UNIVERSITY OF KWAZULU-NATAL

The utility of new generation multispectral sensors in assessing aboveground biomass of *Phragmites australis* in wetlands areas in the City of Tshwane Metropolitan Municipality; South Africa

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Abstract

Wetlands are natural productive systems providing numerous ecosystem goods and services. Carbon sequestration, groundwater recharge, trapping of pollutants and reducing sediments and habitat provision for a wide assortment of flora and fauna are some of the benefits associated with healthy wetlands. Despite all the benefits, wetlands are under threat from anthropogenic activities and other stressors. To prevent further loss and to conserve existing wetland ecosystems for the services rendered, restoration of wetlands has become a common practice worldwide. However, restored wetlands are usually susceptible to invasive plant species such as *Phragmites australis*, which have effects on both wetland structure and function. Vegetation biomass is one of the main attributes used to quantify the extent of wetland rehabilitation success. Aboveground biomass is preferred because it is easy to observe measure and interpret as a basis for comparison between rehabilitated and pristine wetlands. Estimation of *Phragmites* biomass is important to understand its growth and monitor its distribution so that effective plans can be implemented to deal with invasions. Therefore, accurate quantification of existing *Phragmites* aboveground biomass requires techniques that will provide up to date information and improve the ability to detect changes in natural versus rehabilitated wetlands. The advancement of multispectral remote sensing provides rapid and cost effective methods to estimate variability of *Phragmites* biomass production at different scales. The present study sought to investigate the utility of new generation multispectral sensors in assessing the variability of *Phragmites* biomass between natural wetland versus rehabilitated wetland. These included the commercial broadband RapidEye and the cheap freely accessible moderate Sentinel 2 Multispectral Instrument (MSI) and Landsat 8 operational Land Imager (OLI) data. To achieve this objective, the study was limited to (i) testing the utility of high spatial resolution RapidEye data in quantifying the variability of *Phragmites* biomass between natural and rehabilitated wetlands and (ii) comparing the strengths of newly launched multispectral sensor Sentinel 2 MSI and Landsat 8 OLI in *Phragmites* biomass assessment.

The potential of all corresponding sensors for biomass estimation were tested based on Partial Least Square (PLS) regression algorithm. For the first objective, the PLS regression selected the following bands as the most optimum variables that could estimate biomass in both wetlands: blue band (B1), red band (B3), and red edge (B4). The combination of both extracted bands and vegetation indices improved predictive accuracy of natural biomass estimation using PLSR. The study further tested the potential of assessing *Phragmites* aboveground biomass using medium multispectral Sentinel 2 MSI and Landsat 8 OLI data. The results were compared with the findings obtained from RapidEye data. Findings indicated that Sentinel 2 MSI outperformed both Landsat 8 OLI and RapidEye using extracted bands and vegetation indices. However, findings are inconclusive concerning whether Landsat 8 OLI outperformed RapidEye or not for

Phragmites biomass estimation. The increased unique spectral bands coverage of medium multispectral Sentinel 2 MSI has the ability to quantify the variability of *Phragmites* biomass between natural and rehabilitated wetlands with high accuracy. This has huge practical implications for monitoring of wetland vegetation species. The study clearly demonstrated that estimation of vegetation biomass in wetlands could be improved with cheap and freely available data such as Sentinel 2 MSI data.

Declaration

This research project was undertaken in the School of Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg Campus, under the supervision of Professor Onisimo Mutanga (UKZN) and Dr. George Johannes Chirima (Agricultural Research Council-Soil Climate and Water) in partial fulfillment of the requirements for the degree of Master of Science.

I, Kgaogelo Mogano, declare that the research work describe in this thesis is my own original work and that all sources that I have cited or quoted have been indicated and acknowledged by means of references in the text or complete list of references. I further declare that this thesis has not been submitted to any other tertiary institution in any form of diploma or degree.

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Dedication

Dedicated to the memory of my late sister Dolly Mamahlola Mogano

‘*Goodbye is never easy; Pictures will never carry your warmth*

Memories will always pierce my heart

No words can explain it all

I will forever miss you’

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If it was not for your grace, your unconditional love, your mercy, your protection I would not have made it this far. I thank You Lord for the wisdom and the strength you provided me through this entire journey. All I can say is **THANK YOU HEAVENLY FATHER!**

'No man is an island' without the support and contribution of other people and various organization, this project would not have been possible**.**

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My greatest gratitude to my family for instilling the importance and value of education. I cannot ask God for any better family than the one He has already given me. We always stand by each other through thick and thin. The love and support you continued to show me through these years is immeasurable. I **thank the Almighty** to give me such a wonderful family. I could not have got this far without your unconditional love and support. Whenever I need a shoulder to lean on, you are forever there. Thank you for believing in me when I did not believe in myself. ***Bare wa go hloka leriba ga se Mmirwa, KE A LEBOGA BAKGALAKA!!***

It would be ungrateful of me not to say **thank you** to my cousin Khomotso Letsoalo. A week does not pass by without hearing from you. Those text messages may seem like a simple thing to do but it meant the world to me. You have always extended your love even when am far away.

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"I can do everything through Him who gives me strength"

Kgaogelo Mogano

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List of Abbreviations

ALS	Airborne Laser Infrared
ANCOVA	Analysis of Covariance
ANOVA	Analysis of Variance
ARC-SCW	Agricultural Research Council- Soil, Climate and Water
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AVHRR	Advanced Very High Resolution Radiometer
CTMM	City of Tshwane Metropolitan Municipality
ETM	Enhanced Thematic Mapper
FLAASH	Fast Line-of Sight Atmospheric Analysis of Spectral Hypercubes
GPS	Global Positioning System
HyspIRI	Hyperspectral Infrared Imager
LIDAR	Light Detection and Ranging
LOOCV	Leave-one-out cross validation
MERIS	Medium Resolution Imaging Spectrometer
MODIS	Moderate Resolution Imaging Spectroradiometer
MSI	MultiSpectral Instrument
NDVI	Normalised Difference Vegetation Index
NDVI.re	Normalised Difference Vegetation Index red-edge
NDWI	Normalised Water Difference Index
OLI	Operational Land Imager
PLSR	Partial Least Square Regression
ROI	Region of Interest
RMSE	Root mean square error
SAR	Synthetic Aperture Radar
SPOT	Satellite Pour l'Observation de la Terre
SR	Simple Ratio
SR.re	Simple Ratio red-edge
SWIR	Shortwave Infrared

TM	Thematic Mapper

CHAPTER ONE

General Background

1.1. General Introduction

Wetlands are an important component of global ecosystems because of their role in maintenance of environmental quality and are rich in biological diversity (Zedler, 2000; Zedler & Kercher, 2005). They are known as natural assets and infrastructure able to provide numerous benefits freely (Horwitz & Finlayson, 2011). Healthy wetlands should be able to provide numerous social and economic benefits including environmental valuable functions (Lantz & Wang, 2013; Murray et al., 2011). These include regulating water flows throughout the season; purifying water by breaking down some chemicals into usable forms (Islam et al., 2008; Sieben et al., 2011). They aid in replenishing ground water supplies as well as shoreline stabilization. Wetlands act as a natural sponge by absorbing water during flooding periods and releasing it during dry periods (Prior & Johnes, 2002; Uluocha & Okeke, 2004). Most importantly, wetlands store a large portion of the world's carbon and in return, slow down the impact of climate change (Kayranli et al., 2010; Vashum & Jayakumar, 2012a). Wetlands are hard-working ecosystems that provide a critical habitat for fauna and flora (Kotze et al. 2012, Dini and Bahadur 2016). Wetland vegetation control pollution by trapping and reducing sediments in the water. Vegetation is also a good indicator of for early signs of any physical and or chemical degradation in wetland environment (Dennison et al., 1993). Furthermore, wetlands have high economic value providing many natural products and recreational opportunities. However, all the benefits and functions they provide depends on the physical or biological condition of wetlands (Meng et al., 2016; Rivers-Moore & Cowden, 2012).

Despite the provision of these valuable services and functions, wetlands continue to be polluted, drained and converted to agricultural lands and urban development due to increase in human population growth (Carle et al., 2014; Meli et al., 2014; Sieben et al., 2011). It is estimated that 50% of the wetlands globally and 65% of wetlands in South Africa are under threat and 48 % of them are being critically endangered and lost (Kotze et al., 2012; Nel & Driver, 2012). This excessive destabilization of wetlands has triggered an urgent need for protection and restoration in various places globally, including South Africa. Research on wetland rehabilitation, creation and degradation have become more important to understand the structure and function of restored wetlands (Wang et al., 2012). The success of rehabilitation will depend on the component repaired (e.g. hydrology, soil and vegetation). Generally, the purpose of rehabilitation is to restore ecosystem function and structure at all levels by considering the entire ecosystem (Ruiz- Jaen & Mitchell Aide, 2005; Zedler, 2000). Theoretically, a restored wetland should resemble the natural wetland in terms of structure and function (Passell, 2000; Purcell et al., 2002). In practice, measuring the success of rehabilitation is not a straightforward process. This is because some ecosystem functions may become evident after a long time (Mitsch & Wilson, 1996; Ruiz- Jaen & Mitchell Aide, 2005). Vegetation structure such as plant density, species diversity, vegetation cover, and biomass are preferred for wetland condition assessment (Ruiz- Jaen & Mitchell Aide, 2005). Vegetation structure such as aboveground biomass is preferred because it is easy to observe, interpret and is a vital part of wetland structure and function (Eckert & Engesser, 2013; Kay C Stefanik & Mitsch, 2012; Wang et al., 2012). It is reported in literature that not all rehabilitated wetlands perform all functions nor do they all function well. The geographical location and size of a wetland may determine what functions it may perform (Novitski et al., 1996; Siobhan Fennessy et al., 2007). Factors such as the amount of water quality and quantity entering the wetland, climatic conditions, type of vegetation and disturbance within and surrounding wetlands determine how well a wetland will perform its function (Cui et al., 2009; Novitski et al., 1996). In cases where rehabilitation has been successful, rehabilitated wetlands have inherently been more susceptible to invasive species (Kettenring & Adams, 2011; Kettenring et al., 2012). These invasive species have profound effects on the structure (e.g. species distribution) and function (e.g. alteration of water quality) of the rehabilitated wetlands (Litton et al., 2006; Mack & D'Antonio, 2003).

Phragmites australis (Cav.) Trin. Ex Steud known as common reeds, belong to the family of Poaceae. *Phragmites australis* (hereafter *Phragmites*) is one of the most studied and widely distributed perennial grass in freshwater of South African wetlands (Köbbing et al., 2013; Russell & Kraaij, 2008). It plays vital ecological and social roles in most Southern African countries. *Phragmites* control soil erosion, purifying water as well as providing habitat for wildlife (Ailstock et al., 2001; Onojeghuo et al., 2010). Furthermore, it is also of social and economical value as it is used for making mats, baskets, paper, medicine, light construction, and thatching roofs. Despite its environmental and socio-economic values, literature indicates that *Phragmites* has an inclination of dominating other wetland plants by out-competing them for space, nutrients, and sunlight (Kettenring & Adams, 2011; Lantz & Wang, 2013; Russell & Kraaij, 2008). This trait has led to differences in opinions held by natural resource managers concerning the plant's ecological value and its potential usefulness for environmental enhancement (Ailstock et al., 2001). Despite these differences of opinion, studies on *Phragmites* have been focusing on disinfestation, mitigation, fertilization and biological properties (Kettenring & Adams, 2011; Kettenring et al., 2012). Research on the spatial distribution of *Phragmites* and quantifying its quantity (biomass) between rehabilitated and pristine wetland is rare. Because biomass has long been used as an indicator of wetland health (Anderson & Davis, 2013; Ruiz- Jaen & Mitchell Aide, 2005), fresh aboveground biomass of *Phragmites* could be a direct measure of rehabilitated wetland function (Catling & Mitrow, 2011; Hossain et al., 2010). Evaluation of *Phragmites* aboveground biomass in rehabilitated wetland should be compared with pristine sites to estimate the level of rehabilitation success (Passell, 2000; Purcell et al., 2002; Ruiz-Jaén & Aide, 2005).

In order to understand the spatial distribution of *Phragmites* and monitor the growth at different wetland health conditions, there is a need to develop real-time techniques for monitoring *Phragmites* distribution and predicting biomass as an approach to rapid assessment and managements of the species. These techniques should be able to provide required information that will aid monitoring with the aim of implementing an effective plan to deal with invasions. Traditional methods such as field surveys and direct visual observations have been the primary source of invasive species data collection. However, these methods are time-consuming, subjective, and always very limited in spatial extent and lack detailed information about the distribution and quantity of invasive species on a broad scale (E. Adam et al., 2010; Bourgeau-Chavez et al., 2013; Ozesmi & Bauer, 2002). These limitations make it challenging to provide real-time information or data to facilitate assessments of changes in these wetland ecosystems over a certain period of time (Hestir et al., 2008). In this regard, advanced multispectral remotely sensed data offer alternative methods to accomplish this task at no or affordable cost. In contrast to field-based survey, multispectral remote sensing techniques cover a much larger spatial area, in a short period while repeatedly measuring the same areas for a longer time span (E. Adam et al., 2010; Ozesmi & Bauer, 2002; Underwood et al., 2003). These advantages have attracted a significant amount of scientific research especially for natural vegetation biomass assessments and monitoring at different scales (Englhart et al., 2011; Lu, 2006). Although biomass cannot be directly quantified from space, multispectral satellite sensors have been used to estimate biomass through empirical relationship between reflectance and spectral indices when integrated with field measurements (Englhart et al., 2011; García et al., 2010; Mutanga & Adam, 2011).

Various multispectral sensors are available for wetland biomass mapping and been widely used to monitor wetland vegetation status (Byrd et al., 2014; Key et al., 2001). Multispectral sensors such as Advanced Very High Resolution Radiometer (AVHRR), Moderate Resolution Imaging Spectroradiometer (MODIS) and Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM) provide long-term archives for ecological monitoring purposes (Nagendra et al., 2013; Robinson et al., 2016) and are freely accessible. MODIS and AVHRR were reported to mis-represent the spatial variations of invasive plant species due to the wide swaths (Shoko & Mutanga, 2017). Similarly, the moderate spatial resolution MEdium Resolution Imaging Spectrometer (MERIS) and Landsat TM and ETM are insufficient for monitoring and quantifying different vegetation structures such as biomass at high accuracy because of spectral mixing and saturation problems (E. Adam et al., 2010; Ozesmi & Bauer, 2002). These data create ambiguous differentiation among vegetation species (Nagendra et al., 2013; Ozesmi & Bauer, 2002; Thenkabail et al., 2012).

The challenges associated with characterization of wetland vegetation might be improved with the use of finer spatial resolution such as RapidEye and Worldview data. These multispectral satellite sensors increased the potential sources of data that could be used to characterize spectral variability of various wetland vegetation species (Ozdemir & Karnieli, 2011; Ramoelo et al., 2015b; Robinson et al., 2016). RapidEye image was the first commercial satellite sensor with red edge coverage at a finer spatial resolution of 5 m (Houborg et al., 2015). Despite having attractive characteristics and producing good results in other vegetation studies, the potential of RapidEye data for estimating *Phragmites* biomass in wetlands has not yet been explored because of the high acquisition cost. In this regard, quantification of *Phragmites* aboveground biomass lies in the ability of cheap and readily available earth observation data. Recently, advanced new generation medium Landsat 8 OLI (Operational Land Imager) and Sentinel 2 MultiSpectral Instrument (MSI) have attractive characteristics that are promising for improving aboveground biomass estimation (Mutanga et al., 2016; Ozdemir & Karnieli, 2011). Multiple studies have demonstrated the strength of additional bands in these sensors for biomass quantification. For instance, Dube and Mutanga (2015) successfully estimated aboveground biomass of different forest species using Landsat 8 OLI and ETM. The authors reported a good performance achieved from new generation Landsat 8 OLI data. While Sentinel 2 MSI was found to produce high or same accuracy as Landsat 8 OLI and Hyperspectral infrared imager (HyspIRI) for estimating grass aboveground biomass under different fertilizer management (Sibanda et al., 2016). To the best of our knowledge, these multispectral sensors have not been tested in comparing the aboveground biomass of *Phragmites* between natural and rehabilitated wetlands. The availability of these new improved multispectral sensors with lower or no costs make remote sensing attractive for monitoring invasive species and estimating wetland vegetation biomass in natural and rehabilitated wetlands. Choosing between them is a function of cost, spatial and spectral resolution, and revisit period. Each satellite sensor offer different advantages and disadvantages depending on the objective of the study (Byrd et al., 2014; C. Yang & Everitt, 2010).

1.2. Research Objectives

The main objective of this study was to explore the utility of new generation multispectral satellite sensors in quantifying the variability of *Phragmites* aboveground biomass between the natural wetland and rehabilitated wetland in the City of Tshwane Metropolitan Municipality, South Africa.

The specific objectives were as follows:

- To test the potential of fine spectral resolution RapidEye satellite image in assessing the variability of *Phragmites* aboveground biomass between natural and rehabilitated wetlands.

- To compare the strength of newly launched medium spectral resolution Sentinel 2 MSI and Landsat 8 OLI in assessing the variability of *Phragmites* aboveground biomass between natural and rehabilitated wetlands.

