. 2007; Miraliakbari et al. 2010; Shrestha and Wynne 2012). Li et al. (2013) indicate a positive linear correlation between point density and classification accuracy. High point density discrete LiDAR systems and full-waveform LiDAR particularly offer extensive opportunities for tree species classification (Hyypä et al. 2008; Korpela et al. 2010; Pirotti 2011; Vaughn et al. 2012). Primary properties of full-waveform systems are derived from the complete returned signal; they offer additional points for a three-dimensional analysis of species-related differences between leaves and branches (Wagner et al. 2008). Heinzl and Koch (2011) successfully extended the use of secondary LiDAR properties for European tree species classification using width, amplitude, intensity and the total number of targets within one laser beam.

High resolution multitemporal airborne data were successfully applied for tree species classification, as they reflect phenological differences among tree species (Key et al. 2001; Hill et al. 2010). Multitemporal high resolution space-borne approaches of tree species classification are promising; an overall accuracy of 86 percent within monoculture stands in forestry has been reached by combining a summertime and autumn IKONOS image from 2000. In this context, Carleer and Wolff (2004) suggest using higher temporal resolution to improve the separability of a larger number of tree species because accuracy was affected by high variations – from 40 to 100 percent between species.

## Urban Vegetation Classification: Benefits of Multitemporal RapidEye Satellite Data

In the context of the abovementioned studies, a combination of different remote sensors seems promising. For example, tree species classification has been further improved by the combination of high-density LiDAR and multispectral or hyperspectral data (Holmgren et al. 2008; Dalponte et al. 2012). On the other hand, recent satellite technology like RapidEye might offer a beneficial combination of factors within a single system, which could include large area coverage, high spatial and temporal resolution, and additional spectral information.

RapidEye satellite imagery seem to be promising for area-wide in-depth analysis of urban vegetation, as it offers high resolution (6.5 m pixel size), a swath width of 77 km, and a maximum acquisition capacity of 1,500 km per orbit. The sensor supplies 5 bands from visible to near-infrared, including additional spectral information from the red-edge in the wavelength range of 690-730 nm (RapidEye AG 2012). Initial results based on RapidEye data are promising, e.g. in terms of vegetation classification, tree stress and disease monitoring (Marx 2010; Eitel et al. 2011; Schuster et al. 2012). In-depth remote vegetation sensing is supported by RapidEye's multiple satellite constellations, which allow multitemporal data acquisition during one phenological vegetation cycle (Schwartz and Reed 1999; RapidEye AG 2012). Characteristic information about tree species-specific differences in vegetation phenology were identified in earlier studies and can extend our opportunities for urban remote sensing of area-wide tree species classification using multitemporal RapidEye imagery (Lechowicz 1984; Halverson et al. 1986; Richardson et al. 2006). However, the exact start and end of phenological periods may vary slightly due to different conditions regarding location, weather and variations within species (Chmielewsky and Henniges 2006; Wesolowski and Rowinski 2006; Morin et al. 2009; Polgar and Primack 2011).

The aim of this study is to develop a strategy for an urban area-wide classification of frequent tree genera, exemplified by Berlin, the German capital. Our Support-Vector-Machine classification approach is based on intra-annual time-series of RapidEye data. We use ancillary surface and terrain models for orthorectification and improved tree masking. The main research question we explored is: To which extent does multitemporal RapidEye imagery allow tree genera classification within an urban environment?

## 2 Material and Methods

### 2.1 Study Area

The city of Berlin (52° 31' N, 13° 24' E) has a population of about 3.5 million. The city's administrative area is about 890 km<sup>2</sup>, of which 40 percent is covered by vegetation. Berlin's topography is mostly flat, between 30-120 m above sea level. The climate is moderate, and on the border between a maritime and continental influence. More than 290 km<sup>2</sup> of Berlin are urban forests, thus comprising the largest urban forest in Germany; public parks cover about 55 km<sup>2</sup>. More than 400,000 public street trees are registered in Berlin (Berlin Department of Urban Development 2010a). The number of trees on private property is expected to be high as well, but has not yet been systematically assessed for the whole city. Deciduous broadleaf tree genera are prevalent on public land. Evergreen tree genera are mostly limited to pine (*Pinus*), while birch (*Betula*), chestnut (*Aesculus*), lime (*Tilia*), maple (*Acer*), oak (*Quercus*), plane (*Platanus*) and robinia (*Robinia*) are the most dominant tree genera in Berlin (Berlin Department of Urban Development 2010a).

### 2.2 Data and Preprocessing

We acquired five RapidEye images in 2009 within a single growing season for the city of Berlin (Table 1). Cloud coverage was low, except for scattered cumulus clouds in the October images. Imagery was delivered as level 1B (RapidEye AG 2012), which includes radiometric and geometric sensor corrections and is calibrated to at-sensor radiances with a nominal pixel size of 6.5 m at nadir.

We further included preprocessed LiDAR height models, a wintertime digital surface model (DSM: 4 points / m<sup>2</sup>, first return only) and a digital terrain model (DTM: 1 point / m<sup>2</sup>). Both models were based on a wintertime flight campaign, the eastern part of Berlin from November 26-28, 2007, and the western part of Berlin from January 11-13, 2008. RapidEye and LiDAR height models cover an overlapping area of approximately 700 km<sup>2</sup> of the city of Berlin, i.e. our study area sums up to 78 percent of Berlin's administrative area (Fig. 1) (Berlin Partner GmbH 2007; Kolbe et al. 2008).

## Urban Vegetation Classification: Benefits of Multitemporal RapidEye Satellite Data

Table II - 1: 2009 RapidEye satellite imagery (5 bands: RGB, near-infrared, red-edge). Available phenological information for the region of Berlin is related to each date.

Data				Phenology
Image	Date	Cloud Cover (%)	Across track angle	Season (Period); Indicator Species; Leaf Phenology of Case Study Tree Genera
#1	04-13	0	13.6°	<p>Early spring (03-27 to 04-25)</p> <p>Start blossom of <i>Forsythia x intermedia</i></p> <p><i>Aesculus</i>: most advanced leaf development</p> <p><i>Acer, Fagus, Populus, Tilia</i>: early leaves</p> <p><i>Acer</i> more advanced, <i>Tilia</i> least advanced</p> <p><i>Platanus</i>: no leaves yet</p> <p><i>Quercus</i>: dead leaves, leaf development started late April</p> <p><i>Pinus</i>: evergreen coniferous</p> <p><i>Acer, Populus, Tilia</i> and <i>Quercus</i>: consist of 2-3 species</p> <p>Leaf growth may differ among species of the same genus</p>
#2	07-27	0	13.6°	<p>High (06-13 to 07-25) to late (07-26 to 08-26) summer</p> <p>End blossom of <i>Tilia platyphyllos</i></p> <p>All tree genera: leaves fully developed, maximum foliage</p> <p><i>Pinus</i>: evergreen coniferous</p> <p>Least differences among species of the same genus</p>
#3	08-16	0	10.6°	<p>Late summer (07-26 to 08-26)</p> <p>First ripe fruits of <i>Malus domestica</i></p> <p>Leaf status similar to image #2 from 07-27</p>
#4	10-09	< 5	- 02.8°	<p>High autumn (09-14 to 10-17)</p> <p>First ripe fruits of <i>Quercus robur</i></p> <p><i>Aesculus</i>: advanced leaf coloring and leaf fall</p> <p><i>Acer, Populus, Fagus, Tilia</i>: leaf coloring, <i>Acer</i> advanced</p> <p><i>Platanus</i>: successive leaf coloring and fall</p> <p><i>Quercus</i>: yellowing phase not started yet</p> <p><i>Pinus</i>: evergreen coniferous</p> <p><i>Acer, Populus, Tilia</i> and <i>Quercus</i>: consist of 2-3 species</p> <p>Leaf coloring or fall may differ among species of the same genus</p>
#5	10-19	< 5	10.5°	<p>Transition high (09-14 to 10-17) to late (10-18 to 11-01) autumn</p> <p>Start yellowing phase of <i>Quercus robur</i></p> <p>Leaf status similar to image #4 from 10-09 except <i>Quercus</i></p> <p><i>Quercus</i>: start yellowing phase</p>

We first mosaicked the DSM and DTM tiles and projected the data to UTM, Zone 33N, and WGS-84 ellipsoid. We then resampled the DSM LiDAR data to 1 m spatial resolution to fit

## Urban Vegetation Classification: Benefits of Multitemporal RapidEye Satellite Data

the DTM. A 3x3 median filter was applied to the DSM to smoothen missing tree crown values due to the leaf-off data acquisition. This procedure improved the process of orthorectification, as our leaf-off DSM data is particularly affected by gaps in deciduous tree crowns (Ben-Arie et al. 2009). A normalized DSM (nDSM) was produced to extract absolute height information by subtracting the DSM from the DTM (Koch et al. 2009).

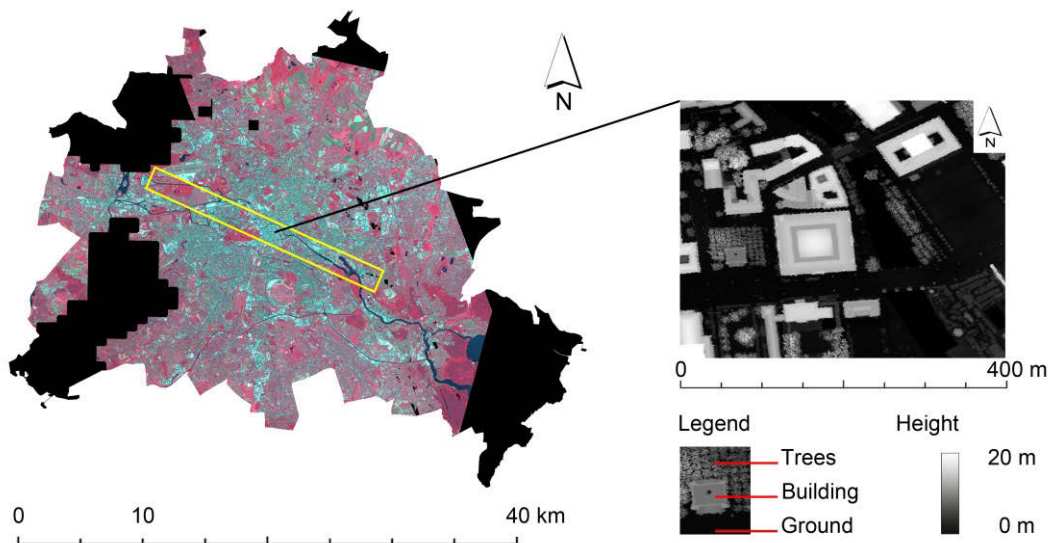


Figure II - 1: Left: Summertime, false color composite (near-infrared, red, green) RapidEye and LiDAR data coverage inside the administrative boundaries of Berlin. Either RapidEye or LiDAR data were not available for masked areas. Field survey corridor marked as yellow rectangle. Right: exemplary subset of DSM.

We then rectified our imagery using 1<sup>st</sup> order rational polynomial coefficients (RPC), the DSM and additional 3D ground control points (GCPs) to improve the spatial accuracy of default-level 1b imagery (RMSE 1-D = 20.90 m) (RapidEye AG 2012). A total number of 22 GCPs for each image were found to be appropriate to account for relief displacement. The selection of GCPs was based on a low residual error with a final root-means-square error below 1.8 m (RMSE 1-D) for the entire image. Each RapidEye image was resampled to 5 m pixel size and projected to UTM, Zone 33N (WGS-84 ellipsoid) (Fig. 2a).

We calculated the NDVI for each date of our orthorectified imagery for building a vegetation mask and stacked all NDVI information (Horler et al. 1983; Dawson and Curran 1998). Each pixel was masked as vegetation if a minimum NDVI of 0.2 was reached for at least one of the image acquisitions (Fig. 2b). We validated the mask based on 200 random points of



## Urban Vegetation Classification: Benefits of Multitemporal RapidEye Satellite Data

vegetation and achieved an overall accuracy of 99 percent. We then generated a tree mask by applying a 3 m threshold from the nDSM to the vegetation mask. The tree mask was resampled (nearest neighbor) to a 5 m pixel size to fit the RapidEye images (Fig. 2c).

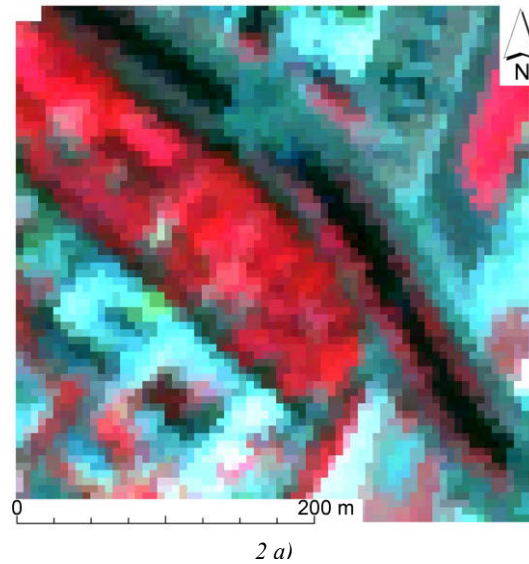
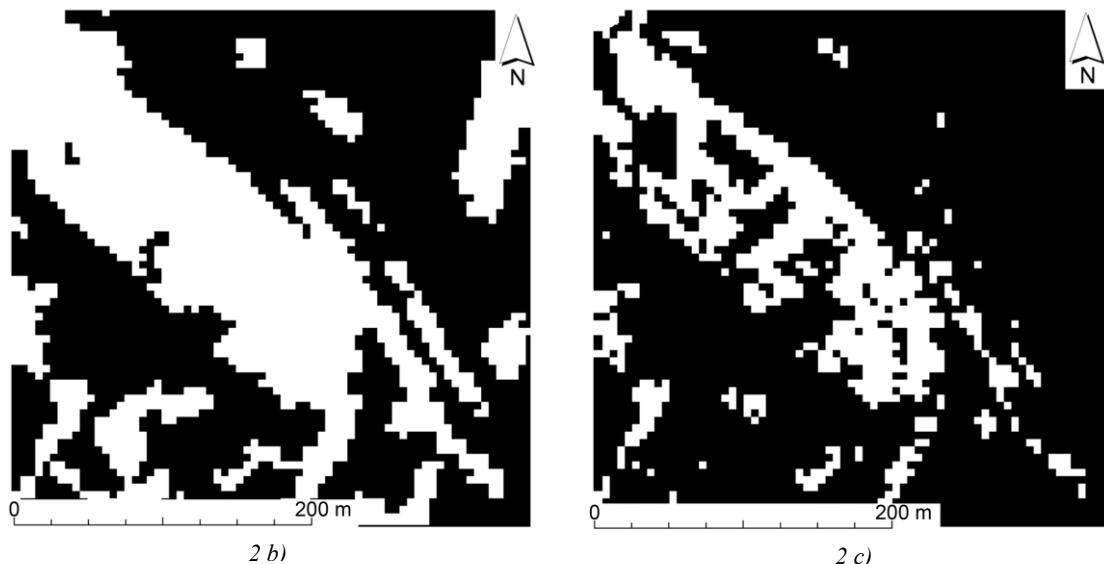


Figure II - 2: a) RapidEye single date (July 27th 2009), false color composite (near-infrared, red, green). b) Vegetation mask (white). c) Tree mask (white) combining a 3 m LiDAR nDSM height threshold and the RapidEye vegetation mask.



Lastly, we stacked RapidEye images into different layers to compare various classification scenarios (Table 2). Scenario 1.1 represented a frequently applied constellation of very high resolution satellite sensors using a single date summertime classification covering a spectral

## Urban Vegetation Classification: Benefits of Multitemporal RapidEye Satellite Data

range of red, green, blue and near-infrared. Our multitemporal scenarios focused on additional phenological information for the classification process using additional springtime (Scenario 2.1) or autumn imagery (Scenario 3.1). A full time series of our five available images was represented by Scenario 4.1. Scenarios 1.2, 2.2, 3.2 and 4.2 represent modifications by including additional spectral information provided by RapidEye's red edge band. We then applied the tree mask to each stack.

Table II - 2: Spectral and temporal classification scenarios.

Scenario	Date (2009)	Objective
1.1	07-27	baseline classification: summertime, 4 bands (no red-edge)
1.2		additional spectral information from red-edge
2.1	07-27; 04-13	additional phenology information from spring
2.2		additional spectral information from red-edge
3.1	07-27; 10-09	additional phenology information from autumn
3.2		additional spectral information from red-edge
4.1	07-27; 04-13; 08-16; 10-09; 10-19	intra-annual time-series
4.2		additional spectral information from red-edge

### 2.3 Reference Data

A field survey was conducted in late summer 2010 and spring 2011 to identify and locate large, homogeneously-structured areas of eight tree genera. These areas were located on a 25 km transect across Berlin in a northwest-southeast direction, and were spatially well localized with GPS (Fig. 1). We digitized areas (polygons) of the same genus with a minimum size of 500 m<sup>2</sup> and an average size of 1500 m<sup>2</sup>. Each area was dominated by a single tree genus and has a closed canopy with a minimum height of 3 m. Our mapped reference tree genera were mainly affected by no or only minor mixing of up to three different tree species, and covered 14,000 m<sup>2</sup> (12 polygons) of maple (*Acer campestre*, *Acer platanoides*, *Acer spec.*), 7,800 m<sup>2</sup> (4 polygons) of chestnut (*Aesculus hypocastanum*), 11,300 m<sup>2</sup> (7 polygons) of beech (*Fagus sylvatica*), 2,500 m<sup>2</sup> (4 polygons) of pine (*Pinus sylvestris*), 32,600 m<sup>2</sup> (18 polygons) of plane (*Platanus hispanica*), 10,300 m<sup>2</sup> (9 polygons) of poplar (*Populus nigra*, *Populus alba*), 7,600 m<sup>2</sup> (7 polygons) of oak (*Quercus robur*, *Quercus rubra*, *Quercus spec.*), and 5,300 m<sup>2</sup> (8 polygons) of lime (*Tilia cordata*, *Tilia x*

## Urban Vegetation Classification: Benefits of Multitemporal RapidEye Satellite Data

*vulgaris*, *Tilia platyphyllos*). We separated those areas into a subset for training the classifier and a subset for validation. Each subset consisted of 100 RapidEye pixels for each reference class selected by a stratified random sampling. We avoided spatial autocorrelation between the training and validation subset by a minimum distance of 10 m; we selected this as a reasonable measure with respect to our classification depth of tree genera, a heterogeneous, highly fragmented urban structure, as well as our quality of orthorectified RapidEye imagery (orthorectified at RMSE 1.8 m, 1-D). The selection of tree genera was based on a pan-sharpened false color composite of QuickBird (May 24<sup>th</sup> 2009, 0.61 m pixel size), true color digital orthophotos (UltraCam X, April 11<sup>th</sup> 2009, 0.1 m pixel size), Google Earth, Google Street View and information on urban forests and green space from the Berlin Department of Urban Development (2009). Our reference data did not include young generation tree populations below an approximate age of 15 years. Mapped tree genera did not show any abnormalities such as diseases or other stresses (e.g. mistletoes), and were not affected by cloud coverage or cloud shadows in the RapidEye imagery.

Table 1 provides available phenological information of our case study tree genera related to each date of our RapidEye imagery. The dates of our imagery were all within the period of phenological activity from the end of March to the beginning of November (Deutscher Wetterdienst 2011). Seasonal information was received by the German Weather Service (DWD), which was normalized by the DWD over a period of time (1991-2011) to account for variance due to voluntary observations. Great phenological differences exist among temperate deciduous tree species in the northern hemisphere during the periods of early and high spring (mid-March to mid-May, leaf growth) and high and late autumn (mid-September to mid-November, yellowing phase and leaf fall) (Schnelle 1955). Our phenological information was based on the comparison of our intra-annual RapidEye imagery to phenological information derived from an in-depth literature review describing periods of tree genera phenological activity (Schnelle 1955; Lechowicz 1984; Halverson et al. 1986; Gitelson and Merzlyak 1994; Key et al. 2001; Nilsson and Källander 2006; Richardson et al. 2006; Wesolowski and Rowinski 2006; Estrella 2007; Morin et al. 2009; Berlin Department of Urban Development 2010b; Hill et al. 2010; Polgar and Primack 2011).

## 2.4 Classification Approach

We applied a Support-Vector-Machine (SVM) classification because of its ability to handle high data dimensionality. The SVM performs well in heterogeneous urban areas, requires few training data, and is less sensitive to training sample size than other programs (van der Linden 2007; Mountrakis et al. 2011). We used imageSVM software, an IDL-based implementation of LibSVM (Chang and Lin 2011) that offers an iterative determination of most important SVM parameters (Janz 2007). A non-linear kernel function transforms the data to a higher dimension to receive a more linear distribution, which can be solved by the SVM principle of a linear optimum hyper plane. We chose a Gaussian radial basis function due to its superior performance compared to other kernel functions (Kavzoglu and Colkesen 2009). The kernel can be adapted by its width in imageSVM. If a class cannot be separated by a linear function of an optimum hyper plane, SVM can adapt to that optimization problem by a regulation parameter, a so-called penalty parameter. This parameter allows the user to define a degree of error. The multi-class classification problem is solved by multi-class SVM probability estimates, which offer an additional quality measure of how far a class separation is affected by other classes. The final classification results refer to each pixel assigned to the best matching tree genus class based on the highest class probability in a one-against-all-approach (Janz 2007, 2010).

We parameterized the SVM classifier by comparing different pairs of kernel width and penalty parameters based on an internal performance estimation (eight-fold cross-validation using kappa statistics) and our reference data subset of randomly-chosen training data (100 pixels per class) (Janz 2007; van der Linden 2007; Congalton and Green 2009; Chang and Lin 2011). We identified an optimum kernel width ( $\gamma$ ) of 4 and a penalty parameter ( $C$ ) of 8.

We applied the SVM classification to better understand spectral and temporal advantages of intra-annual RapidEye data (Table 2), because they best reflect phenological differences in our case study (Franke et al. 2012). We used the same SVM parameters for all scenarios of Table 2 to analyze the effect of temporal and spectral differences, particularly the red-edge band. We finally analyzed the class separability for each reference class according to its SVM-based class probability distributions.

## Urban Vegetation Classification: Benefits of Multitemporal RapidEye Satellite Data

We then used an automatic feature selection approach to rank the most important bands for tree genera classification (Janz 2007). This method is based on a wrapper approach in combination with a stepwise forward selection heuristic for selecting relevant features (Kohavi and John 1997). Beginning with an empty feature set, SVMs are trained for each single feature. The feature corresponding to the best-performing SVM is selected and ranked first. SVMs are then trained iteratively using all previously-ranked features and each remaining unranked feature separately. Next, the remaining feature corresponding to the best-performing SVM is selected and ranked (Rabe et al. 2010). The output of the automatic feature selection provided cumulated total kappa values for each rank, including all features of the preceding ranks (Rabe et al. 2010). We focused on the scenario of highest temporal resolution (Scenario 4) because it offered the most complete intra-annual data space of our case study. We finally compared Scenarios 4.1 and 4.2 to analyze how the red-edge band affects accuracies of the automatic feature selection.

The quality assessment of the classification results was based on field survey data and very high resolution remote sensing data (QuickBird, Google Earth, orthophotos). The statistical accuracy assessment was based on the reference data subset of randomly chosen validation data. We summarized each cross-tabulation matrix to parameters of quantity and allocation disagreement to provide a concise comparison of different classification results (Pontius and Millones 2011). We then calculated kappa statistics and overall accuracy for a general accuracy estimate (Congalton and Green 2009). Producer and user accuracy was calculated to focus on a specific class. The F1 measure was used as a harmonic mean of producer's accuracy (recall) and user's accuracy (precision) to characterize classification performance. It provides a reasonable single measure when computing a mean of ratios like recall and precision (Witten et al. 2011). A visual and on-site accuracy assessment was applied to account for the delineation of tree genera, mixed stands, small groups and the individual tree level.

### 3 Results

#### 3.1 Classification Output

Our tested scenarios clearly indicate a good classification result for tree genera using multitemporal RapidEye imagery (Fig. 3). Including the red-edge band shows an increment in kappa (Fig. 3). The baseline classification from a single summertime image (Scenario 1.1) shows a low classification accuracy of 0.46 in kappa. We consider the accuracy as too low to be useful for classifying eight tree genera. Adding temporal information of high phenological differences among tree species (spring or autumn) causes a notable increase in accuracies of classified tree genera. Our spring imagery (Scenario 2.1) provides a slightly higher increase in accuracy by 0.25 in kappa than 0.19 by our autumn imagery (Scenario 3.1). Additional intra-annual RapidEye imagery further improves classification accuracy (Scenario 4.1).

