This thesis has been submitted in fulfilment of the requirements for a postgraduate degree (e.g. PhD, MPhil, DClinPsychol) at the University of Edinburgh, Please note the following terms and conditions of use:

- This work is protected by copyright and other intellectual property rights, which are retained by the thesis author, unless otherwise stated.
- A copy can be downloaded for personal non-commercial research or study, without prior permission or charge.
- This thesis cannot be reproduced or quoted extensively from without first obtaining permission in writing from the author.
- The content must not be changed in any way or sold commercially in any format or medium without the formal permission of the author.
- When referring to this work, full bibliographic details including the author, title, awarding institution and date of the thesis must be given.
Using satellite Earth observation & field measurements to assess the above ground woody biomass in the tropical savanna woodlands of Belize

Dimitrios Michelakis

Doctor of Philosophy

The University of Edinburgh
School of Geosciences

2014
DECLARATION

I confirm that this work is my own, except where indicated otherwise. The thesis contains three research chapters; one chapter accepted for publication as an article in an international peer-reviewed journal, one chapter composed of one article published at an international symposium and one article published in an international peer-reviewed journal, and a third chapter published as an article in an open-access international peer-reviewed journal. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others. No part of this thesis has been submitted for any other degree or qualification.

The candidate, as lead researcher, performed the field data collection, the field data analysis, the image analysis, and writing of the research articles. Co-authors provided support and guidance on the scope and design of the project, the analyses performed and contributed to the editing of the following manuscripts:

Michelakis D, Stuart N, Furley P., Lopez, G, Linares V, Woodhouse IH, ‘Woody structure and population density of pine dominated tropical savanna woodlands under different protection and management regimes’. Accepted for publication subject to minor revision with the Caribbean Journal of Science. (Chapter 3)


Signed: ..............................................
Dimitrios Michelakis

Date: .............................................
Dedicated to my newborn son, Georgios

To my wife, Elina,

And my parents Maria Fthenou, and Georgios Michelakis

“The heroes of the foundational quest of logic were just that, map makers. They reduced messy reality to the clarity of maps (i.e. simpler things), where logic could apply more naturally!

But maybe eventually they confused their reality with their maps...”

From Apostolos Dxiadi’s and Christos Papadimitriou graphic novel – ‘Logicomix – An epic search for truth’
ABSTRACT

The aim of this thesis is to evaluate the capability of radio detection and ranging (radar) data collected by the Advanced Land Observing Satellite (ALOS) Phased Array type L-band Synthetic Aperture radar (PALSAR), supported by field measurements obtained through ground survey, to predict and map Above Ground Woody Biomass (AGWB) in the tropical savannas of the developing country of Belize, and to understand how the forest structure may influence the backscatter observed.

Firstly, an extensive inventory of the woody vegetation of the tropical savannas of Belize was created by measuring the diameter at breast height (dbh), the total height (ht) and the location of 6547 trees in plots covering a total woodland area of 30.8 hectares, located within four protected areas (the Rio Bravo Conservation and Management Area (11×1ha), Deep River (108×0.1ha) and Manatee Forest Reserve (1ha) and the Bladen Nature Reserve (1ha) and also from plots located in unprotected areas (7×1ha). These measurements of forest structure, when combined with information about forest management practices obtained from local organisations revealed that different forms of protection and management may lead to the development of pine woodlands with different structural characteristics in these savannas.

Secondly, a case-study was conducted to establish the sensitivity of the ALOS PALSAR backscatter data to AGWB and determine the effect of sample plot size to their relationship. The findings of this case-study show that the L-band backscatter in these low density pine woodlands is a possible predictor of AGWB and confirm that the appropriate sample plot size for predicting AGWB is one hectare; while the sensitivity degrades significantly with decreasing sample plot size.

Taken together, the findings described above were combined to assess the capability of ALOS PALSAR backscatter to predict AGWB in these woodlands. A semi-empirical Water Cloud Model (WCM) describing the interaction between the backscatter and vegetation was re-arranged to enable the prediction of AGWB. Non-linear regression analysis revealed that the ALOS PALSAR backscatter predicted AGWB with an $R^2=0.92$; an external validation conducted with additional ground reference data estimated this AGWB prediction to have an RMSE ~13 t/ha. The form of the regression
model linking backscatter to AGWB appears to be particularly influenced by sample plots with higher tree numbers and by plots in which the trees were more homogeneous. The presence of many similar sized individuals within some plots is postulated as one explanation for the elevated saturation level for predictions in this study (> 100 t/ha) compared to other models. The model developed here predicts complete saturation in the backscatter - AGWB relationship to occur primarily as a result of increases in the tree number density and often concurrently in basal area, two parameters which are usually strongly correlated with AGWB in these woodlands.

Thirdly, the locally validated relationship between ALOS PALSAR backscatter and AGWB is used to map AGWB for the lowland pine savannas of Belize at a spatial resolution of 100m. The mapping estimates that over 90% of these pine woodlands have an AGWB below 60 t/ha, with the average woody biomass estimated at 23.5 t/ha. When these new predictions are mapped and aggregated over the extents of two protected areas (Rio Bravo and Deep River), the totals obtained agree closely (error ≤20%) with previous estimates of AGWB obtained from ground data and previous research. The combined evidence suggests that woodland protection may produce a small, positive effect upon AGWB, with the mean of the AGWB/ha predictions higher in areas that are protected and managed for biodiversity (29.55 ± 0.84 t/ha) than in other areas that are not protected (23.29 ± 0.19 t/ha). When the fine scale local AGWB mapping produced using ALOS PALSAR is compared cell-by-cell with global biomass products at coarser spatial resolutions (500m and 1000m), the AGWB differences observed range from 115-120%. When the coarser AGWB estimates are aggregated over the extents of Deep River and Rio Bravo, the AGWB totals obtained differ significantly (~280 – 300%) from AGWB estimates from ground data and previous research.

Overall, these findings suggest that where sufficient ground data exists to build a reliable local relationship to radar backscatter, more detailed biomass mapping can be produced from ALOS and similar satellite sensor data at resolutions of ~100m. This more accurate and spatially detailed information about the distribution of woody biomass within tropical lowland savannas is more appropriate for monitoring local changes in forest cover and for supporting management decisions for forested areas of
around ~10,000ha than estimates based upon previously available, but coarser scale, global biomass products.
ACKNOWLEDGEMENTS

I owe my deepest gratitude to a number of people who have offered help and support during the past four years. These include especially: Dr. Neil Stuart, Prof. Iain H. Woodhouse, Prof. Peter Furley, Dr. Iain Cameron, Dr. Karin Viergever, Dr. Matthew Brolly, Mr. German Lopez, and Mr. Vinicio Linares.

Particular thanks to my primary supervisor Dr. Neil Stuart for his support, advice, and mentorship, which has been invaluable for developing my scientific skills, and ethics in research. Many thanks to my second supervisor Prof. Iain H. Woodhouse whose guidance in developing leadership skills has been key to my progressing career in making Earth observation operational for a range of applications.

I am grateful to Prof. Peter Furley for sharing his invaluable knowledge and experience of the tropical ecosystems during a one week visit in Belize, as well as reading and commenting on my research article submitted to the Caribbean Journal of Science.

To Dr. Iain Cameron and Dr. Karin Viergever go particular thanks for kindly providing me with access to previous field datasets and Earth observation imagery covering savanna areas in Belize, and advice on field data collection, and image analysis techniques.

Dr. Matthew Brolly generously shared his knowledge in the interactions between radar and vegetation, as well as patiently replying to my emails and providing comments to my research article submitted to IEEE J-STARs.

I am grateful to the University of Belize Environmental Research Institute (UB ERI) for providing office space during my stay in Belize, allowing the invaluable assistance of German Lopez for assisting in the collection of the entire field dataset, and offering an off-road 4x4 vehicle to collect key parts of this thesis’s field data in remote savanna areas.

Particular thanks go to the Programme of Belize (PfB) for contributing the forest team of Rio Bravo Conservation and Management area (RBCMA) to support my field data collection for three days, and to the Royal Botanical Gardens of Edinburgh (RBGE) for
offering me the opportunity to plan and deliver a forest inventory exercise to the students of the MSc in Biodiversity and Taxonomy of Plants (class, 2012). This helped to collect an additional hectare of field measurements.

I greatly appreciate the support that I received from my colleagues in Drummond Street, especially by Mr. Bruce Gittings, Mr. Owen McDonald, Dr. Gemma Cassells, and Dr. John Carson. Many thanks go to the friendly staff of the school of Geosciences and especially Mrs. Rosanna Maccagnano, Mrs. Helena Sim, and Mr. Alasdair Howie for providing me with prompt answers on administrative issues and questions.

This work was supported by an IKY Scholarship from the resources of O.P. “Education and lifelong Learning”, European Social Fund (ESF) and the NSRF 2007–2013 (Grant Number: 2011/1083), by the School of Geosciences of the University of Edinburgh and the “Centenary Research Fund: Support for postgraduate Research”

Data for this thesis were provided by a range of organisations and individuals who I wish to acknowledge:

- radar data were provided by the Darwin Initiative project “Savanna Ecosystem Assessment / Belize 2009”, 17-022, and the NASA Alaska Satellite Facility (NASA-ASF) through an ALOS PALSAR proposal
- Optical Earth observation data and software were provided by PLANET-ACTION – AN ASTRIUM INITIATIVE through a ‘Working Together Grant’.
- Field data which were used to validate key results of this research were collected in the context of a sustainable forest management plan funded by USAID (Grant Number: 412FO-APSO1-THOM) and were provided by Vinicio Linares.
- Parts of the precipitation data that are presented in this thesis were generously provided by the Belize National Meteorological Service.

Most importantly I would like to pay tribute to my parents who educated me to appreciate science and embrace constructive criticism.

Above all, thanks to my wife Elina for putting up with my persistence in this work and my explanations during relaxing evenings on the blue colour of the sky and the white colour of the clouds.
# TABLE OF CONTENTS

## CHAPTER ONE

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>INTRODUCTION</td>
<td>1</td>
</tr>
<tr>
<td>1.1 OVERVIEW</td>
<td>1</td>
</tr>
<tr>
<td>1.2 THE DEVELOPMENT OF BELIZE AND THE GROWING PRESSURES ON ITS WOODLAND RESOURCES</td>
<td>2</td>
</tr>
<tr>
<td>1.3 HUMAN PERTURBATION AND THE CARBON CYCLE</td>
<td>3</td>
</tr>
<tr>
<td>1.4 SFM AND REDD+</td>
<td>5</td>
</tr>
<tr>
<td>1.4.1 Monitoring carbon stocks for SFM and REDD+</td>
<td>6</td>
</tr>
<tr>
<td>1.4.2 Quantifying above ground biomass using EO</td>
<td>8</td>
</tr>
<tr>
<td>1.5 THE IMPORTANCE OF THE SAVANNA ECOSYSTEM IN BELIZE</td>
<td>9</td>
</tr>
<tr>
<td>1.5.1 The savanna woodlands</td>
<td>9</td>
</tr>
<tr>
<td>1.6 IMPROVING MONITORING THROUGH BETTER MAPPING USING EO IN TROPICAL SAVANNAS</td>
<td>12</td>
</tr>
<tr>
<td>1.7 THE NEED FOR THIS RESEARCH AND ANTICIPATED USER VALUE</td>
<td>13</td>
</tr>
<tr>
<td>1.8 AIMS</td>
<td>14</td>
</tr>
<tr>
<td>1.9 STRUCTURE OF THE THESIS</td>
<td>15</td>
</tr>
<tr>
<td>REFERENCES</td>
<td>18</td>
</tr>
</tbody>
</table>

## CHAPTER TWO

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>EARTH OBSERVATION &amp; SAVANNA WOODLANDS</td>
<td>22</td>
</tr>
<tr>
<td>2.1 INTRODUCTION</td>
<td>22</td>
</tr>
<tr>
<td>2.2 STAND STRUCTURE FOR PROTECTION AND MANAGEMENT</td>
<td>24</td>
</tr>
<tr>
<td>2.3 SATELLITE DATA OVERVIEW</td>
<td>28</td>
</tr>
<tr>
<td>2.3.1 Earth observation data concepts</td>
<td>29</td>
</tr>
<tr>
<td>2.3.1.1 Passive Optical Earth observation</td>
<td>29</td>
</tr>
<tr>
<td>2.3.1.2 Passive Optical Earth observations in tropical savannas</td>
<td>29</td>
</tr>
<tr>
<td>2.3.1.3 Passive Optical EO in Tropical savannas of Belize</td>
<td>32</td>
</tr>
<tr>
<td>2.3.1.4. Issues when using passive optical Earth observation in tropical savannas</td>
<td>34</td>
</tr>
<tr>
<td>2.3.1.5 Radio Detection and Ranging (radar)</td>
<td>35</td>
</tr>
<tr>
<td>2.3.1.6 Synthetic aperture radar (SAR)</td>
<td>36</td>
</tr>
<tr>
<td>2.3.2 SAR EO and tropical savannas</td>
<td>38</td>
</tr>
<tr>
<td>2.3.3 Why use SAR in Belize</td>
<td>42</td>
</tr>
<tr>
<td>2.4. SUMMARY</td>
<td>42</td>
</tr>
<tr>
<td>2.5 SYNOPSIS OF SAR DATA COLLECTION AND DATA INTERPRETATION</td>
<td>46</td>
</tr>
<tr>
<td>2.5.1 Satellite SAR – what is within a pixel?</td>
<td>46</td>
</tr>
<tr>
<td>2.5.2 Impact of topographic effects and speckle to SAR data quality</td>
<td>48</td>
</tr>
<tr>
<td>2.5.3 The radar cross-section</td>
<td>49</td>
</tr>
<tr>
<td>2.5.4 Polarisation</td>
<td>50</td>
</tr>
<tr>
<td>2.5.5 The SAR phase</td>
<td>51</td>
</tr>
<tr>
<td>2.6 SAR TO ASSIST WITH AGWB PREDICTION</td>
<td>51</td>
</tr>
<tr>
<td>2.6.1 SAR data texture calculation to enhance SAR images</td>
<td>52</td>
</tr>
<tr>
<td>2.6.2. Using the SAR data phase to assist with AGWB prediction</td>
<td>53</td>
</tr>
<tr>
<td>2.7 THE FIXED AREA PLOT</td>
<td>55</td>
</tr>
<tr>
<td>2.8 DESCRIPTION OF THE EO DATA</td>
<td>58</td>
</tr>
<tr>
<td>2.8.1 SPOT 5</td>
<td>58</td>
</tr>
<tr>
<td>2.8.2 WORLDVIEW 1 &amp; 2</td>
<td>59</td>
</tr>
<tr>
<td>2.8.3 ALOS PALSAR</td>
<td>60</td>
</tr>
<tr>
<td>2.8.4 GIS data</td>
<td>62</td>
</tr>
<tr>
<td>2.9 L-BAND BACKSCATTER AND VEGETATION INTERACTIONS</td>
<td>63</td>
</tr>
<tr>
<td>2.9.1 Vegetation structure prediction using ALOS PALSAR</td>
<td>64</td>
</tr>
<tr>
<td>2.10 SUMMARY</td>
<td>66</td>
</tr>
<tr>
<td>REFERENCES</td>
<td>69</td>
</tr>
</tbody>
</table>
5.3. INTRODUCTION ........................................................................................................ 136
5.3.1. Why map tropical savannas at more local scales?............................................. 136
5.3.2. Mapping of savanna woodlands with active satellite Earth observation.......... 138
5.3.3. The use of more detailed mapping of woody biomass in savannas.................. 140
5.4. EXPERIMENTAL SECTION.................................................................................... 141
5.4.1. Description of the lowland savanna ecosystem............................................... 141
5.4.2. ALOS PALSAR data..................................................................................... 142
5.4.3. Biomass Mapping Using ALOS PALSAR and Semi-Empirical Modelling......... 144
5.4.4 Consistency of Biomass Estimate of two Protected Areas.................................. 148
5.4.6. Comparing the new mapping with national level carbon stock maps from pan-tropical data sets .......................................................... 151
5.5. RESULTS AND DISCUSSION ............................................................................ 153
5.5.1. Evaluating the new biomass map against field data and previous ground surveys 153
5.5.2 Using the Map to Characterize AGWB in the Lowland Savannas of Belize........ 155
5.5.3. Comparison of the local map estimates with pan-tropical carbon stock maps...... 157
5.6. CONCLUSIONS ....................................................................................................... 160
REFERENCES ................................................................................................................. 162

CHAPTER SIX
CONCLUSION & RECOMMENDATIONS ..................................................................... 167
6.1. THESIS CONTRIBUTIONS .................................................................................... 167
6.2 SUMMARY OF FINDINGS ..................................................................................... 169
6.2.1 Chapter 3 – Accepted subject to minor revision: Caribbean Journal of Science........ 170
6.2.2 Chapter 4 – This chapter integrates the results and discussions of two published articles (a) at the IEEE International Geoscience and Remote Sensing Symposium, 2013 and (b) at the IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2015 ....................... 171
6.2.3 Chapter 5 – Published: Special Issue on Applications of Remote Sensing to Forestry, 2014 ................................. 174
6.2.4 Calibration and Validation using different sample plot sizes.................................. 176
6.3. RECOMMENDATIONS AND SUGGESTIONS FOR FURTHER WORK ............... 177
6.3.1 Recommendations for forest managers ............................................................... 177
6.3.2 Recommendations for further research ............................................................... 179
6.3.2.1 Assessing consistency over time of L-HV backscatter for AGWB estimation and seasonal influences .......................................................... 179
6.3.2.2 AGWB prediction using L-HV in other protected areas.................................. 180
6.3.2.3 Contribution of other high and very high spatial resolution optical data to supplement ground measurements .......................................................... 181
6.3.2.4 Further research specific to savanna woodlands in Belize.............................. 182
6.3.3 Recommendations to policy makers & advisers .................................................. 184
REFERENCES ................................................................................................................. 188

APPENDICES ................................................................................................................. 189
APPENDIX ONE - TECHNICAL FEASIBILITY ARTICLE PRESENTED AND PUBLISHED AT THE INTERNATIONAL GEOSCIENCE AND REMOTE SENSING SYMPOSIUM (IGARSS, 2013), THIS ARTICLE IS PART OF CHAPTER FOUR .................................................. 190
APPENDIX TWO - PUBLISHED ARTICLE AT THE IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING (2015), THIS ARTICLE IS PART OF CHAPTER FOUR .................................................. 195
APPENDIX THREE - PUBLISHED ARTICLE AT THE JOURNAL MDPI FORESTS (2014), THIS ARTICLE IS CHAPTER FIVE ................................................................................................. 207
APPENDIX FOUR - COMMENTED SCRIPT DESCRIBING THE SAR PROCESSING FROM LEVEL 1.0 (RAW) TO LEVEL 1.1 (SLC) USING THE FACILITIES OF GAMMA SOFTWARE, FOR THE SCENE ‘ALPSRP138740310’, ...................................................................................................................... 231
APPENDIX FIVE - COMMENTED SCRIPT DESCRIBING THE SAR PROCESSING FROM LEVEL 1.1 (SLC) DATA (HH & HV) TO LEVEL 1.5 USING THE FACILITIES OF GAMMA SOFTWARE, FOR THE SCENE ‘ALPSRP138740310’, ...................................................................................................................... 235
APPENDIX SIX - NAME AND DESCRIPTION OF THE EM SPECTRAL BANDS THAT ARE COLLECTED BY THE SPOT AND WORLDVIEW SENSORS ACCOMPANIED BY THE SPATIAL RESOLUTION FOR EACH BAND. ................................................................. 240