1.3. Research Questions

- How well can RapidEye with red band coverage quantify *Phragmites* aboveground biomass?
- Can the new medium Sentinel 2 MSI with red edge and Landsat 8 OLI with refined near infrared coverage improve biomass quantification accuracy than finer spatial resolution RapidEye?

1.4. Thesis Structure

This thesis is comprised of four chapters. Chapter 1 provides the general background, highlighting the importance and problems associated with wetlands. The different types of multispectral remote sensing data used for wetland vegetation and their limitations provided in the context of published literature. This is in laying groundwork and exploring new remote sensing techniques that can help estimate *Phragmites* biomass with high accuracy at affordable cost.

Chapter 2 and 3 are written as a stand-alone article in the form of publishable manuscript format that can be read separately from the rest of the thesis. However, these chapters draw conclusions that link the overall research objectives and questions. In that regard, replications occur in the introduction and methods sections. Chapter 2 investigates the potential of using RapidEye satellite data to estimate the variability of *Phragmites* biomass between natural and rehabilitated wetlands. This chapter highlights the significant correlation between measured biomass with spectral bands and vegetation indices. Furthermore, PLS regression was implemented to predict aboveground biomass based on three different predictor variables. All RapidEye predictor variables were tested to determine which predictor has the potential to estimate *Phragmites* biomass better with high accuracy.

Chapter 3 (manuscript in preparation), investigates the potential of using cheap available earth observation data and compared it with commercial sensors. Specifically, we compared the strength of Sentinel 2 MSI with its counterpart Landsat 8 OLI for quantifying *Phragmites* biomass between natural and rehabilitated wetlands. The results obtained from both satellite images were compared with the findings achieved from chapter two. This chapter explore the increased spectral coverage in Sentinel 2 MSI (specifically, red edge) and Landsat 8 OLI (near infrared) with moderate resolution with red edge contained in high spatial resolution.

Research synthesis is presented in chapter 4. The findings are provided in light of the objectives and questions of the study. Conclusion is based on the results obtained in relation to the existing published literature and answers the proposed research question. Some recommendations for future research on the application of multispectral remote sensing of *Phragmites* biomass estimation are highlighted. A long list of references is provided at the end of the thesis.

CHAPTER TWO

The utility of new generation RapidEye multispectral sensor in assessing aboveground biomass of *Phragmites australis* (common reeds) in wetlands areas.

This chapter is based on:

Mogano K, Chirima J.G, Mutanga O (submitted). Testing the potential of RapidEye multispectral sensor in assessing aboveground biomass of *Phragmites australis* (common reeds) in wetlands areas. Journal of Wetlands

Abstract

Wetland rehabilitation has become a common important practice to recover critically degraded ecosystem services. Wetland biomass is one of the main attributes used to quantify the extent of wetland rehabilitation. Most wetlands are vulnerable to invasive species such as *Phragmites australis*. To evaluate the success of wetland rehabilitation, we quantified the fresh aboveground biomass of *Phragmites*, an invasive species, in a rehabilitated wetland. A pristine wetland was used as a control. Convectional measurements are accurate and reliable; however, it is difficult to harvest the required amounts of materials over large areas in a wetland where mobility is restricted. This study explored the potential of using RapidEye data to estimate the aboveground biomass of *Phragmites* in wetlands. We performed a correlation analysis between measured *Phragmites* biomass and the predicted biomass derived from RapidEye data on both wetlands. The results showed that natural wetland had high aboveground biomass than the rehabilitated wetland. However, the rehabilitated wetland showed wider biomass distribution pattern. All RapidEye spectral bands were significantly correlated with *Phragmites* measured aboveground biomass. The coefficient of determination (R^2) and root mean square error (RMSE) did not generate consistent results through all models. The individual models were weaker than pooled dataset. The findings of the study are as follows: The spectral bands estimated biomass better with an RMSE value of 449.6 g/m². The vegetation indices achieved high accuracy for rehabilitated biomass estimation with RMSE value of 387.1 g/m². When both bands and vegetation indices were combined, the model estimated *Phragmites* slightly better than spectral band model (RMSE = 434.2 g/m²). Our study suggests that estimation of aboveground biomass of *Phragmites* is possible with RapidEye imagery.

Keywords: natural wetland, rehabilitated wetland, aboveground biomass, *Phragmites australis*, RapidEye imagery

2.1. Introduction

Wetlands are important and productive ecosystems (Mitsch & Gosselink, 2000). They provide a range of ecosystem services, such as storm protection, biodiversity support, nutrient removal, water quality improvement, and, carbon sequestration (Zedler & Kercher, 2005). Furthermore, wetlands provide habitat to an array of wildlife animals and plants (Klemas, 2013) and have high economic, cultural, and recreational values (Desta et al., 2012). Despite the goods and services they provide globally, wetlands are being lost at an alarming rate because of anthropogenic disturbances such as agriculture, urban development, water abstraction, and mining (Carle et al., 2014; Meli et al., 2014; Sieben et al., 2011). The loss or degradation of wetlands could increase the net global carbon dioxide level in the atmosphere by 6% per year (Hopkinson et al., 2012; Vashum & Jayakumar, 2012b). Therefore, damaged and degraded wetlands require effective protection and restoration. Wetland restoration has become a common practice worldwide to recover critical and degraded ecosystem services (Wang et al., 2012). Recently, research on wetland restoration has become important in order to understand the structure and ecological functioning of restored wetlands.

It is difficult to measure the function of restored wetlands directly, because changes in some properties (e.g. soil nutrients, soil organic) can only be observed after a long time (Matthews et al., 2009). Furthermore, the direct assessments of restored wetlands are rare, as are data supporting the use of indicators of the success and function of these ecosystem (Zedler & Lindig-Cisneros, 2002). This is because in an ideal world, restored wetlands would be assessed with long term, large-scale data, however some indicators may not be determined in few years after restoration (Eviner et al., 2012; Wortley et al., 2013). Several authors have suggested that restoration success could be based on vegetation characteristics, species diversity and wetland ecological processes (Ruiz-Jaén & Aide, 2005). In practice, vegetation is often used as the indicator of success of failure of restoration, because it is assumed that with the recovery of vegetation follow the ecological processes (Eckert & Engesser, 2013; Kay Christine Stefanik, 2012). Most importantly, these measurements are helpful and practical for determining whether rehabilitated wetlands begin to approximate the pristine wetlands both structurally and functionally as they age or not. However, restored wetlands are particularly susceptible to rapid spread of invasive plants that can hinder restoration success (Kettenring & Adams, 2011; Saltonstall & Stevenson, 2007).

Phragmites australis (common reeds) is one of the most important and widely distributed invasive grasses in wetland environments (Russell & Kraaij, 2008; Wang et al., 2012) and considered highly productive (Soetaert et al., 2004). *Phragmites* is known to invade natural, rehabilitated and created wetlands , forming monotypic stands and displacing other native species (Engloner, 2009; Kettenring & Adams, 2011; Kettenring et al., 2012). Although some studies indicated the uncertanities regarding how best to measure the success of rehabilitation (Matthews et al., 2009), the standing fresh biomass of *Phragmites* invasive species may be a direct measure of wetland ecosytem functioning (Catling & Mitrow, 2011; Hossain et al., 2010). The aboveground biomass is an essential index for monitoring the stabilility and productivity of wetland ecosystems (Klemas, 2013; Mutanga & Adam, 2011). Although aboveground biomass is important for determining wetland health and function, the biomass of *Phragmites* received little attention. Furthermore, the response of *Phragmites* under different wetlands management is essential for understanding factors that promte invasion. To understand the distribution and quantity of *Phragmites* requires accurate monitoring and assessment in a spatial context at finer scale (Pengra et al., 2007). Given the fact that wetlands are complex ecosystems (Javier Martínez-López et al., 2014; Mwita, 2016),obtainig relaible estimates poses a major challenges (Schino et al., 2003; Xie et al., 2009).

Conventional field measurements for quantifying the variability of aboveground biomass of invasive species across different wetland management sites are accurate and reliable (E. Adam et al., 2010; Q. Chen et al., 2012). Although these methods are considered accurate, it is difficult to harvest the required amounts of materials to accurately measure aboveground biomass over large spatial extents, especially in wetland ecosystems where mobility is usually restricted (Silva et al., 2008; Zomer et al., 2009). Therefore, field methods are impractical for quantification of aboveground biomass of wetland vegetation, especially in closely dense stands of plants and dangerous locations. It is well documented that optical remote sensing imagery is a primary source of data that provides valuable information regarding wetland vegetation characteristics since it offers instant and repetitive information from local to global scales at a low cost (E. Adam et al., 2014; Goetz & Dubayah, 2011; Sibanda et al., 2015). Because of these advantages, remotely sensed data have attracted a significant amount of scientific research, especially concerning estimating natural vegetation biomass at different scales (Englhart et al., 2011; Lu, 2006). Although biomass cannot be directly quantified from space, remote sensing has been used to estimate biomass through empirical relationship between reflectance and spectral indices when integrated with field measurements (E. M. Adam & Mutanga, 2012a; Englhart et al., 2011; García et al., 2010; Mutanga et al., 2012). As a result, different remote sensing methods have been used to estimate the aboveground biomass of wetland vegetation successfully (Byrd et al., 2014; Dronova et al., 2015; Mutanga et al., 2012). However, literature suggests that low to moderate spatial resolution of multispectral sensors (e.g. Landsat, SPOT, ASTER and MODIS) are valuable for mapping biomass at a global scale rather than at a local scale (Abdel-Rahman et al., 2014; E. Adam et al., 2014; Dube et al., 2014). These multispectral sensors pose a challenging task of dealing with mixed pixels due to larger sensor footprint (E. Adam et al., 2010; Carreiras et al., 2012; Reschke & Hüttich, 2014). Moreover, the use of traditional indices showed to have limited success especially in wetlands areas dominated by *Phragmites* with high productivity. It is documented in the literature that traditional indices saturate when the aboveground biomass reach 300g/m² (E. Adam et al., 2010). Provided with this limitation, biomass estimation of individual plant species with moderate broadband sensors will be impossible in wetland ecosystems. Therefore, optical sensors that are characterized by high spectral and spatial resolution are required for biomass estimation in wetland areas.

The development of new multispectral sensors with improved high spatial and spectral resolution such as WorldView-2 and 3, and, Rapid Eye, designed with a red-edge band provide a better opportunity for biomass retrieval at local to regional scales (Ozdemir & Karnieli, 2011; Ramoelo et al., 2015a; Ramoelo et al., 2012). The presence of the red-edge band contained in these multispectral sensors is seen as an advantage over coarse multispectral sensors (Schuster et al., 2012). In remote sensing, the "red edge" is the transitional region between the red absorbance and near infrared reflection. This region positioned between 680 and 780nm has the ability to provide additional information about vegetation characteristics (Filella & Penuelas, 1994; Gitelson, 1993). This raises the question of whether commercial broadband RapidEye image with high spatial resolution of 5 m can enhance aboveground biomass rietrival of water borrne invasive species within wetland ecosystems. A number of successful studies have been conducted using RapidEye data in classifying land use (Schuster et al., 2012), derivation of leaf area index (Asam et al., 2013) , estimating forest biomass and structure (Dube et al., 2014; Ramoelo et al., 2015a; Wallner et al., 2015), and crop biomass (Imukova et al., 2015; Kross et al., 2015). Although this technique has not been fully tested on wetland vegetation, it is considered one of the promising and effective method for quantifying the aboveground biomass of vegetation (Malatesta et al., 2013). Therefore, this study explored the utility of RapidEye image data for quantifying the variability of aboveground biomass across different wetland management sites.

Optical remote sensing of wetland vegetation aboveground biomass has not been widely done due to problems of water inundation, nutrient variability and state of maturity. These physiological factors have influence on the relationship between spectral reflectance and field measurements (E. Adam et al., 2010; Byrd et al., 2014). We explore the potential of RapidEye data for assessing the variability of *Phragmites* biomass across a natural and a rehabilitated wetland. It is necessary to understand how the biomass of same invasive species under different wetland management relates to the satellite observed reflectance during a single growing season. The overall goal of this study was therefore; to quantify the variability of *Phragmites* aboveground biomass in wetlands located in the City of Tshwane Metropolitan Municipality (CTMM) using RapidEye satellite image data. In order to achieve this task, we measured the fresh aboveground biomass of *Phragmites* across the natural and rehabilitated wetlands. We evaluated the relationship between *Phragmites* measured biomass and RapidEye extracted data (bands and indices) across both natural and rehabilitated wetlands in order to compare the performance of each spectral data as well as evaluating the success of intervention measures in invasive species control.

2.2. Methods and Material

2.2.1. Study Area

The study was conducted in Kaalplaas Spruit (25º 36' 43.87"S and 28º 05' 39.87" E) and Rietvlei Nature Reserve (25º 41' 22" S and 26º 37' 48" E), which are part of City of Tshwane Metropolitan Municipality, South Africa (Figure 1). The study areas receive average summer rainfall ranging between 600-750 mm per annum, with maximum temperatures of 28º C [Agricultural Research Council- Soil, Climate and Water and Climate (ARC-SCW)]. The Kaalplaas Spruit is a natural wetland while the Rietvlei is a rehabilitated wetland. Currently these wetlands are being invaded by P*hragmites* and *Typha* species. However, other species such as *Impoea, Leerzia, Ragweed, Cyperus spp, Bidens pilose, Conyza albida, Loostroof, Percacia*, *Amaranthas* and *Common dodder* are also found on the two wetlands. The Rietvlei wetland was selected as the reference for study sites. Historically, the wetland was degraded due to large amount of water drained, which, subsequently became dry and led to vegetation alteration.

The rehabilitation process started in 2000 to rewet the peatland and allow the hydrophytic vegetation to re-establish.(Oberholster et al., 2008). The wetland was dominated by *Persicaria*, *Phragmites*, *Phytolacca octandra*, and, *Cyperus communities* . Sewage water, alien invasive species, residential development, burning, and roads are the major disturbance of wetland vegetation (Grundling, 2004). Although both sites are dominated by *Phragmites*, the height and shape were not the same. The *Phragmites* from Kaalplaas Spruit mostly were above 2 m. On the other hand, the Rietvlei invasive vegetation were less than 2 m high and very thin at most sites. Furthermore, ragweed species of Kaalplaas Spruit were found in most sites where *Phragmites* was dominant and accessible for sampling.

2.2.2. Field Data Collection

The fieldwork was carried out between 16 November and 16 December 2015 on both wetlands. Prior to field sampling, 52 sample plots were generated randomly from Kaalplaas Spruit and 47 from Rietvlei wetland. At each point, a quadrat of 1 x 1 m was placed and the locality of that plot was recorded using global positioning system (GPS-Garmin Montana 650). Where *Phragmites* were taller and impossible to place the quadrat, a measuring tape was used to generate 1 x 1 m quadrat. The percent cover of all measured plant species were estimated following the nine-grade Braun-Blanquet scale (Van der Welle & Vermeulen 2003). In each sampling plot, the following data was recorded in a rellevee sheet: plant species, density of dead and live stems, percent ground cover, and description of quadrant. The fresh aboveground biomass of *Phragmites* and other species identified within the boundaries of quadrat were harvested and placed in a labelled bag. The dry leaves and roots were not considered for measurements. The harvested fresh biomass was taken to laboratory on the same day for measurement using a digital weighing scale.

2.2.3. Remotely sensed data

A RapidEye multispectral image that covered the study sites were acquired on 02 November 2015 with zero cloud cover from GeoData Company. The RapidEye image comprised of five multispectral bands with a spatial resolution of 5 m. The spectral ranges of the five bands are 440-510 nm (B1-blue), 520-590 nm (B2-green), 630-685 nm (B3-red), 690-730 nm (B4-red-edge), and 760-850 nm (B5-near-infrared). The image was already orthorectified and geometrically corrected when received. Atmospheric correction was implemented in ENVI 5.1 software using the Fast Line-of Sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) algorithm.

2.2.4. Extraction of spectral data

A point map of biomass plots was generated using data collected in the field using a GPS (n = 99). This point map was overlaid on the RapidEye image to extract a region-of-interest (ROI). The spectral bands reflectance were extracted for each sampled plot. The values of each spectral band were also used to calculate the vegetation indices (Table 2.1). All the extraction of data was performed using ESRI ArcGIS 10.3. The spectral bands derived from RapidEye image, the computed vegetation indices, and the measured aboveground biomass were used as an input variable in Partial Least Square Regression (PLSR) model to measure the importance of each spectral data in quantifying the variability of *Phragmites* aboveground biomass. This was done to evaluate the utility of the red-edge band derived vegetation indices biomass estimation relative to the traditional indices.

Table 2.1. The spectral bands of RapidEye image and derived vegetation indices.