Additional spectral information from the red-edge band shows a positive effect of 0.06 in kappa for our single summertime image (Scenario 1.2). Adding spectral information from the red-edge band to our multitemporal spring and autumn Scenarios (2.2 and 3.2) further improves the classification accuracy. Adding the red-edge band to our autumn Scenario (3.2) shows a higher increase by 0.10 in kappa than 0.04 by our spring Scenario (2.2), but they both reach the same maximum value. Further temporal imagery (Scenario 4.2) shows a very small increment by 0.02 in kappa compared to our Scenario (4.1) without red-edge information.

The overall error decreases with an increasing number of features from multitemporal imagery. Scenario 4.2 achieved the best results, with an overall accuracy of over 85.5 percent. In general, the overall disagreement is dominated by an allocation problem; both the quantity disagreement and the allocation disagreement decrease with higher temporal and spectral resolution. The inclusion of the red-edge band shows a general decrease in disagreement for a single image and multitemporal imagery (Fig. 3). The quantity disagreement becomes minimal for the highest temporal resolution of this case study (Scenario 4.2).

## Urban Vegetation Classification: Benefits of Multitemporal RapidEye Satellite Data

The highest classification accuracy is derived from Scenario 4.2. Table 3 shows class-specific accuracies. Producer's and user's accuracy differ between 1 and 15 percent, which causes little changes to the compact F1 measure. In our case study we found the lowest accuracy for class *Quercus* as demonstrated by the low F1-measure of 63 percent.

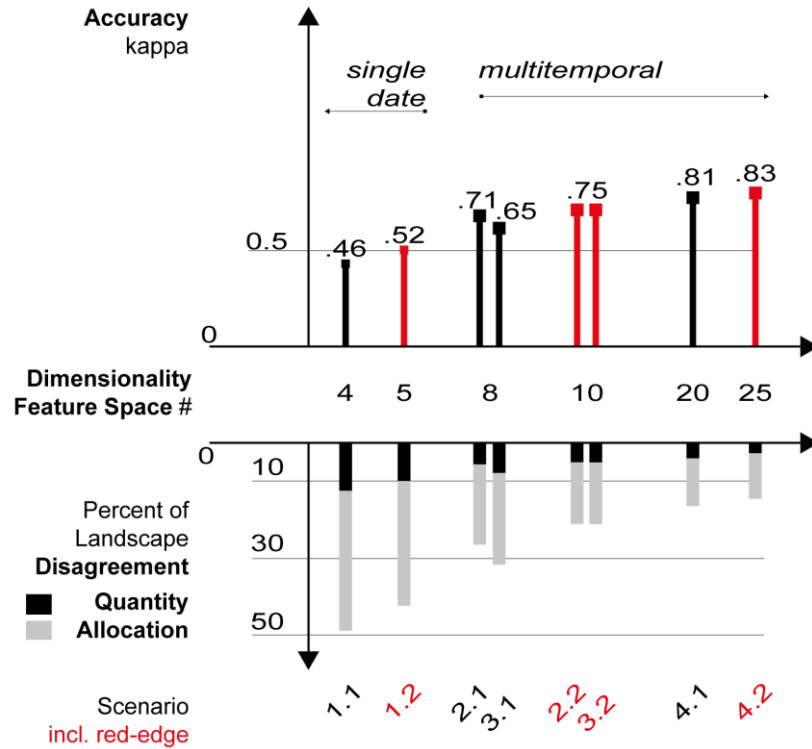


Figure II - 3: Classification accuracy and allocation and quantity disagreement of tested scenarios (Table 2).

Table II - 3: Classification accuracy (F1-measure) of urban tree genera (Scenario 4.2, all available imagery of this case study).

Tree Genus	F1 Accuracy (%)	User's accuracy (%)	Producer's accuracy (%)
<i>Pinus</i>	100	99	100
<i>Aesculus</i>	100	99	100
<i>Platanus</i>	92	93	91
<i>Tilia</i>	85	78	93
<i>Acer</i>	84	86	81
<i>Populus</i>	83	88	79
<i>Fagus</i>	78	76	80
<i>Quercus</i>	63	66	60

## Urban Vegetation Classification: Benefits of Multitemporal RapidEye Satellite Data

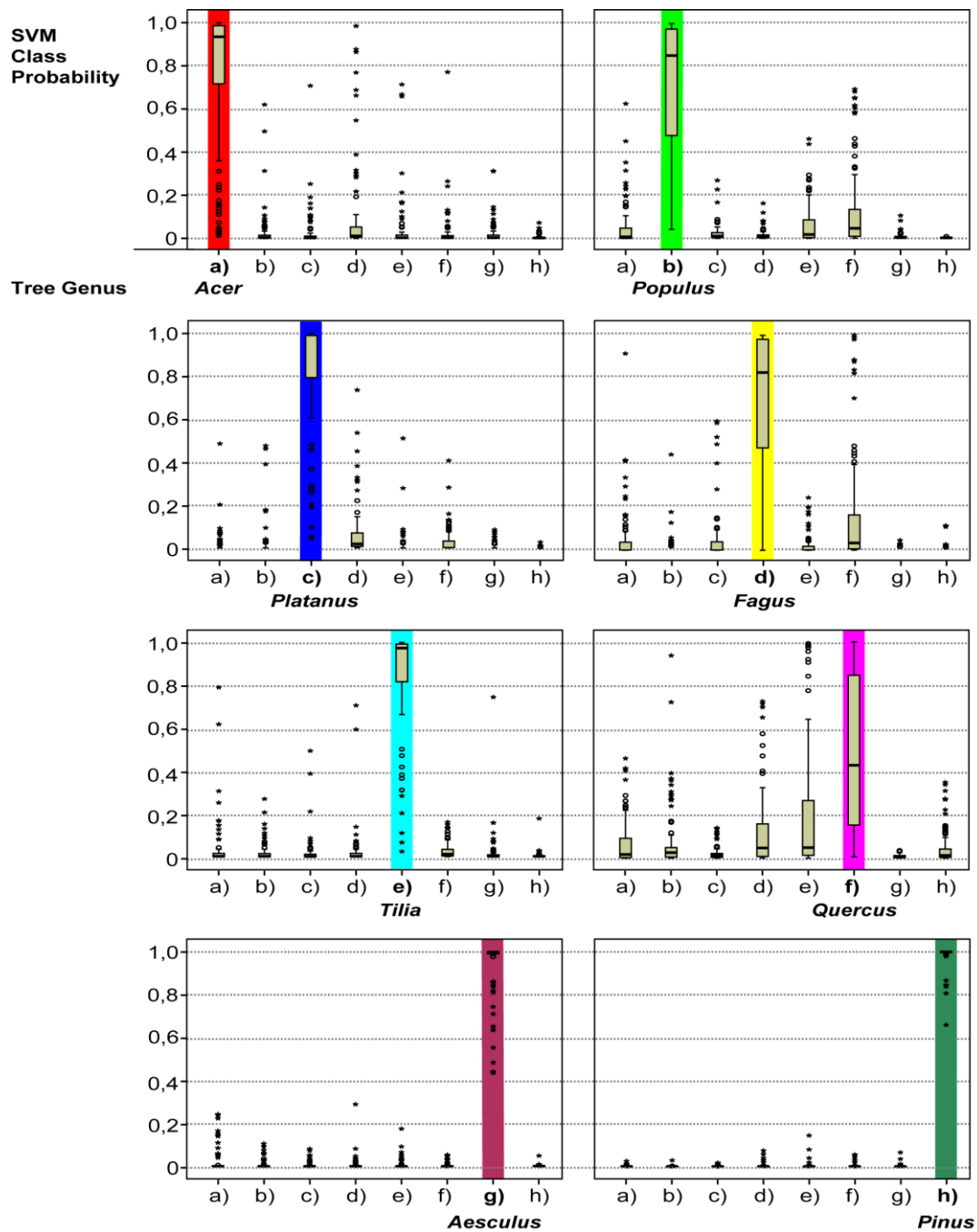


Figure II - 4: Variability of SVM class probability values for each reference class of Scenario 4.2. The classes are: a) Acer, b) Populus, c) Platanus, d) Fagus, e) Tilia, f) Quercus, g) Aesculus, h) Pinus.

Boxplots of Fig. 4 describe SVM probability values of the most accurate Scenario (4.2) based on the validation data. Each boxplot indicates the variability for each reference class compared to all other classes. Concerning our one-against-all-approach, high probability



values of the reference class, along with low values of all other classes indicate the best results. Likewise, a high range of probability values across several classes indicates deficient class separability. Accordingly, *Pinus* and *Aesculus* were classified as having the highest accuracies (Fig. 4, g and h). *Platanus*, *Tilia* and *Acer* form a second group with slightly less but still very good classification accuracies. A higher range of the reference class values of class *Populus* and *Fagus* allows them to reach the third-best classification accuracies. The class *Quercus* had the worst classification accuracy, as most values concentrated at a low level, making it likely to interfere with other classes.

### 3.2 Automatic Feature Selection

The ranking of multitemporal RapidEye data is represented by Table 4, and refers to the most complete data set of this case study (Scenario 4.2), as well as a variation by excluding red-edge spectral information (Scenario 4.1). We managed to achieve high classification accuracies at the level of tree genera when combining crucial dates of high phenological differences (spring and autumn) with a summertime image (Table 4). Overall, six bands of three points in time were sufficient to produce an accuracy of 0.77 in kappa from our multitemporal stack of 25 features (Scenario 4.2). A total of eleven bands are needed to reach an accuracy of 0.77 in kappa if red-edge information is excluded (Scenario 4.1). The overall accuracy of both scenarios plateaus after reaching 0.77 in kappa, and only moderately increases when selecting additional features (Table 4).

The ranking of Scenario 4.2 shows April 13<sup>th</sup> and July 27<sup>th</sup> to be the most important dates. Generally, spectral information from the red, near-infrared and red-edge band contribute most to overall accuracy. The first two features that are chosen are the red and near-infrared band from the April 13<sup>th</sup> image. Mapping the eight tree genera based only on these two spectral features already achieves a kappa of 0.49. The red-edge and red from the July 27<sup>th</sup> image each contribute 0.09 in kappa, respectively. Next, the green band of the early phase of tree phenology (April 13<sup>th</sup>) is selected, which adds 0.05 in kappa. The sixth selected feature is the near-infrared band from the October 9<sup>th</sup> (yellowing phase) scene, with another kappa increase of 0.05. We needed at least 6 more bands from the stack to notably increase overall accuracies by an additional 0.02 in kappa, and another 6 more bands for the next

## Urban Vegetation Classification: Benefits of Multitemporal RapidEye Satellite Data

increase of 0.02 in kappa. Based on a temporal stack of one spring, one summertime and one autumn image, additional temporal features only slightly contribute to overall accuracies by 0.03 for the image of August 16<sup>th</sup>. The same holds true for the image of October 19<sup>th</sup>. This slight increase is not related to a single spectral band, but to red, red-edge, near-infrared and blue. The optimum differentiation of tree genera is possible with over 20 bands from 5 images, but the maximum kappa of 0.83 based on all 25 bands is only slightly above the accuracies reached with 6 features from 3 images.

Table II - 4: Ranking of multitemporal RapidEye imagery from 2009. Total kappa is listed for cumulated ranks.

Scenario 4.1 (no red edge)				Scenario 4.2 (incl. red-edge)		
Date	Band	Kappa	Rank	Kappa	Band	Date
04_13	Near-infrared	0.23	1	0.23	Near-infrared	04_13
04_13	Red	0.49	2	0.49	Red	04_13
07_27	Red	0.58	3	0.58	Red-edge	07_27
07_27	Near-infrared	0.62	4	0.67	Red	07_27
04_13	Green	0.69	5	0.72	Green	04_13
07_27	Green	0.70	6	0.77	Near-infrared	10_09
10_19	Near-infrared	0.72	7	0.76	Red-edge	04_13
10_19	Green	0.76	8	0.76	Red	10_09
07_27	Blue	0.75	9	0.76	Green	07_27
08_16	Blue	0.76	10	0.76	Red-edge	08_16
10_09	Red	0.77	11	0.77	Red-edge	10_19
04_13	Blue	0.78	12	0.79	Near-infrared	10_19
10_19	Blue	0.78	13	0.79	Blue	10_09
10_09	Green	0.78	14	0.79	Blue	04_13
08_16	Green	0.78	15	0.80	Red	08_16
10_09	Blue	0.78	16	0.79	Red	10_19
10_09	Near-infrared	0.78	17	0.79	Blue	07_27
10_19	Red	0.80	18	0.79	Green	10_09
08_16	Red	0.80	19	0.80	Near-infrared	07_27
08_16	Near-infrared	0.81	20	0.81	Blue	08_16
			21	0.82	Blue	10_19
			22	0.82	Green	10_19
			23	0.82	Red-edge	10_09
			24	0.82	Green	08_16
			25	0.83	Near-infrared	08_16

The comparison of Scenarios 4.1 and 4.2 shows no differences at the two most important rankings, the near-infrared and red band, both from April 13<sup>th</sup>. Additional red-edge spectral information only causes a high increase in kappa by our July 27<sup>th</sup> image. The red-edge band from further dates of high phenological changes only show small changes with a maximum value of 0.01 in kappa, either decreasing, increasing or exhibiting no changes at all (Table 4). The comparison of highest ranking features considers a multitemporal springtime scenario of April and July reaching 0.70 in kappa for the first six features of Scenario 4.1, compared to 0.72 in kappa for the first five features of Scenario 4.2. The positive effect in accuracy of additional red-edge spectral information resulting from our automatic feature selection are similar to our springtime Scenario 2.1 (eight features) and 2.2 (ten features) with a small increase in kappa from 0.71 when excluding the red-edge band to 0.75 using all available bands.

#### **4 Discussion**

In this case study, we applied an urban area-wide classification approach to the city of Berlin, targeting eight frequent tree genera in central Europe using an SVM classification (van der Linden 2007; Lakes and Kim 2012). Our results show that multitemporal RapidEye imagery helps to extend the classification of urban trees up to the genus level. To the best of our knowledge, this is the first urban study to have been conducted of area-wide tree genera classification examining time-series of multi-spectral satellite imagery within a single growing season. We further evaluated the role of the red-edge in improving such classifications.

The summertime single date classifications (Fig. 3, Scenario 1.1, 1.2) provide only limited information for tree genera differentiation. Multitemporal RapidEye time series from April to July (Fig. 3, Scenario 2.1, 2.2) or October to July (Fig. 3, Scenario 3.1, 3.2) allow tree genera classification, which shows similarities to earlier field studies of e.g. Halverson et al. (1986), who point out crucial differences in phenology among tree genera in the spring and autumn. Hill et al. (2010) point out best classification results for tree species classification by combining spring or autumn images with a summertime image. This follows our increase

in overall accuracy with increasing temporal resolution (Fig. 3). A higher accuracy for our springtime Scenario (2.1) than the autumn Scenario (3.1) might be explained by already more visual differences in leaf development shown by our RapidEye image and orthophotos from April 2009. Urban hardwood trees like *Platanus* are already affected by leaf senescence and leaf-fall in late autumn (October 9<sup>th</sup> and 19<sup>th</sup>), thus supporting class separability among tree genera for Scenarios 3.1, 3.2, 4.1 and 4.2 (Halverson et al. 1986). The allocation disagreement remains the largest source of error, which is likely to be caused by sub-optimal points in time from our RapidEye time series or by variation between the different tree genera, which we could not consider for our case study.

Overall, we achieved moderate to optimal classification accuracies for eight tree genera in this case study using all available features (Table 3, Fig. 4, Scenario 4.2). Our classification results mirror tree-wise phenology characteristics, underscoring the importance of optimal dates of RapidEye imagery. Unique phenological patterns of tree genera, along with image acquisition dates reflecting these phenological peculiarities, offer optimal conditions for tree genera classification. Best classification results of a deciduous tree genus are exemplified by the *Aesculus* class. In our context, *Aesculus* leafs out earliest, resulting in a unique phenological pattern in this case study (Schnelle 1955). Our RapidEye imagery from spring matched this point in time (Table 1) (Deutscher Wetterdienst 2011). Similarly, differences among the early leafing out of *Populus* and the late leafing out of *Platanus* can be separated well in our analysis (Lechowicz 1984). Our case study focuses on tree genera; in practice the observed accuracy would be somewhat lower than that reported, since our accuracy assessment did not consider other tree genera as an additional class. Furthermore, if our case study genera were dominated by a single species like *Aesculus*, *Platanus* or *Pinus*, it might cause less variance in class probability values, and support higher class separability. On the other hand, similar phenological trajectories of tree genera like *Fagus*, *Tilia* and *Acer* (Schnelle 1955) affect our class separability negatively. This is indicated by higher variations in our SVM class probabilities (Fig. 4) and a reduced overall accuracy for the class *Fagus*, even though the class *Fagus* was not affected by different species of *Fagus* in our case study. The dates of our RapidEye imagery are less optimal for the class *Quercus*, and are likely to support low class separability, which is indicated by extremely high variations of class probability values (Fig 4). Our spring image (April 13<sup>th</sup>) is dated two weeks before the actual

leafing out of *Quercus* in Berlin, and the yellowing phase had hardly started on October 18<sup>th</sup> when our autumn imagery was acquired (Deutscher Wetterdienst 2011). Consequently, *Quercus* provides the least phenological characteristics to support class separability in our case study.

The results of the automatic feature selection confirmed our findings from the classification scenarios (Fig. 3) because they indicate that the availability of multitemporal RapidEye data provides additional information that is as important as spectral information itself for classifying tree genera. The phenological period of early spring is supposed to be crucial, as phenological differences among tree genera are likely to be higher in early spring than in summer (Halverson et al. 1986). However, our early spring classification (Table 4, rank 1-2) provides only slightly higher classification accuracies (+ 0.03 in kappa) than our single date baseline classification based on summertime data only (Fig. 3, Scenario 1.1). Spectral bands of single date RapidEye data generally seem to be insufficient to discriminate phenological differences between tree genera. A multitemporal feature set from April and July proves that the phenological trajectory during leaf development greatly supports class separability for tree genera in an urban setting (Fig. 3). The green band from April is ranked fifth because tree genera like chestnut can be easily separated as leafing out before other trees, at least in our setting (Schnelle 1955). Visual interpretation of available true color digital orthophotos from April 11<sup>th</sup> 2009 confirmed this phenological singularity. Imagery from July 27<sup>th</sup> and August 13<sup>th</sup> relate to a phenologically similar state in our case study (Table 1), adding little additional information on phenological change. This is also true for RapidEye imagery from October 9<sup>th</sup> and 19<sup>th</sup>, which both fall in the phenological periods from high autumn to late autumn (Table 1). Consequently, the increase in classification accuracy is low, and plateaus at the lowest-ranked features (Table 4). Additional variation of the “accuracy plateau” of the lowest-ranked features (Table 4) are most likely due to variations within the SVM training data (Waske et al. 2010). Hill et al. (2010) report comparable results of time-series classification, with the highest accuracies of tree species classification resulting from combining imagery from March, July, and October. No notable increase in classification accuracy was achieved when adding further imagery in a phenologically-similar region. Short-term variations during the yellowing phase (October 9<sup>th</sup> to 19<sup>th</sup>) do not present notable differences in our classification accuracy (Table 4).

## Urban Vegetation Classification: Benefits of Multitemporal RapidEye Satellite Data

Classification accuracies already slightly increase by additional spectral information from the red-edge (Fig. 3). This holds true for the red-edge spectral band of summertime imagery in particular (Fig. 3, Scenario 1.2). The red-edge spectral band of summertime imagery is selected before near-infrared by the automatic feature selection (Table 4). Gitelson and Merzlyak (1994) and Sims and Gamon (2002) found a higher saturation for the summertime near-infrared than for the red-edge spectral band; therefore, saturation might decrease the differentiation potential between tree genera. However, as no in-situ spectral data were available to match the exact observation dates of the archived satellite imagery, proving this hypothesis was beyond the scope of the present study. Temporal changes of the red-edge can also be an indicator of early leaf aging of specific tree genera such as chestnut and maple (Gitelson and Merzlyak 1994). Dalponte et al. (2012) indicate a notable influence of red-edge spectra concerning hyperspectral data and tree species classification, which requires further research concerning the width of RapidEye's red-edge band. Our autumn Scenario 3.2 shows a similar increase in accuracy using additional red-edge spectral information (Fig. 3). The increase in accuracy by additional red-edge information is expected to be lower for our spring Scenarios (2.1 and 2.2), as our April image already explains most of the overall accuracy using the near-infrared and red (Table 4). Any variation in accuracy might also relate to a wider spectral range of RapidEye's red-edge band that is likely to diffuse spectral details, which could improve tree genera classification (RapidEye AG 2012).

Our results indicate no notable changes within the same phenological period (July 27<sup>th</sup> and August 13<sup>th</sup>), and no notable short-term differences (Oct 9<sup>th</sup> and Oct 19<sup>th</sup>). Therefore, we suggest an image acquisition strategy for tree genera classification based on one summertime image and images of different phenological periods during the spring and autumn. The timeframe for image acquisition must be adapted to fall within the period of phenological indicators marking early spring and early winter. This will allow us to identify tree genera with early and late leafing out or leaf fall.

Due to time and budget constraints, we could not provide further details on leaf phenology, especially on dates of our RapidEye imagery, thereby limiting phenological research of our case study. Polgar and Primack (2011) mention that the variety of definitions of leaf development status, as well as the possibilities of monitoring vegetation phenology, remains a great challenge for a consistent and comparable database, especially at the local level. We

also found this to be the case. Furthermore, anthropogenic effects of temperature due to climate change particularly influence trees in temperate climate regions, which leads to an intensification of general year-to-year variations in leaf development, as well as local variations in leaf development due to the urban heat island effect (Chmielewsky and Henniges 2006; Polgar and Primack 2011). Therefore, further research is required to provide more up-to-date regionalized information on the phenological differences at the level of tree species to clearly identify similarities and differences both among and within species at the time of leaf development. Tree species classification will benefit from such optimal dates of multitemporal remote sensing imagery.

Our results extend the field of application towards the role of mitigating climate change and can provide new input for area-wide urban modeling of carbon storage, as biomass estimates highly depend on specifics like tree genus (McHale et al. 2009). We verified by a visual and on-site accuracy assessment that large urban trees can be classified ( $> 100 \text{ m}^2$ ). Calculations on estimates of carbon sequestration will benefit from this classification, as such estimates highly depend on large and healthy trees, which sequester considerably greater amounts of carbon than do young trees (Nowak and Crane 2002). Besides urban applications in tree genera classification, multitemporal RapidEye data offers new possibilities for monitoring vegetation phenology in general, as it offers capabilities for long-term-ecological monitoring of large areas at high spatial and temporal resolution. Such phenological records can help mitigate a problem of scales between satellite phenology and ground observations, as well as provide new knowledge of forest ecosystem dynamics and future models of climate change (Wesolowski and Rowinski 2006; Liang et al. 2011).

In our case study we offer new possibilities within ecological research considering multitemporal satellite imagery of RapidEye, which fills a gap between very high spatial resolution (e.g. QuickBird) and moderate spatial resolution (e.g. Landsat) remote sensing (Hostert et al. 2010). In this context, our case study of tree genera classification explicitly extends the existing knowledge about urban vegetation details towards a better understanding of urban ecosystem services (Pickett et al. 2011).

## 5 Conclusion

Results of this case study showed the possibilities of classifying frequent tree genera within the urban environment by multitemporal RapidEye data. Our results were successfully applied at an urban scale across Berlin, Germany's capital and largest city. Our study showed that a heterogeneous urban structure could be classified using high resolution satellite imagery from RapidEye, and enabled the classification of large urban groups of trees ( $> 400\text{m}^2$ ), trees aligned in a linear manner, as well as large individual trees ( $> 100\text{m}^2$ ). Further assessment is needed on the individual tree level and mixed stands regarding the quality of mapping urban individual trees, as our sampling approach mainly focused on larger stands with only a single tree genus.

We identified multitemporal data from RapidEye imagery as being necessary for tree genera classification. A total of 6 spectral bands of three points in time (spring, summer, autumn) were sufficient to achieve high class separability. RapidEye's red-edge spectral band supported our tree genera classification, specifically in the summertime and autumn imagery of a multitemporal dataset. We achieved the best results for *Pinus*, *Aesculus*, *Platanus* and *Tilia*, which was due to their specific phenological patterns. Considering a standard acquisition time window of 45 days for tasking, and acquisition limitations depending on the area of interest, conflicting other acquisition tasks and weather conditions, we suggest making use of this higher temporal resolution to further supplement basic research on tree genera phenology (RapidEye AG 2012). Even though we achieved good overall results for differentiating the selected tree genera, we propose further enlarging the group of tree genera addressing the benefits of multitemporal RapidEye data on a more detailed level of tree species. Future studies should compare the advantages we describe from dense multitemporal RapidEye data analysis to those made possible with hyperspectral and high point density or full-waveform LiDAR data for urban vegetation analysis. Further, combining multitemporal spectral imagery and LiDAR is another promising approach to improve urban vegetation classification.

