Quantifying ecosystem services within a reforested urban landscape using remote sensing in eThekwini region of KwaZulu-Natal, South Africa

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Thesis submitted to the College of Agriculture, Engineering and Science, at the University of KwaZulu-Natal, in fulfilment of the academic requirements of the degree of Doctor of Philosophy in Environmental Science

Pietermaritzburg, South Africa

June 2022

Abstract

Unprecedented changes in land use-land cover patterns have led to the deterioration of environmental quality and crucial ecological services. Urbanisation for instance, coupled with continuous deforestation and forest degradation have increased atmospheric carbon emissions and climate change risks and impacts within urbanized areas. In this regard, the emergence of reforestation has been viewed as a potential long-term alternative for restoring ecosystem services within urban landscapes, including carbon sequestration and climate change mitigation. However, information on the contribution of reforestation initiatives to the global carbon balance has remained largely unavailable. In this regards, accurate and concise quantification of carbon stock and net primary productivity in reforested urban landscape is critical for providing informed understanding on the value of reforestation on the global carbon flux and climate change mitigation potential. Achieving this demand necessitates adoption of affordable and reliable datasets and techniques that can be used to reliably quantify these forest services. The utility of remotely sensed data, particularly freely and readily available multispectral sensors with improved spatial and spectral characteristics have shown unprecedented potential in carbon modelling. Although commercially owned high spatial resolution sensors are highly accurate, the associated high costs limits their adoption, especially in resource and financially constrained regions like sub-Saharan Africa. Therefore, newly launched freely available multispectral sensors remain the most feasible source of primary data for carbon quantification in Africa. The main aim of this study was therefore to quantify climate regulating ecosystem services (i.e., carbon stock and net primary productivity) in reforested urban landscape using freely and readily available remotely sensed dataset. To achieve this aim, five objectives were established. One; to review remote sensing application in quantifying ecosystem services in sub-Saharan Africa’s urban landscape. The results demonstrated that accurate and precise quantification of urban ecosystem services in sub-Saharan Africa using high spatial resolution sensors has been a major problem due to acquisition costs and unavailability. In this regard, freely and readily available multispectral sensors have gained popularity in quantifying the past, current and future urban ecosystem services in sub-Saharan Africa. Two; to estimate aboveground net primary productivity of reforested trees in urban landscape using integrated biophysical variables and remotely sensed data. The findings showed that the utility of spectral data derived from Sentinel-2 multispectral image integrated with biophysical parameters successfully estimated net primary productivity (NPP) in reforested urban landscape with reasonable accuracy (R^2: 0.92 and RMSE: 0.82 Mg ha^{-1}). The findings also showed a significant variation in NPP among the reforested tree species with

Acacia and *Dalbergia* obtaining the highest NPP (i.e., 7.61 Mg ha^{-1} and 7.58 Mg ha^{-1}), while *Syzygium* and *Artimisia* had the lowest (4.54 Mg ha^{-1} and 5.26 Mg ha^{-1}). This variation was attributed to the fact that different species have unique biophysical and biochemical characteristics which influence carbon uptake per unit of absorbed sunlight. Three; to explore the utility of Sentinel-2 spectral data in quantifying above-ground carbon stock in an urban reforested landscape. The study demonstrated that indices derived from Sentinel-2 MSI, especially those generated within the red-edge were reliable and effective in quantifying carbon stock of reforested trees with reasonable accuracy (R^2: 77.96 to 79.82% and RMSE:0.378 to 0.466 t.ha^{-1}). Furthermore, the adoption of the random forest model was instrumental for selecting optimal variables required for the best regression model. These results are crucial for understanding the contribution of reforestation initiative in the global carbon budget and climate change mitigation potential. Four; to quantify carbon stock variability across urban reforested tree species using texture measures derived from remotely sensed imagery. The findings of this work showed a significant variation in carbon stock between reforested tree species with *Acacia* (*robusta* and *caffra*) and *Brideliar micrantha* producing the highest mean carbon stock (4.81 to 6.96 t.ha^{-1}), while *Erythrina caffra* and *Syzygium cordatum* had the lowest (3.97 to 4.26 t.ha^{-1}). Moreover, the utility of texture measures derived from Sentinel-2 MIS proved effective and robust for estimating carbon stock variability in reforested urban landscape. These findings present a useful image processing technique (i.e., texture metrics) which can significantly boost quantification of reforestation carbon stock at species level using Sentinel-2 MSI. Five; to test the efficacy of combining Sentinel-1 C-band and Sentinel-2 MSI datasets in enhancing reforestation carbon stock estimation in urban landscape. The study demonstrated that combining spectral reflectance of optical Sentinel-2 and backscatter of Sentinel-1 (SAR) imagery using nearest neighbour diffused fusion technique optimizes carbon stock estimation in an urban landscape. The results also showed that cross-polarisation produced carbon estimates which are highly correlated with measured carbon, compared to co-polarisation operation. These results provide valuable methodology that can be effectively adopted by forest managers and urban planners to establish informed management and monitoring strategies of reforestation ecosystem.

Overall, this study presents valuable knowledge on the contribution of reforestation initiatives in the global carbon balance and climate change regulation within urban landscapes. Furthermore, urban reforestation program has shown promising potential in meeting the requirements of Reducing Emissions from Deforestation and Forest Degradation (REDD+) and

Kyoto-Protocol of reducing atmospheric carbon emissions and promote climate resilient urban environment. The study also provides unprecedented information that sensitize forest managers, land-use planner and policy makers to integrate reforested ecosystems and their benefits to informed management and monitoring policies, including planning for larger-scale reforestation projects to increase carbon sequestration potential.

Key words: reforestation, urbanization, climate change, Sentinel-2, synthetic aperture radar

Preface

This study was conducted in the School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg, South Africa, from June 2019 to June 2022, under the supervision of Professors John Odindi and Onisimo Mutanga.

I declare that the work presented in this thesis has never been submitted in any form to any other institution. This work represents my original work except where due acknowledgements are made.

Mthembeni Mngadi Signed ….. [redacted] Date …11/06/2022……………....

As the candidate's supervisor, I certify the statement and have approved this thesis for submission.

Professor John Odindi Signed…… [redacted] Date…11/6/2022

Professor Onisimo Mutanga Signed… [redacted] ate…11/6/2022…………….

Declaration 1: Plagiarism

I Mthembeni Mngadi, declare that:

1. The research reported in this thesis, except where otherwise indicated is my original research.
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Declaration 2: Publication

1. **Mngadi, M.**, Odindi, J., Mutanga, O. and Sibanda, M., 2022. Quantitative remote sensing of forest ecosystem services in sub-Saharan Africa's urban landscapes: a review. *Environmental Monitoring and Assessment*, *194*(4), pp.1-19.
2. **Mngadi, M.**, Odindi, J., Mutanga, O. and Sibanda, M., 2022. Estimating aboveground net primary productivity of reforested trees in an urban landscape using biophysical variables and remotely sensed data. *Science of The Total Environment*, *802*, p.149958.
3. **Mngadi, M.**, Odindi, J. and Mutanga, O., 2021. The Utility of Sentinel-2 Spectral Data in Quantifying Above-Ground Carbon Stock in an Urban Reforested Landscape. *Remote Sensing*, *13*(21), p.4281.
4. **Mngadi, M.**, Odindi, J. and Mutanga, O., 2022. Quantifying carbon stock variability of species within a reforested urban landscape using texture measures derived from remotely sensed imagery. In: Arellano, P. and Pandey, P. (Eds), Advances in remote sensing for forest monitoring, Wiley (*in press*).
5. **Mngadi, M.**, Odindi, J. and Mutanga, O., 2022. The efficacy of combining Sentinel-1 C-band and Sentinel-2 MSI datasets in enhancing reforestation carbon stock estimation in urban landscape. *Journal of Environmental Management* (under peer-review), manuscript no: JEMA-D-22-04770.

Dedication

This dissertation is dedicated to healthcare, police services and shops workers for sacrificing their lives servicing society during the most devastating global pandemic COVID-19, which lasted for at least three consecutive years.

Acknowledgements

Growing from disadvantaged deep rural environment I feel privileged to reach such a milestone journey in the academic space. It has been always my dream and passion to reach doctoral level and have a recognisable contribution in scientist knowledge. I am grateful for remaining strong and positive despite a traumatizing COVID-19 pandemic, which never ended for at least three consecutive years of my PhD.

I would like to send my gratitude to the University of KwaZulu-Natal, particularly the School of Agricultural, Earth and Environmental Science for granting me the opportunity to pursue doctoral degree. I also acknowledge the DST-NRF SARChI Chair in Land Use Planning and Management (Grant No. 84157) for financing this research project. A special appreciation to eThekwini municipality through Durban Research Action Partnership (DRAP) for allowing this study to be carried out in one of their protected reforestation site located in Buffelsdraai. I further thank the European Space Agency (ESA) for furnishing me with Sentinel's dataset, which enabled me to achieve all established research objectives. To my kind supervisor **Professor John Odindi**, for his constructive scientific criticism, patience, and commitment in guiding this work, and most importantly for extending his professional expertise and knowledge towards the success of this research. I wish my words of appreciation to you Prof match the contribution you made to my life, but I believe the best knower "**God**" shall bless you. A huge thanks to **Professor Onisimo Mutanga** (my co-supervisor), for his commitment and passion to see this work progresses, especially his advices and expertise towards the completion of this research. Similarly, to you Prof, my words of appreciation are insufficient compared to your contribution in grooming me to be the person I am today. Furthermore, I would like to sincerely thank **Dr Mbulisi Sibanda** (co-author) for his valuable assistance and ideas he shared with me to ensure excellence of this research. He taught me many things in research, which include among other things; the utility of complex equipment for fieldwork. Working together with Dr Sibanda I learnt a lot in research space and life in general. To my dearest friends and colleagues for their motivational and constructive words which kept me working hard and tirelessly under stressful conditions, especially Amanda Nyawose, Sanelisiwe Ngcobo, Anita Masenyama and Xolile Zuma. Selectively, I thank **Odebiri Omosalewa**, Lwando Rhoyimani and Trylee Matongera for proof reading and strengthening this work. I really appreciate your time and comments which made huge impact to the end of this research. To the staff members within the Discipline of Geography and Higher Degrees Office, I thank you all for your kind support and assistance.

Above all, to the most beneficent and omnipotent Nazareth Baptist church leader **Shembe** ("**uNyazilweZulu**") for his teachings and reviving conscious on me to be a better and most respecting person. Lastly, a special thanks to my family for giving me this chance to pursue doctoral degree, despite difficult times we experiencing as a family. Specifically, my siblings Mphile, Majuba, Thabani, Senzeni, Skholiwe, Sabathile, Nontokozo and Siyabonga Mngadi, they all played a significant role in grooming me and teaching me life, not to mention motivating me not quit when time was difficult. A selective and special gratitude to **Simangele Mdletshe** for her prayers and endless support which kept me focused and believing to my potential and strengths.

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Acronyms

AGB	Aboveground Biomass
ANOVA	Analysis of Variance
APAR	Absorbed Photosynthetic Active Radiation
ASM	Angular Second Moment
AVI	Advanced Vegetation Index
B	Band
BPLUT	Biome Parameter Look-Up Table
C	Carbon
Cl_{green}	Green Chlorophyll Index
Cl_{RE}	Red-edge Chlorophyll Index
CON	Contrast
COR	Correlation
d	Co-occurrence displacement vector
dB	decibel
DBH	Diameter at Breast Height
DI	Dissimilarity
DOS	Dark Object Subtraction
DRAP	Durban Research Action Partnership
ENT	Entropy
ENVI	Environment for Visualizing Images
ERTS-1	Earth Resource Technology Satellite
ESA	European Space Agency
ES's	Ecosystem Services
ETM	Enhanced Thematic Mapper
EVI	Enhanced Vegetation Index
FLAASH	First Line-of-sight Atmospheric Analysis Hypercube
fPAR	fraction of Phytosynthetically Active Radiation
GLCM	Grey Level Co-occurrence Matrix
GNDVI	Green Normalized Difference Vegtetation Index
GPP	Gross Primary Production
GPS	Global Positioning System
H	Height
HO	Homogeneity

IPBES	Science-Policy Platform on Biodiversity and Ecosystem Services
IPCC-GPG	Inter-Governmental Panel on Climate Change Good Practice Guidance
IW	Interferometric Wide Swath
LAI	Leaf Area Index
LUE	Light-Use Efficiency
MAE	Mean Absolute Error
ME	Mean
MEA-EEB	Millennium Ecosystem Assessment and Economics of Ecosystems and Biodiversity
Mg	Mega gram
ML	Maximum Likelihood
MLR	Multiple Linear Regression
MODIS	Moderate Resolution Imaging Spectroradiometer
MSI	Multispectral Image
MSRI	Modified Simple Ratio Index
$MSRI_{RE}$	Modified Simple Ratio Red-edge Index
MTVI	Modified Triangular Vegetation Index
NDVI	Normalized Difference Vegetation Index
$NDVI_{RE}$	Red-edge Normalized Difference Vegetation Index
NGHGI	National GreenHouse Gas Inventories
NIR	Near Infrared
NND	Nearest Neighbour Diffused
NPCRI	Normalize Pigment Chlorophyll Ratio Index
NPP	Net Primary Productivity
OLI	Operational Land Imager
OOB	Out-Of-Bag
PAR	Photosynthetically Active Radiation
PRI	Photochemical Reflectance Index
QGIS	Quantum Geographic Information System
r	Correlation Coefficient
R^2	Coefficient of Determination
REDD	Reducing Emissions from Deforestation and forest Degradation
RF	Random forest
RMSE	Root Mean Square Error

RVI	Ratio Vegetation Index
SAR	Synthetic Aperture Radar
SAWS	South African Weather Services
SNAP	Sentinel Application Platform
SNR	Signal-to-Noise Ratio
SPOT	Satellite pour l'Observation de la Terre
STARFM	Spatial and Temporal Adaptive Reflectance Fusion Model
SWIR	Shortwave Near Infrared
t	Tonne
TM	Thematic Mapper
TVI1	Transformed Vegetation Index
TVI2	Triangular Vegetation Index
UAV	Unmanned Aerial Vehicle
UNFCCC	United Nations Framework Convention for Climate Change
UNFCCC	United Nations Framework Convention for Climate Change
VAR	Variance
VH	Vertical transmit/Horizontal receive
VIF	Variance Inflation Factor
VIP	Variable Importance in Projection
VV	Vertical transmit/Vertical receive
θ	Direction
σ_0	Sigma naught
Ra	autotrophic respiration

Chapter One: General introduction

1.1 Introduction

Ecosystem services (ES's) are defined as processes and benefits derived from a properly functioning ecosystems for human well-being and the environment (Davids et al., 2016, 2018; Tavares et al., 2019). Such ecosystems include forests, grassland, agro and aquatic, which provide a range of services that are subdivided into four classes; provision, regulation, supporting and cultural (Davids et al., 2018; de Araujo Barbosa et al., 2015; Roberts et al., 2012; Tavares et al., 2019). Among these, forests are the most dominant terrestrial ecosystem, providing numerous services that are critically important for human-being and the environment. Forest ecosystems cover approximately 31% of the world landscape's (Adams, 2012; Siry et al., 2005) and support a range of ecological, social and economic functions (Ke and Quackenbush, 2011; Kumar, 2011; Porter-Bolland et al., 2012). Furthermore, forest ecosystems play a key role in carbon-oxygen cycling, and regulate both local and regional climate systems through biosphere and atmospheric interactions (Dube and Mutanga, 2015b; Roy and Ravan, 1996). Moreover, forests provide habitat to a variety species, protect soil and water resources and improve nutrient cycling (Ke and Quackenbush, 2011; Kumar, 2011; Potapov et al., 2008). In South Africa, natural forest ecosystems cover approximately 0.4% of the country's land surface (DAFF, 2015), providing socio-economic goods and services (e.g. medicinal plants, food, fibre, firewood, timber etc.) and improving the environment (Mansourian and Vallauri, 2005). However, these forest ecosystems are highly fragmented and vulnerable to land use change that include urban development, agriculture and mining (Mucina et al., 2003; Roongtawanreongsri et al., 2015).

Over the last decades, conservation and protection of forest ES's has been challenged by persistent urbanisation which exert enormous pressure on natural resources around and within urban landscapes (Delphin et al., 2016; Dobbs et al., 2014). Urbanisation, with reported population density exceeding 50% leads to extensive natural landscape transformation into impervious infrastructure and settlements, hence disproportionately contribute to environmental change (Odindi and Mhangara, 2012a; Sithole et al., 2018). Such landscape transformation is associated with increasing urban thermal heat, air pollution, loss of biodiversity and accelerated climate change risks and impacts (Livesley et al., 2016a; Sithole et al., 2018; Xu et al., 2016). Although urban areas cover a small global land-surface, they account for highest amount of global carbon emissions due to higher energy and resource consumption (Luederitz et al., 2015). Furthermore, continuous urban expansion contribute to extreme deforestation and forest degradation, which among others include forest clearance for agriculture and uncontrolled timber and non-timber harvesting schedules (Cho et al., 2012; Murthy et al., 2002); posing serious constrains on the ecosystem productivity and composition. Forest loss and degradation constitute approximately 12% of the world's greenhouse gas emissions (Ernst et al., 2013; Saatchi et al., 2011). These emissions result in rapid global climate change, and the bulk of these emissions are accounted from urban landscapes (Ernst et al., 2013; Saatchi et al., 2011). Consequently, the increasing forest ecosystem loss and degradation attributed to the current land use - land cover change, have raised serious concerns pertaining to the long-term strategy and policy framework to sustain natural resources for current and future generation. In this regard, the United Nations Framework Convention for Climate Change (UNFCCC) has established a new program for reducing emissions from deforestation and forest degradation (REDD). REDD is an initiative designed for combating climate change by promoting agroforestry and ensuring appropriate forest ecosystem conservation and protection (Curiel-Esparza et al., 2015; Gara et al., 2016). Recently, reforestation has emerged as the most practical approach to reinstating resilient forest ES's (Livesley et al., 2016a; Mansourian and Vallauri, 2005). In the 20th century, forest plantations (especially commercial forests) was encouraged to meet the increasing global demands for timber and non-timber products, and to a lesser purpose of climate change regulation and ES's restoration (Dudley et al., 2005; Lamb and Gilmour, 2003). However, the establishment of Kyoto Protocol in 1997 presented the necessity of reforestation (both exotic and indigenous trees) as a cost-effective initiative for reducing greenhouse gas emission and climate change (Mansourian and Vallauri, 2005; Trotter et al., 2005).

Establishment of highly diverse indigenous trees with close canopy is valuable for the restoration of ecological benefits (i.e. biodiversity) and enhancing ecosystem functions, while increasing carbon sequestration capacity and mitigating effects of climate change (Cunningham et al., 2015; Livesley et al., 2016a; Manes et al., 2012). As aforementioned, these ES's can be grouped as provisioning (i.e. freshwater, food, fibre), regulating (i.e. air quality, water and climate), cultural (i.e. recreational, spiritual and religious values) and supporting (i.e. soil formation, nutrients and water cycling) (Thompson et al., 2009). Although such ES's are critically important to human welfare, their consideration in urban planning, management and decision making has been insufficiently integrated (Davids et al., 2018; Nemec and Raudsepp-Hearne, 2013). The lack of their consolidation in urban planning and decision making can be attributed to limited information benchmarking ES's hotspot, lack of implementable policy-framework and difficulty for public authorities to regulate ecosystems (Baró et al., 2016; Davids et al., 2018). Despite the key role of urban reforestation initiative on ES's restoration and climate change-adaptation, the knowledge on ES's generated from urban reforested trees remains limited, whereas, continuous information on the quantification and mapping of ES's derived from urban reforested trees is necessary for understanding the response of ecological functions and processes to the global carbon balance and climate change. Specifically, regulating ES's have become critical in addressing climate change related challenges (i.e. carbon sequestration or stocks, aboveground biomass, net primary productivity etc.). However, this ES category has not been adequately retrieved within urban reforested landscapes. Hence the quantification of such ES could provide valuable information for developing policy, and conservation and monitoring measures that are useful in governing ecological processes and functions. Additionally, effective administration and monitoring of ecosystem processes and functions could ensure balanced interaction between environmental, social and economic functions, while preserving ecological systems (i.e. ecosystem services) and mitigating climate change.

Whereas numerous studies have assessed climate regulating ES's such as carbon stock or sequestration, biomass and primary productivity, these assessments have been restricted to natural and commercial forests outside urban landscapes (Baccini et al., 2008; Dube and Mutanga, 2015a; Henry et al., 2011). Hence, there is a dearth in information presenting the contribution of urban reforested trees to the global carbon flux and climate regulation. Therefore, the quantification of regulating ES's (e.g. carbon sequestration or stocks, biomass and net primary productivity) can bridge the knowledge gap on the value of urban reforestation programmes. Generally, concise quantification of ES's has been significantly challenged by a number of limitations that include unavailability of resources, limited standardised methodology and technological expertise (Amuzu-Sefordzi et al., 2016; Baccini et al., 2008), especially in developing regions like Sub-Saharan Africa. Nonetheless, adequate information on the current and future spatial distribution of urban ES's could be essential to reforestation managers and practitioners for their planning and decision-making phases. In this regard, there is a need to establish affordable and robust techniques and datasets for effective local and regional forest ES's quantification and monitoring.

Previously, the quantification and monitoring of forest ES's was based on conventional field surveys that involve field measurements and destructive methods (Dube and Mutanga 2015, Mngadi et al. 2019b). However, although highly accurate and reliable, this approach is laborious and costly, (Gara et al., 2016; Lu, 2006; Mngadi et al., 2019a). Furthermore, conventional methods are often impractical in remote areas and large spatial extents, making regional assessment and acquisition of sufficient number of tree samples a major challenge (Lu, 2006; Mngadi et al., 2019a). It is therefore necessary to adopt methods and datasets that can complement conventional approach. Recently, the Inter-Governmental Panel on Climate Change Good Practice Guidance (IPCC-GPG) on Land Use, Land Use Change and Forestry have prioritised remote sensing as robust technique in providing cost effective and reliable primary data necessary for wall-to-wall mapping and estimation of forest ecosystem dynamics (Gara et al., 2016; Muukkonen and Heiskanen, 2005). Remote sensing data is characterized by larger spatial coverage that allows for acquisition of spectral information at both local and regional scale, and in complex landscapes (Dube and Mutanga, 2015a; Mngadi et al., 2019a; Peerbhay et al., 2013b). In complementarity with field surveys, these benefits have prompted its adoption in forestry for effective decision making on forest ES's management, monitoring and conservation.

Recently, the newly launched multispectral sensors (i.e. Landsat 8 OLI and Sentinel-2) have gained popularity in vegetation mapping and monitoring due to their significant improvement in radiometric, spectral and spatial properties, that improve their precision and accuracy in wall-to-wall forest assessment and conservation (Laurin et al., 2016; Mngadi et al., 2019a; Shoko and Mutanga, 2017). The sensors are readily-available, cost effective and are characterised by larger spatial coverage, hence useful for both large and small-scale ES's mapping and monitoring (Mngadi et al., 2019a; Shoko and Mutanga, 2017). For example, Sentinel-2 MSI captures information at 10, 20 and 60 m spatial resolutions aboveground and larger swath width (about 290 km), hence facilitating both local and regional forest mapping and monitoring. Furthermore, the sensor is characterised by unique band settings that are strategically located in red-edge region of electromagnetic spectrum, valuable for vegetation assessment. Generally, the spectral-bands within the red edge region are more sensitive to various vegetation properties such as chlorophyll content, leaf area index, biomass and leaf angle distribution, which are critical for improving forest ecosystem mapping and monitoring (Laurin et al., 2016; Shoko and Mutanga, 2017; Sibanda et al., 2016). Despite the sensor's unprecedented properties, its capabilities have not been exploited in the quantification and mapping of ES's of reforested urban trees for effective decision-making and monitoring schedules. Furthermore, the sensor's complementarity with Sentinel-1's synthetic aperture radar (SAR) counterpart has not been effectively explored for estimating climate regulating urban ES’s within reforested landscapes. Generally, medium spatial resolution multispectral sensors suffer from saturation and shadowing effects, particularly in dense forest cover characterised by heterogeneous trees. However, high penetrating wavelength of SAR imagery can overcome such challenges, hence providing pure backscatter capable of enhancing multispectral sensor’s performance in estimating climate regulating services within an urban reforested environment. Thus, there is a need to test the efficacy of combining SAR imagery with optical sensors to improve estimation performance of urban reforested ES’s. Additionally, remote sensing techniques provide spectral information that are highly correlated and less variable (Mngadi et al., 2019a; Peerbhay et al., 2013b). This could significantly impede predictive performance of urban reforested ES’s. A strong correlation between and within the spectral predictors limits the statistical techniques to precisely analyse a remotely sensed data (Peerbhay et al., 2013b). Therefore, predicting urban forest ES’s using remote sensing data requires robust statistical method/s that can improve predictive performance of climate regulating ES’s. For instance, ensemble methods such as random forest have proven effective in enhancing predictive accuracy of ecological processes and services. Random forest is a non-parametric statistical method capable of dealing with complex correlation between predictor variables through variable importance technique (Dube et al., 2014; Mutanga et al., 2012). This model also provides crucial optimization parameters (e.g., *Ntree* and *Mtry*) which can be effectively used to improve the final prediction model (Breiman, 2001; Forkuor et al., 2018). In this regard, random forest model could be valuable in quantifying ES's of reforested trees within an urban landscape.

Overall, there is a need to understand the value of reforestation in restoring crucial ES’s so as to inform management and conservation policies that intend to integrate ES’s into urban planning and decision-making. Therefore, this study sought to provide comprehensive information benchmarking the contribution of reforestation initiative to the global carbon cycles and climate change regulation potential. The study specifically focused on regulating ecosystem services such as carbon stocks and net ecosystem exchange (i.e. net primary productivity), which are instrumental in understanding carbon balance and climate change mitigation potential of reforestation. In addition, this research adopted Sentinel (1 and-2) satellite imagery, random forest and multiple linear regression techniques for the analysis of regulating ES’s within urban landscape.

1.2 Research aim

The main aim of this research was to assess climate regulating ecosystem services (e.g., carbon stock and net primary productivity) in reforested urban landscape using freely and readily available remote sensing dataset.

1.3 Specific objectives were:

1. to review the adoption of remote sensing in quantifying forest ecosystem services in sub-Saharan Africa urban landscapes,

2. to estimate aboveground net primary productivity of reforested trees in urban landscape using integrated biophysical variables and remotely sensed data,
3. to explore the utility of Sentinel-2 spectral data in quantifying above-ground carbon stock in an urban reforested landscape,
4. to quantify species carbon stock variability of within a reforested urban landscape using texture measures derived from remotely sensed imagery, and
5. to test the efficacy of combining Sentinel-1 C-band and Sentinel-2 MSI datasets in enhancing reforestation carbon stock estimation in an urban landscape

1.4 Study site description

The study was conducted at Buffelsdraai Reforestation site located within eThekwini municipality in KwaZulu-Natal province, South Africa (Figure 1.1). The area is geographically situated between 30°58'20.08"E and 29°37'55.17"S. The reforestation site, which is strategically positioned around a landfill, spans approximately 809 ha (Douwes et al. 2015). The reforestation project was originally developed by the eThekwini Municipality to regulate greenhouse gas emissions during the 2010 FIFA World Cup (Douwes et al. 2015). The intention of the project was to establish an indigenously diverse, functional, forest ecosystem that would sequester large volumes of atmospheric carbon and mitigate the effects of the landfill site over time. The site was also envisioned to contribute to the municipality's climate protection strategy, through the management of water flow and soil erosion. The project employs local community members to assist with planting a variety of indigenous trees within previously cultivated areas, contributing to livelihoods. The average precipitation for the site ranges between 600 mm to 1000 mm per year, while mean annual temperature ranges from 22°C in winter to 27°C in summer (Sithole, Odindi and Mutanga 2018). Furthermore, the area is characterised by an uneven topography with soils that range from deep, well-drained red Hutton soils, to shallow and poorly drained Glenrosa soil forms, which are supported by dwyka tillite (Sithole et al. 2018). In addition, the site consists of a variety of indigenous tree species (e.g. *Acacia caffra*, *Acacia robusta, Apodyties dimidata, Combretum spp, Heteropyxis natalensis, Strelitzia nicolai*, *Erythrina caffra, Silver oak*, *Syzygium cordatum, Dalbergia obovate, Rothmannia glabosa*), which facilitates ecological diversity within the area (Douwes et al. 2015).

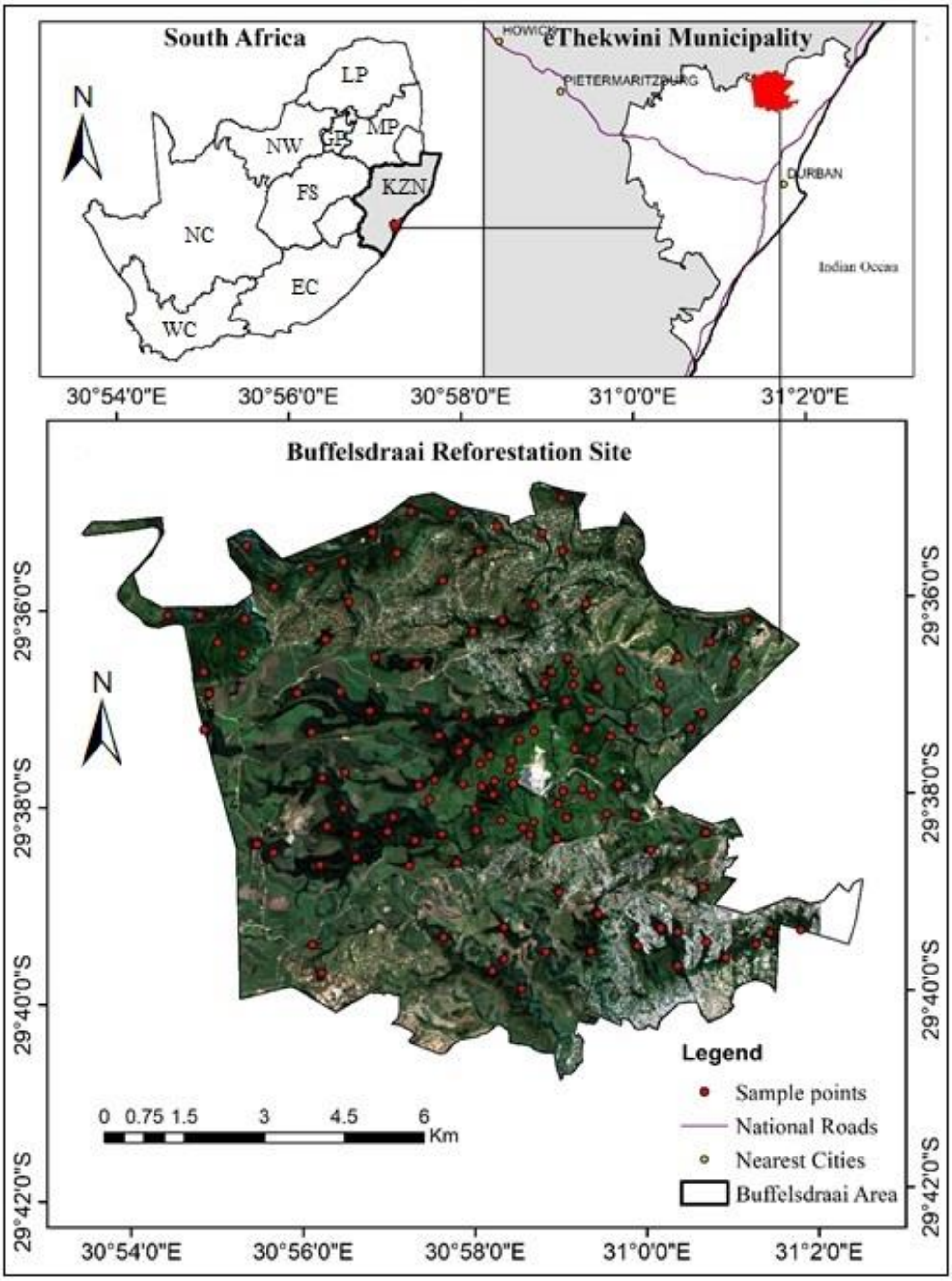


Figure 1.1 Location of Buffelsdraai reforestation site and sample points, within the eThekwini Municipality in KwaZulu-Natal Province.

1.5 Research scope

This study aimed at quantifying climate regulating ecosystem services within reforested urban landscape using freely available remote sensing data. The study focused on the contribution of reforestation initiative to the global carbon balance and climate systems regulation potential. Furthermore, this study presents the strength of medium-to-fine spatial resolution Sentinel-2 MSI in accurately quantifying ecosystem services generated in a heterogeneous reforested trees within an urban landscape. The study demonstrates robustness of advance image processing technique such as texture measures in quantifying carbon stock variability among reforested tree species. In addition, the study illustrates the reliability and effectiveness of synthetic aperture radar backscattering in optimizing predictive performance of optical Sentinel-2 through image fusion technique. In this study, the robust non-parametric statistical method (random forest regression model) was adopted for carbon stock analysis using remotely sensed dataset, while multiple linear regression method was used for net primary productivity estimation.

1.6 Dissertation structure

This dissertation comprises five articles (which respond to research objectives) that have been submitted to peer-reviewed journals. Three articles have been already published, one is in press and one under review. The articles present independent information, but contribute to the overarching objective (in chapter one) and synthesis (chapter seven). The literature review and methodology encompassed in all papers could present some overlap and duplication. The entire dissertation consist of seven chapters highlighted below:

Chapter one

This chapter presents the general introduction and contextualizes the research study; underlining the importance of reforestation initiative in restoring critical ES's and the need to understand its contribution towards climate change mitigation. The chapter also highlights on methods and datasets that can be adopted to quantify climate regulating ES's within urban landscape. The research aim and objectives are also presented.

Chapter two

This chapter provides an explicit overview of urban ES's quantification using remote sensing technique in sub-Saharan Africa. The chapter present trends, challenges and future prospects of remote sensing in quantifying urban ES's. It further highlights research gaps and need to establish cost effective methods for urban ES's quantification and monitoring in resource constrained regions like sub-Saharan Africa.

Chapter three

This chapter focuses on the estimation of aboveground net primary productivity within reforested urban landscape using biophysical variables and remotely sensed data. The information presented in this chapter is fundamental for understanding the value of reforestation in the global carbon budget and climate change regulation potential. In this chapter, the net carbon uptake per unit of absorbed radiation by each reforested tree species is also presented.

Chapter four

Although reforestation initiatives are assumed to be reliable in carbon sequestration and climate systems regulation, their carbon accumulation have remained largely unknown. Therefore, this chapter examines the prospect of medium-to-fine spatial resolution Seninel-2 MSI in quantifying aboveground carbon stock of reforested trees within urban landscape. The chapter also explore the potential of new and unique vegetation indices derived from a strategically positioned red-edge region of electromagnetic spectrum in boosting reforestation carbon stock estimation.

Chapter five

This chapter focused on the quantification of carbon stock variability among reforested tree species using texture measures derived from Sentinel-2 MSI. The chapter highlights the importance of texture measures in quantifying carbon stock variability across reforested tree species. It further outlines the need for understanding the contribution of individual tree species in the carbon budget and their potential to mitigate climate change.

Chapter six

This chapter test the efficacy of integrating Sentinel-1 synthetic aperture radar with Sentinel-2 MSI to enhance the estimation of reforested carbon stock within an urban landscape. The study provide detailed information on the importance of combining backscatter and spectral reflectance in improving estimation performance of forest carbon stock within an urban landscape. In this chapter, the performances of individual interferometric polarization (e.g., cross-polarization and co-polarisation) in predicting reforestation carbon stock are also compared.

Chapter seven

This chapter provide synthesis of all findings and conclusions from the research objectives. The chapter further provides important recommendations for future research. The list of references is provided at the end of this chapter.

Chapter Two: Quantitative remote sensing of forest ecosystem services in sub-Saharan Africa's urban landscapes: A review

This chapter is based on:

Mngadi, M., Odindi, J., Mutanga, O. and Sibanda, M., 2022. Quantitative remote sensing of forest ecosystem services in sub-Saharan Africa's urban landscapes: a review. *Environmental Monitoring and Assessment*, *194*(4), pp.1-19.

Abstract

A dearth of information on urban ecosystem services in the past decades has led to little consolidation of such information for informed planning, decision-making and policy development in sub-Saharan African cities. However, the increasing recognition of the value of urban ecological processes and services as well as their contribution to climate change adaptation and mitigation has recently become an area of great research interest. Specifically, the emerging geospatial analytical approaches like remote sensing, have led to an increase in the number of studies that seek to quantify and map urban ecosystem services at varying scales. Hence, this study sought to review the current remote sensing trends, challenges and prospects in quantifying urban ecosystem services in sub-Saharan Africa cities. Literature shows that consistent modelling and understanding of urban ecosystem services using remotely sensed approaches began in the 1990s, with an average of five publications per year after around 2010. This is mainly attributed to the approach's ability to provide fast, accurate and repeated spatial information necessary for optimal and timely quantification and mapping of urban ecosystem services. Although commercially available high spatial resolution sensors (e.g. the Worldview series, Quickbird and RapidEye) with higher spatial and spectral properties have been valuable in providing highly accurate and reliable data for quantification of urban ecosystem services, their adoption has been limited by high image acquisition cost and small spatial coverage that limit regional assessment.. Thus, the newly launched sensors that provide freely and readily available data (i.e., Landsat 8 and 9 OLI, Sentinel-2) are increasingly becoming popular. These sensors provide data with improved spatial and spectral properties, hence valuable for past, current and future urban ecosystem services assessment, especially in developing countries. Therefore, the study provides guidance for future studies to continuously assess urban ecosystem services (especially net primary productivity and carbon stock) in order to achieve the objectives of Kyoto Protocol and Reducing Emissions from Deforestation and forest

Degradation (REDD+) of promoting climate resilient and sustainable cities, especially in developing world.

Keywords: reforestation, regulating, supporting, provisioning, cultural

2.1 Introduction

Ecosystem services (ESs) are the natural processes that benefit human well-being and sustain environmental quality. These services are derived from a range of ecosystems that include forests, grasslands, aquatic and agro-systems (Costanza and Liu, 2014; Davids et al., 2016; de Araujo Barbosa et al., 2015). Forests are the most influential terrestrial ecosystems and play a significant role in the global carbon-oxygen exchange and regulation of regional, national and local climate systems through biosphere-atmospheric interactions (Dube and Mutanga, 2015c). Although forest ecosystems are the largest reservoirs of ecological processes, services and biodiversity, they are the most vulnerable to natural and physical changes (Mashapa et al., 2014; Solomon et al., 2018; Tetemke et al., 2019; Ubuy et al., 2018). In urban areas, the increasing loss of forest ecosystems due to anthropogenic drivers has particularly raised concerns on the long-term strategies for protecting and monitoring biodiversity and ESs. Generally, the rate of forest lost due to anthropogenic activities, particularly between 1990 to 2015 amount to 6% (i.e., 3961 to 3721 million hectares) (Keenan et al., 2015; Odebiri et al., 2020b; Payn et al., 2015).

Ecosystem Services provided by urban forests are generally categorised as regulating (i.e. air quality, water and climate), provisioning (i.e. freshwater, food, fibre), supporting (i.e. soil formation, nutrients and water cycling) and cultural (i.e. recreational, spiritual and religious values) (Mugwedi et al., 2017; Munien et al., 2015). Commonly, these services are compromised by excessive socio-ecological interdependences associated with urbanisation, resulting in decline of environmental quality that threatens life quality and triggers climate change. In urban areas, literature indicates that the transformation of natural landscapes and ecosystems into impervious surfaces increases temperature, air pollution, loss of biodiversity and ESs (Livesley et al., 2016a; Nguyen et al., 2019; Sithole et al., 2018; Sutherland et al., 2016; Xu et al., 2016). Furthermore, although urban areas cover small proportion of the global land surface, they exert enormous pressure on the ability of urban forest ecosystems to provide crucial socio-ecological services that include sequestration of emitted carbon (Fu et al., 2013; Luederitz et al., 2015; Yu et al., 2020). Generally, existing studies on urban ESs are often conducted in the Global North, with less focus on the Global South including Africa, hence, little is known about ESs conservation and monitoring potential in sub-Saharan Africa cities (Guenat et al., 2019; Magle et al., 2012).

Sub-Saharan Africa has been noted as the fastest urbanising region, with many cities encroaching on a variety of ecosystems and biodiversity (Guenat et al., 2019; Jaligot et al., 2018). This has consequently compromised and degraded the preservation and provisioning potential of ESs essential for human well-being and climate-change adaptation. Thus, reforestation has been proposed as a viable and effective initiative to restore lost and degraded urban forests ecosystems (Curiel-Esparza et al., 2015; Mugwedi et al., 2017). According to Mugwedi et al. (2017) and Curiel-Esparza et al. (2015), urban reforestation based on indigenous trees is valuable for reinstating lost biodiversity and ESs that include regulation of regional and local climate systems through eco-biosphere and atmospheric interactions. Few cities in sub-Saharan Africa have begun adopting such innovative initiative for re-instating urban ESs. For instance, the city of Durban in South Africa has begun its reforestation initiative through the Durban Research Action Partnership (DRAP) (Mngadi et al., 2021). Similarly, the city of Analamanga in Madagascar has embarked on reforestation project supported by Reforest ‘Action (Brunet et al., 2020). In Ivory Coast’s Agnéby-Tiassa city, authorities have implemented a reforestation policy through Reforest ‘Action project initiative (Moïse et al., 2019). Despite numerous cities in sub-Saharan Africa adopting reforestation initiative, there is still paucity in literature on the amount of urban ESs derived from reforested trees. Hence, quantification of services derived from reforestation could be valuable to among others, reforestation practitioners, urban planners and policy makers to better understand the value of reforested trees in reinstating resilient ecological functions, biodiversity and climate change adaptation.

The lack of information to facilitate spatial quantification and mapping of ESs has been a critical challenge in understanding the productivity of urban ecosystem services and for making accurate decisions and policy. Previously, scientific approaches for quantifying ESs such as conversion of primary and proxy data of main land covers into assessments and generation of potential services using coefficients accumulation have been widely adopted (Grêt-Regamey et al., 2015; Villa et al., 2009). However, such approaches neglect the complexity and multi-scale variability of ESs, hence do not offer spatially explicit and accurate information for informed decision-making. Although such traditional approaches are highly accurate and reliable, they are impractical at large spatial extents, are environmentally destructive and often impeded by complex geographic terrains (Dube and Mutanga, 2015b, c; Mngadi et al., 2019b).