Parameters	Abbreviation	Formula	Reference
Blue, Green, Red, NIR and Red-edge			
Simple Ratio	SR	NIR/Red	Jordan (1969)
Simple Ratio. Red-edge	SR.re	NIR/Red-edge	Gitelson &Merzlyak (1994)
Normalised Difference Vegetation Index	NDVI	(NIR-Red)/(NIR+Red)	Rouse et al., (1974)
Normalised Difference Vegetation Index. Red-edge	NDVI.re	(NIR-Red-edge)/(NIR+Red-edge)	Gitelson &Merzlyak (1994);Mutanga et al., (2012)
Normalised Water Difference Index	NDWI	NIR)/(Blue+NIR)	Gao (1996)

2.3. Data analysis

Across the natural and rehabilitated wetlands, sampling plots were measured during the growing season. The sampled plots with more than 85 percent coverage of *Phragmites* were considered for the analysis (n=99). This was done to avoid the effects of different species in the spectral reflectance of *Phragmites* within sampled plots. One way analysis of variance (ANOVA) was used to test whether there is a significant difference in mean biomass between the natural and rehabilitated wetlands at 95% confidence level (α = 0.05). Furthermore, analysis of covariance (ANCOVA) was used to evaluate the relationship between *Phragmites* aboveground biomass and RapidEye derived spectral data, using wetland type as a qualitative variable. From those results, it was possible to observe predictor variables that correlate highly with measured biomass. Before each measured variable was used to build regression model with bands and or indices, the outliers were removed using the box and whisker plots before regression analysis was performed. The remaining samples (89) were implemented in R software using the Partial Least Square Regression (PLSR) library package as explained in section 3.1. The distribution maps were produced and displayed using version 10.3 of the ArcMap software ESRI.

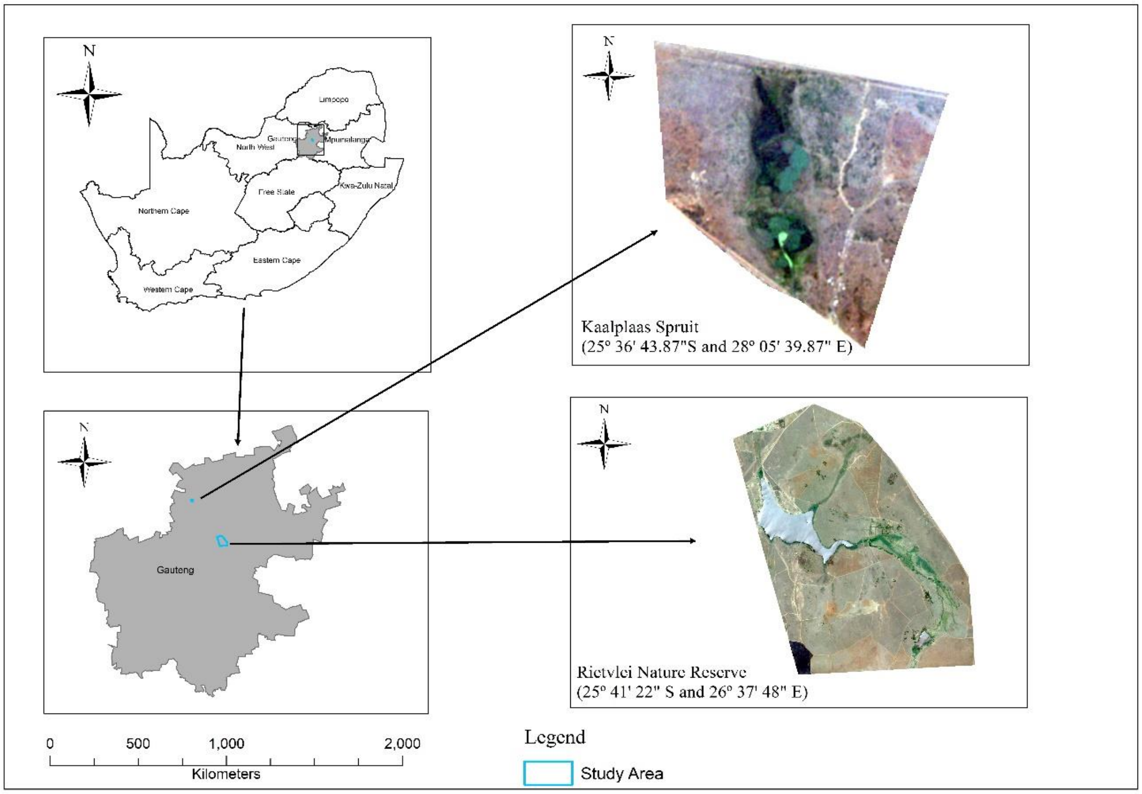


Figure 2.1. Map of the study area, including an insert of RapidEye image

2.3.1. Partial Least Square Regression (PLSR) method

Partial Least Square Regression (PLSR) is an advanced multivariate statistical analysis technique for selecting optimal spectral features when estimating aboveground biomass (Carrascal et al., 2009; Hansen & Schjoerring, 2003). It has become popular and gaining recognition in the field of remote sensing of ecology (Adjorlolo et al., 2015; Liu & Rayens, 2007) for developing predictive models of biophysical and biochemical plant parameters (Hansen & Schjoerring, 2003). Similar to Sparse partial least squares regression (SPLSR), instead of extracting all spectral data (bands and vegetation indices) as predictors, it selects one optimal spectral variable that is suitable for estimating the item of interest (Byrd et al., 2014; Liu & Rayens, 2007). The selected component explains the variation in both the predictors and response variables. This capability makes PLSR model desirable, for evaluating RapidEye spectral data for biomass estimation. More importantly, we tested the capability of using RapidEye data to quantify the variability of *Phragmites* aboveground biomass between natural and rehabilitated wetlands. The aboveground biomass of *Phragmites* was built in PLSR from each of the two predictors groups (bands and indices) based on 89 samples following the same procedure. The detailed procedure conducted for quantifying the variability of

Phragmites aboveground biomass on both wetlands is illustrated as follows: 1) the biomass, was plotted against the spectral bands using PLSR. 2) The aboveground biomass of *Phragmites* were plotted against the vegetation indices individually. 3) The aboveground biomass was then plotted against combined data (bands and indices). This procedure was performed in order to assess the importance of each predictor separately in predicting the aboveground biomass of *Phragmites*.

Due to a limited available sample size in both study areas (n = 99), the leave-one-out cross validation (LOOCV) was performed on a single calibrated dataset to evaluate the performance of PLSR model. The goodness fit of each model was evaluated based on LOOCV coefficient of determination (R^2) and root mean square error (RMSE) of the regression. The measured and predicted biomass model across both wetlands were compared. The model that resulted in the lower RMSE and high R^2 were selected as an indication of the model that performed better than the other models. The spectral bands and indices with the first minimum RMSE in all stages were selected as the best predictor to estimate the component of interest (Abdel-Rahman et al. 2014). The contribution of each raw bands and vegetation indices to the selected component was evaluated using loading factors derived from PLSR model. All regression models were performed using PLS package library (Mevik & Wehrens, 2007) implemented in R statistical software version 3.3.1(Core).

2.4. RESULTS

2.4.1. Measured Phragmites aboveground biomass

Across both wetlands, the highest average biomass was 4215.1 g/m², with range in plot from a low of 408 g/m² to over 4768 g/m². The sampled plots from the natural wetland were generally higher in biomass with low density compared to the rehabilitated wetland. After the outliers were omitted, the highest average value for biomass was 1915.9 g/m² for natural wetland and 1423.1 g/m² for rehabilitated wetland. The difference in average biomass between wetlands was significant at ($p = 0.01$). The red edge indices were plotted to illustrate their sensitivity in both wetlands (Figure 2.2). The NDVI.re were significant at ($p = 0.05$) and SRI.re at ($p = 0.006$). Figure 2.3 show a distinct aboveground biomass distribution patterns available within the study area. The biomass distributions appear quite variable across both sites with rehabilitated wetland showing wide range.

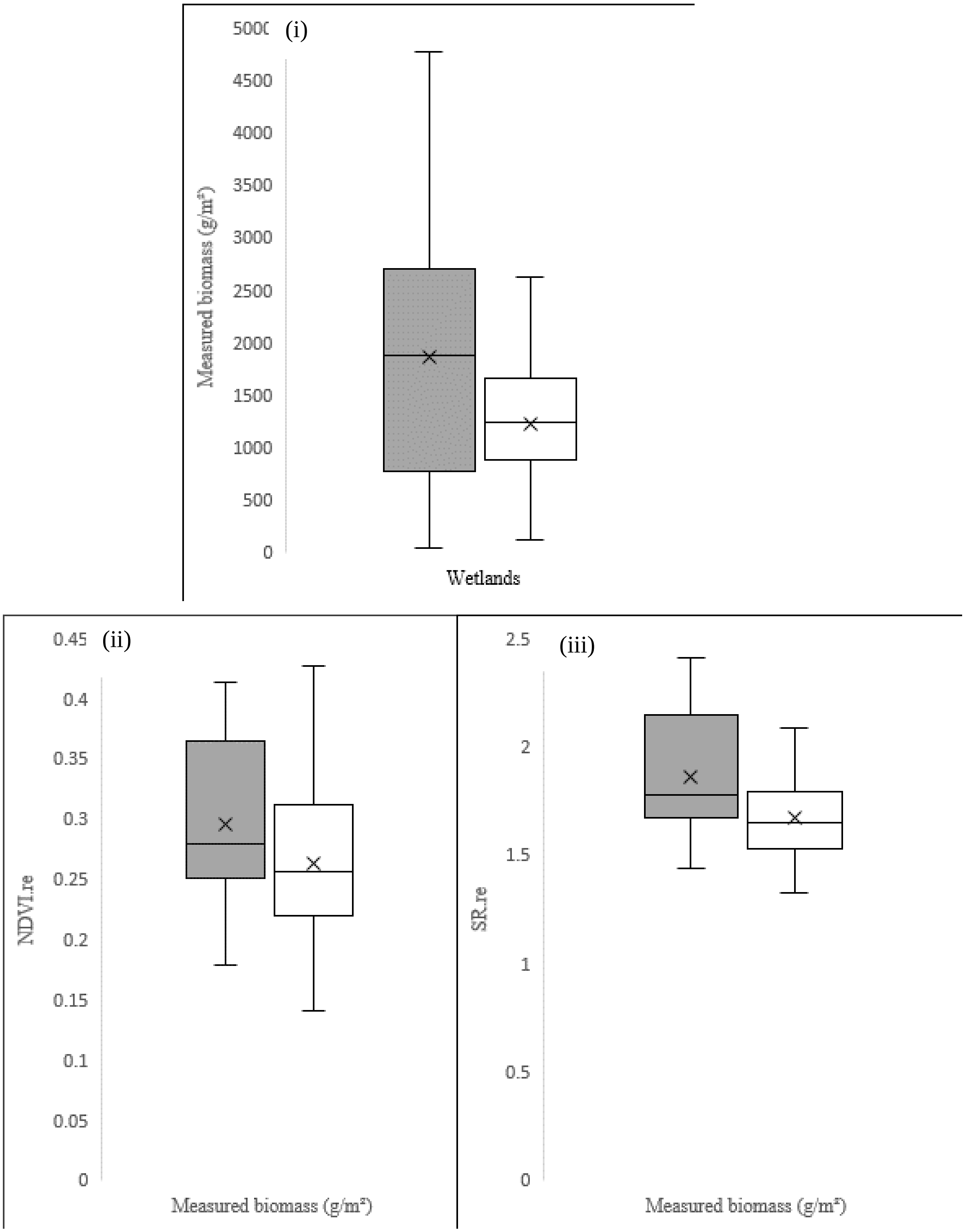
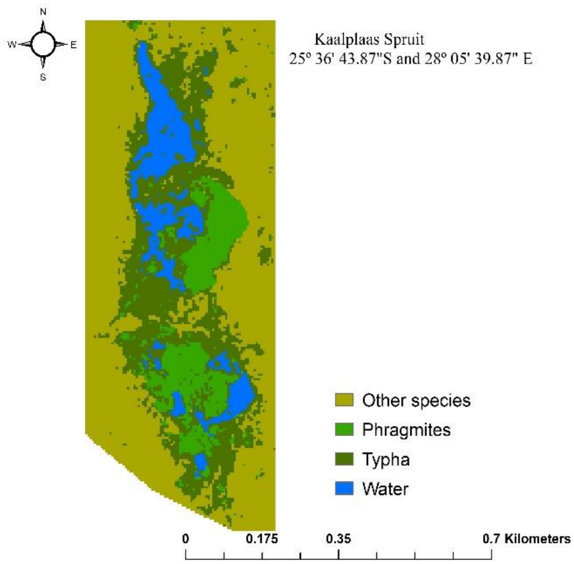


Figure 2.2. Box plots of *Phragmites* aboveground biomass. In box (i) actual measured biomass and box (ii) NDVI.re indices and box (iii) SR.re indices respectively, where grey boxes represent natural wetland and white box rehabilitated wetland.



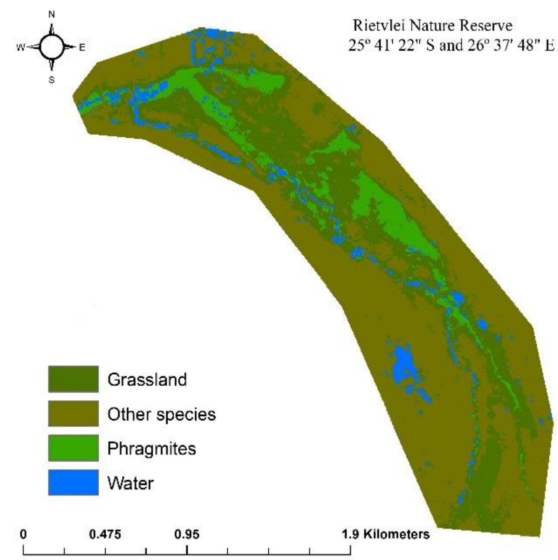


Figure 2.3. Maps of *Phragmites* biomass distribution and other dominant species

2.4.2. Correlation between Phragmites measured biomass and RapidEye spectral data

The correlation analysis was carried out between *Phragmites* measured biomass and RapidEye spectral data based on pooled dataset. The relationship was evaluated by examining Pearson correlation coefficient (r). A summary of basic information obtained from correlation coefficient is given in Table 2.2. The results shows that all of RapidEye bands were found to be significantly correlated ($p < 0.05$) with *Phragmites* biomass. The blue, green and red edge bands yielded high correlation ranging from 0.60 to 0.65. However, the indices were poorly correlated with *Phragmites* biomass. The red edge indices were significantly correlated with *Phragmites* biomass, although the correlation was poor.

Table 2.2. Correlation coefficient (r) between *Phragmites* aboveground biomass and the RapidEye spectral data based on pooled dataset.

Variable	Correlations coefficient(*r*)
Blue	0.62
Green	0.65
Red	0.46
Red edge	0.6
Near-infrared	0.59
NDVI	0.26
NDVI.re	0.37
SR	0.24
SR.re	0.36
NDWI	0.22

2.4.3. *Performance of RapidEye bands in quantifying the aboveground biomass of Phragmites*

The accuracies obtained in estimating the variability of *Phragmites* aboveground biomass using only the spectral bands is illustrated in Table 2.3. The PLSR model for biomass extracted only one optimal component for site-specific model and pooled dataset. Specifically, the best model performance came from pooled datasets with the RMSE value of 548.8 g/m². When the dataset was divided by wetland type, the natural wetland estimated *Phragmites* biomass better with the RMSE values of 966.1 g/m² than the rehabilitated wetland with RMSE value of 1013 g/m², respectively. The contribution of each band to the prediction of measured biomass is displayed in Figure 2.3(i). All RapidEye sensor bands were important for assessing the variability of *Phragmites* biomass in both wetlands. The strongest component loadings of natural biomass were those in the red edge band (690-730nm), near infrared band (760-850 nm) and visible blue band (440-510 nm). The rehabilitated biomass component loadings were strongest in the absorption red band (630 – 685 nm), near infrared band and followed by the red edge band. The negative loadings can be observed from the red band of natural biomass, which made the lowest contribution to biomass estimation. On the other hand, both the red band and near infrared band resulted in negative loadings, and contributed higher in the estimation of *Phragmites* biomass. It is evident from the results that there is a variation in performance of RapidEye bands between the natural and rehabilitated wetlands for *Phragmites* biomass estimation. Furthermore, all spectral bands may have comparable importance for *Phragmites* biomass estimation in both wetlands.

Table 2.3. Summary of PLSR for assessing the variability of *Phragmites* aboveground biomass between natural and rehabilitated wetlands.

	Natural Wetland			Rehabilitated Wetland	
Variables	Components	R^2	RMSE	R^2	RMSE
Bands	1	0.41	966.1	0.27	1013
Indices	4	0.16	944.8	0.37	1013
Bands & Indices	7	0.56	778.9	0.2	1054
Pooled data	Components	R^2	RMSE		
Bands	1	0.66	548		
Indices	3	0.75	413		
Bands & Indices	2	0.71	440.8		

2.4.4. *Performance of RapidEye derived indices in quantifying the aboveground biomass of Phragmites*

The number of components, R^2 and RMSE obtained using derived vegetation indices in estimating *Phragmites* aboveground biomass is shown in Table 2.3. The contribution of each index towards the prediction of all measured aboveground biomass is illustrated in Figure 2.3(ii). The natural biomass retained component two while rehabilitated wetland retained component four with the RMSE of 1035 g/m² and 944.8 g/m², respectively. *Phragmites* was estimated better with pooled dataset. The model retained component three and resulted in the lowest RMSE value of 413 g/m². Although site-specific model were weaker, the rehabilitated model showed a slight improvement in biomass estimation. This could be attributed to short *Phragmites* height and indices not reaching saturation level. For component two, the contribution of each index for biomass estimates were strongest, in decreasing order, from SRI, NDVI, DVI.re, SRI.re and NDWI with least loadings. The loading values for component four were weaker, with the NDWI being more sensitive to biomass quantification followed by SRI.re. The NDWI and NDVI showed positive loadings and NDVI.re, SRI, and SRI.re resulted in negative loading values. The high loading value of NDWI suggests that it has the potential for estimating *Phragmites* aboveground biomass in rehabilitated wetland.