RapidEye fills a gap for quantifying and assessing urban ecosystem services more accurately and with more detail across relatively large areas. Moreover, RapidEye offers the



opportunity to extend research beyond the administrative borders of cities. This is easily possible, as RapidEye features a swath of 77 km and continuous mapping of 6,000 km<sup>2</sup> (RapidEye AG 2012). This will allow for various new applications in interdisciplinary research on genera-dependent assessments like quantifying above-ground carbon storage, assessing the share of grassland for conservation purposes, or disease mapping (Davies et al. 2011; Percival et al. 2011; Franke et al. 2012).

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## Urban Vegetation Classification: Benefits of Multitemporal RapidEye Satellite Data

Modeling Above-ground Carbon Storage: A Remote Sensing Approach  
to Derive Individual Tree Species Information in Urban Settings

**III: Modeling Above-ground Carbon Storage: A Remote Sensing Approach  
to Derive Individual Tree species Information in Urban Settings**

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## Modeling Above-ground Carbon Storage: A Remote Sensing Approach to Derive Individual Tree Species Information in Urban Settings

### Abstract

Vegetation has gained importance in respective debates about climate change mitigation and adaptation in cities. Although recently developed remote sensing techniques provide necessary city-wide information, a sufficient and consistent city-wide information of relevant urban ecosystem services, such as carbon emissions offset, does not exist. This study uses city-wide, high-resolution, and remotely sensed data to derive individual tree species information and to estimate the above-ground carbon storage of urban forests in Berlin, Germany. The variance of tree biomass was estimated using allometric equations that contained different levels of detail regarding the tree species found in this study of 700 km<sup>2</sup>, which had a tree canopy of 213 km<sup>2</sup>. The average tree density was 65 trees/ha per unit of tree cover and a range from 10 to 40 trees/ha for densely urban land cover. City-wide estimates of the above-ground carbon storage ranged between 6.34 and 7.69 tC/ha per unit of land cover, depending on the level of tree species information used. Equations that did not use individually localized tree species information undervalued the total amount of urban forest carbon storage by up to 15 %. Equations using a generalized estimate of dominant tree species information provided rather precise city-wide carbon estimates. Concerning differences within a densely built area per unit of land cover approaches using individually localized tree species information prevented underestimation of mid-range carbon density areas (10–20 tC/ha), which were actually up to 8.4 % higher, and prevented overestimation of very low carbon density areas (0–5 tC/ha), which were actually up to 11.4 % lower. Park-like areas showed 10 to 30 tC/ha, whereas land cover of very high carbon density (40–80 tC/ha) mostly consisted of mixed peri-urban forest stands. Thus, this approach, which uses widely accessible and remotely sensed data, can help to improve the consistency of forest carbon estimates in cities.

# Modeling Above-ground Carbon Storage: A Remote Sensing Approach to Derive Individual Tree Species Information in Urban Settings

## 1 Introduction

Reducing carbon emissions is important to avoid a steep increase in the effects of climate change (IPCC 2013). Cities are among the key contributors of carbon emissions, and many have set up mitigation strategies with a focus on infrastructure and energy (Castán Broto and Bulkeley 2013). However, green infrastructures like urban forests have hardly been addressed as an additional source of climate change mitigation, partly because of the lack of consistent area-wide urban forest carbon estimates (Hutyra et al. 2011; Pickett et al. 2011; Davies et al. 2013; Demuzere et al. 2014).

Studies of above-ground carbon storage have been applied on forestry at the national level; however, most studies do not address urban forests (McHale et al. 2009). Carbon estimates from urban forests focused US cities starting from the 1990s, and have spread across selected global cities to the present (Nowak and Crane 2002; Stoffberg et al. 2010; Liu and Li 2012; Strohbach and Haase 2012; Chen 2015). Davies et al. (2013) investigated 13 independent urban forest studies and demonstrated multiple reasons for the high variability that exists between urban carbon estimates—most of which either under- or overestimate the carbon storage of urban forests. They found that a lack of uniform methods and standardized metrics makes it difficult to conduct comparisons within and between cities. Therefore, the precision of carbon estimates is likely to get affected by a patchwork of different data sources, lack of up-to-date information, varying data quality, and inconsistency of input parameters. Furthermore, the assessment of parameters like the tree canopy size might vary concerning the methodology and data used, which causes additional uncertainty for following applications like carbon estimates (Richardson and Moskal 2014). For example, Raciti et al. (2014) accounted for 14 % variability in class accuracy occurring by chance concerning the tree canopy mapping. Urban forest carbon estimates of different land use classes can be beneficial to account for a heterogeneous urban structure, as Hutyra et al. (2011) used different degrees of urbanization in the US city of Seattle. Strohbach and Haase (2012) applied multiple land use classes in the German city of Leipzig, and also pointed out, an even higher level of details would better address the variability within certain land use classes, and therefore could provide more precise estimates of urban forest carbon storage.

## Modeling Above-ground Carbon Storage: A Remote Sensing Approach to Derive Individual Tree Species Information in Urban Settings

Most challenging of all is the lack of up-to-date data, in particular, that regarding vegetation on private property.

In fact, globally available city-wide studies showed differences, as selected US cities had a city-wide average of 26.9 tC/ha per unit of land cover compared to the city of Leipzig with  $11.81 \pm 3.25$  tC/ha. Though, the heterogeneity of tree canopies and different land covers showed high variability of urban forest carbon storage from below 10 tC/ha to above 100 tC/ha per unit of tree cover, which would require improved assessments of more refined estimates between and within cities. (Strohbach and Haase 2012; Nowak et al. 2013) Besides, the contribution of urban vegetation to the total carbon storage of cities should not be underestimated, as it can add a considerable amount—as much as 20 %—as shown by Churkina et al. (2010).

Recent research has further illustrated the importance of urban forests by investigating the role such forests play as carbon sinks. For example, carbon offset analyses have indicated that using vegetation to reduce urban CO<sub>2</sub> emissions has positive correlations with sequestration, storage, and reduced energy demand because of the shading and cooling provided by vegetation (Akbari et al. 2001; Zhao et al. 2010; Liu and Li 2012). The positive effects of highly vegetated urban areas acting as a carbon sink have also been shown through urban CO<sub>2</sub> flux models (Grimmond et al. 2002). Other selected surveys of urban forests have hinted at potential future applications for carbon credits as part of the governments' ongoing mitigation strategies (Poudyal et al. 2011b; O'Donoghue and Shackleton 2013). Further studies have suggested integrating urban forests into regional carbon balancing, since the contribution of urban forests has been underestimated in past decades (Churkina et al. 2010; Zhang et al. 2012b).

Ground-based methods currently provide the most accurate carbon storage estimates; however, such approaches rely on the harvesting and weighing of trees and have been rarely applied to urban and non-commercial forestry because of their destructive nature (Jo and McPherson 2001; McHale et al. 2009). Findings from ground-based samples are frequently used to model woody biomass using growth functions for general or species-specific allometric equations (Weissert et al. 2014). The most common input variables for allometric

## Modeling Above-ground Carbon Storage: A Remote Sensing Approach to Derive Individual Tree Species Information in Urban Settings

equations include the dendrometric parameters of diameter at breast height (dbh), height, volume, number (quantity), age, and type of species (Nowak and Crane 2002).

McHale et al. (2009) showed, that specific urban conditions might cause an increase in variability of forest carbon storage, which depended on multiple factors like the allometric equations used, scale, species, population, and community characteristics. Therefore, urban forest carbon estimates might require a more standardized methodology or even allometric equations adapted to urban conditions. As Zhao et al. (2012) pointed out, carbon storage of densely vegetated areas can be underestimated when using national equations similar to that used by Jenkins et al. (Jenkins et al. 2003). The availability of specific urban allometric equations is not likely to rise rapidly any time in the near future because creating such specific equations is highly labor intensive. Thus, other studies have suggested carefully selecting allometric equations before drawing a final conclusion regarding urban forest carbon estimates (Aguaron and McPherson 2012). Important decisive parameters regarding urban carbon estimates are tree size, tree density and tree species composition (McPherson et al. 2013). Schmitt-Harsh et al. (2013) pointed out the necessity of addressing species-specific size distributions on private parcels, in particular, those of dominant trees, which contribute most to aboveground carbon storage. Though, most studies apply tree species information for forest carbon estimates (Nowak et al. 2002; Zhao et al. 2010; Ren et al. 2011), remotely sensed individual tree species data has rarely been analyzed in urban studies so far. Developments in urban remote sensing techniques are very promising as far as assessing the necessary data to estimate the carbon stored in urban vegetation, and particularly, in urban trees in a consistent and comparable manner (Weng et al. 2012). Therefore, remote sensing data can be seen as a highly useful complementary source of information beside field surveys. Laser scanners and high-resolution multi-spectral sensors show promising applications for area-wide estimates of the location, height, crown shape, and species of individual trees (Zhao et al. 2009; Shrestha and Wynne 2012; Holopainen et al. 2013; Tigges et al. 2013; Nielsen et al. 2014). Remotely sensed light detection and ranging (LiDAR) height metrics have been successfully used for individual tree detection and classification in urban areas (Kwak et al. 2007; Koch 2010; Jung et al. 2011; Yao et al. 2012; Dandois and Ellis 2013; Zarco-Tejada et al. 2014). Field surveys have been supplemented by terrestrial (TLS) and mobile laser scanning (MLS), which can offer

## Modeling Above-ground Carbon Storage: A Remote Sensing Approach to Derive Individual Tree Species Information in Urban Settings

accurate measures of an individual tree's shape, quick estimates for a larger number of trees, and support for ground-based validation (Gibbs et al. 2007; Hyyppä et al. 2008; Nielsen et al. 2014). Combining recently available satellite data of RapidEye's multispectral, high-spatial, and temporal information with LiDAR derived height information might allow for improved assessment of individual trees in cities. On the one hand, existing ground sampling approaches already provide accurate information for carbon estimates. On the other hand, remote sensing provides more comprehensive coverage of tree variables across the city, which might help to better assess variability of urban forest carbon estimates.

In this study we estimate the above-ground carbon storage of urban forests in Berlin, Germany. We use a remote sensing approach to derive individual tree species information, which are input for allometric biomass equations. The tree species composition data used is derived from RapidEye satellite data, and the dendrometric parameters of individual trees are derived from airborne LiDAR data. The major aim is to assess the variability of carbon estimates concerning tree species information of each individual tree compared to more general tree coverage information. Our approach might improve the retrieval of urban forest carbon estimates' details across large cities, and indicate spatial differences within cities. Furthermore, this might also assist sampling approaches to better address differences within land use classes.

## 2 Material and Methods

### 2.1 Study Area

The city of Berlin (52° 31' N, 13° 24' E) has a moderate climate and is characterized by a mostly flat topography. Its administrative area is approximately 890 km<sup>2</sup>, 40 % of which is covered by vegetation such as urban forests, parks, street trees, and urban agriculture (Berlin Department of Urban Development 2010a). More than 290 km<sup>2</sup> of Berlin is taken up by urban forests, which constitutes the largest urban forest in Germany; Berlin's public parks cover approximately 55 km<sup>2</sup>. Deciduous broadleaf tree species are prevalent on public land: according to official statistics, the most frequent street or park tree species (100 %) are the lime tree (*Tilia*, 35 %), maple (*Acer*, 20 %), oak (*Quercus*, 9 %), plane tree (*Platanus*, 6 %),



## Modeling Above-ground Carbon Storage: A Remote Sensing Approach to Derive Individual Tree Species Information in Urban Settings

chestnut (*Aesculus*, 5 %), birch (*Betula*, 3 %), and locust (*Robinia*, 3 %) (Berlin Department of Urban Development 2010b). The remaining percentage of public street and park trees are mostly dominated by mixed deciduous trees. The forest of Berlin is dominated by pine (*Pinus*), oak (*Quercus*) and beech (*Fagus*) (Berlin Department of Urban Development and Ministry of Infrastructure and Agriculture Brandenburg 2014). According to the authors' knowledge, there is no statistical data regarding different tree species on private property.

### 2.2 Data

Tree species classification from 2009 (Tigges et al. 2013) and a normalized digital surface model (nDSM) derived from airborne laser scanning data from 2007 and 2008 (Berlin Partner GmbH 2007) were available for this study. The overlapping area of both datasets covers approximately 700 km<sup>2</sup> of the city of Berlin, resulting in a study area that is 78 % of the total area of Berlin (Fig. 1). Tree canopy covered 30.4 % (213 km<sup>2</sup>) of the study area. Eight dominant tree species (Table 1) were classified with a high degree of accuracy (kappa values of 0.83) (Tigges et al. 2013). Because of the pixel size of RapidEye imagery (6.5 m), high accuracy of classified tree species data was limited to large groups of trees, trees aligned in a linear manner (i.e., alley), and large individual trees. We did not consider further corrections of those trees due to its already high accuracy. Though, small sized fragments of the tree canopy were likely to be a source of error. Therefore, we assigned fragments of grouped pixels covering less than 100 m<sup>2</sup> to a mixed class of dominant tree species in our case study area (Classes 1–10, Table 1), which should avoid potential over- or underestimation of a specific tree species.

An individual tree with a stem diameter of 40 cm is listed as an example in Table 1, which we applied its associated allometric biomass equation. The carbon weight accounts for 50 % of above-ground tree biomass (dry) (Table 1). We calculated the final percentage of tree species pixels assigned to each class. Fig. 1 shows the spatial distribution of the tree canopy and tree species classification across the study area.

A normalized height model (nDSM) with a minimum height of 3 m is used for the tree crown height estimates (ALS data, winter 2007–08, 4 points/m<sup>2</sup>, first pulse) (Kolbe et al. 2008; Tigges et al. 2013). A 3 × 3 median filter was applied to the nDSM during preprocessing to

## Modeling Above-ground Carbon Storage: A Remote Sensing Approach to Derive Individual Tree Species Information in Urban Settings

smooth gaps in the tree crown values that were caused during leaf-off data acquisition (Popescu et al. 2003; Ben-Arie et al. 2009).

Two field surveys of trees were conducted in the city of Berlin in late autumn of 2011 and summer of 2014. Different plots included a total of 318 trees. Two plots comprising 220 trees were used for calibration and four plots comprising 98 trees were used for validation of an individual tree detection approach. In these surveys, tree locations were mapped using global position system and the number of trees and their stem diameters (dbh) 1.3 m above ground were assessed. Sites considered the spatial heterogeneity of urban trees by including public and private property; isolated, lined, and grouped trees; different species; and various tree crown conditions. We defined a tree as dominant if its tree crown covered other trees.

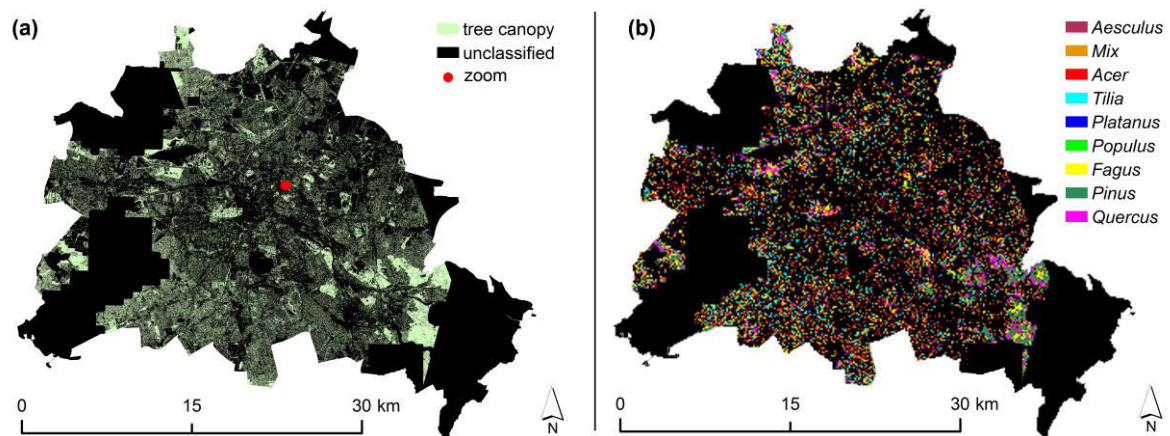


Figure III - 1: a Tree canopy inside the administrative boundaries of Berlin. "Unclassified" refers to areas where either RapidEye or LiDAR data were not available for classification. The red dot represents a densely built part of the city and is shown in greater detail in Figs. 3 and 6. b Spatial distribution of eight dominant tree species classified using multitemporal RapidEye satellite imagery. Class "mix" refers to difficult-to-classify tree species in the tree canopy.

### 2.3 Modeling Above-ground Carbon Storage Estimates

Our major aim was to derive urban forest carbon estimates and analyze the effects concerning the availability of tree species information details (Table 2). Therefore we used dbh estimates of individual trees in allometric equations for biomass approximations. We derived the stem diameter (dbh) of each tree by applying an individual tree detection (ITD) approach and high resolution remotely sensed LiDAR data. Tree species information were allocated from our remotely sensed RapidEye tree species classification data.

## Modeling Above-ground Carbon Storage: A Remote Sensing Approach to Derive Individual Tree Species Information in Urban Settings

The ITD approach refers to a local maxima filter algorithm that is integrated into Fusion software (McGaughey 2013); this approach proved to be applicable to both natural and urban forests as well as to parks (Holopainen et al. 2013). The absolute tree height ( $LH$ ) of individual trees and their tree crown diameters ( $LCD$ ) could be estimated using this approach. The stem diameter ( $dbh$ ) of individual trees was derived using laser scanning calculations from Zhao et al. (2009).

$$dbh = 0.95 + 0.7 * LH + 3.14 * LCD + 0.37 * LCBH, \quad (1)$$

where  $LH$ : tree height;  $LCD$ : tree crown diameter; and  $LCBH$ : crown base height with several constants for mixed forests (Hyypä et al. 2001).

$LCBH$  values were simplified using half of the maximum tree height, which reflects a growth form used in forestry (McGaughey 2013). Other  $LCBH$  data were not available for calibration or validation of urban deciduous trees. Wack et al. (2003) successfully applied a similar approach combining local maxima and a decreasing height order to define edges of individual tree crowns (Hyypä et al. 2008). The algorithm in the Fusion software sets local maxima as the highest location of surrounding pixels, and thus estimates the absolute tree height of an individual tree (Popescu and Wynne 2004). That algorithm uses a moving, circular, and variable size evaluation window that varies with the CHM's height information. It assumes that local minima are the edge of a rounded tree crown and a linear regressive dependency of  $LH$  and  $LCD$  as follows:

$$LCD = a + b * LH^2, \quad (2)$$

Furthermore, the edge of a tree crown will be set if the absolute height value falls below 66 % of the local maxima height value within a 3-pixel distance (McGaughey 2013). The local conditions of our case reflect a dominant deciduous stand of trees. This could be adapted by using 220 trees from the field survey to calibrate the variable evaluation window size equation with coefficients  $a = 3.09632$  and  $b = 0.00895$  (Popescu and Wynne 2004).

Stem diameter estimates from this method were systematically below the values derived from field data and were corrected by multiplying an overall weighted arithmetic mean previously developed by Schreyer et al. (2014) for Berlin as follows:

$$dbh_{cor} = dbh * 1.36, \quad (3)$$

## Modeling Above-ground Carbon Storage: A Remote Sensing Approach to Derive Individual Tree Species Information in Urban Settings

Table III - 1: Most dominant tree species in the study area are listed as classes 1–10. Classes 1–8 are classified using RapidEye satellite data. Class "mix" includes all other species of the total tree canopy, mostly comprising classes 9 and 10. The area and fraction of the total tree canopy (CHM) taken by each classified class is listed. The allometric equation used with an example of the above-ground carbon storage of an individual tree (40 cm dbh) is shown for classes 1–10.

Class	Dominant Species of Study Site	Area [ha]	CHM [%]	Allometric Equation	Carbon Storage [kg]
1	<i>Acer</i> ( <i>Acer campestre</i> , <i>Acer platanoides</i> , <i>Acer</i> sp.)	2744	12.9	Equation 2, <i>Acer saccharum</i> (Ter-Mikaelian and Korzukhin 1997)	588
2	<i>Aesculus</i> ( <i>Aesculus hypocastanum</i> )	2852	13.4	Table 1, <i>Aesculus indica</i> (horse chestnut) (Adhikari et al. 1995)	687
3	<i>Fagus</i> ( <i>Fagus sylvatica</i> )	2216	10.4	Appendix A, Equation 89, <i>Fagus sylvatica</i> (Zianis et al. 2005)	585
4	<i>Pinus</i> ( <i>Pinus sylvestris</i> )	2397	11.3	Table 3, <i>Pinus sylvestris</i> (Muukkonen 2007)	260
5	<i>Platanus</i> ( <i>Platanus hispanica</i> )	402	1.9	Volume Equation, <i>Platanus acerifolia</i> (London Plane), average specific gravity of <i>Platanus</i> (Alden 1995; Pillsbury et al. 1998)	342
6	<i>Populus</i> ( <i>Populus nigra</i> , <i>Populus alba</i> )	387	1.8	<i>Populus tremula</i> (Zianis et al. 2005)	310
7	<i>Quercus</i> ( <i>Quercus robur</i> , <i>Quercus rubra</i> , <i>Quercus</i> sp.)	1839	8.6	Table 3, <i>Quercus</i> sp. (Muukkonen 2007)	568
8	<i>Tilia</i> ( <i>Tilia cordata</i> , <i>Tilia</i> × <i>vulgaris</i> , <i>Tilia platyphyllos</i> )	2810	13.2	Appendix A, Equation 607, <i>Tilia cordata</i> (Jenkins et al. 2003; Zianis et al. 2005)	299
9 (extra)	<i>Betula</i> ( <i>Betula pendula</i> )	not classified	/	Appendix A, Equation 31, <i>Betula pendula</i> (Zianis et al. 2005)	387
10 (extra)	<i>Robinia</i> ( <i>Robinia pseudoacacia</i> )	not classified	/	Table 2, Equation 6, <i>Robinia pseudoacacia</i> (Böhm et al. 2011)	400
Mix	grouped pixel < 100 m <sup>2</sup>	5643	26.5	Mixture of different tree species concerning equations of class 1–10	443

This correction factor is based on the average stem diameter of each plot used for calibration, weighted according to the number of trees per plot. Classified results of the stem diameter (dbh) were validated by 98 trees from the field survey. High cranes on construction sites and voltage electricity lines led to classification errors. These were avoided after implementing a height threshold of 30 m, which did not affect very tall trees. Using dendrometric data, we calculated the tree density and stem diameter. Individual tree data was stored in a geospatial database and used to calculate carbon storage estimates as follows: We applied and compared four methods to estimate tree biomass (Table 2, methods 1–4) concerning the availability of additional tree species information. The previously built basic dataset of remotely sensed individual dbh estimates were input in allometric biomass equations, if no

## Modeling Above-ground Carbon Storage: A Remote Sensing Approach to Derive Individual Tree Species Information in Urban Settings

local tree species information were available (methods 1), and contrasted by adding higher details of local information regarding our high resolution remotely sensed RapidEye tree species classification data (Table 1). Methods 2–3 were set up to reflect only general local information, such as dominance or fraction of dominant species, rather than the highest level of details by allocating remotely sensed RapidEye species information to each LiDAR derived individual tree (method 4).

*Table III - 2: Methods used to estimate biomass using different levels of tree species information.*

Method		Tree Species Information				
#	Details	Level	Dominant	Fraction	Location	Allometric Equations
1	low	general				national scale, mixed deciduous forest (Jenkins et al. 2003)
2	medium	general	x			averaged using general information of dominant tree species (class 1–10, Table 1)
3	high	general	x	x		averaged and weighted by each class fraction of the tree canopy (class 1–8 and Mix, Table 1)
4	very high	specific	x	x	x	specific using tree species information of each individual tree (class 1–8 and Mix, Table 1)

Method 1 (Eq. 4): We applied the allometric equation developed for mixed deciduous forests of the US to each individual dbh tree estimate (Jenkins et al. 2003). This equation was frequently used for miscellaneous tree types if no site- or species-specific information or equations are available (McHale et al. 2009; Hutrya et al. 2011).

$$biomass = \sum_{i=1}^n x_i, \quad (4)$$

where  $x$ : biomass;  $i$ : individual tree; and  $n$ : total number of trees.

Method 2 (Eq. 5): We formed a generalized above-ground carbon estimate based on the suggestions of McHale et al. (2009) and Aguaron and McPherson (2012). This estimate reflected the general knowledge of local dominant tree species, but had no further additional or spatial species information. Therefore we used data on the 10 most dominant tree species of Berlin (classes 1–10, Table 1), applied those species-specific allometric equations to each individual dbh tree estimate, and finally averaged the results to create a generalized biomass estimate.