Furthermore, traditional methods require extensive field work, which is time consuming, labour-intensive and costly (Dube et al., 2016; Mngadi et al., 2019b). However, the emergence of remote sensing has shown remarkable potential in addressing limitations associated with traditional methods. Therefore, this study reviewed the utility of remote sensing approaches as a cost effective means of providing precise, reliable and up-to-date information, critical for the quantification and mapping of urban ESs complexity and variability.

Remote sensing captures important vegetation characteristics related to biochemical and biophysical attributes (Fatoyinbo et al., 2018; Mngadi et al., 2019b; Sithole et al., 2018), which are critical indicators of ESs. Furthermore, remote sensing techniques provide spatial data characterised by larger swath-width, useful for the quantification and mapping of ESs at varying spatial scales (de Araujo Barbosa et al., 2015; Dube and Mutanga, 2015b; Matongera et al., 2018). Critically, it allows for repetitive acquisition of information of an area (Dube et al., 2016; Matongera et al., 2018), valuable for the quantification and mapping of the temporal changes of urban ESs. Additionally, the spatial information captured by remote sensing can be easily integrated with ancillary data, optimising the available datasets for informed decision-making. Considering the growing popularity of optical and active sensors for the quantification and mapping of urban ESs in sub-Saharan Africa, it is necessary to review their adoption to understand their current state, opportunities and challenges. Such knowledge is useful for tracking their use for urban ESs management and for determining uncertainties in the application of remote sensing satellite datasets for future assessments. Although few studies have reviewed urban ESs in sub-Saharan Africa, such reviews have focused on ecosystem governance and conventional approaches (e.g. field survey, laboratory experiments and statistics) (Cilliers et al., 2013; Du Toit et al., 2018; Mngumi, 2020; Wangai et al., 2016). Generally, there is a dearth in literature on the adoption of remote sensing approaches in quantifying urban ESs. Therefore, this study sought to review opportunities, challenges and future prospects of remote sensing in quantifying urban ESs.

2.2 Data sources

In this review, we collected peer-reviewed papers based on urban ESs using Web of Science, Scopus, Science Direct and Google Scholar search engines. The following key words were used for our literature search; 'urban ecosystem services', 'urban ecosystem services in Africa', 'urban ecosystem services and remote sensing', 'cultural services in Africa', 'quantification of carbon stock using remote sensing', 'climate regulation in Africa', 'air quality in Africa', 'soil accumulation', and 'recreational services in Sub-Saharan Africa'. Ninety (90) publications were identified from 2003 January to December 2020 (Figure 2.1). These studies were separated into specific ecosystem services categories (i.e. regulating, provisioning, supporting and cultural) based on Millennium Ecosystem Assessment classification (2003). Studies that used traditional approaches were separated from studies that used remotes sensing approaches (Table 2.1). The search result was used for analysis.

2.3 Number of ecosystem services publications in sub-Saharan Africa

Historically, the assessment of urban ESs has been minimal, especially those not considered to be of direct economic value (Andrew et al., 2014; Costanza et al., 1997). Thus, their consolidation into environmental policy and decision making has been limited. Following the release of Millennium Ecosystem Assessment and Economics of Ecosystems and Biodiversity (MEA-EEB) frameworks, urban ecosystems have received increasing attention (Carpenter et al., 2006; Costanza et al., 1997). Specifically, understanding the value of urban ecosystems on ecological, socio-economic and environmental functions has received great interest (Gómez-Baggethun and Barton, 2013; Mngumi, 2020). However, to date, there is no study that has reviewed the quantification of urban ESs using remote sensing approaches in sub-Saharan Africa. Literature for instance, shows that only four studies have reviewed urban ESs in sub-Saharan Africa, mainly focusing on the conventional methods and ecosystem governance (Cilliers et al., 2013; Du Toit et al., 2018; Mngumi, 2020; Wangai et al., 2016). The study (Table 2.1) found that 48 studies quantified urban ESs using traditional/conventional approaches, whereas only 42 studies used remote sensing techniques. Results in Figure 2.1 show that literature on the quantification of urban ESs sharply increased between 2010 and 2020 in relation to the period between 2000 and 2009, where relatively few studies (9) were published. This indicates that urban ESs is a recent phenomenon on the African continent (Egoh et al., 2012; Mngumi, 2020; Müller and Burkhard, 2012). These findings are consistent with Costanza and Kubiszewski (2012) who reported that only eight authors published at least five (5) papers on urban ESs in sub-Saharan Africa over the last decades (2000 to 2009). The increasing ESs studies in sub-Saharan Africa could be attributed to the increasing requirement of knowledge referring to the balance between the rapid growths of impervious surfaces brought by urbanisation and urban vegetation cover that balance urban ecosystems and offset carbon emission (Mngumi 2020, Egoh et al. 2012, Müller and Burkhard 2012). Thus far, most of the reviewed studies focused on urban ESs derived from indigenous forests (Kaoma and Shackleton, 2015; Mashapa et al., 2014), wetlands (Schuyt, 2005), urban green spaces (Munien et al., 2015; Richardson and Shackleton, 2014) and agricultural areas (Padgham et al., 2015;

Stenchly et al., 2017). Generally, there is a dearth in the literature on urban reforestation initiatives in Africa.

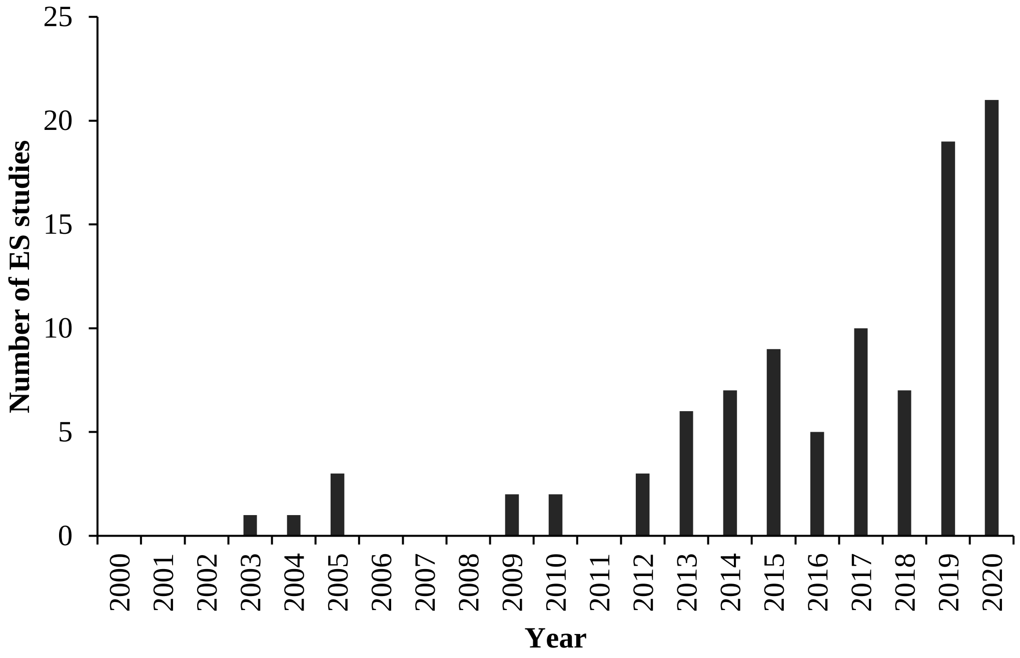


Figure 2.1: Number of studies published per year during the period of 2000 to 2020 on urban ecosystem services in sub-Saharan Africa.

This study found that 75% of the total urban ESs studies were conducted in South Africa, Zimbabwe, Zambia and Mozambique (Figure 2.2). The majority (52%) of the 75% studies were conducted in South Africa, attributable to higher levels of industrialisation, urbanisation and socio-economic development in relation to other sub-Saharan Africa countries (Vaughn and Ryan, 2006; Winkler, 2007). The remaining 25% of urban ESs studies were conducted in East and Central Africa; mostly in Ethiopia, Kenya, Ghana, Tanzania, Nigeria, Senegal, Burkina Faso and Uganda (Dieye et al., 2012; Girma et al., 2019; Hurford and Harou, 2014; Lompo et al., 2019; Moore et al., 2019; Scuderi et al., 2019; Wakuru, 2013; Zabbey and Tanee, 2016). Insufficient urban ESs studies in these countries could be associated with limited resources and investment to support such studies (Kumwenda et al., 2017). Furthermore, as shown in Figure 2.3, most of the urban ESs related studies in sub-Saharan African cities have been evaluated in eThekwini (South Africa), Harare (Zimbabwe), Nairobi (Kenya) and Dar es Salaam (Tanzania). These findings are consistent with Du Toit et al. (2018) who reported that most of the urban landscape ESs studies have been conducted in South African, Kenyan and Tanzanian cities. These cities are characterised by rapid growth of demographic and land use boundaries, encroaching and degrading ecosystem productive zones (Du Toit et al., 2018; Mulligan et al., 2020; Munien et al., 2015; Mushore et al., 2019), hence necessitating assessments. Conversely, there are other larger cities in sub-Saharan Africa such as Abuja in Nigeria, Bulawayo in Zimbabwe and Gaborone in Botswana among the others, without studies evaluating the status of their ecosystem services.

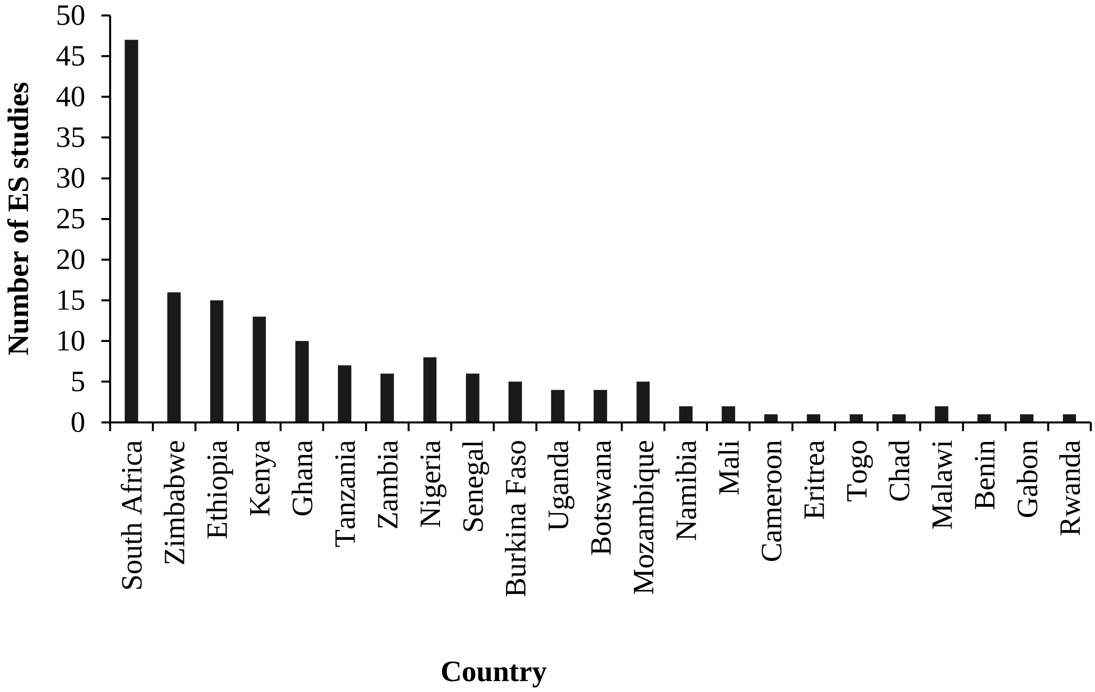


Figure 2.2: Number of studies on urban ecosystem services published from each country in the sub-Saharan Africa.

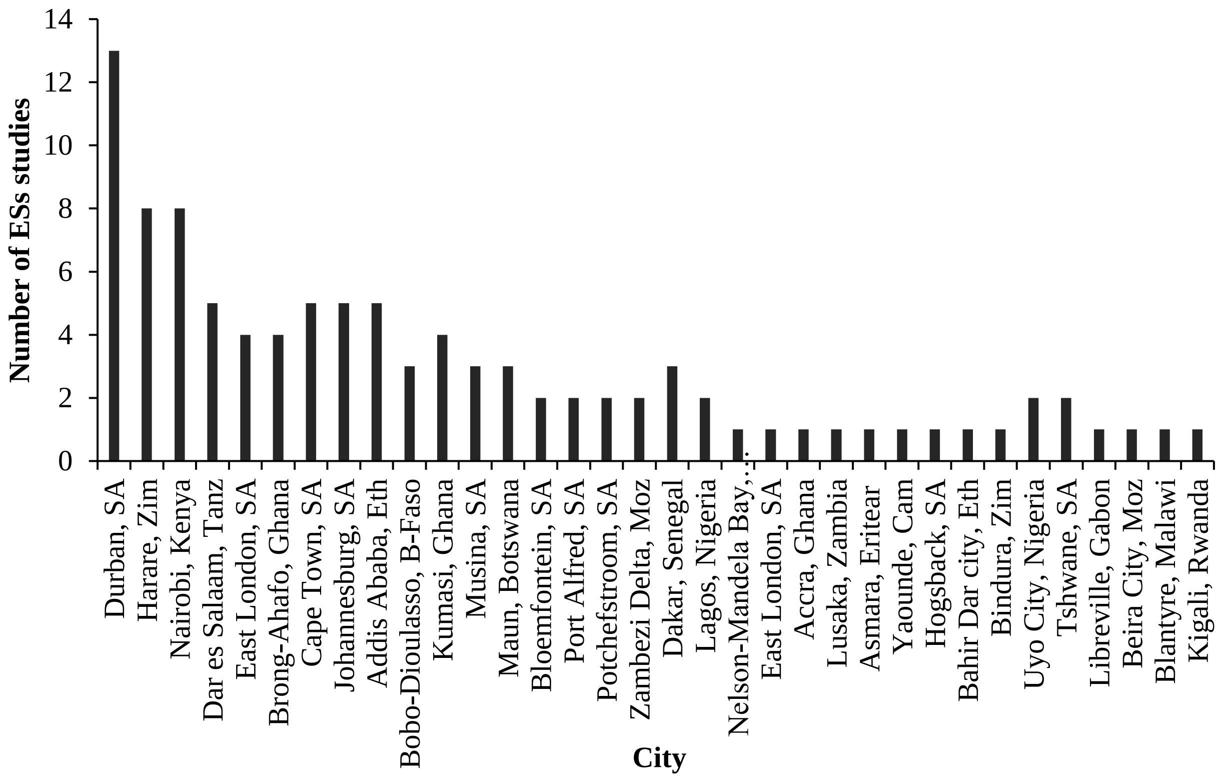


Figure 2.3: Number of ESs studies published from each city in the sub-Saharan Africa.

2.4 Quantification of urban ecosystem services

There has been a growing body of literature on urban ESs in relation to ecological (Escobedo et al., 2011; Pataki et al., 2011), economic (Jim and Chen, 2009; Sander et al., 2010) and socio-cultural benefits (Barthel et al., 2010; Mngumi, 2020). The increasing recognition and awareness of provisioning, regulating, supporting and cultural ecosystem services has been important for integrating ecosystem services into policy, planning and building climate change resilient and sustainable urban landscapes (Costanza and Kubiszewski, 2012; Mngumi, 2020). Such services rely on ecological processes and functions, which are scientifically measurable and quantifiable. Thus, the number of studies referring directly to urban ESs quantification has increased exponentially (Figure 2.4).

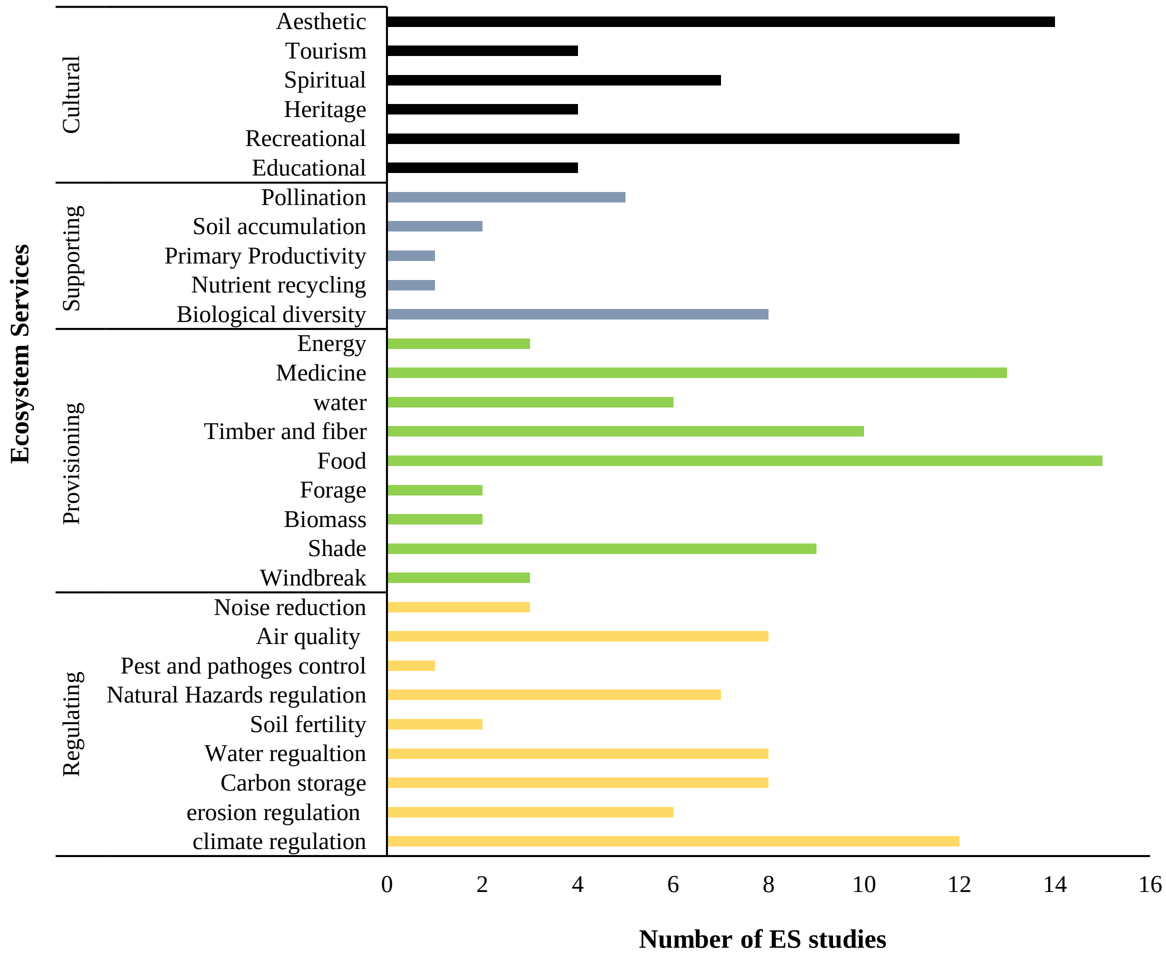


Figure 2.4: The number of studies published under the cultural, supporting, provisioning and regulating urban ecosystem services in sub-Saharan Africa.

Ecosystem Services in sub-Saharan Africa have been assessed using traditional approaches such as field data (Byrne et al., 2017; Scuderi et al., 2019), interviews (De Lacy and Shackleton, 2017) and questionnaires (Ward et al., 2010) covering categories such as provisioning, cultural and supporting (Figure 2.4). Meanwhile, key ES such as carbon storage or sequestration, air temperature, primary productivity and air quality have not been adequately assessed in sub-Saharan Africa. Such services are fundamental for decision making and policy adoption targeted to meet the requirement of REDD+ and Kyoto Protocol for climate change mitigation and adaptation. It is notable that ESs, which are critically important for maintenance and human welfare such as food, medicinal plants, timber and fibre, aesthetic and recreational values are extensively covered in literature.

Generally, the most common source of information and quantification technique in most studies has been based on traditional approaches, compared to remote sensing approach (Table 2.1). Although traditional approaches are highly accurate, they are costly, labour intensive, impractical in remote areas and at landscape scales and may lack spatial representativity. Therefore, they are not ideal for regional and immediate need for ESs assessment. Meanwhile, as aforementioned, remote sensing provides cheap and spatially explicit spectral information at a larger spatial extent, necessary for local and regional assessment of ecological processes and services. In this regard, there is need for more studies on urban ESs using cutting-edge remote sensing techniques to meet the REDD+ and sustainable objectives.

Table 2.1. Number of studies published based on each urban ecosystem service and the total number of studies that applied remote sensing in sub-Saharan Africa

Ecosystem services	**No. of studies**	**Traditional approaches**	**Remote sensing studies**
Regulating	41	5	36
Provisioning	20	17	3
Supporting	11	8	3
Cultural	18	18	-
Total	90	48	42

2.5 Use of remote sensing in quantifying urban ecosystem services

The adoption of remote sensing has been valuable for studying complex environmental phenomena based on social-ecological interactions (de Araujo Barbosa et al., 2015; Fatoyinbo et al., 2018; Sithole et al., 2018). Remote sensing techniques are often used in the quantification and mapping of ecosystem processes and functions such as carbon stock, air temperature, biomass and primary productivity (de Araujo Barbosa et al., 2015; Fatoyinbo et al., 2018; Sithole et al., 2018). It has the capability to provide accurate and up-to-date spatial and spectral records of earth features required for the quantification and mapping of urban ESs. With the emergence of new and improved products, remote sensing continues to contribute extensively to quantifying, mapping and evaluating ESs. Among the satellite borne earth observation sensors, conventional medium-to-coarse spatial resolution optical (passive) sensors such as Landsat series, MODIS and SPOT have been widely used to quantify natural ESs (Table 2.2). Most of these sensors images are freely available and are characterised by larger swath-width with short revisiting time, making them suitable for repeated acquisition of information needed for multi-temporal assessments of urban ESs. According to Dube et al (2016), the popularity of medium-to-coarse spatial resolution sensors such as Landsat could be explained by the large volumes of archived information dating back to 1972 during the first launch of Earth Resource Technology Satellite (ERTS-1), commonly referred to as Landsat. Hence, numerous urban ecosystem services studies in sub-Saharan Africa have been conducted using aforementioned satellite sensors, with reasonable accuracies (Dieye et al., 2012; Feyisa et al., 2014; Mushore et al., 2017; Odindi et al., 2017; Wangai et al., 2019).

Feyisa et al (2014), for instance, used Landsat-7 ETM+ derived bio-geophysical variables such as normalized difference vegetation index (NDVI) spectral properties to quantify land surface temperature in the parks-vegetation of Addis Ababa, Ethiopia. The study established that the cooling effect of urban parks was highly correlated to the NDVI-spectral data (R^2: 0.83) and *Eucalyptus* species had a higher cooling effect, thus regulating urban land surface temperature. Similarly, Mushore et al. (2017) predicted future distribution of land surface temperature in relation to the rapid urban growth using Landsat series (e.g. TM-5 and ETM-7) in Harare city, Zimbabwe. Their results demonstrated a high prediction coefficient (R^2: 0.98) and reliable classification performance (accuracy: 87-89%). They concluded that continuous urban expansion would increase land surface temperature in the near future. Dieye et al (2012) quantified soil organic carbon variation across different land use-land cover classes using the Landsat-7 ETM spectral profiles and achieved a 90.7% accuracy in Dakar, Senegal. Their findings showed a reasonable coefficient of determination of 0.60 between soil organic carbon and various land management practices. They concluded that the rich Landsat series archive provides cost-effective multi-temporal information for understanding urbanization and its impact on ecosystem services in an urban landscape. Chapungu et al. (2020) estimated aboveground biomass as a proxy of carbon stock using spectral vegetation indices derived from Landsat-7 ETM in Mashonaland Central city of Zimbabwe. Their results showed a significant relationship (p-value = 0.0386) between NDVI generated from Landsat-7 ETM and aboveground biomass, despite low coefficient of determination (R^2: 0.35). Their study deduced that Landsat-7 ETM derived NDVI between the red and near-infrared bands has great potential in assessing and monitoring biomass and carbon stock within urban landscapes. Based on these studies, there is a noticeable bias on the use of the Landsat series in understanding urban temperature and soil organic carbon in comparison to other ESs (e.g. carbon sequestration, primary productivity, water purification etc.) critical for climate change regulation and environmental risks control. Despite noticeable successes of Landsat series shown in these studies, there is a need for future research to explore the value of newly launched remote sensing satellite sensors with improved optical and thermal characteristics (i.e. spectral and spatial resolutions) that can detect green biomass and permit estimation of urban ESs across different types of plant species. Understanding the contribution of individual plant types into urban environmental quality and climate systems regulation is necessary for sound management and monitoring policies (Peerbhay et al., 2013a).

Furthermore, the use of MODIS data characteristics has been useful in understanding urban ESs. Using thermal values derived from the mid-infrared spectroscopic reflectance of MODIS imagery, Odindi et al (2017) for instance successfully estimated the implications of land use land cover change on urban thermal characteristics (R^2: 0.68-0.88) in eThekwini, Buffalo and Nelson Mandela Bay urban municipalities of South Africa. The study concluded that eThekwini Municipality was more vulnerable to increasing urban heat and climate change due to its high proportion of impervious surfaces. Similarly, Far et al (2015) estimated seasonal variation of foraging areas in urban landscape of Accra in Ghana using MODIS spectral wavebands. Despite the low regression coefficient (R^2: 0.38), the study successfully delineated changes in foraging areas between wet and dry season with a 95% confidence interval. These two studies highlight the significance and sensitivity of the freely available MODIS spectral-wavebands imagery for predicting and mapping air temperature and forage variability in urban areas. The strength and importance of MODIS in quantifying ecosystem services within urban landscape is also affirmed by studies outside sub-Saharan Africa. For instance, Boegh et al (2009) used spectral indices (i.e. NDVI) derived from MODIS imagery to model essential forest regulating services such as evapotranspiration and runoff fluxes in Sjaelland city, Denmark. Their study showed a reasonable relationship between simulated and measured evapotranspiration (R^2: 0.67 and RMSE: 0.18 mm day^{-1}) and a strong correlation between near-surface runoff and stream discharge (R^2: 0.73). Moreover, they found that urban forest ecosystems had a significant influence on evapotranspiration and runoff fluxes and deduced that MODIS derived spectral information can be used to understand important vegetation parameters and services. Fu et al (2013) evaluated net primary productivity variability in response to urban expansion in Guangzhou city, China using MODIS satellite data. Their results presented a rapid loss of carbon uptake potential ($167*10^6$ g. C) within six years, attributed to the conversion of vegetation cover into impervious infrastructure and settlements. These two studies illustrate the effectiveness and capability of MODIS data in modelling numerous ESs in urban environments. However, development in remote sensing technology has seen a shift from the utility of MODIS imagery to new generation sensors for urban ESs studies (Mushore et al. 2019, Potgieter et al. 2019, Simwanda et al. 2019).

Advancement in sensor technology has led to cheaper or freely-available data with optimal spectral properties suitable for urban ESs assessment and monitoring. Hence, there is a need to shift towards the adoption of newly launched, freely available and cost-effective multispectral sensors such as Landsat 8 OLI, SPOT-7 and Sentinel-2 multispectral instruments in urban ESs quantification and monitoring. Numerous studies have embraced the application of new generation multispectral sensors with improved spatial, spectral and radiometric resolutions (Dube and Mutanga, 2015b; Mngadi et al., 2019b; Mngadi et al., 2020). This has provided refined spectral data derived from plants biochemical and biophysical properties, which depicts and facilitates ESs quantification and mapping. Recently, newly generated space-borne sensors have been gaining popularity in urban forest ESs quantification and monitoring. Results in Table 2.2 show that only nine studies have quantified ESs using Landsat 8 OLI imagery in sub-Saharan Africa (Di Leo et al., 2016; Mushore et al., 2019; Odindi et al., 2017; Orimoloye et al., 2019; Simwanda et al., 2019; Sithole and Odindi, 2015). Majority of these studies quantified climate regulation services (i.e. land surface temperature) and noted that air temperature decreases with the increases in vegetation densities and increases in impervious and built-up structures. These studies demonstrated the sensitivity and effectiveness of Landsat 8's thermal wavelengths and NDVI derivation for delineating the cooling effect of vegetation in urban landscapes. Meanwhile, Orimoloye et al. (2019) investigated vegetation health and drought severity using vegetation indices generated from Landsat 8 OLI and normalized drought dryness index in the city of Cape Town, South Africa. The study discovered that spatial decrease in vegetation cover in favour of built-up increases near surface temperature and drought severity. They concluded that Landsat 8 OLI offers improved spatial and spectral information valuable for vegetation health and drought severity modelling in urban landscape.

Surprisingly, despite its unprecedented attributes relevant for ESs estimation, Landsat 8 OLI data has not been popular for assessing other important urban ESs such as carbon stocks and net primary productivity in sub-Saharan Africa. The robustness and reliability of Landsat 8 OLI in quantifying various urban ESs is further supported by studies outside sub-Saharan Africa (López-Serrano et al., 2020; Safari et al., 2017; Sakici and Günlü, 2018; Wolanin et al., 2019). Sakici and Günlü (2018) for instance, successfully predicted forest biomass and carbon stock using Landsat 8 OLI spectral variables in Kastamonu region of Turkey, obtaining reasonable prediction coefficient of determination (R^2: 0.65), while Walonini et al (2019) estimated forests net primary productivity using Landsat 8 OLI's derived spectral reflectance and achieved remarkable prediction performance (R^2: 0.82 and RSME: 1.97 gC $d^{-1}.m^{-2}$) in

Berlin, Germany. These studies deduced that freely available multispectral Landsat 8 OLI offers important spectral information critical for concise prediction and monitoring of forest ESs at both local and regional scales. Using SPOT-7 imagery, Potgieter et al. (2019) successfully estimated the variation in ESs productivity with an accuracy of 87.7% and coefficient value of 0.83 (Table 2.2) in Capetown, South Africa, which was much higher than the application of mixed-pixel MODIS data reported in literature. The unprecedented SPOT-7 performance could be explained by the sensor's sensitivity to the critical ecological properties such as chlorophyll concentration and leaf area index, which directly influence energy reflected in the visible and NIR regions of electromagnetic spectrum and higher spatial resolution.

According to Morfitt et al (2015), the spectral wavebands of new generation sensors record data with reduced atmospheric effects and high signal-to-noise ratio (SNR), which produces relatively pure and robust spectral reflectance data required for accurate quantification and mapping of ESs when compared to traditional sensors characterised by low signal-to-noise ratio. Traditional sensors are sensors on satellite platforms which have been upgraded over time, such as Landsat with 8 and SPOT with 7 imaging archives. Furthermore, some of the new and readily available multispectral sensors such as Sentinel-2 provide strategically positioned band settings such as those located within in the red-edge section of the electromagnetic spectrum, hence comparable to high spatial resolution commercial sensors such as WorldView-2 and RapidEye. The red-edge region has been proven to be sensitive to numerous vegetation leaf properties such as biomass, chlorophyll content and canopy structure, required for optimal quantification of ecological processes, structures and services (Mngadi et al., 2019b; Sibanda et al., 2016). Many studies have reported that sensors with red-edge configuration produce optimal overall performance when delineating vegetation. To the best of our knowledge, no studies have attempted to develop new indices from red-edge region of Sentinel-2 MSI to enhance urban ESs estimation and monitoring. Furthermore, sensors like Landsat 8 OLI and Sentinel-2 MSI cover the shortwave near infrared (SWIR) region, which is essential for the estimation of ecological processes and services.

Several studies have acknowledged the performance of SWIR wavebands for vegetation assessments (Mngadi et al., 2019b; Ramoelo et al., 2015; Wang et al., 2004b). This region reflects vegetation biochemical properties such as lignin, starch and nitrogen (Ramoelo et al., 2015; Wang et al., 2004b). Although new generation sensors like Landsat 8 OLI, Sentinel-2 and SPOT-7 VGT offer unprecedented opportunities for ecological assessments, very few studies have explored their potential. Thus, to fulfil the objectives of Intergovernmental

Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) as well as Kyoto Protocol that proposes continuous vegetation and its services monitoring, there is a need to explore their potential for quantifying and mapping a wide-range of urban ESs (i.e. carbon stock, primary productivity, biomass, water quality, amongst others), especially in sub-Saharan Africa.

Table 2.2. Application of remote sensing technique in urban ecosystem services and its performances from different studies in sub-Saharan Africa

Type of Sensor	No. ES studies	% avg. accuracy	% avg. error	Avg. R^2	Avg. coefficient	City
Active:						
Lidar (>15 cm)	2	87.7	23.85	0.84	0.88	Hout City and Asmara
Passive:						
Landsat ETM (30 m)	16	90.7	33	0.83	0.57	Harare, Addis Ababa, Dakar, Uyo City, Libreville, Nairobi and Mashonaland
Landsat 8 OLI (30 m)	14	93.9	19	0.86	0.71	Durban, Harare, Bobo-Dioulasso, Nairobi, Lagos, Addis Ababa, Lusaka and Johannesburg
SPOT (>5 m)	2	87.7	14.7	-	0.83	Hout City and Tshwane
MODIS (>250m)	5	84	2.4	0.62	0.75	Durban, Nairobi, Malindi, Mbita and Accra,
Sentinel (>10m)	4	71.7	-	0.72	0.82	Brong Ahafo, Hogsback
UAV-Drones (>0.5cm)	2	90	-	0.86	-	Aboabo

However, despite their robustness in vegetation assessments, passive space-borne sensors have major limitations, that include (1) the inability to provide information related to biophysical properties such as structural geometry, water/moisture content and surface roughness, (2) the lack of short-wavelengths that hinder penetration of thin clouds and dense canopy cover and (3) data acquired by passive/optical sensors is often restricted to aboveground biochemical attributes such as leaf area index and chlorophyll content due to low penetration-ratio. These challenges remain a serious impediment, especially in critical assessments and understanding of ecological dynamics of ESs associated with urban forests. The utility of active sensors such as Lidar and radar have been used to address the above-named limitations. Literature has shown that vegetation's bio-geophysical properties (i.e. height and structural attributes) could be easily extracted from Lidar or radar with remarkable accuracies (Lin et al., 2016; Shikwambana et al., 2019). Airborne Lidar's unique ability to characterise vegetation properties has attracted research interests in sub-Saharan Africa as proxy for quantifying and mapping ESs (Potgieter et al., 2019; Shikwambana et al., 2019). For instance, Potgieter et al (2019) successfully extracted height information of various forest ecosystem based on Lidar data to a high vertical accuracy of 87.7% and R^2: 0.84 as a proxy for assessing urban vegetation ecosystem productivity in Capetown, South Africa (Table 2.2). Their results demonstrated the strength of airborne Lidar data in overcoming cloud and shadow effects, while providing accurate information on vegetation structure, useful for assessing urban ESs.

Although active airborne sensors are highly accurate and provide robust geometric dataset, they are characterised by small spatial coverage (swath-width: 0.5cm-6m) (Table 2.3) that hinders concise wall-to-wall urban ESs quantification and mapping. Furthermore, the acquisition and mosaicking of airborne imageries (i.e. Lidar, radar and UAV-drones) is costly and cumbersome, hence their adoption could be a serious challenge to data scarce and financially constrained regions like sub-Saharan Africa. Hence, the new generation and freely available space-borne multispectral sensors (e.g. Landsat 8 OLI, Sentinel-2 and SPOT-7) remain the most viable and relatively affordable source of remotely sensed data in the region for characterising urban ES elements. To enhance the utility of new generation sensors data, there is need to integrate these datasets with ancillary information. Numerous studies outside Africa have shown that ancillary data improve the capability of remotely sensed data for optimal estimation of ESs (Lu et al., 2018; Maselli et al., 2009; Mondal et al., 2017). For example, Lu et al (2018) used Landsat data in conjunction with ancillary data (i.e. slope length and steepness, soil moisture, elevation and vegetation indices) to predict and map soil organic carbon. Their results showed high coefficient of determination (R^2: 0.909) and low RMSE (2.47 g kg^{-1}), concluding that ancillary data effectively improves remotely sensed data estimation capability. Similarly, Maselli et al (2009) evaluated a combination of SPOT-VGT and ancillary data to estimate primary productivity of water-scarce forest ecosystems in Lazio, Italy, and established that the combination significantly improves estimation performance (R^2: 0.67) of the model. These two studies demonstrate the importance of integrating remotely sensed and ancillary data to improve the estimation accuracy of the models.

Table 2.3. Sensors specifications and their integration with ancillary data for the assessment of urban ecosystem services in sub-Saharan Africa.

Satellite sensor	Spatial resolution and coverage	Ancillary data integration	Type of ES quantified	References
Lidar UAV-Drones	High (0.5cm-5m) Swath width (<50 km)	-	Aboveground biomass (AGB), ecosystem productive areas, net primary productivity (NPP)	(Potgieter et al. 2019 ; Fatoyinbo et al. 2018 ; Moore et al. 2019 ; Esmail and Geneletti 2017)
SPOT Landsat Sentinel-2	Medium (5m-100m) Swath width (60-290km)	NDVI, temperature, rainfall	High ecosystem productive areas, soil organic carbon, air temperature, flood, soil erosion, drought and biomass	(Potgieter et al. 2019; Sithole and Odindi 2015; Simwanda et al. 2019; Di Leo et al. 2016; Dieye et al. 2012 ; Feyisa et al. 2014 ; Guenat et al. 2019 ; Mushore et al. 2017 ; Mushore et al. 2018 ; Mushore et al. 2019; Odindi et al. 2015, Wangai et al. 2019)
MODIS	Coarse (250m-1000m) Swath width (2330 km)	Rainfall, NDVI, temperature, slope, EVI	Forage area, natural hazards control, air quality, air temperature and soil nutrient cycling	(Fahr et al. 2015; Winkler et al. 2017; Odindi et al. 2017; Boiyo et al. 2017)

2.6 Empirical techniques for assessing urban ecosystem services based on RS data

The findings of this review show that most of the RS based studies often use machine learning algorithm approaches for quantifying urban ESs as compared to other traditional approaches, such as statistical analysis (Figure 2.5). Machine-learning algorithms such as decision tree, maximum likelihood, random forest, gradient boosting and support vector machine shows that they have been widely used in urban ESs quantification. Reviewed literature show that most remote sensing based urban vegetation studies in sub-Saharan Africa often utilize the traditional maximum likelihood technique in the classification of vegetation species and structure (Moore et al., 2019; Potgieter et al., 2019; Simwanda et al., 2019; Sithole and Odindi, 2015). The maximum likelihood (ML) technique is known for its classic ability of separating between and within-classes with maximum statistical probability ratios and variances (Sisodia et al., 2014; Sun et al., 2013). Studies that used the conventional maximum likelihood technique for urban ESs mapping obtained high overall accuracies ranging between 73.85% and 90% (Moore et al., 2019; Potgieter et al., 2019; Simwanda et al., 2019).

However, conventional techniques such as ML can be heavily biased at plot-level estimation, and the integration of ancillary data could reduce the likelihood of a normal distribution, while increasing the error rate due to overfitting (Sisodia et al., 2014). Therefore, improving urban ESs quantification and mapping requires adoption of robust and advanced algorithms capable of overcoming problems of overfitting and producing optimal classification or regression models. Such non-parametric algorithms include decision tree, random forest, gradient boosting and support vector machine, which have often been used for analysing remotely sensed data with optimal accuracies (Dieye et al., 2012; Hengl et al., 2017). For example, the average error rate exhibited by nonparametric algorithms such as decision trees in characterising land cover/use for soil organic carbon assessment is below 2%, whereas ML exhibited 10% error rates. Also, some of the powerful and reliable machine learning algorithms which could be effectively used for urban ESs quantification and mapping include the artificial neural network (Linderman et al., 2004) and linear discriminant analysis (Calviño-Cancela and Martín-Herrero, 2016; Mngadi et al., 2020). These techniques have been successfully used in mapping vegetation elements such as structure, biomass and species productivity (Mngadi et al 2020, Mugiraneza et al 2019, Linderman et al. 2004). In a related study, Mugiraneza et al (2019) used a support vector machine to map land cover dynamics and their impacts on rural ESs, obtaining an overall accuracy of 87%. Mngadi et al (2020) applied linear discriminant analysis to discriminate commercial forest species and achieved 88.9% accuracy. The robustness of these algorithms lies in their ability to pick up covariances that are associated with vegetation elements, which vary in space and time without overfitting the models. These abilities include bagging and bootstrapping operations stochasticity as well as numerous iterations which facilitate rigorous data mining required to optimally characterise ESs elements with high accuracies (Ganjisaffar et al., 2011; Sun and Pfahringer, 2012). Furthermore, these algorithms have the ability to select optimal spectral variables suitable for vegetation mapping using variable importance in projection (VIP) techniques when compared to traditional RS techniques (Calviño-Cancela and Martín-Herrero, 2016; Odebiri et al., 2020b). Although the emerging algorithms optimally perform and yield better accuracies in quantifying ESs, there is no standard technique that has been proven to be optimal for mapping specific ESs at various spatial and temporal scales. Therefore, there is need to evaluate the utility of most robust algorithms in estimating urban forest ESs in sub-Saharan Africa.

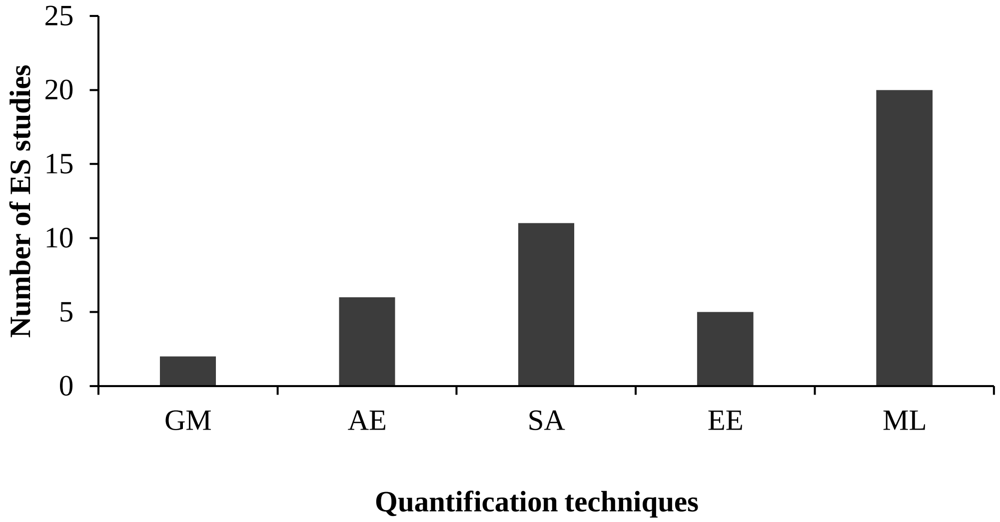


Figure 2.5. Quantification techniques that has been often used for assess urban ecosystem services using remote sensing data in sub-Saharan African (GM: Generalized models, AE: Allometric equations, SA: Statistical Analysis, EE: Energy Equations, ML: Machine Learning).