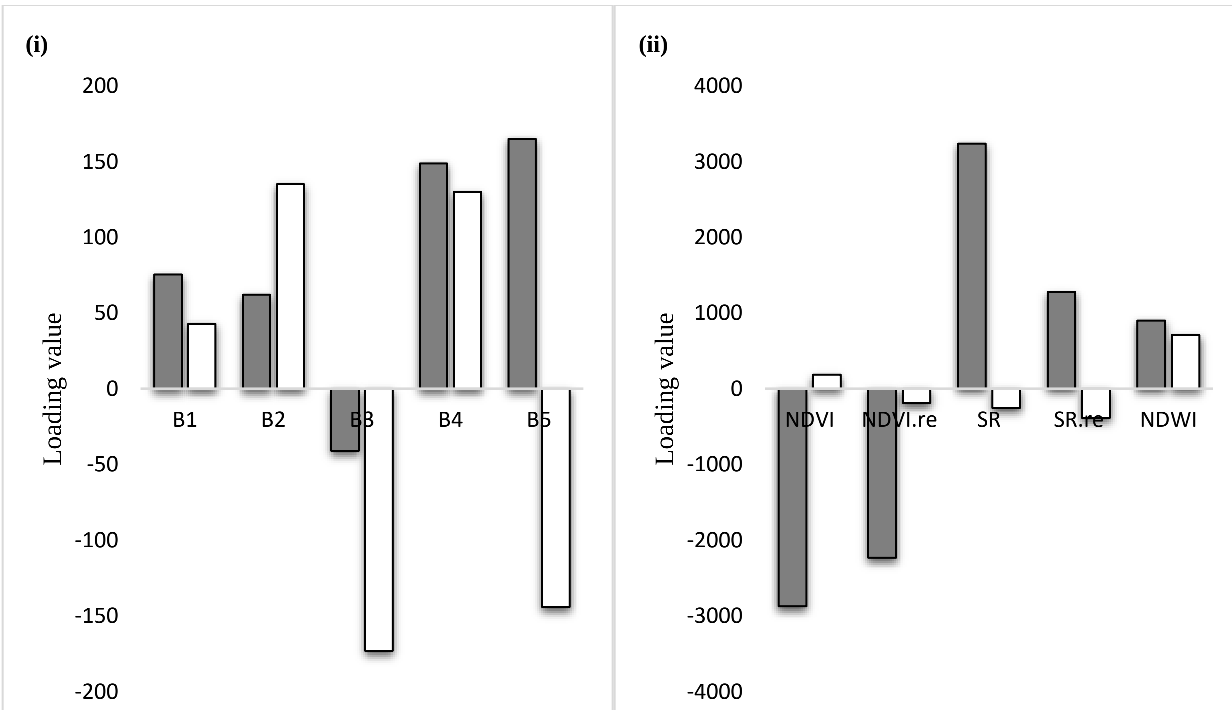


Figure 2.4. Loading values for the PLSR components plotted against the RapidEye spectral bands and indices on both natural and rehabilitated wetlands. Dark grey represents natural wetland and white represents rehabilitated wetland. In box (i) bands and (ii) vegetation.

2.4.5. Combination of both reflectance bands and derived indices from RapidEye in estimating the aboveground biomass

Table 2.3 illustrates the performance of using combined data in estimating *Phragmites* aboveground biomass. In general, combination of spectral data was more successful for natural biomass in comparison to single regression analysis. However, separate regression model for rehabilitated biomass were successful compared to model from combined data. The bands and indices that could estimate the biomass of *Phragmites* in both wetlands were those in the visible region of the spectrum (blue band), chlorophyll absorption (red band) and high reflectance (red-edge band). Specifically, the natural biomass retained component seven with RMSE of 778.9 g/m² and rehabilitated wetland retained component one with RMSE 1054 g/m² respectively. When both sites were pooled together, the model retained component two with the lowest RMSE value of 440.8 g/m². The relationship between measured and predicted aboveground biomass is shown in Figure 2.4. Noticeably, the individual prediction models were weaker than pooled datasets. The pooled spectral bands and combined datasets produced somewhat similar results. The indices outperformed both spectral bands and combined data. This proves that indeed the red edge band has the potential to estimate *Phragmites* biomass with high accuracy and overcome saturation problem that is a challenge in most conventional multispectral sensors. Measured and predicted aboveground biomass figures are based on the pooled datasets due to greater success in predicting *Phragmites* biomass. It is evident from the results that there is a variation in performance of RapidEye spectral data between *Phragmites* biomass in both wetlands.

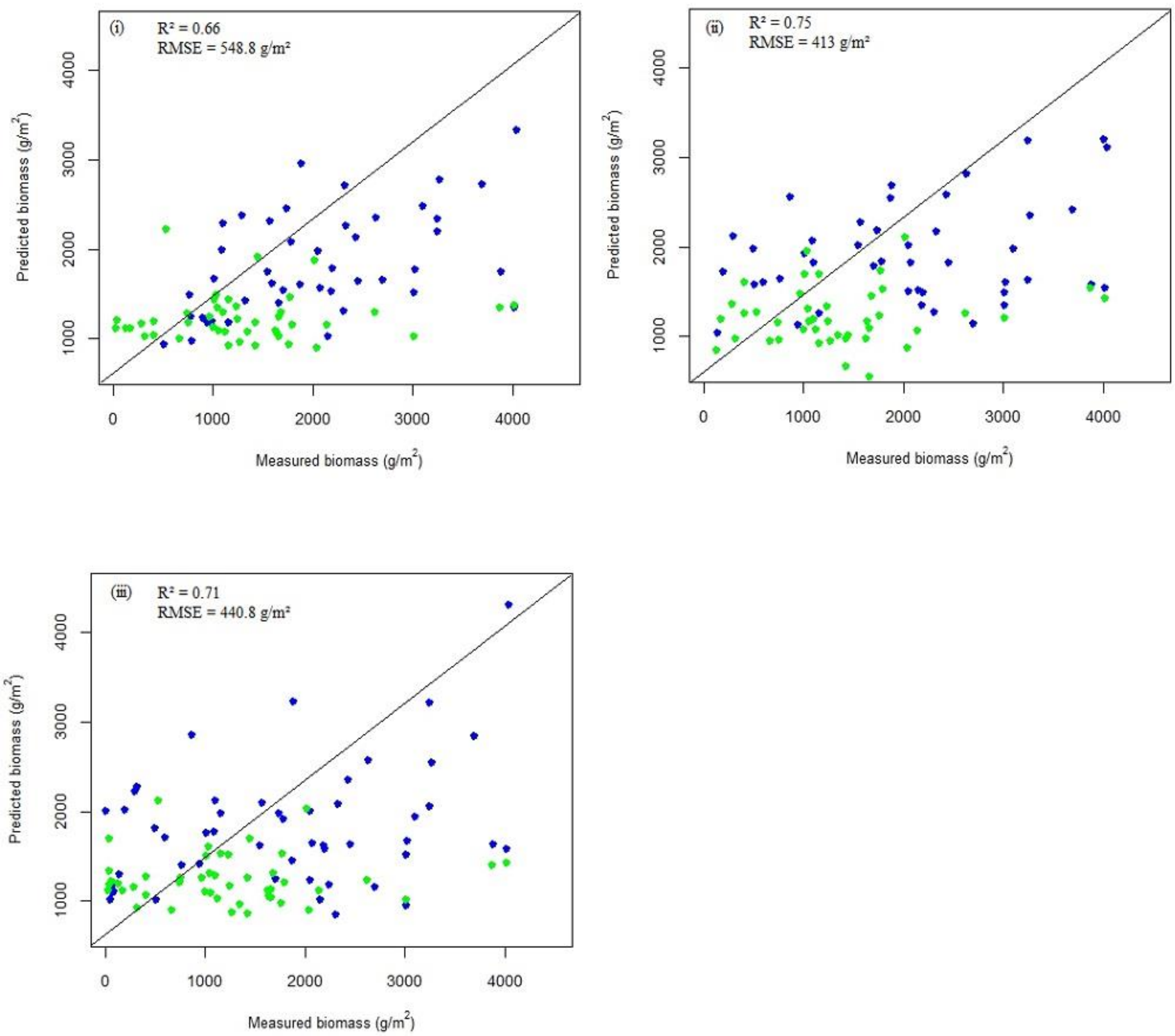


Figure 2.5. The relationship between measured and predicted aboveground biomass of *Phragmites* based on (i) RapidEye spectral bands and (ii) vegetation Indices (iii) both bands and indices. Where blue colour represents natural wetland and green is rehabilitated wetland. The models were fitted with all observed measurements.

2.5. Discussion

2.5.1. *Variability in Phragmites biomass distribution*

By estimating the quantity of biomass and producing distribution maps, we can start examining the underlying factors that contribute to variable distribution pattern of invasive species (Saatchi et al., 2007). *Phragmites* biomass estimation appears to be high under natural wetland. While the biomass distribution of rehabilitated wetland exhibited greater variability than that of natural wetland. We can assume that field measurement underestimated the rapid growth in rehabilitated wetland. Our results are consistence with the findings of (Matthews et al., 2009; Wang et al., 2012; Zedler & Lindig-Cisneros, 2002). The authors reported high biomass estimation in natural wetland than in created or restored wetlands. While (Havens et al., 1997) reported wide biomass distribution in created wetland than natural wetland. Venter et al. (2003) conducted vegetation survey a year after rehabilitation measures were implemented to determine the nature of the pioneer communities. Their study reported that the pioneer vegetation was dominated by annual weedy species. They further indicated that grazing by animals and trampling by buffalo in the reserve is some of the disturbance that could have caused the degeneration of some plant species. The quantity of biomass variation across wetlands could be because of different activities such as grazing, harvesting, and burning (Zedler & Lindig-Cisneros, 2002) and these activities are likely to be similar in wetland sites. Our findings answer the study conducted by Venter et al. (2003) and prove the theory of Matthews et al. (2009). The grazing of herbivores disturbed colonization of native plant species and accelerated weedy species in rehabilitated wetland. Furthermore, burning of *Phragmites* occur annually in the middle of dry season as a control measure in rehabilitated wetland (Brian, personal communication). Literature also indicated that once-off cutting results in increased density of shorter and thinner *Phragmites* Russell and Kraaij (2008). Supporting the findings of Zedler and Lindig-Cisneros (2002) and Saatchi et al. (2007) the aboveground biomass of *Phragmites* alone cannot explain variability across different wetlands. This wide variation of biomass between wetlands suggests the need for a better understanding of both environmental and anthropogenic activities influencing the distribution of *Phragmites.* Understanding of these factors controlling *Phrgmites* biomass distribution will allow for the production of precise biomass maps at different scales (Svob et al., 2014).

2.5.2. Assessing the variability of Phragmites aboveground biomass using RapidEye imagery

The study adopted the PLSR model in order to evaluate different procedures, which could best estimate *Phragmites* aboveground biomass with high accuracy in natural and rehabilitated wetlands. The bands and indices derived from RapidEye imagery were tested to quantify the variability of *Phragmites* biomass across the pristine and rehabilitated wetlands. First, the potential of using spectral bands reflectance for quantification of *Phragmites* aboveground biomass was assessed in both wetlands. Biomass prediction based on site-specific model estimated natural wetland better than rehabilitated wetland. The pooled dataset estimated biomass better than site-specific models. The effectiveness of spectral bands for assessing the variability of *Phragmites* biomass relied on the visible blue band. All RapidEye bands showed high contribution towards quantification of *Phragmites* biomass [Figure 2.3 (i)] and were significantly correlated with observed biomass. However, in the analysis, the red, red-edge, and near infrared bands contributed highly towards the quantification of *Phragmites* biomass in both wetlands. These bands are located in the wavelength known for estimating aboveground biomass and assessing wetland ecological function. This finding is consistent with the study by J. Chen et al. (2009) who reported the potential of blue band toward estimating aboveground biomass of grassland having high canopy cover. The most important findings in this study is that information for quantifying the variability of *Phragmites* biomass is probably concentrated in all the different spectral bands of RapidEye satellite image.

Secondly, we assessed the potential of using vegetation indices derived from RapidEye sensor for *Phragmites* biomass quantification in natural wetland and rehabilitated wetland. The findings of the study further demonstrated that vegetation indices derived from RapidEye have the strength to estimate *Phragmites* biomass with high accuracy. For the estimation of all combined sites, the vegetation indices model outperformed the spectral bands. Similar with bands results, site-specific models were weaker using vegetation indices. However, rehabilitated wetland performed better than natural wetland. There could be two possible reason for plausible performance of vegetation indices. The first explanation could be because of red edge indices that were selected as the best variables to estimate *Phragmites* biomass. As indicated from substantial literature, aboveground biomass proved to be challenging with vegetation indices especially during the wet season when *Phragmites* biomass is above (400g/m^2) within sampled plots (J. Chen et al., 2009; Mutanga et al., 2012; Mutanga et al., 2004). The inclusion of red edge in vegetation indices was found to enhance biomass estimation and overcome the saturation problems especially in high dense vegetation (Mutanga et al. 2012; Adam et al. 2010). Kross et al. (2015) also indicated that red edge indices yielded high prediction accuracy for LAI and biomass of corn and soybean crops using RapidEye satellite image. Secondly, vegetation indices are products of more than one band, which are more sensitive to green invasive species as compared with a single band that maybe hindered by background effects and yield poor prediction accuracy of *Phragmites* biomass (J. M. Chen, 1996; Sibanda et al., 2015). For instance, the two indices are a combination of red band and red-edge band. Healthy vegetation absorbs radiation by leaves' chlorophyll in the red band while reflecting highly in the red-edge wavelength.

Therefore, RapidEye red edge indices has the potential to quantify the aboveground biomass of *Phragmites* during the wet season when the area of interest is above 80 percent covered and the biomass is above 400 g/m².

Finally, the potential of combining both bands and indices for assessing the variability of *Phragmites* aboveground biomass was also explored. The purpose of combining datasets is to increase the validity and robustness of the relationship between measured biomass and predicted biomass. Theoretically, the use of high multispectral sensor with the additional red-edge band should improve the quantification of *Phragmites* biomass. For instance, it is expected that when the bands increase, the biomass estimation will increase in accuracy (D Rocchini et al., 2007). The findings of this study indicated that combined spectral data outperformed spectral bands and resulted in slightly less than vegetation indices model based on pooled dataset. The site-specific model improved the aboveground biomass of natural wetland and resulted in lower accuracy for rehabilitated wetland. The present study has demonstrated that assessing the variability of *Phragmites* biomass between natural and rehabilitated wetlands is possible with RapidEye data. This variability performance of bands and indices in both wetlands can therefore serve as a surrogate for water borne invasive plant species productivity and condition in other wetlands.

It is difficult to directly compare our study with other studies on *Phragmites* biomass due to difference in satellite data and the methods used. Furthermore, most studies on *Phragmites* using remote sensing pay attention on its distribution or spectral discrimination. For example, Ihse and Graneli (1985) reported that hand-held digital instrument was useful for estimating biomass of *Phragmites* in two Swedish reed stand. Ailiana et al. (2008) used Landsat TM and ETM to retrieve biomass of *Phragmites* in China. These authors did not implement any regression model to estimate the biomass as a function of the spectral information captured by the sensors. Instead of regression model, the biomass of *Phragmites* was estimated using the vegetation indices and classification of satellite image. Statistics could not be provided from their research. The current study achieved the highest R^2 value of 0.75, which is higher than the findings of Luo et al. (2017) who retrieved *Phragmites* biomass using Hyperspectral and Light detection and ranging (LIDAR) data. The author achieved the highest R^2 value of 0.48 with Hyperspectral and 0.58 with Lidar from only one wetland with short *Phragmites*. Wallner et al., (2014) estimated forest structural information with RapidEye data and achieved the R^2 value of 0.63. Dube et al., (2014) also used RapidEye to predicted intra-and-inter species biomass of forest and achieved R^2 value of 0.58 for combined species. RapidEye image was praised for its potential to estimate biomass with high accuracy in areas of closed and dense vegetation. These findings suggest that RapidEye sensor performs considerably different depending on the geographic location and object of interest. Considering that data were collected in two different wetland areas with diverse vegetation species under natural condition, the results reaffirm the capability of RapidEye spectral bands for estimating *Phragmites* biomass. This new generation multispectral sensor can still compete with other higher spectral resolution data with regard to the information they provide (Asam et al., 2013; Wallner et al., 2015; Zandler et al., 2015).

2.6. Conclusion

The current study conducted field measurement to reveal the variability of *Phragmites* biomass distribution and explore the potential of using RapidEye to estimate biomass of *Phragmites* between natural and rehabilitated wetlands. The new multispectral RapidEye sensor data has the potential to quantify the variability of *Phragmites* biomass. Although our study focused on comparing single species over one season across different wetland settings, the study suggest that it is possible to assess variability of biomass of invasive *Phragmites* with RapidEye satellite imagery in two different wetland sites, an important insight for management of wetland ecosystem. However, there is still more to be taken into consideration to improve upon. Most importantly, similar studies should be carried out in other different wetlands and over large areas to provide an understanding of the utility of RapidEye for quantifying biomass of *Phragmites.*

CHAPTER THREE

Comparison of medium spatial resolution Sentinel 2 MSI and Landsat OLI in assessing the variability of *Phragmites australis* (common reeds) biomass in wetlands areas.