Modeling Above-ground Carbon Storage: A Remote Sensing Approach  
to Derive Individual Tree Species Information in Urban Settings

$$biomass = \sum_{i=1}^n \bar{x}(c_1 + c_2 + \dots + c_{10})_i, \quad (5)$$

where  $\bar{x}$ : averaged total tree biomass;  $i$ : individual tree;  $n$ : total number of trees; and  $c_{1-10}$ : tree biomass concerning each class 1–10 (Table 1).

Method 3 (Eq. 6): We formed a generalized estimate as in method 2 based on the suggestions of McHale et al. (2009) and Aguaron and McPherson (2012). Furthermore, we included additional information regarding the amount of tree canopy (CHM) considered by each dominant species. Therefore we applied species-specific allometric equations to each individual dbh tree estimate regarding the availability of data on the fraction of dominant tree species (classes 1–8 and “mix”, Table 1). We could not assign a specific dominant tree species to the fraction of our mixed class, and applied an average of most dominant tree species as in method 2. Each result was weighted by multiplying its percentage fraction of the total CHM (Table 1). The final sum was a general estimate concerning the fraction of prevalent dominant tree species.

$$biomass = \sum_{i=1}^n x(c_1 * CHM_1 + c_2 * CHM_2 + \dots + c_8 * CHM_8 + c_{MIX} * CHM_{MIX})_i, \quad (6)$$

where  $x$ : total tree biomass;  $i$ : individual tree;  $n$ : total number of trees;  $c_{1-MIX}$ : tree biomass concerning classes 1–8 and “mix” (Table 1); and  $CHM_{1-MIX}$ : fraction of the tree canopy taken up by each class 1–8 and “mix” (Table 1).

Method 4 (Eq. 7): We applied species-specific equations to each individual dbh tree estimate. Each individual dbh estimate was assigned the class concerning our remotely sensed RapidEye tree species classification data (classes 1–8 and class “mix”, Table 1). Input class “mix” refers to classified trees less than 100 m<sup>2</sup>, to which we could not assign a specific dominant tree species. Therefore, we assigned a general estimate from method 2 to class “mix”, which comprised all available information of dominant tree species. Estimates of method 4 were expected to provide the highest level of detail by providing individual tree species information.

$$biomass = \sum_{i=1}^n x(c_{class})_i; c_{class} = c_1 \text{ or } c_2 \text{ or } c_3 \text{ or } c_4 \text{ or } c_5 \text{ or } c_6 \text{ or } c_7 \text{ or } c_8 \text{ or } c_{MIX}, \quad (7)$$

where  $x$ : total tree biomass;  $i$ : individual tree;  $n$ : total number of trees; and  $c_{class}$ : tree biomass concerning the specific class (classes 1–8 and “mix”, Table 1) of each individual tree.

## Modeling Above-ground Carbon Storage: A Remote Sensing Approach to Derive Individual Tree Species Information in Urban Settings

We examined the differences that occurred between these methods in both the complete study area as well as in a selected and densely built area that is typical of such areas in Berlin. We matched equations to our case study tree species (Table 1), and if no species-specific equations were available, we followed the approach taken by Hutyra et al. (2011): selecting equations for trees in the same genus. We multiplied our biomass estimates by 0.5 to convert above-ground dry biomass into units of carbon (C) (Nowak and Crane 2002). Because we did not include root biomass, we expected the actual total carbon storage of the urban trees included in our study to be higher than our estimates. However, we did not include a correction factor for root biomass as Nowak and Crane (2002) because of lack of data and a high degree of uncertainty regarding species and local growth conditions in the urban area studied (Johnson and Gerhold 2003).

### 3 Results

Our methods show a variability of urban forest carbon storage estimates up to 21 % (Table 3). Most of the differences can be explained by the use of different carbon equations by either integrating local knowledge of tree species information or not having any local tree species information available. The maximum variability was 9 % concerning tree species information of each individual tree and more general and aggregated coverage information of local tree species. In other words, individual tree species information notably but slightly affected our urban forest carbon estimates. If tree species information of each individual tree were used in method 4, we can claim that method 1, which used no local tree species information, results in an underestimation of 15 %. We can also state, that more general and aggregated coverage information of local tree species information either underestimated carbon storage by 3 % (method 2, 7.08 tC/ha) or overestimated it by 6 % (method 3, 7.69 tC/ha) compared to tree species information of each individual tree (method 4, 7.32 tC/ha). Therefore, method 2, which provides a generalized estimate using information regarding the most dominant tree species, and method 3, which uses information regarding the most dominant tree species and their percentage of the total tree canopy, were slightly off results of method 4, which required higher input details concerning species information of each individual tree.

## Modeling Above-ground Carbon Storage: A Remote Sensing Approach to Derive Individual Tree Species Information in Urban Settings

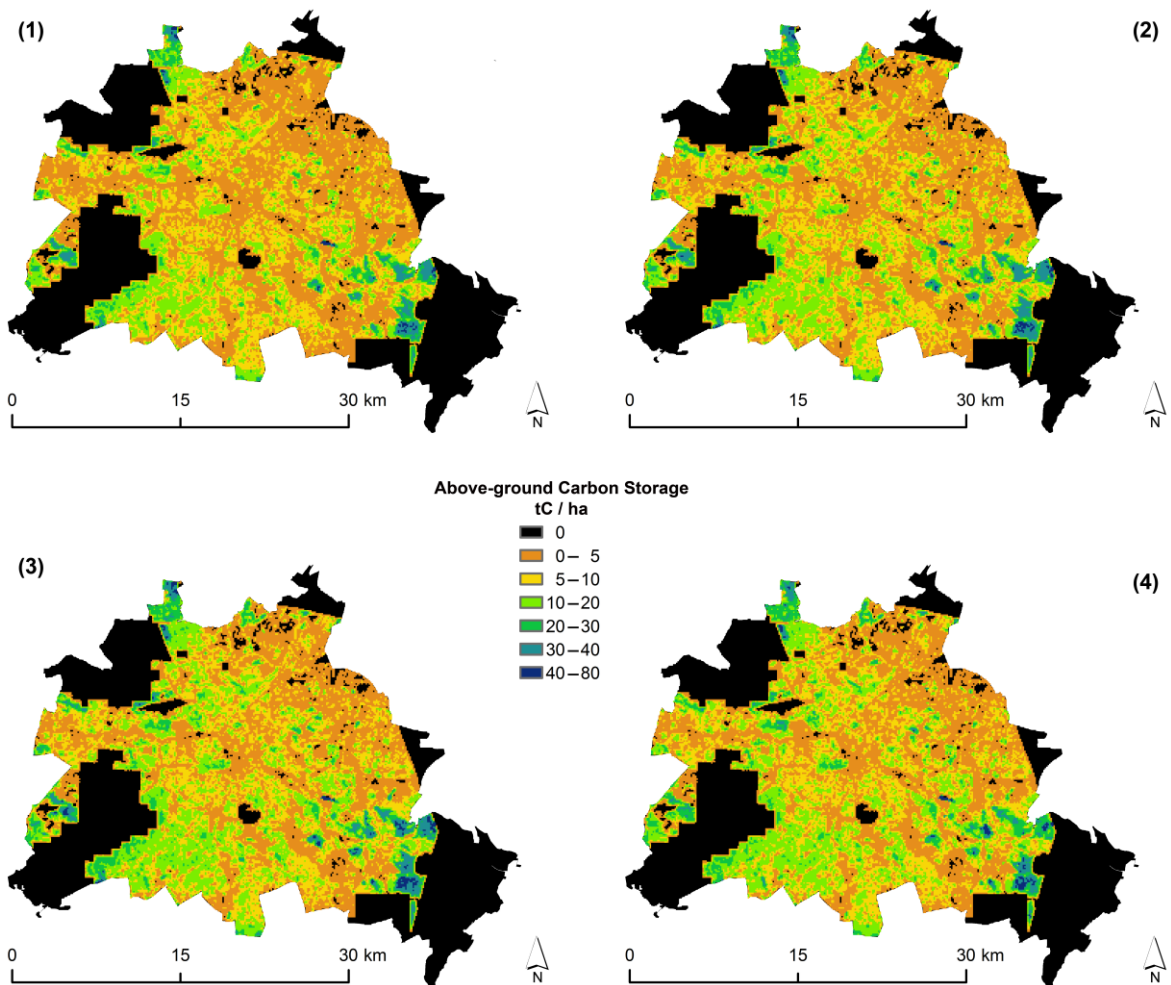
*Table III - 3: City-wide average of carbon estimates of trees in Berlin obtained using different levels of input detail (Table 2)*

General Carbon Estimates				Individual Tree Statistics		
Method	Total	Land Cover (Tree Cover)	$\Delta$	Maximum	Mean	SD
# Details	[MtC]	Average [tC/ha]	[%]	[kg]	[kg]	[kg]
1 low	0.444	6.34 (20.83)	reference	3.151	322	200
2 medium	0.496	7.08 (23.29)	12	2.838	360	195
3 high	0.538	7.69 (25.29)	21	2.728	391	195
4 very high	0.512	7.32 (24.06)	15	4.500	372	227

The different methods tested in this study (Table 2) clearly affect carbon storage density numbers. Methods of increasing details show both over- and underestimations. The area classified as very low carbon densities (0–5 tC/ha) decreases if methods involving greater levels of detail are used for calculation (Figs. 2 and 4). For example, method 1 overestimates areas of very low carbon densities by 11.4 %. Areas of low carbon density (5–10 tC/ha) show the smallest differences between methods (with maximum differences of 1 % in the study area and 3.3 % in densely built areas). Densely built areas (Figs. 3 and 4) show a high level of very low to low carbon densities (0–10 tC/ha). The largest discrepancies occur between areas of very low (0–5 tC/ ha) and mid-range (10–20 tC/ha) carbon densities. Very low and mid-range carbon density areas take up a major fraction (60 %) of the total tree canopy. This is important because the percentage of very low carbon density is overestimated and that of mid-range carbon density is underestimated if high levels of tree species detail are not used.



## Modeling Above-ground Carbon Storage: A Remote Sensing Approach to Derive Individual Tree Species Information in Urban Settings



*Figure III - 2: Estimated average carbon density (tC/ha) per unit of land cover for urban trees in Berlin. Spatial distributions of carbon densities are displayed for each method from Table 2. Areas with zero carbon density either did not contain trees or did not have data available for classification.*

In particular, areas of medium (20–30 tC/ha) carbon density (such as in park-like areas) increase when higher levels of tree species detail are used. Areas with very high (40–80 tC/ha) densities comprise only a small part of the study area, though individual tree species information shows a notable impact on carbon densities. High (30–40 tC/ha) and very high (40–80 tC/ha) carbon densities are not found at the selected densely built area (Fig. 4).

## Modeling Above-ground Carbon Storage: A Remote Sensing Approach to Derive Individual Tree Species Information in Urban Settings

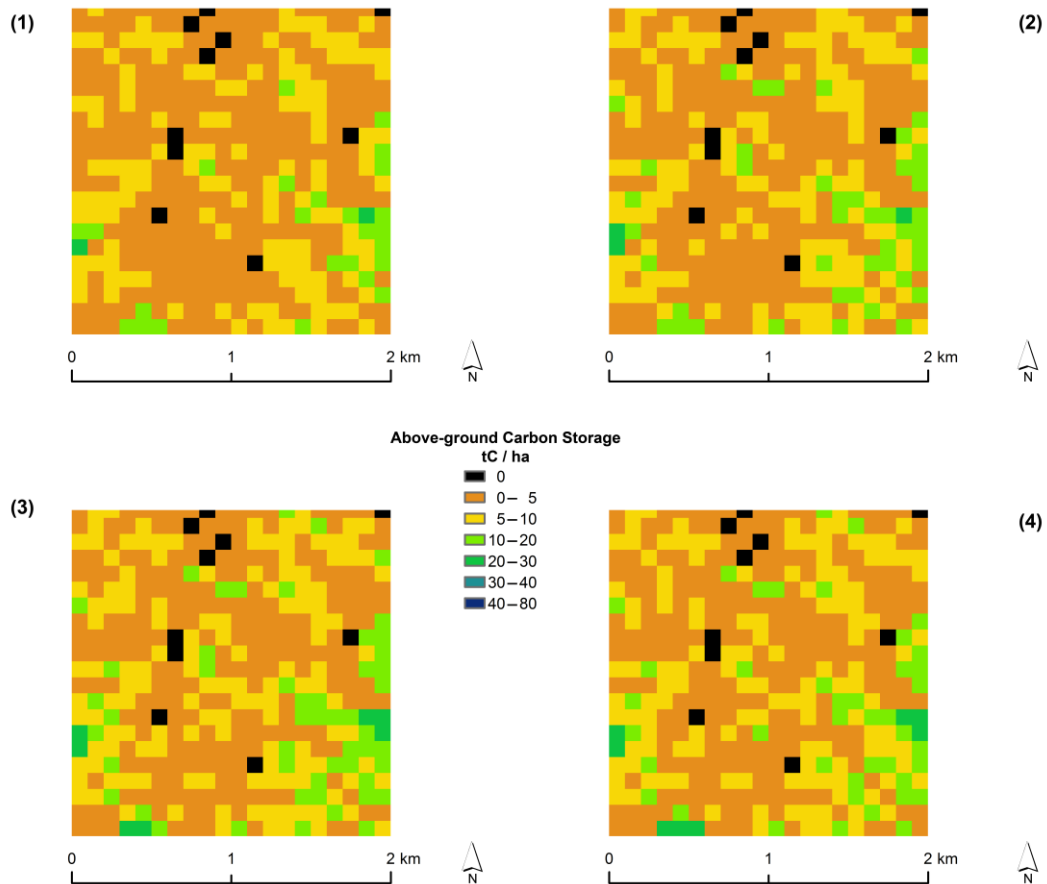


Figure III - 3: Spatial distribution of tree carbon density (tC/ha) per unit of land cover in a densely built part of Berlin (red dot, Fig. 2). Differences in spatial distribution are displayed at a given density range for each method listed in Table 2. Areas with zero carbon density did not contain trees. Areas with low carbon density (0–5 tC/ha) had few trees and contained a higher number of buildings and impervious surfaces.

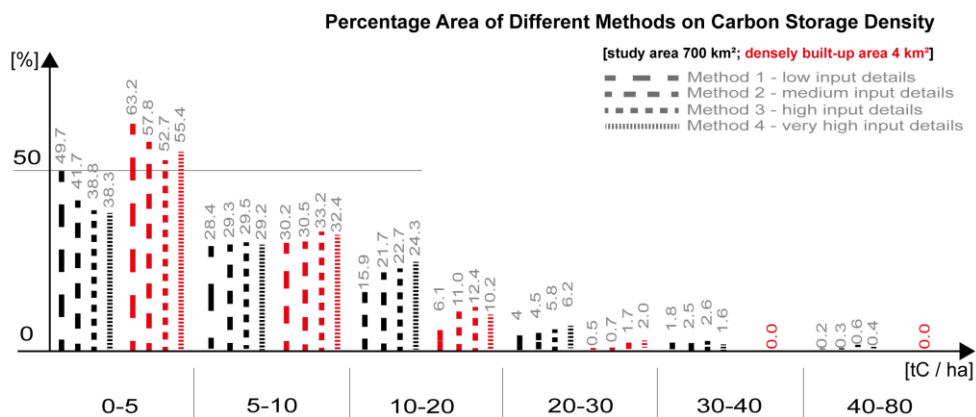


Figure III - 4: Differences in carbon storage density (tC/ha) per unit of land cover within the city of Berlin for methods listed in Table 2

## Modeling Above-ground Carbon Storage: A Remote Sensing Approach to Derive Individual Tree Species Information in Urban Settings

The mean stem diameter (dbh) for all detected trees is 36 cm. Few mature trees exhibit a dbh up to 92 cm. Most trees within a densely built area show an average dbh of 30–35 cm (Figs. 5b and 6a). Trees with the largest stem diameter values are found in parks and forests (Fig. 5b). Densely built areas contain approximately 3 % of the total number of large trees with dbh of 80 cm (Fig. 6a). The spatial distribution of individual trees and tree species are heterogeneous in our study area, which is densely built (Fig. 6b). Validation of the stem diameter (dbh) shows moderate to good accuracy. This study’s classified average mean diameter of 36 cm differs by 11 % (4.1 cm) from the average mean of our filed survey data (40.10 cm). From 98 trees of the field survey, 80.1 % of dominant trees and 65.3 % of less dominant trees are classified.

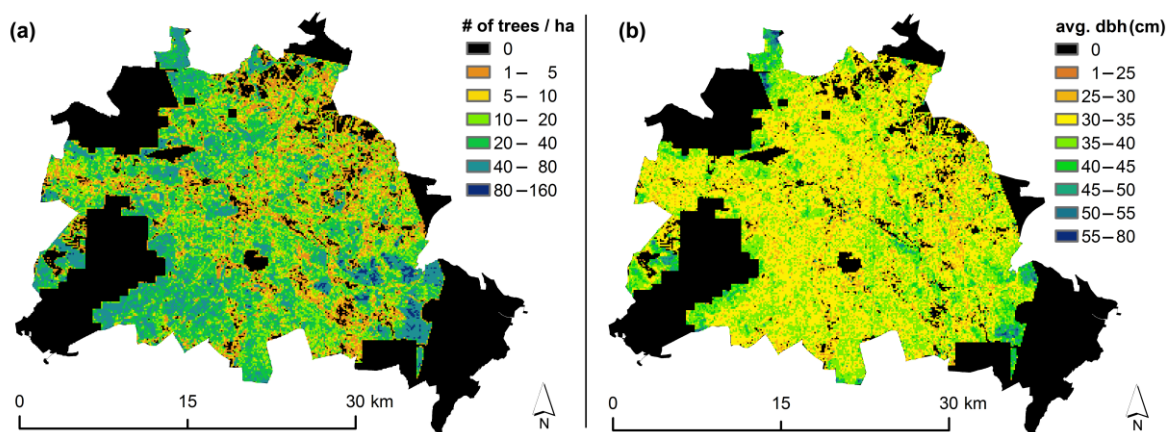


Figure III - 5: a Spatial distribution of the average tree density (#/ha) per unit of land cover. b Spatial distribution of the average tree diameter at breast height (dbh in cm) across the study area. For a and b, black areas indicate that no data was available for classification.

Approximately 1.4 million trees are classified within our highly heterogeneous urban area using an individual tree detection approach. The maximum tree height is set at 30 m since higher values tend to be misclassified. We visually verified that the majority of tall, dominant trees are not affected by this threshold. The mean height for all detected trees is 15 m. The average tree density is 65 trees/ha per unit of tree cover. This accounts for trees classified using first pulse LiDAR height data, which is less appropriate to account for potential understory. Though, in situ observations revealed a majority of large open grown trees in Berlin. The spatial distribution of tree density per unit of land cover varies greatly across the city (Fig. 5a). Most areas have an average tree density of between 10 and 40 trees/ha. Urban

## Modeling Above-ground Carbon Storage: A Remote Sensing Approach to Derive Individual Tree Species Information in Urban Settings

parcs have large patches of high tree densities (40–80 trees/ha). Very high tree densities (80–160 trees/ha) are found in the forests located in the southeastern portion of our study site (Fig. 5a).

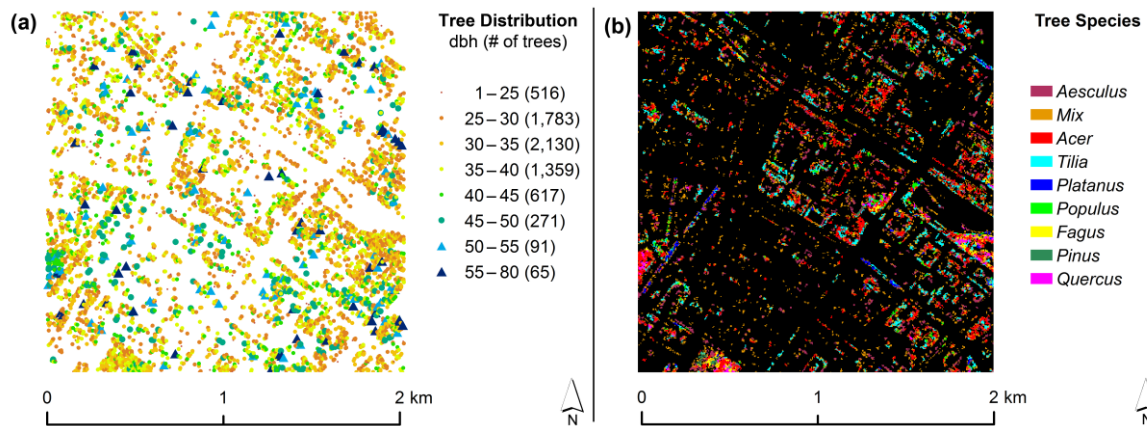


Figure III - 6: a Spatial distribution of the average tree diameter at breast height (dbh in cm) of a densely built area. Individual trees are grouped at different ranges of dbh. The absolute number of individual trees classified is shown in brackets. Very large trees are marked with a triangle or star symbol. b Spatial distribution of tree species classified for the same area.

## 4 Discussion

The tree information we derived from remote sensing could improve our assessment of the above-ground carbon storage of urban forests and provided a high degree of detail that allowed carbon estimates to be analyzed across the city of Berlin. The combination of RapidEye satellite data and airborne LiDAR data was beneficial in providing important details of individual trees for biomass equations. Regarding additional tree species information we determined that city-wide carbon estimates are sufficient when an average of dominant tree species information is used. Further precision of carbon estimates could be enhanced on a city-wide scale if we considered the spatial distribution of tree species. Not using individual tree species information undervalued urban forest carbon estimates by up to 15 %.

Including high levels of detail for dominant tree species has a notable effect on the precision of carbon storage estimates, i.e., 15 %–21 % higher values in our case study (methods 3 and

## Modeling Above-ground Carbon Storage: A Remote Sensing Approach to Derive Individual Tree Species Information in Urban Settings

4, Table 3). Zhao et al. (2012) obtained similar results for forests; in their study, selection of specific allometric equations and individual trees could provide notable improvements concerning the precision of regional carbon estimates. Our reference method, Jenkins' national scaled approach for mixed deciduous forest (method 1, Tables 2 and 3), considers an average from all national forests in the US and does not reflect the local tree species composition of our study site (Jenkins et al. 2003). Such averaged conditions tend to level results. Our results also suggest, that the fraction or exact location of tree species (methods 3 and 4, Table 3) might be less important for city-wide carbon estimates than for an analysis of differences within a city since results differ only slightly from an averaged general carbon estimate of dominant tree species (method 2, Table 3). Concerning differences within a typical densely built area using individual tree species information prevented underestimation of mid-range carbon density areas (10–20 tC/ha), which were actually up to 8.4 % higher, and prevented overestimation of very low carbon density areas (0–5 tC/ha), which were actually up to 11.4 % lower. However, further studies are needed to prove those assumptions.

Our area-wide remote sensing approach uses individual tree detection and tree species information instead of averaged results from large regional areas, because these appear better suited to consider spatial differences within a highly heterogeneous urban forest structure (Figs. 2 and 4). However, results of our Berlin case study appear to be a substantial underestimation of carbon and tree density compared to other cities due to various reasons of local differences: The urban forest carbon estimates we obtained using the highest level of detail have a total of 0.512 megatons C (tree cover of 213 km<sup>2</sup>, average of 65 trees per hectare of tree cover, and a total area of 700 km<sup>2</sup>). The total case study area of Berlin showed an average of around 7 tC/ha, whereas Strohbach and Haase (2012) showed an average of about 11 tC/ha for the city of Leipzig, which has a similar built structure like Berlin. However, 22 % of Berlin's administrative area (ca. 190 km<sup>2</sup>) was unavailable for our case study, which makes it difficult to compare differences between and within cities. That unavailable area is mostly covered by dense broad-leaf and mixed woodlands (Berlin Department of Urban Development and Ministry of Infrastructure and Agriculture Brandenburg 2014). It shows similarities to the Leipzig case study concerning land cover of high tree coverage like broad-leaf (68 tC/ha; 80 tC/ha per unit of tree cover) and mixed urban

## Modeling Above-ground Carbon Storage: A Remote Sensing Approach to Derive Individual Tree Species Information in Urban Settings

forests (76 tC/ha; 77 tC/ha per unit of tree cover). A high fraction of those forest-like areas in the city of Leipzig certainly contributed to a high city-wide average of 68 tC/ha per unit of tree cover compared to our Berlin case study of around 24 tC/ha per unit of tree cover (Strohbach and Haase 2012). Therefore including such less urbanized land of high tree coverage in our calculations could have substantially affected and increased the average urban forest carbon density of the city of Berlin. Schreyer et al. (2014) calculated the carbon densities of urban trees for selected urban Berlin structure types. Those calculations were extrapolated across the total city including those dense woodlands resulting in an average density of 11.53 tC/ha for the city of Berlin. Similar differences were shown for the city of Karlsruhe, Germany, which stated urban forest carbon estimates of 9.5 tC/ha carbon for highly urbanized areas, and an exponential increase to a total average of 32.3 tC/ha, if state and city forests were included as they are part of the administrative boundaries of Karlsruhe (Kändler et al. 2011). Tree density is influenced by various factors in different case studies such as land use, differences between countries and city development. For example, our results of Berlin had an average range of 10–40 trees/ha across densely built areas (excluding parks and forest-like areas), which is close to the average of 30.7 trees/ha in the city of Karlsruhe, Germany (Kändler et al. 2011). Residential areas of Cambridge, UK, showed a range from 33.7 to 55.7 trees/ha (Wilson et al. 2015). Almost 80 % of 167 cities in the state of Gujarat, India, showed values below 30 trees/ha compared to its capital Gandhinagar with an average of 152 trees/ha (Singh 2013). For selected US cities, the average tree density had a large range from below 25 (Casper, Wyoming) up to 280 trees/ha (Atlanta, Georgia) (Nowak et al. 2008). Hence, tree density differences certainly have a large impact on carbon density values, which needs to be considered for comparisons between and within cities. Additionally, carbon density would slightly increase, if we included root biomass. Though, our case study excluded it since little research has been conducted on the carbon storage of urban tree root systems and high uncertainty surrounds the research that has been conducted (Nowak and Crane 2002; Johnson and Gerhold 2003).