2.7 Challenges of quantifying urban ecosystem services

Although very high spatial resolution airborne sensors such as Lidar and UAV-data produce accurate ESs estimations, their application has been limited to only small areas (plot-scale) due to small spatial coverage and high image acquisition cost (table 2.2). Thus, high spatial resolution airborne sensors are best suited for local-scale, rather than concise wall-to-wall estimations of urban ESs at large spatial extent as required by REDD. Despite the advancement in the spatial and spectral characteristics of new generation multispectral sensors, most push-broom scanners (e.g., Landsat 8 OLI and SPOT series) suffer from mixed-pixel issues, which hinders accurate quantification and mapping of urban ESs (Basuki et al., 2012; Carreiras et al., 2012). Literature indicates that along track scanners record signals from a mixture of surfaces (i.e. bare soil, shadow cast and canopy) due to larger pixel-size, resulting in the spectral confusion and higher possibilities of misclassification (error of commission) and inaccurate prediction models (Basuki et al., 2012; Carreiras et al., 2012; Matongera et al., 2018). In addition, the establishment of standardized and effective techniques that permit integrated delineation of ESs supply and benefits (or demand) to human welfare remains a major challenge, despite the need to provide comprehensive information based on the links between where services are produced and consumed by beneficiaries. Recently, many studies have emphasised the requirement of adopting reliable and practical techniques that can permit integrated assessment of socio-ecological interdependences around urban landscape as numerous off-site benefits may be difficult to determine using remote sensing technology (de Araujo Barbosa et al., 2015; Grêt-Regamey et al., 2015; Tallis and Polasky, 2009).

2.8 Remote sensing prospects for quantifying urban ecosystem services

Although numerous studies have assessed ESs using remote sensing spectral information in sub-Saharan Africa, these assessments have focused on natural (Simwanda et al., 2019) and commercial forests (Dube and Mutanga, 2015b, c; Odebiri et al., 2020b) outside urban landscapes. To the best of our knowledge, there are very few studies, if any, which have characterised ESs associated with urban reforestation activities. This is despite the increasing concern and need for knowledge on the impact and contribution of urban reforestation to the global carbon cycle and climate regulation (Mugwedi et al., 2017). It is therefore necessary for future studies to focus on the quantification and mapping of ESs in reforested areas using remote sensing techniques. To achieve this, new and readily accessible multispectral sensors such as Landsat 8 OLI, Sentinel-2 and SPOT-7, with enhanced spatial, spectral and radiometric capabilities could be useful in characterising ESs elements from reforested areas.

Despite the aforementioned limitations, reliable operational machine learning algorithms with robust data processing capacities such as random forest, stochastic gradient boosting and linear discriminant analysis can be used to optimize freely and readily available new generation sensors (e.g. Landsat 8 OLI, Sentinel-2 and SPOT-7). These machine-learning algorithms, in concert with freely and readily accessible earth observation data have exhibited reliable accuracies (Dube and Mutanga, 2015c; Mngadi et al., 2020; Odebiri et al., 2020b). These models could also be improved by integrating ancillary biophysical (e.g. environmental variables, climatic variables and leaf areas index) and bio-geochemical variables (e.g. chlorophyll content). Furthermore, the exploitation of Sentinel's (i.e. Sentinel-1 and 2) data is still lacking in the assessment of urban landscape ESs in sub-Saharan Africa. A Sentinel-1 (SAR) and Seninel-2 hybrid provides reliable datasets that facilitate robust ecological mapping with unprecedented accuracies (Balzter et al., 2015). For instance, Sentinel-1 provides data related to biophysical properties (e.g. structural geometry, roughness and water/moisture content), while Sentinel-2 captures data based on biochemical characteristics (e.g. pigment, chlorophyll) (Balzter et al., 2015). In sub-Saharan Africa, most studies have used Sentinel data for land use land cover characterisation and general vegetation assessments (del Río-Mena et al., 2020; Guenat et al., 2019), rather than quantifying specific urban ESs such as carbon stock, air temperature and primary productivity. Thus, there is a need for future studies to explore the effectiveness of Sentinel datasets for specific urban ESs estimation (e.g. aboveground carbon/sequestration, net primary productivity). There is also a need for future research to establish and evaluate new and unique red-edge indices to strengthen the quantification accuracy of urban ecological processes and services in sub-Saharan Africa cities. In addition, future research should explore Sentinel-2's red-edge inflection point for optimal urban ESs quantification.

Furthermore, future studies can also improve the application of Landsat 8 OLI in quantifying ESs within urban landscape using pan-sharpening technique. Landsat images provide panchromatic data with better spatial resolution (15 m) which can be used to enhance multispectral data for ESs estimation. Pan-sharpening is an image enhancement technique in which a panchromatic data is fused with medium spatial resolution multispectral data to produce an image with higher spatial resolution characteristics (Mngadi et al. 2019). Despite reliability of pan-sharpening technique in generating high spatial resolution image, the fusion of panchromatic data and Landsat 8 OLI multispectral image for urban ESs estimation has not been explored. In addition, the integration of Landsat and MODIS datasets using spatial and temporal adaptive reflectance fusion model (STARFM) can effectively increase both spatial and temporal resolutions of MODIS image dataset for urban ESs quantification.

The utility of cost effective Unmanned Ariel Vehicles (UAVs) also known as drones in urban ESs quantification in sub-Saharan Africa is still at infancy. UAVs provide high-spatial resolution imagery with less clouds and haze interference, suitable for accurate quantification of urban ESs (Moore et al., 2019). Thus, the utility of UAVs in the quantification of urban ESs require extensive evaluation. In addition, quantifying a full range of ESs using the imagery as a stand-alone dataset is not sufficient. Thus, future research needs to shift towards integration of earth observation (i.e. remote sensing) data with social evaluation methods derived data to understand the complexity of socio-ecological interdependences (i.e. interviews and indigenous knowledge). This could be a practical and reliable approach for a holistic and well-informed decision-making and policy implementation in the African urban forests.

2.9 Conclusion

The current study sought to review the trajectory of remote sensing application on urban ESs quantification and mapping in sub-Saharan Africa. Although remote sensing has shown remarkable potential and capability in quantifying and mapping urban ESs, this work demonstrates that most of studies often use conventional methods when compared to remote sensing related techniques. Despite their reliability, conventional methods are costly, labour intensive and logistically impractical in remote areas and landscape scales, hence their application is limited to only small-scale assessment. Meanwhile, a few remote sensing based studies demonstrate that its techniques offer spatially explicit information covering various spatial extents, necessary for local to regional scale urban ESs assessments. The utility of medium spatial resolution multispectral sensors has proven successful and useful in quantifying urban forest ESs elements with unprecedented accuracies, regardless of their mixed-pixels and saturation limitations. Their data is cheaper and readily available, hence ideal for immediate requirement of urban forest ESs information, especially in resource scarce and financially constrained regions like sub-Saharan Africa. The use of airborne sensors is still a challenge in sub-Saharan Africa. This is due to their high image acquisition costs and small spatial extent coverages, which limit their application at regional scales. Furthermore, studies outside Africa have shown that the utility of multisource data sets such as remotely sensed and ancillary data (weather and topographic data) can greatly improve the estimation and characterisation of urban forest ESs elements, especially when using freely available multispectral datasets. Therefore, the application of integrated multisource data needs further investigation in assessing sub-Saharan Africa's urban forest ESs, especially in reforested areas. Deriving accurate information on urban ESs using spatially explicit techniques such as remote sensing techniques is critical for well-informed decision-making and policy adoption for ensuring sustainable utilisation and resilience of urban ecosystems in sub-Saharan Africa.

2.10 Summary

Literature have explicitly revealed unprecedented capabilities of remote sensing information in estimating and monitoring urban ES's. Despite numerous studies predominantly addressing the importance of regulating ES (i.e., net primary productivity and carbon stock), such studies focused on natural and commercial forest ecosystems. To date, the contribution of reforested trees in carbon cycle and climate regulation (particularly net primary productivity contribution) have remain unknown. In this regard, Chapter 3 estimate net primary productivity of reforested trees based on biophysical parameters and remotely sensed information.

Chapter Three: Estimating aboveground net primary productivity of reforested trees in an urban landscape using biophysical variables and remotely sensed data

This chapter is based on:

Mngadi, M., Odindi, J., Mutanga, O. and Sibanda, M., 2022. Estimating aboveground net primary productivity of reforested trees in an urban landscape using biophysical variables and remotely sensed data. *Science of The Total Environment, 802,* p.149958.

Abstract

Recently, urban reforestation programs have emerged as potential carbon sinks and climate mitigates in urban landscapes. Thus, spatially explicit information on net primary productivity (NPP) of reforested trees in urban environments is central to understanding the value of reforestation initiatives in the global carbon budget and climate regulation potential. To date, numerous studies have mainly focused on natural and commercial forests NPP at a regional scale based on coarse spatial resolution remotely sensed data. Generally, local scale NPP studies based on fine spatial resolution data are limited. Therefore, this study sought to estimate aboveground NPP of an urban reforested landscape using biophysical and Sentinel-2 Multispectral Imager data derived variables. Using the MOD17 model, results showed that mean NPP ranged between 6.24 Mg C ha^{-1} with high coefficient of determination (R^2: 0.92) and low RMSE (0.82 Mg ha^{-1}) across all reforested trees within the study area. Results also showed a considerable variation in NPP among the reforested trees, with deciduous *Acacia* and *Dalbergia obovate* species showing the highest NPP (7.62 Mg C ha^{-1} and 7.58 Mg C $ha^{-1,}$ respectively), while the evergreen *Syzygium cordatum* and shrub *Artemisia afra* had the lowest NPP (4.54 Mg C ha^{-1} and 5.26 Mg C ha^{-1}). Furthermore, the multiple linear regression analysis showed that vegetation specific biophysical variables (i.e. leaf area index, Normalized Difference Vegetation Index and Fraction of Photosynthetically Active Radiation) significantly improved the estimation of reforested aboveground NPP at a fine-scale resolution. These findings demonstrate the effectiveness of biophysical and remotely sensed variables in determining NPP (as carbon sequestration surrogate) at fine-scaled reforested urban landscape. Furthermore, the utility of species biometric measurements and MOD17 model offers unprecedented opportunity for improved local scale reforestation assessment and monitoring schedules.

Keywords: photosynthetic active radiation, carbon flux, MOD17, species

3.1 Introduction

Increased atmospheric carbon concentration due to anthropogenic activities has raised serious concerns on the global land surface energy balance and the changing climate system (Moore et al., 2019). Thus, terrestrial ecosystems such as forests have been noted as key in sequestrating considerable amounts of atmospheric carbon; counteracting the impact of climate change (Ahl et al., 2004; Verma et al., 2015). In this regard, estimation, mapping and monitoring of forest benefits such as NPP are central to global climate modelling due to their importance in net carbon accumulation. Specifically, information on NPP is central to understanding the rate of vegetation carbon uptake through photosynthetic process and other consumptive and non-consumptive ecosystem goods and services (Pachavo and Murwira, 2014; Ruimy et al., 1994; Turner et al., 2005; Zhao et al., 2005). However, natural landscape transformation into urban environment has been considered a major driver of global environmental change (Odindi and Mhangara, 2012a; Sithole et al., 2018). Such landscape transformation is often linked to increasing atmospheric greenhouse gases and climate change related impacts. Although urban areas cover small land-surface, they account for considerable volumes of carbon emissions around the world due to higher energy and resource consumption (Luederitz et al., 2015). Generally, urbanization contributes to extreme deforestation and forest degradation, changing the dynamics of energy flow between biosphere and atmosphere, while posing serious constrains on carbon sequestration potential (Chagas et al., 2019; Cho et al., 2012; Murthy et al., 2002). Literature has revealed that forest loss and degradation constitute approximately 12% of the world greenhouse gas emissions, resulting in rapid global climate change (Cho et al., 2012; Ernst et al., 2013; Saatchi et al., 2011). This has raised serious concerns attributed to the long-term strategy and policy framework for reducing carbon emissions and climate change effects. Consequently, urban reforestation (plantation of native trees to enhance regeneration of natural vegetation) has emerged as the most effective approach for offsetting carbon emissions and regulating climate change impacts and risks. Furthermore, the Reducing emissions from deforestation and forest degradation (REDD+) and Kyoto Protocol have emphasized that reforestation is the most viable long-term and low-cost initiative for reducing the impact of greenhouse gas emissions on the global climate systems, particularly in developing regions such as Africa (Curiel-Esparza et al., 2015; Gara et al., 2016; Trotter et al., 2005). Despite the need for spatio-temporal information on carbon dynamics in urban reforested trees to inform decision making and adoption of sound policies for monitoring and management of urban forest ecosystems and their services, the magnitude of carbon uptake by reforested trees in Africa's urban landscapes remains largely uncertain. In this regard, timely and precise estimation of NPP is important for understanding the contribution of urban reforestation initiative in the global carbon cycle.

Furthermore, the conceptual understanding of NPP is based on energy flow within the ecosystems (Goetz and Prince, 1996; Zhu and Southworth, 2013). For instance, green plants in an ecosystem absorb considerable amount of incident photosynthetically active radiation (PAR) (between 400-to-700 nm wavelengths), which is either re-radiated or stored in organic substances during photosynthetic process (Sala and Austin, 2000). Thus, the amount of energy stored in organic matter of plant tissues represent the productivity. Literature indicates that large amounts of energy accumulated in plant biomass constitute 50% of carbon stock as dry mass per unit area per year (g C m^{-2} yr^{-1}) (Dube and Mutanga, 2015c; Hu et al., 2015a; Pitman, 2000), hence, absorbed energy in ecosystems is critical for NPP quantification. According to Ahl et al (2004), NPP has a linear relationship with absorbed photosynthetic active radiation (APAR) on the basis of light-use efficiency (LUE) conversion approaches. However, different vegetation plants may have varying energy absorption indices due to differences in leaf structure influencing carbon uptake and productive capacity. For instance, Goetz et al (1999) reported that LUE for estimating NPP using APAR could not be reliable for different functional plant types due to varying relative respiratory capacity. In this regard, understanding the contribution of different tree plants in the global carbon flux budget, especially in reforested areas is central for planning large scale projects and meeting the demand of Kyoto Protocol that aim to counteract climate change.

Net Primary Productivity cannot be directly measured or observed in the field. This necessitates development of models that integrate vegetation biophysical factors and atmospheric dynamics. Commonly, APAR and LUE, among other vegetation parameters are integrated into NPP models. APAR is a product of the fraction of phytosynthetically active radiation (fPAR) (which is derived between the spectral reflectance of near-infrared and red-band as a function of normalized difference vegetation index-NDVI) and sum of in-situ measurements of photosynthetically active radiation (PAR). LUE on the other hand is derived from meteorological data (i.e. temperature) obtained from biome properties look-up table. Models that permit consolidation of remotely sensed vegetation parameters offer invaluable information for estimating and monitoring spatio-temporal variation of ecosystems primary productivity (Turner et al., 2005; Zhao et al., 2005). This is because remote sensing provides robust spectral reflectance based on greenness' critical for measuring vegetation health and productivity, which does not require extensive field work. Moderate Resolution Imaging

Spectroradiomer (MODIS) MOD17 algorithm is one of the most reliable models used to integrate remotely sensed information and ecological biophysical dynamics (Robinson et al., 2018; Sims et al., 2008; Smith et al., 2016). The model is designed for global estimation and monitoring of ecological functions, and currently the only regular model used for NPP estimation and monitoring (Robinson et al., 2018; Zhu and Southworth, 2013). Furthermore, MOD17 estimation of NPP depends on the interaction between solar radiation and plants canopy, and is known to be the canopy photosynthesis model that converts absorbed photosynthetic active radiation into carbon flux using LUE (Heinsch et al., 2003; Smith et al., 2016; Zhao et al., 2005). Although MOD17 model has been frequently used at broad spatial-scale, its application is not restricted to coarse resolution information such as 250 m MODIS products (Robinson et al., 2018). This is because the spatio-temporal variability of NPP across landscapes occurs at multiple scales (ranging from small-to-broad). MOD17 model permits integration of photochemical reflectance index (PRI) derived from narrow-wavebands (e.g. 530-570 nm) as a surrogate of LUE (Lin et al., 2019; Pachavo and Murwira, 2014) and aforementioned APAR. In urban landscapes, numerous ecosystem processes and production often occur at fine resolutions, thus coarse resolution remotely sensed imagery such as MODIS is not best suited for evaluating fine-scale ecological processes and impacts. To effectively improve assessment and monitoring of NPP, there is need to adopt high resolution remote sensing datasets that permit fine-scale evaluations and monitoring of vegetation characteristics and dynamics.

The emergence of high resolution sensors like Sentinel-2 multispectral imager, with a minimum spatial resolution of 10m has shown promising capability in ecological assessment and monitoring with high leaf chlorophyll absorption index and vegetation senescing (Mngadi et al., 2019b; Wolanin et al., 2019). Sentinel-2 is characterized by its improvement on the spatial (10, 20, 60 m), spectral (443–2190 nm) and radiometric (12-bit) resolutions, including high temporal resolution (5-day revisit time), important for frequent and precise mapping and monitoring of vegetation characteristics. The sensor is characterized by 13 strategically positioned spectral wavebands within the electromagnetic spectrum, including additional red-edge bands, valuable for vegetation modelling at fine spatial-scale. According to Robihnson et al (2018) MOD17 model allows replacement of coarse input datasets with fine-resolution datasets, hence Sentinel-2 spectral wavebands-reflectance and locally measured biophysical variables can be adopted in the model. Robinson et al (2018) for instance, replaced global biome input variables obtained from biome parameter look-up table (BPLUT) with finer resolution (30 m) Landsat 8 OLI spectral information in MOD17 model to estimate NPP variability at small-scale. Similarly, Chagas et al (2019) used spectral information derived from Landsat 8 OLI and MOD17 model to estimate gross primary productivity. These studies demonstrate the flexibility of the model to allow multiscale resolutions assessment. Fine-scale ecological assessments such as urban landscape reforested trees are critically important for species-specific NPP estimates rather than biome-specific evaluation at broad scale. Thus, the application of Sentinel-2 could be used to reliably estimate tree species-specific NPP variability within urban landscape due to fine spectral and spatial attributes. Therefore, this study sought to estimate aboveground net primary productivity of reforested trees in an urban landscape using fine resolution Sentinel-2 remote sensing and biophysical variables (i.e. PAR). Since NPP cannot be directly derived, this study adopted the MOD17 model and validated the estimated NPP using field measured vegetation-specific biophysical variables such as leaf area index and chlorophyll concentration. Other essential predictor variables based on vegetation greenness (i.e. NDVI and enhanced vegetation index-EVI) and fPAR were generated from a remotely sensed Sentinel-2 image.

3.2 Material and methods

3.2.1 Field data collection

Field datasets were collected between 21st and 25th of February 2020. During this period, climatic conditions (i.e. temperature and rainfall) were favourable for maximum biomass productivity and vegetation health. In this study, we established 130 random sample points, which were inserted into a GPS and used as way points to navigate to the sites. From each point, a 10m x 10m plot-window was adopted and numerous biophysical (i.e. photosynthetic active radiation and leaf area index) and biochemical (i.e. chlorophyll concentration) variables measured at a species-level within the plot. The photosynthetic active radiation (PAR) was recorded using quantum sensor (ACCU-PAR-LP80) - Decagon Devices Inc. version Dec 13 2013, with different species capturing varying absorption indices. Tree species chlorophyll concentration and leaf area index parameters were recorded using Chlorophyll Meter SPAD-502Plus and Light Sensor Logger (LI-COR-1500). The structural attributes of trees required for understanding aboveground biomass such as height (H) and diameter at breast height (DBH) were also measured using clinometer and tree Haglof Digitech Calliper instruments. The allometric model that consolidate tree height and diameter was utilized to generate in-situ AGB productivity estimates, which was used to train and assess the accuracy of remotely sensed estimates of net primary productivity. Literature indicates that approximately 50% of tree biomass (as dry mass) comprise of carbon, hence we used the factor of 0.5 to convert biomass into in-situ carbon stock, which was utilized as surrogate for primary productivity (Dube and Mutanga, 2015c; Hu et al., 2015b; Tang et al., 2016). The location of each tree was captured using Trimble global positioning system (GPS). Furthermore, climatic data (i.e. temperature and rainfall) acquired from the South African Weather Services (SAWS) was used.

3.2.2 Image acquisition and pre-processing

A cloud free Sentinel-2 MSI image acquired on the 01st of April 2020 was downloaded from the European Space Agency (ESA) portal (https://scihub.copernicus.eu/dhus/#/home). The sensor consists of 13 spectral bands from the visible including the red edge, NIR and SWIR sections of the electromagnetic spectrum positioned between 10 m, 20 m, and 60 m spatial resolutions. The image was atmospherically and radiometric corrected using First Line-of-sight Atmospheric Analysis Hypercube (FLAASH) embedded in ENVI (64-bit) software where radiance values were transformed into reflectance.

3.2.3 Modelling approach

Although NPP is established through the difference between carbon gain during gross photosynthesis and carbon lost through autotrophic respiration (Ra), estimating NPP through this difference remains a significant challenge. This is due to uncertainties associated with estimation of autotrophic growth and maintenance respiration (Clark et al., 2001). Despite few studies indicating progress in estimating respiration, challenges related to the quantification of critical plant tissues (i.e. leaves, roots, stem and canopy structure) remain formidable (Waring et al., 1998). Thus, the use of absorbed photosynthetic active radiation based-model for simulating carbon flux, which determines gross and net primary productivity, remains the most reliable and precise approach. In this study, we estimated NPP (Mg C ha^{-1}) using modified MOD17 model following Pachavo and Murwira (2014) and Rahman et al (2004) approaches expressed by equation:

$$NPP = 0.5139(PRI * APAR) - 1.9818 \quad (3.1)$$

Where PRI represent photochemical reflectance index and APAR refers to the absorbed photosynthetic active radiation by vegetation canopy, while 0.5139 and 1.9818 are constants. The absorption of photosynthetic active radiation (APAR) by vegetation canopy is directly related to the total amount of carbon (C) sequestered during photosynthesis process, thus the estimates of APAR is linearly related to gross primary production (GPP). Literature indicates that photosynthetic response of APAR is an important driver of simulated carbon stock, which is expressed as grams of C per unit of APAR. In this study, the APAR was estimated following Pachavo and Murwira (2014) and Goetz et al (1999) equations:

$$APAR = fPAR * \Sigma PAR \quad (3.2)$$

Where fPAR refers to the fraction of absorbed photosynthetic active radiation stored into organic dry matter and PAR is the incident photosynthetically active radiation. FPAR is an important photosynthetic biophysical variable, which is related to normalized difference vegetation index (NDVI) through the absorption and reflection of radiative light-wave in the visible region of the electromagnetic spectrum by vegetation foliage (Ruimy et al., 1994). Therefore, fPAR was estimated using NDVI reflectance derived from Sentinel-2 near infrared (NIR) and Red bands (i.e. b4 and 8) located in the visible region;

$$fPAR = (1.24 * NDVI) - 0.168 \quad (3.3)$$

Where; $NDVI = \left(\frac{NIR-Red}{NIR+Red}\right)$

The daily incident photosynthetic active radiation was directly measured on-site during field survey. Furthermore, the estimation of APAR necessitates determination of photochemical reflectance index (PRI), which is used as surrogate of LUE (Pachavo and Murwira, 2014; Rahman et al., 2004). LUE is a significant relative constant used in many NPP models for estimating and converting APAR into carbon flux, while PRI measures reflectance variability in the carotenoid pigments such as xanthophyll pigments (Pachavo and Murwira, 2014). Literature indicates that carotenoid pigments are essential indicators of LUE, and could be used to assimilate the rate of carbon uptake by vegetation per unit of absorbed energy (Rahman et al., 2004). In remote sensing, PRI is derived from narrow-bands (i.e. 530-570 nm) spectral reflectance, which are critical indicators of photosynthetic efficiency (Pachavo and Murwira, 2014). Thus, in this study, PRI was estimated from Sentinel-2's band 2 (blue: 458-523 nm) and band 3 (green: 543-578 nm) reflectance. These spectral wave-bands are significantly sensitive to leaf chlorophyll absorption, carotenoids and vegetation senescing. Following Pachavo and Murwira (2014) and Rahman (2004) formulation, we estimated PRI using equation:

$$PRI = [0.53 * \left(\frac{rband3-rband2}{rband3+rband2}\right) + 1] \div 2 \quad (3.4)$$

3.2.4 Statistical analysis

The relationship between estimated aboveground net primary productivity and predictor variables was tested using multiple linear regression (MLR) analysis in r-studio (version 3.5.3). However, we first evaluated the spatial autocorrelation of net primary productivity using *Moran's I* test (Legendre, 1993) and there was no spatial correlation on the data. We also tested collinearity between predictor variables using variance inflation factor (VIF) and all variables produced VIF values less than 10 (Gara et al., 2016), hence no collinearity existed between predictor variables. In this study, the estimated aboveground net primary productivity was recognized as response variable in all regression analyses, while LAI, NDVI, EVI, fPAR, APAR, Chlorophyll content and PRI were assigned as predictor variables. Based on the descriptive statistical p-value ($\alpha \leq 0.05$), we identified predictor variables which significantly improved prediction performance of aboveground productivity.

3.2.5 Accuracy assessment

The coefficient of determination (R^2) and root mean square error (RMSE) based on multiple linear regression analysis were utilized to validate model performance in estimating species-specific aboveground NPP. Generally, high R^2 and low RMSE values illustrates good model performance (Pachavo and Murwira, 2014). In addition, the estimated species-specific NPP in this study was further validated against biome-specific NPP at regional-scale found in literature using an African context model. The results were compared at forest type level, where the average NPP estimated from reforested deciduous trees (i.e. *Acacia caffra, Acacia robust, Bridellia microntha* and *Albizia adianthofolia*), evergreen trees (i.e. *Syzygium cordatum* and *Silver oak*) and shrub trees (i.e. *Artimisia afra*) were correlated against the literature derived NPP values for the respective forest trees.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}} \qquad (3.5)$$

Where y_i represent observed values, while $\hat{y}_i$ representing predicted values and n the number of data points.

3.3 Results

The overall mean of estimated NPP obtained within reforested landscape was 6.23 Mg C ha^{-1} with the estimation accuracy (R^2) of 0.92 and RMSE of 0.82 Mg ha^{-1} (14.7%) based on

MOD17 model using Sentinel-2 MSI image data (Table 3.1). For individual tree species, deciduous trees such as *Acacia caffra* and *Dalbergia obovate* yielded higher NPP between 7.58 and 7.62 Mg C $ha^{-1}$with accuracy performance (R^2) of 0.83 and 0.98 , and error rate (RMSE) of 1.77 Mg ha^{-1} (25.9%) and 0.47 Mg ha^{-1} (7.12%). The evergreen *Syzygium cordatum*, deciduous *Albizia adianthofolia* and shrub *Artemisia afra* species achieved lower NPP of 4.54 to 5.26 Mg C ha^{-1}, with the R^2 of between 0.95 and 0.99, and RMSE of 0.22 to 0.73 Mg ha^{-1} (17.9%).

Table 3.1. Aboveground net primary productivity and its relationship with measured AGB productivity of individual reforested tree species.

Forest type	**Species**	**Estimated NPP**	**Accuracies**	
		(Mg C ha^{-1})	**R^2**	**RMSE(Mg/ha)**
	Acacia caffra	7.62	0.83	1.77(25.9%)
	Acacia robusta	6.70	0.95	0.73(12.0%)
Deciduous trees	*Bridellia microntha*	6.09	0.72	1.79(32.4%)
	Albizia adianthofolia	4.98	0.99	0.22(4.87%)
	Dalbergia obovata	7.58	0.97	0.47(7.12%)
	Erythrina caffra	6.70	0.88	0.73(12.0%)
Evergreen trees	*Syzygium cordatum*	4.54	0.95	0.73(17.9%)
	Silver oak	6.70	0.95	0.75(12.3%)
Shrub trees	*Artemisia afra*	5.25	0.99	0.24(5.03%)
Overall mean	-	**6.24**	**0.92**	**0.82(14.7%)**

Among the seven variables used in the model, three predictor variable (i.e. LAI, NDVI and fPAR) obtained higher correlation performance and lower error rate (RMSE) against the observed aboveground biomass productivity (Table 3.2). Leaf area index (LAI) produced the highest correlation coefficient (0.71) and lowest RMSE (2.029 Mg ha^{-1}), followed by NDVI with R^2 of 0.57 and RMSE of 2.465 Mg ha^{-1}, whereas fPAR achieved R^2 of 0.54 and RMSE of 2.561 Mg ha^{-1}.

Table 3.2. Correlation performance of individual predictor variable in estimating aboveground net primary productivity.

Predictor variables	**R^2**
LAI	0.71
NDVI	0.57
fPAR	0.54
EVI	0.49
PRI	0.48
APAR	0.44
Chlorophyll	0.21

The predictor variables that were significantly important in the estimation of NPP achieved *p*-values of less than 0.05 (Figure 3.1). For instance, LAI, NDVI and fPAR generated *p*-value of between 0.01 and 0.00, and were considered optimal in the modelling of aboveground net primary productivity.

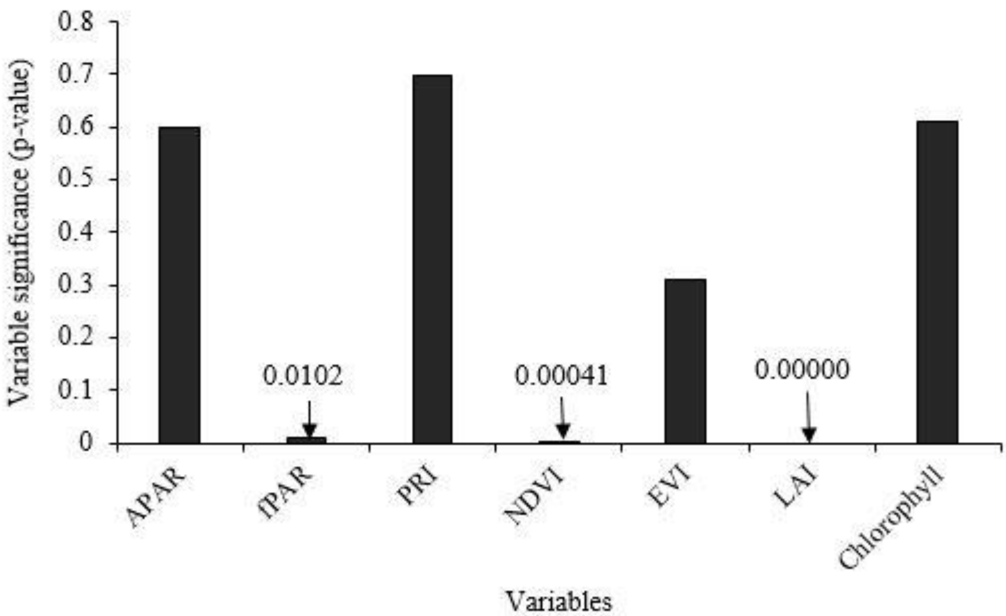


Figure 3.1. Significance of individual variables in estimating aboveground net primary productivity. The variables indicated with arrows were optimal and selected for the modelling of AG-NPP.

The correlation of LAI against estimated AG-NPP produced higher coefficient of determination (0.89) and lower RMSE (1.077 Mg ha^{-1}), NDVI against estimated AG-NPP obtained 0.70 and 1.737 Mg ha^{-1} and fPAR achieved R^2 of 0.66 and RMSE of 1.859 Mg ha^{-1} (Figure 3.2). Similarly, the measured aboveground biomass (AGB) productivity showed a reasonable correlation (e.g. R^2 of 0.81 and RMSE of 1.66 Mg ha^{-1}) against the estimated AG-NPP (Figure 3.2). The *p*-values ($\alpha < 0.05$) show that all correlations were significant. Furthermore, the results in Figure 4 illustrate the spatial variation of AG-NPP across reforested urban landscape. Based on Figure 3.3, the AG-NPP increases with the increase in forest canopy density and decreases with the decrease in canopy density.

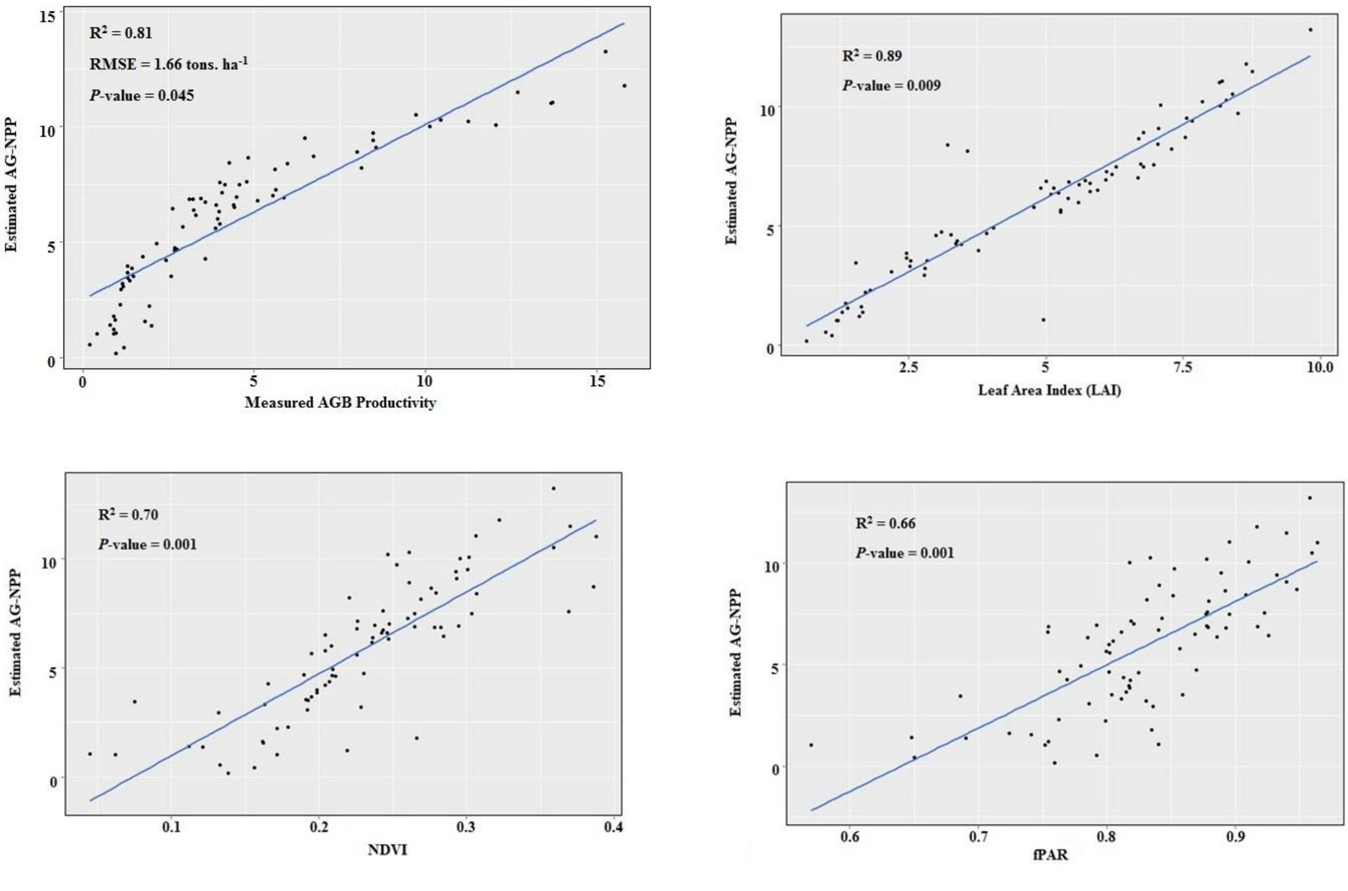


Figure 3.2. Estimated aboveground net primary productivity (AG-NPP) against (a) measured aboveground biomass, (b) leaf area index, (c) normalized vegetation index and (d) fraction of absorbed photosynthetically active radiation.

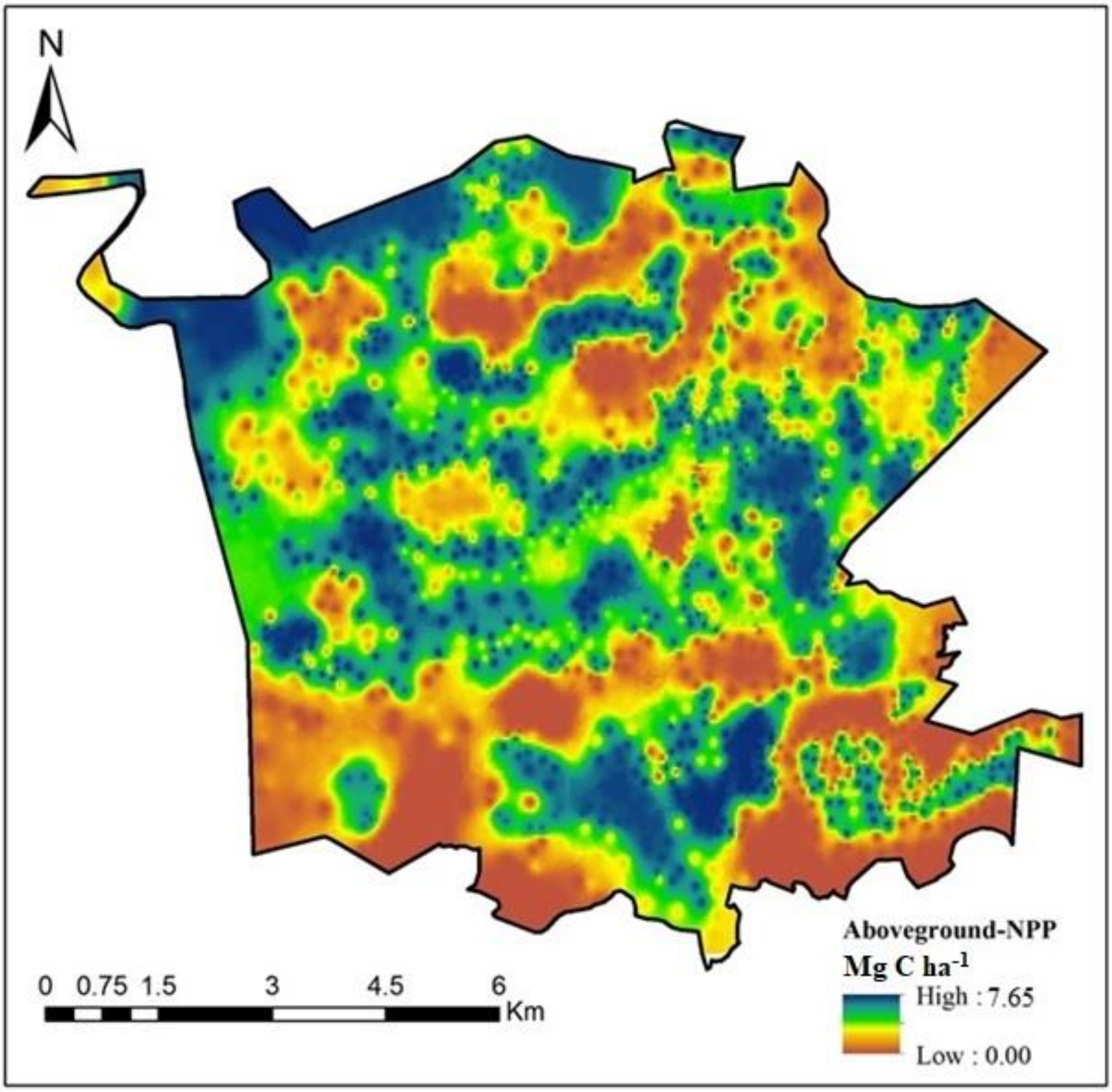


Figure 3.3. Map of estimated aboveground net primary productivity using MOD17 model in conjunction with 10-20 m spatial resolution (Sentinel's) derived reflectance of reforested trees within urban landscape.

The estimated average NPP for deciduous trees (6.35 Mg C ha^{-1}), evergreen trees (5.62 Mg C ha^{-1}) and shrub trees (5.26 Mg C ha^{-1}) were relatively similar to the NPP found in literature for the related forest types (Table 3.3). For instance, literature found that deciduous trees produced average NPP of 6.15 Mg C ha^{-1} (Gower et al., 2001; Pachavo and Murwira, 2014), evergreen trees yield 4.84 Mg C ha^{-1} (Gower et al., 2001) and shrub trees yield 4.85 Mg C ha^{-1} (Hanan et al., 1998; Pachavo and Murwira, 2014). Furthermore, the estimated NPP showed a positive correlation (R^2: 0.85 and RMSE = 0.2801 Mg ha^{-1}) with literature's NPP. In addition, the McNemar's test shows that the differences between the estimated NPP and literature's NPP were not significant (*p*-value: 0.4441).

Table 3.3. Estimated NPP at fine-scale spatial resolution against broad-scale spatial resolution NPP found in literature using MOD17 model in Africa.