This chapter is based on:

Mogano K, Chirima J.G. Mutanga O (in preparation). Comparison of newly launched medium multi-scale satellite sensors Sentinel 2 MSI and Landsat 8 OLI in assessing the variability of *Phragmites australis* (common reeds) biomass in wetlands areas. Journal of Wetland Ecology and Management

Abstract

The purpose of wetland restoration is to enhance biodiversity and recover natural ecosystem services. Unfortunately, restored wetlands are susceptible to invasive plant species such as *Phragmites australis*. Aboveground biomass is a common metric used to evaluate the function of restored wetlands. Accurate estimate of *Phragmites* aboveground biomass is required to assess the condition of restored wetland. The biomass of restored wetland was compared with that of natural wetland to understand the ecological function of these ecosystems. Given that wetlands are not easily accessible, on-site survey is time consuming, laborious and feasible to small areas. Multispectral remote sensing data offer cost effective approach for estimating wetland vegetation characteristics at varying resolution scale in a short period. Hence, the present study compared the potential of newly launched Sentinel 2 Multispectral Instrument (MSI) and Landsat 8 Operational Land Imager (OLI) in quantifying the variability of *Phragmites* biomass between the natural and rehabilitated wetlands. To evaluate the potential of Sentinel 2 MSI and Landsat 8 OLI, the extracted spectral bands, derived vegetation indices and combined datasets (spectral bands and vegetation indices), were used as predictor variables for *Phragmites* biomass. The results were compared with those derived from commercial RapidEye satellite data. The results showed that extracted spectral bands derived from Sentinel 2 MSI quantified *Phragmites* biomass with higher accuracy than vegetation indices and combined datasets for both wetlands. The results obtained from Landsat 8 OLI and RapidEye data were not consistence in all models producing weaker and higher accuracy. The results were inclusive concerning whether Landsat 8 OLI outperformed RapidEye or not for *Phragmites* biomass estimations. Overall, Sentinel 2 MSI exhibited Landsat 8 OLI and RapidEye in quantifying *Phragmites* biomass in both wetlands. These findings showed that *Phragmites* biomass could be improved with the use of cheap earth observation Sentinel 2 MSI with improved spectral bands.

***Keywords*:** natural wetland; rehabilitated wetland; *Phragmites* biomass; medium spatial resolution

3.1. Introduction

The products, function and ecosystem services provided by wetlands are quantifiable and numerous. At local scale, wetlands provide food, recreation and habitat to numerous fauna, flora species, and other functions (Kotze et al., 2012; Zedler & Kercher, 2005). At broader scale, wetland vegetation serve as an excellent filter of excessive nutrients including those from agricultural runoff (Engelhardt & Ritchie, 2002; Thompson et al., 2007) and industrial waste (Klemas, 2013). Unfortunately, anthropogenic activities and climate change worldwide threaten wetland ecosystems (Sieben et al., 2011; Verhoeven, 2014).

Restoration of wetland ecosystems has the potential to reverse degraded wetlands, increase biodiversity and recover important ecosystem services (Bullock et al., 2011; Mitsch & Gosselink, 2007; Wortley et al., 2013). Studies have reported that the main goal of restoration or creation of wetlands is to enhance the re-establishment of both biodiversity and ecological services lost due to over exploitation and degradation (Bullock et al., 2011; Sink et al., 2012). However, determining appropriate variables needed to evaluate the success of restoration is a problem (Kentula, 2000; Lockwood & Pimm, 1999). Preferably, wetland restoration should be assessed using the same variables before, during and after restoration. At times consistent data for such variables are rare or do not exist (Carpenter et al., 2006; Eckert & Engesser, 2013; Kay C Stefanik & Mitsch, 2012). In general, restoration indicators differ by wetland ecosystem types and across the scale, making comparison between restored and natural wetlands difficult. Vegetation structure such as aboveground biomass is a common metrics used to evaluate wetland restoration ecosystems (Ahn & Dee, 2011; J Martínez-López et al., 2011; Spieles, 2005). The aboveground ground biomass serve as an important indicator of wetland ecological conditions and management (Miller & Fujii, 2010). Furthermore, aboveground biomass provides a good measure of plant types dominating on restored or natural wetlands. Biomass reflects the amount of water, nutrients and sunlight an individual plant is capable to absorb and turn into plant mass (Russell & Kraaij, 2008; Wang et al., 2012).

The main problem hindering the success of restoration is colonization by invasive species (Havens et al., 1997). Restored wetlands are vulnerable to invasion from both native and alien invasive plant species due to the disturbances and increased resource availability than natural wetlands (Garbutt & Wolters, 2008; Kettenring & Adams, 2011). Aquatic invasive species such as *Phragmites australis* (Phragmites) are widely distributed in most wetlands of Southern Africa (Russell & Kraaij, 2008). This invasive species has the ability to displace other wetland vegetation and decrease biodiversity (A. Chen et al., 2008; Kettenring & Adams, 2011; Ozbay et al., 2012). Its rapid growth and high reproductive rate has attracted researchers and resource managers around the globe with respect to its environmental value (e.g. controlling soil erosion, wastewater treatment) (A. Chen et al., 2008; Van Meerbeek et al., 2015). Knowledge on the type of vegetation and its growth is critical for understanding and assessing the status of wetland restoration. Instead of considering invasive species as s burden, the aboveground biomass produced by *Phragmites* can be considered a measure of ecosystem services (Van Meerbeek et al., 2015). Aboveground biomass of *Phragmites* not only reveal wetland ecological health conditions (Zhou et al., 2014) but also provide evidence that managers and scientists can use to evaluate the success or failure of restoration in wetland ecosystems (X. Yang & Guo, 2014). This information could provide some clarity concerning whether the restored wetland has met certain goals such as nutrient supply, habitat type and biodiversity (Phinn et al., 1999; Zedler, 2000). Furthermore, comparisons between restored wetland and pristine wetland can provide insight changes into the conditions of the ecosystem invaded by *Phragmites* invasive species.

Wetland are often located in remote and sensitive areas and are difficult to survey due to delicate habitat conditions and thick dense vegetation (Buchanan et al., 2009; Javier Martínez-López et al., 2014; Mwita, 2016). On-site assessment in these ecosystems are laborious, time consuming and inefficient especially for large wetlands due to restricted mobility. Furthermore, the number of points measured in the field does not capture the information at the scale required for monitoring (E. Adam et al., 2010; Ashraf et al., 2010). Therefore, accurate estimation of *Phragmites* biomass in these ecosystems is restricted by the spatial and temporal frequency of data collection. Furthermore, the distribution of collected data might not adequately capture factors causing rapid invasion (Powell et al., 2010). In that regard, remote sensing offer a straightforward choice for estimating aboveground biomass of wetland invasive species under different wetland management systems in a short space time (Robinson et al., 2016; Somodi et al., 2012) and monitoring rehabilitated wetland ecosystem (Maguigan et al., 2016). Remote sensing techniques such as hyperspectral, Light detection radar (LIDAR), RapidEye and Worldview are widely used to estimate the aboveground biomass of wetland vegetation. For instance, Luo et al. (2015) successfully estimated wetland vegetation height and leaf are index using airborne laser scanning (ALS) data. Mutanga et al. (2012) also estimated wetland vegetation biomass successfully using Worldview-2 data. The author concluded that worldview- 2 can optimally estimate wetland vegetation biomass which was challenging with conventionally satellite sensors. E. Adam et al. (2014) successfully estimated papyrus biomass in wetlands using hyperspectral data. Although the data produced reliable biomass estimates due to high spatial and spectral resolution, this dataset are unlikey to support regular monitoring due to high acqusition cost. Furthermore, in nature conservation financial resources are often severely limited (Margules & Pressey, 2000), therefore cost effectiveness has to be taken into account probably more than in basic science (Naidoo & Ricketts, 2006). Therefore, the use of high spatial and spectral resolution cannot be afforded especially in resource scarce countries like South Africa. In spite of these financial constraints, the quantity of *Phragmites* biomass using remote sensing between natural and rehabilitated wetlands has not received much attention. Thus there is a need to test the potential of using freely and readily available remotely sensed data that could effectively quantify the variability of *Phragmites* aboveground biomass accurately.

The recent improvement of space borne multispectral remotely sensed data is a promising source of information for understanding wetland vegetation (Oumar & Mutanga, 2013). With the availability of Landsat 8 Operational Land Imager (OLI) and Sentinel 2 MSI data and their enhanced strategically positioned spectral bands (Roy et al., 2014), it becomes possible to monitor vegetation accurately at a varying spatial and temporal scales for specific wetland ecosystems. For instance, Sentinel 2 MSI with three bands in the red edge and two bands in the shortwave infrared (SWIR) are perceived to have the ability to estimate vegetation biomas and biochemical properties (Ramoelo et al., 2015b; Sibanda et al., 2015). Additionaly, the red edge spectral bands contained in Sentinel 2 MSI are reported to be highly sensitive to vegetation species characteristics (Rapinel et al., 2014) and improve the accuracy to estimate the biomass of individual plant species (Shoko & Mutanga, 2017). The three red edge bands offer an opportunity to estimate vegetation productivity across different wetland management areas. Ramoelo et al. (2015b) and Sibanda et al. (2015) successfuly highlighted the potential of Sentinel-2 red edge for grass nutrients and biomass studies. The Landsat 8 OLI was successfuly applied to estimate aboveground biomass of forest (Dube & Mutanga, 2015), soybeans and corn crops (Kross et al., 2015), floristic variation in grassland (Feilhauer et al., 2013) and quantifying shrub biomass in arid environments (Zandler et al., 2015). These studies revealed the potential of refined near infrared and SWIR coverage in Landsat 8 OLI for improving the assessment of vegetation parameters in a cost effective manner at regional scale. There is no specific recommendation on the suitability of specific sensors for invasive plant species especially in wetland environment (Feilhauer et al., 2013; Zandler et al., 2015). However, literature indicate that sensors with red edge spectral region such as Sentinel 2 MSI may be more effective than conventional sensors such as Landsat 8 OLI (Eisfelder et al., 2012; Li et al., 2012). So far, the spectral settings of these new generation medium sensors in quantifying *Phragmites* biomass has not yet been tested under differernt wetland management systems.

It is therefore our aim to compare the potential of existing spectral configuration from two different remotely sensed data for assessing variability of *Phragmites* biomass in different wetlands areas. The primary objective was to compare the utility of using multi-scale medium resolution Sentinel 2 MSI versus Landsat 8 OLI data in estimating the variability of *Phragmites* biomass between natural and rehabilitated wetlands. We further tested the full potential of both Sentinel 2 MSI and Landsat 8 OLI for *Phragmites* biomass estimation by comparing their performance with higher resolution multispectral RapidEye data. RapidEye image provides five spectral bands with red edge coverage and high spatial resolution of 5 m x

5 m. The multi-scale comparison was done to test the sensitivity of spectral bands contained within an individual sensor type for *Phragmites* biomass estimation.

3.2. Materials and Methods

3.2.1. Study area

The Rietvlei Nature Reserve (25º 41' 22" S and 26º 37' 48" E) is located in the east of the City of Tshwane Metropolitan Municipality, South Africa while Kaalplaas Spruit (25º 36' 43.87"S and 28º 05' 39.87" E) is located in the northern part of the metropolitan municipality. The Rietvlei Nature reserve was established because of Rietvlei Water Scheme providing drinking water to the local communities. The wetland was extensively drained due to peat mining activities. This degradation has led to rehabilitation process, which began in 2000 with the aim of preventing further loss (Oberholster et al., 2008; Venter et al., 2003). Hence, Rietvlei wetland was chosen as a reference site in order to assess the success of rehabilitation measures using vegetation parameters. The Kaalplaas Spruit was chosen as a control site to compare the difference in vegetation parameters with the reference site. Both Rietvlei and Kaalplaas Spruit are urban inland wetlands and threatened by variety anthropogenic activities such as construction and water pollution. These wetlands are currently invaded by variety of invasive species such as *Typha* and *Phragmites* including many others. Although both Rietvlei and Kaalplaas Spruit are dominated by *Phragmites*, the structural parameters were not the same. *Phragmites* in the Rietvlei wetland were mostly less than 2 m in height and very thin. On the other hand, Kaalplaas Spruit had very thick *Phragmites* of more than 2 m tall in most sampled plots. Furthermore, ragweed plant species was dominant in most sampled measured plots especially for Kaalplaas Spruit wetland. Figure 3.1 shows a map of the study area in the context of South Africa extracted from Landsat 8 OLI satellite image.

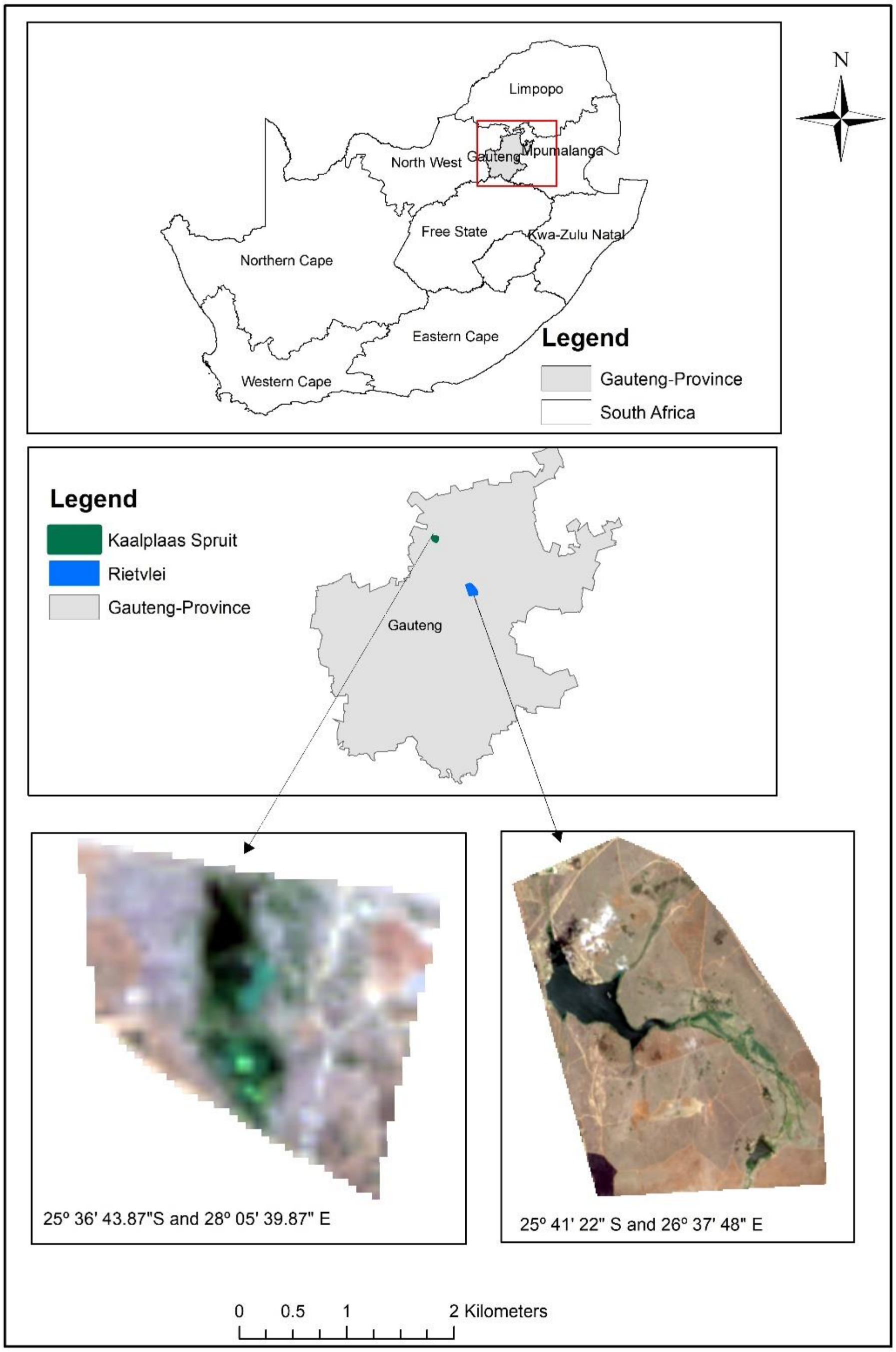


Figure 3.1. Location of the study area, including an insert of Landsat 8 OLI image.

3.2.2. In situ field measurements

Within natural and rehabilitated wetlands, *Phragmites* sampling measurements were conducted during a single growing season between November and December 2015. Across both wetlands, 99 vegetation plots, each with an area of 1 x 1 m were measured. The locality of the field plot was recorded using global positioning system (GPS-Garmin Montana 650). Measuring tape was used to generate 1 m x 1 m where Phragmites were taller and impossible to throw the quadrat. The plot location was used to extract the spectral reflectance from remote sensing images. At each sampling plot, the number of stems and percent cover of all measured plant species was recorded (0-100%). The green leaves and stem of *Phragmites* and other species identified within the boundaries of quadrat were harvested and placed in a labelled bag. The harvested materials were taken to laboratory on the same day for measurement using a digital weighing scale. The observed measurement was used to build the relationship between fresh biomass and spectral reflectance of corresponding satellite imagery for further analysis.