Our city-wide average of carbon density in Berlin, Germany, most likely falls in the lower range of urban forest studies obtained from globally selected cities of temperate climate zones (11–38 tC/ha) (Strohbach and Haase 2012). Hutyrá et al. (2011) related the average carbon estimates of urban forests in Seattle, WA, US to the degree urbanization, which

## Modeling Above-ground Carbon Storage: A Remote Sensing Approach to Derive Individual Tree Species Information in Urban Settings

means that Berlin's results (approximately 7 tC/ha) are comparable with values between their class of heavy ( $2 \pm 2$  tC/ha) and medium urbanized areas ( $15 \pm 8$  tC/ha). Most of Berlin's residential areas are less dispersed than for example US suburbs of detached houses, which are most likely to have a high tree coverage. As well as European cities show a tendency towards higher densification, which is likely to decrease carbon estimates. (Davies et al. 2011) In this context, a high range of carbon density values are mainly due to the different structures of the urban forests, higher tree density and tree coverage in particular (Liu and Li 2012). For example, carbon density values between US cities showed values from 31.4 tC/ha to 141 tC/ha concerning differences per unit of tree cover (Nowak et al. 2013), 14.6 tC/ha to 54.1 tC/ha between different forest types within the city of Changchun, China (Zhang et al. 2015b), or from 6.8 tC/ha to 98.5 tC/ha per unit of tree cover concerning differences between afforestation areas and riparian forests in the city of Leipzig, Germany (Strohbach and Haase 2012).

Our individual tree detection approach has a good level of accuracy (>80 %) compared with other studies, such as that previously published by Schreyer et al. (2014). As Schreyer et al. pointed out, less dominant trees were likely to be overlooked in their study, which would have led to them calculating a lower level of total carbon storage than what actually exists. Temporal changes, such as leaf-dropping, pruning, and cutting, add further challenges for obtaining accurate carbon estimates of urban trees (McPherson 1998). However, the application of different methodological approaches and levels of detail for urban forest carbon estimates makes it difficult to compare results (Nowak and Crane 2002; Hutyra et al. 2011; Kändler et al. 2011). Thus, previous studies on forest carbon estimates have demanded more detailed data and methods (Nowak and Crane 2002; Nowak et al. 2013). Differences in sampling sizes, data types, and prediction methods are also important factors not to be forgotten when comparing carbon estimates between cities (Fassnacht et al. 2014). Future applications should follow a more generic approach concerning methodology and the general availability of data to improve comparisons between urban forest carbon estimates, similar to what Pasher et al. (2014) established for Canadian cities. To improve the evaluation of results and track changes over time, we suggest that researchers at least provide additional information regarding the spatial distribution of individual trees concerning the total city area, tree canopy, and tree density.

## Modeling Above-ground Carbon Storage: A Remote Sensing Approach to Derive Individual Tree Species Information in Urban Settings

The selection of appropriate allometric biomass equations will remain a major source of uncertainty since few equations are adapted to the local urban environment. High expertise will be necessary to complete the selection process of allometric biomass equations (Zhao et al. 2012). Different climate conditions influence urban growth functions, and species-specific equations lack established accuracy or general availability, which might affect large-scale estimates (McHale et al. 2009). Averaged equations, such as method 2 (Table 1), may be a way to reduce the variability for city-wide estimates (McHale et al. 2009). Sileshi (2014) pointed out, that various reports on allometric models are often uninformative, in particular, as regards the selection of criteria, adaptation, and validation. Sileshi also calls attention to so-called “locally tailored” models, which tend to be less transferable to other study sites. Creating new equations will be both labor- and time-intensive and will require further improvements. Therefore, Zapata-Cuartas et al. (2012) suggest an approach that requires less destructive sampling of trees. Even though less bias by a higher number of equations is likely to cause a higher variance of carbon estimates (Weissert et al. 2014), other studies recommend the use of generalized results from a group of equations to reduce biased estimates (McHale et al. 2009; Aguaron and McPherson 2012). Such bias could affect the results we obtain using the highest level of detail regarding individual tree species (method 4, Table 3). A higher variance is expected for our input class “mix” (Table 1), and further uncertainty might be caused by differences in the classification accuracy of input data.

Automatic processing of tree species classification can be a future goal since information regarding dominant tree species is important for biomass estimates. Our multitemporal remote sensing approach on tree species classification should therefore be extended at different study sites since different species show correlation to tree phenology (Tigges et al. 2013). For example, high-resolution and carrier systems like unmanned aerial vehicles (UAV) might easily offer accessible information on temporal differences and tree phenology. Further information could be used to address either temporal changes or the prevalence of other native and alien species, which still contains an information gap (Kowarik et al. 2013; Nowak et al. 2016). The combination of different remotely sensed data can further improve the classification of forest details and be beneficial for carbon modeling approaches (Popescu and Wynne 2004; Yu et al. 2011). Very high resolution data have become more available for cities and can be used for improved delineation of individual



## Modeling Above-ground Carbon Storage: A Remote Sensing Approach to Derive Individual Tree Species Information in Urban Settings

trees, e.g., airborne UltraCamX data with a pixel size of 10 cm for downtown Berlin (Berlin Department of Urban Development 2014). The application of very-high-resolution data should still consider the potential over-segmentation of individual trees, which would reduce overall accuracy (Holopainen et al. 2013). Even manual delineation of trees does not always provide superior results as input for biomass estimates stated by Gleason and Im (2012). Ground-truth data for training and validation should be extended by terrestrial laser scanning since studies show that dendrometric measures of individual trees are highly accurate (Holopainen et al. 2013).

Common approaches to estimating the above-ground carbon storage of urban forests often use random sampling and generalized estimates of land use classes, which can consider high levels of detail. Though, they can lack expansive spatial data in extent of area, which might cause higher variability of carbon estimates within a certain land use class (Davies et al. 2011; Hutryra et al. 2011; Strohbach and Haase 2012). Therefore, high resolution remote sensing could be recommended as a cost-efficient methodology to supply more sufficient data on local differences and temporal changes (Raciti et al. 2014), and as a necessary standard inventory procedure (Davies et al. 2013; McPherson et al. 2013). This would help to better reflect local differences of land use patterns and processes, or differences in tree canopy structure. Future applications can use remotely sensed carbon storage estimates as a consistent baseline reference that is annually updated by sequestration estimates. Additionally, more site-specific information has helped to refine that high range of estimates. For example, the availability and improvements of remotely sensed imagery and interpretation contributed to correct the average forest carbon density of US cities (2002: 92.5 tC/ha per unit of tree cover; corrected 2013: 76.9 tC/ha per unit of tree cover). (Nowak et al. 2013) Following recent approaches like the first global map on tree density by Crowther et al. (2015), future availability of global (very) high resolution remote sensing imagery might help to give more precise answers to the questions of how much urban forests contribute to carbon offset. The CO<sub>2</sub> emissions offset might be another marketable regulating option to allow for an improved consideration of urban forests (Poudyal et al. 2010). This implies, that urban forests can act as a carbon sink, which has been indicated by some studies, but they lack future usage and climate mitigation strategies for urban vegetation (Weissert et al. 2014). This will also require appropriate information regarding

## Modeling Above-ground Carbon Storage: A Remote Sensing Approach to Derive Individual Tree Species Information in Urban Settings

tree species that maximize sequestration capacity, water use efficiency, and stress resistance (Muñoz-Vallés et al. 2013). Furthermore, the capacity of trees to act as a system should be continued to be considered in more detail, as a recent study by Klein et al. (2016) showed, that trees do not use carbon for themselves in particular, but also trade large quantities of carbon even between different tree species using fungi in the soil. Moreover, the benefits of high-resolution, remotely sensed, tree species information should be evaluated with regard to other ecosystem services, such as cooling and shading (Demuzere et al. 2014), which are still less prevalent in recent urban forest management plans (Ordóñez and Duinker 2013).

### 5 Conclusion

Our remote sensing approach allows us to retrieve area-wide and consistent information regarding urban heterogeneous forest structures, and our results show a measurable impact of tree species composition on urban carbon estimates. To the authors' knowledge, this is the first study that applies city-wide, high-resolution, and remotely sensed data to individual tree detection and tree species information. Providing additional sensitive information when assessing the uncertainty of carbon estimates can be beneficial, and furthermore, the methods discussed in this study may provide new techniques to increase the comparability of different cities with specific heterogeneous urban forest structures. Our findings may provide a baseline of urban forest carbon storage for future climate action planning, for identifying conservation areas where urban forest carbon densities are highest, and for identifying areas in which carbon density may be expanded in the long-term. Further studies will have to demonstrate whether a higher spatial resolution or LiDAR point density might address very heterogeneous areas more adequately on a consistently comparable basis. This applies for dendrometric estimates, species richness, and information on private property, in particular.

ALS, airborne laser scanning; C, carbon; CHM, canopy height model; dbh, diameter at breast height;  $\Delta$ , delta; GPS, global position system; kg, kilogram; ITD, individual tree detection; LCBH, LiDAR crown base height; LCD, LiDAR crown diameter; LH, LiDAR height;

## Modeling Above-ground Carbon Storage: A Remote Sensing Approach to Derive Individual Tree Species Information in Urban Settings

LiDAR, Light Detection And Ranging; Mt., megatons; MLS, mobile laser scanning; nDSM, normalized digital surface model; SD, standard deviation; t, tons; TLS, terrestrial laser scanning; UAV, unmanned aerial vehicle.

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### **Compliance with ethical standards**

### **Competing interests**

The authors declare that they have no competing interests.

Modeling Above-ground Carbon Storage: A Remote Sensing Approach  
to Derive Individual Tree Species Information in Urban Settings

**IV: Progress in High Resolution Remote Sensing to Advance  
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## Progress in High Resolution Remote Sensing to Advance Life Cycle Assessments of Urban Forest Carbon Offset

### **Abstract**

**Background:** Urban forests reduce greenhouse gas emissions by storing and sequestering considerable amounts of carbon. However, few studies have considered the local scale of urban forests to effectively evaluate their potential long-term carbon offset. The lack of precise, consistent and up-to-date forest details is challenging for long-term prognoses. Therefore, this review aims to identify uncertainties in urban forest carbon offset assessment and discuss the extent to which such uncertainties can be reduced by recent progress in high resolution remote sensing. We do this by performing an extensive literature review and a case study using a simplified life cycle assessment of urban forest carbon offset in Berlin, Germany.

**Results:** Recent progress in high resolution remote sensing and methods is adequate for delivering more precise details on the urban tree canopy, individual tree metrics, species, and age structures compared to conventional land use/cover class approaches. These area-wide consistent details can update life cycle inventories for more precise future prognoses. Additional improvements in classification accuracy can be achieved by a higher number of features derived from remote sensing data of increasing resolution, but first studies on this subject indicated that a smart selection of features already provides sufficient data that avoids redundancies and enables more efficient data processing. Regarding temporal changes and reliable long-term estimates, more attention is required to detect changes of gradual growth, pruning and abrupt changes in tree planting and mortality. Our case study from Berlin could use remotely sensed individual tree species as consistent life cycle inventory. However, a lack of growth, mortality and planting data forced us to make assumptions, therefore creating uncertainty in the long-term prognoses. As such, precise long-term ecological monitoring using high resolution remote sensing should be intensified, especially due to increasing climate change effects. This is important for calibrating and validating recent prognoses of urban forest carbon offset, which have so far scarcely addressed longer timeframes. Additionally, higher resolution remote sensing of urban forest carbon estimates can improve upscaling approaches, which can be extended to reach a more precise global estimate for the first time.

**Conclusion:** Urban forest carbon offset can be made more relevant by making more standardized assessments available for science and professional practitioners, and the increasing availability of high resolution remote sensing data and the progress in data processing allows for precisely that.

## 1 Background

Studies around the world have confirmed the role urban forests play in reducing greenhouse gas emissions by storing and sequestering a considerable amount of carbon (Churkina et al. 2010; Stoffberg et al. 2010; Liu and Li 2012; Chen 2015). However, urban forest carbon offset is still regarded with uncertainty due to the lack of precise details on global coverage (Churkina 2016). Additionally, the urban scale has become more relevant due to the steady failure of global policies to effectively regulate local carbon emissions. Recent carbon ratings and initiatives should therefore not underestimate the local scale of urban forest carbon offset and should be sure to effectively evaluate their potential long-term offset. (Scyphers and Lerman 2014)

Urban forests have been discussed as a potential new source of carbon credits, such as by raising revenue for future green investments. Therefore, knowledge of local conditions is essential to better evaluate future opportunities, such as urban carbon offset markets, which have gained considerable interest among local governments (Poudyal et al. 2010; Poudyal et al. 2011a; Dhanda and Hartman 2012). Avoided emissions and climate change damage are commonly referred to as “Social Costs of CO<sub>2</sub> Emissions” (SCC) (van den Bergh and Botzen 2015). According to the estimated SCC for 2010 (USD 80 per ton of carbon), US urban forests have stored approximately USD 50 billion in value (2005 level) and have sequestered USD 2 billion in value annually (Nowak et al. 2013). This creates awareness of the matter by monetizing urban forest carbon offset, but the “real” costs can also be underestimated—for instance, SCC calculations do not necessarily fully consider how climate change affects ecosystems, biodiversity loss and limits of resources, which cause uncertainty in SCC estimates (Baveye et al. 2013; van den Bergh and Botzen 2015).

Urban forest carbon offset is by no means a static value, as its complexity and dynamics need to be considered in order to properly assess its long-term net contribution. An example of a more holistic consideration is a life cycle assessment (LCA) to consider urban forests’ carbon balance throughout a lifetime (cradle-to-grave approach) (Klöpffer 2014). This allows for more precisely addressing urban forest heterogeneity and dynamics, for instance: its aspects of structure, planting, maintenance, growth, mortality and more. However, precise

information on these features is scarce, not up-to-date or does not cover large spatial expanses, and therefore more standardized methods are required for consistent spatially explicit information (Kremer et al. 2016). Traditional sampling approaches using land use classes for urban forest carbon estimates are less feasible for precisely addressing in-class variability (Tigges et al. 2017). There is also no consistent global urban tree canopy model considering precise details (Churkina 2016). Fortunately, this lack of precise, up-to-date and area-wide urban environmental information can be narrowed using recent innovative technology, such as high resolution remote sensing (Kadhim et al. 2016).

The aim of this review is to identify high uncertainties in urban forest carbon offset assessment and discuss the extent to which such uncertainties can be reduced by recent progress in high resolution remote sensing. This would help to improve long-term prognoses of urban forest carbon offset, which is essential for better evaluating the effectiveness of local projects like urban forest carbon offset markets. Details of a large spatial expanse would also be useful concerning the global role of urban forest carbon offset. First, we evaluate state-of-the-art studies on urban forest carbon storage and sequestration. We discuss the complexity of long-term carbon offset under LCAs, the supply and demand, and major challenges of assessment. We identify high resolution remote sensing's potential for updating a life cycle inventory and refer to potential and limitations of classifying urban tree canopies, individual trees and urban tree species. In the subsequent section, we apply a simplified LCA of urban forest carbon offset for the city of Berlin, Germany. This points out the recent progress of remotely sensed individual trees and the major challenges of assumed tree growth, mortality and planting. Finally, we evaluate the remote sensing potential of high temporal resolution for improving the validation and calibration of long-term prognoses of urban forest carbon offset, and discuss the link between local and global scales.

## **2 Urban Forest Carbon Offset—Status Quo and Future Prognoses**

Quantitative studies on the status quo of urban forest carbon offset are still rare compared to studies on forestry at the national level, but in the 1990s, the availability of urban studies began to spread globally with a focus on US cities. Urban forest carbon storage estimates



## Progress in High Resolution Remote Sensing to Advance Life Cycle Assessments of Urban Forest Carbon Offset

highly differ between cities with a range from below 10 tC/ha to above 100 tC/ha per unit of tree cover, most of which refers to above-ground carbon storage of a heterogeneous age structure and a mixture of different tree species regarding a set point in time (Stoffberg et al. 2010; Strohbach and Haase 2012; Nowak et al. 2013; Chen 2015; Tigges et al. 2017). In general, forest carbon storage estimates are typically based on well-established allometric biomass equations, with approximately 50 % of above-ground dry biomass related to carbon (C) (Nowak and Crane 2002). However, most biomass equations have not been developed specifically for urban trees, resulting in variability in carbon estimates. Few studies have precisely addressed the heterogeneity of urban forests. Area-wide spatially explicit information has subsequently remained a major source of uncertainty and thus requires further assessments (McHale et al. 2009; Peper et al. 2014).

Research on spatiotemporal changes in urban ecosystem services still faces challenges due to non-uniform and multifunctional approaches, different methodologies, diverging stakeholders' interests or a lack of relevant information (Luederitz et al. 2015), among others, information on urban forest carbon offset. Especially the lack of information refers to the dynamics of urban forests, which are associated with natural disturbances like differences in growth, diseases, stresses and natural hazards, or to other anthropogenic disturbances in particular, such as influences of environmental actors, management, political discourses and related land use change dynamics (Strohbach and Haase 2012; Bahadur and Tanner 2014; Lauf et al. 2014). Climate change effects can also lead to further exacerbations and stress for urban forests (Kuttler 2011). Furthermore, the consideration of urban ecosystem service dynamics have rarely been considered as a common practice across cities. However, it could serve as advice for sustainable future implementation policies (Haase et al. 2014), or for improved climate change resilience of and through urban ecosystem services (McPhearson et al. 2015). Because of all of this, it is challenging to account for a thorough consideration for future prognoses, such as for urban forest carbon offset in the long-term.

An even more holistic perspective on urban forest carbon offset LCA seems to be a promising forward-looking approach for assessing the effects of not just a single stage, but the complete life cycle from creation and use to end-of-life (cradle-to-grave). Until today, few studies have examined urban forest carbon offset using LCA, and most of them addressed select stages concerning planting, growth, maintenance, mortality, reuse of dead

## Progress in High Resolution Remote Sensing to Advance Life Cycle Assessments of Urban Forest Carbon Offset

biomass or a combination of these qualities. For instance, McPherson and Kendall (2014) showed that, for a one million tree planting initiative for Los Angeles, US, an adequate life cycle management of urban forests can function as a carbon sink to support mitigation goals concerning a 40-year LCA. McHugh et al. (2015) also addressed potential tree planting on a citywide scale in Leicester, UK, which showed an as of yet unutilized city area of 15 % to increase forest carbon storage concerning a 25-year LCA. Of that area, approximately 50 % was also suitable for short-rotation coppice using willow and poplar trees and could therefore act as an additional renewable energy source to replace fossil CO<sub>2</sub> emissions. Strohbach et al. (2012) simulated the carbon footprint (sequestration minus emissions) of selected park trees planted in the city of Leipzig, Germany, with a total net of up to 162 tC/ha for a 50-year LCA (averaging 3.24 tC/ha/year per unit of tree cover) concerning mean tree growth and low annual tree mortality. Although high annual tree mortality (from 0.5 to 4 %) could reduce the carbon footprint by over 70 %, additional differences in growth rates caused a range of up to 45 %. Compared to a citywide scale and simplified tree mortality and decay rates, the urban forests of 28 US cities across 6 states showed a net carbon sequestration rate averaging 2.05 tC/ha/year per unit of tree cover with a range of 0.81 in Minneapolis to 4.01 tC/ha/year in Omaha, demonstrating regional differences in urban forest structure. However, these results are simplified assumptions for the next year and do not account for a complex LCA for long-term prognoses (Nowak et al. 2013). Strohbach et al. (2012) showed relatively small emissions—less than 10 % of total sequestration—related to construction and maintenance over a long life cycle for tree planting initiatives. However, uncertainty measures on emissions have barely been stated by experts or literature. Emissions due to tree maintenance had been below even 2 % concerning the total annual energy consumption of an urban park, as Solà et al. (2007) showed in a case study at Montjuïc Park in Barcelona, Spain. However, McPherson and Kendall (2014) addressed the necessity for more efficiency concerning the potential to further avoid emissions during maintenance: irrigation and removal of trees accounted for more than 15 % of total CO<sub>2</sub> emissions, and mulch decomposition of dead tree biomass was responsible for 65.1 % during a 40-year LCA of urban trees planted in Los Angeles, US. It also remains unclear the extent to which an increase in maintenance of a single tree and the resulting increase in CO<sub>2</sub> emissions can lead to extended tree longevity and a positive effect on the net carbon balance (Nowak et al.

2002), or if more efficient maintenance can result in both lower emissions and higher tree longevity.

### *Supply and Demand*

Information on the supply of urban forest carbon storage and sequestration is not commonly available, and information of the demand side is even scarcer. It has been suggested that there is a need to address the supply and demand of such urban ecosystem services in a more spatially explicit manner (Larondelle and Lauf 2016), and environmental quality and policy goals would need to set a standard for the supply and demand (Baró et al. 2015). However, it is still arguable just what the minimum standard for this is, though it would be a certain boundary for assessing and managing urban ecosystem services like urban forest carbon offset. Zhao and Sander (2015) focused on differences in forest carbon offset (supply) and total carbon emissions (demand) across the Twin Cities (Minneapolis–Saint Paul) metropolitan area of Minnesota, US: sequestration of 2010 could compensate a small rate of 1 % of local anthropogenic carbon emissions, but the avoided emissions of carbon storage should not be underestimated. Additionally, there have been obvious spatial differences that have demonstrated that some counties could compensate more than 10 % of local carbon emissions using trees, which is slightly higher than what US forests compensate for total US averaged carbon emissions according to information from the Environmental Protection Agency (EPA). Chen (2015) showed for 35 major Chinese cities that urban vegetation could offset fossil emission of cities from 0.01 % in Hohhot to 22.45 % in Haikou in 2010. Furthermore, the dominance of young trees stand of those Chinese cities should not be underestimated, as they will experience substantial growth in the near future. Therefore, forest growth and planting can notably supplement carbon offset in the matter of urban carbon footprinting, which has so far been underestimated. Additionally, the demand of anthropogenic carbon emissions has been dominated by fossil energy up until this point, followed by agriculture, transportation and residential areas, which offers a great deal of potential for being reduced and substituted by alternatives. Consequently, a higher contribution of urban forests' carbon offset could increase environmental awareness.

*Major Challenges of Carbon Offset Long-Term Prognoses*

Up until now, studies on urban forest carbon offset dynamics have: covered prognoses with a focus on urban tree sequestration, management, planting and related emissions (Nowak et al. 2002; Solà et al. 2007; Scharenbroch 2012; Strohbach et al. 2012; McPherson and Kendall 2014; McHugh et al. 2015); offered the further potential of short-rotation coppice for energetic purposes (McHugh et al. 2015); focused on aspects of the expected tree growth of planted trees and carbon trade potentials (Stoffberg et al. 2010); assessed the status quo and expected net sequestration for the upcoming year (Nowak and Crane 2002; Nowak et al. 2013; Pasher et al. 2014; Zhao and Sander 2015); and addressed aspects of urban forest carbon offset demands (Liu and Li 2012; Chen 2015; Zhao and Sander 2015; Tang et al. 2016). Concluding the complexity of urban forest carbon offset, LCA seems to be a promising approach for better understanding urban forest dynamics. However, studies on this differ, and most of them address only parts of a complex LCA or consider a small temporal horizon. This has left plenty of space for interpretation regarding how to entirely fulfill the phases of an LCA concerning its suggested formal standard (ISO 14040 and 14044) (Klöppfer 2014), including: (1) goal and scope definition, (2) inventory analysis, (3) life cycle assessment and (4) interpretation, critical review and reporting. For example, McPherson and Kendall (2014) stated that the available studies on the LCA of urban forest carbon offset have so far failed to account for the full scope of emissions associated at each life stage of a tree. The traditional forestry sector shows similar challenges. Although such studies have been performed since the 1990s, and before urban applications, there is still a lack of consistent and comprehensive studies. Instead LCA studies differed due to decisive assumptions and their subsequent results concerning system boundaries, functional units, impact categories, considered processes, allocation, LCA methods, available databases and accuracy metrics (Klein et al. 2015). It would certainly be worthwhile to discuss the LCA of urban forest carbon offset in the matter of harmonization or better comparability, such as by increasing precision and data consistency. This should reduce the high variability of LCA results, and especially address differences in tree mortality and growth; forest structures concerning size, age, tree species; data on private and public areas; related data retrieval; (re)planting; actual and potential reuse of dead biomass; and other aspects. It has been challenging to retrieve such necessary data, especially due to the heterogeneous urban forest

structure, as well as get access to details across public and private space or beyond administrative boundaries that are also consistent and up-to-date (Davies et al. 2011; Hutyra et al. 2011; Strohbach and Haase 2012). Improvements should definitely aim at reducing the expensive and time consuming data collection process, as it is an important part of LCAs (Klöpffer 2014).