Forest types	**Estimated avg.NPP (Mg C ha^{-1})**	**Avg.NPP in literature (Mg C ha^{-1})**	**References**	**Location**
Deciduous trees	6.35	6.15	Pachavo and Murwira (2014), Gower et al (2001)	South Africa, Zimbabwe, Cote d'Ivore
Evergreen trees	5.62	4.84	Gower et al (2001)	Cote d'Ivore
Shrub trees	5.26	4.85	Hanan (1989), Pachavo and Murwira (2014)	Niger, Mozambique
Mean NPP	5.74	5.28	-	-

Coefficient of determination (R^2) = 0.85   RMSE = 0.2801 Mg ha^{-1} (5.37%) and

P-value of 0.44417

3.4 Discussion

Reliable estimation of reforested tree species net primary productivity is central to understanding the contribution of reforestation initiative in the global carbon balance and ensuring effective management and monitoring of forest ecosystems and their services. Trees contribute to carbon sequestration through the photosynthesis process that generates carbohydrate and stores carbon in biomass. The variation in carbon sequestration during photosynthesis results in the variation of carbon uptake by different plant species. Reforestation is a novel approach to increase atmospheric carbon uptake and mitigating climate change (Lamb and Gilmour, 2003; Sithole et al., 2018). Therefore, this study provides estimates of reforested tree species contribution in the global carbon flux at a local urban environment.

3.4.1. Application of MOD17 model in estimating species-specific NPP

Results in this study show that MOD17 model successfully estimated net primary productivity at a fine-spatial resolution with the average mean NPP between 6.24 Mg C ha^{-1} and R^2 of 0.92 with low RMSE (0.82 Mg ha^{-1}) across all reforested trees within the study area. These findings are consistent with previous studies conducted in indigenous or natural forests ecosystems using similar models. For instance, Nayak et al (2009) obtained an overall NPP of 6.0 Mg C ha^{-1} in native forest, while Pachavo and Murwira (2014) estimated a NPP of 6.06 Mg C ha^{-1} in South Africa and Zimbabwe native forests. The reliable NPP estimation can be attributed to MOD17 model's ability to consolidate photosynthetic variables which are critical for plant productivity through conversion of absorbed energy by green-plant into carbon stock stored in plant biomass. This is supported by Ardö (2015) who demonstrated that MOD17 model produces higher estimates of NPP due to its sensitivity to incident radiation absorbed by green-plants biomass. According to Rahman et al (2004), the assumption in the spatial and temporal invariability of MOD17 biome-specific input biophysical variables and dependence on coarse resolution information limits the robustness and application of the model in multiscale resolution. Meanwhile, the consolidation of species-specific data in this study demonstrated the capability of MOD17 to effectively estimate NPP at finer spatial resolution. Alh et al (2004) reported that site-specific (i.e. local scale) estimates of NPP are more accurate than coarse and generalized regional and global NPP quantification. Furthermore, the results also demonstrate a considerable variation in aboveground net primary productivity among the species, with *Acacia* and *Dalbergia* species contributing the highest NPP (6.70 to 7.62 Mg C ha^{-1}) compared to *Syzygium* and *Artemisia* species the lowest (4.54 to 5.26 Mg C ha^{-1}). This can be explained by the distinct variation in the biochemical (i.e. lignin, chlorophyll content, carotenoids etc.) and biophysical (leaf stomata, leaf area, canopy structure etc.) attributes between the taxon's

(Jacquemoud and Ustin, 2008), which greatly influences the vegetation's photosynthetic process and carbon uptake. According to Waring et al (1997), the unequal absorption of radiation by green-plants due to differences in pigments, leaf optical properties and leaf distribution results in uneven primary productivity between the species of different genera. For instance, deciduous tree species such as *Acacia* and *Dalbergia* have larger stomatal leaf properties which increases fraction of absorbed photosynthetically active radiation and plants productivity (Hong et al., 2018; Myneni et al., 1997). Conversely, shrub trees such as *Artemisia* have low light absorption ratio due to limited canopy structural geometry, leaf and stem biomass (Myneni et al., 1997), hence low carbon uptake per unit of absorbed energy. Street et al (2007) reported that variation in leaf-level photosynthetic characteristics between species facilitates their differences in primary productivity.

3.4.2. Relationship between optimal variables and estimated NPP

The findings of this study showed a close relationship between the estimated net primary productivity and optimal predictor variables (e.g. LAI, NDVI and fPAR). Among the predictor variables, LAI exhibited the strongest relationship (i.e. R^2: 0.89 and RMSE = 1.077 Mg ha^{-1}) with the estimated NPP. The correlation in this study is considered remarkable given differences in forest composition and variation in leaf-level photosynthetic activities among the species. Numerous studies show that leaf area is an important primary driver of photosynthesis in forest ecosystems, hence a major long-term control of plant productivity (Oberbauer et al., 1989; Street et al., 2007; Williams and Rastetter, 1999). Maximum LAI indicates high canopy absorption index associated with foliage and various leaf stomatal properties (i.e. density, area, shape etc.), which increases plants primary productivity (Li-li et al., 2016). A similar study by Luo et al (2004) established a positive relationship (R^2: 0.70) between LAI and NPP. Also, this finding is supported by Fang et al (2014) and Myneni et al (1997) who demonstrated that the spatial extents of leaf surfaces are primary borders of essential canopy processes which includes among others light interception, evapotranspiration and gross photosynthesis, significantly influencing net primary productivity. Furthermore, studies have shown that green-biomass as represented by NDVI for instance, is a significant measure of photosynthetic activity and can be utilized to monitor spatio-temporal dynamics of vegetation productivity (Fang et al., 2003; Myneni et al., 1997; Odebiri et al., 2020a; Rafique et al., 2016; Wang et al., 2004a). Results in this study show that Sentinel-2's derived NDVI between the near-infrared (band 8) and red (band 4) region strongly correlates (R^2: 0.70, RMSE = 1.737 Mg ha^{-1}) with the estimated NPP. A strong relationship of NDVI with NPP can be attributed to the sensitivity of internal photosynthetic leaf mesophyll function of healthy green-leaves to the near-infrared region (Rafique et al., 2016; Wang et al., 2004a). Therefore, variability in annual productivity and net carbon flux directly relate to the spatial and temporal patterns of NDVI as green-biomass (i.e. NDVI) represent vegetation response to climate. These findings are supported by numerous studies which correlated NDVI against net primary productivity and carbon flux. For instance, Rafique et al (2016) demonstrated an R^2:0.80 relationship of NPP and NDVI and found that land productivity increases with the increase in NDVI values. Similarly, Odebiri et al (2020) established a strong relationship (R^2: 0.86) between vegetation-green biomass (i.e. NDVI) and soil carbon flux, hence concluded that NDVI is an important indicator of ecosystem productivity.

Furthermore, this study shows that the estimated species-specific NPP at fine-scale is comparable with broad-scale biome-specific estimation found in literature. However, the present study provides great detail and insight of species-specific contribution in the global carbon cycle and trigger sound decision making for local-scale management and monitoring of urban forests. The findings demonstrate unprecedented correlation (R^2: 0.85 and RMSE = 0.2801 Mg ha^{-1}) between the estimated NPP in this study and NPP found in literature. Such comparison is important for authenticating current study results and effectiveness of MOD17 model at local *vis-a-vis* regional-level. Current results indicate that the application of MOD17 model are not only limited to coarse resolution datasets and biome-specific information derived from look-up table. The utility of forests biometric measurements in the model improved and allowed the spatial estimation of reforested species-to-species NPP with plausible coefficient of determination and proved the model flexibility to consolidate field-dataset at fine-scale. Finally, this study proves that high spatial resolution multispectral Sentinel-2's derived indices are better suited for local-scale NPP assessments and monitoring, especially reforested urban landscape. Additionally, the study shows that urban reforestation plays an invaluable role in carbon sequestration and mitigation of climate systems within urban landscape, necessitating effective management and conservation of reforestation ecosystem and its services.

3.5 Conclusion

This study sought to estimate aboveground reforested trees net primary productivity within an urban landscape using biophysical variables and Sentinel-2 derived spectral variables. The consolidation of Sentinel-2's derived indices and measured biophysical variables successfully estimated aboveground net primary productivity. The most optimal predictor variables were LAI, NDV and fPAR. Based on the results, a considerable variability of net primary productivity was observed among species, which can be attributed to the differences in biochemical and biophysical parameters of individual species that influence photosynthetic processes. The study provides the value of reforestation initiative to the global carbon budget and climate change mitigation as required by Reducing Emissions from Deforestation and Forest Degradation (REDD+) and Kyoto-Protocol. This information also benefits policy-and decision-makers and forest managers to plan for monitoring for smaller and larger scale projects. Overall, we deduce that MOD17 model is not only restricted to coarse resolution data and larger landscapes, it can also be successfully adopted to quantify and monitor carbon fluxes at a species-level within a small geographic scale using indices derived from fine resolution dataset such as Sentinel-2.

3.6 Summary

In this study, the estimation of net primary productivity shown that reforesting heterogeneous trees can promote atmospheric carbon sequestration and climate resilient cities. However, to the best of our knowledge, Sentinel-2 MSI spectral bands and indices have not been explicitly adopted to understand and monitor the spatial distribution of carbon stock in reforested urban landscape. Thus, the following Chapter 4 examined the prospect of Sentinel-2 spectral information in quantifying and mapping the spatial distribution of reforestation carbon stock within urban environment.

Chapter Four: The utility of Sentinel-2 spectral data in quantifying aboveground carbon stock in an urban reforested landscape

This chapter is based on:

Mngadi, M., Odindi, J. and Mutanga, O., 2021. The Utility of Sentinel-2 Spectral Data in Quantifying Above-Ground Carbon Stock in an Urban Reforested Landscape. *Remote Sensing*, *13*(21), p.4281.

Abstract

The transformation of natural landscape into impervious surface due to urbanization has often been considered an important driver of environmental change, affecting essential urban ecological processes and ecosystem services. Continuous forest degradation and deforestation due to urbanization have led to an increase in atmospheric carbon emissions, risks and impacts associated with climate change within urban landscapes and beyond. Hence, urban reforestation has become a reliable long-term alternative for carbon sink and climate change mitigation. However, there is an urgent need for spatially accurate and concise quantification of these forest carbon stocks in order to understand and effectively monitor the accumulation and progress on such ecosystem services. Hence, this study sought to examine the prospect of Sentinel-2 spectral data in quantifying carbon stock in a reforested urban landscape using the random forest ensemble. Results show that Sentinel-2 spectral data estimated reforested forest carbon stock to an RMSE between 0.378 and 0.466 $t.ha^{-1}$ and R^2 of 79.82 and 77.96% using calibration and validation datasets. Based on random forest variable selection and backward elimination approaches, the Red-Edge Normalized Difference Vegetation Index, Enhanced Vegetation Index, Modified Simple Ratio Index and Normalized Difference Vegetation Index were the best subset of predictor variables of carbon stock. These findings demonstrate the value and prospects of Sentinel-2 spectral data for predicting carbon stock in reforested urban landscape. This information is critical for adopting informed management policies and plans for optimizing urban reforested landscapes carbon sequestration capacity and improving their climate change mitigation potential.

Keywords: Reforestation; Ecosystem services; Carbon stock; Random forest

4.1 Introduction

Urbanization, typified by transformation of natural landscape into impervious built-up surfaces, is considered a major driver of environmental change (Odindi and Mhangara 2012, Sithole et al. 2018, Adamu et al. 2021). Such transformation significantly affects the integrity of important ecological processes and ecosystem services that include deterioration of water quality, increase in urban thermal heat, air and noise pollution, loss of biodiversity and acceleration of climate change (Sithole et al. 2018, Xu et al. 2016, Livesley et al. 2016a). Despite covering small land-surface, urban areas account for the highest amount of global carbon emissions due to higher energy and resource consumption (Luederitz et al. 2015). Commonly, urban vegetation, especially forest ecosystems sequestrate the emitted carbon and regulate climate systems within urban landscapes. However, deforestation and forest degradation that typifies urbanization processes reduces urban areas' carbon sequestration potential and increases greenhouse gas accumulations (Odebiri et al. 2020, Keenan et al. 2015, Payn et al. 2015, Cho et al. 2012). In sub-Saharan Africa for instance, studies show that urbanization exert enormous pressure on the spatial distribution of urban forest ecosystems, hence decreasing substantial amount of sequestrated carbon and accelerate potential risks and impacts of climate change (Pellikka et al. 2018, Mundia and Aniya 2005).

Recently, the United Nations Framework Convention for Climate Change (UNFCCC) established the Reducing Emissions from Deforestation and forest Degradation (REDD+) that requires countries to report their carbon emissions and sink estimates through national greenhouse gas inventories (NGHGI) (Deo et al. 2017, Curiel-Esparza et al. 2015). Furthermore, the REDD+ and Kyoto Protocol programs have identified reforestation initiatives as the most efficient, low-cost and long-term approach for reducing greenhouse gas emissions and climate change impacts, especially in urban landscapes (Livesley et al. 2016b, Sithole et al. 2018). The emergence and recognition of reforestation as the potential carbon sink in urban landscapes is expected to significantly influence global carbon cycle, improve urban environmental quality and regulate climate systems. Subsequently, an explicit investigation in the methods and procedures for quantifying these carbon emissions and sinks are paramount.

Numerous studies have assessed regulating ecosystem services such as carbon stock or sequestration and aboveground biomass (Baccini et al. 2008, Dube and Mutanga 2015a, Henry et al. 2011). However, existing assessments are biased towards natural/indigenous and commercial forests. Despite the need for knowledge on the contribution of urban reforestation on the global carbon cycle and climate change regulation potential, information on carbon stocks in reforested urban areas remain largely unknown. Hence, there is a need to establish affordable, spatially explicit and robust techniques as well as datasets to effectively quantify and monitor carbon stocks in urban reforested landscapes.

Traditionally, field surveys have been used to determine aboveground carbon (Hickey et al. 2018, Dube and Mutanga 2015b). Whereas field surveys and observations are known to be highly accurate, their shortcomings are widely documented in literature (Dube and Mutanga 2015a, Matongera et al. 2017). Meanwhile, among others, the Inter-Governmental Panel on Climate Change Good Practice Guidance (IPCC-GPG) on Land Use, Land Use Change and Forestry has proposed remote sensing as a cost-effective and reliable primary data source and technique for wall-to-wall mapping and estimation of forest carbon dynamics, useful for long-term climate change regulations and policy formulation (Gara et al. 2016). Remote sensing techniques offer spatially-explicit spectral information at a larger spatial extent, necessary for both local and regional prediction and monitoring of the aboveground carbon stock in reforested areas (Hickey et al. 2018, Dube and Mutanga 2015b). Recently, new generation commercial sensors such as the WorldView series have been widely used in estimating aboveground carbon stock and biomass (Eckert 2012, Karna 2012, Dube et al. 2014). These sensors consist of fewer but strategically positioned spectral wavebands, including unique band settings within the red-edge region invaluable for enhancing vegetation spectral response (Mutanga et al. 2012, Dube et al. 2014, Eckert 2012). However, despite their effectiveness in modelling carbon stocks, they are costly and not readily available. Such limitations hinder frequent quantification and monitoring of aboveground forest carbon stocks in regions such as Southern Africa where financial constraints limit the availability of spatial data. Hence, improved and freely-available multispectral sensors remain the most feasible sources of spatio-temporal data for predicting forest carbon stock. Specifically, the emergence of cutting-edge freely available multispectral sensors such as the Sentinel-2 offer better prospects for vegetation modelling and monitoring. The sensor is characterised by improved spatial, spectral and radiometric properties that offer unprecedented opportunities for estimating aboveground carbon stock at both local and regional scales. Sentinel-2 is regarded as an intermediate spatial data source between medium spatial resolution (e.g. Landsat series) and high spatial resolution sensors (e.g. Worldview-2 and RapidEye) due to its strategically positioned band settings in the red-edge region and varying spatial resolution ranging from 10 to 60 m (Korhonen et al. 2017, Thanh Noi and Kappas 2018). In addition, Sentinel-2 has a higher (5 days) temporal resolution, suitable for frequent quantification, monitoring and management of forest ecosystems and carbon stocks. Despite the recent popularity of Sentinel-2 datasets in vegetation mapping, no study, to the best of our knowledge has used it to characterise an urban reforested landscape. In addition, new and unique indices derived from red-edge region of Sentinel-2 multispectral image (MSI) for carbon stock estimation in reforested urban landscape have not been concisely explored. Such indices optimise spectral reflectance that can significantly improve prediction accuracy of terrestrial carbon stock. Studies that have evaluated red-edge indices (e.g., red-edge normalised difference vegetation index, red-edge chlorophyll index and red-edge modified simple ratio index) have particularly focused on leaf area index and biomass estimation (Dong et al. 2019, Delegido et al. 2013, Mutanga et al. 2012). Thus, there is a need to test such unique indices derived from strategically positioned red-edge bands of Sentinel-2 MSI for enhancing carbon stock estimation in reforested urban landscapes.

Multiple linear regression approaches based on a range of variables are often used for modelling aboveground vegetation biomass and carbon stocks (Mutanga et al. 2012, Lu 2006). However, optimal prediction of carbon stocks in urban reforested areas requires robust machine learning algorithms that do not have assumptions of data normality. For instance, non-parametric ensemble techniques such as the random forest have proven to be successful in modelling forest ecosystems properties with unprecedented performance (Dube and Mutanga 2015b, Mutanga et al. 2012, Grimm et al. 2008). Random forest is an algorithm known for its bootstrapping and creation of a subset of explanatory variables that are randomly selected from the input dataset, hence overcoming overfitting (Dube et al. 2014, Ließ et al. 2016). RF is also capable of addressing complex correlation problems existing between predictor variables due to large volumes of data and noise (Vincenzi et al. 2011). Literature shows that random forest regression model performs better than other machine learning algorithms in vegetation modelling (Roy 2021, Ghosh and Behera 2018, Safari et al. 2017, Wan et al. 2018). Ghosh and Behera (2018) for instance, established that random forest regression model outperforms stochastic gradient boosting in estimating forest aboveground biomass. Similarly, Safari et al. (2017) found that random forest model was robust in modelling forest aboveground carbon stock, compared to support vector machine and boosted regression trees. In comparing the performances of random forest, back-propagation neural network, and support vector regression in estimating wetland aboveground biomass, Wan et al. (2018) found that random forest performed better than other regression algorithms. However, studies that have utilised random forest to estimate aboveground biomass and carbon content have been restricted to natural and plantation forests. For example, Dube et al (2014) used random forest ensemble to estimate above ground biomass of Eucalyptus and pine species in a commercial forest. Similarly, Odebiri et al (2020) adopted ensemble random forest model to predict soil organic carbon stock in plantation forests, while Mutanga et al (2012) demonstrated that random forest model is critical in predicting biomass on a wetland. Furthermore, it has been widely proven that the integration of Sentinel-2's spectral bands and vegetation indices in a robust machine learning algorithm facilitates accurate determination of aboveground vegetation carbon stocks (Korhonen et al. 2017, Forkuor et al. 2018, Baloloy et al. 2018, Dang et al. 2019, Wang et al. 2019). Dang et al (2019) for instance, integrated spectral indices and bands derived from Sentinel-2 MSI in the random forest algorithm to estimate aboveground biomass of forest ecosystems in Yok Don Park, Vietnam. Likewise, Wang et al (2019) used spectral indices derived from Sentinel-2 MSI bands to predict aboveground biomass and leaf area index using robust algorithms such as support vector machine and random forest. The study conducted by Baloloy et al (2018) also indicated that Sentinel-2 derived indices and spectral bands are critical in modelling vegetation metric such as biomass and carbon. In this regard, this study sought to examine the prospect of Sentinel-2 image spectral-data in quantifying carbon stock within a reforested urban landscape.

4.2 Materials and methods

4.2.1. Field-survey and data collection

Field survey and data collection were conducted between 21st and 25th of February 2020; during the summer season at peak biomass productivity. In this study, about 130 pre-determined random sampling points inserted in a global positioning system (GPS) were used to access the sampling sites. From each random point, a plot-size window of 10 m * 10 m was established and structural attributes such as height and diameter at breast height of reforested trees recorded. A clinometer (Vertex IV Hypsometer) was used to measure tree height, while diameter at breast height (DBH) was measured using a calliper. In this study, Trimble Global Positioning System (GPS) with 0.5 m accuracy was used to record geographic location of each sampled tree.

4.2.2. Allometric modelling of aboveground biomass and carbon stock

The allometric relationship between the tree diameter and height can significantly affect tree biomass, hence their measurements could be effectively used for vegetation biomass estimation (Dube and Mutanga 2015b, Dube and Mutanga 2015a). A non -environmental destructive approach such as allometric model for biomass estimation has been recommended by the Intergovernmental Panel on Climate Change (IPCC) (Clark III, Saucier and McNab 1986, Toochi 2018). In this study, a field measured diameter at breast height (DBH) and height (H) of individual reforested trees were integrated into the allometric model to compute aboveground biomass using the following generic equation:

$$w = a(D^2H)^{\mathrm{b}}$$

Where W is the aboveground biomass, D represents diameter at breast height (cm), H indicates tree height (m), while a and b are regression coefficients (Clark III et al. 1986).

Generally, the aboveground dry biomass holds about 50% of carbon, as such, a friction factor of 0.5 is commonly used for converting dry mass into carbon concentration (Birdsey 1992, Toochi 2018). Therefore, in this study, we converted the computed biomass into carbon stock using the factor of 0.5.

4.2.3. Image acquisition and pre-processing

A multispectral Sentinel-2A satellite image was captured on the 26th of February 2020 during cloud-free day and freely downloaded on the 02nd of March 2020 through Quantum Geographic Information System (QGIS) portal. Sentinel-2 sensor acquires images at 13 spectral channels (e.g. coastal-b1, blue-b2, green-b3, red-b4, red-edge-b5, red-edge-b6, red-edge-b7, near infrared-b8, red-edge-b8A, water vapour-b9, cloud-b10, shortwave infrared-b11 and shortwave infrared-b12) at varying spatial resolutions of 10, 20, and 60 m. This sensor covers strategically located red-edge region (i.e. b5, 6, 7 and 8A) of the electromagnetic spectrum with unique band settings that are critical for vegetation modelling (Korhonen et al. 2017). Sentinel-2A data is readily available for frequent vegetation assessment and monitoring. In this study, the spectral data was atmospherically corrected using Dark Object Subtraction (DOS) embedded in QGIS software, which also converted spectral radiances to reflectance. Furthermore, the spectral data were extracted from a series of waveband combinations representing vegetation green biomass indices (Table 4.1). Indices which were ideal for vegetation assessment and monitoring include; normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), green NDVI (GNDVI), transformed vegetation index (TVI1), green chlorophyll index (Cl_{green}), modified simple ratio index (MSRI), ratio vegetation index (RVI), triangular vegetation index (TVI2), advanced vegetation index (AVI), modified triangular vegetation index (MTVI 1 and 2) and normalize pigment chlorophyll ratio index (NPCRI). We also derived indices from a combination of red-edge bands such as red-edge normalized difference vegetation index ($NDVI_{RE}$), red-edge chlorophyll index (Cl_{RE}) and modified simple ratio red-edge index

($MSRI_{RE}$). In addition, the derived indices were combined with spectral data extracted from the individual bands.

Table 4.1. Spectral indices derived from Sentinel-2 MSI and their formulae.

Indices	Formulae	References
NDVI	$\frac{NIR - Red}{NIR + Red}$	(Rousel et al., 1973)
EVI	$2.5*[\frac{NIR-Red}{(NIR+6*Red-7.5Blue+1)}]$	(Huete et al., 1999)
TVI	$\sqrt{(NDVI)} + 0.5$	(Deering, 1975)
GNDVI	$\frac{NIR - Green}{NIR + Green}$	(Gitelson and Merzlyak, 1998)
Cl_{green}	$\frac{NIR}{Green} - 1$	(Gitelson et al., 2003)
RVI	$\frac{NIR}{Red}$	(Baret and Guyot, 1991)
MSRI	$\frac{\frac{NIR}{Red} - 1}{\sqrt{\frac{NIR}{Red}} + 1}$	(Wu et al., 2008)
TVI	$0.5 * [120 * (NIR - Green) - 200 * (Red - Green)]$	(Broge and Leblanc, 2001)
AVI	$\sqrt[3]{[NIR * (1 - Red) * (NIR - Red)}$	(Plummer, 1994)
MTVI1	$1.2 * (NIR - Green) - 2.5 * (Red - Green)$	(Haboudane et al., 2004)
MTVI2	$\frac{1.5 * (1.2 * (NIR - Green) - 2.5 * (Red - Green)}{\sqrt{(2 * NIR + 1)^2} - (6 * NIR - 5 * \sqrt{(Red)} - 0.5}$	(Haboudane et al., 2004)
NPCRI	$\frac{Red - Blue}{Red + Blue}$	(Peñuelas et al., 1994)
$NDVI_{RE}$	$\frac{NIR - RE}{NIR + RE}$	(Dong et al., 2019)
Cl_{RE}	$\frac{NIR}{RE} - 1$	(Gitelson et al., 2003)
$MSRI_{RE}$	$\frac{\frac{NIR}{RE} - 1}{\sqrt{\frac{NIR}{RE}} + 1}$	(Wu et al., 2008)

4.2.4. Statistical analysis

In this study, random forest algorithm was used for regression analysis. Random forest (RF) operates as an ensemble learning that creates multitude of decision trees (*ntree*) and selects the final best tree based on the majority vote. RF uses a bootstrapping technique to reduce model variance without increasing bias while enhancing accuracy and reducing overfitting (Ließ et al. 2016, Breiman 2001). Such an ensemble model has a modified technique (e.g. feature bagging) for selecting a random subset of features (*mtry*) in order to determine the split at each tree node (Breiman 2001). Each node in the model represents a predictor variable and all selected subset of the data are used as response variables. Random forest first examines and tests all predictors from each node before randomly selecting the best split from a set of predictors (Dube et al. 2014, Breiman 2001). Furthermore, random forest permits model optimization for better results using two parameters, namely; *ntree*, based on large sets of decision trees and bootstrap training sample and *mtry*, based on the individual predictor variables selected from each tree node (Forkuor et al. 2018, Mutanga et al. 2012). Normally, the standard value of *ntree* is set at 500, while *mtry* takes square-root of the total number of an input predictor variable on a normal classification, whereas on the regression, it divides all predictor variables by a default factor of three (Breiman 2001, Odebiri et al. 2020). The optimal *ntree* and *mtry* values for best prediction performance are determined based on the smallest out-of-bag error (Breiman 2001). In this study, the *ntree* was adjusted between 100 and 500 at the interval value of 100, whereas *mtry* was adjusted from 1 to 25 with interval value of 1. The best *ntree* and *mtry* was determined at the interval value of 300 and 18 based on the least root mean square error of the training dataset (n = 56).

4.2.5. Optimal predictor variables selection

Commonly, regression analysis suffers a problem of multi-collinearity due to high correlation or less variability between some inputs predictor variables (Forkuor et al. 2018, Odebiri et al. 2020). Despite the capability of ensemble method such as random forest in dealing with strong correlation between certain variables, it is necessary to select and utilize optimal predictor variables that improve regression model performance. In this study, the out-of-bag (OOB) approach based on backward elimination was used to determine a subset of predictor variables that were ideal for the best regression model. Backward elimination is critical for removing highly correlated variables, which are not important until a subset of ideal predictor variables remain in the model. In addition, the values of carbon stock estimated from a subset of predictor variables were used to generate a spatially varying map of carbon stock.

4.2.6. Model validation and accuracy assessment

Random forest effectiveness in predicting carbon stock within the urban landscape was tested using 10-fold cross-validation. Initially, the total dataset (n = 80) was partitioned into 70% (n = 56) as training sets and 30% (n = 24) as testing datasets. The RF model performance was evaluated using the coefficient of determination (R^2), root mean square error (RMSE) and mean absolute Error (MAE).

4.3 Results

4.3.1. Carbon stock of reforested trees

Based on the descriptive statistics, the minimum and maximum value of measured carbon stock within reforested urban landscape are 0.244 and 10.20 $t.ha^{-1}$ with the mean value of 3.386 $t.ha^{-1}$ and standard deviation of 2.475 $t.ha^{-1}$.

4.3.2. Random forest model optimization

Figure 4.1 shows random forest optimization parameters (*Ntree* and *Mtry*). In this study, the *Ntree* value of 300 and *Mtry* value of 18 produced the lowest RMSE (0.125 $t.ha^{-1}$) and were selected for further carbon stock prediction.

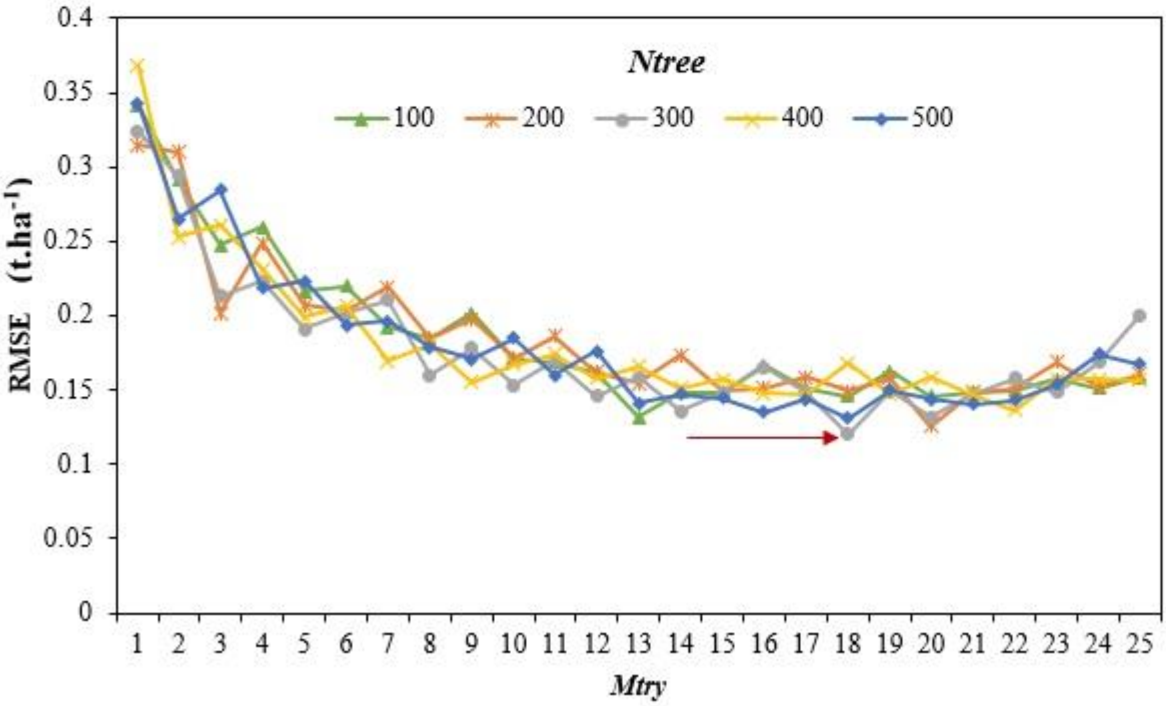


Figure 4.1. Best random forest optimization parameters (*Ntree* and *Mtry*) selected based on the lowest RMSE indicated by the red arrow.

4.3.3. Variable importance selection

Results in Figure 4.2 show the predictive performance of individual variables used in the model and their ranking in terms of importance based on the OOB error rate, which increases with importance, while Figure 4.3 illustrates the number of variables selected for optimal carbon stock prediction. Using the backward elimination approach, a subset of four predictor variables (i.e. NDVI, EVI, MSRI and $NDVI_{RE}$) with the smallest error rate was selected for the final carbon stock model. The integration of this subset into one random forest model produced the lowest OOB RMSE of 0.143 $t.ha^{-1}$ and a 10-fold cross-validation RMSE of 0.153 $t.ha^{-1}$. The RMSE increased to 0.331 $t.ha^{-1}$ and 0.345 $t.ha^{-1}$ for both OOB and 10-fold cross validation when using all 25 variables in the training dataset. Finally, this study used four predictor variables (i.e. NDVI, EVI, MSRI and $NDVI_{RE}$) in the final random forest regression model for predicting carbon stock within the study area.

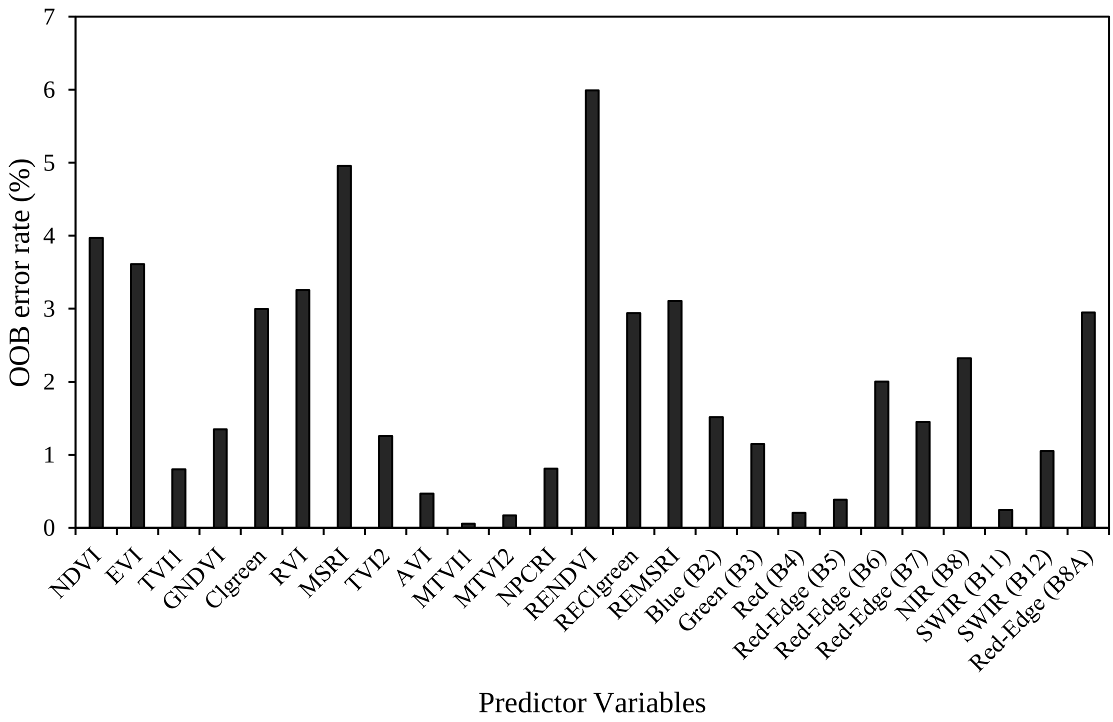


Figure 4.2. The importance of variables in predicting carbon stock using the random forest model. The mean increase in OOB error rate shows greater variable significance.

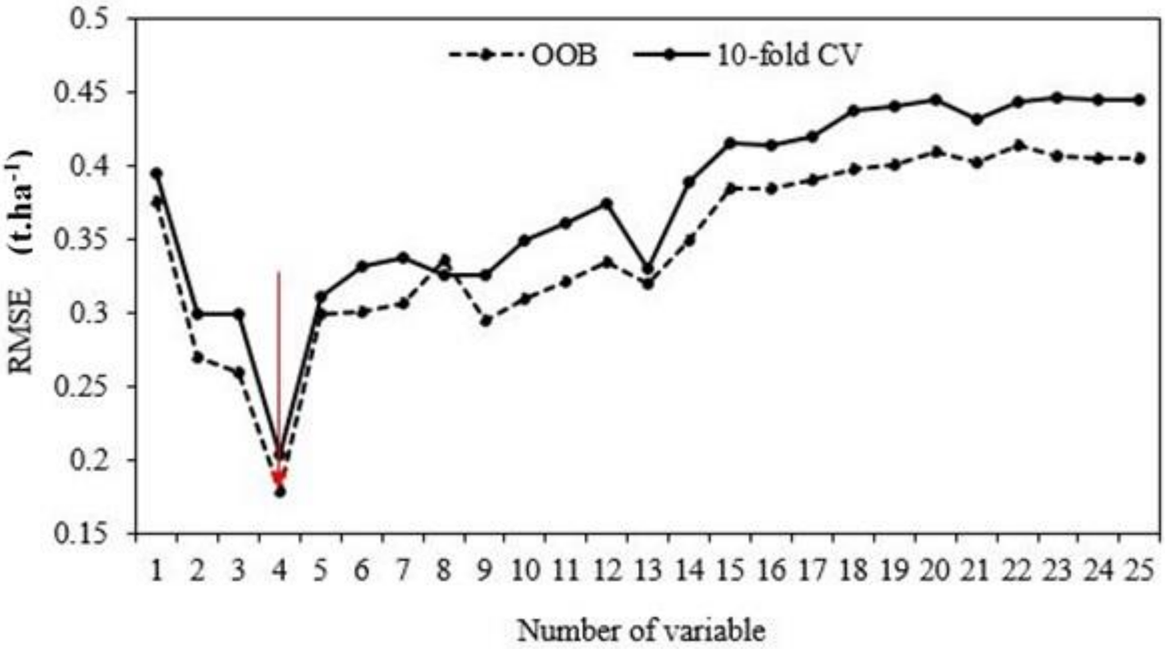


Figure 4.3. Selection of optimal number of predictor variables using backward elimination approach. The ideal number of variables (indicated with red arrow) was selected based on the RMSE generated from the training dataset using OOB and 10-fold cross validation.

4.3.4. Random forest model prediction performance

Results in Table 4.2 show the overall mean carbon stock and prediction performance of Sentinel-2's spectral data and the random forest model. The integration of optimal variables selected by random forest produced an overall mean carbon stock of 3.389 and 3.642 t.ha^{-1} using calibration (training) and validation (testing) datasets. The random forest regression model obtained highest R^2 (77.96 to 79.82%) with lowest RMSE (0.378 to 0.466 t.ha^{-1}) and MAE (0.189 to 0.233 t.ha^{-1}) when predicting carbon stock using four selected indices combined together, compared to the use of individual indices into the model. Figure 4.4 illustrates the relationship between predicted carbon stock with allometric derived carbon stock and optimal variables that greatly improved the random forest prediction model. Results in Figure 4.4 also show a strong correlation coefficient (r) of 0.951 to 0.978 between predicted and measured carbon stock. Furthermore, Figure 4.5 represent spatial variability of carbon stock across reforested urban landscape. Generally, the spatial variability of carbon stock increases with increasing canopy cover and decreases with the decrease in green biomass.

Table 4.2. Performance of random forest model in predicting reforested carbon stock using selected subset of variables separated into calibration and validation datasets.

Prediction dataset	Mean C ($t.ha^{-1}$)	R^2 (%)	RMSE ($t.ha^{-1}$)	MAE ($t.h^{-1}$)
Calibration	3.389	79.82	0.378 (11.15%)	0.189
Validation	3.642	77.96	0.466 (12.79%)	0.233

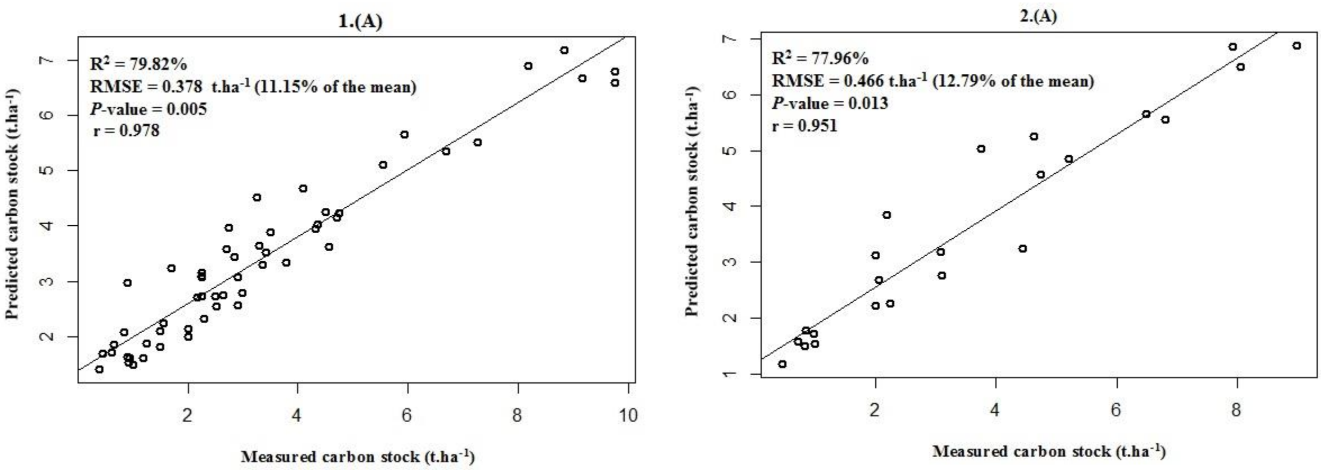


Figure 4.4. Relationship between predicted and measured carbon stock of reforested urban landscape for calibration (1) and validation (2) datasets. The regression analysis between predicted and measured carbon stock was established using a combined subset of optimal indices (A).

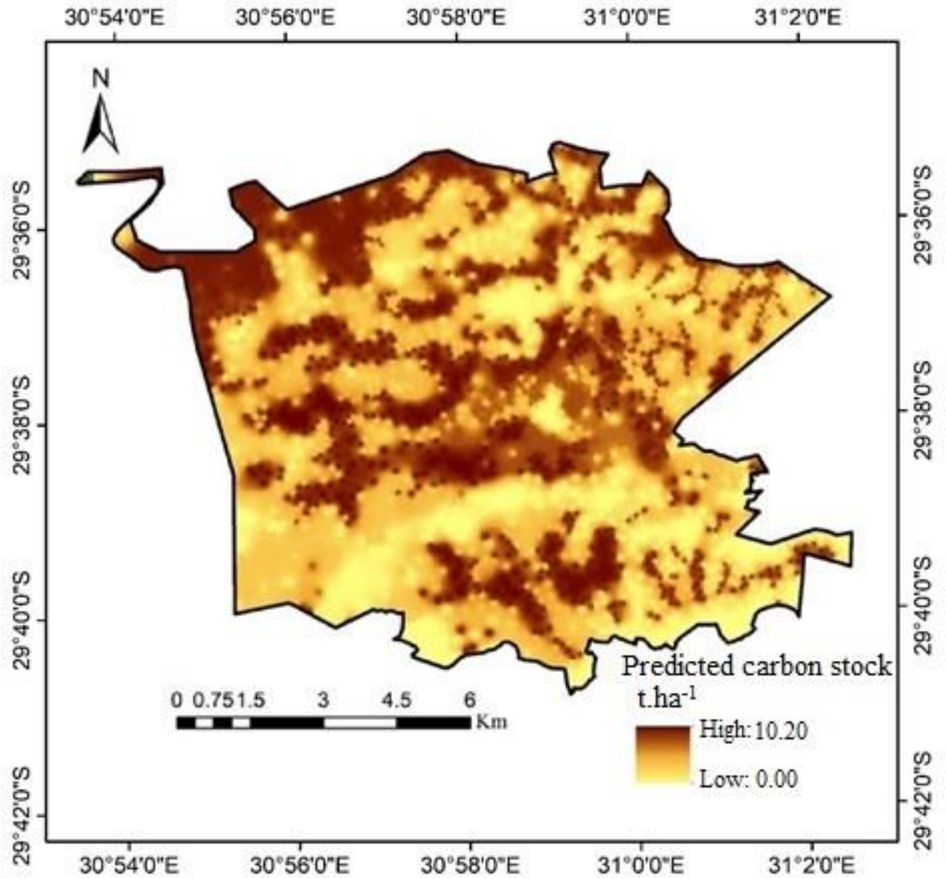


Figure 4.5. Prediction map of carbon stock within reforested urban landscape using random forest model.