3.2.3. Image acquisition and pre-processing

Three different multispectral data were acquired to quantify the variability of *Phragmites* above ground biomass between natural and rehabilitated wetlands. The Landsat 8 OLI and Sentinel 2 MSI cover the study areas with one tile. RapidEye uses one tile for each study site. The images were acquired in the same period that corresponds with field measurement dates, 16 November to 16 December 2015. Both Landsat 8 OLI and Sentinel 2 MSI were obtained free from US Geological Survey website (http://landsat.usgs.gov/). The Landsat 8 OLI was downloaded as Level 1T and Sentinel 2 MSI as Level 1C products. The Level 1T and Level 1C means that the supplier applied radiometric and geometric correction. (USGS 2013; Sentinel MPS 2016). However, the Level 1C provides top of the atmosphere that is not included in Landsat 8 OLI. The Landsat 8 OLI captures images on the earth at 16-day temporal resolution. Compared to Landsat 7 ETM $^{+}$, Landsat OLI provides additional two new bands and advanced signal to noise radiometric performance, which gives an advantage for natural resource applications (El-Askary et al., 2014; Pahlevan & Schott, 2013). Sentinel- 2 with a spatial resolution ranging from 10 m to 60 m has revisit time of 5 days interval (Cole et al., 2014). Sentinel 2 MSI provides 13 spectral bands ranging from visible through red edge to the short wave infrared at different spatial resolution. Sentinel 2 MSI provides three unique red edge bands (5, 6, and 7) which are designed for vegetation studies. The visible bands (2, 3, 4 and 8) of Sentinel 2 MSI are closely matched with bands 2, 3, 4, and 5 of Landsat 8 OLI. These similarities present the opportunity to use both images as complementary instrument with promising characteristics for remote sensing of vegetation. The Level 3A orthorectified RapidEye provides five spectral bands including a single red edge coverage with a daily temporal resolution. The 3A products were delivered with radiometric and geometric correction on the data.

Detailed information on spectral bands of both Landsat 8 OLI, Sentinel-2 and RapidEye is present in Table 1. Atmospheric correction was implemented in ENVI 5.1 software using Fast Line-of Sight Atmospheric analysis of Spectral Hyperculus (FLAASH) module after both scenes were converted to surface reflectance for Landsat 8 OLI and RapidEye. For Sentinel 2 MSI, QGIS software 2.18 was used for atmospheric correction and layer stacking. Next, the bands that were reported not useful for vegetation (Féret et al., 2015; Immitzer et al., 2016) were removed during layer stacking. For instance, when stacking Landsat 8 OLI, band 1 (ultra blue), band 10 (panchromatic band), and thermal infrared were removed. From Sentinel 2 MSI, band 1(aerosol detection), band 9 (water vapour), and 10 (SWIR-cirrus) were also removed. For RapidEye, all bands were considered for analysis. All the remaining bands were stacked together and imported into ESRI ArcGIS 10.3 for further analysis.

Table 3.1. Spectral and spatial resolution of Sentinel 2 MSI and Landsat 8 OLI.

Sentinel 2 MSI				Landsat 8 OLI		
Bands	Name	Bands (nm)	Resolution	Name	Range	Resolution
B1	Coastal aerosol	443	60	Coastal Blue	0.43-0.45	30
B2	Blue	490	10	Blue	0.45-0.51	30
B3	Green	560	10	Green	0.53-0.59	30
B4	Red	665	10	Red	0.63-0.67	30
B5	Red edge	705	20	NIR	0.85-0.88	30
B6	Red edge	740	20	SWIR1	1.57-1.65	30
B7	Red edge	783	20	SWIR2	2.11-2.29	30
B8	NIR	842	10	Pachromatic	0.50-0.68	15
B8a	Red edge	865	20			
B9	Water vapour	945	60	Cirrus	1.36-1.38	100
B10	SWIR-Cirrus	1375	60	TIRS1	10.6-11.19	100
B11	SWIR	1375	20	TIRS2	11.5-12.51	
B12	SWIR	2190	20			

3.2.4. Variables for assessing Phragmites aboveground biomass variability

To compare the potential of Landsat OLI and Sentinel MSI in assessing variability of *Phragmites* biomass against RapidEye data, we used spectral reflectance bands and vegetation indices. Table 3.2 shows the specific spectral bands and vegetation indices selected for biomass estimation. The spectral reflectance values from Landsat 8 OLI, Sentinel 2 MSI and RapidEye were extracted corresponding to each field biomass plot based on the exact plot location using ESRI ArcGIS 10.3. The value of each spectral reflectance band was used to calculate the vegetation indices. Among dozens of available vegetation indices, the study selected vegetation indices that are commonly used in remote sensing for ecological applications (Yan et al., 2015; Zengeya et al., 2013) and were previously used studying *Phragmites* (Ailstock et al., 2001; Luo et al., 2017). All selected indices were computed using any two possible combination bands from all corresponding satellite images. In total, 13 spectral data derived from Landsat 8 OLI, 26 Sentinel 2 MSI, and 10 from RapidEye were used as predictor variables for assessing the variability of *Phragmites* aboveground biomass in between the natural and rehabilitated wetland wetlands. For each satellite image, we evaluated the relationship between actual measured biomass with spectral reflectance band values and computed vegetation indices. These data was analyzed using Partial Least Square regression (PLSR) described in section 2.5 in details. Again, all observed data were used as a single calibrated dataset in the model.

3.2.5. Regression Algorithm

The variability of *Phragmites* between natural and rehabilitated wetlands was evaluated based on PLSR analysis between fields measured biomass and remotely sensed derived variables. The PLSR is an advanced multispectral analysis technique for selecting optimal spectral features when estimating the biochemical and biophysical parameters in wetland areas (Carrascal et al., 2009; Hansen & Schjoerring, 2003). PLSR is a technique that reduces the number of multicollinear spectral variables to few independent variables that increases correlation among predictors and single response variable (Atzberger et al., 2003; Hansen & Schjoerring, 2003). This technique is gaining recognition in the field of remote sensing and vegetation applications for predicting biophysical and biochemical parameters (Adjorlolo et al., 2015; Liu & Rayens, 2007). Instead of selecting all image predictor variables (bands and vegetation indices), PLSR pre-select the most relevant variable from all available full set of spectra data that is suitable for estimating the item of interest (Byrd et al., 2014; Liu & Rayens, 2007). The advantage of PLSR algorithm is that it can deal with small number of samples. This advantage provides an opportunity to compare few multispectral satellite data using small samples to assess their potential for estimating the aboveground biomass of *Phragmites* between natural and rehabilitated wetlands. At each selection process (spectral bands and vegetation indices), the leave-one out cross validation (LOOCV) was performed by removing a single field measured plot points until each point was withheld once. For LOOCV, one sample is withheld and the remaining samples are used to train the model. For example, if the model is trained with 99 samples, each sample will be estimated by the remaining 98 samples to determine the performance of the model for biomass estimation (Ramoelo & Cho, 2014). The coefficient of determination (R^2) and root mean square error (RMSE) were used to evaluate the strength and significance of the relationship between actual measured *Phragmites* biomass and the data derived from corresponding satellite images. The contribution of each raw bands and vegetation indices to the selected component was evaluated using loading factors derived from PLSR model. All regression models were implemented in R statistical environment version 3.31 (Core) using PLS library package (Mevik & Wehrens, 2007). The process followed for computing *Phragmites* biomass in both wetlands with varying multispectral satellite images is discussed in section 2.6.

3.2.6. Experiments

Partial Least Square Regression (PLSR) was used to compare the strength of Sentinel 2 MSI and Landsat 8 OLI relative to RapidEye in estimating the variability of *Phragmites* aboveground biomass between natural and rehabilitated wetlands. Four set of data analysis (analysis I-IV) based on different data type combinations were (Table 3.2) implemented in PLSR algorithm. For each satellite image, the number of predictors varied, depending on the sensor's spectral bands coverage and derived vegetation indices. The analysis was conducted following as follows:

i. The first set of analysis was conducted based on image spectral bands only (Landsat 8 OLI: 6 variables; Sentinel 2 MSI: 10 variables; RapidEye: 5 variables). All these variables were plotted against field measured biomass separately, to identify the most relevant band that could estimate *Phragmites* biomass in both wetlands. The predictor variable that resulted in the first minimum root mean square error (RMSE) in all corresponding images was selected as the best biomass predictor in both wetlands.
ii. The second set of analysis was based on computed vegetation indices only, where Landsat 8 OLI used 07 variables, Sentinel 2 MSI (12 variables) and RapidEye (10 variables). All predictors were also plotted against field measured biomass using PLSR algorithm individually, to select the vegetation index that could best quantify *Phragmites* biomass in both wetlands. The index that resulted in the lowest RMSE was selected as the relevant predictor for *Phragmites* biomass quantification based on the same procedure explained in the first set of analysis.
iii. The third set of analysis was conducted based on the combination of both spectral reflectance bands and computed indices used in analysis I and II. The combined datasets was plotted against field-measured biomass to select the most relevant variable between bands and indices that could quantify *Phragmites* biomass in both wetlands following the same procedure conducted in the first set of analysis.

Table 3.2. Predictor variables used in assessing *Phragmites* biomass between natural and rehabilitated wetlands.

Variables	Sensor Type	Details	Analysis Stage
Spectral bands	Landsat 8 OLI	blue, green, red, near-infrared, SWIR I & II	I
	Sentinel 2 MSI	blue, green, red, red edge (5,6,7,8,8a) and SWIRI & II	
	RapidEye	5 bands (blue, green, red, red edge & near-infrared)	
Vegetation Indices	Landsat 8 OLI	NDVI, SR, NDWI	II
	Sentinel 2 MSI	NDVI, SR, NDWI	
	RapidEye	NDVI, SR,NDWI	
Spectral bands and Indices	Landsat 8 OLI	(6 bands) + (7 Indices)	III
	Sentinel 2 MSI	(10 bands + (13 indices)	
	RapidEye	(5 bands + (5 indices)	

*NDVI: Normalized Difference Vegetation Index, SR: Simple Ration, NDWI: Normalized Difference Water Index. The selected vegetation indices were previously used *Phragmites* studies (Ailstock et al., 2001; Lantz & Wang, 2013; Luo et al., 2017)

3.3. Results

3.3.1. Measured Phragmites aboveground biomass descriptive statistics (g/m²)

Ninety-nine sampling plots were measured across the natural and rehabilitated wetlands. High aboveground biomass was observed from natural wetlands with an average of 4215 g/m². After the outliers were omitted, the average biomass was 1915 g/m² for natural wetland and 1423.1 g/m² for rehabilitated wetland. It can be observed from Figure 3.2 (i), that the biomass box plots vary between the two wetlands. The spectral reflectance of red edge from Sentinel 2 MSI and RapidEye between the two wetlands are presented in Figure 3.2 (i) and (ii).

3.3.2. Comparison of spectral reflectance bands from Sentinel 2 MSI and Landsat 8 OLI bands relative to RapidEye bands in estimating Phragmites aboveground biomass

The results on all analysis (I-III) for *Phragmites* biomass quantification in terms of the coefficient of determination (R^2), root mean square error (RMSE) and the number of optimal components considered in each model are shown in Table 3.3-3.5. Based on spectral reflectance bands, the results indicated that site-specific models were weaker for Landsat 8 OLI and RapidEye in comparison to Sentinel 2 MSI data (Table 3.3). For example, when using Sentinel 2 MSI the natural wetland produced an R^2 value of 0.68 with the lowest RMSE of 886.6 g/m². On the other hand, the spectral reflectance of Landsat 8 OLI and RapidEye produced lower results ($R^2 = 0.34$, RMSE = 983.3 g/m²; $R^2 = 0.41$, RMSE = 966.1 g/m²) for natural wetland respectively. The Landsat 8 OLI and Sentinel 2 MSI showed good predictive power in estimating rehabilitated biomass. The model increased accuracy for all corresponding satellite images with pooled dataset. Sentinel 2 MSI estimated *Phragmites* biomass better than RapidEye bands producing R^2 0.79 and RMSE of 323.6 g/m ². Comparatively, the Landsat 8 OLI produced somewhat similar results as Sentinel 2 MSI ($R^2 = 0.71$; RMSE = 469 g/m²). It can be observed that RapidEye spectral bands was the least performer for predicting *Phragmites* biomass.

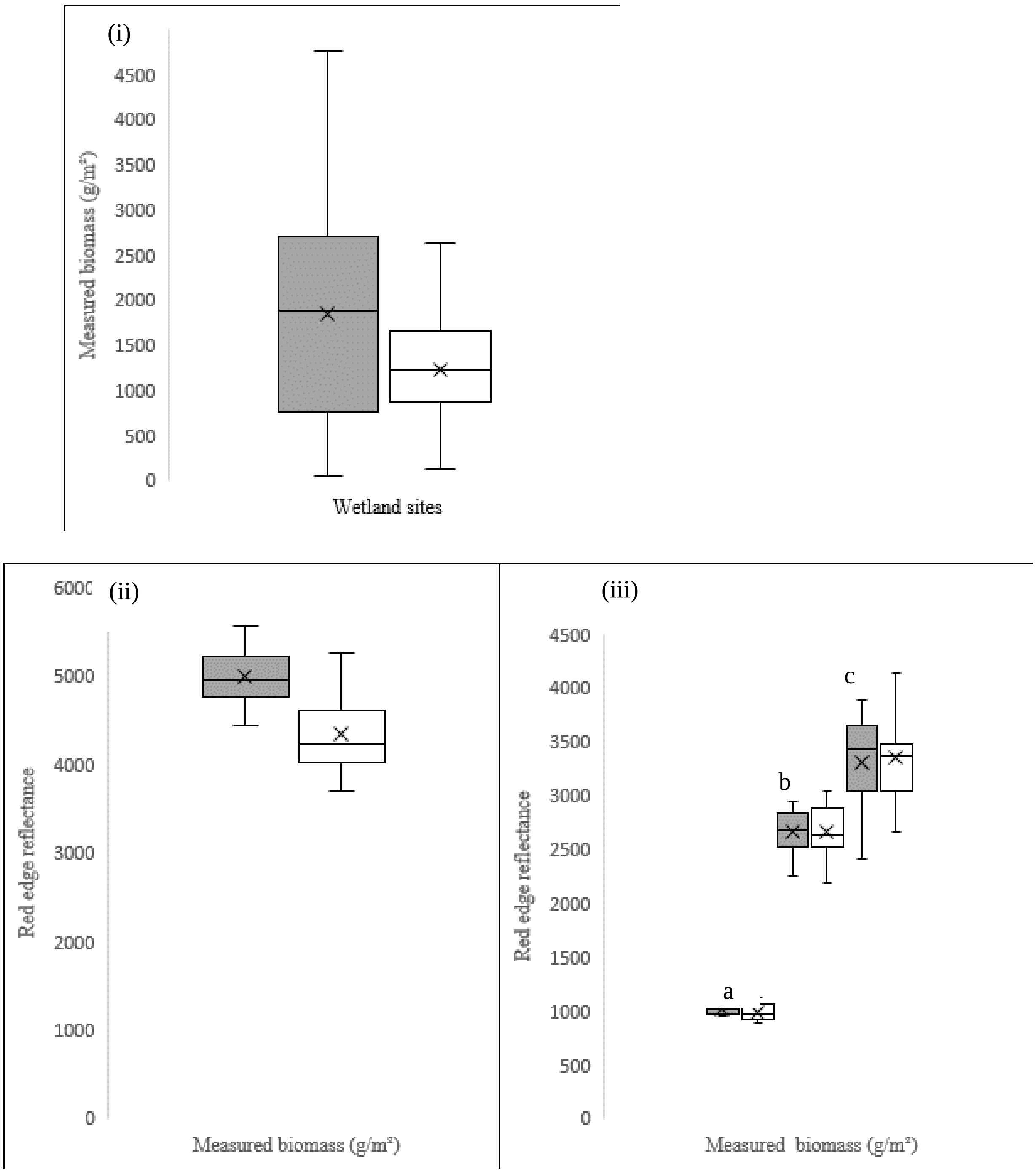


Figure 3.2. Box plots of *Phragmites* aboveground biomass. In box (i) is the actual measured aboveground biomass, box (ii) red-edge reflectance from RapidEye and box (iii) Sentinel-2 MSI red edge reflectance. In box (iii), (a) is Band 5, (b) Band 6, and (c) Band 7 respectively.

Table 3.3. *Phragmites* biomass estimation from Landsat 8 OLI, Sentinel 2 MSI and RapidEye using spectral reflectance bands.