## **2.1 LCA Inventory—Remotely Sensed Updates**

The development and contributions of high resolution urban remote sensing have been successfully applied to provide input for improved modeling of urban ecosystem services concerning area-wide information that is consistent and up to date, which can help to increase the comparability of different sites (Lakes et al. 2011). High resolution spatial data is helping to overcome the problem of assessing ecosystem services like urban forest carbon storage provided by small land parcels (Davies et al. 2013). Increasing spatial, spectral and temporal resolutions have successfully shown an increase in precision, for example, to monitor the change detection of individual trees or to identify the diversity of urban tree species (Ardila et al. 2012; Tigges et al. 2013). Moreover, unmanned aerial vehicles (UAVs) have expanded the possibilities of urban vegetation mapping and field surveys, and have thus contributed to the growing data availability of remotely sensed imagery (Kaneko and Nohara 2014). Hence, recent remote sensing offers new monitoring options for dynamic urban environments, as well as a complementary input for urban forest LCAs. High resolution remote sensing has been recommended for supplying more adequate data on local and regional differences and changes in urban forest cover (Nowak and Crane 2002), and as a promising standard inventory procedure for assessing the status quo of urban forests (Davies et al. 2013; McPherson et al. 2013; Shojanoori and Shafri 2016). The benefits of high resolution remote sensing data have already been shown by several studies on urban forest carbon offset (Nowak et al. 2013; Rao et al. 2013). However, few studies have identified the extent to which an increasing resolution of remotely sensed data can reduce uncertainties in mapping carbon estimates of urban forests (Raciti et al. 2014; Chen et al. 2017). This also refers to precise remotely sensed data retrieval on urban tree canopies, individual trees and species, which are of utmost importance for an LCA.

## Progress in High Resolution Remote Sensing to Advance Life Cycle Assessments of Urban Forest Carbon Offset

### *Urban Tree Canopy*

The urban tree canopy is most often used as a baseline parameter for carbon estimates. Urban forests have been classified from remotely sensed data with a threshold of vegetation indices like NDVI (normalized difference vegetation index), which considers the sensitivity of spectral bands near-infrared and red. Combined thresholds of remotely sensed height data have commonly been used to classify the urban tree canopy. (Hanes 2014) However, the absence of standardized metrics make it difficult to compare available urban carbon studies; for instance, the combination of data sets with different acquisition times causes inconsistency (Davies et al. 2013). Uncertainty in urban tree canopy classification is often not reported, or is stated with a bias (Richardson and Moskal 2014). Despite very high resolution data, Raciti et al. (2014) accounted for 14 % of the variability in class accuracy occurring by chance when mapping the urban tree canopy using airborne LiDAR height data (1 height point/m<sup>2</sup>) and QuickBird satellite data (2.4 m pixel size). Similar errors were stated in other very high resolution studies. They occurred with objects that were smaller than a remotely sensed pixel (mixed pixel problem), which mostly occurred for urban vegetation pixels with high proximity to the edges of buildings (Schreyer et al. 2014). As this situation is frequently found in densely built areas, it is likely to bias spatially explicit carbon estimates in the end. The quantitative effects of such very high resolution problems have rarely been considered as of yet. This can be overcome by further increasing the resolution in the centimeter range, but at the cost of extensive resource requirements, especially for processing (Weng et al. 2012). Therefore, we suggest a minimum quality of urban tree canopy mapping because it is a standard baseline parameter of forest carbon offset and will have a significant influence within an LCA.

### *Individual Tree Detection*

Individual tree information, such as tree growth and mortality issues, is highly relevant for urban carbon estimates if we want to address variability within land cover/use classes. However, the acquisition of urban tree inventory data is resource intensive and still lacks systematic monitoring (Jenkins et al. 2003). This has made remotely sensed individual tree detection (ITD) a great advantage, though it has so far only rarely been applied in the urban

## Progress in High Resolution Remote Sensing to Advance Life Cycle Assessments of Urban Forest Carbon Offset

context (Zhang et al. 2015a). The ITD for urban forest carbon estimates has minimal scaling effects compared to traditional accurate sampling approaches of land use classes, which instead address a coarse neighborhood or city level (Popescu 2007; Raciti et al. 2014). Remotely sensed individual trees would also be less affected by differences within land use classes, allocation errors at transition zones between land use classes or information beyond administrative boundaries.

Early ITD approaches have made use of multispectral remote sensing data for classifying overstory tree crowns (Key et al. 2001). The feasibility of ITD for estimating tree dimensions and biomass has grown alongside the availability of high resolution LiDAR data as three-dimensional point clouds (echo-based), the very high point densities of which can penetrate the tree canopy and subsequently improve understory estimates (Garcia et al. 2017). Alternatives are the frequently available processed height products, such as canopy height models (CHM), most of which are simplified discrete return LiDAR data reduced to the first return signal (upper tree canopy) (Zhang et al. 2015a). Additional adequate height data for ITD has been offered by photogrammetry options of very high resolution multispectral sensors (Baltasvias 1999), which has gained attention due to the ever decreasing equipment costs of UAVs offering accuracy at cm-level resolution (Colomina and Molina 2014; Hassaan et al. 2016).

Kaartinen et al. (2012) provided a comprehensive review of tree detection methods based on the international benchmarking study “Tree Extraction.” The results of a heterogeneous forest test site were highly affected by the chosen algorithm rather than a CHM of different point density (2 to 8 points/m<sup>2</sup>). This showed that a local maxima finding provides fast and ready to use results, as well as advanced algorithms like minimum curvature-based tree detection to deliver precise estimates for a tree inventory. The tree height reached a RMSE of 0.5 m. Automated methods also outperformed manual tree detection from remotely sensed data, which implies that field data can be more relevant as a reference for validating and correcting derived estimates. Compared to very high point density LiDAR data, Orka et al. (2010) showed fairly accurate estimates of tree height (RMSE, 0.76 to 0.84 m) and derived stem diameter (RMSE, 3.10 to 3.17 cm) for a highly heterogeneous non-urban forest structure (echo-based LiDAR point clouds, small footprint < 21 cm, a mean pulse density of about 5 per m<sup>2</sup> with a total return of 30 to 100 echoes). The ITD of very small and young

trees could benefit from a higher point density ( $> 10$  points/m<sup>2</sup>) (Kaartinen et al. 2012). Additionally, the results of original LIDAR point clouds seemed to output more realistic forest structures than CHM-based ITD (Jakubowski et al. 2013). Higher variability of CHM-based results could also be due to smoothing algorithms, interpolation methods and chosen grid spacing during model production (Zhang et al. 2015a).

Unfortunately, the above-mentioned ITD approaches have not yet been developed specifically for urban forests. The heterogeneous urban forest structure is extremely challenging due to a mixture of spatial arrangements and a high diversity of tree species, height and age structure. Lee et al. (2016) accounted for a mixture of 20 predominant urban tree species using LiDAR data (4 returns per pulse in addition to a LiDAR intensity value). The results provided fairly accurate estimates of tree height (RMSE, 1.64 m) and derived stem diameter (DBH) (RMSE, 10.32 cm). Lee et al. suggested an adequate validation of different tree sizes and groupings to correct potential over- or underestimates. Zhang et al. (2015a) developed a new algorithm for automated urban tree detection using original echo-based LiDAR point clouds (3.5 points/m<sup>2</sup>) with promising results ( $R^2$  above 0.84, RMSE 0.57 m for tree height, RMSE 1.9 m for crown diameter). They adapted a local maxima and constrained tree climbing algorithm to detect tree peaks by incorporating a horizontal threshold to better address less pointed forms of deciduous tree species. They also felt that a minimum height threshold was appropriate in order to exclude shrubs. The outer boundaries of individual trees were segmented using an inverse tree climbing method referred to as “the donut expanding and sliding method.” The results should be improved regarding more complex crown shapes, as individual trees were assumed to have a circular shape. For example, Ardila et al. (2012) successfully used an automated region-based active contours approach for multispectral data, which allowed for better addressing realistic crown shapes and could better handle the spectral variability of neighboring pixels, which has been a significant challenge for very high spatial resolution imagery. This active contours approach might be improved if extended by photogrammetric three-dimensional data of multispectral imagery. An object-based segmentation approach could also be used to reduce the spectral variability of remotely sensed data (Chen et al. 2014), but this is more labor intensive and sensitive to the expert’s classification rules (Ardila et al. 2012). Recent progress in low-altitude UAV photogrammetry could also provide precise terrain models to reduce the effect



of heterogeneous vegetation cover (Gruszczyński et al. 2017), as the lack of adequate ground points can also lead to significantly underestimating urban tree dimensions (Hecht et al.). However, algorithms for tree segmentation would have to consider potential over-segmentation of individual tree crowns, especially due to very high resolution data (Holopainen et al. 2013). Original full waveform LiDAR, which samples a returned signal at the LiDAR sensor with a very high rate appearing as a wave, or synergies combining different sensors using higher spatial, spectral and temporal resolution, could further increase the precision of urban tree dimensions (Chang et al. 2008; Holmgren et al. 2008; Shrestha and Wynne 2012; Wei and Yuzhang 2013; Zhang et al. 2015a; Zhen et al. 2016).

The increasing resolution of remotely sensed imagery and the development of methods and carrier systems are likely to supplement traditional urban field surveys if no up-to-date data is available or there is no data at all. However, a comprehensive review published by Zhen et al. (2016) pointed out that ITD methods and data would require more suited applications, such as for urban conditions, and that assessment metrics are inconsistent for evaluating and comparing results. More than 200 studies from 1990–2015 were published on ITD, and applications in urban settings have increased during the last 10 years. In the near future, the use of low-cost UAVs is likely to increase as it offers multiple options. For instance, Jaakkola et al. (2010) attached a GPS/IMU positioning system, two laser scanners, a CCD camera, a spectrometer and a thermal camera to UAVs. This setup allowed for classifying individual tree heights with a standard deviation of 30 cm for a heterogeneous urban forest.

### *Urban Tree Species*

The composition of tree species becomes relevant for a heterogeneous forest structure particularly, for instance, concerning stress resistance, species and site-specific differences in growth and mortality, or differences across large areas. Therefore, numerous studies have addressed tree species classification using high resolution remote sensing.

Recent Worldview 2 multispectral satellite imagery from late spring (May, 8 spectral bands, 2 m pixel size) could improve the classification of seven urban tree species in Tampa, Florida, US using a higher number of spectral bands. For example, the overall accuracy could be increased by approximately 5 % compared to IKONOS satellite imagery of early spring

## Progress in High Resolution Remote Sensing to Advance Life Cycle Assessments of Urban Forest Carbon Offset

with less spectral information (April, 4 spectral bands, 4 m pixel size). However, the classification accuracy could be improved to a maximum of 63 %, but did not exceed this moderate level (Pu and Landry 2012). Immitzer et al. (2012) classified 10 tree species with a good overall data accuracy of 82 % in a temperate heterogeneous structured non-urban forest in Austria using Worldview 2 satellite imagery of high summer (July, 8 spectral bands, 2 m pixel size). However, species-specific results highly varied and could drop by 40–60 %. The classification of urban tree species has been improved by increasing the temporal resolution of satellite imagery, such as seasonal data of RapidEye satellite imagery (5 spectral bands, 6.5 m pixel size), which correlates to differences in vegetation phenology. Such multitemporal data could significantly decrease the allocation problem between eight dominant tree species in Berlin, Germany, whereas a single image did not provide sufficient information for classifying tree species. Furthermore, only few selected spectral information from a multitemporal feature space were relevant for reaching high classification accuracy (Tigges et al. 2013). The benefits of multitemporal satellite imagery reflecting seasonal differences were confirmed by Li et al. (2015a), who applied WorldView 2 and 3 imagery of late summer and high autumn to classify urban tree species with satisfying results at two study sites in Beijing, China (overall accuracy > 80 and 90 %). Hyperspectral remote sensing offers a very high number of bands with precise spectral information, which showed fairly accurate results for tree species classification (Jensen et al. 2012; Ballanti et al. 2016). Structural features derived by high point density LiDAR data allowed similar overall accuracies above 75 % within a heterogeneous non-urban forest (Li et al. 2013). Original full waveform LiDAR could further improve the overall accuracy compared to approaches using traditional preprocessed LiDAR data, which is mostly decomposed to discrete peak data in particular (Vaughn et al. 2012). The intensity data recorded for each laser point in a LiDAR system also contributed to some improved species classification (Kim et al. 2009). The combination of sensors can further increase the availability of different high resolution data. For instance, combining LiDAR and hyperspectral in particular increased the accuracy for specific tree species (Alonzo et al. 2014). Recent progress in three-dimensional hyperspectral remote sensing should receive more attention in the future, which Nevalainen et al. (2017) applied for ITD (number and location) and species classification in boreal forests using a combination of a low-altitude UAV-based photogrammetric point cloud for

## Progress in High Resolution Remote Sensing to Advance Life Cycle Assessments of Urban Forest Carbon Offset

CHM model production (10 cm raster) and hyperspectral imaging (33 spectral bands, 10 cm ground sampling distance). Nevalainen et al. applied a Random Forest classifier for tree species and reached an overall accuracy of 95 %, but varied between 40 % and 95 % for detecting individual trees due to the heterogeneous site conditions using a local maxima filter algorithm integrated into Fusion software by McGaughey (2013). In this context, we suggest comparing the accuracy and precision of further available ITD approaches.

Recent available studies clearly indicate a high potential for classifying tree species under heterogeneous conditions using high resolution remote sensing. Fassnacht et al. (2016) reviewed currently available tree species classification studies and identified promising local scale approaches with multiple options of available remote sensing data. However, recent results still lack adequate transferability across large areas. Experts requested a better understanding of tree species differentiation concerning structural, spectral or phenological indicators rather than solely data-driven statistics, most of which are highly locally tailored classification achievements. To the authors' knowledge, an approach does not yet exist that solely addresses a single tree species. This would be highly appropriate concerning the prevalence of other native and alien species within urban forests, which is still an information gap (Kowarik et al. 2013). More specifically, future research will need to discover whether there is a unique indicator or a combination for a single tree species using remote sensing data, or if we are limited to distinguishing between species using a more locally tailored approach. This should not be taken to underestimate recent options for making use of remotely sensed tree species classification. However, approaches should be adapted to the selected location and at least include the area's most dominant tree species, therefore employing a more representative tree population. This would contribute to better assessing the overall classification accuracy of tree species.

### **2.2 The Berlin Case—Simplified LCA of Urban Forest Carbon Offset**

To relate our findings of this review to a more concrete situation, we conducted a simplified LCA of urban forest carbon offset for Berlin, the capital of Germany. The aim of this case study is to assist scientists and professional practitioners to provide basic long-term prognoses for environmental awareness and to make use of the recent progress made in

## Progress in High Resolution Remote Sensing to Advance Life Cycle Assessments of Urban Forest Carbon Offset

remote sensing, such as providing an LCA tree inventory. We pointed out the challenges of assumed tree growth, mortality and planting to achieve the sensitization for the role of urban forest carbon offset.

### *Data—LCA Inventory of Remotely Sensed Trees*

The city of Berlin (52° 31' N, 13° 24' E) has a moderate climate and is characterized by a mostly flat topography. Its administrative area is approximately 890 km<sup>2</sup>, 40% of which is covered by vegetation such as urban forests, parks, street trees and urban agriculture (Berlin Department of Urban Development 2010a). More than 290 km<sup>2</sup> of Berlin is taken up by urban forests, which constitutes the largest urban forest in Germany; Berlin's public parks cover approximately 55 km<sup>2</sup>. Because a consistent and up-to-date tree database covering private and public areas does not exist, we updated our LCA tree inventory using a high resolution remote sensing approach using the final results of individual tree species information, previously published by (Tigges et al. 2013); Tigges et al. (2017): The final tree database contained consistent information concerning location, height, crown width and DBH for each individual tree as well as its species and species fraction of the total tree population. The tree species (Fig. 1) had been derived by applying advanced machine learning on a time series of RapidEye satellite imagery reflecting phenological differences between tree species (5 images during the growth season of 2009; pixel size of 6.5 m). Individual tree metrics were derived from a LiDAR-based tree crown model (winter 2007/2008; regular grid of 4 height points/m<sup>2</sup>), a local maxima filter algorithm that is integrated into Fusion software (McGaughey 2013) and laser scanning calculations for DBH estimates from Zhao et al. (2009). Remotely sensed data covered an overlapping area of approximately 700 km<sup>2</sup> of the city of Berlin, which resulted in a classified urban tree canopy of 213 km<sup>2</sup> (Fig. 1).

## Progress in High Resolution Remote Sensing to Advance Life Cycle Assessments of Urban Forest Carbon Offset

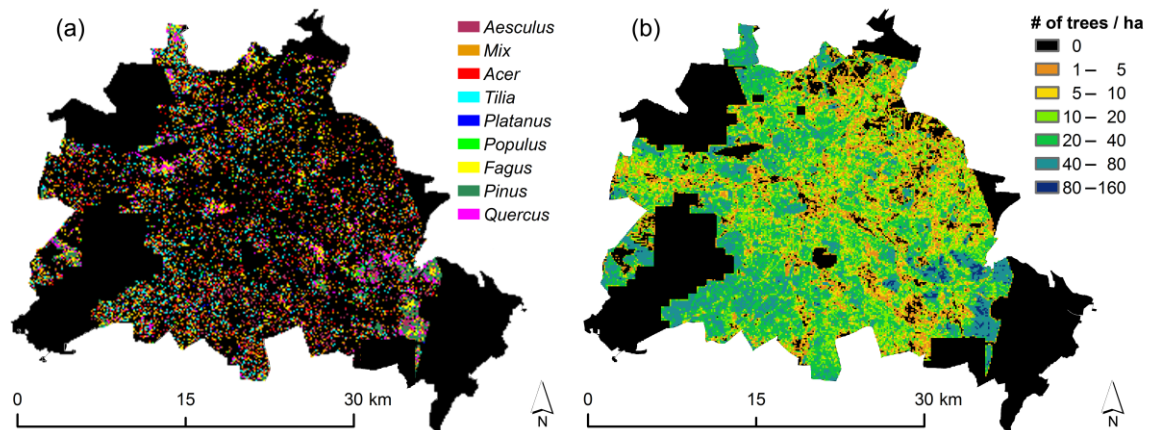


Figure IV - 1: LCA inventory of remotely sensed trees in Berlin, Germany. Spatial distribution of (a) dominant tree species and (b) tree density per unit of land cover (Tigges et al. 2017). Class “mix” refers to difficult-to-classify tree species in the tree canopy. Approximately 1.4 million trees were classified with a mean tree height of 15 m and a mean DBH of 36 cm. No data was available for the outer black areas, which are mostly covered by forests.

### Method—LCA of 60 Years

Our tree inventory data was entered for an LCA of urban forest carbon offset. The carbon accounting referred to alive and dead above-ground tree biomass and followed a time period of 60 years. We then discussed the role of alive and dead biomass. The initial year of our LCA was set to 2008, according to the date of the LiDAR data. Results were presented at regular 10-year intervals. We accomplished the LCA stages of growth, mortality and planting as follows:

**Growth:** we used allometric biomass equations and DBH-growth functions (cm per year) for each tree class listed in Table 1 to receive future estimates on tree size and biomass: most dominant individual tree species in the study area are listed as classes 1–10; classes 1–8 are classified using RapidEye satellite data with its fraction of the total tree canopy (CHM); Class “mix” includes all other species of the total tree canopy, mostly comprising classes 9 and 10. Strohbach et al. (2012) applied growth data from a street-tree database of Leipzig, Germany, which was utilized for this case study, as non-linear regression functions better reflect a more natural pattern concerning a smaller annual DBH-growth for mature trees (Table 1). We used those functions to convert DBH estimates from our remotely sensed data from 2008 to age estimates of each individual tree. We then simulated a 60-year life cycle for annual estimates of DBH using our adapted growth functions. The results of each year

## Progress in High Resolution Remote Sensing to Advance Life Cycle Assessments of Urban Forest Carbon Offset

were used as input for allometric equations of above-ground biomass approximations (Table 1). We multiplied our biomass estimates by 0.5 to convert above-ground dry biomass into units of carbon (C) (Nowak and Crane 2002). Because allometric equations demonstrate high under- and overestimates, recent studies require them to be adapted for use in specific urban applications (McHale et al. 2009). However, we did not have any specific information for Berlin. Therefore, we carefully selected the species that best matched our case study (Table 1) and did not apply any correction factor for urban biomass estimates as Nowak and Crane (2002) had done. If no species-specific equations were available, we followed the approach taken by Hutyra et al. (2011) by selecting equations of the same genus. If we could not classify a tree species (Class mix, Table 1), we used the average estimate of dominant tree species in our case study area. Our results summarized the total alive biomass for each land use class at 10-year intervals.

Mortality: estimates of urban tree mortality are affected by high uncertainty due to differences in tree physiology, biophysical and environmental conditions, planting strategies, social-ecological behavior, future climate change and more (Nowak et al. 2004; Koeser et al. 2014; McPherson and Kendall 2014; Roman 2014). Due to high uncertainty and simplification we assumed annual static mortality rates. We also did not have specific information on young tree or long-term tree mortality for our case study. However, we considered differences between the urban heterogeneous environment and management conditions according to land use classes of parks, streets and mixed residential or commercial use. We consequently assigned our classified individual tree species to these classes, the boundaries of which we took from digital OpenStreetMap data. We also applied a buffer zone of 10 m for streets to account for trees with high proximity. The highest annual mortality rate of 3.5 % was assigned to street trees due to multiple stress factors, such as pollution, sealed surface, traffic safety issues and other growth-limiting conditions. Recent studies showed similar mortality rates between 3.5 % and 5.1 % for urban street trees (Roman and Scatena 2011). A tree mortality of 1 % was set for parks, which we assumed to have

Progress in High Resolution Remote Sensing to Advance  
Life Cycle Assessments of Urban Forest Carbon Offset

fewer stress factors than street trees. We assigned a tree mortality of 2 % to mixed areas because the space was likely to be limited for large tree growth.

Table IV - 1: Most dominant tree species for biomass and growth calculations.