APPENDIX EIGHT - ALOS PALSAR DATA ACQUIRED BY THE NASA ALASKA SATELLITE FACILITY ........................................................................................................................................................................ 244
# ABBREVIATIONS

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Full Form</th>
</tr>
</thead>
<tbody>
<tr>
<td>AGWB</td>
<td>Above Ground Woody Biomass</td>
</tr>
<tr>
<td>ALOS</td>
<td>Advanced Land Observing Satellite</td>
</tr>
<tr>
<td>BA</td>
<td>Basal Area</td>
</tr>
<tr>
<td>CBD</td>
<td>Convention on Biological Diversity</td>
</tr>
<tr>
<td>CC</td>
<td>Canopy Cover</td>
</tr>
<tr>
<td>DBH</td>
<td>Diameter at Breast Height</td>
</tr>
<tr>
<td>DD</td>
<td>Diameter Distribution</td>
</tr>
<tr>
<td>EO</td>
<td>Earth Observation</td>
</tr>
<tr>
<td>FDB</td>
<td>Forest Department of Belize</td>
</tr>
<tr>
<td>FR</td>
<td>Forest Reserve</td>
</tr>
<tr>
<td>GEF</td>
<td>Global Environment Facility</td>
</tr>
<tr>
<td>GOB</td>
<td>Government of Belize</td>
</tr>
<tr>
<td>KBA</td>
<td>Key Biodiversity Areas</td>
</tr>
<tr>
<td>LIDAR</td>
<td>Light Detection And Ranging</td>
</tr>
<tr>
<td>MaxEnt</td>
<td>Maximum Entropy (Machine Learning Algorithm)</td>
</tr>
<tr>
<td>NPAPSP</td>
<td>National Protected Area Policy &amp; System Plan</td>
</tr>
<tr>
<td>NR</td>
<td>Nature Reserve</td>
</tr>
<tr>
<td>PA</td>
<td>Protected Area</td>
</tr>
<tr>
<td>PFB</td>
<td>Programme for Belize (Management organisation for RBCMA)</td>
</tr>
<tr>
<td>PRAM</td>
<td>Protected and Actively Managed (Protection and management group)</td>
</tr>
<tr>
<td>PRPM</td>
<td>Protected and Passively Managed (Protection and management group)</td>
</tr>
<tr>
<td>UPR</td>
<td>Unprotected (Protection and management group)</td>
</tr>
<tr>
<td>RBCMA</td>
<td>Rio Bravo Conservation and Management Area (Protected Area)</td>
</tr>
<tr>
<td>PALSAR</td>
<td>Phased Array L-band Synthetic Aperture radar (on ALOS)</td>
</tr>
<tr>
<td>PMG</td>
<td>Protection and Management Group</td>
</tr>
<tr>
<td>RADAR</td>
<td>Radio Detection And Ranging</td>
</tr>
<tr>
<td>REDD</td>
<td>Reducing Emissions from Deforestation and forest Degradation</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root Mean Squared Error</td>
</tr>
<tr>
<td>RRMSE</td>
<td>Relative RMSE</td>
</tr>
<tr>
<td>SAR</td>
<td>Synthetic Aperture radar</td>
</tr>
<tr>
<td>SFMP</td>
<td>Sustainable Forest Management Plan</td>
</tr>
<tr>
<td>SFM</td>
<td>Sustainable Forest Management</td>
</tr>
<tr>
<td>SPOT</td>
<td>Système Pour l’Observation de la Terre (French Satellite)</td>
</tr>
<tr>
<td>TIDE</td>
<td>Toledo Institute for Development and Environment</td>
</tr>
<tr>
<td>UN</td>
<td>United Nations</td>
</tr>
<tr>
<td>SAOCOM</td>
<td>Satélite Argentino de Observación Con Microondas (Argentinean Satellite)</td>
</tr>
<tr>
<td>WB</td>
<td>World Bank</td>
</tr>
<tr>
<td>WCM</td>
<td>Water Cloud Model</td>
</tr>
</tbody>
</table>
INTRODUCTION

1.1 Overview

This thesis presents the outcomes of a research project which aimed to map the above ground woody biomass (AGWB) of the lowland savanna ecosystem in Belize, Central America. This research utilizes a combination of Earth observation data (EO) (optical, and microwave) and in situ observations from sample plots established in lowland savanna woodlands under different protection and management regimes (unprotected areas, protected areas with passive management, and protected areas with active management).

The results are arranged as three research chapters. Taken together, these chapters present a coherent methodology for developing a capacity to map AGWB in the lowland savanna woodlands at national and sub-national scales (i.e. ground extent ≤ 10000ha) at fine mapping scales (i.e. mapping resolution ~ one hectare), together with an assessment of the accuracy of these predictions.

The methodology begins with the creation of an extensive field inventory for the pine savanna woodlands of Belize, Central America. The quality of the measurements is controlled using optical satellite data, and the suitability of these measurements for forest management requirements is established. The feasibility of using these observations in combination with microwave satellite imagery to support AGWB mapping in these woodlands is then studied and the performance of the method is evaluated. The relationship that is established between the satellite microwave data
and the field measurements is then exploited to create the first hectare resolution AGWB map of Belize, Central America.

1.2 The development of Belize and the growing pressures on its woodland resources

Although the developing countries of Latin America and the Caribbean are showing a lower increase in population growth in comparison to the countries of Sub-Saharan Africa and Asia, the population of Belize was found in 2012 to be growing at a rate of 2.43%, which is the second highest rate in the region, although from a small base of ~325K. It is noteworthy that Guatemala, which shares borders with Belize, heads the list of population growth in Central America, at 2.53%, since the most deforestation in Belize is occurring in the borders with Guatemala (Cherrington et al., 2010).

Whilst a historically low and stable population has led to relatively low pressure on Belize’s natural resources up until now, this is changing rapidly, with the increasing population growth rate expected to have an increasing and negative impact on the use of the country’s natural environment in the future, if the existing protection and management policy in the country is not strengthened and enhanced (Walker & Walker, 2009). There are presently some 70 protected areas (PA) in Belize, and approximately 45% of the terrestrial area is under some form of protection (World Bank Data Catalogue, 2014); however there is a wide variety of protection and management taking place in these different PAs. In some PAs, protection is not effective, due to factors such as insufficient resource management and a lack of capacity, raising questions about the overall effectiveness of protection within the national protected areas system of Belize (Walker & Walker, 2009; Government of Belize, 2010).

Belize has grown significantly during the past 50 years from ~92K to ~325K individuals today, while the density of the population has also significantly increased (4.51 individuals per km² in 1961 in comparison to 13.86 individuals per km², which translates to 207%\(^1\) percentage change) (World Bank Catalogue, 2013). Today, approximately 55% of the population of Belize still resides in rural areas, and the

\(^1\) The percentage change is calculated using the following equation: \[\text{Percentage change} \, (\%) = \frac{13.86 - 4.51}{4.51} \times 100\]
average population growth per year in rural areas is greater than in urban areas (~2.8% in comparison to 2.0%). The combination of population growth in rural areas, and poverty at extreme (<2.5$ a day, 2005PPP) or moderate (<4$ a day, 2005 PPP) levels (18% of rural households, and 43% respectively), may become key drivers of change upon the natural environment, and specifically any land outside PAs.

Recent statistics derived by the Belize statistical organisation (2012) show that 15% of the population is still using wood and charcoal for cooking, while ~17% of forest land in the country have been converted to other land uses during the previous 30 years (Cherrington et al., 2010). During the same time increases in the area of agricultural activity have been observed (66%, 70%, and 137% net gain in percentage of land used for agriculture, arable land, and permanent cropland respectively (World Bank Catalogue, 2013). These land use changes to agriculture and other uses (Fig. 1C&D) contributes to the increasing pressure on forest resources in Belize, especially outside the PAs, where there is increased clearing of forests. For example, FAOSTAT, (2011) estimates that 35.1% of the greenhouse gas emissions (GHG) in Belize now come from land use change.

In recent years there are initiatives which aim to increase the efficiency of protection for the forested ecosystems in Belize and reverse the forest cover loss, although it is still the lowest in the region of Latin America and the Caribbean (World Bank, 2013). Belize is on target at keeping their annual deforestation rate low (~0.6%), and also implementing a national protected areas expansion plan which was initiated in 2003 (Meerman and Wilson, 2005). Present emphasis is on the rationalisation and strengthening of management in PAs (Walker, 2013), and more coordination nationally of management activities and good practices in PAs (Rosado, 2013).

1.3 Human perturbation and the carbon cycle

In Latin America the Intergovernmental Panel on Climate Change (IPCC) predict with high confidence that human actions in the region will intensify land use change while degradation of vegetation cover will increase (IPCC, 2007). The scientific community and international organisations acknowledge the necessity for meaningful actions that will substantially limit further increases in the concentration of carbon dioxide in the
atmosphere. To support these actions, better mapping and monitoring of vegetative land cover, carbon sources and sinks is required. The main human impacts on atmospheric CO\textsubscript{2} accumulation come from land use conversion (~45\% of direct emissions) of these ~12\% come from deforestation and afforestation activities (Lal 2008; Le Quere, Raupach et al. 2009).

FIGURE 1.1 (A) Belize in the region of Central America, (B) the ecosystems map of Belize (2012) with the dissolved protected areas shaded as light grey, (C) rice paddy adjacent to savanna areas and forest, (D) uncontrolled fire in savannas, and (E) pine tree that has been logged using a machete in an unprotected savanna area. The bar-charts show the national area and percentage of land (labels) covered by each ecosystem in (A).
1.4 SFM and REDD+

The protection and development of forests and wooded areas should be pursued after taking into consideration all the needs of present and future peoples (UN, 1992). This may include, among many services, the production of timber for housing and cooking, food and water, the creation of employment and conservation of wildlife; action should also be taken to protect forest resources against damaging effects such as fire and over-exploitation. Sustainable Forest Management (SFM) makes an attempt to produce and maintain these services by utilising a wide range of principles indicated in the Report of the UN Conference on Environment and Development signed during the Rio Convention (UN, 1992).

Among others, in that report mention is made of the need for new economic resources which need to be provided to developing countries to assist them with SFM activities. In the developing world, frameworks such as the UN Programme for Reduced Emissions from Deforestation, Degradation and Enhancement (UN-REDD+) provide a means for both reducing carbon emissions and supporting economic development. REDD+ recognises that, rather than simply being carbon sinks, forests provide a wider set of ecosystem services for local communities; thus, in addition to reducing deforestation and degradation, initiatives for the conservation, sustainable management and enhancement of forest stocks are also directly supported (Global Canopy Programme, 2008). For example under a small scale REDD+ project (~5000 hectares) in a tropical forest in Belize (Boden Creek Ecological Preserve) multiple objectives are being addressed including the avoidance of carbon emissions by forest burning, conserving habitats for rare species such as the jaguar (*Panthera onca*) and providing work to local communities. At recent count, 338 REDD+ projects have been recorded worldwide with the involvement of 52 countries managing a total forest area of 4,033,063 hectares and a total carbon stock of 270,265 million tonnes (FAO, 2010).

Garcia *et al.*, (2011) showed that Belize has been preparing for the opportunities found in REDD+ in recent years, through enhancing its legislative framework for PAs and improving the country’s protected areas to include a greater range of representative habitats for the country. However the study by Garcia *et al.*, (2011) also recognises that
there has not been a strong incentive to develop a forest monitoring network in the country, which is attributed to lack of motivation among local communities to participate and a lack of economic resources among many organisations managing PAs. Until today there have been only three projects exploring the return on investment for carbon sequestration in Belize; Programme for Belize managing the Rio Bravo Conservation and Management Area (RBCMA), the Friends of Conservation and Development (FCD), managing the Chiquibul National Forest, and the pilot project in Boden Creek Ecological Preserve. The main problems that have been identified in those projects are difficulties in accessing capital and markets for carbon trading and the limited in-country capacity to develop baselines against which carbon sequestration can be measured.

1.4.1 Monitoring carbon stocks for SFM and REDD+

Central to REDD+ and SFM at global, national and sub-national levels is the need for robust, reliable and replicable monitoring of above ground forest carbon stocks in developing countries. Monitoring can be used to assess the performance of a REDD or SFM project to support its success. In the context of REDD+ this process is embedded within the monitoring, reporting, and verification (MRV) of forest carbon stocks, and it is key to successful REDD+ project implementation because MRV provides the necessary toolbox to assess changes in the greenhouse gas budget. Specifically the REDD+ MRV refers to the implementation of methods and protocols which may assist the collection and analysis of forest carbon stock data and support the assessment of the results (i.e. increase or decrease of greenhouse gases) of a REDD+ project (GOFC-GOLD, 2013). The above ground carbon stocks have been identified as a key forest and woodland attribute for the implementation of a greenhouse gas inventory (IPCC, 2006) mainly because they account on average for more than two thirds of the total woody carbon stocks found within forests, making it a good indicator for greenhouse gases quantification. The monitoring of greenhouse gas emissions is founded on the continuous observations of two main groups of above ground biomass; biomass gains

---

2 In this thesis, a REDD baseline or a reference level is a predicted emission rate of carbon dioxide equivalent, due to deforestation or forest degradation in the absence of interventions to reduce those emissions (TNC, 2009)
(i.e. woodland growth), and biomass losses (i.e. human or natural disturbances – fire, logging, biomass removal).

Up to recent years, researchers and practitioners have tended to focus on extensive field measurements to measure and verify carbon stocks to support the REDD+ MRV aims in developing countries (Hewson *et al.*, 2013). For example, they would estimate carbon stocks within a small area (e.g. one or more hectares) and then extrapolate these carbon estimates to larger geographical areas (e.g. whole stands of forest or protected areas) to measure the total carbon stocks. Within that approach workers would estimate forest carbon stocks at sampling units (e.g. sample plots of different shapes and sizes) either by measuring architectural attributes of all individual or representative trees in the sample plot and inserting these into allometric equations\(^3\) to estimate the sample plot carbon stock, or by complete deforestation of the sample plot and weighting the dry woody matter for a more precise carbon stock estimate. Although these field driven methods for estimating carbon stocks yield relatively low carbon estimation errors (i.e. less than 20 t/ha or less than 20% of the estimated carbon stocks per hectare), a major drawback of these approaches is their cost in monetary resources and time, while their results (i.e. allometric equations) are often not easily transferable to other regions because of the very localised field measurements used to develop these carbon stock estimates (Gibbs *et al.*, 2007). There are a significant number of carbon stock quantification standards (e.g. Plan Vivo and the Verified Carbon Standard - VCS) which utilise field measurements to support key components of MRV activities (i.e. for measuring the carbon stocks in above ground vegetation). One of these methodologies to support REDD+ projects is described in the VCS module VMD0001, where the estimation of above ground biomass is made solely by using permanent sample plots of different shapes to avoid bias and allometric equations which can be local or more generic if the former are not available.

\(^3\) In Forestry an allometric equation describes the relationship between an attribute that is difficult to quantify (i.e. biomass-dependent variable) and one or more easily measurable attributes (i.e. diameter, total height, or crown area – independent variables).
1.4.2 Quantifying above ground biomass using EO

A significant amount of research has been conducted to assess the value of satellite EO for biomass mapping in many developing tropical regions (Carreiras et al., 2012; Valerio et al., 2011; DeFries et al., 2007). The use of EO has been found to be able to supplement data collected during forest inventories and thus increase measuring and monitoring quality of above ground biomass and reduce the costs of field measurements (Gibbs et al., 2007; De Sy et al., 2012). There are many carbon quantification standards which utilise EO to support key components of their carbon stock quantification methodologies. For example, in the module VMD0022 from VCS, the estimation of carbon stocks is made using very high spatial resolution satellite imagery (e.g. from Quickbird or Worldview) for the larger trees which can be identified by the satellite sensor (i.e. the tree crowns) and using ground measurements and allometry for the smaller trees which cannot be identified using the Earth observation technique. In a tropical forest in Belize, in the Boden Creek Ecological Preserve REDD+ project, EO data collected by Landsat TM and WorldView to assist with the mapping of land cover and monitor changes in the cover. However the assessment of the carbon stocks in a more quantitative way is made using a field-based VCS module (VM0007), where permanent sample plots are used and allometric equations. If a reliable relationship between the field measurements and satellite data was established it could be used to repeatably assess the forest stocks without re-measuring data on the ground or with reduced cost and effort.

In Belize, only a few studies have assessed the capacity of EO to provide useful information on biomass (Viergever et al., 2008; Pope et al., 1994) while only one has made an attempt to establish the sensitivity of satellite imagery to biomass (Michelakis et al., 2013). Belize needs a continuous and effective way of biomass quantification to assist organisations that manage protected areas to enhance readiness for mapping and monitoring.
1.5 The importance of the savanna ecosystem in Belize

The Neotropical savannas of the American tropics cover approximately 2 million km$^2$ (Mistry, 2000b). The lowland savannas of Belize represent the most northern distribution of those savannas (Furley 2011), and in combination with the savannas of Yucatan and Peten they have been identified as a biologically distinctive bio-region (Lenthal et al., 1999). Recent carbon mapping of Belize using a synergy of data (EO and field measurements) shows that these savanna areas contain approximately 10% of the total carbon stocks of the country (Baccini et al., 2012; Saatchi et al., 2011), whilst botanical surveys by Goodwin et al. (2011) of the lowland savannas of Belize have highlighted the importance of these areas as centres of plant diversity and endemism. Bridgewater et al. (2012) identifies that savannas are poorly conserved in Central America.

Traditionally tropical savannas have always been an important resource for the local deprived populations through benefits that can be derived from economic and ecological services provided by those ecosystems. In a recent study in a savanna area near a small community in Belize (Crooked Tree), Wells (2013) interviewed local population and identified 18 ecosystem services (ES). Wells (2013) estimates that a combination of the five most important ES (i.e. Medicinal herbs and fruits, game species and palmetto provisioning, cattle habitat provision, and environmental setting for recreation) could input roughly ~$28000/year to the community of Crooked Tree.