	Natural Wetland			Rehabilitated Wetland		
	Components	R^2	RMSE	Component	R^2	RMSE
Sentinel 2 MSI	5	0.68	888.6	2	0.65	891.2
RapidEye	1	0.41	966.1	1	0.27	1013
Landsat 8 OLI	2	0.34	966.1	2	0.54	814.4
Pooled dataset	Components	R^2	RMSE			
Sentinel 2 MSI	5	0.79	323.6			
Landsat 8 OLI	2	0.71	469			
RapidEye	1	0.66	48.8			

*Number of components selected using spectral reflectance bands from corresponding sensor types

3.3.3. Comparison of Sentinel 2 MSI and Landsat 8 OLI derived vegetation indices in estimating Phragmites biomass relative to RapidEye derived vegetation indices

The results in Table 3.4 illustrate the accuracy achieved from analysis II in quantifying *Phragmites* biomass using Landsat 8 OLI, Sentinel 2 MSI and RapidEye derived vegetation indices. It can be noted that the best biomass estimates obtained for analysis II were those from Sentinel 2 MSI relative to Landsat 8 OLI. However, Sentinel 2 MSI derived vegetation indices did not quantify *Phragmites* biomass with high accuracy compared with extracted spectral bands. The highest R^2 achieved came from natural biomass (R^2 = 0.55; RMSE = 863.5 g/m²). The Landsat 8 and RapidEye produced weaker results for both natural and rehabilitated biomass. However, both datasets showed improvements for estimating rehabilitated wetland (see Table 3.4.). Although there was little improvement from both datasets, the Landsat 8 OLI performed better that RapidEye in both wetlands while the Sentinel 2 MSI performed better than Landsat 8 OLI in estimating rehabilitated biomass using vegetation indices. When both sites were pooled together, the vegetation indices derived from RapidEye estimated *Phragmites* biomass better (R^2=0.75; RMSE=413 g/m²). Sentinel 2 MSI and Landsat 8 OLI did not improve biomass prediction in comparison to spectral bands. However, Sentinel 2 MSI predicted *Phragmites* biomass better with an R^2 of 0.66 and RMSE of 605 g/m² compared to Landsat 8 OLI with an R^2 of 0.49 and RMSE of 635.5 g/m² respectively. The results indicate that the vegetation indices computed from finer spectral satellite images with red edge coverage has the potential to achieve high biomass estimation accuracy. Notably, the accuracy achieved from Landsat 8 OLI and Sentinel 2 MSI decreased when the number of predictor variables increased.

Table 3.4. *Phragmites* biomass estimation from Landsat 8 OLI, Sentinel 2 MSI and RapidEye derived vegetation indices.

	Natural Wetland			Rehabilitated Wetland		
	Component	R^2	RMSE	Component	R^2	RMSE
Sentinel 2 MSI	2	0.55	863.5	3	0.52	803.5
Landsat 8 OLI	2	0.19	998.2	4	0.43	859.9
RapidEye	4	0.16	944.8	2	0.37	1013

Pooled dataset	Component	R^2	RMSE
RapidEye	3	0.75	413
Sentinel 2 MSI	3	0.66	605
Landsat 8 OLI	3	0.49	635.5

*Number of components selected using spectral reflectance bands from corresponding sensor types

3.3.4. Comparison of Phragmites biomass estimation from Sentinel 2 MSI and Landsat 8 OLI spectral bands and derived vegetation indices relative to RapidEye combined spectral data

The results in Table 3.5 show the number of predictor variables selected, R^2 and RMSE obtained from combined spectral bands and derived vegetation indices in estimating *Phragmites* biomass using Landsat 8 OLI, Sentinel 2 MSI and RapidEye data. Firstly, it can be noted that no multispectral datasets produced consistence results for site-specific models through all sets of analysis compared to pooled dataset (see Table 3.3-3.5). Furthermore, combination of bands and indices produced weaker results for rehabilitated wetlands. It can be observed that RapidEye performed slightly higher (R^2 = 0.56; RMSE = 778.9 g/m²) than Sentinel 2 MSI data (R^2 = 0.53; RMSE = 990.0 g/m²) in estimating natural biomass. The same consistency can be observed when both sites were pooled together, combination of spectral and indices derived from RapidEye yielded better results (R^2 = 0.71; RMSE = 440.8g/m²) than Sentinel 2 MSI (R^2 = 0.62; RMSE = 683.1 g/m²). Landsat 8 OLI produced poor results for site-specific model and pooled dataset models using combination of both bands and indices. The findings showed that medium spectra resolution Sentinel 2 MSI with red edge could compete with high spectral resolution RapidEye data. It is worth noting that although Sentinel 2 MSI performed better than Landsat 8 OLI, the R^2 decreased with the number of predictor variables increases. The same performance can be observed with Landsat 8 OLI. The results indicate that the bands contained in Sentinel 2 MSI and Landsat 8 OLI have more predictive power individually compared to when combined (e.g. vegetation indices). Figure 3.3 show the scatter plots between measured and predicted *Phragmites* biomass obtained using pooled datasets. Overall, the results indicates that *Phragmite*s biomass estimation based on site-specific models were weaker than pooled datasets. The effort to estimate *Phragmites* biomass at site level indicate that it is possible to predict biomass using Sentinel 2 MSI compared than RapidEye and Landsat 8 OLI datasets.

Table 3.5. *Phragmites* biomass estimates using combined spectral reflectance bands and derived vegetation indices from Landsat 8 OLI, Sentinel 2 MSI and RapidEye

	Natural Wetland			Rehabilitated wetland		
	Component	R^2	RMSE	Component	R^2	RMSE
RapidEye	7	0.56	778.9	1	0.22	1054
Sentinel 2 MSI	3	0.53	871.2	3	0.41	88.7
Landsat 8 OLI	11	0.33	900.5	2	0.31	853

Pooled dataset	Components	R^2	RMSE
RapidEye	2	0.71	440.8
Sentinel 2 MSI	4	0.62	683.1
Landsat 8 OLI	2	0.5	734.3

*Number of components selected using spectral reflectance bands from corresponding sensor types

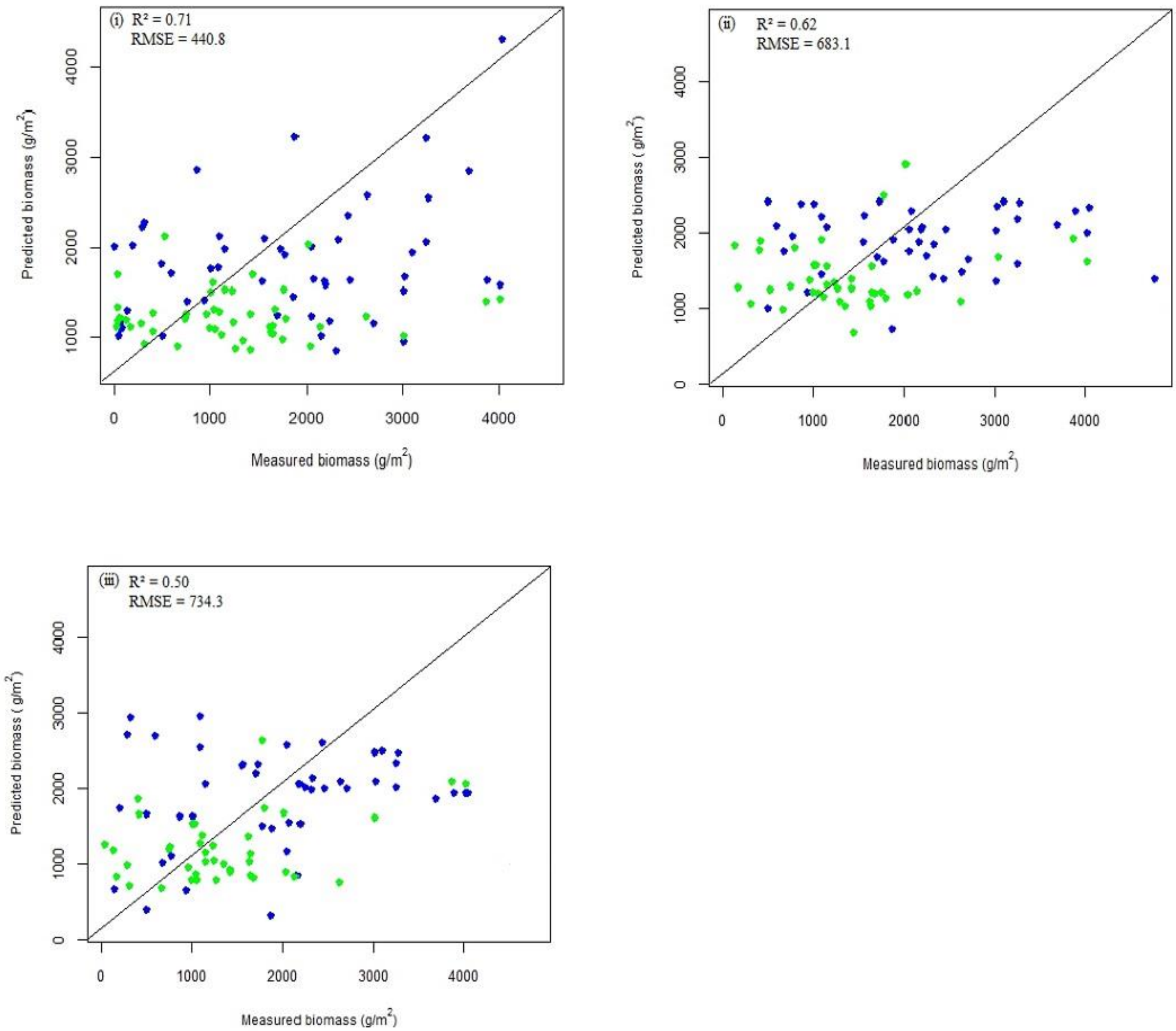


Figure 3.3. One to one relationship between measured and predicted *Phragmites* biomass using a combination of the spectral bands and vegetation indices derived from (i) RapidEye, (ii) Sentinel 2 MSI, and (iii) Landsat 8 OLI. The blue dots represent natural and green represent rehabilitated wetlands respectively. The model was fitted with all observed measurements.

3.3.6. Loading values of each band and index towards the contribution of Phragmites biomass from all satellite images

The contribution of each bands and vegetation indices towards the selected number of component in assessing *Phragmites* biomass is shown in Figure 3.5. The findings shows that when using spectral bands Sentinel 2 MSI used five predictor variables out of ten for estimating *Phragmites* biomass. The highest loadings were found in the visible blue, green band and near infrared region of the spectrum. For Landsat 8 OLI, bands with the highest loadings in component two in descending order were those in the blue, green and near infrared region. Only one component was selected for biomass estimation between the wetlands when using RapidEye spectral reflectance bands. All RapidEye bands showed high positive loadings with blue bands having the strongest followed by green and red-edge bands. It can be observed that the spectral bands from all corresponding sensors reflect similar pattern. All satellite images retained three components when using vegetation indices. The red edge indices from RapidEye and Sentinel 2 MSI showed high loadings value. While NDWI and SR were the heaviest loadings from Landsat 8 OLI data. The performance of each bands and indices demonstrate the sensitivity of red edge coverage in satellite sensors. For both of the datasets, the blue band and near infrared have high positive loadings values.

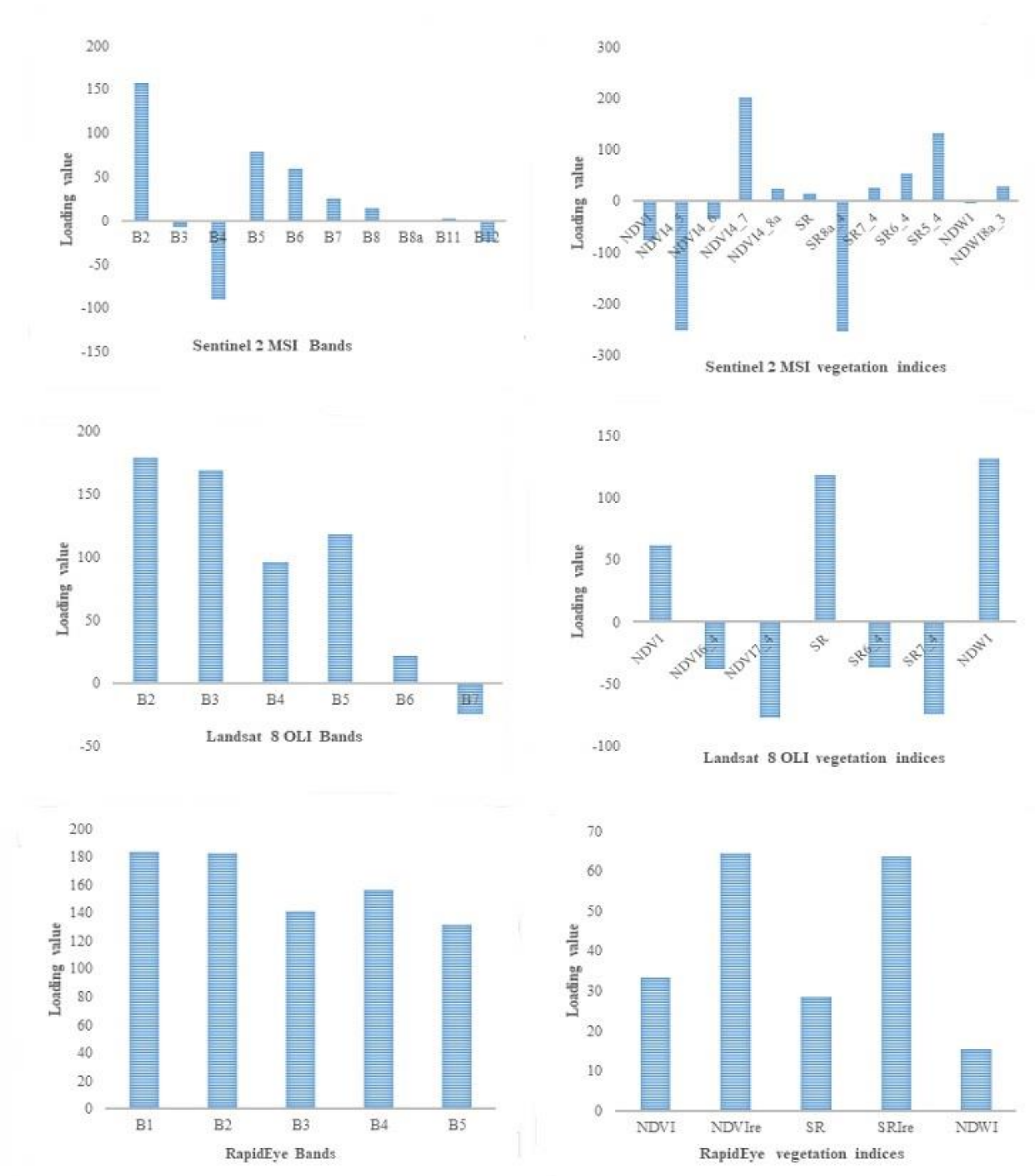


Figure 3.4. Loading values of each band and vegetation indices toward the contribution of *Phragmites* biomass estimation derived from Sentinel 2 MSI, Landsat 8 OLI and RapidEye datasets.

3.4. Discussion

The primary objective of this study was to explore the feasibility of medium multispectral Sentinel 2 MSI with red edge bands in quantifying the variability of *Phragmites* compared to the use of Landsat 8 OLI with refined near infrared in the City of Tshwane Metropolitan Municipality. Comparison of multi-scale approach is important for biomass quantification where high spectral resolution satellite sensors can be used to validate the accuracy obtained from moderate resolution sensors (Ramoelo and Cho (2014). The results obtained from both Sentinel 2 MSI and Landsat 8 OLI were compared to high spatial commercial RapidEye sensor to further understand the productivity of *Phragmites* growing between the natural and rehabilitated wetlands. The abovementioned satellite sensors were investigated since there is no sensor that is suitable to overcome all challenges associated with wetland vegetation. To achieve our objective, we examined different spectral features using Partial Least Square Regression (PLSR), to find the best estimation method that could quantify *Phragmites* aboveground biomass between both wetlands.

The present study has shown that Sentinel 2 MSI data yielded the best accuracy in predicting the variability of *Phragmites* biomass between natural and rehabilitated wetlands compared to Landsat 8 OLI and RapidEye data. For instance, when the spectral reflectance bands were tested for quantifying *Phragmites* biomass, Sentinel 2 MSI performed strongly for both natural and rehabilitated wetlands outperforming Landsat 8 OLI and RapidEye spectral bands. Similar results were also observed when the dataset was pooled together (Table 3.3). Of notable interest is that in the case of Sentinel 2 MSI, the green band (B3) and red edge (B6) band were selected as the best variables for quantifying green aboveground biomass for both wetlands. These bands were more influential towards Sentinel 2 MSI achieving better accuracy than its counterpart Landsat 8 OLI does. It is well documented that red edge band is the inflection point in vegetation spectra between low reflectance in the visible region and low absorbance in the near infrared (Curran et al., 1990; Frampton et al., 2013). The reflectance in this inflection point as well as green band region is well related to chlorophyll content (Kumar et al., 2002) and consequently to fresh aboveground biomass. Although the accuracy achieved from Landsat 8 OLI and RapidEye are inconclusive, both satellite images relied on blue bands for estimation aboveground biomass in both wetlands. Other studies demonstrated the potential of blue bands in estimating grass aboveground biomass in high canopy cover using hyperspectral data (J. Chen et al., 2009). These sensor variation performances can be explained by the difference in the bandwidth (Sibanda et al., 2015). Compared with other previous studies on vegetation, the study underscores the potential of RapidEye and Landsat 8 OLI in estimating biomass. The current study demonstrates that red edge coverage in Sentinel 2 MSI provide an advantage over preferred Landsat 8 OLI for biomass estimation, a component that was previously limited to broadband sensors.