Class	Genera	CHM	Biomass Estimates	Growth Function
	Tree Species	[%]	Allometric Equation	[DBH]; Residual Error
1	<i>Acer campestre</i> , <i>Acer platanoides</i> , <i>Acer sp.</i>	12.9	Equation 2, <i>Acer saccharum</i> (Ter-Mikaelian and Korzukhin 1997)	$202.9173 * (1 - e^{(age * -0.0019)})^{0.7992}$ ; 5.48
2	<i>Aesculus hypocastanum</i>	13.4	Table 1, <i>Aesculus indica</i> (Adhikari et al. 1995)	$175.5828 * (1 - e^{(age * -0.0042)})^{0.8958}$ ; 6.57
3	<i>Fagus sylvatica</i>	10.4	Appendix A, Equation 89, <i>Fagus sylvatica</i> (Zianis et al. 2005)	$202.9173 * (1 - e^{(age * -0.0019)})^{0.7992}$ ; 6.15
4	<i>Pinus sylvestris</i>	11.3	Table 3, <i>Pinus sylvestris</i> (Muukkonen 2007)	$135.4549 * e^{(-3.1143 * e^{(age * -0.0152)})}$ ; 4.74
5	<i>Platanus hispanica</i>	1.9	Volume of <i>Platanus acerifolia</i> , gravity of <i>Platanus</i> (Alden 1995; Pillsbury et al. 1998)	$170.5888 * (1 - e^{(age * -0.0047)})^{0.913}$ ; 4.95
6	<i>Populus nigra</i> , <i>Populus alba</i>	1.8	<i>Populus tremula</i> (Zianis et al. 2005)	$93.5402 * (1 - e^{(age * -0.0152)})^{1.1518}$ ; 10.77
7	<i>Quercus robur</i> , <i>Quercus rubra</i> , <i>Quercus sp.</i>	8.6	Table 3, <i>Quercus sp.</i> (Muukkonen 2007)	$70.2797 * e^{(-2.8528 * e^{(age * -0.0289)})}$ ; 4.03
8	<i>Tilia cordata</i> , <i>Tilia × vulgaris</i> , <i>Tilia platyphyllos</i>	13.2	Appendix A, Equation 607, <i>Tilia cordata</i> (Jenkins et al. 2003; Zianis et al. 2005)	$56.4678 * (1 - e^{(age * -0.0182)})^{1.053}$ ; 5.71
9	<i>Betula pendula</i>	/	Appendix A, Equation 31, <i>Betula pendula</i> (Zianis et al. 2005)	$199.1001 * (1 - e^{(age * -0.0029)})^{0.8865}$ ; 4.48
10	<i>Robinia pseudoacacia</i>	/	Table 2, Equation 6, <i>Robinia pseudoacacia</i> (Böhm et al. 2011)	$116.6451 * e^{(-3.1542 * e^{(age * -0.0198)})}$ ; 5.40
Mix	Mix of dominant species above	26.5	Average of equations listed above	Average of equations listed above

## Progress in High Resolution Remote Sensing to Advance Life Cycle Assessments of Urban Forest Carbon Offset

Although our mortality rates were based on the assumption of high uncertainty, results could be used to generally reflect a sensitivity concerning a mortality range of 1 % to 3.5 %. We achieved the mortality rates of our land use class by applying an annual stratified random selection of individual trees in our tree database. We also excluded very old trees using a threshold of a maximum age. However, we indicated high uncertainty when the average age of the tree population exceeded 80 years, which is unlikely for the majority of urban trees (Roman et al. 2016). Our results summarized the dead biomass for each land use class, which was accumulated at 10-year intervals.

**Planting:** we applied a separate calculation of a potential tree planting initiative of 100,000 trees with a growth period of 70 years. Tree growth and alive biomass were calculated using a mixture of dominant tree species (Class mix, Table 1). We indicated the tree population half-life in our results— the years until 50 % of the tree population is dead— for an annual static mortality rate of 3.5 % (20 years), 2 % (35 years) and 1 % (69 years), and discussed how far an extensive replanting could compensate for alive biomass loss of our 60 year-LCA.

**Miscellaneous:** due to limitations of this study our calculations did not account for emissions of maintenance, tree production, planting, irrigation, processing of dead biomass, tree removal and residual biomass from regular pruning. We added the consequences of these limitations to our discussion.

### *Results and Discussion—LCA of Growth, Mortality and Planting*

Our LCA of 60 years on urban forest carbon offset clearly indicates the dominant impact of an increasing annual tree mortality between our land use classes of parks (low, 1 %), mixed areas (moderate, 2 %) and streets (high, 3.5 %) (Fig. 2). Street trees show a continuous decline in absolute alive biomass. After 20 years the amount of accumulated dead biomass is already higher than alive biomass. Trees of mixed areas reveal a slight increase in alive biomass, which levels off after 30 years and then continuously declines. Accumulated dead biomass of mixed areas exceeds alive biomass after 40 years. Park trees show a dominant



## Progress in High Resolution Remote Sensing to Advance Life Cycle Assessments of Urban Forest Carbon Offset

effect of growth with an increase in alive biomass for 50 years and with a marginal decrease for the last 10 years of our assumed 60-year LCA.

The assumed low mortality for park trees leads to consistently larger quantities of alive than accumulated dead biomass. The average age of our total tree population was approximately 52 years. There were no extreme differences in the age structure between our land use classes. However, older trees are more likely to be found in parks, which have an average age of 56 years. Street trees have the youngest average age of 49 years and trees of mixed areas; 52 years. Our land use classes have a similar age standard deviation (streets: 15 years; mixed: 17 years; parks: 15 years). In this context, the average age structure for parks (high), mixed areas (moderate) and streets (low) corresponds to our assumed mortality differences between land use classes: low for parks, moderate for mixed areas and high for streets. Our land use classes exceed the average age of 80 years after 30 years of our LCA.

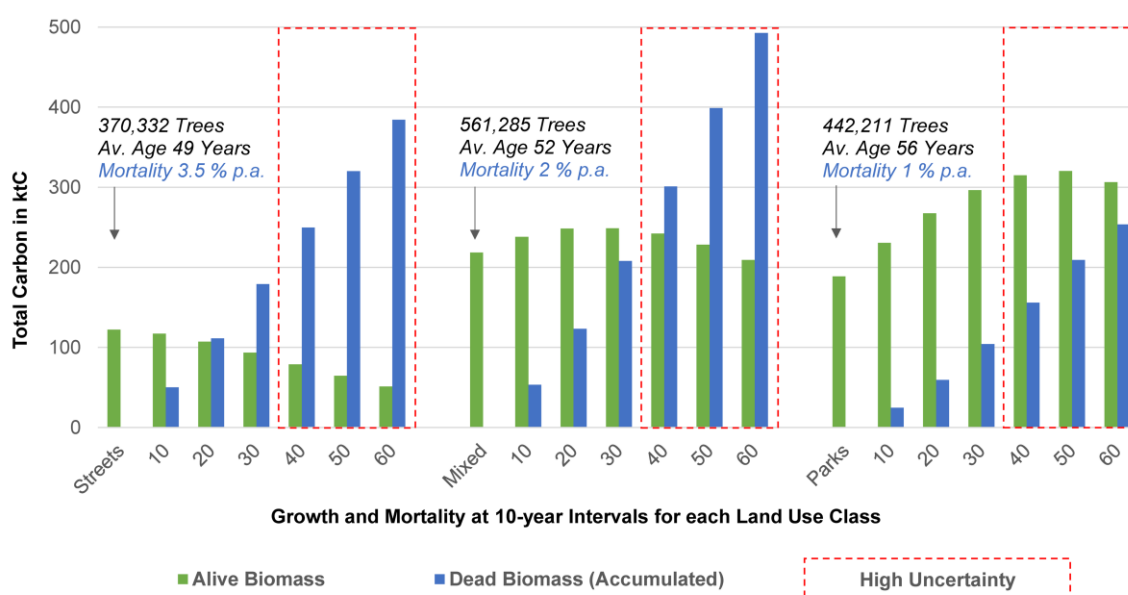


Figure IV - 2: LCA of 60 years on urban forest carbon offset in Berlin. The carbon weight for alive and accumulated dead biomass is presented in kilotons (ktC) for our land use classes (streets, mixed, parks). The absolute tree population, the assumed mortality rate of each land use class and its average age is indicated for the LCA start in 2008. A red border marks a tree population of an unlikely very high age.

The carbon estimates per unit of land cover are consolidated for all land use classes at 10-year intervals in Table 2. We found that the carbon density of alive biomass in Berlin

Progress in High Resolution Remote Sensing to Advance  
Life Cycle Assessments of Urban Forest Carbon Offset

increases by almost 25 % for the first 30 years of our LCA (2008–2038); thereafter, it continuously decreases. Our study concludes that the carbon density of alive biomass is always higher than the initial year of 2008 (7.3 tC/ha) if the average age of the total tree population is allowed to exceed 80 years. The initial sequestration rate decreases rapidly for the first 30 years. After this time period, the growth of the remaining tree population cannot compensate for its previous losses and the total alive biomass declines. The carbon density of accumulated dead biomass exceeds alive biomass density at 40 years of our LCA. At the end of our LCA (2068), the carbon density of dead biomass (16.2 tC/ha) is more than 100 % higher than alive biomass (8.0 tC/ha).

*Table IV - 2: Temporal development of urban forest carbon estimates in Berlin*

<b>Carbon Estimates</b>	<b>LCA</b>						
Land Cover of 700 km <sup>2</sup>	Start	10	20	30	40	50	60
<hr/>							
<b>Alive Biomass</b>							
Density Average [tC/ha]	7.3	8.3	8.9	9.1	9.0	8.7	8.0
<hr/>							
<b>Dead Biomass (Accumulated)</b>							
Density Average [tC/ha]		1.8	4.2	7.0	10.0	13.3	16.2

Results of our potential tree planting of 100,000 trees of mixed dominant tree species (Table 1) show an increase of alive biomass with a total of approximately 68 ktC for 70 years of growth (Fig. 3). The planted tree population decreases to 50 % (population half-life), resulting from a high annual mortality (3.5 %) with a alive biomass of approximately 3.5 ktC after 20 years of growth. A moderate mortality (2 %) leads to an alive biomass of approximately 10 ktC after 35 years of growth and approximately 35 ktC after 69 years of growth for a low mortality (1 %). Street trees continuously lose alive biomass (Fig. 2): 15.2 ktC in the first 20 years of our LCA. Our assumed extensive tree planting of 100,000 trees (+ ca. 3.5 ktC at population half-life of 20 years) needs to be more than four times larger to compensate for this short-term loss of alive biomass. Trees of mixed areas initially lose less than 1 ktC of alive biomass for the first 40 years of our LCA (Fig. 2). Therefore, planting 100,000 trees (+ 10 ktC at population half-life of 35 years) is likely to compensate for the loss of alive biomass of mixed areas. Park trees initially lose 14.1 ktC of alive biomass at the

## Progress in High Resolution Remote Sensing to Advance Life Cycle Assessments of Urban Forest Carbon Offset

very end of our assumed 60-year LCA (Fig. 2). A tree planting initiative of 100,000 trees (+ 35 ktC at population half-life of 69 years) is likely to extend the amount of alive biomass for long-term purposes.

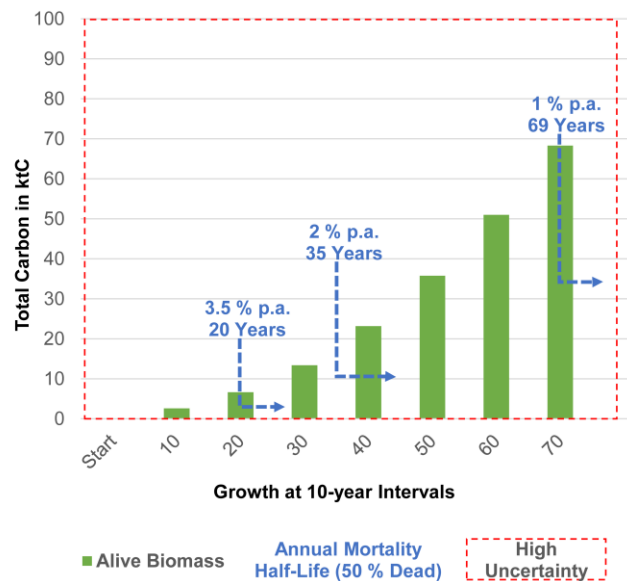


Figure IV - 3: Potential tree planting initiative of 100,000 trees. Calculations of alive biomass were based on a mixture of dominant tree species in Berlin (Class mix, Table 1) with a 70-year growth period. The carbon weight is presented in kilotons (ktC). Tree population half-life is shown for high, moderate and low annual mortality. High uncertainty (red border) is generally assumed due to lack of knowledge concerning factors such as young tree mortality and other natural and anthropogenic disturbances.

In this case study, we could make use of recent progress in high resolution remote sensing to increase consistency of an LCA inventory on urban forest carbon offset. We did this by providing area-wide details of remotely sensed individual tree species. To the best of our knowledge, this is the first urban study combining individual tree metrics with spatially explicit species information for a LCA of urban forest carbon offset. Our results point out the challenges of assumed tree growth and mortality of street trees, mixed areas and parks, which greatly affect the future role of urban forest carbon offset. Furthermore, our findings call attention to the potential of tree planting to compensate for losses of alive biomass.

Our results show that urban forest carbon offset is dominated by our assumed tree mortality. The significant impact of an increasing mortality rate on urban forest carbon offset was also

confirmed by Strohbach et al. (2012). Only park trees have a positive balance of alive biomass minus accumulated dead biomass for a 60-year LCA. In particular, the high loss of street and mixed trees reduced the overall growth potential of the remaining tree population. The increasing average age structure is also likely to augment the risk of tree loss. Therefore, our results certainly underline the necessity of adequate forest management applications across the city. It remains unclear, in how far the high amount of dead biomass contributes to net carbon offset, which grew twice as much as alive biomass after 60 years (Table 2). Other LCA approaches utilized advanced processing of dead biomass, such as composting or wood chip production for energy consumption (Strohbach et al. 2012; McPherson and Kendall 2014). Consequently, the decomposition of dead biomass means a release of carbon emissions, and urban forests of our case study would be a net carbon source. However, our case study can become a net carbon sink if dead biomass is used for energetic purposes and substitutes fossil energy.

Our results show the possibilities of extensive tree planting. Replanting 100,000 trees has the capability to compensate for losses in alive biomass. However, this potential requires rapid replanting, low mortality rates (< 2% p.a.) as well as extended tree longevity exceeding 80 years. The lack of relevant data on future tree replanting rates, mortality, growth and longevity make it difficult to provide long-term prognoses for our case study. Increasing disturbances in growth, mortality and replanting rates would affect the spatial expanse and quantity of alive biomass. Today's financial constraints of cities might limit investments into green infrastructure, such as an extensive tree replanting program (Kabisch 2015). In particular, the lack of young tree mortality data causes high uncertainty concerning the true quantitative requirements to compensate for tree loss (Roman et al. 2014). As such, further discussion is needed on urban forest management plans and political decision-making concerning urban dwellers' desires and climate change adaptation in particular (Ordóñez Barona 2015). In this context, our city-wide average of carbon density in Berlin most likely falls in the lower range of urban forest studies obtained from globally selected cities of temperate climate zones (11–38 tC/ha) (Strohbach and Haase 2012). The temporal development of our carbon density shows that estimates will remain in the lower range if management plans do not consider extensive replanting and densification.

## Progress in High Resolution Remote Sensing to Advance Life Cycle Assessments of Urban Forest Carbon Offset

It should be made clear that, in reality, our assumed values for tree growth, mortality and planting would be an exception rather than the rule. These values can vary widely and be extremely site- and species-specific (Roman 2014; Moser et al. 2017). Climate change especially could increase stresses on urban forests and change their value, which would then require adapted management strategies (Yang 2009; Ordóñez Barona 2015). Our assumed constant mortality rates did not describe the complexity of natural and anthropogenic disturbances adequately (Roman et al. 2016). However, the lack of mortality relevant statistics and in-situ data from Berlin did not allow us to further calibrate or validate our case study. Moreover, the high uncertainty of our case study results refers to the high average age of the tree population, which had already reached an average of 80 years after 30 years of our LCA. Therefore, our results should be taken carefully and one should consider the possibility of an extensive underestimation of dead biomass for the period from 2038 till 2068. In this regard, only few studies exist on urban tree growth and longevity and require further improvements in quantitative assessments (Leibowitz 2012). Due to limitations we did not consider pruning trees, which would increase the amount of dead biomass for our estimates. Pruning of 10 % above-ground biomass at 10-year intervals could be considered a common practice according to recent studies (Strohbach et al. 2012; McPherson and Kendall 2014). Our simplified case study also excluded emissions related to tree planting, such as maintenance, tree production, transportation, planting, irrigation, processing of dead biomass and tree removal. These might be considered less relevant for the net carbon offset of our case study because recent studies on LCA of urban tree planting showed a relative small share on emissions of 1–5 % of the total tree biomass (alive plus dead) (Strohbach et al. 2012; McPherson and Kendall 2014). However, an accounting for decomposition of dead biomass, dead roots and irrigation can significantly increase the share of carbon emissions.

In general, our LCA inventory data of remotely sensed individual tree species contributed consistent details across large areas, and therefore avoided current disadvantages of general field data-based methods or requirements of widely used approaches of the i-Tree ECO model. Zhao and Sander (2015) confirmed the advantages of LiDAR data and individual tree detection to retrieve consistent and area-wide LCA inventory data, which our case study could increase in precision by providing additional tree species information. However, Zhao's and our LiDAR-based remote sensing approach did not include understory and very

## Progress in High Resolution Remote Sensing to Advance Life Cycle Assessments of Urban Forest Carbon Offset

small trees (< 3 m) (Tigges et al. 2017), which might grow to a considerable quantity in the long term. Further differentiation for our tree species (Table 1) is also a suggestion for improvement because our mixed class covered a considerable fraction (> 25 %) of the total tree population. This can be of utmost importance when considering the role of invasive species. For instance, Horn et al. (2015) pointed out the role of invasive species on urban forest carbon offset, which was approximately 5 % for a subtropical urban forest. Even more relevant were temporal changes of the urban species structure. Nowak et al. (2016) showed slight changes in tree canopy size from 1999 to 2009, in Syracuse, New York; however, the number of trees increased by more than 20 % with invasive species as the main cause. This indicates the importance of the individual tree level and changes in forest composition. Therefore, high resolution remote sensing has great potential to monitor necessary environmental details and should considerably improve tree species classification and individual tree detection in urban settings.

We can conclude that our simplified LCA of urban forest carbon offset offers new insights into how high resolution remote sensing can be used as a consistent baseline of individual tree species. Future progress in remote sensing will show if we can extend the classification of tree species and the detection of individual trees with increasing precision. This might change the way we assess major knowledge gaps regarding the role of invasive tree species and private properties in particular. Time series of remotely sensed data can offer the potential to validate and calibrate predictive models due to changes in tree size, species structure, age structure and replanting. This is particularly true for the current lack of urban tree mortality data, where remote sensing can help to detect potential risks and stresses and reveal irregular or chaotic spatiotemporal patterns of disturbances. All of this can help cities and other stakeholders to consider the role of urban forest carbon offset more adequately; for instance, to complement current carbon balances.

### **2.3 Improvements—Remotely Sensed Changes over Time**

Remotely sensed high resolution monitoring would certainly contribute to improving an LCA of urban forest carbon offset by providing additional data for calibration and validation. Researchers and professional practitioners have requested long-term ecological studies to extend the knowledge of urban forest dynamics. However, few studies on urban tree growth

## Progress in High Resolution Remote Sensing to Advance Life Cycle Assessments of Urban Forest Carbon Offset

and related changes exist, and they all rely on regional networks or research related projects, such as the International Tree Failure Database (ITFD), for instance. Experts are aware of remote sensing's opportunities for developing a more consistent urban forest database, but it is still far from being realized as a common international standard (Leibowitz 2012).

### *Tree Growth and Pruning*

Diameter at breast height (DBH) has commonly been used for tree growth analysis (Peper et al. 2001; Stoffberg et al. 2008). Nonlinear and linear regression models have successfully shown accurate estimates of DBH using crown width or a combination with tree height (Kalliovirta and Tokola 2005; Popescu 2007). Performing ITD with high resolution remote sensed data is appropriate for predicting crown width and tree height, but the variability of the resulting estimates can be high. For example, additional age to DBH-growth functions allow for estimating the urban forest age structure, but available studies rarely address the various urban tree species, tree dimensions and site conditions. Additionally, increasing climate change effects can cause water and heat stress, substantially reducing tree growth (Semenzato et al. 2011; McPherson and Peper 2012; Moser et al. 2015; Moser et al. 2017). The variability of remotely sensed tree dimensions, as mentioned earlier in this review, does not allow for deriving the specific age of a single tree. We rather suggest providing a certain range of the tree age, which can be used as a baseline for additional processing or modeling.

Recent progress in high resolution remote sensing has placed greater focus on urban forest dynamics. Detailed characterizations and monitoring highly benefit from increasing temporal resolution in particular. This allows for potential change detection of urban tree growth and pruning and for monitoring abrupt changes like replanting or tree loss. However, precise estimates would come at a high price, as change detection errors are likely to significantly increase as a function of heterogeneity, quality and resolution of imagery, or misregistration errors of remotely sensed time series (Wang and Ellis 2005). This makes it difficult to reliably estimate changes over time for an individual tree. Regarding precise estimates of urban forests, little is known on monitoring the changes of individual trees using very high resolution remote sensing. Ardila et al. (2012) successfully used a region-based active contours approach for a time series of multispectral data to detect abrupt and gradual

## Progress in High Resolution Remote Sensing to Advance Life Cycle Assessments of Urban Forest Carbon Offset

changes of individual trees. Due to the variability of remotely sensed tree dimensions, we suggest stretching the intervals for monitoring urban forests in order to retrieve notable physical changes of tree growth and derived parameters. For this very reason, further research is necessary to confirm the precision of gradual changes like tree growth (height and crown) and pruning using high temporal resolution remote sensing. For example, remotely sensed tree dimensions would allow for improved monitoring of residual biomass, large quantities of which can be obtained from urban forests for energy purposes (Velázquez-Martí et al. 2013). Additionally, Sajdak et al. (2014) applied predictive modeling approaches and showed correlations between residual biomass and the parameters of crown diameter or stem DBH, which could be derived from remotely sensed individual trees.

### *Mortality and Replanting*

Temporal increases and decreases of the urban forest canopy is crucial information for a LCA of urban forest carbon offset. Until now, few studies have addressed urban forest dynamics across large areas, and most of them use moderate resolution (30 m pixel size) and adapt ground-based carbon measures to vegetation indices using spectral bands of Landsat satellite data (Myeong et al. 2006; Yao et al. 2015). Moderate resolution of Landsat satellite imagery is likely to underestimate urban forest cover. However, Landsat satellite time series was sufficient for indicating a long-term trend of urban forest increase (growth + replanting) and decrease (mortality), which was likely to be balanced for urban forests in Syracuse, US from 1985–1999 (Myeong et al. 2006), or to have highly increased for urban forests and shrubs in Xi'an, China from 2004–2010 (Yao et al. 2015). The importance of temporal changes has also made remote sensing a source for validating reported facts. Nowak and Greenfield (2012) chose higher resolution time series to better address the trend of urban tree cover across the US. They manually digitized high resolution paired aerial photographs and Google Earth imagery (selection of 2001–2009 for 20 US cities and 1,000 randomly selected urbanized areas). The results of this sampling approach indicated a decline of forest cover for most US cities at a rate of approximately 7,900 ha/year, or 4 million trees per year. The tree canopy cover report of Boston, US showed significant overestimation due to



misclassification of grass and shrubs as tree canopy compared to an assessment performed with high resolution QuickBird satellite and LiDAR data (Raciti et al. 2014).

Due to the increasing availability of high resolution three-dimensional remote sensing data, the individual tree level is the most promising level for future applications of urban forest dynamics (Zhen et al. 2016). Multiple reasons of mortality and replanting have remained unresolved as of yet, but a time series of individual trees across large areas would provide spatially explicit information, which is rarely available. This would at least contribute to better understanding urban forest dynamics, such as hot spots of mortality, species and site-specific differences, for example. Multitemporal LiDAR is of growing interest for better understanding and monitoring spatiotemporal dynamics of forest carbon (Goetz and Dubayah 2011; Hudak et al. 2012; Liang et al. 2012; Srinivasan et al. 2014). To the authors' knowledge, multitemporal LiDAR has not yet been applied to changes of urban forest carbon. However, due to a lack of resources a precise timing of acquiring a single image at the growing season (leaf development) might be considered advantageous for detecting dead trees (no leaf development). Additionally, tree health issues, which, for instance, correlate to multispectral information of remote sensing data, should be used to indicate areas of potential risk (Xiao and McPherson 2005). This can advance an LCA to better consider the effects of temporal urban forests' stresses.

#### **2.4 At Different Scales—From Local to Global**

Urban forest carbon estimates at different scales exemplify the importance of spatially explicit information. The local carbon estimates (individual tree level) of Boston, US were highly underestimated by available national datasets of the same area by 30 % (NBCD, National Biomass and Carbon Dataset, 30 m pixel size) to more than 90 % (United States Department of Agriculture Forest Service Forest Inventory and Analysis, USDA FS-FIA, 250 m pixel size) (Raciti et al. 2014). Less uncertainty for increasing resolution has been confirmed for urban forest carbon estimates at the neighborhood level by up to 11 % (LiDAR point density 1.2 to 5.8 points/m<sup>2</sup>) (Chen et al. 2017). Singh et al. (2015) addressed the challenges of decreasing resolution from a maximum of ca. 14 to 0.15 points/m<sup>2</sup> for regional carbon estimates of urban forests in Charlotte, North Carolina, US because processing very

## Progress in High Resolution Remote Sensing to Advance Life Cycle Assessments of Urban Forest Carbon Offset

high point density LiDAR data is resource intensive and is likely to hold redundant information. Just 40 % of the available LiDAR points were sufficient without compromising the accuracy of biomass estimates. This was also confirmed by Garcia et al. (2017) for national forest carbon estimates, who found that a reduction of LiDAR point density could be sufficient (10 to 5 points/m<sup>2</sup>) except for very low point density. It remains unclear for urban forest carbon estimates if metrics derived from processed discrete returns of a crown height model show a higher dependence on point density than metrics derived from the original echo-based LiDAR data as they did for forests in the study by Garcia et al. (2017).