1.5.1 The savanna woodlands

The Belizean lowland savannas include a significant amount of woody vegetation (~680 km$^2$) which can provide a variety of economic and ecological services such as sustainable timber extraction, controlled hunting and protection of Belize’s coasts, as well as ecotourism and non-timber forest products (i.e. resin and turpentine). These savanna woodlands consist of patches of trees such as Pine (*Pinus caribaea var. hondurensis*) and oaks (*Quercus oleoides Schiltd*) while scattered indicator trees and shrubs of Neotropical savannas within those patches are also abundant. Such vegetation species include the Craboo (*Byrsonima crassifolia*), Yaha (*Curatella*...
*Americana* and the palmetto palms (*Aceolorraphe wrightii H. Wendl*). According to Dinerstein *et al.* (1995) the pine dominated woodland patches represent a unique and one of the few example of lowland tropical pine forests in the Neotropics, whose biological importance leads them to being priority on the conservation list of regional management organisations, and is classified by the World Wide Fund (WWF) as a critical and endangered ecosystem. These pine communities are not just scattered trees within grassland dominated savanna areas, but a significant portion of them can be defined as forests according to the FAO definition. Previous researchers have also pointed out the importance of the denser pine areas as producers of timber and secondary forest products such as turpentine and rosin (Standley and Samuel, 1936), while their importance in flora and fauna biodiversity is also significant (Bridgewater *et al.*, 2012). The denser patches of the pine areas provide shelter and food source for many fauna species such as the IUCN endangered species of jaguar (*Panthera onca*), the yellow-headed parrot (*Amazona oratrix*), and for other mammals such as the tapir (*Tapirus bairdii*) as well migratory birds like the jabiru stork (*Jabiru mycteria*).

The extent of the savanna ecosystem of Belize was recently mapped as part of a Darwin Initiative project (Bridgewater *et al.*, 2012; Cameron *et al.*, 2011) using a combination of satellite images and field observations (Fig 1.2A). The woody vegetation types that were identified using the synergy between remote sensing and field observations were mapped as short-grass savannas with dense trees or shrubs’ and ‘forest inclusions’. Meerman *et al.*, (2011) incorporated these classes into producing a new version of the UNESCO classified national ecosystems map of Belize in ‘VA2a (1) (2)’ and ‘VA2a (1/2)’ (Fig. 1.2A-C). This mapping work was significant because it provided the foundations for an assessment of the extent at a national scale of the savanna landscape, with the new data providing a more comprehensive delineation of the savanna land cover and a division into its less woody and woodier components.

---

4 *Forests according to the FAO are defined as minimum surface areas of 500 – 10000 m², minimum canopy area of 10 – 30% and minimum tree height at maturity from 2 – 5m.*
FIGURE 1.2 (A) the three lowland savanna subtypes with the dissolved protected areas with savannas shaded light grey, (B) and (C) representative photographs for the VA2a(1)(2), and VA2a(1/2) savanna subtypes respectively. The bar-charts show the national area and percentage of land (labels) covered by the area of the three UNESCO savanna subtypes.

The lowland savanna areas are threatened by increasing fire as shown by satellite products derived by the MODIS Active Fire and Burned Fire Products (Warmerdam, 2010), increasing housing and road infrastructure development, while the whole country is prone to hurricanes (i.e. Belize comes sixth out of 31 Central America and Caribbean countries using a hurricane destruction index developed by Strobl (2012) putting lowland savannas which cover a significant amount of Belize’s coast in a
challenging position. The woody vegetation is also under human and natural threat due to uncontrolled fire and damage from hurricanes which can result in the conversion from savanna woodlands to grassland (Furley, 1974; Hicks et al., 2010; Bridgewater et al., 2012). To assist mapping and monitoring of the woody component of these savanna areas the country of Belize needs a more detailed identification of the woody cover founded on a sound methodology and data which would allow monitoring of this resource in the future. Such method could be used to protection and management for conservation planning at finer scales (i.e. forest management at the hectare scale).

1.6 Improving monitoring through better mapping using EO in tropical savannas

One of the most significant cross-cutting current discussions in ecology, biogeography, and EO science today is whether the available EO data and methods are adequate for mapping and monitoring the structure and dynamics of communities within tropical savanna ecosystems (Saatchi et al., 2011; Baccini et al., 2011). In forestry also managers and researchers question whether EO data and techniques that are now used in operational forestry (i.e. planning of primary production or assessment in carbon stocks) can be transferred and made operational for more heterogeneous forest types and more open woody environments. Some successful examples exist in heterogeneous tropical savannas, such as the use of aerial photography to assess the development of models for development of woodland communities and landscape change (Archer, 1995).

Despite some mission failures, continuous and established collections of satellite EO data are creating excellent conditions for monitoring changes over time in tropical savanna woodlands (Aplin, 2005), using the more frequently collected data by satellites over smaller time intervals as well as improvements in digital analysis methods. The wider range of EO data available today at finer temporal and spatial resolutions creates opportunities for exploring change in savannas at several ecological scales. For example EO data and derived products can be used in combination with ancillary
INTRODUCTION

information such as such as fire history, drainage, climatic factors, and land cover and land-use as well other layers (Stuart et al., 2006) to enable conservation assessments and monitoring of savanna woodlands to be conducted for multiple purposes.

1.7 The need for this research and anticipated user value

Developing countries such as Belize presently have limited means to collect all the necessary information needed for effective conservation and management of forest resources; however this data is essential in the context of international climate change and biodiversity agendas such as REDD+ and the UN-CBD, since these agreements require reliable and consistently collected information about forest stocks, forest harvesting and carbon sequestration baselines. For example due to constraints of finance and personnel resources, both governmental (GO’s) and non-governmental organisations (NGO’s) within Belize do not routinely collect vegetation structure data for their monitoring and managing activities unless these are essential and generate a direct income. Although these data can be very useful for establishing baseline information about forest stocks and carbon sequestration estimations for small areas, there are limitations of the small volumes of data that can be sampled and it is difficult to up-scale these limited area and occasional surveys to construct reliable results at national and sub-national scales.

An EO approach for assessing woodland cover, based upon a combination of passive optical and active microwave satellite data and methods can possible provide a feasible and cost-effective means for management organisations to measure and monitor the extent and structure of their forests and wooded areas from regional, down to national and sub-national scales (i.e. ≤ 10000ha). EO approaches are providing data at higher spatial, spectral and temporal resolutions at lower cost, enabling forest managers to acquire comprehensive images for the assessment of wooded environments. Although the analyst cannot directly measure the same tree structural attributes of a wooded area (e.g. tree canopy width, tree location) from this imagery, the passive optical imagery can be exploited using long-established image visual interpretation techniques or statistical image analysis for exploring the statistical relationships between the EO image model and the ground reality (Lillesand, 1994). In a discussion article on the
value of active microwave EO as a means for biomass prediction Woodhouse et al. (2012) discuss the links between the active microwave data and biomass that have been observed using empirical models datasets but they also clarify that microwave datasets are not a direct measure of biomass.

This research will allow methods to be developed which produce information to assist in the management and conservation plans of NGO’s and GO’s through:

(A) Enabling more reliable information extraction from EO about the vegetation structure of the pine dominated areas within the lowland savannas.

(B) Update and add understanding concerning the use and limits of the existing methodologies for identifying and monitoring the woody component of the lowland savannas.

1.8 Aims

The aim of this research is to determine whether it is possible to use satellite EO, combined with in situ measurements as a reliable and a cost-efficient means to assess the vegetation structure of pine dominated areas occurring throughout the tropical lowland savannas of Belize under different protection and management regimes. The key objectives for achieving the aim above are summarised as:

(1) Describe quantitatively the structure of the lowland pine-dominated savanna woodlands and to understand if these characteristics are similar or different for woodlands under different types of protection and management.

(2) Investigate the sensitivity of satellite microwave EO collected by ALOS PALSAR to AGWB as measured by field survey in these woodlands.

(3) Develop and validate a statistical model to predict AGWB from ALOS PALSAR backscatter intensity data, and examine any effects of woodland structure upon the backscatter signal.
Produce and evaluate the first fine-scale mapping of AGWB (i.e. 1ha spatial resolution) within the savanna woodlands of Belize using the prediction model developed in (3).

The pine dominated areas examined in this research study are the most Northern component of tropical lowland savannas (Furley, 2011). These areas are dominated by one pine species (*Pinus caribaea var. hondurensis*) which shows only minor differences in the individual trees architecture in comparison to other species, whilst allowing differences in the structural characteristics that may relate to differing growing conditions and protection and management to be examined. Occupying the lowland savannas in Belize their geographical distribution is widespread within the country and covers different climatic conditions and management practices. Passive optical EO data collected by the sensors SPOT 5, and Worldview I, and II, and microwave EO data collected by the satellite sensor ALOS PALSAR are employed, in conjunction with both, primary forest inventory data collected by the author and from existing forest inventories.

**1.9 Structure of the thesis**

This introductory chapter has presented an overview of the research, its rationale and a justification for undertaking this research, its anticipated uses and the benefits of this new understanding for potential uses of this information and how it may provide and advance existing knowledge and expertise.

Chapter 2 expands on this introductory section by reviewing the literature relating to the importance of understanding vegetation structure as well previous work conducted using EO in tropical savannas, and presents both the technical approach and specific methods that will be followed in this research project. The main EO datasets that are used are presented and the background methodology for using EO and field observations to predict AGWB within forested environments is also discussed.

The three chapters which follow are individual research articles (chapter 3, and chapter 5) while chapter 4 has been derived using results and discussions from two articles. All have been published or have been accepted subject to editorial revisions at the time of
submitting the thesis. The individual research chapters that form this thesis were conceived and planned from the beginning of this PhD research in response to the objectives to be achieved to complete the overall aim. They thus have similarity in that they are all connected by a common purpose and country context, but each tackles a particular objective as part of the overall aim. The connections between the chapters and the way they interact and combine is illustrated schematically in Fig.1.3.

Chapter 3 establishes the use of ALOS PALSAR backscatter as the means for predicting biomass in the pine-dominated lowland savanna areas in Belize. It also examines how relationships between radar backscatter data and AGWB measurements may vary depending on the size of the field plot used, the intrinsic variability that is recorded and the number of ALOS pixels that are averaged.

FIGURE 1.3 the interactions between research chapters

In chapter 4 the relationships between vegetation structure and tree population density in these woodlands are analysed, and any influence of protection and management upon these structural characteristics is examined. Chapter 4 also establishes a statistical relationship between backscatter and field measured AGWB examining the vegetation structure attributes that may drive the ALOS PALSAR backscatter response; a semi-empirical model which predicts backscatter attenuation in relation to AGWB is utilised to predict AGWB/ha in the areas of study.
In chapter 5, the semi-empirical model developed in the previous chapter is then used to map AGWB at fine scale (100mx100m) designed for use in national and sub-national vegetation biomass assessments; the mapping is then evaluated using previous ground based and aerial estimates of biomass for two selected areas in Belize, and the new predictions are compared with estimates for the same ground areas derived from two pan-tropical AGWB maps.
References


INTRODUCTION


Ministry of Natural Resources & the Environment (2013) Rationalization exercise of the Belize national protected areas system.


Standley, P.C & Samuel J (1936) The forests and flora of British Honduras; in cooperation with the Conservator of Forests and the Agricultural Officer of the Colony


UN Doc. A/CONF.151/26 (Vol. III) (1992) Non-legally binding authoritative statement of principles for a global consensus on the management, conservation and sustainable development of all types of forests, report of the united nations conference on environment and development


Chapter Two

Earth Observation & Savanna Woodlands

2.1 Introduction

Earth observation (EO) is increasingly used as a practical means for characterising forest ecosystems in many parts of the world. Particularly during the last five years, researchers have increased their interest in developing their understanding of how optical and microwave EO data can be used together to estimate various structural parameters of tropical woodlands in Africa and Australia. This has resulted in a considerable literature published on how various structural parameters of trees can be estimated by active or passive EO. Once developed, such methods can be used to estimate various parameters of an ecosystem over relatively extensive areas, an ecosystems capacity for storing carbon and maintaining its biodiversity. This chapter specifically reviews the literature concerning:

(A) How various measures of the structure of wooded ecosystems can provide information to support decisions about their protection and management, and

(B) How optical and microwave EO can be used for quantifying forest structure and stocking\(^5\) within tropical savanna woodlands, with particular reference to Belize.

Researchers from different disciplines acknowledge that forest structure is a broad concept and can acquire multiple meanings depending on the problem being addressed.

---

\(^5\) In this research we define stocking as the amount of trees present within a forest stand in relation to what should be there for the ideal productivity to be achieved.
for a wooded ecosystem or the management purposes. A general definition which is widely used by many forest and woodland managers whose interests may range from wood yield to carbon storage is given by Wenger et al. (1984) who describe stand structure as the number of trees by species and tree size within a forested or wooded area.

Within this definition structure can be considered as a function of response to local environmental conditions and management practices. In a wooded area that is for example managed for yield production and carbon storage, decision makers often use a range of many structural attributes that can be measured per tree and at the stand scale which in combination may inform management decisions at the stand scale. These attributes can be the plant age, species composition, diameter at breast height (DBH), total basal area (BA), AGWB, total height (Ht), canopy cover (CC), tree number density (N), volume and site quality (Husch et al., 2003) (table 2.1).

### TABLE 2.1 Description of different stand structure attributes used in operational forestry and research

<table>
<thead>
<tr>
<th>Forest Structure attribute</th>
<th>Attribute Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plant Age</td>
<td>Mean age of plants within the stand</td>
</tr>
<tr>
<td>Diameter at Breast Height (DBH)</td>
<td>Mean diameter of plant stem at the height of 1.3 meters above ground</td>
</tr>
<tr>
<td>Basal Area (BA)</td>
<td>Sum of basal area of all individual trees within a stand</td>
</tr>
<tr>
<td>Mean Height</td>
<td>Mean top height of sample trees within the stand</td>
</tr>
<tr>
<td>Canopy Cover (CC)</td>
<td>Percentage of ground covered by vertical projection of the outermost edges of the foliage of the plants within a stand</td>
</tr>
<tr>
<td>Above Ground Woody Biomass (AGWB)</td>
<td>Sum of biomass of all individual trees within a stand</td>
</tr>
<tr>
<td>Volume</td>
<td>Amount of merchantable wood classified to the size and quality of wood</td>
</tr>
<tr>
<td>Stand Density</td>
<td>Various quantitative measures of stocking on a per unit area basis - [e.g. Volume/Area, Tree Numbers/Area, Canopy Cover/Area]</td>
</tr>
</tbody>
</table>

6 In Forest science a forest stand is defined as a group of trees. The area and nature of the forest stand differs by region and forestry law. For example in Belize, for the Rio Bravo Conservation and Management area forest stands have irregular shapes with a size of 45 or 180 hectares each (SmartWood Program, 2005).

7 The diameter at breast height (DBH) is measured at different heights, something which is dependent on the geographical region. In Belize, previous researchers measured DBH at 1.3m; thus for the DBH observations in this thesis 1.3m is used as the breast height to be consistent with previous research.
Stand density is an illustration of a structural parameter which is often vaguely described by woodland managers. For example at the stand scale density is often quantitatively described by a single numerical value representing the number of living trees present within a certain area. A woodland manager often characterizes the density attribute of wooded areas with qualitative measures or as Zeide (2005) describes it:

“...Vague adjectives such as under stocked or dense...”

Such qualitative characterisation of structure, although it provides some information regarding tree density within an area, often does not provide information about the spatial distribution of the trees or enough information about sizes and crowding within a given spatial extent. Stamatelos and Panourgias, (2005) have found that the tree sizes and crowding attributes are equally important as knowing absolute tree numbers when attempting to describe tree number density, biomass or volume within a wooded ecosystem because these provide insights on the underlying ecological processes and management activities.

2.2 Stand structure for protection and management

An illustrative set of indicator variables often used for the description of structure at the stand scale, according to Noss (1990), often includes the number of trees and the canopy cover per area. These two parameters have also been found by other researchers to provide significant information for guiding biodiversity management and conservation decisions. For example, Andrén (1994) investigated the impact of the number of scattered trees within a landscape as well as tree canopy cover upon the observed biodiversity of mammals and birds and suggested that these structural attributes seem to have a significant influence upon the local population density of fauna. Manning et al. (2006) reviewed the implications for conservation of scattered trees and also found that tree density and canopy cover appeared to be major factors controlling local levels of biodiversity. Specifically his findings illustrated that a landscape can be a hospitable habitat for fauna when the number of trees per area within the landscape and the CC are above a certain minimum value; however it can quickly become a very inhospitable environment when these minimum levels are not
attained. CC is also considered an important biophysical parameter within savanna ecology, especially in relation to biomass, since increased tree CC implies increased amounts of woody biomass.

In that context, Martens et al. (2000) emphasize the dynamic relationships between CC and light that reaches the understory within grassland/forest continuum ecosystems. According to their findings light becomes a very important factor which has a negative impact on below ground biomass and AGWB within such ecosystems when CC percentage increases. Increasing CC appears to reduce the production rate of biomass per unit of ground cover according to Kennard & Walker (1973), and Mordelet & Menaut (1995) have observed higher biomass under more open canopies but lower biomass under canopies with higher CC. Belsky & Canham (1994) also put forward the importance of light through its relationship upon soil temperature within savanna ecosystems that have a scattered woody component. The relationship between soil temperature and light penetrating the canopy of a forested patch within a savanna varies as a function of light intensity and duration; thus soil temperature below thicker canopy is reduced while the opposite effect is observed in canopy gaps within the patch. Muoghalu & Isichei (1991) also suggest that open and closed canopy cover savannas contribute positively or negatively to grass growth on the woodland floor and attribute this mainly to the shade preference for the grasses.

Often playing the role of decomposers in biochemical cycles, below-ground species are very important for ecosystem processes and resilience. When trying to characterise below-ground biodiversity in a heterogeneous mosaic landscape, David et al. (1999) discovered strong correlations between above ground vegetation and structure relating to ‘openness’ of the landscape which could be expressed through tree number density and percentage canopy cover.

Cramer et al. (2001) mentioned the significant influence that vegetation structure seemed to have upon the capacity of natural ecosystems to act as CO₂ sinks. They argued that major changes are observed in the spatial pattern of carbon fluxes and the importance of carbon sinks in places where changes are also detected in the vegetation structure of the ecosystem. Various measures of vegetation structure have also been
found to be strongly correlated to an ecosystem’s capacity for absorbing and storing carbon. Chen et al. (2003) conducted research on the large scale vegetation structure, exploring the relationships between the architectural parameters of tree canopies such as the leaf area index (LAI) and foliage clumping index (FCI) upon the net primary productivity (NPP) of boreal forests. They found that they could estimate with high confidence the net primary production (NPP) using a multi-angular EO method and measuring two of the most important vegetation canopy architectural parameters of LAI and FCI instead of using more traditional NPP estimation methods which are based on ground measurements.

A distinctive element of structure that is often used within wooded ecosystems and which is primarily managed for biodiversity conservation is vegetation vertical structure. In their book relating to how vegetation vertical structure is important in maintaining biodiversity in a forested ecosystem, Brokaw (1999) explains vertical vegetation structure as the ways in which woody biomass is apparent from bottom to top in space starting from the tree roots and stem to boles and canopy volume. Measured parameters of vertical structure can provide volumetric quantification of individual trees or stands as well as describing the distribution of vegetation material along the vertical axis (Lefsky et al., 1999). According to Brokaw (1999) and Wulder & Franklin (2003) two of the parameters that are commonly utilized for describing stand vertical structure are the total tree height and CC. Information such as the woody vegetation at the individual tree scale as well as canopy area and geometry, canopy volume, tree height, CC and tree density per area can be utilized to provide a comprehensive characterisation of savanna woodlands and used to develop mapping classes. Stand vertical structure is important because it can assist the development of more comprehensive Earth observation methods to predict forest structure. For example the canopy volume has been found to have an effect on prediction of forest structure at the stand scale (i.e. biomass) using EO methods. Previous studies within forests and other wooded areas have shown that horizontal and vertical structural parameters are often linked and can have strong relationships. For example the size of tree crowns is most likely to increase with the increasing diameter of the tree stems and both crowding and tree number density can be determined by the space that trees
occupy (e.g. crown and roots) (Zeide, 2005). This implies that if one structural descriptor such as canopy size can be measured and quantified, an established correlation with other structural characteristics can be used to estimate, for example, the number of stems, volume, and biomass. These relationships (e.g. biomass vs number of stems) can be used to design effective ground survey effort.