4.4. Discussion

Concise estimation of climate regulating ecosystem services provided by reforested urban trees such as carbon stock is key to understanding the role and value of reforestation strategy in the global carbon dynamics and climate change regulation potential. Hence, this study sought to test the utility of Sentinel-2 satellite data in quantitatively evaluating the amount of carbon in an urban reforested landscape.

Results showed that Sentinel-2 spectral data could be used to estimate carbon stocks in an urban reforested area. In this study, a mean carbon stock of between 3.389 and 3.642 t.ha^{-1}, with high R^2 (77.96 and 79.82%) and low RMSE (0.378 and 0.466 t.ha^{-1}) and MAE (0.189 and 0.233) was obtained using calibration and validation subsets dataset. This reasonable estimation performance can be explained by Sentinel-2's strategically positioned wavebands, particularly the red-edge region. The region records numerous leaf properties such as chlorophyll concentration, leaf area index and green-biomass, necessary for measuring forests services such biomass and carbon stock (Gara et al. 2016, Dube et al. 2014, Sibanda et al. 2016). Hence, its inclusion as an explanatory variable significantly improved carbon stock modelling accuracy. Our results concur with the hypothesis that sensors (e.g. Sentinel-2 MSI) with strategically located band settings such as red-edge, offer unprecedented spectral information critical for measuring vegetation metrics and services such as biomass and carbon uptake (Dube et al. 2014, Mutanga et al. 2012). In addition to the red-edge, Sentinel-2's near infrared (NIR) bands also provide sensitive spectral reflectance capable of explicit estimation of vegetation metrics such as biomass and carbon stock. The near-infrared region offers a refined narrow spectral wavelength ranging between 850 and 880 nm and highly sensitive to the biophysical and biochemical response of vegetation (Jia et al. 2017, Matongera et al. 2017). Biophysical (e.g. leaf area, biomass) and biochemical (e.g. chlorophyll content) properties are critical for detecting vegetation health and productivity; useful for determining carbon uptake by reforested trees.

Results of this study also showed a strong correlation (r: 0.95 to 0.98) between the estimated aboveground carbon stock and measured carbon stock using calibration and validation datasets. Such strong relationship is associated with the consolidation of optimal variables (i.e. NDVI, EVI, MSRI and $NDVI_{RE}$) selected by backward elimination process for the final prediction model of carbon stock. Among the integrated vegetation indices, NDVI was valuable in the estimation of carbon stock within reforested urban landscape. This could be attributed to the fact that NDVI is an important indicator of green-biomass, which can be effectively used for deriving and monitoring spatio-temporal dynamics of aboveground carbon stock/sequestration (Moumouni et al. 2018, Bindu et al. 2020, Gizachew et al. 2016). The findings in this study are consistent with those of Moumouni et al (2018) who predicted aboveground carbon stock variability across different forest biomes to a R^2 of 0.91 using an NDVI. Meanwhile, in a related study, Bindu et al (2020) attained an R^2 of 0.71 in estimating carbon stock of mangroves trees using NDVI. Such a strong predictive performance of NDVI in carbon stock estimation can be explained by the sensitivity of the near-infrared region to the internal leaf mesophyll, which is a major indicator of vegetation health and is responsible for maximum biomass productivity (Rafique et al. 2016, Wang et al. 2004), hence critical for simulating the amount of carbon stored in forest ecosystems. NDVI contain robust spectral information derived from Red and NIR bands, which are sensitive in detecting vegetation health and productivity, which are valuable carbon accumulation indicators. According to Moumouni et al (2018), the spatio-temporal variability in green-biomass reflectance as measured by NDVI is proportional to the simulated carbon flux. Interestingly, the inclusion of new and unique red-edge indices such as $NDVI_{RE}$ boosted the predictive performance of carbon stock within reforested urban landscape. The robustness of red-edge indices (i.e. $NDVI_{RE}$) lies with the ability to provide spectral reflectance that have less atmospheric, soil background and water absorption influence or effects (Dong et al. 2019, Mutanga et al. 2012). The findings in this study are congruous with previous studies, which also established that red-edge indices are highly sensitive to vegetation metrics (e.g. leaf area index and biomass) (Dong et al. 2019, Delegido et al. 2013, Mutanga et al. 2012, Xie et al. 2018). For instance, Xie et al (2018) found that the red-edge derived spectral indices are better prospects for improving estimation coefficient of leaf area index in agroecosystems. While Mutanga et al. (2012) established that red-edge indices can significantly increase biomass estimation of wetland vegetation. These studies suggested that red-edge indices could be effectively used to measure vegetation productivity and health (which includes carbon sequestration and stock). Red-edge derived indices are less prone to saturation that is common to standard NDVI (Delegido et al. 2013, Dong et al. 2019), hence can be effectively applied in dense vegetation cover. In addition, red-edge indices contain sensitive spectral data as red-edge wavebands record rapid variations in plants chlorophyll content and leaf structure, hence critical for monitoring the spatial and temporal dynamics of vegetation health and productivity (Zarco-Tejada et al. 2018, Kim and Yeom 2014). Furthermore, the results on the carbon stock map show the variability of carbon stock across the study area, which decreases with the decrease in canopy density. This variability in carbon stock within the study area can be attributed to the variations in landscape topographic characteristics, which influence vegetation density and productivity. For example, studies have shown that slope, elevation and aspect can significantly affect the spatial distribution of carbon stock across forest landscapes (Zhu et al. 2019, Odebiri et al. 2020, Young et al. 2014). Variations can also be triggered by forest species composition due to the differences in biophysical (i.e. leaf area, stomata and canopy structure) and biochemical (i.e. leaf pigments, lignin and carotenoids) characteristics (Liu et al. 2018, Jacquemoud and Ustin 2008, Waring et al. 1998). For instance, deciduous trees (e.g. *Acacia* and *Dalbergia*) consist of large leaf stomatal properties which increase plant productivity and carbon storage, whereas shrub trees such as *Artemisia* have limited structural geometry, stem and leaf biomass, hence contributing low carbon stock (Hong et al. 2018, Myneni et al. 1997).

In addition, the application of robust regression models such as random forest significantly improved the prediction performance of carbon stock in the reforested urban landscape. The robustness of the random forest algorithm is associate with the ability to select important variables required for the best regression model (Mutanga et al. 2012, Odebiri et al. 2020). For instance, the consolidation of NDVI, EVI, MSRI and $NDVI_{RE}$ derived from Sentinel-2 MSI as selected by random forest model offers a remarkable methodology for predicting carbon stock in a reforested urban landscape. Overall, this study presents a better and cost-effective option for quantifying carbon stock in the reforested urban landscape using freely and readily available new generation Sentinel-2 MSI. Moreover, the study demonstrates the significance of the reforestation initiative in reducing atmospheric carbon emissions and regulating climate systems within the urban landscape, hence suggesting effective management and monitoring practices for reforested ecosystems and their services. The information presented in this study is useful for planning large-scale reforestation projects in order to maximize sequestration capacity and improve climate change regulation potential within urban landscapes. Our approach presents a concise methodology to monitor the progress of urban reforestation projects locally and similar reforestation projects around the world. In addition, although these results may benefit forest managers and decision makers, multi-temporal information on aboveground carbon stock variability across seasons and years and effect of topography on carbon sequestration within reforested urban areas still requires investigation. Furthermore, the inaccessibility of high spatial resolution images (e.g. Worldview-3, Quickbird etc.) and associated costs limited the opportunity to estimate carbon stock at a species level.

4.5 Conclusions

This study sought to examine the prospect of Sentinel-2 image spectral-data for predicting carbon stock in the reforested urban landscape. Based on the findings it is concluded that;

- the spectral information derived from Sentinel-2 MSI can be effectively used to model or predict climate regulating ecosystem services such as carbon stock in reforested urban landscape.
- spectral indices (e.g. NDVI, EVI, MSRI and $NDVI_{RE}$) are useful in enhancing prediction performance of carbon stock in reforested urban environment.

The findings of this study are critical for understanding the contribution of reforestation strategy in the global carbon balance and climate change regulation potential as required by Kyoto-Protocol and Reducing Emissions from Deforestation and Forest Degradation (REDD+). The study also provides information that is beneficial to decision-and policy-makers and forest managers to design optimal management policies and increase reforestation projects.

Also, the study demonstrates the significance of the reforestation initiative in reducing atmospheric carbon emissions and regulating climate systems within the urban landscape, hence can be used to suggest effective management and monitoring practices for reforested ecosystems and their services. Overall, we conclude that Sentinel-2 spectral information can be effectively used for predicting and monitoring carbon flux in the reforested urban landscape. Furthermore, dataset and approaches adopted in this study are easily transferable to similar initiatives globally due to S-2’s free availability and global coverable. Also, the random forest ensemble has been proven to be robust in estimating forest carbon.

4.6 Summary

This study presented the effectiveness of Sentinel-2 spectral data in quantifying reforestation carbon stock in urban landscape and provided useful methodology that can been adopted by forest managers and policy makers to monitor and plan for larger scale reforestation project. However, the unique image processing such as texture measures generated from Sentinel-2 MSI have not been utilized to quantify carbon stock variability across reforested tree species. Therefore, the next Chapter 5 test the capability of texture measures derived from Sentinel-2 MSI in quantifying carbon stock variation between reforested tree species within urban landscape.

Chapter Five: Quantifying carbon stock variability of species within a reforested urban landscape using texture measures derived from remotely sensed imagery

This chapter is based on:

Mngadi, M., Odindi, J. and Mutanga, O., 2022. Quantifying carbon stock variability of species within a reforested urban landscape using texture measures derived from remotely sensed imagery. In: Arellano, P. and Pandey, P. (Eds), Advances in remote sensing for forest monitoring, Wiley (in press).

Abstract

Urban reforestation initiatives have been identified as valuable for among others, ecosystem services restoration, carbon sequestration and climate change mitigation. Hence, information on carbon stock accumulation and growth within an urban reforested landscape is critical for understanding the contribution of a reforestation initiative in the global carbon cycle and climate change regulation potential. Specifically, quantification of carbon stock variability is useful in understanding the contribution of reforested species to the global carbon cycle and provision of ecosystem goods and services. Hence, this study sought to quantify carbon stock variability across tree species within a reforested urban landscape using texture metrics derived from remotely sensed data. The study adopted grey level co-occurrence matrix (GLCM) technique to derive texture metrics from a Sentinel-2 imagery. Next, the random forest model was used for species carbon stock estimation. The results showed significant variation in carbon stock among reforested tree species. For instance, *Acacia robusta*, *Brideliar micrantha* and *Acacia caffra* produced the highest mean carbon stock (4.81 to 6.96 t/ha) while *Erythrina caffra* and *Syzygium cordatum* yielded lowest (3.97 to 4.26 t/ha). Furthermore, the results demonstrated carbon stock varies significantly ($\alpha \leq 0.05$) between the reforested tree species. These results are essential for understanding the contribution of different tree species in sequestrating carbon emission within urban landscapes, thereby providing evidence-based species prioritization for reforestation. This is ultimately invaluable for promoting the value of urban ecosystem goods and services, carbon sink capacity and climate resilient cities, particularly in the developing world.

Keywords: reforestation, carbon stock, species, remote sensing, texture metrics

5.1 Introduction

Continuous transformation of natural into impervious urban landscapes that typifies urbanization has been considered a major driver of environmental change (Odindi and Mhangara, 2012b; Sithole et al., 2018). This transformation adversely affects the quality of critical ecosystem processes and services, resulting in, among others, an increase in urban thermal heat, air and noise pollution (Livesley et al., 2016b; Xu et al., 2016). Although urban landscapes cover marginal land surface worldwide, they account for approximately 70% of the global carbon emissions due to dense settlement and high energy consumption (Esch et al., 2017; Ribeiro et al., 2019). Literature shows that urbanization is often associated with unprecedented deforestation and forest degradation; resulting in declining ecosystem goods and services and sequestration potential, while increasing greenhouse gas emissions and risk of climate change (Delphin et al., 2016; Keenan et al., 2015; Payn et al., 2015). Hence, the recently launched program for reducing emissions from deforestation and forest degradation (REDD) has identified urban reforestation as the most practical and long-term alternative for assimilating emitted carbon and reducing the impacts of climate change (Curiel-Esparza et al., 2015; Deo et al., 2017; Livesley et al., 2016b; Mansourian and Vallauri, 2005). The recognition of urban reforestation initiatives as reliable carbon sinks is presumed to greatly contribute to the local, regional and global carbon budget (Sithole et al. 2018, Curiel-Esparza et al. 2015, Mngadi et al. 2021). However, despite the immediate need to understand their value on the global carbon cycle and climate change mitigation potential, information on carbon stock variability in reforested trees remains largely unknown. In this regard, there is need for carbon quantification in reforested landscapes in order to facilitate timely and accurate information necessary for informed urban ecosystem services regulation, urban environmental sustainability and carbon and climate change policy formulation. Despite the recent increasing interest in carbon stock assessment in sub-Saharan Africa, especially South Africa, there is paucity in literature that seek to understand carbon variability within re-forested landscapes.

Quantification of carbon stock variability between reforested tree species is an important step towards understanding the contribution of urban reforestation initiatives to the global carbon balance and climate change (Dube and Mutanga, 2015c; Giardina and Ryan, 2002; Van der Werf and Nagel, 1996). For instance, Chen et al. (2015) noted that *Eucalyptus urophylla* produced highest aboveground carbon stock compared to *Castanopsis hystrix* and other 10-mixed plantation species, while Dube and Mutanga (2015) showed that *Pinus taeda* and *Eucalyptus grandis* species constitute the highest proportion of aboveground carbon stock. Also, Wei et al. (2013) affirmed that aboveground carbon stock varies with different forest species. These studies demonstrate that explicit knowledge on carbon balance necessitate an understanding of variability of carbon stock between and within forest species.

Despite numerous studies estimating carbon variations across different forest species types, most of the work has been done on commercial forests; with limited information on indigenous reforested urban trees (Chen et al., 2015; Dube and Mutanga, 2015c; Wei et al., 2013). Furthermore, available studies have often relied on conventional quantification approaches such as field measurements and survey models; which are costly, labour intensive and time consuming. Literature for instance has demonstrated that field surveys or models result in underestimation and uncertainty of the actual magnitude of carbon stored in terrestrial ecosystems (Dube and Mutanga, 2015c; Guo et al., 2010; Raich et al., 2014; Zhang et al., 2012). Meanwhile, the emergence of remote sensing has shown remarkable potential in providing reliable spectral-data necessary for accurate and concise quantification of carbon stock variability (Gara et al., 2016; Hickey et al., 2018). Remote sensing minimizes the costs associated with extensive field survey and data collection at large spatial coverage, thus valuable for wall-to-wall quantification of aboveground carbon variability. However, despite the suitability of high spatial resolution remotely sensed datasets (e.g. Worldview series, QuickBird and RapidEye) in forest carbon quantification, they are costly and not readily available. These limitations impede recurrent quantification and monitoring of carbon stock, especially in resource constrained regions such as Southern Africa. Hence, the adoption of freely and readily available optical sensors remains the most convenient sources of spatial and temporal datasets for forest ecosystems carbon stock estimation. For instance, the recently launched Sentinel-2, with improved spatial, spectral and radiometric properties has shown promising potential in modelling forest biomass and carbon stock (Adamu et al. 2021, Khan et al. 2020). The sensor consists of strategically positioned bands in the red-edge region of the electromagnetic spectrum, which increases vegetation sensitivity and spectral response. However, whereas the utility of Sentinel-2 multispectral image (MSI) is gaining popularity, the rich information contained by the sensor is yet to be fully explored using texture-measures for estimating forest carbon stock, especially in a reforested urban landscape. Literature shows that analysis using spectral vegetation indices have been the most commonly used techniques in remote sensing for biomass and carbon modelling (Pandit et al. 2020, Foody et al. 2003, Dube and Mutanga 2015, Steininger 2000). The strength of spectral vegetation indices relies on the relationship between red and near infrared bands, which are critical for detecting green biomass, including the ability to reduce atmospheric effects, senesced vegetation and soil background (Lu 2006, Foody et al. 2003, Sarker and Nichol 2011). However, estimating biomass and carbon stock using spectral indices generated from medium-to-coarse spatial resolution sensors in dense tropical and sub-tropical forests have been challenging, due to saturation problems and complexity of forest structure ecosystems (Lu, 2006).

Recently, numerous studies have advocated for integration of texture measures with spectral data to enhance the quality and accuracy of image dataset (Kupidura 2019, Lottering and Mutanga 2012, Dube and Mutanga 2015). Image texture characteristics are considered a valuable source of information capable of detecting forest structural attributes, leaf area index, age and density using medium-or-high spatial resolution image data (Dube and Mutanga 2015, Pandit et al.2020, Lottering and Mutanga 2012, Sarker and Nichol 2011). Texture represent spatial arrangement of gray levels of pixels in an image based on local variance of spectrally unique and size of dominant objects (Zhu and Yang 1998, Kupidura 2019). Hence, texture measures provide robust information on the spatial distribution of pixel-values. Dube and Mutanga (2015) for instance showed that texture measures derived from medium spatial resolution remote sensing can be effectively used to estimate carbon stock variations across different forest species on plantation forests. Generally, the value of texture measures to understand carbon variation in indigenous reforested trees remain largely unknown. It is therefore necessary to evaluate the value of texture measures computed from Sentinel-2 Multispectral Imager (MSI) to estimate carbon stock variability within reforested urban landscape. Therefore, this study sought to quantify carbon stock variation across different species of reforested trees within an urban landscape using Sentinel-2 computed texture measures.

5.2 Materials and methods

5.2.1 Field survey and data collection

Data collection and field surveys were conducted from 13th to 17th of April 2021 during summer season at which climatic conditions (i.e. rainfall and temperature) are favourable for maximum biomass productivity. In this study, pre-determined 120 random sample points were generated and loaded into a global positioning system (GPS) and used to navigate to the sites. Thereafter, 10 m * 10 m plot-size windows were developed around each point, and tree height and circumference (at basal-height of 1.3 m) of the dominant tree species measured and recorded onsite. The tree species height was measured using clinometer (Vertex IV Hypsometer), while the circumference was measured using tape measure. The tree diameter (D) was then computed from circumference measurements using the generic diameter equation (eq.5.1). In addition, the geographic location of each sampled tree species was recorded using Trimble GPS.

$$d = \frac{C}{\pi} \qquad 5.1$$

Where d represent diameter, C is the circumference and $\boldsymbol{\pi}$ is a constant (3.14).

5.2.2 Allometric modelling of aboveground biomass and carbon stock

The adoption of allometric model to estimate aboveground biomass has been recommended by Intergovernmental Panel on Climate Change (IPCC, 1988) as the most ideal none destructive approach (Clark III et al., 1986; Toochi, 2018). Literature indicates that allometric relationship between the tree height and diameter affect tree biomass, thus their measurements can be accurately adopted to compute aboveground biomass (Dube and Mutanga 2015, Mngadi et al. 2021). Hence, this study consolidated tree height (H) and diameter (D) of different reforested species in the allometric model to produce aboveground biomass using generic equation (eq.5.2).

$$AGB = a(D^2H)^{\mathrm{b}} \qquad 5.2$$

Where AGB represent aboveground biomass, D is the diameter at breast height (cm), while H indicates tree height (m), and a and b are regression coefficients.

Furthermore, literature indicates that dry biomass contains approximately 50 % of carbon, thus, the factor of 0.5 is commonly used to convert dry biomass into carbon stock (Dube and Mutanga, 2015c; Hu et al., 2015a; Tang et al., 2016). Hence, in this study, the factor of 0.5 was used to compute the actual carbon stock from aboveground biomass.

5.2.3 Image acquisition and pre-processing

In this study, a freely and readily available Sentinel-2 multispectral image captured under clear weather conditions on the 18th of April 2021 was downloaded on the 05th of May 2021 from the European Space Agency (ESA) portal. The image consists of 13 spectral wavebands located in the visible (443.9 – 664.5 nm), near infrared (835.1 – 864.8 nm) and shortwave infrared (1613.7 – 2202 nm) regions of the electromagnetic spectrum. The sensor also provides unique and strategically positioned band settings in the red-edge region (i.e. b5, 6, 7 and 8A) of the electromagnetic spectrum; valuable for vegetation modelling. Sentinel-2 MSI captures spectral information at varying spatial resolutions of 10, 20 and 60 m with high (5 days) temporal resolution. The sensor's spectral data was atmospherically and radiometric corrected in QGIS software using Dark Object Subtraction (DOS) approach.

5.2.4 Sentinel-2 MSI texture metrics derivation

In this study, texture metrics were statistically derived from Sentinel-2 MSI using grey level co-occurrence matrix (GLCM) technique embedded in ENVI 3.4 software. The texture measures were calculated using a co-occurrence displacement vector (d) of 1:1 and the direction (θ) of 45˚ in GLCM algorithm. However, the effect of angle parameter is considered minimal on the coefficient of determination (Kayitakire et al. 2006, Lottering and Mutanga 2012), hence texture measures were computed at a constant angle. Although GLCM technique offers many texture metrics, this study selected nine-texture metrics which includes; mean, variance, correlation, contrast, entropy, dissimilarity, homogeneity and angular second moment (Table 5.1). These texture measures are considered valuable in remote sensing image analysis (Baraldi and Panniggiani 1995, Rao et al. 2002). The content of these texture metrics depends on the sensor's spectral domain, spatial resolution and characteristics of sensed features (i.e. shape, dimension and spatial distribution). Image-texture measures are robust in detecting forests structure, leaf area index, biomass, density and age (Sarker and Nichol 2011, Dube and Mutanga 2015). These ecosystem parameters are strongly related to remote sensing spatial and spectral information often used to estimate aboveground biomass and carbon stock. Furthermore, one of the key parameters of the GLCM technique is the moving window size. Thus, in this study, the window size of 3 x 3 was established to compute texture metrics. In addition, texture values from individual band-metric were extracted using ArcMap (version 10.6).

Table 5.1. Image-texture metrics derived from Sentinel-2 MSI s and their formulae.

Texture variables	Formulae	Reference
Mean (ME)	$\sum_{i=1}^{Ng}\sum_{j=1}^{Ng} i * P(i,j)$	(Materka and Strzelecki 1998)
Variance (VAR)	$\sum_{i=1}^{Ng}\sum_{j=1}^{Ng}(i-\mu)^2\, P(i,j)$	(Materka and Strzelecki 1998)
Correlation (COR)	$\frac{\sum_i \sum_j (i,j)P(i,j)-\mu_x\mu_y}{\sigma_x\sigma_y}$	(Kayitakire et al. 2006)
Contrast (CON)	$\sum_{i=1}^{Ng}\sum_{j=1}^{Ng} P(i,j)(i-j)^2$	(Kayitakire et al. 2006)
Entropy (ENT)	$-\sum_{i=1}^{Ng}\sum_{j=1}^{Ng} P(i,j)\log(P(i,j))$	(Yuan et al. 1991)
Dissimilarity (DI)	$\sum_{i=1}^{Ng}\sum_{j=1}^{Ng} P(i,j)\,\lvert i-j\rvert$	(Puzicha et al. 1999)
Homogeneity (HO)	$\sum_{i=1}^{Ng}\sum_{j=1}^{Ng}\frac{1}{1+(i-j)^2}\, P(i,j)$	(Tuttle et al. 2006)
Angular Second Moment (ASM)	$\sum_{i=1}^{Ng}\sum_{j=1}^{Ng}\{P(i,j)\}^2$	(Yuan et al. 1991)

Note: $P(i,j)$ is the frequency in which two compared pixels occur (e.g. one with grey level *i* and the other with grey level *j*.

5.2.5 Statistical analysis

In this study, aboveground carbon stock estimates across different tree species was performed using random forest model implemented in RStudio (version 3.6.3.) software. Random forest is an ensemble machine learning algorithm established to improve regression trees approach by combining multiple sets of decision trees. In a regression, random forest builds individual trees by randomly selecting a subset of variables from the input dataset. The optimal random forest model is determined using three parameters: *ntree*; which is based on a great set of decision trees computed from the observed input bootstrap sample (with default value set to 500), *mtry*; which is the number of predictor variables tested at each tree node (*mtry* takes the square-root of the total number of variables as a default value in the classification, whereas, in the regression divides all predictors with a default value of three) and *node-size*; which is the lowest value of terminal nodes size of the trees (with default value of one). Commonly, the out-of-bag error is often adopted to discover optimal *ntree* and *mtry* value for the best prediction model. In this study, *ntree* was evaluated between 100 and 500 at an interval of 100, while the *mtry* values were evaluated between 1 and 12 using interval value of 1. The *node-size* was accepted at a default value of 1 and used throughout the prediction analysis. Furthermore, backward elimination methods embedded in random forest algorithm was used to determine a subset of predictor variables which were ideal for the final prediction model. Backward elimination is necessary for removing predictor variables that suffer from multicollinearity, while remaining with optimal predictors which provide better estimation performance. In this study, the prediction output of random forest model was integrated into the statistical analysis of variance (ANOVA) embedded in OriginPro (version 9.0) software for testing significant difference ($\alpha \leq 0.05$) in carbon stock variability between different tree species.

5.2.6 Model accuracy assessment

The prediction performance of random forest was tested based on 10-fold cross validation approach. The total dataset (N = 82) was initially separated into training (n = 58) and testing (n = 26) datasets. Coefficient of determination (R^2) and root mean square error (RMSE) values were used for rating the prediction performance of random forest model. The RMSE was performed based on the following equation (eq5.3):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}} \qquad 5.3$$

Where y_i represent observed values, while $\hat{y}_i$ representing predicted values and n the number of data points.

5.3 Results

5.3.1 Carbon stock of reforested tree species

Figure 5.1 illustrates the statistical summary of measured carbon stock variability between five different species. The *Acacia caffra* for instance had the highest mean carbon stock of 6.91 t/ha, compared to *Erythrina caffra* and *Syzygium cordatum*, which had the lowest carbon stock of 3.98 and 4.25 t/ha, respectively.

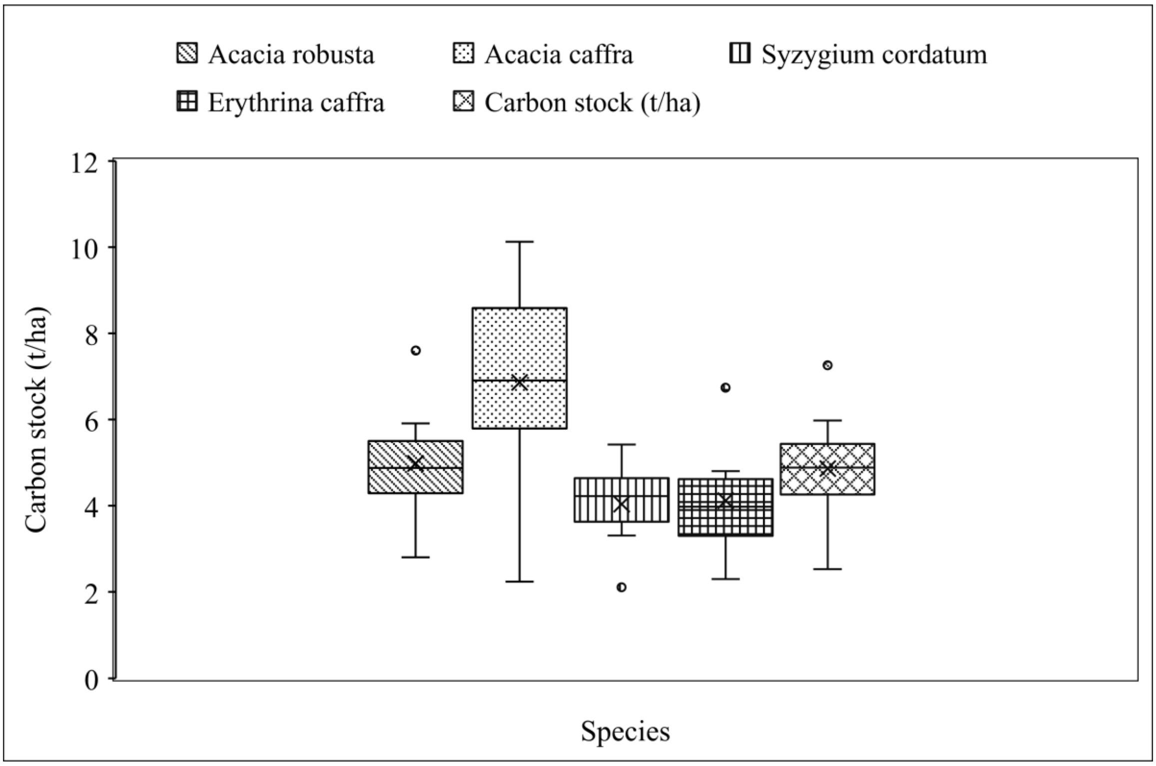


Figure 5.1: Descriptive statistics of the aboveground measured carbon stock variability between tree species.

Results in Table 5.2 show the optimal Sentinel-2 bands derived texture measures for estimating carbon stock across different forest species using cross-validation and backward elimination approaches. Optimal texture measures for *Acacia caffra* and *Acacia robusta* species carbon stock estimations were mean, variance, homogeneity, contrast and correlation, while optimal texture measures for *Briderliar microntha* and *Syzygium codartum* species were dissimilarity, second moment, mean, contrast and correlation. Contrast, second moment and correlation were selected as the most optimal texture predictors for *Erythrina caffra*. Majority of these texture measures were commonly derived from the wavebands located between the visible (e.g. B2, 3 and 4), red-edge (e.g. B5, 6 and 7) and near infrared (e.g. B8 and 8A) regions of electromagnetic spectrum. The selected texture measures were used to build final model for predicting carbon stock variability across different species.

Table 5.2. Selection of optimal bands texture measures at the best moving window size (3 x 3) using random forest model for estimating carbon stock across different tree species.

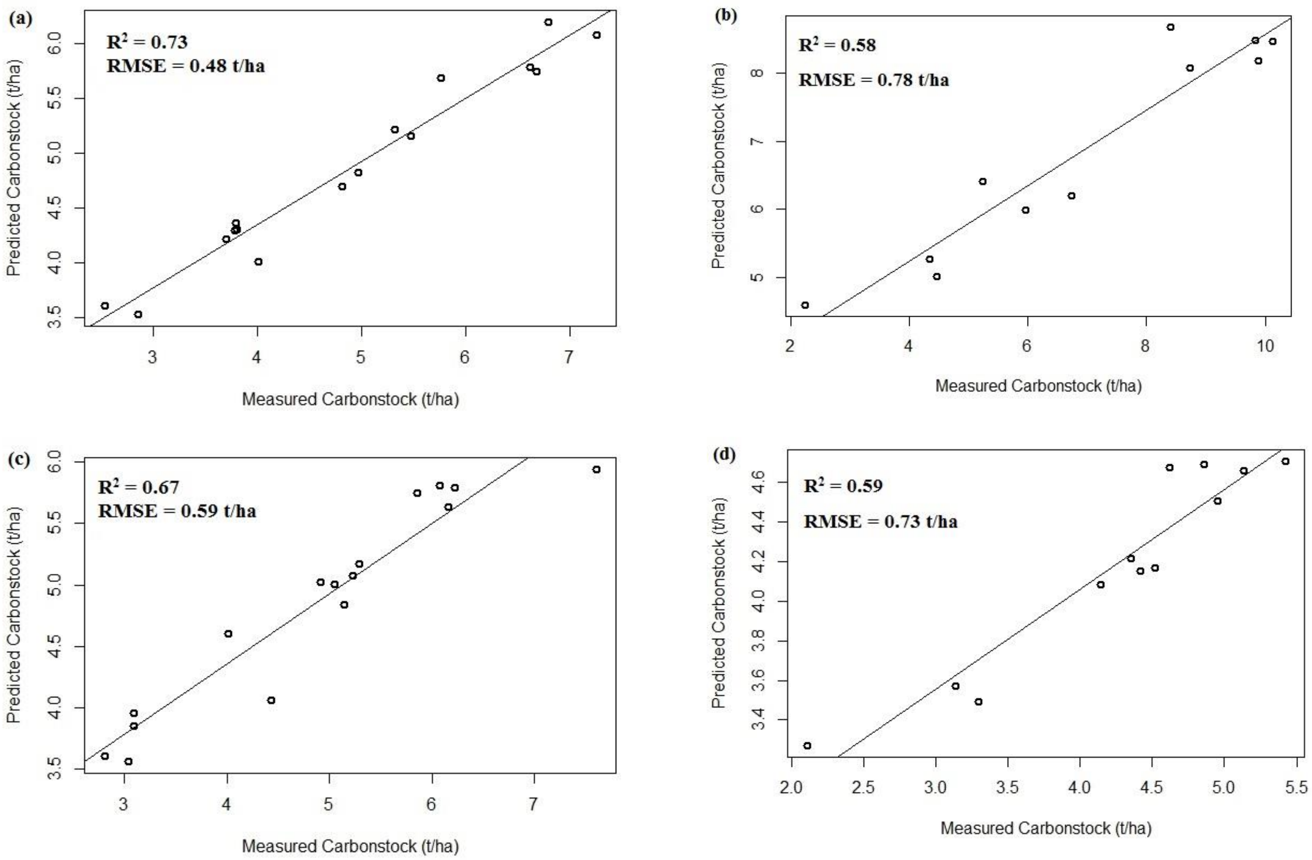
Species	**Image bands**	**Texture measures**	**R^2**	**RMSE (t/ha)**
	B2 (Blue)	Mean	0.29	1.62
Acacia robusta	B8 (NIR)	Variance	0.43	1.03
	B6 (Red-Edge)	Homogeneity	0.46	1.01
	B11 (SWIR)	Contrast	0.38	1.27
	B6 (Red-Edge)	Variance, correlation	0.49	1.00
Acacia caffra	B7 (Red-Edge)	Homogeneity	0.55	0.81
	B8A (Red-Edge)	Correlation	0.51	0.87
	B4 (Red)	Contrast	0.31	1.45
Bridelia micrantha	B2 (Blue)	Dissimilarity	0.52	0.84
	B5 (Red-Edge)	Second moment	0.45	1.01
	B3 (Green)	Correlation	0.40	1.16
	B11 (SWIR)	Mean	0.32	1.41
Syzygium cordatum	B7 (Red-Edge)	Variance, dissimilarity	0.56	0.79
	B2 (Blue)	Dissimilarity	0.39	1.21
	B4 (Red)	Contrast, correlation	0.36	1.33
Erythrina caffra	B3 (Green)	Contrast	0.39	1.22
	B8A (Red-Edge)	Second moment	0.45	1.01

5.3.2 Prediction performance of carbon stock using remotely sensed data and the random forest model

Results in Table 5.3 show the performance of remote sensing derived texture measures and random forest model in estimating carbon stock in the reforested tree species. The consolidation of optimal texture measures in the model produced a reasonable prediction performance (R^2) of between 0.56 and 0.88 and error rate (RMSE) of 0.80 to 0.31 t/ha for estimating carbon stock among reforested tree species. The relationships between texture predicted carbon against field-measured carbon stock for individual species and combined datasets are shown in Figure 5.2.

Table 5.3. Performance of optimal texture measures in predicting carbon stock variability among different tree species.

Species	R^2	RMSE (t/ha)
Acacia robusta	0.58	0.78
Acacia caffra	0.73	0.48
Bridelia micrantha	0.67	0.59
Syzygium cordatum	0.59	0.73
Erythrina caffra	0.56	0.80
All data	0.88	0.31



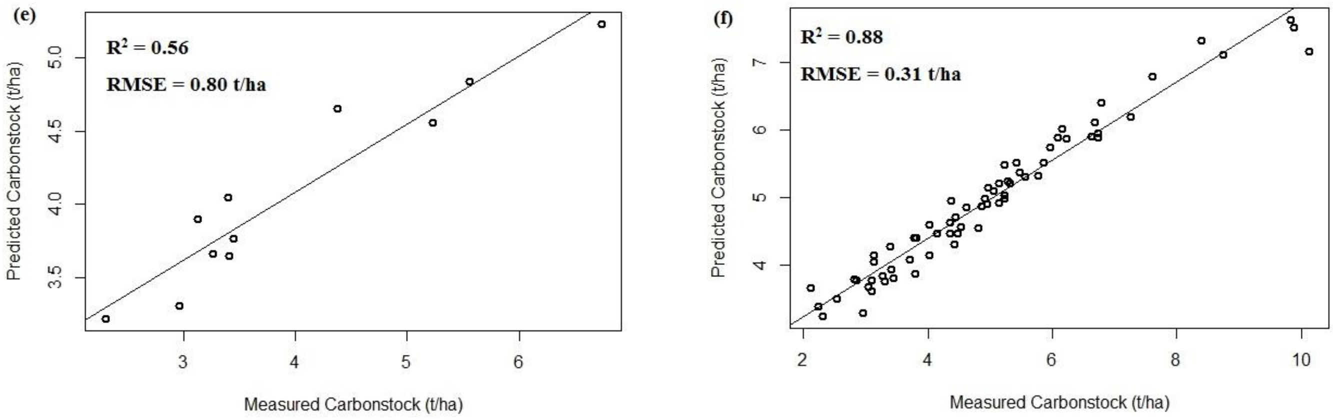


Figure 5.2. Relationship between predicted versus measured carbon stock of *Acacia robusta* (a), *Acacia caffra* (b), *Bridelia micrantha* (c), *Syzygium cordatum* (d), *Erythrina caffra* (e) and combined dataset for all species (f).

5.3.3 Carbon stock estimates and variability between reforested tree species

The estimates of aboveground carbon stock in reforested urban landscape for all studied tree species are shown in Figure 3.3. The results of this study demonstrate that *Acacia robusta, Bridelia micrantha* and *Acacia caffra* contain the largest proportion of carbon stock estimates, compared to *Syzygium cordatum* and *Erythrina caffra*, which contain lower carbon stock. Based on the statistical analysis of variance (ANOVA), the variation in total mean carbon stock between reforested tree species is significantly different ($\alpha \leq 0.05$). The spatial distribution or variation of estimated carbon stock across different reforested species (i.e. *Acacia caffra, Acacia robusta, Bridelia micrancha, Syzygium cordatum* and *Erythrina cafffra*) is shown in Figure 5.4.

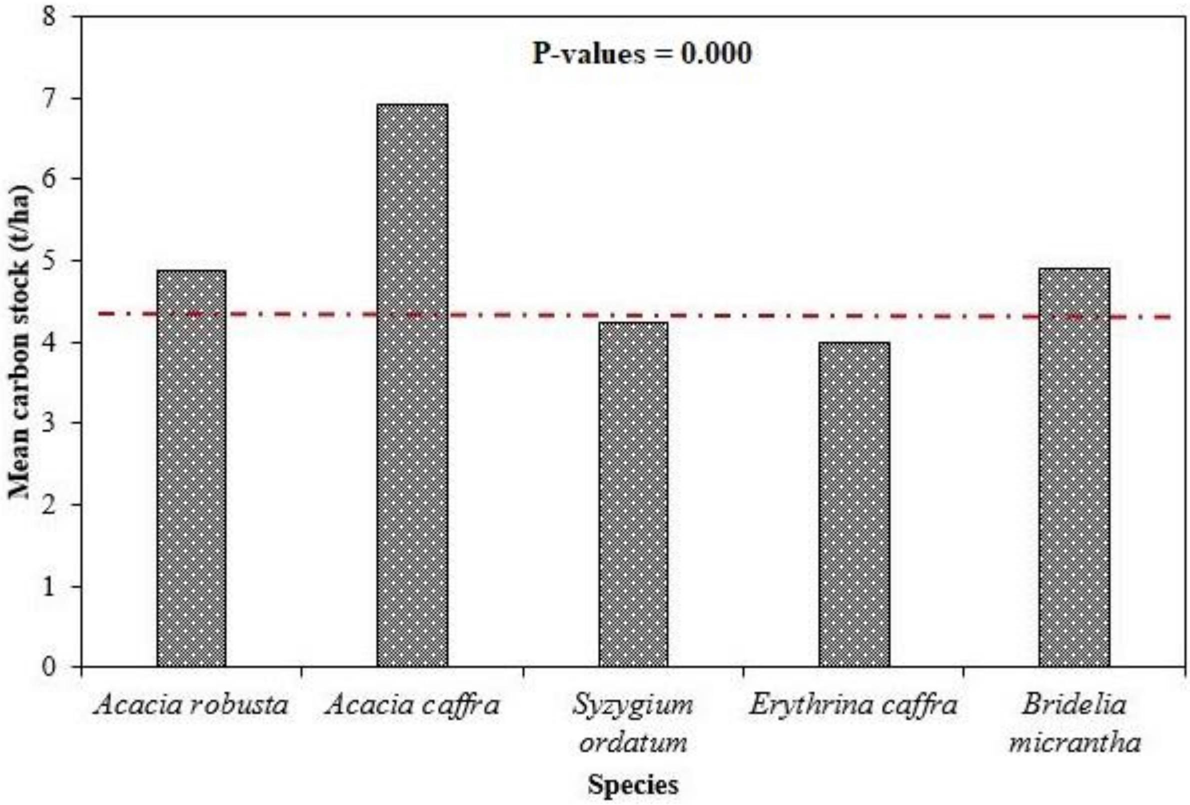


Figure 5.3. Total mean carbon stock variability between different reforested tree species. Red line separates higher and lower mean carbon stock derived from reforested urban landscape.