Regarding a national scale of urban forest carbon offset, Nowak and Crane (2002) set a standardized urban forest carbon value from selected cities and upscaled it across the US using national tree canopy data retrieved from 1991 remote sensing imagery of advanced very high resolution radiometer (AVHRR). Due to its coarse spatial resolution of 1 km pixel size, higher resolution Landsat TM satellite imagery of 28.5 m pixel size was used for defined regions to determine their proportion of tree canopy within a coarse AVHRR pixel, which correlates to the magnitude of the spectral response. Such an unmixing approach could then be used to determine the tree canopy's density within other AVHRR pixels (Zhu 1994). Nowak et al. (2013) updated this approach in 2002 due to an increased availability of better tree cover estimates derived from high resolution remote sensing imagery, which led to a correction of the national average of urban forest carbon density (2002: 92.5 tC/ha per unit of tree cover; corrected 2013: 76.9 tC/ha per unit of tree cover). Pasher et al. (2014) assessed Canada's urban forests at the national scale, with carbon storage and sequestration data adapted from US urban forests by Nowak et al. (2013): They selected administrative boundaries (reconciliation units) of dominant urban land use. These selected areas were divided by a 1 km grid. A random selection of grid cells was used for each reconciliation unit to classify the urban tree canopy using a point sampling approach. Samples were manually classified using very high resolution remote sensing orthophotos (10–25 cm pixel size) and upscaled for the total urbanized area of each associated reconciliation unit, which resulted in a final carbon estimate. Due to the extensive requirements of resources and manual workload, Pasher et al. (2014) suggested (semi) automated processing of remote sensing imagery to advance their approach for assessing the urban tree canopy or to provide general rapid re-assessments. They referred to medium resolution satellite imagery (20–30

## Progress in High Resolution Remote Sensing to Advance Life Cycle Assessments of Urban Forest Carbon Offset

m pixel size), which is widely available at the national scale and can improve the upscaling process of regional estimates.

The local results of Zhao and Sander (2015) made a promising step towards extending spatially explicit information on carbon storage and sequestration at the individual tree level using high resolution remote sensing, which should be further extended. Both Nowak et al. (2013) and Pasher et al. (2014) were able to update national urban forest carbon storage and sequestration estimates, especially concerning higher resolution remote sensing data for a precise urban tree canopy. Their applied methodologies of estimated urban forest carbon removals of Canada and the US are consistent with IPCC (2006) standards and can therefore be used for annual inventory reporting to the United Nations Framework Convention for Climate Change (UNFCCC). As such, this could be a first step towards a consistent global approach for urban forest carbon offset and related dynamics. Unfortunately, the individual tree level is too resource intensive to be applied globally as of yet, though a global urban tree density map would highly advance carbon estimates for an LCA equivalent to a recent available global tree density map of 1 km<sup>2</sup> resolution by Crowther et al. (2015). In this context, continuous evaluation of recent satellite missions of extensive area coverage could further improve global urban forest estimates, such as RapidEye (6.5 m pixel size, 5 spectral bands, daily revisit), TerraSAR X Tandem (e.g. global digital surface model, 12 m pixel spacing) or Sentinel 2 (down to 10 m pixel size, 13 spectral bands) (RapidEye AG 2012; DLR 2017; ESA 2017).

### **3 Conclusion and Outlook**

Recent progress in high resolution remote sensing and methods is adequate for delivering more precise details on the urban tree canopy, individual tree metrics, species, and age structures compared to conventional land use/cover class approaches. These area-wide consistent details can update life cycle inventories for more precise future prognoses.

Additional improvements in classification accuracy can be achieved by a higher number of features derived from remote sensing data of increasing resolution, but first studies on this

## Progress in High Resolution Remote Sensing to Advance Life Cycle Assessments of Urban Forest Carbon Offset

subject indicated that a smart selection of features already provides sufficient data that avoids redundancies and enables more efficient data processing. Automated and efficient processing of very high resolution data should be employed if possible due to the increasing workload, variability of data and user interaction, which can cause unresolved uncertainties. More consistent reporting of uncertainties and a better understanding of today's locally tailored approaches would allow for more generic and transferable approaches. However, this will not neglect today's advantages of high resolution remote sensing, which already extend the possibilities of traditional field-based retrieval of heterogeneous urban forest structures across large and private areas and should be applied more frequently.

In the matter of temporal changes and reliable estimates, more attention is required to detect the changes of gradual growth, pruning and abrupt changes to the planting and mortality of individual trees. Therefore, precise long-term ecological monitoring of urban forest dynamics should be intensified, especially due to increasing climate change effects. The results would be beneficial for calibrating and validating recent studies of urban forest carbon offset, which have so far focused on the status quo and net sequestration for the following year but have scarcely addressed a longer timeframe. Furthermore, precise change detection is highly relevant for the supply and demand of urban forest carbon offset.

A precise global estimate of urban forest carbon offset is still missing. However, upscaling approaches have improved national estimates in the US and Canada using higher resolution remote sensing data, which should be continued to reach an initial global coverage.

The future role of urban forest carbon offset can be made more relevant if more standardized assessments are made available for science and professional practitioners, and the ever increasing availability of high resolution remote sensing data and the progress in data processing allows for exactly that.

### **List of Abbreviations**

AVHRR, advanced very high resolution radiometer; C, carbon; CHM, canopy height models; CO<sub>2</sub>, carbon dioxide; DBH, diameter at breast height; EPA, Environmental Protection Agency; FIA, Forest Inventory and Analysis; ha, hectare; IPCC,

## Progress in High Resolution Remote Sensing to Advance Life Cycle Assessments of Urban Forest Carbon Offset

Intergovernmental Panel on Climate Change; ISO, International Organization for Standardization; ITD, individual tree detection; ITFD, International Tree Failure Database; LCA, life cycle assessment; LiDAR, Light Detection And Ranging; NBCD, National Biomass and Carbon Dataset; NDVI, normalized difference vegetation index; RMSE, root means square error; t, ton; TM, Thematic Mapper; UAV, unmanned aerial vehicles; USDA, United States Department of Agriculture.

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### **Compliance with Ethical Standards**

### **Competing Interests**

The authors declare that they have no competing interests.

## Synthesis

**V: Synthesis**

## 1 Findings, Plausibility and Transferability

Rapid urbanization, a heterogeneous and fragmented urban environment, and natural and anthropogenic disturbances make it essential to monitor changes in order to better understand them (Kraas 2007; Kuttler 2011; Pickett et al. 2011). Recent developments in high resolution remote sensing are likely to contribute essential details for urban ecosystem service analyses for future cities and their environment (Kadhim et al. 2016). Hence, this work is valuable for showing recent options in high resolution remote sensing for more precisely addressing urban forest dynamics by classifying tree species from seasonal differences. Furthermore, those tree species results could be combined with remotely sensed individual tree dimensions, which present spatially explicit information on related urban ecosystem services. This information would be best used as a baseline for more holistic approaches, such as LCAs of urban forest carbon offset. Additionally, high resolution remote sensing showed promising options for reducing the uncertainty of such advanced holistic approaches in order to improve future prognoses.

As stated previously, urban forests are the main object of this work. Unveiling the potential benefits of high resolution remote sensing required in-depth scientific analysis and was answered concerning our research questions (1–3, Chapter I). Although our findings are novel, the plausibility of our research results are discussed in the following. We also point out further requirements for methodological improvements and transferability.

### *1) Can we advance the classification of urban forest details by considering seasonal changes using recent technological options of RapidEye satellite imagery?*

According to our findings, the answer to this question would be “yes.” Frequent tree genera can be derived from urban forests using past events reflecting a RapidEye time-series of seasonal changes, which correlated well with the phenology of different tree genera. This is a substantial finding for spatially explicit environmental information across large cities. Very little temporal and spectral information were able to notably increase classification accuracy, which can be used to provide more efficient data processing. The red-edge band of RapidEye



## Synthesis

imagery supported classification of tree genera, which outlined the benefits of additional spectral information that is sensitive to vegetation.

Time-series of RapidEye satellite imagery seems to be a promising avenue for classifying tree species. To the authors' knowledge, few studies have examined time-series of multispectral data for classifying tree species, but the authors underlined the findings of the studies that remotely sensed seasonal changes supporting tree species classification (Blackburn and Milton 1995; Mickelson et al. 1998; Key et al. 2001; Hill et al. 2010). Aside from these, this is the first area-wide urban study of tree species' classification (Tigges et al. 2013). In this context, Li et al. (2015a) also confirmed a substantial increase in overall accuracy for selected urban tree species classification in Beijing, China using seasonal differences of WorldView-2 and WorldView-3 satellite imagery. The red-edge band was also highly relevant.

Machine learning has recently gained attention due to the increasing amount of data to be handled. It performed well for this case study, especially considering the heterogeneous and fragmented urban forest structure, and it is recommended for use in future urban studies. The ranking and importance of features should be used in order for more efficient processing using few selected features, and to better understand why selected tree species can be classified. The published results of previous studies showed multitemporal data of high seasonal differences to be of utmost importance for classifying tree species, which was also notably affected by red-edge spectral information, which underlines the plausibility of this RapidEye case study. It is important to mention that the ranking of features could be affected by the randomized selection process and any redundancy problems in the features, and variations within the SVM training data could cause variations in the accuracy ranking.

This study's results work could be indirectly supported by other studies, but further steps would be required to draw a more generic approach for an intra-annual time-series of remotely sensed data to classify tree species. Future studies should cover most tree species of the study site's tree population to better address class variability. Additional comparisons with in-situ data under varying site conditions could then allow a first general hypothesis. A more systematic approach is suggested, which acquires monthly or weekly remote sensing imagery, because most datasets of available studies were limited to very few stages of the

## Synthesis

phenological cycle of vegetation. A higher temporal resolution could also reveal more precise spatially explicit differences, as a 2006 field survey of vegetation phenology in Berlin found significant phenological differences in the same trees species related to microclimatic characteristics of the urban heat island effect (Chmielewsky and Henniges 2006; Mimet et al. 2009). This can help to better address class variability, and therefore, which dates are best for classifying most or a specific tree species. If future research generally confirms that specific seasonal differences allow the differentiation of (selected) tree species, regular flight campaigns could adapt their schedule to guarantee a continuous combination of seasonal differences. This would increase urban environmental information without additional costs. In this context, RapidEye's advantages of consistent large area coverage should be used to extend the validation of results beyond the boarder of the intended study site in order to better point out spatially explicit transferability, such as across elevation differences or different regional climate zones. This would be beneficial for a more robust approach.

2) *To what extent do details on additional remotely sensed tree species provide more precise estimates of urban forest carbon storage?*

To the authors' knowledge, this is the first study to apply city-wide, high resolution, remotely sensed data combining individual tree detection and tree species information. Tree species information on the individual tree level enhances the analysis of carbon estimates within cities and can better point out small-scale differences. This helped to prevent notable percentages of underestimation or overestimation on the neighborhood scale in particular. City-wide carbon estimates were quite sufficient using an average estimate of dominant tree species information without its spatially explicit location. This already prevented underestimation compared to a national forestry estimate. Therefore, the results of this case study indicate that improved consistency and comparisons of urban forest carbon estimates can be achieved by further developing combined approaches of individual tree detection and tree species classification, especially if the study site lacks up-to-date information or any information at all.

## Synthesis

This study used individual tree detection and tree species information to better address spatially explicit differences, which supports a more generic approach. Other than that, urban forest carbon storage cannot simply be extrapolated to other regions, because forest structures differ significantly between cities and countries (Davies et al. 2011). The results of this study showed notable variation in urban forest carbon estimates, which can suggest that local and regional tree species populations are not well represented in national scale allometric equations (Aguaron and McPherson 2012). There is currently a lack of species-specific equations adapted to the urban environment, regional differences and tree age classes, making it rare and expensive to produce such equations (McHale et al. 2009). This can cause substantial uncertainty in carbon estimates if a tree population is dominated by a single tree species (very large fraction) and would need to be addressed more adequately. This is particularly true for the mixed class (fraction of  $> 25\%$ ) of this study, to which a specific tree species could not be assigned. Therefore, comparing spatially explicit carbon estimates on the individual tree species level would actually require more locally or regionally adapted allometric biomass equations. Consequently, the results of this study are more likely to be suggested for the neighborhood scale and above.

The underlying tree species classification improved the retrieval of urban forest carbon estimate details across large cities. However, unclassified species covered a remaining uncertainty, which would need to be more adequately addressed. This study's individual tree detection approach referred to a local maxima filter algorithm that is integrated into FUSION software (McGaughey 2013). In this study an underestimation of 36% was corrected for the diameter at breast height for each individual tree. Similar underestimation of LiDAR-derived tree measures had been stated by Edson and Wing (2011) within a conifer forest stand using FUSION. This could suggest an improved individual tree detection approach. However, there is no consistent comparison of different methods and data for urban forests, as few exist for forest stands, as stated in a study by Kaartinen et al. (2012), for instance. However, algorithms based on local maxima findings, such as FUSION, have produced usable results so far. In the matter of derived count, height and species information, the count of trees contributed the most to biomass calculations. The results of this study delivered a good level of accuracy for the count of dominant trees concerning a heterogeneous urban forest structure. This underlines that the selected individual tree detection algorithm was

## Synthesis

appropriate for this urban study. Tree density was an important and dominant indicator of high carbon estimates. Furthermore, this study's above-ground carbon storage approach excluded very young trees of small size, understory, bushes and shrubs. This was due to a height threshold, which was applied to retrieve the urban tree canopy. It prevented bushes and shrubs from being misclassified as small trees. Therefore, above-ground carbon estimates of vegetation could be expected to be higher. Additionally, tree roots could significantly influence carbon storage estimates, but there is currently not enough information to address the high degree of uncertainty (Johnson and Gerhold 2003).

The effects of tree species composition should not be ignored, as functional diversity is highly related to the richness of the prevalent species at the study site, which is likely to affect the magnitude and direction of future disturbances and environmental changes. The number of classified tree species should therefore be extended to provide more precise information regarding the study site's tree population. This will help to refine the high range of urban forest carbon estimates if differences are addressed at the individual tree level. Unmixing (separating) approaches of multitemporal RapidEye (6.5 m pixel size) or very high resolution WorldView series satellite imagery (< 1.5 m pixel size, down to 0.31 m using pan-sharpening) could provide options for improved classification of area-wide tree species. However, a higher spatial resolution can cause higher spectral variability, which would need to be investigated regarding its effects on tree species classification. High resolution remote sensing combining individual tree detection and tree species information can be recommended as a cost-efficient method for acquiring more sufficient data on local differences. It is independent on land use classes and considers in-class variability. It is scale-invariant due to the individual tree level. However, it is resource intensive to develop a high number of species-specific allometric biomass equations, which are adapted to urban conditions. In this context, experts and practitioners should agree to a more common standard for selecting allometric equations from the current available pool rather than selecting to their best knowledge independently. The validation of results should more adequately address the heterogeneity of urban forest structure. All of this can improve the consistency of above-ground carbon storage, which is necessary to compare estimates between and within cities. It is recommended to further develop individual tree detection algorithms adapted to a heterogeneous urban forest structure rather than choosing locally

## Synthesis

tailored area-based regression models. Improvements in the development of allometric biomass equations can then be simply updated if individual tree metrics are available. In this context, individual tree detection could contribute to a more systematic and consistent approach for future assessments and can act as a baseline reference. Recent options of full waveform LiDAR warrants further possibilities for improved understory assessments and small tree detection.

### *3) How can recent progress in remote sensing advance life cycle assessments of urban forest carbon offset?*

It can be stated that recent progress in high resolution remote sensing and methods are adequate to deliver precise information on the urban tree canopy, individual tree metrics, species and age structures. This is important for LCA studies on urban forest carbon offset to better address the lack of area-wide and up-to-date information. An increasing spatial, spectral and temporal resolution allows for better addressing spatially explicit information of a heterogeneous forest structure and its dynamics across a city. Besides updating an LCA inventory using remotely sensed tree information, few studies have addressed LCAs of urban forest carbon offset so far. Therefore, remotely sensed data would be beneficial for more consistently calibrating and validating recent and future studies. Consequently, remote sensing and LCAs could be an effective tool for creating environmental awareness, monitoring targets of a recommend environmental aim or identifying the challenges of future growth.

Automated and efficient processing of very high resolution remote sensing data should be followed if possible due to the increasing workload, variability of data and requested user interaction, which can cause unresolved uncertainties. In this context, more generic and transferable approaches could benefit from more consistently reported uncertainties and from a better understanding of today's locally tailored approaches. Regarding temporal changes and reliable carbon estimates, more attention is required for detecting the changes in gradual growth, pruning and abrupt changes in the planting and mortality of individual trees. Therefore, more precise long-term ecological monitoring of urban forest dynamics should be intensified. Additionally, precise change detection is highly relevant for the supply

## Synthesis

and demand of urban forest carbon offset, for instance, if urban forest carbon offset markets were established, high precision would become necessary.

Today's limitations of high resolution remote sensing should not be neglected concerning a complex LCA of urban forest carbon offset. A complex LCA could skip aspects of tree maintenance and related emission because available studies have stated a small effect on the net carbon balance. However, emissions due to maintenance could increase and play a bigger role in other climate regions or due to future climate change effects, such as increasing irrigation requirements. Global warming and regional effects, as well as micro-climate conditions, will significantly affect tree growth and mortality, which is currently a major research gap (Roman et al. 2014; Moser et al. 2017). The limitations of a simplified statistical model could be overcome by using more complex dynamic modeling approaches. However, intended spatially explicit improvements in modeling still lack empirical in-situ data on individual trees, which would be helpful in more precisely revealing the mechanisms of climate change effects. Stem growth, for instance, is highly dynamic, species and site-specific, and related to water and carbon changes inside the stem (Steppe et al. 2016).

A precise global estimate of urban forest carbon offset is still missing as of yet. However, it would be relevant concerning the role of organization in the global carbon cycle, which lacks data regarding the distribution and types of vegetation in cities globally (Churkina 2016). Upscaling approaches have improved national estimates of the United States and Canada using higher resolution remote sensing data, which should be continued to reach an initial global coverage. A global remotely sensed height model—the TanDEM-X (DLR 2017), for instance—would certainly improve the calibrations for such a global approach concerning a consistent base year. The increasing availability of high resolution remote sensing could also close the gap of less frequently analyzed forests of different climate zones, such as subtropical urban forests and their temporal dynamics (Tucker Lima et al. 2013).

### **2 Main Conclusion**

This work provides an example of recent progress in high resolution remote sensing of cities using a multi-dimensional feature space of 3-dimensional data, temporal changes and additional spectral information. This allowed for a consistent area-wide assessment of transformation processes like seasonal changes, which can be used to retrieve more details like tree species and should be continued toward a more robust and potentially generic classification approach. State-of-the-art methodological approaches of machine learning and individual tree detection proved to be highly advantageous for analyzing urban ecosystem services within a heterogeneous urban environment. This increasing precision of environmental information has helped to reduce the uncertainty of estimates like urban forest carbon storage. It also indicated high potential for improved future prognosis and decision-making using a life cycle assessment. This work is not intended to overemphasize urban forest carbon storage besides the diversity of urban ecosystem services. Rather, it is about recent technological options for monitoring urban biodiversity and spatially explicit information of a heterogeneous forest structure. It can be used to retrieve a consistent baseline to better address aspects of resilience, which might refer to long-term requirements of a minimum value of urban forest stock, biodiversity and stress resistance. In this context, future research should emphasize spatially explicit tree growth and mortality, which is still a major gap in the knowledge concerning urban forests and forests in general (Roman et al. 2014; Ryan 2015; Moser et al. 2017). Methods should be improved to better monitor gradual and abrupt changes, especially where very high resolution remote sensing and automated processing is promising.

### **3 Outlook**

#### *High Resolution Remote Sensing for Improved Vegetation Phenology Data Across Cities*

Our findings of a RapidEye intra-annual time-series and individual tree detection can be used for a straightforward mapping of individual tree species information. Beyond this scope, it

## Synthesis

allows to extend additional research options and applications. For example, a gap could be narrowed concerning today's lack of area-wide, high spatial and temporal resolution data on vegetation phenology due to RapidEye's pixel size of 6.5 m, swath width of 77 km, continuous mapping of 6000 km<sup>2</sup> and a high revisit time (RapidEye AG 2012). This could help to better identify spatially explicit differences or shifts in phenology across large cities and beyond administrative boundaries due to increasing climate change effects. By contrast, most phenological information has usually been derived and interpolated from selected sites or contains a high degree of spatial phenological variability within coarser-scales of remotely sensed satellite imagery (Landsat, 30 m; MODIS, 500 m; AVHRR; 1 km) (Fisher and Mustard 2007). As such, RapidEye time-series could be an essential value for future climate research across multiple "urban laboratories." A systematic and continuous mapping of selected sites would be required. Area-wide time-series of recent satellites like Sentinel 2 (down to 10 m pixel size, 13 spectral bands) also need to be considered for improved urban area-wide assessments (ESA 2017).

Additional applications refer to area-wide, comparable and up-to-date results on a species level, which can be used as an indicator for pollen emissions and is of great interest to epidemiological studies (Ranta and Satri 2007). High resolution remote sensing studies of phenological phases would be beneficial for improving the prediction of temporal pollen distribution. Additionally, the knowledge of remotely sensed allergy relevant plants could then improve a risk assessment adapted to the regional or urban neighborhood level, which is scarcely available (Seyfang 2008).

### *Innovative Future – Drones and Big Data*

The recent progress of drones, also referred to as unmanned aerial vehicles (UAV), is very promising for urban applications in retrieving spatially explicit environmental information concerning automated acquisition and vegetation analysis (Valavanis et al. (eds.) 2009; Kaneko and Nohara 2014). Low-cost and low-altitude UAV acquisitions could be the first choice for consistent long-term ecological research with very high spatial and temporal resolution. This rapidly evolving field could extend today's limitations of city-wide coverage



## Synthesis

by combining multiple UAVs and swarm intelligence in the near future (Wei et al. 2013; Hocraffer and Nam 2017).

Open data sharing platforms have offered democratized online access to extend applications between users of different background knowledge in order to handle the increasing amount of digital data and to reduce necessary expertise for data processing ([www.lidar-online.com](http://www.lidar-online.com), [www.opentopography.org](http://www.opentopography.org)). The increasing possibility of deep learning to handle extremely large data has initiated new projects like “terrattern,” which offers simplified access for visual query-by-example from satellite imagery (<http://terrattern.com>) (Levin et al. 2016). Additional progress refers to spatially explicit real-time in-situ data, which is rare but highly important for climate change research. For example, Treewatch.net is a tree water and carbon monitoring network initiated by the University of Ghent, Belgium. Sensors attached to trees twitter on the internet in real time, which can be used for long-term ecological research, education or public awareness (<https://treewatch.net>) (Steppe et al. 2016).

### *Dissemination – A Critical Turning Point to Make Use of Knowledge*

A former heavy storm event, and urban residents start to remove healthy trees to reduce risks of property damage by trees (Conway and Yip 2016). This points out why better documentation of disservices and urban ecosystem services is required. It can prevent an impulsive behavior, which does not properly account for risks. This behavior also stands for a large discrepancy between what we know and what we do, and it requires more transdisciplinary approaches. It will not be enough to simply promote nature-based solutions of urban forests if we fail to guarantee continuous tending. It remains vague whether we have the necessary resources, knowledge and willingness to implement more nature based solutions to adapt to climate change in particular, and the answer cannot be solely limited to prevailing financial constraints (Kabisch 2015). Cities already have to consider limited natural resources, for instance, increasing water requirements for large tree planting initiatives in Los Angeles, US concerning its already limited water resources and arid climate exacerbated by future climate change effects and population growth. This raises the question of what we can actually demand from urban ecosystem services besides political intentions. Hence, initiatives of making cities more green should not be misunderstood, rather cities,

## Synthesis

experts and practitioners have to supply and demand scientifically sound information of more locally adapted conditions (Pincetl 2013). To that end, remote sensing of precise environmental information and life cycle assessments are suggested as complementary tools to make experts and non-professionals more sensitive to future changes and the value of urban nature. Future cities and their environment will demonstrate just how much use we have made of this increasing amount and ongoing process of digital environmental information.

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### **Eidesstattliche Erklärung**

Hiermit erkläre ich, die vorliegende Dissertation selbstständig und ohne Verwendung unerlaubter Hilfe angefertigt zu haben. Die aus fremden Quellen direkt oder indirekt übernommenen Inhalte sind als solche kenntlich gemacht. Die Dissertation wird erstmalig und nur an der Humboldt-Universität zu Berlin eingereicht. Weiterhin erkläre ich, nicht bereits einen Dokortitel im Fach Geographie zu besitzen. Die dem Verfahren zu Grunde liegende Promotionsordnung ist mir bekannt.

Jan Tigges

Berlin, den 09.05.2017