Similar results were observed when vegetation indices were tested for quantifying the variability of *Phragmites* aboveground biomass between natural and rehabilitated wetlands. The indices did not significantly improve the biomass accuracy in both wetlands compared to other wetland vegetation studies using multispectral data. For example, (J. Chen et al., 2009) indicated that the best model for grass biomass estimation was achieved using original bands than vegetation indices. Shoko and Mutanga (2017), indicated that indices did not significantly improve classification accuracy for detecting and discriminating seasonal grass species using different multispectral sensors. Although Sentinel 2 MSI outperformed both Landsat 8 OLI and RapidEye, vegetation indices produced low R^2 value 0.55 (the highest achieved in both wetlands) compared to spectral reflectance bands ($R^2 = 0.68$) model. Surprisingly, the vegetation indices derived from Landsat 8 OLI slightly exhibited RapidEye indices in both wetlands for quantifying the variability of *Phragmites* aboveground biomass. The highest accuracy achieved was at least 0.43 derived from rehabilitated biomass. In this regard, variability of *Phragmites* biomass between natural and rehabilitated wetlands could be quantified using freely available medium multispectral sensor. Interestingly, the results indicate that indices computed from red edge indices were the most influential towards the quantification of aboveground biomass in both wetlands. Specifically, when using Sentinel 2 MSI the NDVI.re was the most influential toward biomass estimation. For Landsat, both SR and NDVI computed using SWIR1were the most useful indices toward *Phragmites* biomass quantification at the site-level. In previously published literature, it was reported that inclusion of red edge bands in vegetation indices improve fresh aboveground biomass, reduce background effects and saturation challenges (Mutanga & Adam, 2011; Ramoelo et al., 2015c) especially in wetland ecosystem where spectral reflectance of plants are similar during growing season. Ramoelo and Cho (2014), reported the potential of SWIR for estimating grass aboveground biomass during dry season. While Feilhauer et al. (2013) indicated its utility for assessing floristic variability in different seasons. RapidEye, with red edge coverage did not show any improvement over Sentinel 2 MSI and Landsat 8 OLI data for site-specific models. However, when the data was pooled together (both wetlands) vegetation indices derived from RapidEye exhibited Sentinel 2 MSI vegetation indices in terms of the prediction accuracy achieved. The findings of this study are comparable to the findings of Zandler et al. (2015) and Feilhauer et al. (2013) who reported that sensors with both visible near infrared and SWIR were consistently showing high accuracy compared to RapidEye, IKONOS and Quickbird that are limited to visible near infrared only.

When the spectral reflectance bands and vegetation indices pooled together, Sentinel 2 MSI and RapidEye produced better accuracy and comparable results for quantifying *Phragmites* aboveground biomass of natural wetland. However, high accuracy was obtained from RapidEye with an R^2 value of 0.56 compared to Sentinel 2 MSI with 0.53. This proves that Sentinel 2 MSI can compete with finer spectral resolution in terms of accuracy produced. The Landsat 8 OLI was the least predictor of natural *Phragmites* biomass. Similar pattern can be observed when both sites were pooled together. The variability of prediction accuracy between Sentinel 2 MSI and RapidEye is slightly different. Although RapidEye provides finer spectral resolution that is compatible for local scales, at regional level may require more scene coverage that could be hindered by high cost acquisition. In that regard, Sentinel 2 MSI could be used as an alternative to RapidEye and Landsat 8 OLI for *Phragmites* biomass estimation and frequent monitoring at local and regional scale.

The main challenge with our study was comparing the results with other published studies who explored the potential of newly produced medium multispectral Sentinel 2 MSI against Landsat 8 OLI data. The challenges are based on the type of vegetation and area under investigation, the difference with how sampling measurement was conducted, the regression method applied and the procedure followed when selecting variables that could best estimate aboveground biomass makes it difficult. For example, Sibanda et al. (2016) compared the spectral bands of Sentinel 2 MSI with that of Hyperspectral infrared imager (HyspIRI) for estimating grass aboveground biomass under different management. The Sentinel 2 MSI outperformed HyspIRI when estimating burning, mowing and fertilized grass biomass. The work by Glenn et al. (2016) compared Landsat 8 OLI with Landsat TM and Lidar for shrub aboveground biomass. The author indicated that Lidar outperformed Landsat OLI while Landsat 8 OLI and Landsat TM produced similarly good results. Korhonen et al. (2017), investigated the use of Sentinel 2 MSI and Landsat 8 OLI in estimating boreal forest canopy cover and leaf area index. Their finding indicate that Sentinel 2 MSI outperformed Landsat 8 OLI when using all spectral bands coverage. However, when using the bands that are available in both Sentinel 2 MSI and Landsat, the results did not differ from one another. The similarity of the present study with the abovementioned findings is the success of Sentinel 2 MSI applied in different site conditions against other sensors. The findings implies that indeed Sentinel 2 MSI is a promising tool for biomass estimation in a cost effective manner due to its red edge coverage. Several studies have reported the potential of Sentinel 2 MSI red edge for vegetation monitoring (Aria et al., 2012; Ramoelo et al., 2015b; Sibanda et al., 2016). The results obtained from site-specific models using Landsat 8 OLI and RapidEye data are difficult to make general conclusion. Hypothetically, the results suggest two reasons for their performance. One is that if Landsat 8 OLI had red-edge coverage region will outperform RapidEye data. On the other hand, if RapidEye had SWIR wavelength coverage may have outperformed Landsat 8 OLI data and produce high or same accuracy as Sentinel 2 MSI data. However, considering the spectral resolution of both satellite images and the scale of study the areas, it can be assumed that variability of

Phragmites biomass between natural and rehabilitated wetlands can be achieved with high accuracy using commercial RapidEye data (see Figure 3.5).

3.5. Conclusion

This study concludes that Sentinel MSI data:

- Provides increased performance in quantifying *Phragmites* biomass in wetland ecosystem compared to its counterpart Landsat 8 OLI and RapidEye data.
- Offer more spectral bands in the visible near infrared which provide an advantage over Landsat 8 OLI and RapidEye data. Among all the red edge bands, B6 showed to be more influential in assessing *Phragmites* biomass in both wetlands.

In terms of overall performance, the study demonstrated that Sentinel 2 MSI offer a cheap and useful data source that is required for accurate biomass estimation, which was proved a challenge using broadband multispectral sensors, especially in resource scare environments. This great performance of Sentinel 2 MSI is due to its red edge and SWIR spectral coverage with enhanced spatial resolution characteristics compared to its counterpart Landsat 8 OLI data. RapidEye with finer red edge band poorly estimated *Phragmites* biomass at site-specific level compared to pooled dataset. To the best of my knowledge, this is the first study to examine compare the potential of Sentinel 2 MSI and Landsat 8 OLI in assessing the variability of water borne invasive *Phragmites* biomass estimation.

CHAPTER FOUR

Research synthesis

4.1. Introduction

Estimation of invasive wetland vegetation biomass at species level using multispectral remote sensing is challenging. This is because different plant invasive species have similar spectral reflectance during growing season among different types of wetland (Ozesmi & Bauer, 2002). Furthermore, conventional multispectral sensors saturate when estimating high-density biomass (E. M. Adam & Mutanga, 2012b; Mutanga et al., 2012). Therefore, accurate and estimation of existing *Phragmites* aboveground biomass require tools that will provide real-time information and improve the ability to detect changes in both natural and rehabilitated wetlands at fine spatial scale in order to aid in decision making. High spatial resolution that have appropriate spectral characteristics can overcome problems associate with saturation and spectral confusion (E. M. Adam & Mutanga, 2012b; Ashraf et al., 2010). The most promising one seems to be RapidEye data, which potentially provides a tool for better *Phragmites* biomass estimation due to its red edge channel and pixel size of 5 m that is not present in conventional multispectral satellite sensors (Ramoelo et al., 2012; Shang et al., 2015). However, the high cost associated with acquiring RapidEye data may hinder its utilization in resource scare countries. High spatial resolution sensors have the potential for providing large-scale biomass estimation independently and moderate resolution imagery could serve as a complementary for the development of vegetation monitoring (Dragozi et al., 2016; Ramoelo & Cho, 2014). In that regard, newly launched Sentinel 2 MSI and Landsat 8 OLI maybe reliable earth observation data for quantifying the aboveground biomass of *Phragmites* in wetland ecosystem. Nevertheless, previous literature reported that a novel feature in the Sentinel 2 MSI is red edge spectral bands coverage that are comparable to RapidEye commercial sensor (Ramoelo et al., 2015c). Because of these unique well-designed bands, it is expected that Sentinel 2 MSI would improve biomass accuracy to the level of commercial RapidEye data (Frampton et al., 2013; Houborg et al., 2015). For instance, Ramoelo and Cho (2014) compared the potential of using RapidEye against Landsat 8 OLI data in estimating dry biomass of rangeland quantity. The author reported a marginal difference accuracy achieved. This marginal difference in sensor performance could have been as results of refined near infrared in Landsat 8 OLI and red-edge band coverage in RapidEye. On the other hand, Feilhauer et al. (2013) reported that Sentinel 2 MSI and Landsat 8 OLI outperformed RapidEye for assessing the variability of floristic. The author indicated that the low accuracy from RapidEye is due to its limitation to visible and near infrared coverage only. Although the results from other studies brought promising results, there is a need to fill an existing gap in understanding the performance of these satellite sensors in estimating *Phragmites* biomass in wetland ecosystem. Hence, chapter two of the study investigated the utility of high spatial resolution RapidEye with red edge coverage in quantifying the variability of *Phragmites* biomass between natural and rehabilitated wetlands. Then, we further tested medium satellite sensors Sentinel 2 MSI and Landsat 8 OLI to evaluate their strength against RapidEye in chapter three. This was done to compare which satellite image can estimate *Phragmites* biomass better irrespective of spectral and spatial coverage. These two objectives were to answer the following questions (i) how well high spectral resolution RapidEye can quantify *Phragmites* aboveground biomass? (ii) can newly launched Sentinel 2 MSI and Landsat with improved spectral coverage biomass estimation better than finer spatial resolution RapidEye data?.

4.2. Assessing the variability of *Phragmites* aboveground biomass using RapidEye data

The inclusion of red edge bands in broadband multispectral sensors is recognized as a tool for improving aboveground biomass estimation. In this study, the utility of red-edge band of RapidEye sensor was investigated for estimating aboveground biomass of *Phragmites* between natural and rehabilitated wetlands. Specifically, the study examined different variable predictors (bands, vegetation indices and combined dataset) that could quantify *Phragmites* biomass with high accuracy. The findings have shown that assessment of *Phragmites* biomass using RapidEye predictor variables at site-specific did not consistently generate high accuracy in both wetlands. For rehabilitated wetland, the indices resulted in moderate improvement accuracy for biomass estimation. The best performance achieved resulted from natural biomass using combined datasets. The results are consistence with the findings of Löw and Duveiller (2014) who reported that identification of crops using RapidEye is dependent on the landscape and pixel size is " not size fits all' and that led to inconstancies of accuracy achieved. Krofcheck et al. (2014) achieved slightly less accuracy when detecting mortality structural and functional changes in a pinon-juniper woodland using RapidEye during wet conditions. The results reported by Wallner et al. (2014) were slightly higher in comparison to the study findings for estimating forest structural parameters. The findings in this chapter proved that assessing the biomass of invasive water plant species under different conditions with commercial RapidEye data does not guarantee high accuracy. However, acceptable results can be achieved. The findings obtained are suitable for natural biomass proved to be specific to a given wetland management and for each plant species they differ across different wetland management. Literature reported that smaller pixel size does not always increase the accuracy of vegetation assessment especially when the distribution of individual species is constitutes a mixture of other plants (Nagendra, 2001; Duccio Rocchini et al., 2010). With these unclear results obtained from broadband RapidEye sensors with red edge band, it is important to evaluate the potential of downscaling sensors to cheap techniques. The findings of this chapter suggest that we further investigate other earth observation techniques in order to test which sensor may be responsible for success or failure in estimating *Phragmites* biomass across both wetlands.

4.3. Comparison of multi-scale medium sensors in assessing the variability of *Phragmites* aboveground biomass

Literature reported that no multispectral sensor is suitable to address all the challenges associated with aboveground biomass of wetland vegetation estimation (Feilhauer et al., 2013; Nagendra et al., 2013). The lack of SWIR wavelength in broadband sensors proved to be limiting factor in most studies (Feilhauer et al., 2013; Korhonen et al., 2017; Zandler et al., 2015). The availability of new generation multispectral data such a Sentinel 2 MSI and Landsat 8 OLI with improved spectral coverage at no cost, proved to be promising in other vegetation studies (Korhonen et al., 2017; Mallinis et al., 2017; Sibanda et al., 2015). After finding that RapidEye data (chapter 2) did not produce high accuracy as expected at site level, we found the need to evaluate freely accessible medium spatial resolution data in quantifying the variability of *Phragmites* biomass between natural wetland versus rehabilitated wetland. The question is whether medium multispectral data can enhance the *Phragmites* biomass accuracy compared to broadband RapidEye data. Despite encouraging findings from other studies, to the best of our knowledge no study has compared the utility of Sentinel 2 MSI and Landsat 8 OLI in quantifying the aboveground biomass of *Phragmites* across different wetlands management beyond small scale. In that regard, the utility of these sensors were tested based on three predictor variables (i) extracted spectral bands, (ii) derived vegetation indices and (iii) combined datasets. The findings were compared with the results obtained from chapter 2 to answer the study question. Based on the results, Sentinel 2 MSI estimated *Phragmites* biomass better than Landsat 8 OLI and RapidEye data using all three different predictor variables. The Landsat 8 OLI provided better accuracy for rehabilitated wetlands in comparison to RapidEye data. On the other hand, RapidEye data achieved better accuracy for natural biomass estimation. Both Landsat 8 OLI and RapidEye complement each other for assessing *Phragmites* biomass. Furthermore, the work by Feilhauer et al. (2013) reported the good performance of multispectral sensors covering the SWIR for achieving consistently high accuracy than broadband multispectral sensors for assessing the floristic variation in nutrient poor grassland. Sentinel 2 MSI outperformed Landsat 8 OLI estimating leaf area index in boreal forest (Korhonen et al., 2017). (Zandler et al. (2015)) reported that both Landsat 8 OLI and RapidEye data did not perform considerably better than the other for quantifying shrub biomass. This suggest that improved *Phragmites* biomass is possible with Sentinel 2 MSI sensor. Therefore, medium multispectral sensor Sentinel 2 MSI has the potential to estimate aboveground biomass with high accuracy under different wetland management system. The high accuracy achieved with Sentinel 2 MSI may be related to the red edge (B6) which occurred in most selected predictor variables.

4.4. Conclusion

The main aim of this research was to test the utility of new generation multispectral remote sensing techniques in assessing the variability of *Phragmites* aboveground biomass between the natural wetland versus rehabilitated wetland. The findings of this research demonstrated that the use of new multispectral satellite sensors still pose challenges, however they can estimate biomass with acceptable accuracy depending on the area of interest and species type. Based on the findings carried out in this study the following conclusion can be drawn:

- When using RapidEye data, the best accuracy was obtained from natural biomass estimation with the combination of spectral bands and vegetation indices. The indices improved rehabilitated biomass estimation, however produced weaker results. RapidEye data was not consistence in all models performed across the natural and rehabilitated wetlands. However, models based on pooled dataset achieved high results for all predictor variables.
- Sentinel 2 MSI provided good estimation of *Phragmites* aboveground biomass in both wetlands. The spectral bands performed better than vegetation indices and or combined datasets. However, the accuracy decreased with the number of predictor variables increasing. Similar results were also observed from pooled dataset. This means that the spectral bands alone have more strength in biomass estimation. The results indicate that Sentinel 2 MSI can achieve high biomass estimation accuracy to the level of commercial RapidEye data.
- The Landsat 8 OLI did not produce consistence accuracy for all models across both wetlands. The best accuracy obtained from rehabilitated biomass using extracted spectral bands. Combined datasets produced similar results for both natural and rehabilitated wetlands. Pooled dataset increased *Phragmites* biomass with spectral bands only.
- Combination of both extracted bands and derived vegetation indices increased natural biomass estimation. In contrast, no sensor types showed any improvements estimating rehabilitated biomass. The findings demonstrates the challenges of comparing same species growing under different wetland ecosystem management.
- Sentinel 2 MSI outperformed both Landsat 8 OLI and RapidEye data in both wetlands. RapidEye with red edge band did not show any improvement against Landsat 8 OLI data. The results obtained from RapidEye and Landsat are inconclusive.
- The uses of cheap multispectral satellite sensors have the potential to increase biomass estimation of *Phragmites* in wetlands ecosystems especially Sentinel 2 MSI.

- Overall, this research demonstrated that sensors with visible near infrared and SWIR coverage played a vital role in estimating *Phragmites* biomass estimation.

4.5. Recommendations

- The present study used multispectral sensor to assess the variability of *Phragmites* biomass, it will however be good to test the potential of other multispectral sensors such as Worldview and Sumbandilasat data.
- Due to uncertainties regarding the passive multispectral data used in this study, future studies can be explored with the use of active spaceborne sensors such as Light Detection and Ranging (LIDAR) and Synthetic Aperture Radar (SAR) data.
- More research is required to compare different types of remote sensing data and determine how spatial and spectral resolution affect biomass estimation of wetland invasive species.
- Furthermore, future studies should investigate biochemical, height and phenology of *Phragmites* under different management system. In that regard, knowledge on difference between both wetlands will help ecologist and wetland mangers to understand when is best to put control measures in place.
- Moreover, future studies should consider collecting data over several years under different wetland management.
- For monitoring purposes, wetland managers and ecologist should rely on Sentinel 2 MSI based on the accuracy achieved and it is freely accessible at no cost.

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