These inter-correlations have been studied extensively in plantations and forested environments and are well established; however for tropical savanna woodlands only recent research has produced promising results. Salis et al. (2006) demonstrated the strong relationship between DBH and AGWB for individual trees as well as with wood volume using destructive sampling and regression methods within savanna woodland in Brazil. In Belize, Brown et al. (2005) researched the relationships between biomass carbon per tree and the product of crown area and height (crown area x height) within a lowland savanna woodland and established relationships for Pine trees, broadleaf trees as well as for palmetto and other common savanna tree species. They used 3D aerial photography to map the horizontal (tree number density, crown area) and vertical (total height) structure for samples of main savanna vegetation communities located in a protected area in Belize. Their findings showed that local variations in biomass revealed a strong positive correlation between biomass and vertical structure for all three classes of tree vegetation. The ground data used in the research by Brown et al. (2005) were collected at 0.1ha circular sample plots covering approximately 10000ha of savanna area in the Rio Bravo Conservation and Management Area (RBCMA) and the data volume collected by EO (~10cm Aerial photography) was well distributed covering 100% of the ground measurements. However future research for conducting a similar study at a national or regional level this approach is probably unrealistic.

Davis & Roberts (2000) also conceptualize vegetation structure as a three dimensional measure that can provide information about natural ecosystems at different scales and through time. Within their review on stand structure for terrestrial ecosystems it is described how the woody component of an area can be structurally characterized either at the leaf, branch and canopy scale or at the stand or regional scale. Each structural
scale is important within the ecosystem. Each plays different roles and requires different measures to be extracted. However many researchers suggest that a fixed size area sample plot (0.3 – 1ha) is the most frequently sampled component of the woody ecosystem and it can provide information for whole stands. The understanding of the vegetation structure at this scale often provides often valuable information even for extrapolating such data for bigger areas (i.e. multiple forest stands in RBCMA).

2.3 Satellite data overview

For the purpose of this review EO can be defined as the use of electromagnetic radiation (EM) to observe features of the Earth’s surface from above (Rees, 2001). Features and characteristics that are found on the Earth’s surface or belong to it such as vegetation, soil, water or man-made structures, produce distinctive trends on remote sensors when for instance reflect, emit or backscatter EM radiation which is detected by remote sensors. The digital data recorded by the remote sensors are typically converted into two dimensional images comprised of picture elements (pixels) for further processing and analysis.

EO approaches are already extensively used for quantifying vegetation characteristics and structure within tropical ecosystems. The typical methodology uses digital abstractions of the reality known as remotely sensed images, which can be produced from the raw sensor data in several spectral and spatial resolutions. EO data are exploited using long-established image interpretation techniques or digital image processing for exploring relationships between the image model and the ground reality (Lillesand, 1994). Wulder & Franklin (2003) describe EO as a significant resource of natural environment information as well as a sound and increasingly well-established set of methods, with data increasingly available at lower cost and over a wider range of spatial resolutions or scales. Different sensors provide different spatial, spectral and temporal resolutions of data about the ground surface.
2.3.1 Earth observation data concepts

2.3.1.1 Passive Optical Earth observation

Wulder (1998) explains passive optical EO as a series of processes interactions by which EM radiation emitted by the sun, reflected off an area of interest and received by a sensor. The phrase ‘passive’ is because the technique uses the sun as the primary source of the emitted radiation that is captured by the sensor. The technique does not actively emit its own radiation. Optical EO sensors capture radiation in the visible and infrared regions of the electromagnetic spectrum (approximate wavelength $\approx 4 \times 10^{-7}m$ – $10^{-3}m$).

2.3.1.2 Passive Optical Earth observations in tropical savannas

EO data have been successfully utilized for mapping and characterizing terrestrial ecosystems within tropical environments such as tropical savanna ecosystems (Parra et al., 1995, Menges et al., 2001, Johansen & Phinn, 2004). The temporal integrals of the normalised vegetation index (NDVI) derived by the Advanced Very High Resolution Radiometer (AVHRR) were assessed against field data collected by Diallo et al. (1991) to create maps illustrating the primary productivity of savannas in Senegal. The data were collected in 1987 and 1988; however due to different weather conditions in the two data collection dates, strong relationships between NDVI and primary production could not be established. The study concluded that humidity and rainfall in the area are probably the main reasons for the unsuccessful attempt to characterise savannas according to the primary productivity.

Using the vegetation continuous fields (VCF) product derived from MODIS data as an independent variable and the total biomass found within 44 field sample plots as the dependent variable, Anaya et al., (2009) developed linear and exponential empirical relationships ($0.55 \leq R^2 \leq 0.82$) which enabled them to produce regional biomass maps for primary and secondary forests within savannas among other forested areas of Colombia. The authors of the study used these results to argue that increased canopy cover was related to increased biomass levels. Anaya et al., (2009) identified the main
drawbacks of satellite optical sensors to: (A) inability to deliver three-dimensional information about forested areas for biomass estimation, since the reflected signal collected by the optical sensors comes only from the upper layers of vegetation, and (B) previous research has shown that there is a saturation point (~150 t/ha) above which the sensor data was not sensitive to further increases in ground measured biomass. However in the study by Anaya et al., (2009) their linear model does not show a saturation point, while the exponential empirical model that was fitted has a saturation point much larger than that usually cited in the literature (i.e. Anaya et al., 2009) claimed sensitivity up to study ~500 t/ha vs. 150 t/ha that has been previously cited by Steininger, (2000).

Lu et al., (2004) identify strong correlations between forest structure parameters (i.e. AGWB & BA) and LANDSAT TM reflectance data. In their research Lu et al., (2004) measured in the field the above ground biomass and basal area in 338 sample plots and used the LANDSAT TM pixels in each of the plots to assess the relationship between LANDSAT TM and forest structure using Pearson’s correlation. The results show that part of the short-wavelength infrared region of the electromagnetic spectrum sensed by spectral bands 5 and 7 of LANDSAT TM showed the strongest correlation to above ground biomass (band 5, Pearson’s correlation coefficient = -0.826) and basal area (band 7, Pearson’s correlation coefficient = -0.789) in Brazilian savannas in Pedras. In their conclusion Lu et al., (2004) stress the importance of forest structure in using their approach since resulting shadows due to vegetation structure may reduce the value of their method.

Mutanga et al., (2012) used very high spatial resolution EO data collected by the narrow spectral bands of WORLDVIEW-2, to tackle the saturation problem in the passive optical EO and estimate biomass in a savanna wetland within a protected national park in South Africa. The hypothesis of this research was that the narrow spectral bands of WORLDVIEW-2 may improve significantly the biomass estimation above the saturation points (i.e. ≤ 150 t/ha) commonly observed in the passive EO literature. This study showed that a derived NDVI using WORLDVIEW-2 Red edge band (0.705 –
0.895 micrometres) and the near infrared band (0.77 – 0.895 micrometres) may be used in combination with total above ground biomass field measurements made in 57 sample plots in a machine learning algorithm (RandomForests) to predict biomass in dense wetland areas. Validating their RandomForests biomass prediction Mutanga et al., (2012) note the inability of the RandomForests algorithm to predict accurately biomass values for the higher values of the biomass range (i.e. ≥ 35 t/ha). Thenkabail et al., (2004) also used NDVI in their case derived from IKONOS data to estimate dry biomass in oil palm plantations of African savannas. Although the exponential model developed in that study achieved a relatively high coefficient of determination ($R^2 = 0.63$) the authors mention that significant uncertainty was still observed when their model was validated internally (uncertainty: 28% – 36%). In general it seems that satellite passive optical EO data can in theory provide useful information for tropical savanna mapping; however a practical question that needs to be asked is whether these methods and processes can be iterated frequently under all different weather conditions such as humidity, cloud coverage and rainfall.

Asner (2001) in his article about the utilisation of LANDSAT TM imagery for mapping the Brazilian Amazonia argues that the main drawbacks of observing in tropical areas using solely optical data are the extensive cloud coverage for the whole year and the low temporal resolution of some sensors such as LANDSAT. The author also argues that even though there are several other optical satellites that can observe such environment often with higher temporal resolutions such as the AVHRR and MODIS, cloud coverage remains a major problem and for those sensors spatial resolution is often not adequate. This leads Asner (2001) to conclude that the evolution of other sources of EO such as radar should be highly developed to overcome these problems.

To characterise tropical savannas at the stand scale researchers have also utilised higher spatial resolution data collected by other satellite sensors such as Quickbird, IKONOS and SPOT5. In this context, Boggs (2010) performed a series of analysis using SPOT5 and QUICKBIRD satellite imagery as well as object based image analysis (OBIA) and pixel-based (NDVI thresholds) methods for estimating CC in southern African savannas. His conclusions suggest that although QUICKBIRD data can provide results with acceptable accuracy both for thematic and geometric properties of canopy
cover within savannas in either method, SPOT5 provided acceptable results only when the OBIA methodology was used. This is mainly a result of the image limitations of the SPOT5 data (Lower spatial and spectral resolutions than QUICKBIRD). Boggs suggests that OBIA methods show more potential compared to pixel-based when using the medium resolution sensor data such as the SPOT5 data, primarily because within OBIA the image analyst can also incorporate additional information from the higher spatial resolution of the panchromatic band of SPOT5 (Image information in tones of grey – 2.5m spatial resolution) into the segmentation process.

2.3.1.3 Passive Optical EO in Tropical savannas of Belize

Passive optical EO has been successfully used for mapping and characterizing the overall extent of woodlands within tropical savannas and in particular, savannas within Belize. Iremonger & Brokaw (1995) used medium resolution passive optical EO data such as SPOT and LANDSAT in combination with previous classifications which relied to aerial photography and historical field observations (Wright *et al.*, 1959) to map the different vegetation types in Belize. Their work was primarily an attempt to estimate which of the vegetation types were poorly described in 1959 within the protected areas of Belize. Their study identified 51 vegetation types that could be recognised using the combination of satellite data interpretation supplemented by historical sources the resulting map has been widely used as ancillary data for conservation managers (Meerman & Sabido, 2001).

Following this work, Meerman & Sabido (2001) used coarse resolution LANDSAT imagery and ancillary GIS data to update and correct the previous mapping conducted in 1995. Specifically their research focused on the identification of the ecosystems of Belize on a macro-scale. Field checking of their results shows that many of the ecosystems in Belize are mapped accurately in the macro-scale; however they conclude that savannas are complex ecosystems which made them very difficult to map, using these particular EO data and methods. Stuart *et al.* (2006) demonstrated that the broad extents and boundaries of lowland savanna areas could be classified accurately from LANDSAT. Data could be classified using Maximum Likelihood Classifier methods (MLC), using training data produced by GPS held surveys. The weakness of this
approach was that it requires extensive ground surveys to produce the training data and using LANDSAT it was not possible to consistently separate several subtypes of vegetation found within the savannas. The work from Stuart et al. (2006) however remains important since the availability of very high resolution satellite imagery easily accessible from Google Earth as well ground knowledge can be interpreted and used as pseudo-ground truth data, and can now provide researchers with information to support and extend ground truth data and reduces the need for extensive data capture.

A recent study by Cameron et al. (2011) used a combination of land cover classification methods (per-pixel and per-object) as well moderate spatial resolution satellite imagery captured by SPOT for discriminating different lowland savanna land cover classes in Belize. In their study, Cameron et al. (2011) appear to successfully identify vegetation classes such as wetlands, forest inclusions, open savannas and the previously difficult to classify pine dominated savanna woodlands. Their study is still under validation and a full accuracy assessment is not yet available, however preliminary estimates show promising results (Overall accuracy ~ 72%).

These previous research findings on mapping within the lowland savannas of Belize using EO suggest that higher resolution optical sensor data may be needed to characterise these areas with higher accuracies. In 2008, Stuart and co-workers demonstrated that very high spatial resolution data (IKONOS) and object image analysis (OBIA) can provide an acceptable standard of accuracy for classifying some specific savanna land cover classes such as open savanna and gallery forests (Stuart et al., 2008). In this method workers used a semi-automated approach and thus less work on ground surveys was required; however with this approach it was still difficult to automatically identify with adequate accuracy certain savanna vegetation sub-types such as the economically important pine-dominated areas.

Following this previous work using IKONOS data, Michelakis et al. (2008) investigated the capability of very high spatial resolution data and object-based image analysis, which allowed regions to be ‘grown’, for characterizing pine dominated savanna woodland at a local scale according to tree density and canopy cover. In his concluding
remarks Michelakis et al. (2008) suggest that number density and CC were probably underestimated due to neighbouring tree crowns overlapping, the inability of the classifiers to separate individual trees within groups of trees or to capture the complete geometry and the canopy area of each tree. The strategy followed by Michelakis et al., (2008) in that study was to utilize a pan-sharpened product of IKONOS, although it offered improved spatial resolution, such as a loss of spectral information, which is known to be an important information element for the identification of pine, it also introduced some drawbacks.

2.3.1.4. Issues when using passive optical Earth observation in tropical savannas

While optical EO data have been utilized by the scientific community and proved useful for broad scale vegetation mapping and monitoring within savannas and savanna wooded areas, during the recent decades passive optical methods have been also vigorously criticized by a number of researchers. The Achilles’ heel of the optical EO approach according to its critics is that optical EO is not able to capture data when extensive cloud cover is present, and also the reflectance is affected when shadows are present, or to capture data during the night. Additionally Asner and Warner (2003) identify that shadows found in IKONOS imagery played a significant role in tropical savannas in Amazonia decreasing the collected reflectance from IKONOS in the red band, which can have important implications in canopy cover estimation using IKONOS datasets. Extensive clouding is regularly observed in tropical environments while the weather conditions which may influence the optical data characteristics are highly variable at the different data collection dates.

An illustrative example describing the improbability of passive optical EO to being able to capture data sufficiently frequently and comprehensively in tropical environments was shown earlier in this chapter by Asner (2001) where the researcher explores the LANDSAT archive (1984 – 1997) for the Brazilian Amazonia and concluded that sufficient cloud free acquisition to allow regular monitoring of many areas was highly improbable and alternative approaches must be examined for monitoring such natural environments at regular frequencies. Many researchers now argue that it is possible to largely overcome these limitations of the optical approach for frequent monitoring by
using a combination of the occasionally capturing of high resolution optical data supplemented by more frequent acquisition of data from active microwave radar satellites.

2.3.1.5 Radio Detection and Ranging (radar)

Radio Detection and Ranging (radar) EO refers to the microwave region of the EM spectrum (approximate wavelength $\approx 3\text{cm} - 1\text{m}$, or frequency $\sim 300\text{MHz}$ to $30\text{GHz}$). Radar systems typically operate in one frequency; while the system which classifies microwave frequencies that are usually used by radar EO is shown in Fig. (2.1). radar is an important component of microwave EO and can be defined as a system with two elements. The illumination generator which transmits microwave pulses towards the area of interest and the receiver which measures the scattered radiation from that area (Woodhouse, 2006). The microwave region of the EM spectrum is particularly useful for monitoring tropical natural environments since the emitted radiation has the ability to penetrate clouds and thus offers an advantage over optical EO (Fig. 2.1). This ability allows more frequent data capturing and enables repeated monitoring in tropical areas.

![Figure 2.1](http://earthobservatory.nasa.gov/Features/RemoteSensing/remote_04.php)

To examine the contribution of the different radar data collected using different frequencies in real world problems, researchers have used a plethora of models which approximate the complexity of vegetation as abstract volumes and thus the interaction of the radar data with vegetation can be examined. For example Attema and Ulaby (1978) modelled vegetation canopy as a relatively homogeneous volume representing
homogeneous spheres and air to predict the radar backscatter. The microwave radiation wavelength plays an important role for the prediction of backscatter in relation to increasing biomass because it has been found that larger wavelengths (e.g. L-band and P-band) appear to have increased sensitivity to increasing size of the woody parts of the forest\(^{8}\) (e.g. branches, twigs, and stems. Shorter wavelengths such as in the C-band or X-band interact mostly with the green parts of vegetation (e.g. leaves) and do not show increased sensitivity to biomass (Fig. 2.2).

\[\text{FIGURE 2.2 Abstract representation of the ability of L-band radar to interact primarily with the woody parts of trees due to the longer wavelength in comparison to X-band and C-band. Figure created by the author (2014). Figure modified by Le Toan et al., (2001).}\\
\]

2.3.1.6 Synthetic aperture radar (SAR)

Satellite radar is one of the most expensive technologies in EO, mainly because the manufacturing process is significantly more expensive than optical sensors. Synthetic Aperture radar (SAR) is a Side Looking Aperture radar (SLAR) system and has the capacity to collect EO data cost-effectively, and with high spatial resolutions in contrast to the Real Aperture radars (RAR) which require significant economic resources to achieve the same resolutions of a SAR system. A SAR system is equipped with a much shorter antenna, which reduces significantly the manufacturing cost in

---

\(^{8}\) SAR data users loosely attribute the sensitivity of longer radar wavelengths to the ‘penetration’ of the emitted radiation though the upper canopy layers (e.g. leaves) and into the woody parts; however this ‘penetration’ is a result of the changing scattering mechanisms within a forest canopy and specifically the transition of scattering from Rayleigh to Mie scattering.
comparison to a RAR, and at the same time the SAR system can achieve significant higher resolutions than a RAR.

Satellite SAR systems have been utilized extensively for research during the last 25 years for environmental applications, particularly within tropical environments. Since the first SAR system which was mounted on a satellite in 1978 (SEASAT, L-band), the technology has boomed; specifically 15 SAR systems have successfully completed their operations; nine SAR systems are currently operational, while 16 new SAR missions have been planned for the future (CEOS handbook, 2014).

Following a similar process as the radar, the transmitting part of a SAR system which observes the Earth’s surface, emits electromagnetic waves and the backscattered radiation is collected by the receiving part of the SAR system. The process is repeated for multiple positions of the radar platform (e.g. a satellite) and the received signals are then stored and processed in the SAR system. The processing of multiple backscattered signals that have been stored in the SAR system produce a virtual aperture; which can generate two dimensional images of the Earth’s surface with higher resolutions than a real aperture (Fig. 2.3).