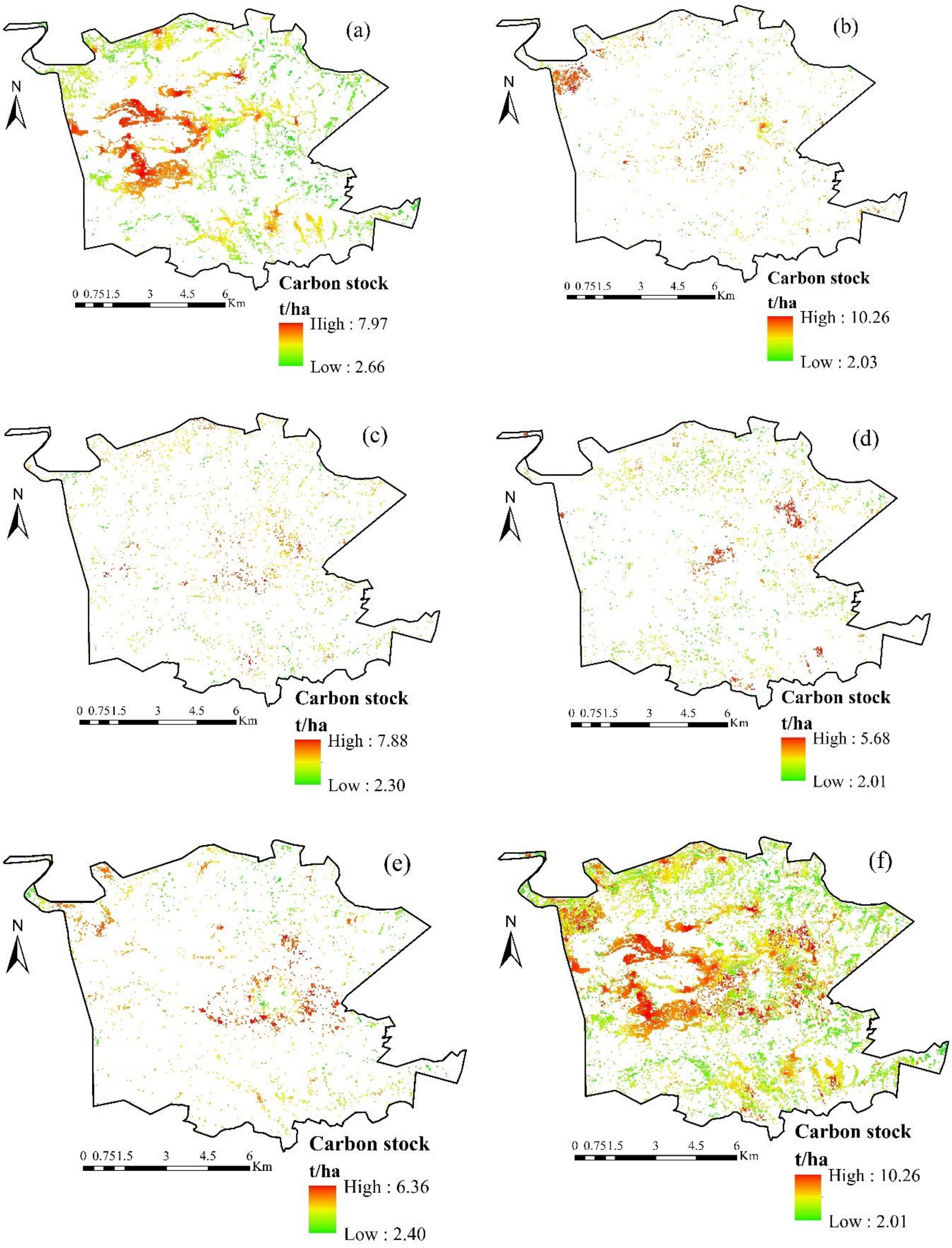


Figure 5.4 Spatial distribution of aboveground carbon stock of *Acacia robusta* (a), *Acacia caffra* (b), *Bridelia micrantha* (c), *Syzygium cordatum* (d), *Erythrina caffra* (e) and combined species (f).

5.4 Discussion

Reliable carbon inventory requires critical understanding of carbon stock variability among different tree species. Nonetheless, carbon stock variability for reforested trees has remained unknown, despite the need to understand the contribution and value of reforestation programs in the global carbon cycle and climate change mitigation. Thus, this study sought to quantify aboveground carbon stock variability across different reforested tree species within an urban landscape using remote sensed imagery texture measures.

This study showed that texture measures derived from Sentinel-2 MSI can be used to explicitly determine aboveground carbon stock variability among different species of reforested trees within an urban landscape. Based on the results, the consolidation of optimal texture measures (i.e. mean, variance, homogeneity, contrast, dissimilarity, angular second moment and correlation) selected across different species using cross-validation and backward elimination techniques yielded R^2 ranging from 0.56 to 0.88 and RMSE from 0.31 to 0.80 t/ha in predicting carbon stock allocation. Most of these texture measures were mostly computed from the red, red-edge and NIR bands; which are highly sensitive to vegetation. The importance of these wavebands in detecting vegetation health and productivity is widely documented in literature (Gara et al., 2016; Sibanda et al., 2016). The results of this study are consistent with Pandit et al. (2020) and Dube and Mutanga (2015) who established that remote sensing derived texture measures are important for improving the estimation performance of biomass and carbon stock. The strength of remote sensing derived texture measures in estimating forest carbon stock variability is attributed to the ability to capture crucial information related to biophysical properties of vegetation such as canopy structure, leaf area index, biomass and tree age (Pandit et al. 2020, Kupidura 2019). According to Lottering and Mutanga (2012), texture measures enhance pixels' relationship, which increases estimation potential of forest structural attributes, including biomass and carbon stock. Furthermore, advanced texture image processing technique appropriately reduced atmospheric effects, sensor's view angle and sun-glint (Fan et al. 2014, Mousivand et al. 2014), hence providing pure texture values valuable for concise estimation of forest carbon stock. In addition, the sensor's improvement in its push-broom scanning properties such as small signal-to-noise ratio and high radiometric resolution (12 bits) boosted the performance of texture measures derived from Sentinel-2 MSI for carbon stock estimation. Moreover, the adoption of grey level co-occurrence matric allowed for homogenization of 20 m bands to 10 m resolution through resampling, which increased the spatial information of Sentinel-2 MSI for invaluable estimation of carbon stock. Overall, the study presents a cost effective and useful option of remote sensing data processing and acquisition using texture measures technique, especially from Sentinel-2 MSI for monitoring and managing the spatial and temporal dynamics of carbon stock variability in reforested urban environment.

5.4.1 Carbon stock variability between reforested tree species

The results of this study demonstrated a significant variation ($\alpha \leq 0.05$) in aboveground carbon stock among reforested tree species, with *Acacia robusta, Brideliar micrantha* and *Acacia caffra* containing higher carbon stock (4.89 to 6.96 t/ha) than *Syzygium cordatum* and *Erythrina caffra* (3.97 and 4.26 t/ha). Similar results were reported by Dube et al. (2015) who established a significant variation in carbon stock between different tree species (i.e. *Eucalyptus grandis* and *dunii* and *Pinus taeda*), while, Chen et al (2015) established a substantial variation in carbon stock between *Acacia crassicarpa*, *Eucalyptus urophylla* and *Castanopsis hystrix* species. Such variation in carbon stock can be explained by differences in biochemical (i.e. lignin, carotenoids) and biophysical (i.e. canopy structure, leaf stomata and area) properties between the taxon's, which significantly control vegetation's net photosynthetic process and carbon uptake. This is supported by Waring et al (1997), who noted that unequal carbon uptake due to differing photosynthetic absorption parameters such as pigments and leaf optical properties result in uneven distribution of carbon stock among tree species of different genera. According to Chen et al (2015) and Dube et al (2015), variations in carbon stock across different forest tree species can be explained by plant traits like maximum net photosynthetic rate (P_{max}) per unit forest land area (P_{max} multiplied by leaf area index) within different forest species. These studies shows that variation in biophysical properties among tree species facilitate differences in carbon stock. Moreover, this study demonstrates that reforestation of different indigenous tree species with great carbon sequestration capacity and storage reserve can promote climate resilient urban landscape and contribute to meeting the requirement of Kyoto Protocol and REDD+ to reduce atmospheric carbon emissions and mitigate climate change. In addition, the study provides basis for determining future optimal reforestation species mix to achieve both carbon assimilation imperatives and provision of other ecosystem goods and services. Thus, the prioritization of tree species such as Acacia and Brideliar for future reforestation projects is necessary for meeting the demands of Kyoto Protocol.

5.5 Conclusion

The current study sought to quantify aboveground carbon stock variability across different reforested tree species using remote sensing derived texture metrics dataset. The results in this study have shown that carbon stock varies significantly among reforested tree species groups. Across species, *Acacia robusta, Bridelia micrantha* and *acacia caffra* have dominant carbon stock, whereas *Erythrina caffra* and *Syzygium cordatum* produced lower carbon stock. The adoption of texture measures derived from freely and readily available Sentinel-2 MSI proved instrumental in estimating carbon stock variability within reforested urban landscape. The findings of this study provides knowledge on the contribution of reforestation initiative in the global carbon budget and climate change mitigation potential. Moreover, the study provides necessary information that can benefit forest managers, decision-makers and policy-makers to establish well-informed management policies and plans for further improvement in sequestration capacity of reforestation program through large-scale projects, especially in urban and peri-urban landscapes.

5.6 Summary

In this study, the adoption of texture measures generated from Sentinel-2 MSI proved invaluable in predicting carbon stock variability among reforested tree species. This study provide insight on robust image-processing technique such as texture metrics for quantifying forests carbon stock at a species-level. However, the utility of complementary information generated from fusing Sentinel-1 C-band and Sentinel-2 MSI have not been explored for enhancing reforestation carbon stock estimation. Hence, subsequent Chapter 6 test the efficacy of combining Sentinel-1 C-band and Sentinel-2 MSI for enhancing reforestation carbon stock estimation within urban landscape.

Chapter Six: The efficacy of combining Sentinel-1 C-band and Sentinel-2 MSI datasets in enhancing reforestation carbon stock estimation in urban landscape

This chapter is based on:

> **Mngadi, M.**, Odindi, J. and Mutanga, O., 2022. The efficacy of combining Sentinel-1 C-band and Sentinel-2 MSI datasets in enhancing reforestation carbon stock estimation in urban landscape. *Journal of Environmental Management* (under peer-review), manuscript no: JEMA-D-22-04770.

Abstract

Accurate information on reforested carbon stock inventories is vital in understanding the value of urban reforestation initiatives and its role in designing climate mitigation strategies. However, the carbon stock estimation capabilities of traditional optical sensors are often plagued by saturation issues, clouding, and canopy shadowing effects. Although the fusion of radar and optical spectral data has shown great promise in reducing these challenges, studies on the utility of fused dataset in reforested urban areas remain limited. To this end, this study examined the efficacy of combining Sentinel-1 C-band and Sentinel-2 MSI datasets in enhancing reforestation carbon stock estimation in urban landscape. To this objective, Sentinel-1 C-band and Sentinel-2 MSI image datasets were combined using a nearest neighbour diffused (NND) fusion technique and reforested carbon stock inventories estimated and mapped using a random forest regression model. The best carbon stock model (R^2 = 0.78 – 0.83; RMSE = 0.31 – 0.41 $t.ha^{-1}$) was produced from the fused sentinel dataset. Among the interferometric polarisation, the results show that cross-polarized VH carbon estimates strongly correlate with measured carbon stock (r = 0.98), compared to co-polarized VV (r = 0.96). These results provide a basis to understand the value and versatility of image fusion in improving carbon stock estimation. Hence, the study provides a framework for monitoring reforested urban ecosystems, useful for facilitating sustainable urban living, optimal urban environmental governance and climate change mitigation.

Keywords: reforestation, synthetic aperture radar, polarization, climate change, image fusion, fusion indices

6.1 Introduction

Unrestrained urban growth has placed considerable pressure natural and ecological infrastructure, causing significant environmental degradation within large cities (Keenan et al. 2015, Odebiri et al. 2020, Payn et al. 2015, Luederitz et al. 2015). Specifically, conversion of natural landscapes to other forms of land uses has resulted in elevated levels of carbon emissions, leaving cities vulnerable to severe climate-related events (Adamu et al. 2021, Mngadi et al. 2021a). To reverse the effects of natural landscape degradation and safeguard against current and future climate change related threats, cost effective and strategic ecosystem restoration strategies are necessary in urbanized areas (Bustamante et al. 2019, Cortina-Segarra et al. 2021). Hence, urban reforestation initiatives have emerged as a reliable and sustainable long-term mechanism for carbon sequestration and climate change mitigation (Livesley et al. 2016, Mngadi et al. 2021a).

Whereas reforested urban areas are generally known to sequester considerable amounts of atmospheric carbon, specific contributions of successful urban reforestation initiatives towards local and global carbon exchange fluxes and climate change mitigation remain largely unexplored in the developing world (Mngadi et al. 2021b, Curiel-Esparza et al. 2015, Deo et al. 2017). Moreover, the rapid and dynamic nature of land-use change within third world cities has made it increasingly difficult to fully comprehend the contribution of urban reforestation programs for global carbon accounting. Thus, cost effective and reliable carbon estimation techniques are necessary for determining the value of urban reforestation projects (Holcomb et al. 2021). In this regards, the Inter-Governmental Panel on Climate Change Good Practice Guidance (IPCC-GPG) has recommended remote sensing as method reliable approach for determining and monitoring of forest carbon stock (Gara et al. 2016).

Optical remote sensing sensors (e.g. Worldview series, Quickbird, RapidEye and Sentinel-2) have been widely used for biomass and carbon stock estimation within forest ecosystems (Dube and Mutanga 2016, Eckert 2011, Aricak et al. 2015, Gonzalez et al. 2010, Imran 2021, Mngadi et al. 2021c). For instance, Dube and Mutanga (2016) used Worldview-2 (400 nm - 1040 nm) to estimate aboveground biomass and carbon stocks for commercial forest species ($R^2 = 0.73$, RMSE = 18.57 $t.ha^{-1}$) within the uMgeni catchment of South Africa, while Aricak et al. (2015) used RapidEye (440 nm - 850 nm) imagery to predict aboveground forest carbon biomass ($R^2 = 0.71$) in Turkey. Additionally Gonzalez et al. (2010) demonstrated the capability of Quickbird data (450 nm - 900 nm) to quantify forest carbon density in California, United States, while Mngadi et al. (2021) estimated reforestation carbon stock using Sentinel-2 with an R^2

value of 0.79 in the eThekwini region of South Africa. Despite these successes, the adoption of optical sensors are often impeded by several challenges. For instance, optical sensors commonly suffer from canopy shadow and clouding effects, and often lack the capacity to detect digital terrain features critical for deriving volumetric measurements of forests (Haack et al. 2000). Moreover, literature shows that biomass values derived from optical sensors are susceptible to asymptotic saturation, particularly within dense vegetation cover (Malhi et al. 2021, Nuthammachot et al. 2020, Dube and Mutanga 2015).

Nevertheless, radar sensors (such as Sentinel-1) offers crucial backscattering information pertaining to the physical properties of surface features (i.e. roughness, structural geometry and moisture content), which can be used to enhance the capabilities of optical sensors and improve forest carbon stock estimation performance (Mngadi et al. 2021c, Balzter et al. 2015). For instance, the Synthetic Aperture Radar (SAR) sensor attached to Sentinel-1 sensor provides advanced information on canopy height and digital terrain using Interferometric Wide Swath (IW) mode and dual polarization techniques, namely; Vertical transmit/Vertical receive (VV) and Vertical transmit/Horizontal receive (VH) (Balzter et al. 2015). The unique wavelength associated with this sensor also provides enhanced penetration through thin clouds and dense canopy cover (Nuthammachot et al. 2020, Mngadi et al. 2021c, Keleş et al. 2021), hence, SAR data has the capacity to circumvent clouding, shadowing and asymptotic saturation challenges associated with multispectral sensors (Haack et al. 2000, Mngadi et al. 2021c).

The fusion of SAR and optical multispectral data has recently demonstrated great potential in biomass and carbon modelling within forested ecosystems (Forkuor et al. 2020, Malhi et al. 2021, Nuthammachot et al. 2020, Agata et al. 2018). For example, Nuthammachot et al. (2020) combined Sentinel-1 and 2 images to boost the estimation performance of aboveground biomass. Similarly, Keleş et al. (2021) found that fusing optical images with SAR data improves the estimation accuracy of the aboveground carbon stock. Although these studies shown the strength and potential of multi-source approaches in modelling biomass and carbon sinks within forests, to the best of our knowledge, such an approach is yet to be adopted to understand and enhance carbon estimates of reforested trees within urban environments. Furthermore, although studies such as Mngadi et al. (2021c), Sarker and Nichol (2011) and Lu (2006) have demonstrated the utility of spectral vegetation indices derived from multispectral sensors in modelling forest biomass and carbon stock, structural complexity and saturation issues within dense heterogeneous forest canopies remains a noticeable challenge. However, the penetrative capacity of Sentinel-1 SAR imagery presents an opportunity to overcome such limitations. Hence it is necessary to explore the utility of complementary information in quantifying reforestation carbon stocks within urban environments. Thus, this study sought to examine the effectiveness of combining Sentinel-1 SAR and Sentinel-2 multispectral datasets in enhancing carbon stock estimation within a reforested urban environment.

6.2 Materials and Methods

6.2.1 Field data collection

Field data collection was carried out from the 13th to 17th of April 2021 during favourable weather conditions. The study generated 120 random sampling points. To correlate with the spatial configuration of the sentinel data, a 10 m x 10 m plot-size window was adopted for each sample point. Thereafter, structural parameters, such as tree height and circumference (at basal height of 1.3 m) of the dominant tree species within each plot were recorded. Tree height and circumference were measured using a clinometer (Vertex IV Hypsometer) and tape measure, respectively. Tree circumference measurements were then used to compute tree diameter (D) based on a generic diameter equation (eq.6.1) (Ngomanda et al. 2012).

$$d = \frac{C}{\pi} \qquad 6.1$$

Where d represent diameter, C is the circumference and $\boldsymbol{\pi}$ is a constant (3.14).

6.2.2 Allometric modelling of aboveground biomass and carbon stock

Literature has shown that vegetation biomass can be derived through the allometric relationship between tree height and diameter (Dube and Mutanga 2015, Clark III et al. 1986, Mngadi et al. 2021b). Furthermore, the Intergovernmental Panel on Climate Change (IPCC) have endorsed allometric models as non-destructive approaches for biomass estimation (Clark III et al. 1986, Toochi 2018). Consequently, the measured height and diameter of reforested trees were input into the allometric equation below (eq.6.2) to generate aboveground biomass (Altanzagas et al. 2019).

$$AGB = a(D^2H)^{\mathrm{b}} \qquad 6.2$$

Where AGB indicates aboveground biomass, D represent diameter (cm), while H is the tree height (m), and a and b are regression coefficients.

In addition, studies have highlighted that aboveground dry biomass contains approximately 50 % carbon; hence a factor of 0.5 is frequently used to convert biomass to overall carbon stock

(Toochi 2018, Mngadi et al. 2021b, Birdsey 1992). Therefore, a 0.5 factor was used in this study to convert allometric biomass to carbon stock.

6.2.3 Images acquisition and pre-processing

A Sentinel-1, dual polarised (VV/VH) interferometric and Sentinel-2 MSI datasets captured on the 18th and 25th of April 2021 and were downloaded for the study area on the 5th of May 2021 from the European Space Agency (ESA) portal. The C-band (SAR) was radiometrically and geometric corrected using the sentinel application platform (SNAP) toolbox and speckle noise filtered using the "Refined Lee" feature within the SNAP software. The feature is often used in speckle filtering due to its ability to preserve edges, linear features and texture information (Filipponi 2019). The terrain corrected sigma naught (σ_0) of VV and VH bands was converted to decibel units (dB) to provide the best radar measurements that correlate to biomass (Small 2011, Huang et al. 2018). In this study, Sentinel-2A's spectral radiance were atmospherically corrected and converted to reflectance using a Dark Object Subtraction (DOS) technique embedded in quantum geographic information system (QGIS) software (version 3.4.2).

6.2.4 Image fusion technique

Sentinel-1 and Sentinel-2 datasets were fused using a pixel level fusion technique within the ENVI (version 3.1.3) software environment. Pixel level fusion has been shown to retain the base image's spectral data without significant levels of distortion or noise (Zhang et al. 2018, Mngadi et al. 2021c). In this study, a Nearest Neighbour Diffused (NND) fusion technique, which utilizes the pixel spectrum as its lowest unit of operation and uses a mixing model to generate a resolution-enhanced spectral image, was used (Zhang et al. 2018). The NND technique assumes that each generated spectrum in a fused high spatial resolution image is a weighted mixture of neighbouring super pixel spectra in the medium-to-low spatial-resolution multispectral image (Sun et al. 2014, Zhang et al. 2018). A diffusion model computed from the high-resolution image controls the weights by establishing the relationship or similarity of the target pixel to the neighbouring super pixels (Sun et al. 2014, Zhang et al. 2018). Unlike traditional techniques (i.e., Gram–Schmidt) that use band-by-band operations, the NND technique incorporates per-pixel-spectrum processing, which reduces noise, and minimizes distortion through pseudo-sharpening and bilinear interpolation (Peery and Messinger 2020, Isidro et al. 2017). This enhances the spatial features of the multispectral image while maintaining the embedded spectral information (Peery and Messinger 2020, Isidro et al. 2017). In this study, 15 vegetation indices were independently generated from the original Sentinel-2 and the fused image. These were used as predictor variables for carbon stock estimation (Table 6.1).

Table 6.1. Indices generated and their description and formulae.

Indices	**Description**	**Formulae**	**Reference**
NDVI	Normalized difference vegetation index	$\frac{NIR - Red}{NIR + Red}$	(Rousel et al. 1973)
EVI	Enhanced vegetation index	$2.5*[\frac{NIR-Red}{(NIR+6*Red-7.5Blue+1)}]$	(Huete et al. 1999)
TVI1	Triangular vegetation index	$0.5 * [120 * (NIR - Green) - 200 * (Red - Green)]$	(Broge and Leblanc 2001)
TVI2	Transformed vegetation index	$\sqrt{(NDVI)} + 0.5$	(Deering 1975)
GNDVI	Green normalized difference vegetation index	$\frac{NIR - Green}{NIR + Green}$	(Gitelson and Merzlyak 1998)
MSRI	Modified simple ratio index	$\frac{\frac{NIR}{Red} - 1}{\sqrt{\frac{NIR}{Red}} + 1}$	(Wu et al. 2008)
RVI	Ratio vegetation index	$\frac{NIR}{Red}$	(Baret and Guyot 1991)
Cl_{green}	Green chlorophyll index	$\frac{NIR}{Green} - 1$	(Gitelson et al. 2003)
AVI	Advanced vegetation index	$\sqrt[3]{[NIR * (1 - Red) * (NIR - Red)}$	(Plummer 1994)
MTVI1	Modified triangular vegetation index	$\frac{1.5 * (1.2 * (NIR - Green) - 2.5 * (Red - Green)}{\sqrt{(2 * NIR + 1)^2} - (6 * NIR - 5 * \sqrt{(Red)} - 0.5}$	(Haboudane et al. 2004)
MTVI2	Modified triangular vegetation index	$1.2 * (NIR - Green) - 2.5 * (Red - Green)$	(Haboudane et al. 2004)
NPCRI	Normalize pigment chlorophyll ratio index	$\frac{Red - Blue}{Red + Blue}$	(Peñuelas et al. 1994)

$NDVI_{RE}$	red-edge normalized difference vegetation index	$\frac{NIR - RE}{NIR + RE}$	(Dong et al. 2019)
$MSRI_{RE}$	Modified simple ratio red-edge index	$\frac{\frac{NIR}{RE} - 1}{\sqrt{\frac{NIR}{RE} + 1}}$	(Wu et al. 2008)
Cl_{RE}	Red-edge chlorophyll index	$\frac{NIR}{RE} - 1$	(Gitelson et al. 2003)

6.2.5 Statistical analysis

A random forest regression algorithm was used within the R statistical software (RCore 2016) to estimate carbon stock within the reforested urban landscape. The random forest regression, which is a deterministic ensemble-based method, contends with highly correlated and noisy variables using a large matrix of decision trees (Breiman 2001). The algorithm selects several bootstrapped samples which are subsequently picked with replacements, the decision tree matrix is then grown to a selected node size, where each specific tree is averaged to obtain a final prediction (Adam et al. 2014, Breiman 2001). Random forest uses two robust optimisation parameters to boost the model performance; namely *ntree* (based on largest subset of decision trees) and *mtry* (based on the predictor variable selected at each node). Generally, the optimal number of decision trees (*ntree)* and predictor variables (*mtry)* are identified and defined based on the smallest cross-validation error (Breiman 2001). For the Sentinel-2 image, the optimal *ntree* and *mtry* values were identified as 300 and 18, respectively. Whereas for the fused image, the best *ntree* and *mtry* was determined at 200 and 14 for cross-polarisation (VH) predictor variables and 300 and 19 for co-polarisation (VV) derived predictors.

The variable importance technique embedded in random forest regression model was used to identify the influence of each predictor variable within the carbon stock estimation model. The total prediction dataset (N = 82) was divided into calibration (n = 58) and validation (n = 26) datasets. The prediction accuracy and error of each carbon stock model were tested using the coefficient of determination (R^2), root mean square error (RMSE) and mean absolute error (MAE) (Adam et al. 2014).

6.3 Results

6.3.1 Reforestation carbon stock

Descriptive statistics show that the value of measured carbon stock within the reforested urban landscape ranged between 0.249 to 10.22 $t.ha^{-1}$, with a mean and standard error of 3.45 $t.ha^{-1}$ and 0.32 $t.ha^{-1}$, respectively.

6.3.2 Variable importance selection

Results in Figure 6.1 show the performance of each individual predictor variable utilized in the model. The level of importance of each variable is based on the Out of Bag (OOB) error rate, which increases with variable importance. Figure 6.2 demonstrates the optimal number of predictor variables selected for carbon stock estimation. For Sentinel-2 derived indices, a subset of four predictor variables (i.e., $NDVI_{RE}$, NDVI, EVI and MSRI) was selected based on the smallest error rate using a backwards feature elimination technique. The consolidation of this subset into the final random forest regression model generated the lowest OOB RMSE (0.121 $t.ha^{-1}$) and 10-fold cross-validation RMSE (0.129 $t.ha^{-1}$). From the training dataset extracted from the fused optical Sentinel-2 with SAR cross-polarization VH, backwards feature elimination selected a subset of three variables (i.e., Red-edge band 8A, EVI and $NDVI_{RE}$) for the final carbon stock model. This subset produced the least OOB RMSE (0.112 $t.ha^{-1}$) and 10-fold cross validation RMSE (0.122 $t.ha^{-1}$), compared to the use of all 25 predictor variables (0.343 and 0.394 $t.ha^{-1}$). Lastly, five variables (i.e., NDVI, $NDVI_{RE}$, NIR band 8, Red band 4 and Red-edge band 8A) were selected from the fused Sentinel-2 MSI with SAR co-polarization VV. An integration of selected variables in the final carbon stock estimation model obtained the smallest OOB RMSE of 0.144 $t.ha^{-1}$ and 10-fold cross validation of 0.164 $t.ha^{-1}$, compared to a consolidation of all predictor variables in the model (0.342 and 0.424 $t.ha^{-1}$).

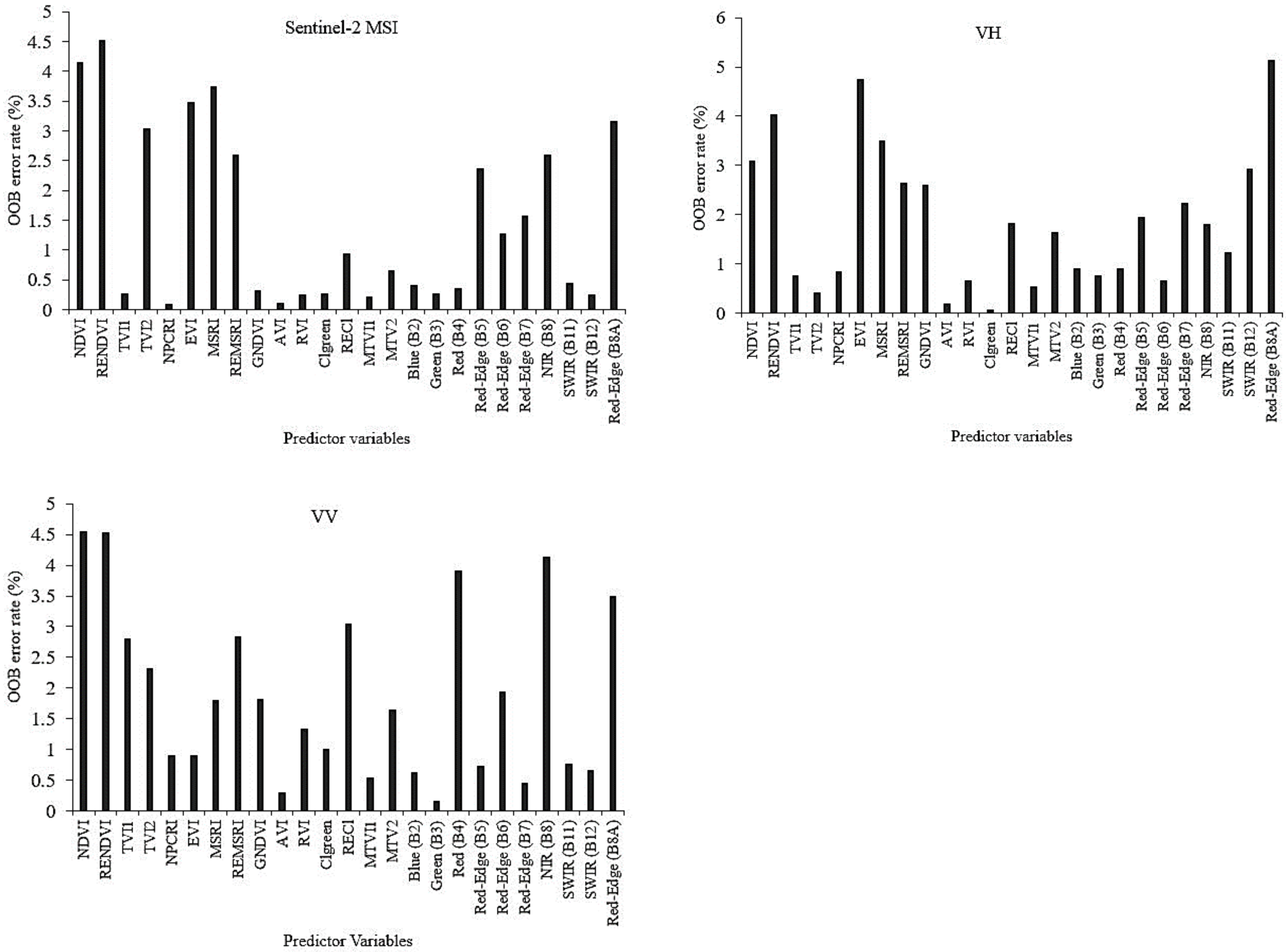


Figure 6.1. The measure of variable importance in predicting aboveground carbon stock using Sentinel-2 MSI and combined Sentinel-2 with individual SAR's (Sentinel-1) polarizations (VH and VV). An increase in OOB error rate indicate higher variable importance.

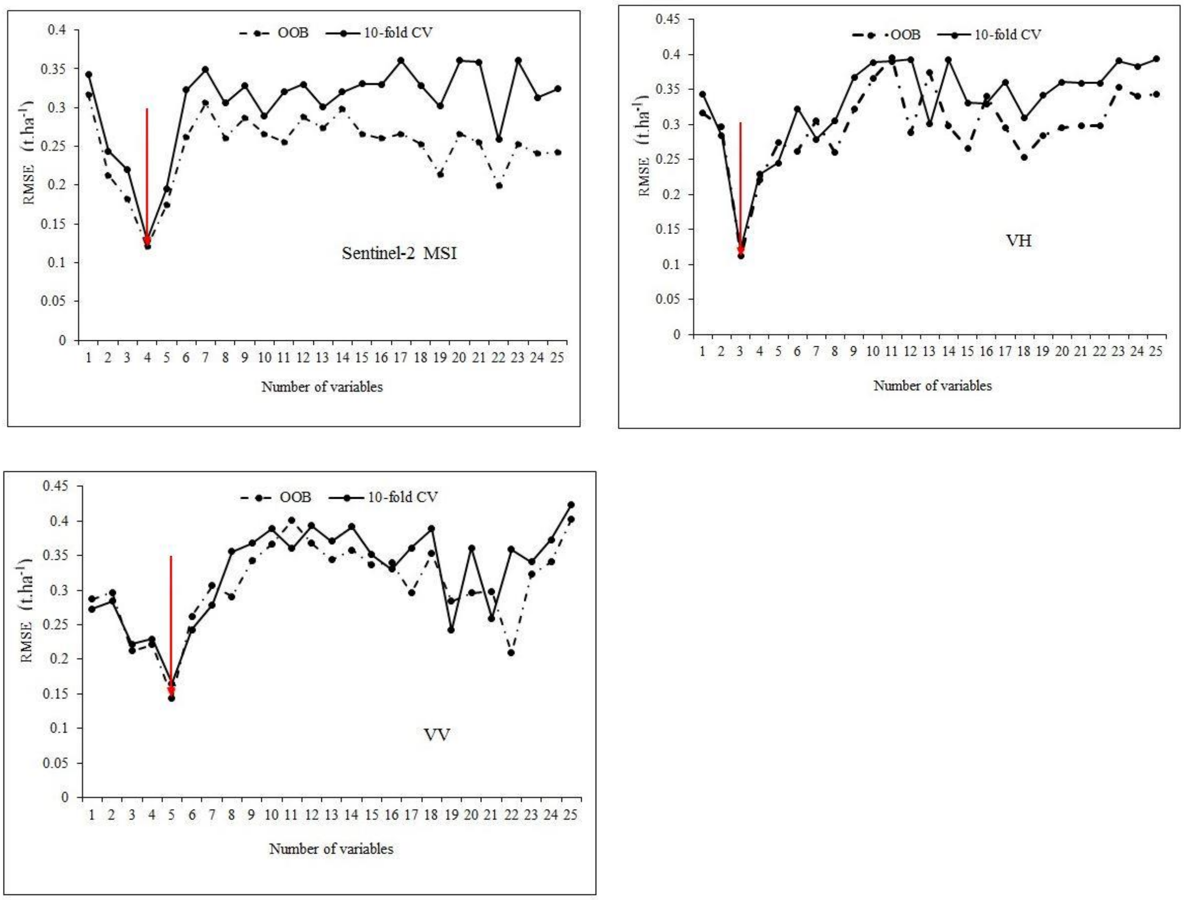


Figure 6.2. Selection of ideal number of variables using random forest's backward feature elimination technique.

The optimal number of predictor variables were selected based on the lowest RMSE (shown with arrow) of OOB and 10-fold cross validation using training datasets extracted from Sentinel-2 MSI and combined optical Sentinel-2 with individual Sentinel-1's VH and VV polarizations.

6.3.3 Carbon stock model performance

The results in Table 6.2 show the mean carbon stock estimates and predictive model performance. The mean carbon estimates of Sentinel-2 MSI for both calibration and validation datasets were 3.64 to 3.89 t.ha^{-1} with an R^2 of 0.76 to 0.78 and RMSE of 0.42 to 0.48 t.ha^{-1} and MAE of 0.21 to 0.24 t.ha^{-1}. In contrast, the integration of optimal spectral predictor variables derived from multisource dataset into random forest model generated better results than the individual Sentinel-2 MSI model. For instance, the fusion of Sentinel-2 MSI with C-band cross-polarized VH operation produced an estimated mean carbon stock of 3.99 to 4.05 t.ha^{-1}, with a better predictive performance (R^2: 0.80 to 0.83) and the smallest error rate (RMSE: 0.31 to 0.35

t.ha^{-1} and MEA: 0.16 to 0.18 t.ha^{-1}) using both calibration and validation datasets. Furthermore, the utility of Sentinel-2 MSI fused with co-polarized VV operation yielded a mean carbon value of 3.98 to 4.01 t.ha^{-1} with a coefficient of determination (R^2) of 0.78 to 0.81 and an RMSE of 0.34 to 0.41 t.ha^{-1} and MAE value of 0.17 to 0.21 t.ha^{-1} for calibration and validation datasets. Among the fused interferometric polarization operations of SAR imagery, results show that cross-polarized VH performed better than co-polarized VV.

Table 6.2. Carbon estimation model performance using Sentinel-2 MSI and the combination of Sentinel-2 MSI with individual co-polarized VV and cross-polarized VH operations of SAR (Sentinel-1) datasets separated into calibration and validation.

Image	**Prediction dataset**	**Mean(t.ha^{-1})**	**R^2**	**RMSE(t.ha^{-1})**	**MAE(t.ha^{-1})**
Sentinel-2	Calibration	3.89	0.78	0.42(10.9%)	0.21
	Validation	3.94	0.76	0.48(12.6%)	0.24
VV	Calibration	3.98	0.81	0.34(8.54%)	0.17
	Validation	4.01	0.78	0.41(10.2%)	0.21
VH	Calibration	4.05	0.83	0.31(7.65%)	0.16
	Validation	3.99	0.80	0.35(8.77%)	0.18

Results in Figure 6.3 demonstrate the relationship between measured and predicted carbon stock using spectral datasets derived from Sentinel-2 MSI and fused Sentinel-2 MSI with cross-polarized VH and co-polarized VV operations of Sentinel-1 SAR imagery. The results show that predicted carbon stock is strongly correlated (r) with measured carbon stock, with a coefficient value of 0.82 to 0.98 (Figure 6.3). The regression analysis shows that the correlation between predicted carbon and measured carbon stock was significant ($\alpha \leq 0.05$). Furthermore, the spatial distribution of aboveground carbon in reforested urban landscape is presented in Figure 6.4. It can be observed that dense canopy cover influences considerable amount of carbon stock, which decreases with a reduction in green biomass concentration.

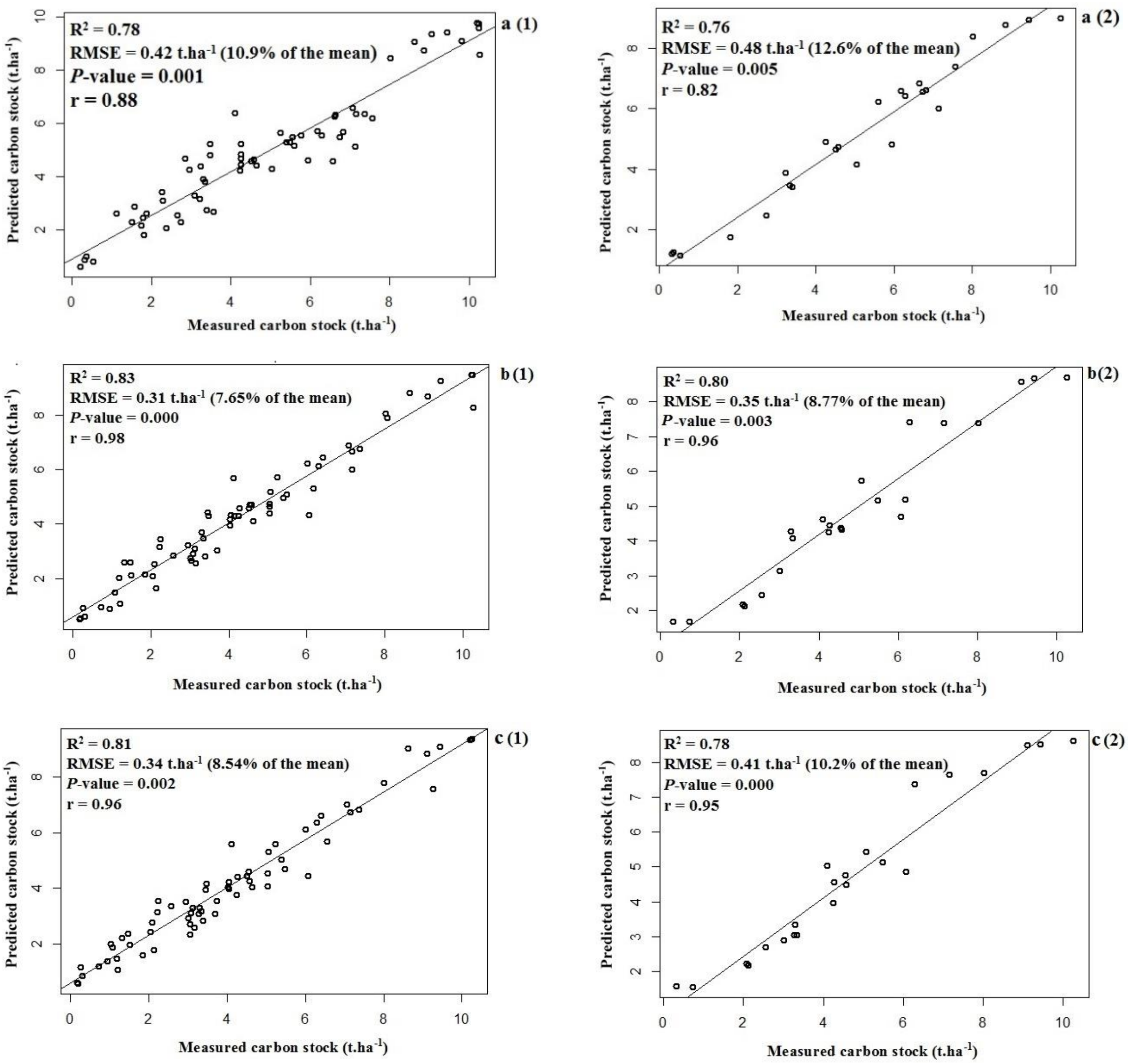


Figure 6.3. Relationship between measured versus predicted carbon stock established using calibration (1) and validation (2) datasets derived from Sentinel-2 MSI (a), and combined Sentinel-2 with cross-polarized VH (b) and co-polarized VV (c) operations.