FIGURE 2.3 Oblique view of an abstract representation of aperture synthesis. The target on the ground is illuminated by multiple SAR beams at different positions of the SAR system on the flight path. The synthetic aperture is produced by processing the signals received by the SAR sensor, during the illumination of the target by the successive beams footprints.
2.3.2 SAR EO and tropical savannas

The evidence from many research studies supports the capability of synthetic aperture radar (SAR) to extract information about several vegetation structural parameters such as mean height, density and the vertical or horizontal distribution of AGWB. Synthetic Aperture radar sensors radar has been useful for studying a number of ecological processes at several scales (Furley, 2010; Kasischke et al., 1997b; Wegmuller & Werner, 1997). During the last decade a considerable literature has been also published on the capability of SAR data captured using the L-band wavelength to reliably predict locations of high AGWB, especially in tropical environments (Dobson et al., 1992, Luckman et al., 1998, Imhoff, 1995). In the context of savanna woodlands Mitchard et al. (2009) in their study within African savanna landscapes identify strong relationships between AGWB and the L-band backscattering coefficient and suggest that L-band SAR data can be potentially used for AGWB estimation at regional scales.

In Mitchard et al. (2009), radar data were tested in three different countries in Africa (Uganda, Cameroon and Mozambique) but notably all the study areas had flat topography, which may limit the generality of the correlation among L-band and AGWB only to areas of similarly flat terrain. Secondly most of the areas where the method was tested were dense woodlands (i.e. in Uganda and Cameroon: mean biomass recorded on the ground was 137 t/ha and 115 t/ha respectively). Thirdly, although most of the studies in the literature that utilise L-band radar to predict biomass find a saturation point less or equal than 100 t/ha in Mitchard et al., (2009) biomass is predicted up to 150 t/ha. This later limitation may be problematic when attempting to establish the same relationships to lower density woodlands (e.g. ≤ 100 t/ha). Also, land topography is a parameter which can have a significant effect upon the backscattering of microwave radiation and so is likely to affect that results derived from the backscatter observed, while the vegetation structure such as the CC topography (i.e.

---

*The point when the sensitivity of SAR to capture changes within wooded areas is reduced is called saturation point and is dependent on structural parameters of vegetation as well as SAR properties (Woodhouse, 2006; Woodhouse et al., 2012, Brolly and Woodhouse, 2012)*
lower percentage of canopy cover) allows the backscatter to interact with other targets besides vegetation such as bare soil. Santos et al. (2002) also investigated the backscattering effects of L-band data collected by satellite JERS-1 on the transition zones of tropical rainforest to savannas in two areas within Amazonia. Their analysis revealed the capability of the L-band to characterise these areas according to the AGWB present; however the authors also suggest that this approach cannot possibly be extrapolated to neighbouring areas of the Amazonia unless the process can be adapted to the local complexity of the landscape, vegetation structure and climate such as precipitation.

Acknowledging the influence of vegetation structure attributes such as density on the radar backscattering, researchers have made several attempts to establish these relationships, especially in woody communities within savannas. Lucas et al. (2010) carried out a series of analyses using satellite radar data collected by ALOS PALSAR against field data collected in 1139 sites for the characterisation according to AGWB of wooded areas with different vegetation structures such as (forests, woodlands, open woodlands) in Queensland, Australia. This research provides an extensive and very analytical discussion on the influence of moisture and vegetation structure at the L-band radar data; however one of the most interesting findings related to this PhD study is that the observed increased rate of the L-band backscattering related to the AGB increase is probably recognized as a result of the structural formations within the areas observed as well the different levels of AGWB. Specifically changes in the L-band backscatter were observed in areas of the same levels of biomass but with different canopy cover densities. This implies that the backscattering range of values collected by ALOS PALSAR for example within an extensive region such as a country, may not be enough for characterising the whole region according to vegetation structure or AGWB if different densities of vegetation are present and additional data will be needed.

Patel et al. (2006) in their recent study seeking to establish the sensitivity of C and L band SAR data to the woody density of the shrub (P. juliflora), hypothesize that since certain wavelengths of SAR data can provide volumetric information about trees (L-
band and P-band can penetrate deep into tree canopy) (Balzter, 2001) (Fig. 2.2) they could also provide a means for the quantification of stand density within an area, since density is effectively a three dimensional measure [density = \( F(\text{plants height, plants CC, plants number per area}) \)]. Their findings support their preliminary hypothesis since their results show that the backscattering coefficient resulting from L band is sensitive to variation in observed plant density. Although that study provides an indication of how L-band backscatter might be used to estimate plant density, Patel et al. (2006) make no attempt to differentiate the backscattering behaviours of L band in areas of mixed woody vegetation or for areas of bigger trees, where both cases L-band’s ability to estimate woody density would potentially saturate. The sensitivity of SAR to capture changes of several parameters within wooded areas is not always the same. Some vegetation parameters that have a significant role at SAR saturation are stem and canopy density, tree species while vegetation moisture is important too (Mitchard et al., 2009).

Recent evidence from research conducted in Belizean savannas suggests that microwave data collected by satellites may be a useful contribution to the EO data already examined for characterisation of savanna areas (Stuart et al., 2006). Zisopoulos (2007), and Cameron (2006) both examined the capability of very high resolution airborne radar data (5m pixel spacing) to characterise vegetation height (former researcher) and to classify broad vegetation types such as pine woodland, mixed vegetation and grasslands (latter researcher) within the same protected area of Belize (RBCMA). The results produced by Cameron (2006) showed that there was an underestimation of the vegetation height attributed to very low tree number density, airborne SAR geometry as well as edge effects. Zisopoulos (2007) compared the classification results produced using very high resolution pan-sharpened optical data (1m, IKONOS) and very high resolution radar data (AIRSAR, C, L, P wavelengths). He found that the radar data performed better than IKONOS in distinguishing the vegetation classes; dense forest, grassland and Pines. Within the same northern savanna areas of Belize, Viergever et al. (2008) conducted a local scale research study of how well AIRSAR data characterised vegetation height and above ground biomass
using SAR Interferometry (InSAR). In her concluding remarks Viergever et al. (2008) suggests that certain wavelengths of microwave radiation (X-band and C-band) can be effective indicators of above ground biomass (AGB) hotspots, as those radar wavelengths appear to be most sensitive to identify changes in vegetation height. However Viergever et al. (2008) found that in low density savanna woodlands such data utilised do not predict the height of the canopy with sufficient accuracy for these retrieved heights to be used to predict as an input AGB through the use of established allometric equations.

In Africa, Okhimamhe (2003) used SAR data collected by the European Remote Sensing satellites (ERS-1/2) which were operating in tandem to examine their capability for differentiating between vegetated woody areas (e.g. savanna woodlands) and exposed areas (e.g. grassland). Using Interferometric SAR techniques (InSAR), Okhimamhe (2003) found that the coherence of the SAR data was low in vegetated areas in comparison to exposed areas in savanna areas in Africa where the radar data coherence was higher implying a difference in vegetation height. He was able to use this information for land cover classification in combination with optical imagery collected by LANDSAT ETM.

Although the scientific community has increasingly used SAR in ecological studies during the last decade, there are some limitations of using active microwave Earth observation which must be taken under consideration. Information extracted by SAR can be usually be very complex as the backscattering of the signal is highly dependent on local surface moisture, topography and vegetation composition. As the benefits and limitations of each EO method (Active microwave and Passive optical) are becoming better understood, researchers are increasingly combining data from optical and microwave sources. This scientific trend is mainly an outcome of research studies showing that the integration of optical data products with microwave data products such as LANDSAT combined with SAR products such as ALOS PALSAR can lead to improved differentiation of land cover classes, woody vegetation and improve the estimation of tree density, especially within heterogeneous environments such as savanna woodlands (Lucas et al., 2006, Lucas et al., 2007).
2.3.3 Why use SAR in Belize

The importance of active microwave EO for protection and management in Belize and possibly other tropical countries can be illustrated by the data in table 2.2.

TABLE 2.2 Number of scenes with cloud cover less than 20%.

<table>
<thead>
<tr>
<th>Optical satellite sensor</th>
<th>National coverage regardless land cover</th>
<th>National coverage (20% within the scene to be lowland savannas)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number of scenes</td>
<td>Number of scenes</td>
</tr>
<tr>
<td>SPOT 4 (^{10})</td>
<td>34</td>
<td>0</td>
</tr>
<tr>
<td>SPOT 5</td>
<td>321</td>
<td>3</td>
</tr>
<tr>
<td>ALOS AVNIR (^{11})</td>
<td>118</td>
<td>14</td>
</tr>
<tr>
<td>LANDSAT 7 (SLC-off) (^{12})</td>
<td>168</td>
<td>29</td>
</tr>
<tr>
<td>ASTER (^{13})</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>DEIMOS-1 (^{14})</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>CBERS-2 (^{15})</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Total Number of scenes</td>
<td>641</td>
<td></td>
</tr>
</tbody>
</table>

Several on-line satellite data browsers were used to explore the availability of optical satellite data with low cloud coverage for Belize. The optical sensors were chosen according to the needs of a manager who needs to estimate parameters at the forest stand level. Table 2.2 shows that only a very small fraction of the optical satellite data collected are sufficiently cloud free for extracting information in a sufficient frequent and comprehensive manner for protection and management.

2.4. Summary

The purpose of the above sections was two-fold. Firstly, it has reviewed the scientific literature and established the importance of being able to measure and monitor vegetation structure at the stand scale, particularly with reference to savanna areas of low density tree cover. Secondly, it examined some of the possibilities and constraints of using passive or active EO sensor data and methods for quantifying these structural attributes within savanna woodland areas.

\(^{10}\) [http://sirius.spotimage.com](http://sirius.spotimage.com)

\(^{11}\) [https://auig.eoc.jaxa.jp/auigs/top/TOP1000Init.do](https://auig.eoc.jaxa.jp/auigs/top/TOP1000Init.do)


\(^{13}\) [https://api-test.echo.nasa.gov/reverb/](https://api-test.echo.nasa.gov/reverb/)


\(^{15}\) [http://www.dgi.inpe.br/CDSR/](http://www.dgi.inpe.br/CDSR/)
The findings of this review suggest that there are a set of potential ecological parameters describing forest structure that might be used to determine not only the economic value but also the conservation value of a fragmented canopy ecosystem such as savanna woodland. The field measured structural attributes of canopy cover (CC), total height (Ht), tree number density (N), basal area (BA), and above ground woody biomass (AGWB) emerge as four possible predictors which may be useful for characterising an ecosystem according to hotspots of AGWB. The relevance of measuring and observing these forest structure attributes to biodiversity conservation of an ecosystem is clearly supported by the findings in these sections. For example the tree numbers within a patch of tree dominated vegetation as well as the proportional canopy cover have been found to be possible predictors of the distribution and density of fauna within that patch or among neighbouring patches (Andrén, (1994); Manning et al., (2006)). A significant number of the forest structure attributes which were identified in this chapter can be estimated using a variety of satellite EO data and methods (table 2.3).

**TABLE 2.3 Forest structure attributes that are economically and ecologically important which have been estimated in tropical savannas using satellite EO data.**

<table>
<thead>
<tr>
<th>Forest structure attribute</th>
<th>EO type</th>
<th>Sensor</th>
<th>Methods</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tree Number Density</td>
<td>Active Microwave</td>
<td>SIR-C/X</td>
<td>Linear regression</td>
</tr>
<tr>
<td>(N)</td>
<td>Passive Optical</td>
<td>QUICKBIRD</td>
<td>Object-based Image Analysis</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SPOT-5</td>
<td>Visual interpretation</td>
</tr>
<tr>
<td></td>
<td></td>
<td>IKONOS</td>
<td></td>
</tr>
<tr>
<td>Basal Area</td>
<td>Active Microwave</td>
<td>JERS-1</td>
<td>Non-linear regression</td>
</tr>
<tr>
<td>(BA)</td>
<td>Passive Optical</td>
<td>LANDSAT TM</td>
<td>Pearson’s Correlation Coefficient</td>
</tr>
<tr>
<td>Above Ground Woody Biomass</td>
<td>Active Microwave</td>
<td>ALOS PALSAR</td>
<td>Non-linear regression Machine Learning</td>
</tr>
<tr>
<td>(AGWB)</td>
<td></td>
<td>JERS-1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Passive Optical</td>
<td>MODIS</td>
<td>Linear &amp; Non-linear Regression</td>
</tr>
<tr>
<td></td>
<td></td>
<td>LANDSAT TM</td>
<td>Pearson’s Correlation Coefficient</td>
</tr>
<tr>
<td></td>
<td></td>
<td>IKONOS</td>
<td>Machine Learning (RandomForests)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>WORLDVIEW-2</td>
<td></td>
</tr>
<tr>
<td>Canopy Cover</td>
<td>Passive Optical</td>
<td>QUICKBIRD</td>
<td>Object-based Image Analysis</td>
</tr>
<tr>
<td>(CC)</td>
<td></td>
<td>SPOT5</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>IKONOS</td>
<td></td>
</tr>
<tr>
<td>Height</td>
<td>Active Microwave</td>
<td>ERS-1</td>
<td>Interferometry, stereo radargrammetry</td>
</tr>
</tbody>
</table>
For example very high spatial resolution optical data (e.g. IKONOS, Quickbird, and Worldview) and high spatial resolution optical data (e.g. SPOT and LANDSAT) have been used extensively in combination with visual interpretation or automatic image analysis techniques (e.g. OBIA) to count individual trees per area and hence estimate canopy cover (CC). However there are two main problems which reduce the value of these optical datasets in tropical areas: (A) the continuous cloud cover (table 2.2) limits the value of useable EO data making these often insufficient or too infrequent to support regular monitoring or mapping at regular intervals that is needed for protection and management, and (B) climatic conditions such as precipitation and haze, and variable sun illumination conditions and shadows further reduce the value of optical datasets in these tropical regions.

These limitations can be addressed using the wide range of long-wavelength active microwave sensors (e.g. C, L, and P-band) which can still collect data under heavy cloud coverage and even during the night. These sensors include the retired ERS 1/2, JERS-1, and ALOS PALSAR, the operational RADARSAT 1/2, ALOS PALSAR-2, and the planned BIOMASS mission. The combination of the active microwave datasets and empirical modelling describing the interaction between microwave radiation and the woody vegetation (e.g. development of empirical regression models) have been successfully utilized during the last 30 years by researchers and workers for predicting BA, AGWB, and tree number density. For example L-band data collected by JERS-1 or ALOS PALSAR have been used in combination with non-linear regression to predict AGWB in savannas. The total height and the mean total height of woody vegetation have been also successfully predicted using advanced SAR analysis methods (e.g. Interferometry) in several natural environments. Although active microwave sensors enable data to be collected at any time and unaffected by weather conditions, they are affected by other limitations: (A) they show sensitivity to forest structure such as AGWB only up to a specific point, called the saturation point (Typically ≤ 100 t/ha for L-band microwave), (B) the microwave EO data are influenced by various ways such as the presence of soil and vegetation moisture, and topographic relief. To fully exploit the benefits of both passive optical and active microwave EO and mitigate their limitations in forest structure prediction and mapping, a combination of these EO data and methods is often needed.
The importance of AGWB mapping and monitoring in the context of international agendas (e.g. REDD+) and in sustainable forest management (SFM) has been stressed in many sections of this thesis. For example, AGWB has been found to be a significant attribute for the development of a GHG inventory (IPCC, 2006) which can support MRV activities to assess the results of REDD+ projects, and inform land managers to apply SFM activities in protected areas. The findings of this literature review suggest that AGWB mapping and monitoring in tropical areas can be supported by satellite microwave data collected in the L-band (i.e. wavelength~0.24m) because of that wavelength’s capability to interact with the woody components of forests (i.e. twigs, branches and stems), in contrast to smaller microwave wavelengths (i.e. X-band and C-band) which interact primarily with the green parts of the forest (i.e. leaves). Although satellite passive optical EO shows limitations with cloud coverage and weather conditions its use can be invaluable for the preliminary differentiation of forests according to vegetation species or structures to support ground sampling. For example, very high spatial resolution optical imagery (e.g. from WorldView: resolution 0.5m – 2m) can be visually assessed to estimate tree number density (N) and may also indicate AGWB hotspots.

Thus, I consider that mapping and monitoring of forest structure in lower density tropical woodlands (≤ 100 t/ha) can be supported by a combination of satellite active microwave and satellite passive EO and field observations by:

**(A)** Establishing the sensitivity of the L-band SAR data (e.g. from ALOS PALSAR) for estimating economically important forest parameters such as AGWB, BA and tree number density in lower density areas.

**(B)** High and very high spatial resolution optical imagery (e.g. WorldView and SPOT) to identify the low density forest areas on the ground and drive field sampling for calibration or validation of the estimates.
2. 5 Synopsis of SAR data collection and data interpretation

In this section the Synthetic Aperture radar (SAR) technique will be explained further and the basic principles and methods of SAR data collection, pre-processing and image analysis that are widely utilised will be also presented and discussed.

2.5.1 Satellite SAR – what is within a pixel?

It is common practice in environmental applications using data collected by SLARs to conduct the processing and analysis using two dimensional images with defined square pixels which contain the backscattered SAR data\(^{16}\). However, the SAR data collection is implemented using oblique observation of the target (Fig. 2.4A&B), and thus confusion is created to users on the creation of each pixel within a SAR image and the information that is contained within each pixel.

![FIGURE 2.4 Views of radar geometry showing the information that is within a radar pixel. (A) Oblique view showing the formation of a pixel using the range (Rr) and azimuth resolutions (Ar) which are proportional to the pulse duration and the beam width respectively, (B) profile view showing the different information that is included within a radar pixel when different pulse durations are used, (C) Top view showing the different information that is included in a radar pixel when different beam widths are used. Figure created by the author.](image)

\(^{16}\)The radar backscatter images that are used for analysis in environmental applications are usually referred as Level 1.5. These backscatter datasets have been terrain corrected, and projected to map coordinates.
Each pixel within a SLAR backscatter image describes the radar cross-section ($\sigma$) of all the scatterers contained within a transmitted pulse of duration ($\tau$) and beam width ($\beta$) while the pixel is formed using the range ($R_r$) and the azimuth ($A_r$) dimensions of the SAR data collection geometry (Fig. 2.4A). The former is dependent on the duration of the pulse ($\tau$, seconds) (eq. 2.1); while the latter is dependent on the range ($R$), and the beam width ($\beta$) (eq. 2.2) which are pre-defined by the manufacturing setup of the SAR system.

$$R_r = \frac{c \times \tau}{2} \quad (2.1)$$

$$A_r = R \times \beta \quad (2.2)$$

Where $R_r$ and $A_r$ are the range and azimuth resolutions respectively, $c$, $\tau$, and $R$ are the speed of light, the pulse duration, and range, and $\beta$ is the 3dB beam width. This means that for example if a long pulse width was used in combination with a wide beam width (e.g. $\tau_1$, $\beta_1$ setup in Fig. 2.4B&C) the resulting resolution cell size would be larger than the $\tau_2$, $\beta_2$ setup in Fig. 2.4B&C. Most importantly the data stored within the ($R_r$, $A_r$) cell would be derived based on the interactions of both targets (Fig. 2.4B&C) with the microwave radiation in contrast to the ($R_r$, $A_r$) cell. To achieve the maximum resolutions in a SAR system advanced signal processing is used (range & azimuth compressing) (Fig. 2.5) to the raw SAR data.

**FIGURE 2.5** the result of the process of azimuth and range compression applied to raw SAR data resulting a higher resolution SAR dataset.
The azimuth resolution is then found to be independent of the range (R) and can be reduced to half the SAR antenna length (l) (eq. 2.3).

\[ A_r = \frac{l}{2} \]  

(2.3)

2.5.2 Impact of topographic effects and speckle to SAR data quality

The interpretation of SAR data can be problematic when significant topographic relief is present in the real world. For example in Fig. 2.6 (A) target III may be mapped closer than expected to target II and further from target IV due to the gentle topographic relief causing the radar pulse to intersect target III faster than if there was a flat terrain in the real world (fore-shortening). Similarly in Fig. 2.6 (B) target II & III are mapped on the same location (i.e. both targets will contribute SAR information on the same pixel of the SAR image) due to the more dramatic topographic relief causing the radar pulse to intersect both II&III at the same time). Extreme topographic reliefs in the real world such as in Fig. 2.6C may also contribute to radar 'shadowing'.

FIGURE 2.6 In (A), (B), and (C) demonstration of the impact of topographic relief on the mapping of targets to ground range coordinates and (D) speckle in radar images. In (D) pixels the neighbouring pixels 1 & 2 have dramatically different pixel values due to different distributions of the targets within – the different distribution of the targets in neighbouring pixels is the major contributor of speckle.
This means that a target on the ground (i.e. target IV in Fig. 2.6C) is not intersected by any radar pulses resulting to reduced information stored in a SAR scene in comparison to the real world. These topographic effects need to be addressed before attempting information extraction from the SAR images since these effects contribute negatively to the quality of the image.

Speckle is another attribute that is inherited by the SAR data collection process. The reason behind speckle is the variation that is observed within neighbouring pixel values due to the different distributions of scatterers within the different pixels (Fig. 2.6D). For example in Fig. 2.6D two pixels with the same number of scatterers (i.e. in this example individual cylinder) scatter back to the SAR sensor dramatically different amounts of radiation due to the scatterers different distributions. These distributions create constructive and destructive wave interference which is key to speckle. This dramatic difference in values of neighbouring pixels in a SAR image is observed as a salt & pepper effect. To mitigate the effects of speckle the process of ‘multi-looking’ \(^\text{17}\) is used.

### 2.5.3 The radar cross-section

The radar cross section can be assumed as a comparison between the strength of the backscattered EM radiation from a target to the backscattered EM radiation from a perfectly smooth sphere of cross-sectional area 1m\(^2\) (Woodhouse et al., 2006). Using the received intensity of the EM radiation collected by the radar receiver and the incident EM radiation on the Earth’s surface the radar Cross Section (Sigma, \(\sigma\)) can be calculated. Sigma (\(\sigma\)) (eq. 2.4) has been found to be dependent on many parameters such as dielectric properties of targets, shape, orientation, and roughness; thus additional parameters such as the radar instrument, size of radar footprint, and pixel size, which can also increase dependencies, need to be normalised. In radar EO a

\(^{17}\) One radar 'look' is the data that were collected within one radar beam of beam-width \(\beta\), while in a SAR image one 'look' is represented as a row of pixels towards the range direction. Multi-looking is the process of averaging multiple successive radar looks to mitigate the effects of speckle. Multi-looking degrades the spatial resolution of the SAR image but improves the radiometric resolution (Curlander & McDonough, 1991). Multi-looking is most properly done in the frequency domain (advanced signal processing), but a similar effect can be achieved in the spatial domain (post-processing) if the target area is relatively homogeneous.
normalisation according to the illuminated area is usually used (Fig. 2.7) producing the normalised radar cross-section (Sigma nought, $\sigma^0$) (eq. 2.4).

\[ \sigma = \frac{\text{Intensity}_{\text{received}}}{\text{Intensity}_{\text{incident}}} \times 4 \times \pi \times R^2 \quad (2.4) \]

\[ \sigma^0 = \frac{\sigma}{\text{area}} \quad (2.5) \]

### 2.5.4 Polarisation

Emitting and receiving microwave radiation at defined polarisations is one important aspect of a radar system. In radar EO, polarisation is defined as the direction of the electric field of the microwave radiation in comparison to the direction of the radiation propagation. The illumination generator of a radar system has the ability to emit EM radiation at horizontal (H) or vertical (V) polarisations, in contrast to the sun for example which emits unpolarised EM radiation (i.e. random polarisations of light); while the receiving part of the radar system can receive the backscattered radiation at H, or V respectively. Four receive / transmit polarisations are primarily used today in EO applications, Horizontal / Horizontal (HH), Horizontal / Vertical (HV), Vertical / Horizontal (VH), and Vertical / Vertical (VV). Although all polarisations can provide useful information in environmental EO applications the VV is not usually used because SAR satellite systems would have to transmit a second pulse increasing the cost of the SAR system, and it is usually the case that radar backscatter images at the
HH, and HV polarisations are utilised for forestry applications. The SAR systems which collect data at all four polarisations (i.e. HH, HV, VH, and VV) are defined as quad-pol SAR systems and are used in SAR Polarimetry\(^\text{18}\).

### 2.5.5 The SAR phase

The difference between the emitted microwave signal and reception of the microwave signal by a SAR sensor causes a change in the signal phase ($\phi$). This phase change is proportional to the travel distance of the microwave signal, which is two-way, and reversely proportional to the wavelength of the microwave signal, while it depends on the interactions between the microwave signal and the scatterers within a resolution cell. The recorded phase of each resolution cell produced by a SAR sensor is recorded within the phase image. Due to its dependence on these parameters, the SAR phase image cannot provide useful information on its own; however if two phase images covering the same area of observation are superimposed and their difference is calculated, where the second phase image has been observed by a different viewing angle in comparison to the first one, then an interferometric image can be created. The interferometric image can then be exploited to create digital surface models of the observation area (e.g. estimate the forest height, or individual tree height) and monitor surface changes (landslides and ground movement). SAR Interferometry can be used in combination with the backscatter collected by quad-pol SAR systems in SAR Interferometric Polarimetry (PolInSAR).

### 2.6 SAR to assist with AGWB prediction

Data collected by satellite SAR systems have been utilised in the literature to support the prediction and mapping of AGWB in many geographical regions and different types of forested areas. In the majority of the studies found in the literature, the SAR information that is being sued to quantify AGWB are (a) the SAR signal backscatter, or (b) the SAR signal phase. In (a), the SAR backscatter data that are collected by the

\[^{18}\text{In SAR Polatimetry, the different polarisations of the emitted and received microwave signal are exploited to acquire information about a target's (scatterer) orientation, shape, and composition by characterizing the scatterer using a 2x2 complex scattering matrix which quantifies the process of change due to the scattering mechanisms, between the emitted microwave radiation and the received radiation (Cloude, 1996).}\]
SAR sensor in different polarisations are used in empirical or semi-empirical statistical models to establish their relationship to AGWB while to further enhance the SAR backscatter before importing these into the models, additional radar image processing may be used such as the calculation of SAR data texture 19 and spatial filtering (see multi-looking in footnote 17). The backscatter collected by quad-pol SAR systems, can also be used in SAR Polarimetry. In (b), the SAR system phase data collected by SAR techniques such as SAR Interferometry (InSAR), Polarimetric SAR Interferometry (PolInSAR), or SAR tomography, are being used to estimate attributes of the forest structure (e.g. forest height) which can then be imported as a variable in an allometric model, to predict AGWB. The SAR signal backscatter described in (a) can also be used to estimate forest height with Radargrammetry 20, and use height estimation in allometric models.

2.6.1 SAR data texture calculation to enhance SAR images

Sarker et al., (2013) calculated the texture of fine-beam dual polarisation data at the C-band, collected by RADARSAT-2, to assist with the prediction of AGWB in high biomass subtropical forests (i.e. up to ~500 t/ha) in the Hong Kong area. More than 20 textural measures were calculated for both C-band polarisations (HH and HV) of one RADARSAT-2 image collected in January, 2009 and used with AGWB estimates based on DBH and height measurements in 53 circular sample plots of 15m radius in stepwise multiple regression analyses. The results of this study indicate that the coefficient of determination in the regression analyses improved when texture measures were used to predict AGWB in contrast to using the raw backscatter values (i.e. normalised radar backscatter), while Sarker et al., (2013) conclude that when the ratio of texture parameters were used (i.e. C-HV / C-HH) the goodness of fit was maximum ($R^2=0.91$)

---

19 In image classification, texture is a statistical measure describing the local variance of the pixel data (Haralick, et al., 1973). As in radar data multi-looking described earlier in this thesis, texture analysis can be conducted within the spatial (i.e. image pixels) or frequency domain (i.e. through wavelet analysis).

20 Radargrammetry utilises the backscatter collected by the SAR sensor from different viewing angles and using stereo-pairs, as in Photogrammetry, to extract three dimensional information for Earth’s surfaces to support the creation of Digital Surface Models (DSM) and Digital Elevation Models (DEM).
and RMSE = 26.95 t/ha. Although this case study in subtropical high biomass forests in Asia, shows the value of image texture to support AGWB prediction the main drawbacks were that only one RADARSAT-2 image was used to derive the texture measures, during field data collection rugged terrain was avoided, and the validation of the regression models was based on the same sample used to train the models.

In Cutler et al., (2012) historical multispectral data collected by LANDSAT TM (from 1992 to 1997) and historical radar backscatter data collected in the L-band by JERS-1 (from 1995 to 1997) were used in combination with historical field measurements (from 1993 to 1997) in 144 sample plots to assist with biomass estimation in tropical forests within three geographical regions (Malaysia, Brazil, and Thailand). In this research, Cutler et al., (2012) use texture measures derived in the spatial domain (e.g. using techniques such as the Grey Level Co-occurrence Matrix or GLCM in SAR data images) or the frequency domain (i.e. using the Coiflet wavelet decomposition, and decomposing the backscatter signal in a number of frequency components) and the multispectral LANDSAT data in neural networks to predict biomass. The results show that when biomass is predicted using a combination of the LANDSAT data and the SAR texture data (derived using the GLCM technique) and biomass data collected from all three regions in 60 sample plots there is a strong relationship ($R^2 = 0.55$). This result indicates that the approach developed by Cutler et al., (2012) may be a solution to perform wall-to-wall mapping of biomass in multiple regions.

2.6.2. Using the SAR data phase to assist with AGWB prediction

Askne et al., (2013) used satellite bistatic SAR interferometry in three InSAR models which describe the physical principles driving the microwave radiation backscatter and coherence when interacting with forested areas (i.e. Interferometric Water Cloud Model, Random Volume over Ground, and Penetration Depth) to estimate the forest height in 201 forest stands in a Boreal forest in Sweden to assist with AGWB prediction using allometric equations which relate biomass to the estimated height produced by the InSAR modelling. The SAR data were collected by the TanDEM-X mission at the X-band with a VV polarisation during 2011 and 2012, and the derived single look
complex images (SLC) were used in combination with a LIDAR DTM to extract the forest height for the test areas (i.e. 201 forest stands). The biomass within the 201 forest stands which were used as training and validation data (100 for training and 100 for validation) was predicted by creating a LIDAR-Biomass model using high density point data (62 points/m²) and 212 circular sample plots (10m radius) with an $R^2$ of 0.81 ($6 \text{ t/ha} < \text{biomass} < 267 \text{ t/ha}$). The results show that when the prediction of biomass is conducted using InSAR data collected during one acquisition date, the Interferometric Water Cloud Model shows a lower relative RMSE in comparison to the other InSAR models, and the combination of all the data (i.e. multitemporal analysis using all 18 images) results an RMSE of 16%. Askne et al., (2013) suggest that these results illustrate the capacity of X-band InSAR to assist with biomass prediction with sufficient accuracy to support forest inventories in the Boreal zone.

Using airborne quad-pol radar data at the L-band and P-band (50m pixel size, multi-looked) in combination with a PolInSAR inversion model (i.e. Random Volume over Ground), linear regression and two machine learning algorithms (i.e. Support Vector Machines and Random Forests), Neumann et al., (2012) predicted biomass in a test-site comprising 27 forest stands within the Krycklan forest in Sweden. In their method, Neumann et al., (2012) constructed two Multi-baseline PolInSAR total covariance matrices, each representing the scattering mechanisms from each interferometric baseline for L-band and P-band respectively. Through the Random Volume over Ground (RVoG) PolInSAR model, each total covariance matrix is then decomposed in two covariance matrices representing the contributions of vegetation and ground, and through inversion of the RVoG, the forest height can be calculated using the total covariance matrix for each radar frequency band (i.e. L-band and P-band) while some PolInSAR indicators, such as the ground-volume ration, can also be calculated using the total, ground, and vegetation covariance matrices. The derived forest height and PolInSAR indicators were used in linear regression, SVM and RF modelling to assess their performance on biomass prediction. The results show that the L-band backscatter calculated as $L_{HH} - L_{VV}$ shows the highest correlation to biomass; however when the forest height information (i.e. derived using the RVoG inversion and covariance matrices) and PolInSAR indicators are combined in linear regression, SVM, and RF
the calculated RMSE using cross-validation improves significantly (17-27% for L-band and 5-43% for P-band).

2.7 The fixed area plot

A variety of field sampling methods are used to assess vegetation structure within forested environments (i.e. distance based sample plots, Bitterlich sampling, fixed-area sample plots etc.); however the most common method remains measurements taken within plots of fixed areas (fixed-area plot) of variable shapes (i.e. square, rectangular, strips, and circular). This approach is used in field studies as well as EO studies for collecting ground truth data to validate EO or use EO data to extend limited volumes of field data to wider areas. The fixed-area plot has a number of attractive features such as the statistical efficiency proportionally to the covering area of the plot as well the simplicity of delineating a fixed area plot on the ground (Schreuder et al., 1987). In sampling it is generally understood that a larger number of smaller fixed-area sample plots (i.e. 10×0.1ha instead of 1×1ha) may be more appropriate for capturing the variability of a target attribute (i.e. DBH, AGWB or BA) in a population (e.g. 100 hectares of surrounding forest). This is because the relative productivity of the different forest stands (i.e. site quality) comprising the total extent of the forest may vary significantly within the geographical extent of the forest; thus a larger number of geographically distributed 0.1ha sample plots are more likely to capture that variability. However two main problems are identified with this sampling approach:

(A) For example sampling a forest of 100ha using a large number of small plots (i.e. 10×0.1ha) would require significantly more resources such as time, financial, and personnel in comparison to using a smaller number of larger fixed-size area plots (i.e. a 1×1ha), which would also achieve the same statistical intensity (1%).

(B) A larger number of smaller fixed-size area plots may provide misleading results at the larger geographical scales for the surrounding forest (i.e. after the extrapolation of one 0.1ha sample plot to estimate a target attribute for the surrounding hectare). This is important because land managers require knowledge not only for the forest population on the whole; but for the hectare scale particularly at specific geographic locations. This effect may be observed in tropical savannas and heterogeneous forests
or woodlands at the landscape ecological scale (i.e. a fragmented landscape of small woodland patches). For example in this research the pine-dominated areas under study are found in variable small patches (usually ≤ 5ha) within the lowland savanna whilst many times the patches are smaller than a hectare.

Overall, in EO studies the size of the fixed-area sample plot is important and is dependent on the pixel-size of the remotely sensed image as well the accuracy that one can associate the image to the ground (McCoy, 2004). Although there is no universal mathematical formula calculating the fixed-size area sample plot relevant for EO applications, Townshend (1981) made an attempt to calculate a minimum sample area dimension for EO applications depending on the EO data using equation 2.6.

\[
\text{Minimum Sample area dimension } m = Ps \times (1 + 2 \times L_a)
\]

Where \(Ps\) is the dimension of the pixel of the remotely sensed image in metres and \(L_a\) is the bias between the location of a sample plot in the real world and the location of the sample plot on the remotely sensed image. For instance using a high resolution satellite SAR sensor such as ALOS PALSAR (\(Ps \approx 12.6\)m) and assuming 12.5m metres bias (\(L_a=1\)) from the real world location of a sample plot on the ground, the minimum sample area dimension should be 37.5m so the establishment of a square fixed-area sample plot on the ground to associate with a remotely sensed image should have minimum dimensions of 37.5m×37.5m or ~0.16ha. Three problems with the above approach are that Townshend (1981) developed eq.2.6 to account only for square sample areas on the ground, the equation assumes that pixels are formed in the same way for both optical and microwave sensors, which is not the case in SAR as explained in this thesis in section 2.5.1, and also the equation does not account for the variability within the image pixels which is also significant in SAR as expressed by speckle and explained in section 2.5.2. For example, the ALOS PALSAR data mentioned above should be further multi-looked at the spatial dimension as described in section 2.5.2 to reduce speckle. This would decrease significantly the spatial resolution of ALOS PALSAR data (i.e. from ~12.6m to 26m); thus the minimum sample area dimension according to eq.2.6 would now be 78m so a minimum fixed area sample plot of 78m×78m or ~0.6ha would be established on the ground. As described in section 2.5.1
the contents of a SAR pixel are determined by many factors including the structure of the targets that the SAR signal interacts with, within the pixel and that suggests that the minimum fixed-size plot would need expansion to include as much variability of the targets’ structure as possible. In this case a larger fixed-area sample plot (i.e. one hectare) may capture significantly more variability of the woody vegetation structure and EO data collected by the sensor for the area contained in the sample plot, in comparison to a smaller sample plot (e.g. ≤ 0.5ha).

Additionally, in the context of collecting field data within forested areas to support biomass prediction using SAR data; it should be noted that the increased variability in biomass observed within the smaller sample plot sizes (i.e. from 0.05ha to 0.5ha can have a negative impact on the prediction of biomass using the radar data, in contrast to the smaller biomass variability found within the larger sample plot sizes (i.e. >0.5ha). For example Fig. 2.8 shows the general trend that has been observed in different forested ecosystems where the variability in the total biomass found within a sample plot (t/ha) is decreasing with increasing sample plot size. To assess the variability of biomass within different sample plot sizes I used the methodology described in Saatchi et al., (2011), and using a small subset of field data (i.e. 15ha) that were collected in the lowland savannas of Belize I summarised the total biomass found within the original 15 sample plots and subdivided these into 30, 60, 150, and 300 sample plots with sample plot sizes of 1, 0.5, 0.25, 0.1, and 0.05 hectares respectively. The mean RCV observed within the five sample plot size groups are shown in Fig. 2.8, while a negative power-law line was fitted to show that the variability of biomass decreases following a negative power–law trend. On the Y-axis of the figure the variability of the biomass around the mean observed biomass observed as expressed by the relative coefficient of variation (RCV) is shown; and on the X-axis the sample plot size that the variability was observed. The observed variation in biomass in the smaller sample plot sizes (i.e. from 0.05 to 0.25) is much higher in comparison to the 0.5ha and 1ha which is close to 5%. In this thesis, the size of the sample plots are chosen to be one hectare because they contain the lowest variation in AGWB, as expressed by RCV.
FIGURE 2.8 Relative Coefficient of Variation (RCV) around the mean of the above ground woody biomass observed in the field, within five sample plot sizes (0.05ha, 0.1ha, 0.25ha, 0.5ha, and 1ha). The different sample plot sizes were generated by dividing the hectare sample plots to 300, 150, 60, and 30 equal sample plot tessellations and summarising the AGWB within the boundaries of the tessellations.