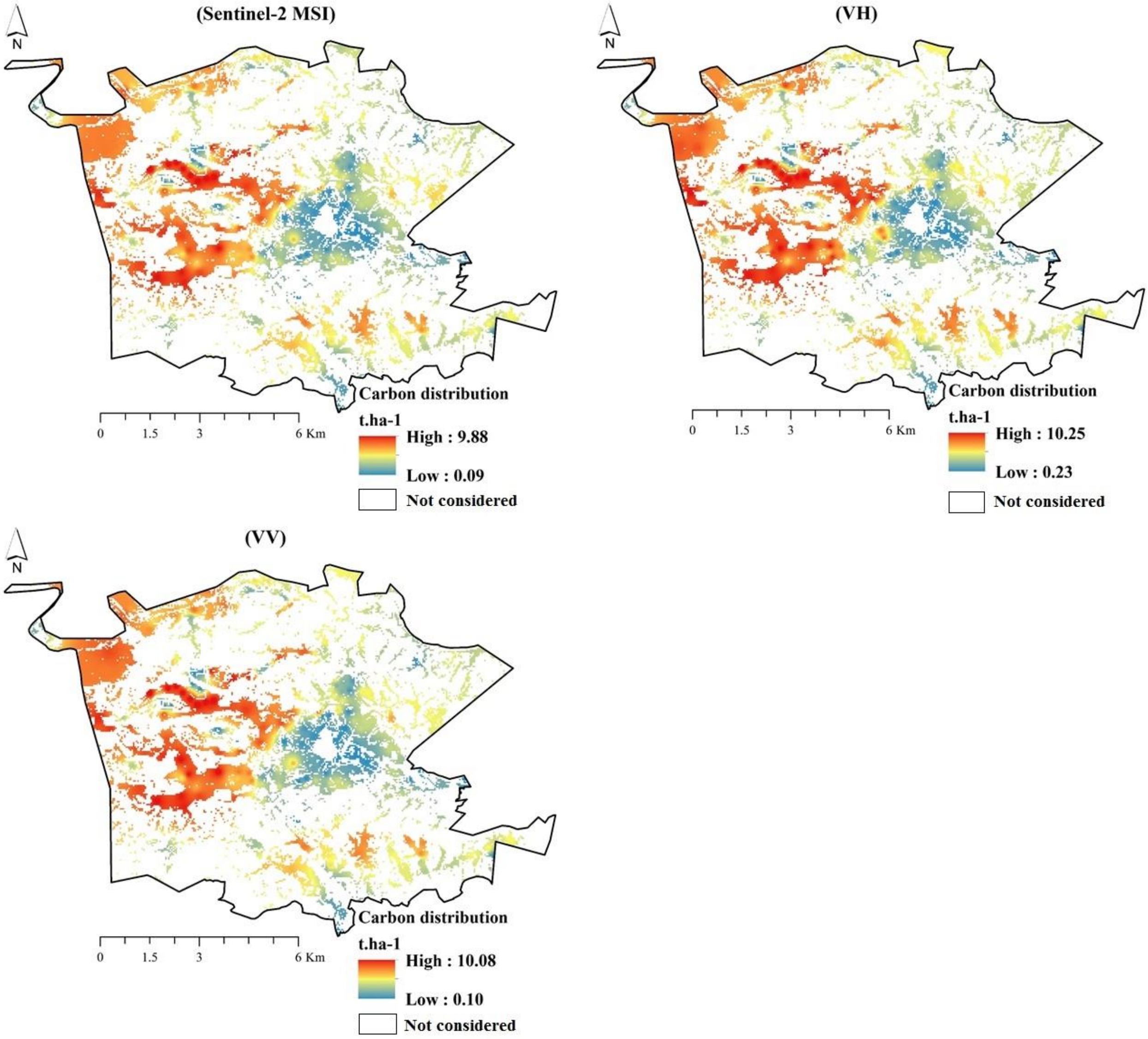


Figure 6.4. Spatial distribution of predicted aboveground carbon stock generated using Sentinel-2 MSI dataset and synthetic aperture radar's cross-polarized VH and co-polarized VV operations fused independently with optical Sentinel-2.

6.4 Discussion

To improve carbon stock monitoring capabilities within reforested urban environments, this study examined the value of fusion-based spectral metrics derived from Sentinel-1 and Sentinel-2 imagery. The outcomes of this study demonstrate that combining optical and radar imagery limits the effect of saturation, clouding, and canopy shadowing, and improve carbon stock estimation within a reforested urban environment.

6.4.1 The utility of Sentinel-1 and Sentinel-2 image fusion in carbon stock estimation

The study findings showed that the inclusion of fusion-based spectral variables noticeably improved carbon stock estimation capabilities, with accuracies increasing from $R^2 = 0.78$ for Sentinel-2 to $R^2 = 0.83$ and 0.81 for fusion-based cross-polarized VH and co-polarized VV, respectively. These findings correspond to Keleş et al (2021) who found that fusion of Sentinel-2 MSI and Sentinel-1 SAR datasets improves the estimation of aboveground carbon stock. This can be attributed to the enhanced sensitivity of backscatter and spectral reflectance to green biomass properties (X. Zhang & Ni-Meister, 2014). For instance, backscatter contains information related to forest structural geometry, moisture content and surface roughness, whereas spectral reflectance provides records of chlorophyll content, leaf area index and biomass (Malhi et al., 2021). Individually, however, optical and radar datasets are prone to soil background noise, saturation, clouding, and canopy shadowing, which may hamper the performance of forest carbon stock estimation (Brede et al. 2015; Gomez et al., 2019). Nevertheless, the fusion of optical and radar data reduces these challenges and provides detailed information that improves the performance of forest carbon stock estimation (Kumar et al. 2015; Lu et al., 2016). For example, Sarker and Nichol (2011) found that multispectral images (e.g., Sentinel-2) provide spectral data with reduced atmospheric and soil background effects, compared to radar sensors. Meanwhile, optical sensors carbon estimation capabilities, whose spectral responses are predominately dependent upon the relationship between solar irradiance and forest canopies, are commonly linked to biomass saturation— which often hinders reliable carbon stock estimation (Ghasemi et al. 2011). This is particularly evident within dense forest canopies (i.e. AGB is ≥ 0.3 g/cm-1), where the relationship between forest biomass and spectral responses becomes saturated (Mutanga et al. 2012; Mutanga & Skidmore, 2004). The use of SAR imagery have demonstrated their value in minimizing the effect of saturation invents within forest canopies (Ghasemi et al., 2011; Luckman et al. 1998). The longer wavelengths, coupled with various polarization signals permits penetration and increases sensitivity of aboveground biomass (Luckman et al., 1998). Consequently, saturation thresholds for SAR imagery have been documented by Mermoz et al. (2015), Cutler et al.

(2012) and Imhoff (1995), with these saturation thresholds averaging 20t/ha for the C-band, 40 t/ha for the L-band, and 100 t/ha for the P-band; considerably higher than the 10.22 t.ha-1 recorded within our study site. Moreover, the high penetration ratio of SAR interferometric polarization reduced clouding and canopy shadowing, by providing pure backscattering values that are highly correlated to green-biomass. This is supported by Keleş et al (2021) who noted that the wavelength transmit of SAR imagery permits penetration through thin clouds and dense canopy cover, and provides robust volumetric measurements of forest, which is critical for concise biomass estimation. Furthermore, the appropriate conversion of sigma-naught to decibels values, which are highly correlated to forest biomass, improved the predictive performance of the Sentinel-2 image. The estimation of carbon stock was further enhanced by the adoption of the Nearest Neighbor Diffused (NND) pixel-level fusion technique that preserved the original image's spectral information by minimizing image distortion and noise during processing. Zhang et al. (2018) and Peery et al. (2020) for instance, established that NND produce high quality images compared to other fusion techniques (e.g., Gram-Schmidt, High Pass Filter and Principal Component) due to its ability to generate image output with high signal-to-noise ratio expressed in decibels.

Overall, the spatial and radiometric dimensions of the SAR imagery effectively pan-sharpened and homogenized the spatial and spectral details of the optical Sentinel-2 image, which enabled explicit carbon stock estimation.

6.4.2 The influence of polarization on carbon stock estimation

Among the interferometric polarization, the vertical transmit/horizontal receive-cross polarization (VH) obtained greater correlation coefficient with carbon stock (r: 0.98), compared to the vertical transmit/vertical receive (VV) polarization (r: 0.96). These findings are similar to Nuthammachot et al (2020) and Chang and Shoshany (2016) who found that cross-polarized VH highly correlated with vegetation green biomass than co-polarized VV operation. Polarization, which refers to the direction of the electric field within the electromagnetic waves, controls the interaction between the signals and reflectors (Li et al. 2018, Geffrin et al. 2012). Consequently, the cross-polarized operation allows for the detection of total scattered light per unit of incident radiation which produces maximum backscattering coefficients necessary for measuring carbon uptake by green biomass, as opposed to co-polarization operations that are highly influenced by surfaces roughness (Laurin et al. 2018). In this study, reforested trees were found to respond more strongly to the decibels values of cross-polarized VH as opposed to co-polarized VV. Thus, the outcomes of this investigation support the notion that cross-polarized backscatter is significantly more sensitive to forests aboveground biomass and carbon uptake compared to co-polarized VV (Nuthammachot et al. 2020, Laurin et al. 2018).

Furthermore, different map models produced in this study showed the variability of carbon stock across the study area (Figure 6.4). The spatial distribution of carbon stock within the area increase with increasing canopy density and green biomass. This variability can be attributed to variations in topographic variables (e.g., slope, aspect and elevation), which significantly influences overall biomass productivity and density. This is supported by Odebiri et al (2020) and Young et al (2014) who noted that slope, aspect and elevation significantly influence the spatial distribution of carbon stock. In addition, forest species composition within the reforested site can also play a key role in carbon variations, due to the differences in biophysical (e.g., canopy structure and leaf stomata) and biochemical (e.g., pigments and carotenoids) properties, which in turn influences the amount of carbon uptake per unit of absorbed light energy (Waring et al. 1998, Mngadi et al. 2021b). For example, the prevalence of *Acacia caffra* and *Acacia robusta*, which favour different soil pH, soil nutrients and elevations (Wakeling, Cramer and Bond 2010) and have different root: shoot biomass ratios (Vadigi and Ward 2012), may have contributed to biomass variations within the study site. Overall, our findings suggest that Sentinel-1 SAR offers reliable and precise backscattering information that complements the capabilities of Sentinel-2 and improves carbon stock estimation and mapping within reforested urban landscapes. This study further demonstrates that pixel-level image fusion techniques, such NND, can be used to combine optical and radar data for forest carbon stock estimation. Hence, this study presents a cost-effective framework valuable to relevant stake holders in establishing informed conservation and monitoring schemes within reforested environments, thus promoting climate resilient and sustainable urban landscapes. Nevertheless, improvement of aboveground carbon stock estimation does not necessarily depend only on SAR dataset, but also requires advance image processing approaches such as texture measurements. Texture measurements provides information related to numerous forest structural aspects such as age, leaf area index and density (Sarker et al. 2012), which are crucial for enhancing SAR data precision. Consequently, the adoption of texture measurements in high-resolution SAR images could significantly boost biomass and carbon stock predictions. In this regard, there is a need for future studies to evaluate texture metrics of dual-polarization C-band synthetic aperture radar data for biomass and carbon stock estimation in reforested urban landscapes.

6.5 Conclusion

This study sought to examine the potential of combining Sentinel-1's synthetic aperture radar imagery and multispectral Sentinel-2 image in enhancing prediction of aboveground carbon stock within reforested urban landscape. Results of this study demonstrated that spectral indices and bands derived from combining Sentinel-1 SAR imagery with multispectral Sentinel-2 effectively improves the estimation of carbon stock within a reforested urban landscape. Among the polarizations, the results shown that cross-polarized VH performs better than co-polarized VV operation in estimating and mapping reforestation carbon stock. The information provided in this study is valuable for urban planners and forest managers to establish well-informed management and monitoring strategies of reforested ecosystem and its services, and to manage large-scale reforestation projects to increase carbon sequestration capacity and climate regulation potential in urban landscapes. Furthermore, the study showed that reforestation program has the potential to greatly meet the requirement of Reducing Emissions from Deforestation and Forest Degradation (REDD+) and Kyoto-Protocol to reduce greenhouse gas emissions and climate change impacts and risks within urban landscapes. Moreover, the study deduced that a pixel-level fusion technique of SAR and optical Sentinel-2 offers reliable and accurate complementary data, necessary for optimizing carbon stock estimation performance within reforested urban landscape.

6.6 Summary

In this study, the combination of Sentinel-1 C-band and Sentinel-2 MSI proved instrumental in boosting reforestation carbon stock estimation performance with urban landscape. The study further shown that cross-polarization produces carbon estimates that are closely correlated with measured carbon stocks, compared to co-polarization. These findings offers invaluable insight on the complementary information in improving forests carbon assimilation within urban landscape. The following Chapter-7 syntheses overall findings of this research study, while providing concise conclusion of entire thesis. The chapter further propose recommendations for future research within reforested urban landscape.

Chapter Seven: Synthesis

7.1 Introduction

Urbanisation, epitomized by natural landscape transformation into impervious surfaces has been recognised as a serious driver of environmental change, degrading critical ecological processes and ecosystem services (Sithole and Odindi 2015, Adamu et al. 2021). The associated deforestation and forest degradation have led to increasing atmospheric carbon emissions and climate change risks in urban areas and beyond (Nuthammachot et al. 2022). Although urban landscapes cover small land-surface, they account for highest amount of global carbon emissions due to higher energy and resource consumption (Luederitz et al. 2015, Mngadi, Odindi and Mutanga 2021). This has necessitated long-term mechanisms to reduce carbon emissions and potential climate change risks within urban landscapes. Consequently, the Reducing Emissions from Deforestation and forest Degradation (REDD+) and Kyoto Protocol have identified reforestation as the most feasible, cheap, and long-term strategy to reduce greenhouse gas emissions and climate change risks (Livesley, McPherson and Calfapietra 2016, Mngadi et al. 2021). The recognition of reforestation as a possible strategy to reinstate ecosystem services within urban landscape is expected to greatly influence global carbon balance, improve environment quality, and regulate climate change (Curiel-Esparza et al. 2015, Deo et al. 2017). Despite these expectations, the contribution of reforestation initiatives to the global carbon balance and climate change mitigation potential remains unknown. Whereas information on carbon accumulation and progress of reforested trees within urban landscape is required for adopting well-informed management and monitoring policies of reforestation ecosystem and its services. Therefore, this study sought to quantify climate regulating ecosystem services such as carbon stock and net-primary productivity across reforested trees within urban landscape. To achieve this, there was a need to establish appropriate and reliable and affordable datasets and techniques.

In this regard, the emergence of remote sensing technology has shown remarkable capability in providing cost effective and reliable primary data necessary for accurate estimation and mapping of forest services such as carbon stock and primary productivity (Hickey et al. 2018, Dube and Mutanga 2015b, Mngadi et al. 2022a). Remotely Sensed imagery are characterised by larger spatial coverage, critical for local and regional-scale modelling and mapping of ecological services (Aricak et al. 2015, Mngadi et al. 2022a, Pachavo and Murwira 2014). Although high spatial resolution sensors (e.g., Worldview series and RapidEye) have been popular in estimating carbon sequestration/stock, the associated image acquisition costs and unavailability of such sensors have been a major limitation for their adoption, particularly in resource and financially constrained regions like sub-Saharan Africa (Dube and Mutanga 2015a, Mngadi et al. 2021). Hence, freely and readily available multispectral sensors remain the most ideal source of primary dataset for ecosystem services estimation and mapping within urban landscape. Despite unprecedented benefits of remote sensing, no study has used recently launched freely available sensors (i.e.., Sentinel-1 and 2) to estimate ecosystem services (i.e., carbon stock and net primary productivity) of reforested trees within an urban landscape. Therefore, the main aim of this study was to quantify climate regulating ecosystem services (i.e., carbon stock and net primary productivity) in reforested urban landscape using freely and readily available remote sensing dataset. To achieve this aim, the following objectives were pursued:

1. to review the adoption of remote sensing in quantifying forest ecosystem services in sub-Saharan Africa urban landscapes,
2. to estimate aboveground net primary productivity of reforested trees in urban landscape using integrated biophysical variables and remotely sensed data,
3. to explore the utility of Sentinel-2 spectral data in quantifying above-ground carbon stock in an urban reforested landscape,
4. to quantify species carbon stock variability within a reforested urban landscape using texture measures derived from remotely sensed imagery, and
5. to test the efficacy of combining Sentinel-1 C-band and Sentinel-2 MSI datasets in enhancing reforestation carbon stock estimation in an urban landscape

7.2 Objective's review

7.2.1 Quantitative remote sensing of ecosystem services in sub-Saharan Africa's urban landscapes: A review

Over the last decades, ecosystem services were rarely integrated in urban planning due to the lack of spatio-temporal information mapping of Ecosystem Services (ESs) productive zones (Davids et al. 2018, Nemec and Raudsepp-Hearne 2013). Recently, the recognition of ESs value and contribution to the climate change mitigation, including emergence of geospatial analytic technique such as remote sensing have led to increasing interest in quantifying urban ESs (Mngadi et al. 2022b). To better understand the efficacy, challenges, and opportunities of remote sensing techniques in quantifying and mapping urban ESs in sub-Saharan Africa, it was necessary to review existing literature (Chapter two). The literature showed that adoption of high spatial resolution images in quantifying urban ESs in sub-Saharan Africa have been limited. This can be attributed to high costs and unavailability of commercially owned images, which remain a serious challenge to financially constrained regions such as sub-Saharan Africa. Hence, studies have often relied on freely and readily available multispectral sensors with improved spectral and spatial characteristics for urban ESs quantification and mapping. Overall, the findings show that the adoption of remote sensing techniques for urban ESs quantification has recently gained popularity in sub-Saharan Africa, hence there is need for more studies to adequately integrate urban ESs into decision making, urban planning and management. In this regard, subsequent chapters focuses on the quantification of regulating ecosystem services (e.g. net primary productivity and carbon stock) using remotely sensed dataset within urban landscape.

7.2.2 Estimating aboveground net primary productivity of reforested trees in urban landscape using integrated biophysical variables and remotely sensed data

The emergence of urban reforestation initiatives has been presumed to be reliable in carbon sequestration and climate change mitigation (Curiel-Esparza et al. 2015). Thus, knowledge on net primary productivity (NPP) as surrogate of net carbon uptake by reforested trees is important for understanding the contribution of reforestation program in the global carbon cycle and climate change regulation. In this study, sufficient evidence on the strength and capability of biophysical variables and remote sensing information to accurately estimate NPP of reforested trees within urban landscape is presented (Chapter three). To achieve this objective, Moderate Resolution Imaging Spectroradiomer (MODIS) MOD17 model and multiple linear regression were adopted to simulate on-site NPP using remotely sensed variables derived from Sentinel-2 multispectral image and biophysical parameters. The results of this study showed that reforested trees store a considerable amount of atmospheric carbon. For instance, the integration of field measured, and remotely sensed datasets produced an average NPP of 6.24 Mg C. ha^{-1} with a coefficient of determination (R^2) of 0.91 and RMSE of 0.83 Mg. ha^{-1}. The findings also demonstrated a significant variation in NPP among reforested trees, where deciduous *Acacia* and *Dalbergia* species obtained highest NPP (7.62 and 7.58 Mg C ha^{-1}), while evergreen *Syzygium* and shrub *Artimisia* produced lowest (4.54 and 5.26 Mg C ha^{-1}). These findings are supported by Pachavo and Murwira (2014), who investigated NPP of native trees in Southern Africa. Our results demonstrate the strength of remote sensing and biophysical parameters in estimating NPP of reforested urban landscape, as well as the potential of reforested trees to uptake reasonable amount of atmospheric carbon emissions.

7.2.3 The utility of Sentinel-2 spectral data in quantifying above-ground carbon stock in an urban reforested landscape

This study investigated the efficacy of Sentinel-2 spectral indices in quantifying carbon stock of reforested trees within an urban landscape (Chapter four). Using the random forest regression model, a series of vegetation indices including novel and unique indices from the red-edge region of the electromagnetic spectrum were derived from Sentinel-2 MSI and used as predictor variables for the estimation of reforestation carbon stock within an urban environment. Based on the results, the estimated mean carbon stock in reforested urban landscape ranged between 3.39 to 3.64 $t.ha^{-1}$ with high coefficient of determination (R^2) of 77.96 to 79.82% and low RMSE of 0.378 to 0.466 $t.ha^{-1}$ using calibration and validation datasets. Our findings are congruous to Muhe and Argaw (2021) who obtained an R^2 of 0.74 in estimating carbon stock of native forest ecosystem using Sentinel-2 MSI derived indices. Similarly, Bindu et al (2020) estimated forest carbon stock to an R^2 value of 0.71 using vegetation indices. Such reasonable estimation performance can be explained by the utility of optimal predictor variables that are highly sensitive to green biomass spectral response selected by cross-validation and backward elimination techniques of random forest regression model. These findings demonstrate the potential of reforestation initiative in contributing to carbon cycles and climate change regulation. Furthermore, the study demonstrated that freely-available Sentinel-2 MSI can be effectively used to monitor reforestation carbon stock accumulation and progress within an urban landscape.

7.2.4 Quantifying carbon stock variability of species within a reforested an urban landscape using texture measures derived from remotely sensed imagery

Accurate information on carbon stock variability among reforested trees is central to understanding the contribution of reforestation program in the global carbon balance and climate change mitigation. To date, spatial information on species carbon variability on reforested urban landscapes have remained scarce. It is crucial to understand carbon sequestration capacity of tree species for reforestation prioritization. This study predicted carbon stock variability across reforested tree species using texture metrics derived from Sentinel-2 multispectral image (Chapter five). The study applied grey level co-occurrence matrix (GLCM) approach to generate texture metrics from Sentinel-2 MSI and random forest algorithm used to predict carbon stock variability between tree species. Among the investigated species, *Acacia robusta*, *Brideliar micrantha* and *acacia caffra* produced highest mean carbon stock ranging from 4.81 to 6.96 t/ha, while *Erythrina caffra* and *Syzygium cordatum* yielded lowest (3.97 to 4.26 t/ha) carbon stock. Such variations can be attributed to the variability in biophysical and biochemical characteristics between taxon's which influence carbon uptake per unit of absorbed radiation. This is affirmed by Chen et al (2015) who noted that unequal carbon sequestration among forest species can be explained by differences in photosynthetic absorption parameters such as carotenoids, pigments and leaf stomatal properties, which govern species carbon uptake. The findings in this study also showed that mean, variance, homogeneity, contrast, dissimilarity, angular second moment and correlation texture metrics were important for predicting species carbon variability. Furthermore, the consolidation of such optimal texture measures using robust random forest model proved instrumental in predicting species carbon stock with reasonable coefficient of determination (R^2) of between 0.56 and 0.88 and root mean square error (RMSE) of 0.31 and 0.80 t/h. Overall, carbon stock assessment at a species level is critical for species prioritization in future reforestation projects.

7.2.5 Testing the efficacy of combining Sentinel-1 C-band and Sentinel-2 MSI datasets in enhancing reforestation carbon stock estimation in urban landscape

Although reforestation programs are expected to meet the requirement of Reducing Emissions from Deforestation and Forest Degradation (REDD+) and the Kyoto-Protocol, information benchmarking spatial distribution of carbon stock in reforested urban environment is still at infancy. As a results, there is need to continuously quantify and map carbon stock accumulation and progress in reforested areas in order to established informed management and monitoring policies, including motivating for larger-scale reforestation projects. Generally, freely available medium spatial resolution are popular in quantifying forest carbon stock, especially in a resource scarce regions like sub-Saharan Africa. However, such sensors are prone to canopy shadowing, clouding and saturation problems attributed to structural complexity and density, particularly in a heterogeneous forest environments. These challenges can be effectively addressed through combining spectral information of multispectral image dataset with backscatter data of synthetic aperture radar (SAR) characterized by high canopy penetration ratio. Therefore, this study tested the capability of combining Sentinel-1 (SAR) C-band with Sentinel-2 MSI for improved reforestation carbon stock estimation within urban landscape (Chapter six). The nearest neighbor diffused (NND) fusion technique was used to combine optical sensor with SAR imagery, while random forest regression model was used to estimate reforested area carbon stock. The utility of complementary information produced highest coefficient of determination (R^2: 0.78 to 0.83) with lowest RMSE (0.31 to 0.41 $t.ha^{-1}$). The results also demonstrated that cross-polarization (VH) generate carbon estimates that are highly correlated with measured carbon stock, compared to co-polarization (VV). The findings in this study are consistent to Keleş et al (2021) who also found that the combination of optical

Sentinel-2 and SAR image datasets enhances estimation performance of forest carbon stock, with cross-polarization operation outperforming co-polarization. These results demonstrate the reliability of cheap complementary data for enhancing reforestation carbon stock estimation, management and monitoring regimes.

7.3 Conclusion

The main aim of this study was to quantify regulating ecosystem services provided by reforestation within an urban landscape using remote sensing technology. The study focused on carbon sequestration/stock and primary productivity. The results of this study showed that reforested trees sequestrate and store a considerable amount of carbon emissions, hence contributing to global carbon balance and climate change mitigation. Moreover, the utility of freely available multispectral images and robust statistical analytic techniques proved instrumental in quantifying ecosystem services within the reforested urban landscape.

Conclusions based on the results from each objective were;

1. Despite their mixed-pixels and saturation limitations, the adoption of newly launched medium spatial resolution optical sensors with improved spectral and spatial characteristics are valuable in quantifying urban forest ESs elements with unprecedented performance. Precise knowledge on urban ESs derived using spatially explicit techniques such as remote sensing technology is valuable for adopting informed decision-making and policy formulation, useful for sustainable utilisation and resilience of urban ecosystems in sub-Saharan Africa.
2. Urban reforestation plays a key role in carbon sequestration and regulation of climate systems, hence effective management and conservation of reforestation ecosystem and its services is necessary. The information presented in this study is beneficial to policy- and decision-makers and forest managers for monitoring both small and largescale reforestation projects. Overall, the study deduced that MOD17 model can be successfully adopted to quantify and monitor net carbon uptake at a species-level within a small geographic scale using spectral information derived from finer resolution images such as Sentinel-2 MSI.
3. The spectral indices generated from Sentinel-2 MSI can be effectively adopted to quantify regulating ecosystem services such as carbon stock in reforested urban environment. The reforestation initiative is essential in sequestrating atmospheric carbon emissions and regulating climate systems within an urban landscape. The

information presented in this study is crucial for decision- and policymakers and forest managers to design effective management policy frameworks and plan for expanding reforestation projects to a larger scale.

4. The adoption of texture measures generated from freely and readily available Sentinel-2 MSI can be effectively used to quantify or predict species carbon stock variability within reforested urban environment. Overall, the study concluded that reforestation programs are capable of promoting crucial urban ecosystem goods and services, carbon sequestration and climate resilient cities, hence facilitating well-informed management and monitoring schemes, including planning for further improvement in sequestration capacity of reforestation initiative.
5. The study concluded that combining SAR and multispectral Sentinel-2 imagery provides reliable and accurate complementary data essential for carbon stock estimation performance within a reforested urban landscape.

7.4 The future

The adoption of recently launched freely available multispectral imagery offers important spectral information valuable for quantifying or predicting regulatory ecosystem processes such as carbon sequestration/stock and net primary productivity, particularly in resource-constrained regions. The results of this study present invaluable insight on the capability and effectiveness of freely available multispectral sensors (e.g., Sentinel-2) in quantifying regulating ESs within reforested urban landscape. The study also demonstrated that reforestation initiatives sequestrate considerable amount of atmospheric carbon emission, thus contributing to global carbon budget and climate change mitigation. For future studies, this study suggests:

- An investigation on the utility of multi-temporal remote sensing datasets in estimating carbon stock variability across seasons and years within reforested urban landscapes; be invest
- An evaluation of the effects of topography, in conjunction with ancillary data (e.g., rainfall and tree age) on the spatial distribution of carbon within reforested urban areas;
- An evaluation of texture metrics derived from dual-polarization C-band synthetic aperture radar for biomass and carbon stock estimation in reforested urban landscape, and

- An exploration of the of the utility of the newly launched freely available medium spatial resolution Landsat 9 Operational Land Imager (OLI) with improved radiometric resolution (14 bits) and signal-to-noise ratio for improving ecosystem services quantification, especially reforestation carbon stock.

References

Adams, E.A. (2012) World forest area still on the decline. Europe 989, 1-5.

Adam, E., O. Mutanga, J. Odindi & E. M. Abdel-Rahman (2014) Land-use/cover classification in a heterogeneous coastal landscape using RapidEye imagery: evaluating the performance of random forest and support vector machines classifiers. International Journal of Remote Sensing, 35, 3440-3458.

Adamu, B., A. Rasul, S. J. Whanda, P. Headboy, I. Muhammed & I. A. Maiha (2021) Evaluating the accuracy of spectral indices from Sentinel-2 data for estimating forest biomass in urban areas of the tropical savanna. Remote Sensing Applications: Society and Environment, 22, 100484.

Agata, H., L. Aneta, Z. Dariusz, S. Krzysztof, L. Marek, S. Christiane & P. Carsten. 2018. Forest aboveground biomass estimation using a combination of Sentinel-1 and Sentinel-2 Data. In IGARSS 2018-2018 IEEE International Geoscience and Remote Sensing Symposium, 9026-9029. IEEE.

Altanzagas, B., Y. Luo, B. Altansukh, C. Dorjsuren, J. Fang & H. Hu (2019) Allometric equations for estimating the above-ground biomass of five forest tree species in Khangai, Mongolia. Forests, 10, 661.

Aricak, B., A. Bulut, A. O. Altunel & O. E. Sakici (2015) Estimating above-ground carbon biomass using satellite image reflection values: a case study in camyazi forest directorate, Turkey. Šumarski list, 139, 369-376.

Ahl, D.E., Gower, S.T., Mackay, D.S., Burrows, S.N., Norman, J.M., Diak, G.R. (2004) Heterogeneity of light use efficiency in a northern Wisconsin forest: implications for modeling net primary production with remote sensing. Remote sensing of Environment 93, 168-178.

Amuzu-Sefordzi, B., Huang, J., Sowa, D.M., Baddoo, T.D. (2016) Biomass-derived hydrogen energy potential in Africa. Environmental Progress & Sustainable Energy 35, 289-297.

Andrew, M.E., Wulder, M.A., Nelson, T.A. (2014) Potential contributions of remote sensing to ecosystem service assessments. Progress in Physical Geography 38, 328-353.

Baccini, A., Laporte, N., Goetz, S., Sun, M., Dong, H. (2008) A first map of tropical Africa’s above-ground biomass derived from satellite imagery. Environmental Research Letters 3, 045011.

Balzter, H., Cole, B., Thiel, C., Schmullius, C. (2015) Mapping CORINE land cover from Sentinel-1A SAR and SRTM digital elevation model data using random forests. Remote Sensing 7, 14876-14898.

Baret, F., Guyot, G. (1991) Potentials and limits of vegetation indices for LAI and APAR assessment. Remote Sensing of Environment 35, 161-173.

Baró, F., Palomo, I., Zulian, G., Vizcaino, P., Haase, D., Gómez-Baggethun, E. (2016) Mapping ecosystem service capacity, flow and demand for landscape and urban planning: A case study in the Barcelona metropolitan region. Land Use Policy 57, 405-417.

Barthel, S., Folke, C., Colding, J. (2010) Social–ecological memory in urban gardens—Retaining the capacity for management of ecosystem services. Global Environmental Change 20, 255-265.

Basuki, T.M., Skidmore, A.K., van Laake, P.E., van Duren, I., Hussin, Y.A. (2012) The potential of spectral mixture analysis to improve the estimation accuracy of tropical forest biomass. Geocarto international 27, 329-345.

Birdsey, R. A. 1992. Carbon storage and accumulation in United States forest ecosystems. US Department of Agriculture, Forest Service.

Breiman, L. (2001) Random forests. Machine learning 45, 5-32.

Broge, N.H., Leblanc, E. (2001) Comparing prediction power and stability of broadband and hyperspectral vegetation indices for estimation of green leaf area index and canopy chlorophyll density. Remote Sensing of Environment 76, 156-172.

Brunet, C., Savadogo, O., Baptiste, P., Bouchard, M.A., Rakotoary, J.C., Ravoninjatovo, A., Cholez, C., Gendron, C., Merveille, N. (2020) Impacts generated by a large-scale solar photovoltaic power plant can lead to conflicts between sustainable development goals: A review of key lessons learned in Madagascar. Sustainability 12, 7471.

Bustamante, M., J. S. Silva, A. Scariot, A. B. Sampaio, D. L. Mascia, E. Garcia, E. Sano, G. W. Fernandes, G. Durigan & I. Roitman (2019) Ecological restoration as a strategy for mitigating and adapting to climate change: lessons and challenges from Brazil. Mitigation and Adaptation Strategies for Global Change, 24, 1249-1270.

Byrne, M., Williams, V., Wojtasik, E. (2017) The viability of propagules of alien plant species sold for traditional medicine in South Africa. South African Journal of Botany 109, 281-287.

Calviño-Cancela, M., Martín-Herrero, J. (2016) Spectral discrimination of vegetation classes in ice-free areas of Antarctica. Remote Sensing 8, 856.

Carpenter, S.R., DeFries, R., Dietz, T., Mooney, H.A., Polasky, S., Reid, W.V., Scholes, R.J., (2006) Millennium ecosystem assessment: research needs. American Association for the Advancement of Science, pp. 257-258.

Carreiras, J.M., Vasconcelos, M.J., Lucas, R.M. (2012) Understanding the relationship between aboveground biomass and ALOS PALSAR data in the forests of Guinea-Bissau (West Africa). Remote Sensing of Environment 121, 426-442.

Chagas, M.C., Delgado, R.C., de Souza, L.P., de Carvalho, D.C., Pereira, M.G., Teodoro, P.E., Junior, C.A.S. (2019) Gross primary productivity in areas of different land cover in the western Brazilian Amazon. Remote Sensing Applications: Society and Environment 16, 100259.

Chen, Y., Liu, Z., Rao, X., Wang, X., Liang, C., Lin, Y., Zhou, L., Cai, X.-a., Fu, S. (2015) Carbon storage and allocation pattern in plant biomass among different forest plantation stands in Guangdong, China. Forests 6, 794-808.

Cho, M.A., Debba, P., Mutanga, O., Dudeni-Tlhone, N., Magadla, T., Khuluse, S.A. (2012) Potential utility of the spectral red-edge region of SumbandilaSat imagery for assessing indigenous forest structure and health. International Journal of Applied Earth Observation and Geoinformation 16, 85-93.

Cilliers, S., Cilliers, J., Lubbe, R., Siebert, S. (2013) Ecosystem services of urban green spaces in African countries—perspectives and challenges. Urban Ecosystems 16, 681-702.

Clark, D.A., Brown, S., Kicklighter, D.W., Chambers, J.Q., Thomlinson, J.R., Ni, J. (2001) Measuring net primary production in forests: concepts and field methods. Ecological applications 11, 356-370.

Clark III, A., Saucier, J.R., McNab, W.H. (1986) Total-tree weight, stem weight, and volume tables for hardwood species in the southeast. Georgia Forest Research Paper.

Cortina-Segarra, J., I. García-Sánchez, M. Grace, P. Andrés, S. Baker, C. Bullock, K. Decleer, L. V. Dicks, J. L. Fisher & J. Frouz (2021) Barriers to ecological restoration in Europe: expert perspectives. Restoration Ecology, 29, e13346.

Costanza, R., d'Arge, R., De Groot, R., Farber, S., Grasso, M., Hannon, B., Limburg, K., Naeem, S., O'neill, R.V., Paruelo, J. (1997) The value of the world's ecosystem services and natural capital. nature 387, 253-260.

Costanza, R., Kubiszewski, I. (2012) The authorship structure of “ecosystem services” as a transdisciplinary field of scholarship. Ecosystem services 1, 16-25.

Costanza, R., Liu, S. (2014) Ecosystem services and environmental governance: comparing China and the US. Asia & the Pacific Policy Studies 1, 160-170.

Cunningham, S., Mac Nally, R., Baker, P., Cavagnaro, T., Beringer, J., Thomson, J., Thompson, R. (2015) Balancing the environmental benefits of reforestation in agricultural regions. Perspectives in Plant Ecology, Evolution and Systematics 17, 301-317.

Curiel-Esparza, J., Gonzalez-Utrillas, N., Canto-Perello, J., Martin-Utrillas, M. (2015) Integrating climate change criteria in reforestation projects using a hybrid decision-support system. Environmental Research Letters 10, 094022.

Davids, R., Rouget, M., Boon, R., Roberts, D. (2016) Identifying ecosystem service hotspots for environmental management in Durban, South Africa. Bothalia-African Biodiversity & Conservation 46, 1-18.

Davids, R., Rouget, M., Boon, R., Roberts, D. (2018) Spatial analyses of threats to ecosystem service hotspots in Greater Durban, South Africa. PeerJ 6, e5723.

de Araujo Barbosa, C.C., Atkinson, P.M., Dearing, J.A. (2015) Remote sensing of ecosystem services: a systematic review. Ecological indicators 52, 430-443.

De Lacy, P., Shackleton, C. (2017) Aesthetic and spiritual ecosystem services provided by urban sacred sites. Sustainability 9, 1628.

Deering, D., (1975) Measuring" forage production" of grazing units from Landsat MSS data, Proceedings of the Tenth International Symposium of Remote Sensing of the Envrionment, pp. 1169-1198.

del Río-Mena, T., Willemen, L., Tesfamariam, G.T., Beukes, O., Nelson, A. (2020) Remote sensing for mapping ecosystem services to support evaluation of ecological restoration interventions in an arid landscape. Ecological indicators 113, 106182.

Delphin, S., Escobedo, F., Abd-Elrahman, A., Cropper, W. (2016) Urbanization as a land use change driver of forest ecosystem services. Land Use Policy 54, 188-199.

Deo, R.K., Russell, M.B., Domke, G.M., Andersen, H.-E., Cohen, W.B., Woodall, C.W. (2017) Evaluating site-specific and generic spatial models of aboveground forest biomass based on Landsat time-series and LiDAR strip samples in the Eastern USA. Remote Sensing 9, 598.

Di Leo, N., Escobedo, F.J., Dubbeling, M. (2016) The role of urban green infrastructure in mitigating land surface temperature in Bobo-Dioulasso, Burkina Faso. Environment, development and sustainability 18, 373-392.

Dieye, A.M., Roy, D.P., Hanan, N., Lui, S., Hansen, M., Toure, A. (2012) Sensitivity analysis of the GEMS soil organic carbon model to land cover land use classification uncertainties under different climate scenarios in senegal. Biogeosciences 9, 631.

Dobbs, C., Kendal, D., Nitschke, C.R. (2014) Multiple ecosystem services and disservices of the urban forest establishing their connections with landscape structure and sociodemographics. Ecological Indicators 43, 44-55.

Dong, T., Liu, J., Shang, J., Qian, B., Ma, B., Kovacs, J.M., Walters, D., Jiao, X., Geng, X., Shi, Y. (2019) Assessment of red-edge vegetation indices for crop leaf area index estimation. Remote Sensing of Environment 222, 133-143.

Douwes, E., M. Rouget, N. Diederichs, S. O’Donoghue, K. Roy & D. Roberts. 2015. Buffelsdraai landfill site community reforestation project. In XIV World Forestry Congress.

Du Toit, M.J., Cilliers, S.S., Dallimer, M., Goddard, M., Guenat, S., Cornelius, S.F. (2018) Urban green infrastructure and ecosystem services in sub-Saharan Africa. Landscape and Urban Planning 180, 249-261.

Dube, T., Mutanga, O. (2015a) Evaluating the utility of the medium-spatial resolution Landsat 8 multispectral sensor in quantifying aboveground biomass in uMgeni catchment, South Africa. ISPRS Journal of Photogrammetry and Remote Sensing 101, 36-46.

Dube, T., Mutanga, O. (2015b) Investigating the robustness of the new Landsat-8 Operational Land Imager derived texture metrics in estimating plantation forest aboveground biomass in resource constrained areas. ISPRS Journal of Photogrammetry and Remote sensing 108, 12-32.

Dube, T., Mutanga, O. (2015c) Quantifying the variability and allocation patterns of aboveground carbon stocks across plantation forest types, structural attributes and age in sub-tropical coastal region of KwaZulu Natal, South Africa using remote sensing. Applied geography 64, 55-65.

Dube, T., Mutanga, O., Elhadi, A., Ismail, R. (2014) Intra-and-inter species biomass prediction in a plantation forest: testing the utility of high spatial resolution spaceborne multispectral rapideye sensor and advanced machine learning algorithms. Sensors 14, 15348-15370.

Dube, T., Onisimo, M., Riyad, I. (2016) Quantifying aboveground biomass in African environments: A review of the trade-offs between sensor estimation accuracy and costs. Tropical Ecology 57, 393-405.

Dudley, N., Mansourian, S., Vallauri, D., (2005) Forest landscape restoration in context, Forest Restoration in Landscapes. Springer, pp. 3-7.

Eckert, S. (2011) Analyzing the relationship between forest inventory biomass and carbon, and Worldview-2 satellite data. Remote Sensing, 3, 1-16.

Egoh, B.N., O'Farrell, P.J., Charef, A., Gurney, L.J., Koellner, T., Abi, H.N., Egoh, M., Willemen, L. (2012) An African account of ecosystem service provision: use, threats and policy options for sustainable livelihoods. Ecosystem services 2, 71-81.

Ernst, C., Mayaux, P., Verhegghen, A., Bodart, C., Christophe, M., Defourny, P. (2013) National forest cover change in Congo Basin: deforestation, reforestation, degradation and regeneration for the years 1990, 2000 and 2005. Global change biology 19, 1173-1187.

Esch, T., Heldens, W., Hirner, A., Keil, M., Marconcini, M., Roth, A., Zeidler, J., Dech, S., Strano, E. (2017) Breaking new ground in mapping human settlements from space–The Global Urban Footprint. ISPRS Journal of Photogrammetry and Remote Sensing 134, 30-42.

Escobedo, F.J., Kroeger, T., Wagner, J.E. (2011) Urban forests and pollution mitigation: Analyzing ecosystem services and disservices. Environmental pollution 159, 2078-2087.

Fang, J., Piao, S., Field, C.B., Pan, Y., Guo, Q., Zhou, L., Peng, C., Tao, S. (2003) Increasing net primary production in China from 1982 to 1999. Frontiers in Ecology and the Environment 1, 293-297.