2.8 Description of the EO data

In this sub-section the EO&GIS datasets that were used in this thesis will be described and discussed. The overall workflows that were used to pre-process the data will be also presented.

2.8.1 SPOT 5

The satellite SPOT 5 is run by the company SPOT IMAGE. The optical sensors mounted on this satellite produce high spatial resolution, multispectral images. The spatial and spectral resolutions of the data as well the sensor’s other important characteristics are described in table 2.4. These data have been used extensively in ecological applications for identification of features at the forest stand scale (Goossens et al., 1991). The SPOT data were carefully selected by Cameron et al. (2011) from the SPOT image archive, to choose the most up to date imagery that was not heavily obscured by cloud cover or haze. A further discussion about the rationale behind the selection of this imagery can be found in the technical report for the conservation and assessment of the lowland savannas in Belize (Cameron et al. 2011). Further SPOT imagery were identified and acquired by the author through a PLANET ACTION proposal in 2011. Some pre-processing of the SPOT data, including geo-referencing, using ground control points, and atmospheric correction has been conducted by
Cameron et al. (2011); The processes used by Cameron et al. (2011) was used in the new SPOT imagery to harmonise these data to each other.2.7.2

2.8.2 WORLDVIEW 1 & 2

Very high spatial resolution (VHR) optical satellite data collected by two sensors were used in this research (WorldView I, and WorldView II). Both satellites are operated by DigitalGlobe offering VHR images of the Earth’s surfaces in panchromatic and multispectral modes (APPENDIX SIX).

Data collected by WorldView have been used in environmental applications to visually assess the woody structure of forested ecosystems (i.e. tree number density prediction and canopy cover estimation e.t.c.). The WorldView datasets were awarded to the author by ‘PLANET ACTION – AN ASTRIUM INIATIATIVE’ and were selected in two protected areas (Deep River, and RBCMA) which contain a significant amount of pine-dominated savanna areas (~10000ha) to visually assess the tree number densities, and canopy cover to assist sampling design, and to quality assess a woodland inventory that was donated by Linares (2009) to assist this research.

**TABLE 2.4 Overview metadata for the SPOT and WorldView data**

<table>
<thead>
<tr>
<th>Scene code</th>
<th>Coordinate System</th>
<th>Level</th>
<th>Resampling Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>56113151003041634352J</td>
<td>WGS84 UTM Zone 16 (North) Metres</td>
<td>Spot View Basic (Ortho)</td>
<td>Nearest Neighbour</td>
</tr>
<tr>
<td>56113171001221622572J</td>
<td>WGS84 Grid Pixels</td>
<td>Level 1A</td>
<td>None</td>
</tr>
<tr>
<td>56113171106041646241J</td>
<td></td>
<td>Ortho-Ready Standard</td>
<td>4 X 4 Cubic Convolution</td>
</tr>
<tr>
<td>1020010007422400 (WV-1)</td>
<td>WGS84 UTM Zone 16 (North) Metres</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1030010009A91300 (WV-2)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
2.8.3 ALOS PALSAR

Satellite Synthetic Aperture radar (SAR) covering the lowland savanna ecosystem in Belize data were made available through the Darwin Initiative Project ‘Savanna Ecosystem Assessment, Belize 2009 – 2012’ (17-022). The data were collected by the satellite Phased Array type L-band (wavelength ~ 0.23 m, frequency ~ 1.2 GHz) SAR (PALSAR) which is mounted on the Advanced Land Observing Satellite (ALOS) and was ran by the Japanese Aerospace Exploration Agency (JAXA). The sensor allowed the collection of cloud-free data at dual (HH, HV) or quad polarisation (HH, VV, HV, VH) and using two collection modes (Fine beam and ScanSAR). ScanSAR mode allows the collection of data at larger swaths (250 – 350Km) but lower spatial resolutions (100m) while fine beam mode allows the collection of data at smaller swaths (40 – 70Km) and improved spatial resolution (7 – 44m). The technical characteristics of the particular ALOS PALSAR scenes used in this study (Scene I, and II corresponding to ‘138740310_34_163887’, and ‘142970330_34_172884’ respectively are described in table 2.5.

TABLE 2.5 General overview of ALOS PALSAR data

<table>
<thead>
<tr>
<th>Scene Name</th>
<th>Looks</th>
<th>Pixel size (m)</th>
<th>Data Coordinates</th>
<th>Datum and Projection</th>
<th>Resampling</th>
<th>Data Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>4</td>
<td>12.6</td>
<td>Map</td>
<td>WGS84 UTM 16</td>
<td>Nearest Neighbour</td>
<td>Sigma0 (σ0)</td>
</tr>
<tr>
<td>II</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The SAR data available for this research project were collected using the fine beam dual polarisation mode (FBD, Fine Beam no. 7) for a swath width of 70Km while the collected spatial resolution is approximately 12.6 m. Further ALOS PALSAR datasets collected in drier periods (i.e. less precipitation) were identified and acquired from the SAR data centre, through an ALOS PALSAR proposal to the NASA Alaska Satellite Facility (ASF)21. These additional datasets were collected using multiple polarisations, and modes (APPENDIX EIGHT). The data were acquired towards the end of this research to examine the impact of the dry / wet conditions to the radar backscatter

21 ALOS PALSAR proposal (Principal Investigator Dr. Matthew Brolly, Co- Investigators Mr. Dimitris Michelakis, Prof. Iain H. Woodhouse)
intensity; however this was not possible due to time restrictions. However these data will be used in a future project to examine these effects; and also the effects of multiple-incidence angles to land cover mapping.

The ALOS PALSAR data that were used have been pre-processed from level 1.0 (raw) to level 1.1 (single look complex - SLC) and from level 1.1 to level 1.5 (Geo-tiff, ~12.6m spatial resolution) in E observation laboratory (EOL – Aberystwyth) where the imagery were also terrain-corrected using the Shuttle radar Terrain Model (SRTM) digital surface model (DSM) and the intensity values were transformed to calibrated backscatter intensity or sigma naught (Appendices three and four, Fig. 2.9 & Fig. 2.10).

![Diagram of different levels of ALOS PALSAR data](image)

**FIGURE 2.9** visual demonstrations of the different levels of ALOS PALSAR data for the same geographical area in Belize, Central America.

---

22 ALOS PALSAR Level 0 is SAR observation data before aperture synthesis and they are not offered to SAR users. Level 0 are used to extract the Level 1.0 PALSAR data.
The radar data have been further processed by Cameron et al. (2011) whereby the imagery were projected to the Universal Transverse Mercator zone 16 (UTM16) using the North American datum 1927 (NAD27). A noise-reduction methodology was also followed whereby the radar imagery were re-sampled to a spatial resolution of 26 metres (16-look image product), in order to reduce speckle in the imagery. The specifics of the radar imagery noise-reduction methodology are described in Michelakis et al., (2014).

2.8.4 GIS data

The GIS data that were utilised within this project can be obtained from freely available sources such as the Biodiversity and Environmental Resource Data Centre for Belize (BERDS), while GIS data that were produced by Cameron et al. (2011) will also be utilised. The data produced by Cameron et al. (2011) contain polygons of the savanna landscape or savannas patch scale in vector GIS format and were derived using several EO datasets (SPOT-5, ALOS PALSAR, ASTER and LANDSAT) and field observations. In their technical report Cameron et al. (2011) also demonstrated how the combination of optical data and data collected from ALOS PALSAR can provide the means for discriminating broad vegetation classes within the savanna landscape. The workers in that study suggest that the lowland savannas of Belize, being a mosaic of woody and
non-woody vegetation, are difficult to map and characterise using just one Earth observation dataset and therefore they suggest that the combination of the NDVI derived product from SPOT and the backscattering intensity collected by ALOS PALSAR can be far more effective when characterising that particular ecosystem.

The findings from that study establish that this approach was very effective to identify woody and non-woody vegetation sub-types such as dense tree savanna, forest inclusion, open savanna, seasonally waterlogged savanna and wetland inclusions. This mapping product, although still under validation (preliminary overall accuracy ~ 75%); it provides the foundation GIS data for this project to focus on the denser pine areas identified in Cameron et al. (2011) classification as the dense tree savanna class. This work is also a starting point for this project, since it was considered that a combination approach of optical and microwave datasets would possibly be valuable for extending the characterisation of the denser pine areas in smaller scales such as at the pine community scale, providing additional knowledge for these areas. This mapping work was part of the Darwin Initiative - conservation assessment for the lowland savannas of Belize and the main goals of the mapping were to provide information for the extent at a national scale of the savanna landscape within the lowland areas of Belize, as well provide information to land managers and policy makers for the extent of the main sub-types.

2.9 L-band backscatter and vegetation interactions

Although the EO scientific community has developed a plethora of robust approaches and methodologies for exploiting multi-spectral and multi-temporal optical EO data such as SPOT for assessing and monitoring the natural environment (Coppin et al., 2004; Hall et al., 1991), satellite radar data such as ALOS PALSAR are still less widely used and understood. This is mainly due to characteristics of radar data such as the topographic effects (Fig. 2.7A,B & C) of the interacting surfaces and image speckle (Fig. 2.7D) as well as the complexity within the data collected in different Pollarimetric modes (Kasischke et al., 1997a). This research study aims to exploit the capability of the L-band SAR satellite imagery produced by ALOS PALSAR to characterise and map
the woody component according to AGWB and establish the sensitivity of such imagery to several structural characteristics of the low density, woody component within the lowland savanna landscape.

The rationale relies on the fact that the L-band microwave radiation can penetrate vegetation canopies, which are opaque to visible and infrared radiation, and interact with the woody component of vegetation such as the canopy elements (i.e. branches), the stems, and even under-story and the ground. This interaction between the L-band backscattering and the target (i.e. woody vegetation) is particularly important because it may provide some indication of the amount of woody vegetation present within a forest. The structural attribute that is usually used to quantify that amount is AGWB. However; the radar backscatter is driven among others by the woody vegetation structure of forested areas such as species, the number of trees and their size (Woodhouse et al., 2012) For example for two different forested areas one with needle-leave trees and one with broadleaf trees but with the same amount of AGWB the backscatter may be different due to the different structure of the canopy elements. Another example is for two forest areas that have the same species (i.e. needle-leaf trees) but with different DBH distributions (i.e. AGWB is stored in many big trees, than in many smaller trees). The latter example is driven mostly by the growth of trees and protection and management activities.

2.9.1 Vegetation structure prediction using ALOS PALSAR

Due to capacity of SAR systems to collect data under all-weather conditions and the interaction of the L-band microwave radiation with the woody parts of the forests, the data collected by ALOS PALSAR have been explored by many researchers as the means to predict, and map AGWB in tropical environments. There are three ways that researchers have examined for the exploitation of the L-band backscatter data for the prediction of forest structure; (a) statistical non-linear regression, (b) semi-empirical non-linear regression, and (c) machine learning techniques. In both (a), and (b) the aim of the non-linear regression is to predict the values of the L-band backscatter data ($\sigma^0$) which were collected in different polarisations (usually HH and HV are preferred) with respect to an attribute which describes forest structure (e.g. AGWB, BA, Density or
Volume). Hence in (a) and (b) the backscatter data are used as the dependent variable and the forest structure data are used as the independent variable. In both methods a satisfactory non-linear model is treated as an algebraic equation and it is inverted to calculate the independent variable (forest structure attribute). However the fundamental difference between these two techniques is that in (a) there is little underlying theory\(^{23}\) justifying the radar-vegetation interaction which can support the selection of a non-linear model, and thus any non-linear model (i.e. logarithmic, exponential, power, polynomial etc.) can be selected (usually the one with highest \(R^2\)).

On the other hand in (b) the non-linear regression model can only take specific sigmoid forms. For example in this PhD the exponential model developed by Attema and Ulaby, (1978) is used where backscatter is predicted using an exponential non-linear regression model. The underlying theory of this is explained in Attema and Ulaby (1978) and in chapter 5 of this PhD but the founding assumptions are that a vegetative area (Fig. 2.5A), can be approximated as a relatively homogeneous volume comprising of vegetation components and air (Fig. 2.5B). The intensity of the SAR backscatter data have been found to decrease with increasing volume (i.e. increased quantity of a forest structure attribute which can describe that volume such as AGWB) (Fig.2.9C).

Machine learning methods for forest structure estimation have not been used extensively; however they are promising as shown in Carreiras et al., (2013). These methods work well with big datasets (i.e. \(N \geq 50\) samples) and are not affected by the data distribution (i.e. assumption for normality, equal variances) while the radar backscatter is usually used as the independent variable and AGWB as the dependent variable. The scientific literature suggests that AGWB and the radar backscatter can be used as dependant and independent variables respectively in statistical linear regression models (Ryan et al., 2012). The advantage of this approach is that after the parameters of the linear regression model are calculated, the linear model is not inverted to estimate AGWB as in (a) and (b).

---

\(^{23}\) The non-linear regression model is usually selected to approach a fixed upper limit asymptotically as the independent variable gets higher. In the methods of the radar EO this is also denoted as the saturation point. If the backscatter values are not in decibels, the logarithmic model can be represented as linear.
2.10 Summary

This section has achieved three things:

(A) Gained insights on how the radar data are collected using Synthetic Aperture radar (SAR) and examined the key topics (i.e. pixel formation, speckle, topographic relief) that need to be addressed before analysing the radar data in applications (i.e. in Forestry)

(B) Established the importance of collecting field inventory data in large fixed-sized area sample plots (i.e. one hectare) to include in radar applications.

(C) Presented and discussed the different techniques used to predict forest structure (i.e. machine learning, semi-empirical modelling, and statistical approaches).

The description of the satellite SAR data collection process, as well the pixel-formation and pre-processing description (i.e. multi-looking and geometric corrections) in section 2.5 suggests that to successfully utilise radar data to support information extraction for forest structure prediction require thorough quality control (QC) before acquisition for an EO application and before using them in analysis workflows (i.e. prediction of AGWB/ha). The main suggestions resulting from this review are the need to visually examine the area of interest either by visiting the area or if this is not possible using VHR optical datasets (e.g. from WorldView-1/2, IKONOS or Quickbird). This will assist the radar specialist to acquire preliminary knowledge of the targeted attributes.
(i.e. spatial distribution and size distribution) and the topography of the area. For example, in a hypothetical scenario where the aim is to predict and map biomass for a forested area using radar, the image analyst should acquire information on the structure of the forest beforehand (i.e. the DBH size distribution and the spatial distribution of the trees). This information may provide qualitative evidence on the degree of the speckle that is expected or even the backscatter responses from the different sampling areas on the ground.

In this section I have established the importance of collecting field observations at the hectare geographical scale to use in radar applications attempting to predict forest structure. Although previous statistical theory suggests that a large number of smaller sample plots is more preferred for statistical analyses and the EO discipline suggests that a ground area in the real world described by roughly 3x3 pixels in the image space (Townshend, 1981) may be a sufficient minimum sample area to compare to the remotely sensed image to acquire information, the nature of SAR data collection (i.e. oblique view, pixel-formation, topography) requires the extension of those proposed dimensions for radar applications.

The discussion of the different methods used in radar EO to predict and map biomass in section 2.8 suggests that the use of radar backscatter from L-band as the dependent variable in a semi-empirical model (Water Cloud Model) and AGWB as the independent variable is the preferable means to establish a direct link between AGWB and radar backscatter to support biomass mapping in low density woodlands. The main reason for this preference is the robust underlying theory of the water cloud model describing the vegetation – radar interactions first conceptualised by Attema & Ulaby, (1978), in contrast to the statistical approaches such as non-linear regression and machine learning algorithms where models are chosen according to statistical measures (i.e. \(R^2\)).

Taken together the findings of chapter two which are summarised in sections 2.4 and 2.9 lead me to take this research forward by pursuing the following objectives which have also been mentioned in chapter 1:
(1) Describe quantitatively the structure of the lowland pine-dominated savanna woodlands and to understand if these characteristics are similar or different for woodlands under different types of protection and management.

(2) Investigate the sensitivity of satellite microwave EO collected by ALOS PALSAR to AGWB as measured by field survey in these woodlands.

(3) Develop and validate a statistical model to predict AGWB from ALOS PALSAR backscatter intensity data, and examine any effects of woodland structure upon the backscatter signal.

(4) Produce and evaluate the first fine-scale mapping of AGWB (i.e. 1ha spatial resolution) within the savanna woodlands of Belize using the prediction model developed in (3).

Each of the objectives above forms the basis of the following three research chapters in this PhD.
References


CHAPTER THREE

POPULATION DENSITY & STRUCTURE IN SAVANNA WOODLANDS

3.1. Overview

Chapter 2 has highlighted two things (a) the importance of forest structure for carbon and biodiversity management and (b) the role of forest structure on the interactions between vegetation and active microwave radiation. This research examines the effects of protection and management in the lowland savannas of Belize using an extensive field data inventory making an attempt to create the first national inventory of density and structure of these areas. We analyse the tree diameter, and tree height distributions, and the above ground woody biomass (AGWB), and basal area (BA) to assess the structural differences found between unprotected savanna woodlands (UPR), protected and passively managed (PRPM), and protected and actively managed (PRAM). The results are significant because they allow the use of the radar data in future chapters to predict AGWB to support protection and management in protected areas.

3.2. Author contributions - declaration

This chapter is accepted for publication subject to minor revisions by the Caribbean Journal of science (CJS), full citation and title: Michelakis D, Stuart N, Furley P, Lopez, G, Linares V, Woodhouse IH, ‘Woody structure and population density of pine dominated tropical savanna woodlands under different protection and management regimes’. Accepted for publication subject to minor revision with the Caribbean Journal of Science.
D.G. Michelakis, Neil Stuart, and Iain H. Woodhouse devised the research; Dimitrios G. Michelakis, Neil Stuart, and German Lopez collected 65% of the field data used in the chapter, & Vinicio Linares contributed the residual 35% collected in the context of a USAID grant in 2009; Dimitrios G. Michelakis conducted the data analysis; Dimitrios G. Michelakis wrote the article with assistance and revisions from all other authors

### 3.3. Introduction

Savannas occupy around 1/5th of the Earth’s surface, representing one of the most widespread types of vegetation in the tropics and subtropics. Although characterised by the dominance or co-dominance of grasses, they often can contain areas of woodland that are dense enough locally to meet the FAO definition of a forest (FAO, 2010; Mistry, 2000; Lehmann et al., 2011; Ratnam et al., 2011). In countries with low population pressure, savanna woodlands are often managed informally for traditional uses such as hunting, grazing, the extraction of wood fuel, timber and a variety of other forest products. In Central America, significant tracts of pine savannas still exist but these woodlands are coming under pressure from an increasing frequency of burning and conversion to uses such as smallholder agriculture for which their soils are poorly suited (Myers et al., 2006; Furley, 2010; Cameron et al., 2011). Viable management and conservation strategies for these woodlands are therefore urgently needed to ensure their long term survival.