Fatoyinbo, T., Feliciano, E.A., Lagomasino, D., Lee, S.K., Trettin, C. (2018) Estimating mangrove aboveground biomass from airborne LiDAR data: a case study from the Zambezi River delta. Environmental Research Letters 13, 025012.

Feyisa, G.L., Dons, K., Meilby, H. (2014) Efficiency of parks in mitigating urban heat island effect: An example from Addis Ababa. Landscape and Urban Planning 123, 87-95.

Filipponi, F. 2019. Sentinel-1 GRD preprocessing workflow. In Multidisciplinary digital publishing institute proceedings, 11.

Forkuor, G., J.-B. B. Zoungrana, K. Dimobe, B. Ouattara, K. P. Vadrevu & J. E. Tondoh (2020) Above-ground biomass mapping in West African dryland forest using Sentinel-1 and 2 datasets-A case study. Remote Sensing of Environment, 236, 111496.

Forkuor, G., Dimobe, K., Serme, I., Tondoh, J.E. (2018) Landsat-8 vs. Sentinel-2: examining the added value of sentinel-2's red-edge bands to land-use and land-cover mapping in Burkina Faso. GIScience & Remote Sensing 55, 331-354.

Fu, Y., Lu, X., Zhao, Y., Zeng, X., Xia, L. (2013) Assessment impacts of weather and land use/land cover (LULC) change on urban vegetation net primary productivity (NPP): A case study in Guangzhou, China. Remote Sensing 5, 4125-4144.

Ganjisaffar, Y., Caruana, R., Lopes, C.V., (2011) Bagging gradient-boosted trees for high precision, low variance ranking models, Proceedings of the 34th international ACM SIGIR conference on Research and development in Information Retrieval, pp. 85-94.

Gara, T.W., Murwira, A., Ndaimani, H. (2016) Predicting forest carbon stocks from high resolution satellite data in dry forests of Zimbabwe: exploring the effect of the red-edge band in forest carbon stocks estimation. Geocarto international 31, 176-192.

Geffrin, J.-M., B. García-Cámara, R. Gómez-Medina, P. Albella, L. Froufe-Pérez, C. Eyraud, A. Litman, R. Vaillon, F. González & M. Nieto-Vesperinas (2012) Magnetic and electric coherence in forward-and back-scattered electromagnetic waves by a single dielectric subwavelength sphere. Nature communications, 3, 1-8.

Giardina, C.P., Ryan, M.G. (2002) Total belowground carbon allocation in a fast-growing Eucalyptus plantation estimated using a carbon balance approach. Ecosystems 5, 487-499.

Girma, Y., Terefe, H., Pauleit, S. (2019) Urban green spaces use and management in rapidly urbanizing countries:-The case of emerging towns of Oromia special zone surrounding Finfinne, Ethiopia. Urban Forestry & Urban Greening 43, 126357.

Gitelson, A.A., Gritz, Y., Merzlyak, M.N. (2003) Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves. Journal of plant physiology 160, 271-282.

Gitelson, A.A., Merzlyak, M.N. (1998) Remote sensing of chlorophyll concentration in higher plant leaves. Advances in Space Research 22, 689-692.

Goetz, S.J., Prince, S.D. (1996) Remote sensing of net primary production in boreal forest stands. Agricultural and Forest Meteorology 78, 149-179.

Gómez-Baggethun, E., Barton, D.N. (2013) Classifying and valuing ecosystem services for urban planning. Ecological economics 86, 235-245.

Gonzalez, P., G. P. Asner, J. J. Battles, M. A. Lefsky, K. M. Waring & M. Palace (2010) Forest carbon densities and uncertainties from Lidar, QuickBird, and field measurements in California. Remote Sensing of Environment, 114, 1561-1575.

Gower, S., Krankina, O., Olson, R., Apps, M., Linder, S., Wang, C. (2001) Net primary production and carbon allocation patterns of boreal forest ecosystems. Ecological applications 11, 1395-1411.

Grêt-Regamey, A., Weibel, B., Kienast, F., Rabe, S.-E., Zulian, G. (2015) A tiered approach for mapping ecosystem services. Ecosystem services 13, 16-27.

Guenat, S., Kunin, W.E., Dougill, A.J., Dallimer, M. (2019) Effects of urbanisation and management practices on pollinators in tropical Africa. Journal of Applied Ecology 56, 214-224.

Guo, Z., Fang, J., Pan, Y., Birdsey, R. (2010) Inventory-based estimates of forest biomass carbon stocks in China: A comparison of three methods. Forest Ecology and Management 259, 1225-1231.

Haack, B. N., N. D. Herold & M. A. Bechdol (2000) Radar and optical data integration for land-use/land-cover mapping. Photogrammetric Engineering and Remote Sensing, 66, 709-716.

Haboudane, D., Miller, J.R., Pattey, E., Zarco-Tejada, P.J., Strachan, I.B. (2004) Hyperspectral vegetation indices and novel algorithms for predicting green LAI of crop canopies: Modeling and validation in the context of precision agriculture. Remote Sensing of Environment 90, 337-352.

Hanan, N.P., Kabat, P., Dolman, A.J., Elbers, J.A. (1998) Photosynthesis and carbon balance of a Sahelian fallow savanna. Global Change Biology 4, 523-538.

Heinsch, F.A., Reeves, M., Votava, P., Kang, S., Milesi, C., Zhao, M., Glassy, J., Jolly, W.M., Loehman, R., Bowker, C.F. (2003) Gpp and npp (mod17a2/a3) products nasa modis land algorithm. MOD17 User's Guide, 1-57.

Hengl, T., Leenaars, J.G., Shepherd, K.D., Walsh, M.G., Heuvelink, G.B., Mamo, T., Tilahun, H., Berkhout, E., Cooper, M., Fegraus, E. (2017) Soil nutrient maps of Sub-Saharan Africa: assessment of soil nutrient content at 250 m spatial resolution using machine learning. Nutrient Cycling in Agroecosystems 109, 77-102.

Henry, M., Picard, N., Trotta, C., Manlay, R., Valentini, R., Bernoux, M., Saint André, L. (2011) Estimating tree biomass of sub-Saharan African forests: a review of available allometric equations. Silva Fennica 45, 477-569.

Hickey, S., Callow, N., Phinn, S., Lovelock, C., Duarte, C.M. (2018) Spatial complexities in aboveground carbon stocks of a semi-arid mangrove community: A remote sensing height-biomass-carbon approach. Estuarine, Coastal and Shelf Science 200, 194-201.

Holcomb, A., B. Tong, M. Penny & S. Keshav. 2021. Measuring forest carbon with mobile phones. In Proceedings of the 19th Annual International Conference on Mobile Systems, Applications, and Services, 495-496.

Hong, T., Lin, H., He, D. (2018) Characteristics and correlations of leaf stomata in different Aleurites montana provenances. PloS one 13, e0208899.

Huang, X., B. Ziniti, N. Torbick & M. J. Ducey (2018) Assessment of forest above ground biomass estimation using multi-temporal C-band sentinel-1 and polarimetric L-band PALSAR-2 data. Remote Sensing, 10, 1424.

Hu, Y., Su, Z., Li, W., Li, J., Ke, X. (2015a) Influence of tree species composition and community structure on carbon density in a subtropical forest. PloS one 10, e0136984.

Hu, Y., Su, Z., Li, W., Li, J., Ke, X. (2015b) Influence of tree species composition and community structure on carbon density in a subtropical forest. PLoS One 10.

Huete, A., Justice, C., Van Leeuwen, W. (1999) MODIS vegetation index (MOD13). Algorithm theoretical basis document 3.

Hurford, A., Harou, J. (2014) Balancing ecosystem services with energy and food security-assessing trade-offs for reservoir operation and irrigation investment in Kenya's Tana basin. Hydrology and Earth System Sciences 11, 1343-1388.

Imran, M. (2021) Geospatially mapping carbon stock for mountainous forest classes using InVEST model and Sentinel-2 data: a case of Bagrote valley in the Karakoram range. Arabian Journal of Geosciences, 14, 1-12.

Isidro, C. M., N. McIntyre, A. M. Lechner & I. Callow (2017) Applicability of earth observation for identifying small-scale mining footprints in a wet tropical region. Remote Sensing, 9, 945.

Jacquemoud, S., Ustin, L. (2008) Modeling leaf optical properties. Photobiological Sciences Online.

Jaligot, R., Kemajou, A., Chenal, J. (2018) Cultural ecosystem services provision in response to urbanization in Cameroon. Land Use Policy 79, 641-649.

Jim, C.Y., Chen, W.Y. (2009) Ecosystem services and valuation of urban forests in China. Cities 26, 187-194.

Kaoma, H., Shackleton, C.M. (2015) The direct-use value of urban tree non-timber forest products to household income in poorer suburbs in South African towns. Forest Policy and Economics 61, 104-112.

Ke, Y., Quackenbush, L.J. (2011) A review of methods for automatic individual tree-crown detection and delineation from passive remote sensing. International Journal of Remote Sensing 32, 4725-4747.

Keenan, R.J., Reams, G.A., Achard, F., de Freitas, J.V., Grainger, A., Lindquist, E. (2015) Dynamics of global forest area: Results from the FAO Global Forest Resources Assessment 2015. Forest Ecology and Management 352, 9-20.

Keleş, S., A. Günlü & İ. Ercanli. 2021. Estimating aboveground stand carbon by combining Sentinel-1 and Sentinel-2 satellite data: a case study from Turkey. In Forest Resources Resilience and Conflicts, 117-126. Elsevier.

Kumar, D. (2011) Monitoring forest cover changes using remote sensing and GIS: a global prospective. Research Journal of Environmental Sciences 5, 105-123.

Kumwenda, S., El Hadji, A.N., Orondo, P.W., William, P., Oyinlola, L., Bongo, G.N., Chiwona, B. (2017) Challenges facing young African scientists in their research careers: A qualitative exploratory study. Malawi Medical Journal 29, 1-4.

Lamb, D., Gilmour, D. (2003) Rehabilitation and restoration of degraded forests. Rehabilitation and restoration of degraded forests.

Laurin, G. V., J. Balling, P. Corona, W. Mattioli, D. Papale, N. Puletti, M. Rizzo, J. Truckenbrodt & M. Urban (2018) Above-ground biomass prediction by Sentinel-1 multitemporal data in central Italy with integration of ALOS2 and Sentinel-2 data. Journal of Applied Remote Sensing, 12, 016008.

Laurin, G.V., Puletti, N., Hawthorne, W., Liesenberg, V., Corona, P., Papale, D., Chen, Q., Valentini, R. (2016) Discrimination of tropical forest types, dominant species, and mapping of functional guilds by hyperspectral and simulated multispectral Sentinel-2 data. Remote sensing of Environment 176, 163-176.

Legendre, P. (1993) Spatial autocorrelation: trouble or new paradigm? Ecology 74, 1659-1673.

Li-li, Z., Jiang-chong, W., Xing-min, P., Yi-xing, Z., Yan-ping, Z. (2016) Phenotypic difference among species and a variation type of Azadirachta. 林业科学研究 29, 162-166.

Li, F., H. Chen, L. Zhang, Y. Zhou, J. Xie, L. Deng & V. G. Harris (2018) Compact high-efficiency broadband metamaterial polarizing reflector at microwave frequencies. IEEE Transactions on Microwave Theory and Techniques, 67, 606-614.

Lin, C., Thomson, G., Popescu, S.C. (2016) An IPCC-compliant technique for forest carbon stock assessment using airborne LiDAR-derived tree metrics and competition index. Remote Sensing 8, 528.

Lin, S., Li, J., Liu, Q., Li, L., Zhao, J., Yu, W. (2019) Evaluating the Effectiveness of Using Vegetation Indices Based on Red-Edge Reflectance from Sentinel-2 to Estimate Gross Primary Productivity. Remote Sensing 11, 1303.

Linderman, M., Liu, J., Qi, J., An, L., Ouyang, Z., Yang, J., Tan, Y. (2004) Using artificial neural networks to map the spatial distribution of understorey bamboo from remote sensing data. International Journal of Remote Sensing 25, 1685-1700.

Livesley, S., McPherson, E., Calfapietra, C. (2016a) The urban forest and ecosystem services: impacts on urban water, heat, and pollution cycles at the tree, street, and city scale. Journal of environmental quality 45, 119-124.

Livesley, S., McPherson, E.G., Calfapietra, C. (2016b) The urban forest and ecosystem services: impacts on urban water, heat, and pollution cycles at the tree, street, and city scale. Journal of environmental quality 45, 119-124.

Lompo, D.J.-P., Compaoré, E., Sedogo, M.P., Melapie, M., Bielders, C., Schlecht, E., Buerkert, A. (2019) Horizontal flows of nitrogen, potassium, and carbon in urban vegetables gardens of Bobo Dioulasso, Burkina Faso. Nutrient Cycling in Agroecosystems 115, 189-199.

López-Serrano, P.M., Cárdenas Domínguez, J.L., Corral-Rivas, J.J., Jiménez, E., López-Sánchez, C.A., Vega-Nieva, D.J. (2020) Modeling of Aboveground Biomass with Landsat 8 OLI and Machine Learning in Temperate Forests. Forests 11, 11.

Lu, D. (2006) The potential and challenge of remote sensing-based biomass estimation. International Journal of Remote Sensing 27, 1297-1328.

Lu, W., Lu, D., Wang, G., Wu, J., Huang, J., Li, G. (2018) Examining soil organic carbon distribution and dynamic change in a hickory plantation region with Landsat and ancillary data. Catena 165, 576-589.

Luederitz, C., Brink, E., Gralla, F., Hermelingmeier, V., Meyer, M., Niven, L., Panzer, L., Partelow, S., Rau, A.-L., Sasaki, R. (2015) A review of urban ecosystem services: six key challenges for future research. Ecosystem services 14, 98-112.

Magle, S.B., Hunt, V.M., Vernon, M., Crooks, K.R. (2012) Urban wildlife research: past, present, and future. Biological conservation 155, 23-32.

Manes, F., Incerti, G., Salvatori, E., Vitale, M., Ricotta, C., Costanza, R. (2012) Urban ecosystem services: tree diversity and stability of tropospheric ozone removal. Ecological Applications 22, 349-360.

Mansourian, S., Vallauri, D. (2005) Forest restoration in landscapes: beyond planting trees. Springer Science & Business Media.

Maselli, F., Papale, D., Puletti, N., Chirici, G., Corona, P. (2009) Combining remote sensing and ancillary data to monitor the gross productivity of water-limited forest ecosystems. Remote sensing of Environment 113, 657-667.

Mashapa, C., Gandiwa, E., Mhuriro-Mashapa, P., Zisadza-Gandiwa, P. (2014) Increasing demand on natural forest products in urban and peri-urban areas of Mutare, eastern Zimbabwe: implications for sustainable natural resources management. Nature & Faune 28, 42-48.

Matongera, T.N., Mutanga, O., Dube, T., Lottering, R.T. (2018) Detection and mapping of bracken fern weeds using multispectral remotely sensed data: a review of progress and challenges. Geocarto international 33, 209-224.

Malhi, R. K. M., A. Anand, P. K. Srivastava, S. K. Chaudhary, M. K. Pandey, M. D. Behera, A. Kumar, P. Singh & G. S. Kiran (2021) Synergistic evaluation of Sentinel 1 and 2 for biomass estimation in a tropical forest of India. Advances in Space Research.

Mngadi, M., Odindi, J., Mutanga, O. (2021) The Utility of Sentinel-2 Spectral Data in Quantifying Above-Ground Carbon Stock in an Urban Reforested Landscape. Remote Sensing 13, 4281.

Mngadi, M., Odindi, J., Peerbhay, K., Mutanga, O. (2019a) Examining the effectiveness of Sentinel-1 and 2 imagery for commercial forest species mapping. Geocarto international, 1-13.

Mngadi, M., Odindi, J., Peerbhay, K., Mutanga, O. (2019b) Examining the effectiveness of Sentinel-1 and 2 imagery for commercial forest species mapping. Geocarto international, 1-12.

Mngadi, M., Odindi, J., Peerbhay, K., Mutanga, O., Sibanda, M. (2020) Testing the utility of multivariate techniques in mapping commercial forest species using freely available Landsat 8 Operational Land Imager (OLI). Journal of Forest Research, 1-4.

Mngumi, L.E. (2020) Ecosystem services potential for climate change resilience in peri-urban areas in Sub-Saharan Africa. Landscape and Ecological Engineering, 1-12.

Moïse, A.A.A., Séraphin, D.Y.K., Akissi, K., Klamansoni Manuela, S., Tenon, C., Philippe, K.K., Hervé, K.K. (2019) Diversity and abundance of termites in a Corossol tree culture (Annona muricata, Linné 1753) in M'Brimbo (Southern Côte d'Ivoire). cancer (Tra-Bi et al. 2008; Le Ven, 2012) 1, 2.

Mondal, A., Khare, D., Kundu, S., Mondal, S., Mukherjee, S., Mukhopadhyay, A. (2017) Spatial soil organic carbon (SOC) prediction by regression kriging using remote sensing data. The Egyptian Journal of Remote Sensing and Space Science 20, 61-70.

Moore, C., Morel, A.C., Asare, R.A., Sasu, M.A., Adu-Bredu, S., Malhi, Y. (2019) Human appropriated net primary productivity of complex mosaic landscapes. Frontiers in Forests and Global Change 2, 38.

Mucina, L., Von Maltitz, G., Geldenhuys, C., Lawes, M., Eeley, H., Adie, H., Vink, D., Fleming, G., Bailey, C. (2003) Classification system for South African Indigenous Forests: An objective classification for the Department of Water Affairs and Forestry.

Mugwedi, L.F., Rouget, M., Egoh, B., Ramdhani, S., Slotow, R., Rentería, J.L. (2017) An assessment of a community-based, forest restoration programme in Durban (eThekwini), South Africa. Forests 8, 255.

Müller, F., Burkhard, B. (2012) The indicator side of ecosystem services. Ecosystem services 1, 26-30.

Mulligan, J., Bukachi, V., Clause, J.C., Jewell, R., Kirimi, F., Odbert, C. (2020) Hybrid infrastructures, hybrid governance: New evidence from Nairobi (Kenya) on green-blue-grey infrastructure in informal settlements:" Urban hydroclimatic risks in the 21st century: Integrating engineering, natural, physical and social sciences to build resilience". Anthropocene 29, 100227.

Munien, S., Nkambule, S.S., Buthelezi, H.Z. (2015) Conceptualisation and use of green spaces in peri-urban communities: Experiences from Inanda, KwaZulu-Natal, South Africa. African Journal for Physical Health Education, Recreation and Dance 21, 155-167.

Murthy, I.K., Murali, K., Hedge, G., Bhat, P., Ravindranath, N. (2002) A comparative analysis of regeneration in natural forests and joint forest management plantations in Uttara Kannada district, Western Ghats. Current Science, 1358-1364.

Mushore, T.D., Dube, T., Manjowe, M., Gumindoga, W., Chemura, A., Rousta, I., Odindi, J., Mutanga, O. (2019) Remotely sensed retrieval of Local Climate Zones and their linkages to land surface temperature in Harare metropolitan city, Zimbabwe. Urban Climate 27, 259-271.

Mushore, T.D., Odindi, J., Dube, T., Mutanga, O. (2017) Prediction of future urban surface temperatures using medium resolution satellite data in Harare metropolitan city, Zimbabwe. Building and Environment 122, 397-410.

Mutanga, O., Adam, E., Cho, M.A. (2012) High density biomass estimation for wetland vegetation using WorldView-2 imagery and random forest regression algorithm. International Journal of Applied Earth Observation and Geoinformation 18, 399-406.

Muukkonen, P., Heiskanen, J. (2005) Estimating biomass for boreal forests using ASTER satellite data combined with standwise forest inventory data. Remote sensing of Environment 99, 434-447.

Myneni, R.B., Ramakrishna, R., Nemani, R., Running, S.W. (1997) Estimation of global leaf area index and absorbed PAR using radiative transfer models. IEEE Transactions on Geoscience and remote sensing 35, 1380-1393.

Nemec, K.T., Raudsepp-Hearne, C. (2013) The use of geographic information systems to map and assess ecosystem services. Biodiversity and conservation 22, 1-15.

Nguyen, T.T., Pham, H.V., Lasko, K., Bui, M.T., Laffly, D., Jourdan, A., Bui, H.Q. (2019) Spatiotemporal analysis of ground and satellite-based aerosol for air quality assessment in the Southeast Asia region. Environmental pollution 255, 113106.

Ngomanda, A., Q. M. Mavouroulou, N. L. E. Obiang, D. M. Iponga, J.-F. Mavoungou, N. Lépengué, N. Picard & B. Mbatchi (2012) Derivation of diameter measurements for buttressed trees, an example from Gabon. Journal of Tropical Ecology, 28, 299-302.

Nuthammachot, N., A. Askar, D. Stratoulias & P. Wicaksono (2020) Combined use of Sentinel-1 and Sentinel-2 data for improving above-ground biomass estimation. Geocarto International, 1-11.

Oberbauer, S., Hastings, S., Beyers, J., Oechel, W. (1989) Comparative effects of downslope water and nutrient movement on plant nutrition, photosynthesis, and growth in Alaskan tundra. Ecography 12, 324-334.

Odebiri, O., Mutanga, O., Odindi, J., Peerbhay, K., Dovey, S. (2020a) Predicting soil organic carbon stocks under commercial forest plantations in KwaZulu-Natal province, South Africa using remotely sensed data. GIScience & Remote Sensing 57, 450-463.

Odebiri, O., Mutanga, O., Odindi, J., Peerbhay, K., Dovey, S. (2020b) Predicting soil organic carbon stocks under commercial forest plantations in KwaZulu-Natal province, South Africa using remotely sensed data. GIScience & Remote Sensing, 1-14.

Odindi, J., Mhangara, P. (2012a) Green spaces trends in the city of Port Elizabeth from 1990 to 2000 using remote sensing. International Journal of Environmental Research 6, 653-662.

Odindi, J., Mhangara, P. (2012b) Green spaces trends in the city of Port Elizabeth from 1990 to 2000 using remote sensing.

Odindi, J., Mutanga, O., Abdel-Rahman, E.M., Adam, E., Bangamwabo, V. (2017) Determination of urban land-cover types and their implication on thermal characteristics in three South African coastal metropolitans using remotely sensed data. South African Geographical Journal 99, 52-67.

Orimoloye, I., Ololade, O.O., Mazinyo, S., Kalumba, A., Ekundayo, O., Busayo, E., Akinsanola, A.A., Nel, W. (2019) Spatial assessment of drought severity in Cape Town area, South Africa. Heliyon 5, e02148.

Pachavo, G., Murwira, A. (2014) Remote sensing net primary productivity (NPP) estimation with the aid of GIS modelled shortwave radiation (SWR) in a Southern African Savanna. International Journal of Applied Earth Observation and Geoinformation 30, 217-226.

Padgham, J., Jabbour, J., Dietrich, K. (2015) Managing change and building resilience: A multi-stressor analysis of urban and peri-urban agriculture in Africa and Asia. Urban Climate 12, 183-204.

Pataki, D.E., Carreiro, M.M., Cherrier, J., Grulke, N.E., Jennings, V., Pincetl, S., Pouyat, R.V., Whitlow, T.H., Zipperer, W.C. (2011) Coupling biogeochemical cycles in urban environments: ecosystem services, green solutions, and misconceptions. Frontiers in Ecology and the Environment 9, 27-36.

Payn, T., Carnus, J.-M., Freer-Smith, P., Kimberley, M., Kollert, W., Liu, S., Orazio, C., Rodriguez, L., Silva, L.N., Wingfield, M.J. (2015) Changes in planted forests and future global implications. Forest Ecology and Management 352, 57-67.

Peerbhay, K.Y., Mutanga, O., Ismail, R. (2013a) Commercial tree species discrimination using airborne AISA Eagle hyperspectral imagery and partial least squares discriminant analysis (PLS-DA) in KwaZulu–Natal, South Africa. ISPRS Journal of Photogrammetry and Remote Sensing 79, 19-28.

Peerbhay, K.Y., Mutanga, O., Ismail, R. (2013b) Investigating the capability of few strategically placed Worldview-2 multispectral bands to discriminate forest species in KwaZulu-Natal, South Africa. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 7, 307-316.

Peery, T. R. & D. W. Messinger (2020) Spatial resolution as a trade-space for low-light imaging of sensitive cultural heritage documents. Journal of Cultural Heritage, 45, 81-90.

Peñuelas, J., Gamon, J., Fredeen, A., Merino, J., Field, C. (1994) Reflectance indices associated with physiological changes in nitrogen-and water-limited sunflower leaves. Remote Sensing of Environment 48, 135-146.

Pitman, J.I. (2000) Absorption of photosynthetically active radiation, radiation use efficiency and spectral reflectance of bracken [Pteridium aquilinum (L.) Kuhn] canopies. Annals of Botany 85, 101-111.

Plummer, S., (1994) The Angular Vegetation Index: an atmospherically resistant index for the second along track scanning radiometer (ATSR-2), Proc. Sixth Int. Symp. Physical Measurements and Signatures in Remote Sensing, Val d'Isere, France.

Porter-Bolland, L., Ellis, E.A., Guariguata, M.R., Ruiz-Mallén, I., Negrete-Yankelevich, S., Reyes-García, V. (2012) Community managed forests and forest protected areas: An assessment of their conservation effectiveness across the tropics. Forest ecology and management 268, 6-17.

Potapov, P., Yaroshenko, A., Turubanova, S., Dubinin, M., Laestadius, L., Thies, C., Aksenov, D., Egorov, A., Yesipova, Y., Glushkov, I. (2008) Mapping the world's intact forest landscapes by remote sensing. Ecology and Society 13.

Potgieter, L.J., Gaertner, M., O'Farrell, P.J., Richardson, D.M. (2019) A fine-scale assessment of the ecosystem service-disservice dichotomy in the context of urban ecosystems affected by alien plant invasions. Forest Ecosystems 6, 46.

Rafique, R., Zhao, F., De Jong, R., Zeng, N., Asrar, G.R. (2016) Global and regional variability and change in terrestrial ecosystems net primary production and NDVI: A model-data comparison. Remote Sensing 8, 177.

Rahman, A., Cordova, V.D., Gamon, J.A., Schmid, H.P., Sims, D.A. (2004) Potential of MODIS ocean bands for estimating CO2 flux from terrestrial vegetation: A novel approach. Geophysical Research Letters 31.

Raich, J.W., Clark, D.A., Schwendenmann, L., Wood, T.E. (2014) Aboveground tree growth varies with belowground carbon allocation in a tropical rainforest environment. PloS one 9, e100275.

Ramoelo, A., Cho, M., Mathieu, R., Skidmore, A.K. (2015) Potential of Sentinel-2 spectral configuration to assess rangeland quality. Journal of Applied Remote Sensing 9, 094096.

RCore, T. (2016) R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL http://www. R-project. org.

Ribeiro, H.V., Rybski, D., Kropp, J.P. (2019) Effects of changing population or density on urban carbon dioxide emissions. Nature communications 10, 1-9.

Richardson, E., Shackleton, C.M. (2014) The extent and perceptions of vandalism as a cause of street tree damage in small towns in the Eastern Cape, South Africa. Urban Forestry & Urban Greening 13, 425-432.

Roberts, D., Boon, R., Diederichs, N., Douwes, E., Govender, N., Mcinnes, A., Mclean, C., O'Donoghue, S., Spires, M. (2012) Exploring ecosystem-based adaptation in Durban, South Africa:"learning-by-doing" at the local government coal face. Environment and Urbanization 24, 167-195.

Robinson, N.P., Allred, B.W., Smith, W.K., Jones, M.O., Moreno, A., Erickson, T.A., Naugle, D.E., Running, S.W. (2018) Terrestrial primary production for the conterminous United States derived from Landsat 30 m and MODIS 250 m. Remote Sensing in Ecology and Conservation 4, 264-280.

Roongtawanreongsri, S., Sawangchote, P., Bumrungsri, S., Suksaroj, C., (2015) Economic Benefit of Management Options for a Suburban Forest (Kho Hong Hill) in South Thailand, Cost-Benefit Studies of Natural Resource Management in Southeast Asia. Springer, pp. 275-297.

Rousel, J., Haas, R., Schell, J., Deering, D., (1973) Monitoring vegetation systems in the great plains with ERTS, Proceedings of the Third Earth Resources Technology Satellite—1 Symposium; NASA SP-351, pp. 309-317.

Roy, P., Ravan, S.A. (1996) Biomass estimation using satellite remote sensing data—an investigation on possible approaches for natural forest. Journal of biosciences 21, 535-561.

Ruimy, A., Saugier, B., Dedieu, G. (1994) Methodology for the estimation of terrestrial net primary production from remotely sensed data. Journal of Geophysical Research: Atmospheres 99, 5263-5283.

Saatchi, S.S., Harris, N.L., Brown, S., Lefsky, M., Mitchard, E.T., Salas, W., Zutta, B.R., Buermann, W., Lewis, S.L., Hagen, S. (2011) Benchmark map of forest carbon stocks in tropical regions across three continents. Proceedings of the national academy of sciences 108, 9899-9904.

Safari, A., Sohrabi, H., Powell, S., Shataee, S. (2017) A comparative assessment of multi-temporal Landsat 8 and machine learning algorithms for estimating aboveground carbon stock in coppice oak forests. International Journal of Remote Sensing 38, 6407-6432.

Sakici, O., Günlü, A. (2018) Artificial intelligence applications for predicting some stand attributes using Landsat 8 OLI satellite data: A case study from Turkey. Applied Ecology and Environmental Research 16, 5269-5285.

Sarker, L. R. & J. E. Nichol (2011) Improved forest biomass estimates using ALOS AVNIR-2 texture indices. Remote Sensing of Environment, 115, 968-977.

Sarker, M. L. R., J. Nichol, H. B. Iz, B. B. Ahmad & A. A. Rahman (2012) Forest biomass estimation using texture measurements of high-resolution dual-polarization C-band SAR data. IEEE Transactions on Geoscience and Remote Sensing, 51, 3371-3384.

Sala, O.E., Austin, A.T., (2000) Methods of estimating aboveground net primary productivity, Methods in ecosystem science. Springer, pp. 31-43.

Sander, H., Polasky, S., Haight, R.G. (2010) The value of urban tree cover: A hedonic property price model in Ramsey and Dakota Counties, Minnesota, USA. Ecological economics 69, 1646-1656.

Schuyt, K.D. (2005) Economic consequences of wetland degradation for local populations in Africa. Ecological economics 53, 177-190.

Scuderi, R., Tesoriere, G., Fasone, V. (2019) Natural events and performance of micro firms: the impact of floods on shops in Uganda. Economia Politica 36, 609-627.

Shikwambana, L., Ncipha, X., Malahlela, O.E., Mbatha, N., Sivakumar, V. (2019) Characterisation of aerosol constituents from wildfires using satellites and model data: a case study in Knysna, South Africa. International Journal of Remote Sensing 40, 4743-4761.

Shoko, C., Mutanga, O. (2017) Examining the strength of the newly-launched Sentinel 2 MSI sensor in detecting and discriminating subtle differences between C3 and C4 grass species. ISPRS Journal of Photogrammetry and Remote Sensing 129, 32-40.

Sibanda, M., Mutanga, O., Rouget, M. (2016) Comparing the spectral settings of the new generation broad and narrow band sensors in estimating biomass of native grasses grown under different management practices. GIScience & Remote Sensing 53, 614-633.

Sims, D.A., Rahman, A.F., Cordova, V.D., El-Masri, B.Z., Baldocchi, D.D., Bolstad, P.V., Flanagan, L.B., Goldstein, A.H., Hollinger, D.Y., Misson, L. (2008) A new model of gross primary productivity for North American ecosystems based solely on the enhanced vegetation index and land surface temperature from MODIS. Remote sensing of Environment 112, 1633-1646.

Simwanda, M., Ranagalage, M., Estoque, R.C., Murayama, Y. (2019) Spatial analysis of surface urban heat islands in four rapidly growing African Cities. Remote Sensing 11, 1645.

Siry, J.P., Cubbage, F.W., Ahmed, M.R. (2005) Sustainable forest management: global trends and opportunities. Forest policy and Economics 7, 551-561.

Sisodia, P.S., Tiwari, V., Kumar, A., (2014) Analysis of supervised maximum likelihood classification for remote sensing image, International conference on recent advances and innovations in engineering (ICRAIE-2014). IEEE, pp. 1-4.

Sithole, K., Odindi, J. (2015) Determination of urban thermal characteristics on an urban/rural land cover gradient using remotely sensed data. South African Journal of Geomatics 4, 384-396.

Sithole, K., Odindi, J., Mutanga, O. (2018) Assessing the utility of topographic variables in predicting structural complexity of tree stands in a reforested urban landscape. Urban Forestry & Urban Greening 31, 120-129.

Small, D. (2011) Flattening gamma: Radiometric terrain correction for SAR imagery. IEEE Transactions on Geoscience and Remote Sensing, 49, 3081-3093.

Smith, W.K., Reed, S.C., Cleveland, C.C., Ballantyne, A.P., Anderegg, W.R., Wieder, W.R., Liu, Y.Y., Running, S.W. (2016) Large divergence of satellite and Earth system model estimates of global terrestrial CO 2 fertilization. Nature Climate Change 6, 306-310.

Solomon, N., Pabi, O., Annang, T., Asante, I.K., Birhane, E. (2018) The effects of land cover change on carbon stock dynamics in a dry Afromontane forest in northern Ethiopia. Carbon balance and management 13, 14.

Stenchly, K., Lippmann, S., Waongo, A., Nyarko, G., Buerkert, A. (2017) Weed species structural and functional composition of okra fields and field periphery under different management intensities along the rural-urban gradient of two West African cities. Agriculture, Ecosystems & Environment 237, 213-223.

Street, L., Shaver, G., Williams, M., Van Wijk, M. (2007) What is the relationship between changes in canopy leaf area and changes in photosynthetic CO2 flux in arctic ecosystems? Journal of Ecology 95, 139-150.

Sun, W., B. Chen & D. Messinger (2014) Nearest-neighbor diffusion-based pan-sharpening algorithm for spectral images. Optical Engineering, 53, 013107.

Sun, J., Yang, J., Zhang, C., Yun, W., Qu, J. (2013) Automatic remotely sensed image classification in a grid environment based on the maximum likelihood method. Mathematical and Computer Modelling 58, 573-581.

Sun, Q., Pfahringer, B., (2012) Bagging ensemble selection for regression, Australasian Joint Conference on Artificial Intelligence. Springer, pp. 695-706.

Sutherland, C., Sim, V., Buthelezi, S., Khumalo, D. (2016) Social constructions of environmental services in a rapidly densifying peri-urban area under dual governance in Durban, South Africa. Bothalia-African Biodiversity & Conservation 46, 1-18.

Tallis, H., Polasky, S. (2009) Mapping and valuing ecosystem services as an approach for conservation and natural-resource management. Annals of the New York Academy of Sciences 1162, 265-283.

Tang, Y., Chen, A., Zhao, S. (2016) Carbon storage and sequestration of urban street trees in Beijing, China. Frontiers in Ecology and Evolution 4, 53.

Tavares, P.A., Beltrão, N., Guimarães, U.S., Teodoro, A., Gonçalves, P. (2019) Urban Ecosystem Services Quantification through Remote Sensing Approach: A Systematic Review. Environments 6, 51.

Tetemke, B.A., Birhane, E., Rannestad, M.M., Eid, T. (2019) Allometric Models for Predicting Aboveground Biomass of Trees in the Dry Afromontane Forests of Northern Ethiopia. Forests 10, 1114.

Thompson, I., Mackey, B., McNulty, S., Mosseler, A., (2009) Forest resilience, biodiversity, and climate change, Secretariat of the Convention on Biological Diversity, Montreal. Technical Series no. 43. 1-67., pp. 1-67.

Toochi, E. (2018) Carbon sequestration: how much can forestry sequester CO2. Forestry Research and Engineering: International Journal 2, 148-150.

Trotter, C., Tate, K., Scott, N., Townsend, J., Wilde, H., Lambie, S., Marden, M., Pinkney, T. (2005) Afforestation/reforestation of New Zealand marginal pasture lands by indigenous shrublands: the potential for Kyoto forest sinks. Annals of Forest Science 62, 865-871.

Turner, D.P., Ritts, W.D., Cohen, W.B., Maeirsperger, T.K., Gower, S.T., Kirschbaum, A.A., Running, S.W., Zhao, M., Wofsy, S.C., Dunn, A.L. (2005) Site-level evaluation of satellite-based global terrestrial gross primary production and net primary production monitoring. Global Change Biology 11, 666-684.

Ubuy, M.H., Eid, T., Bollandsås, O.M., Birhane, E. (2018) Aboveground biomass models for trees and shrubs of exclosures in the drylands of Tigray, northern Ethiopia. Journal of arid environments 156, 9-18.

Vadigi, S. & D. Ward (2012) Fire and nutrient gradient effects on the sapling ecology of four Acacia species in the presence of grass competition. Plant Ecology, 213, 1793-1802.

Van der Werf, A., Nagel, O.W. (1996) Carbon allocation to shoots and roots in relation to nitrogen supply is mediated by cytokinins and sucrose: opinion. Plant and Soil 185, 21-32.

Vaughn, M., Ryan, L.V. (2006) Corporate governance in South Africa: a bellwether for the continent? Corporate Governance: An International Review 14, 504-512.

Verma, M., Friedl, M.A., Law, B.E., Bonal, D., Kiely, G., Black, T.A., Wohlfahrt, G., Moors, E.J., Montagnani, L., Marcolla, B. (2015) Improving the performance of remote sensing models for capturing intra-and inter-annual variations in daily GPP: An analysis using global FLUXNET tower data. Agricultural and Forest Meteorology 214, 416-429.

Villa, F., Ceroni, M., Bagstad, K., Johnson, G., Krivov, S., (2009) ARIES (Artificial Intelligence for Ecosystem Services): A new tool for ecosystem services assessment, planning, and valuation, Proceedings of the 11th Annual BIOECON Conference on Economic Instruments to Enhance the Conservation and Sustainable Use of Biodiversity, Venice, Italy, pp. 21-22.

Wakeling, J. L., M. D. Cramer & W. J. Bond (2010) Is the lack of leguminous savanna trees in grasslands of South Africa related to nutritional constraints? Plant and soil, 336, 173-182.

Wakuru, M. (2013) Urbanization and its impacts to food systems and environmental sustainability in urban space: Evidence from urban agriculture livelihoods in Dar es Salaam, Tanzania. Journal of environmental protection 2013.

Wang, J., Rich, P., Price, K., Kettle, W. (2004a) Relations between NDVI and tree productivity in the central Great Plains. International Journal of Remote Sensing 25, 3127-3138.

Wang, Z., Wang, J., Liu, L., Huang, W., Zhao, C., Wang, C. (2004b) Prediction of grain protein content in winter wheat (Triticum aestivum L.) using plant pigment ratio (PPR). Field Crops Research 90, 311-321.

Wangai, P.W., Burkhard, B., Müller, F. (2016) A review of studies on ecosystem services in Africa. International journal of sustainable built environment 5, 225-245.

Wangai, P.W., Burkhard, B., Müller, F. (2019) Quantifying and mapping land use changes and regulating ecosystem service potentials in a data-scarce peri-urban region in Kenya. Ecosystems and People 15, 11-32.

Ward, C.D., Parker, C.M., Shackleton, C.M. (2010) The use and appreciation of botanical gardens as urban green spaces in South Africa. Urban Forestry & Urban Greening 9, 49-55.

Waring, R., Landsberg, J., Williams, M. (1998) Net primary production of forests: a constant fraction of gross primary production? Tree physiology 18, 129-134.

Wei, Y., Li, M., Chen, H., Lewis, B.J., Yu, D., Zhou, L., Zhou, W., Fang, X., Zhao, W., Dai, L. (2013) Variation in carbon storage and its distribution by stand age and forest type in boreal and temperate forests in northeastern China. PloS one 8, e72201.

Williams, M., Rastetter, E.B. (1999) Vegetation characteristics and primary productivity along an arctic transect: implications for scaling-up. Journal of Ecology 87, 885-898.

Winkler, H. (2007) Energy policies for sustainable development in South Africa. Energy for sustainable Development 11, 26-34.

Wolanin, A., Camps-Valls, G., Gómez-Chova, L., Mateo-García, G., van der Tol, C., Zhang, Y., Guanter, L. (2019) Estimating crop primary productivity with Sentinel-2 and Landsat 8 using machine learning methods trained with radiative transfer simulations. Remote sensing of Environment 225, 441-457.

Wu, C., Niu, Z., Tang, Q., Huang, W. (2008) Estimating chlorophyll content from hyperspectral vegetation indices: Modeling and validation. Agricultural and forest meteorology 148, 1230-1241.

Xu, G., Jiao, L., Zhao, S., Yuan, M., Li, X., Han, Y., Zhang, B., Dong, T. (2016) Examining the impacts of land use on air quality from a spatio-temporal perspective in Wuhan, China. Atmosphere 7, 62.

Yu, J., Li, F., Wang, Y., Lin, Y., Peng, Z., Cheng, K. (2020) Spatiotemporal evolution of tropical forest degradation and its impact on ecological sensitivity: A case study in Jinghong, Xishuangbanna, China. Science of the total environment, 138678.

Zabbey, N., Tanee, F.B. (2016) Assessment of asymmetric mangrove restoration trials in Ogoniland, Niger Delta, Nigeria: lessons for future intervention. Ecological Restoration 34, 245-257.

Zhang, D.-D., F. Xie & L. Zhang. 2018. Preprocessing and fusion analysis of GF-2 satellite Remote-sensed spatial data. In 2018 International Conference on Information Systems and Computer Aided Education (ICISCAE), 24-29. IEEE.

Zhang, H., Guan, D., Song, M. (2012) Biomass and carbon storage of Eucalyptus and Acacia plantations in the Pearl River Delta, South China. Forest Ecology and Management 277, 90-97.

Zhao, M., Heinsch, F.A., Nemani, R.R., Running, S.W. (2005) Improvements of the MODIS terrestrial gross and net primary production global data set. Remote sensing of Environment 95, 164-176.

Zhu, L., Southworth, J. (2013) Disentangling the relationships between net primary production and precipitation in southern Africa savannas using satellite observations from 1982 to 2010. Remote Sensing 5, 3803-3825.