It is argued that greater recognition of the resource value of the wooded formations within savannas, with management strategies enhancing the volume and the variety of tree stocks, could be an effective way forward for conserving these woodlands. Because the above-ground woody biomass (AGWB) of savannas has been assumed to be low, savannas have often been overlooked when determining areas for protection on the basis of their carbon stocks alone (CBD, 2001; UN-REDD, 2008). However, several authors have identified co-benefits in terms of both carbon sequestration (Scurlock and Hall, 1998; Furley, 2010) and the enhanced biodiversity (Williams et al., 2008; Cook et al., 2010) that result when savanna lands are managed to increase their woody stocking and restore their structure. Managing savanna woodlands for the
multiple objectives of biodiversity enhancement, carbon storage and sustainable harvesting of timber and non-timber products may be more economically viable and socially responsible than managing these areas exclusively for a single purpose, such as timber extraction.

To enable organisations to understand the scope for managing these areas for biodiversity, carbon stocks or sustainable logging, information is required on typical stocking densities, the ranges of tree numbers and biomass in these woodlands and how these quantities vary depending on the type of management applied. The present research describes and analyses the structure of pine-dominated savanna woodland areas throughout lowland Belize based on an extensive field survey of forest plots. The results provide the first quantitative national assessment of tree densities and AGWB in these savanna woodlands. The study then examines whether there are differences between woodlands that have been protected or managed sustainably over the past 20 years, compared to other similar woodlands with no protection or formal management.

3.3.1. Background and local context

3.3.1.1. The need to characterise the structure of savanna woodlands in Belize

Our understanding of the structure of savanna woodlands is less well developed than for other more commonly recognised forest types. Field studies that systematically describe savanna woodlands are relatively scarce, especially in the Neotropics (Myers and DanteArturo, 2009). Savanna woodlands have been mostly ignored from forest assessments conducted as part of REDD+ projects because their biomass is lower and much more spatially variable and thus more difficult to estimate than for broadleaf forests (Mertz et al., 2012). As a result, there is very little published field data about the structure of savanna woodlands, with most of the information gathered held privately for operational management purposes by government or individual forest managers.

In Belize, one pilot research project has produced field measurements from limited destructive sampling to develop allometric relationships to estimate the biomass of savanna shrubs and trees in a single protected area (Brown et al., 2005). In 1974, data
from several private logging concessions in the southern coastal plains of Belize were assembled and mapping produced from aerial photo interpretation to create an inventory of the extent of pine savannas and stocking densities at the time, as part of an assessment of the economic potential of the area for pine lumber (Johnson, 1974). This is still the most comprehensive published study for Belize, but needs to be brought up to date with new field measurements and a revised methodology to enable measures such as biomass to be estimated from the field data. Since 1980, some data has been collected by the government forestry department, by private licensees and NGOs managing savanna areas, but the downturn in the price of pine lumber in recent decades has reduced the interest in collecting or maintaining these data. Prior to the current study, there has been no comprehensive examination of the structure of lowland savanna woodlands across the country, nor any investigation of how different management regimes may lead to different stocking levels of stocking or structural complexity. Nevertheless, an indication of the stocking densities and biomass that savanna woodlands may support is needed now, to inform forest departments and NGOs who are currently deciding whether to manage these areas primarily for biodiversity conservation, for carbon credits or for sustainable logging (PfB, 2006; Linares, 2009).

Data from forest plots such as tree diameters at standard heights, tree distributions and tree number densities are widely used to inform management planning for economic extraction, and for monitoring progress towards carbon stock targets and biodiversity goals (Andrén, 1994; Manning et al., 2006). These parameters of forest structure can also provide data for analysing the effect of both natural and anthropogenic disturbances (Franklin et al., 2002).

3.3.1.2. Effects of natural and human disturbances on the structure of savanna woodlands

Most studies of the growth and mortality of trees in savanna woodlands have focused on the effects of natural disturbances such as the frequency and intensity of hurricanes and wild fires (Menaut, 1977; San Jose and Farinas, 1983; Coutinho, 1990) or other ecological factors such as soil fertility or rainfall frequency (Hoffmann and Solbrig,
2003; Cochard and Edwards, 2011; Shackleton and Scholes, 2011). Because of the significant human population living in or utilising savannas, it has also been understood for some time that the effect of anthropogenic pressures such as burning and grazing upon savannas cannot be disregarded (Houghton, 1995; Scholes and Archer, 1997; Mistry, 2000). In recent years, increasing population has led to a step-change in the magnitude of these pressures, resulting in extensive degradation of many savanna areas. In Africa, the main drivers are unsustainable logging, overgrazing and an increased frequency of fire (Ryan and Williams, 2011), whilst South American countries such as Brazil with greater access to capital have witnessed the large-scale conversion of savanna land to extensive ranching or cultivation (Alho and Martins, 1995; Ratter et al., 1997). In areas where savannas remain, their degraded status is measured by various disturbance indicators such as a general reduction in tree cover, reduced structural and species diversity (Pickett and White, 1985), reduced levels of woody stocking and fluctuations in tree number density over space and time (Silva, 1996; Bond and Keeley, 2005; Sirami et al., 2009).

Human activities upon savanna should not be characterised solely as disturbances with negative effects, however. A consequence of the growing exploitation of savanna areas is that many areas are now much more actively managed and in some cases, given some form of protection. Management interventions such as the sustainable logging of the woody components or the active protection of savannas from human pressure to enhance biodiversity have been shown to allow the level of woody stocking to return over time to higher levels (O’Connor, 1985; Novelo, 2003; Sharp and Whittaker, 2003; Grace et al., 2006; Myers et al., 2006; Savadogo et al., 2007). In most studies, woodland recovery is attributed mainly to reduced levels of anthropogenic disturbance and particularly to a greater control of wildfire and lower grazing pressure within protected areas (PAs) or areas where sustainable logging is being practised (Menaut, 1977; San José and Fariñas, 1991; Douglass et al., 2011).
3.3.1.3. Diameter distribution as an indicator of woodland structure and disturbance

Diameter at breast height (dbh) is an easily measurable attribute and the distribution of dbh not only quantifies the volume of resource locally but also provides information about a woodland’s structure, community relationships and sustainability (Meyer, 1952; Leak, 1964; Zeide, 1995; Backeus et al., 2006; Rubin et al., 2006). DD has been found to vary between woodlands that have experienced different frequencies and intensities of fire (Rebertus et al., 1993; Williams et al., 1999; Hoffmann and Solbrig, 2003; Furley, 2008) suggesting that DD can also be used as an indicator of disturbance.

There has been some debate in the literature about the different forms that DD might be expected to exhibit for less disturbed ‘natural’ forests compared to forests undergoing various types of disturbance. For example, building upon earlier geometric theory about the structure of even-aged forests by workers such as Reineke, (1933) and ideas of self-thinning (Yoda et al., 1963), Enquist and Niklas (2001) argued from a biological-driven standpoint that the numbers of trees with increasing diameters should decline according to a power-law relationship (Enquist et al., 1998; West et al., 2009). This is based on the assumption that the woodlands are developing naturally, and are not affected by different degrees of disturbance under different types of management (Midgley, 2001). In contrast, Coomes et al. (2003) propose that in wooded areas where disturbance plays an important role, the DD may be expected to follow a negative exponential distribution, as earlier postulated by Meyer and Stevenson (1943). Whether a power-law or exponential model better characterises the diameter distributions of tropical savanna woodlands is as yet untested. There have been relatively few studies of diameter distributions in savanna woodlands (Myers and DanteArturo, 2009; Shackleton and Scholes, 2011) whilst the possible effects that different management regimes may have upon the observed diameter distributions has to our knowledge yet to be explored.
3.3.2. Tree-grass interaction

The vegetation structure of the savanna landscape is primarily comprised of two vegetation layers; one herbaceous layer (i.e. in Belize the herbaceous layer is dominated by grasses and sedges (Goodwin et al., 2014), which forms a continuous surface within the savanna landscape boundaries, and a woody layer (i.e. trees and/or woody shrubs), which is found as islands of woody vegetation within the continuous herbaceous layer (Frost et al., 1986). Research in a wide range of tropical savannas that are found in different geographical regions, suggests that the attributes driving the relationship between the woody and the herbaceous layers may vary; however researchers have been able to identify two major categories of these driving attributes: (a) attributes describing the competition between the woody and the herbaceous component (i.e. tree-grass competition), and (b) attributes describing the limitations of the savanna ecosystem (demographic bottlenecks) (Sankaran et al., 2004).

3.3.2.1 Tree-grass competition

Walker et al. (1981) made an attempt to describe the competition between woody vegetation and herbaceous vegetation for water resources and soil in south-African semi-arid savannas which are disturbed by herbivore grazing, and extrapolate their conclusions for the average semi-arid savanna. The methods used were graphical and quantitative, while in their simplified quantitative model to describe the semi-arid savannas, Walker et al., (1981) used three variables (i.e. biomass of grass, biomass of woody vegetation, and infiltration). Their method is founded on the hypothesis that the woody component and grasses compete primarily for water resources near the surface of the ground while the woody component can also access water deeper in the ground. Their modelling results suggest that there can be two significantly different states of the savanna; one with significant amounts of woody vegetation and very little grass biomass, or extensive biomass amounts and very little woody vegetation.
Although water is a factor which has been found to partly determine the tree-grass competition the available nutrients, as well other climatic and environmental factors have been found to determine the tree-grass competition (Sarmiento, 1984; Frost et al., 1986). In his classic review for tree-grass interactions Scholes and Archer (1997) suggest that it is not possible to predict the tree-grass competition dynamics using only one determinant such as water. Assimilating experimental evidence from different studies, Scholes and Archer (1997) reach the conclusion that in undisturbed savanna ecosystems (i.e. fire, large herbivores etc.) the tree component benefits in comparison to the grass component while the grasses will reach significant amounts only in arid savanna ecosystems while in moist savannas the tree component may reach tree number densities which will form closed woodlands. Scholes and Archer (1997) also suggest that the nutrient poor soils (i.e. sandy soils) which are found in semi-arid savannas may have a negative impact in grass development; however will not act as a bottleneck for trees.

3.3.2.2 Demographic bottlenecks

In their article Staver et al., (2009) examine the impact of disturbances such as fire and herbivory browsing to tree density in an African savanna. Their method is founded on excluding herbivores within 10 locations in the study area of Hluhluwe iMfolozi Park, Natal, South Africa. In their study they find that herbivores and fire acted as demographic bottlenecks in sapling growth suggesting that browsing has a negative impact in tree density.

In tropical savannas in Mozambique, Saito et al., (2014) performed process-based ecosystem modelling using the ORCHIDEE-FM global scale land surface model, and the SPITFIRE model, and DBH and climate-forcing data in two Miombo woodland sites; one with areas of land recovering for the past 2-25 years from agricultural activity and one site with areas which had been burned using prescribed fires, to understand the impact of fire regime and climate on woody vegetation of the Miombo woodlands. The results of this study suggest that decreasing fire intensity due to a limited grass layer within the savanna under study has a positive impact on
the woody biomass since it prevents the savanna landscape of becoming grass-dominated. In their conclusion Saito et al., (2014) support that fire, depending the regime, can become a demographic bottleneck for trees in the Miombo landscape, preventing them to reach maturity.

3.4. Materials and Methods

3.4.1 Study area

The study was conducted in Belize, located between 15° 52’ and 18° 30’N and between 87° 28’ to 89° 13’ W. The climate in Belize is subtropical to tropical with an annual rainfall around 1500m in the northern parts of the country and up to 3800mm in the south. There are distinct dry and wet seasons, with the dry season extending from February to April. Some 60% of the precipitation falls in May and June, after which rainfall frequency and amount declines to November. The mean temperature ranges between 21 – 30 °C throughout the year.

There are two main savanna vegetation distributions in Belize, referred to as the upland and lowland savannas. In both, the vegetation varies from open grasslands to woodlands and the soils are very nutrient poor. The upland savannas of the Maya Mountains drain rapidly because of the steep topography (Furley, 2011), while the lowlands have sub-soils with high silt and clay contents which result in poor drainage and seasonal flooding. Approximately 40% of the lowland savannas (680 km²) are characterised as dense tree savannas (Cameron et. al., 2011). These semi-open to dense woodlands are dominated by Pinus caribaea var. hondurensis, the Central American variety of Caribbean pine. Canopy cover typically ranges from 10 – 60%. Other woody species which can be interspersed with the pine are oak (Quercus oleoides), craboo (Byrsonima crassifolia), the sandpaper tree (Curatella americana) and the palmetto palm (Acoelorraphe wrightii) which sometimes occurs in dense groves, especially around damp depressions. The herbaceous layer in these pine woodlands is often dominated by grasses such as Diodia apiculata, Spermacoce spp. and Hypericum spp. (Bridgewater et al., 2012).
3.4.2 Protection and management of dense tree savannas in Belize

The protected pine savanna areas studied here fall under three different protection regimes as defined by the IUCN: forest reserves, private reserves and nature reserves (Dudley, 2008). Several NGOs and the Forest Department of Belize (henceforth FDB) are responsible for managing most of these protected pine savannas (Fig. 3.1). The government of Belize (henceforth GOB) protects and actively manages pine savannas in its forest reserves (FR) (IUCN category VI) for the sustainable extraction of timber. These include the Manatee and Deep River FRs. In these areas, timber is extracted according to sustainable forest management plans (Linares., 2009).

FIGURE 3.1. From left to right: (A) Location of the sample plots in relation to the distribution of savannas and protected areas throughout the country; insets B and C show detail in areas where 1 ha plots were closely spaced; inset D shows location of 0.1ha plots in the Deep River reserve and the 1km grid used for aggregating these into 1 ha cluster plots.

The NGO Programme for Belize (henceforth PfB) has protected and managed the Rio Bravo Conservation and Management Area (henceforth RBCMA) as a private reserve
Dimitrios Michelakis (PR - IUCN category VI) with sustainable use of natural resources since 1988 (Zisman, 1996). Approximately 10,000ha or 8 % of the RBCMA is lowland savanna and more than a third of this is dense pine woodland. Since 2005, the area has been managed mostly to promote biodiversity; while actions focused on prescribed burning to reduce wildfire and the detection and treatment of pine stands affected by beetle infestations. Whilst sustainable harvesting of pine is permitted, none is occurring at present and the savanna woodlands are managed primarily for the benefit of biodiversity and associated ecotourism (PfB, 2006).

The Bladen management consortium comprises four NGOs which assist the FDB in enforcing the strict protection of this area as a nature reserve (NR, IUCN category Ia). The dense tree savannas found in this remote, protected area are an important and potential source of genetic diversity for Caribbean pine.

### 3.4.3 Sampling design

The sampling unit adopted in this research is the fixed area plot. Field observations and analysis of satellite data revealed that patches of pine woodland within the lowland savannas are rarely larger than two hectares. A hectare plot size was considered large enough to capture the overall characteristics of each woodland patch, while accounting for the micro-scale variability that typically occurs in these low density (100 – 700 trees / ha) and open (canopy cover 10 – 60%) woodlands. For the data collected over the period 2011-2013, 100m square plots were used to sample 20 pine dominated areas within the lowland savanna landscape at a variety of protected and unprotected locations across the country as indicated on Fig. 3.1A. Plots were established in various locations across the country to ensure the full range of tree densities occurring for pine savannas was represented. Six classes of tree density ranging from 100-700 trees per hectare were sampled. Plots were established within three different types of protection or management (Table 3.1 & Fig. 3.2) and described below.
Twelve 1 ha sample plots were established within the Rio Bravo Conservation and Management Area (RBCMA) and the Bladen nature reserve, both of which are highly protected and passively managed areas (henceforth termed the PRPM group); one plot was located within the Manatee forest reserve which is protected and actively managed (henceforth PRAM), whilst seven sample plots were located in areas of pine savanna were considered to be unprotected (henceforth UPR). To supplement the observations from PRAM areas, data from 108 circular sample plots of 0.1 ha for pine woodland in Deep River were provided by Linares et al. (2009). These pine savannas had been previously logged but since 2009 private licensees have been extracting pine timber under a government approved sustainable forest management plan. The data contributed by Linares et. al. (2009) were collected originally as part of a sustainable logging operation in the Deep River forest reserve. These one tenth of a hectare circular
sample plots (17.84m radius) were arranged in a regularly spaced pattern to permit a thorough sampling of both the broadleaf and savanna woodland areas of the reserve. The present study extracted a subset of these for the savanna areas only. The circular plots were first screened by overlaying their ground areas upon very high spatial resolution imagery from the WorldView II satellite (0.5m panchromatic, 2m multispectral data) and interpreting this to ensure that only those plots entirely within pine woodland patches were chosen for aggregation to create the 1 ha equivalent data described later (Fig. 3.1C). These data from the Deep River forest reserve were combined with the data from the Manatee forest reserve to create the data set for woodlands in protected and actively managed areas (the PRAM group).

3.4.4. Vegetation measurements

Each tree within a hectare plot with a dbh (cm) ≥ 10cm was positioned using GPS; structural attributes including the diameter at breast height (dbh), total height (h), bole height (H_b) and canopy width in two orthogonal directions (D_1 and D_2) were measured. These data were then used to calculate properties for each tree, sample plot, and PMG such as AGWB, basal area (BA), and Lorey’s mean height for each PMG. 6,547 trees were measured over three field seasons from plots covering a total ground area of 30.8 hectares. 6,417 were pine trees, with 130 other trees including oak, craboo and the sandpaper tree. For the Deep River reserve, a single co-ordinate representing the centroid of each circular plot was recorded with GPS and the number of trees contained within the plot recorded, but the location of each tree was not recorded.

3.4.5. Data analysis

All data were processed and analysed using Sigmaplot 12.3. Expansion factors (Ef) were used to standardise the reporting of the number of trees in each dbh or height class into per hectare equivalents. The actual number of trees collected for each dbh and total height class was multiplied by an expansion factor calculated using equation 3.1 to produce results per hectare.

\[ Ef = \frac{1}{\text{Area}_{(ha)}} \]
For the denominator, the total area sampled within the PRAM, PRPM, and UPR areas respectively was used in each case. The expansion factors calculated to analyse the pooled data using all observations and for each of the three PMGs were $E_{f_{\text{all data}}} = 0.038$, $E_{f_{\text{PRAM}}} = 0.0847$, $E_{f_{\text{PRPM}}} = 0.0833$ and $E_{f_{\text{UPR}}} = 0.1428$. The AGWB was calculated for each standing tree using the allometric equation 3.2 (Viergever et al., 2009).

\[
\text{Pine Biomass}(\text{kg}) = 0.0407 \times \text{dbh}^{2.4323} \quad (3.2)
\]

This equation was developed previously for pine trees using destructive sampling within savanna woodland in the RBCMA, which is also where 12 of the square plots measured in this study are located. The ground data for the development of the allometric equation were collected during 2002 and 2003 by harvesting 53 individual pine trees and saplings in the RBCMA with their height ranging from 1 – 19.1 m, dbh ranging from 10.0 – 52.4 cm, crown area ranging from 2.8 – 104.8 $\text{m}^2$ and dry AGWB per tree ranging from 4×10-4 to 1.035 tonnes (Brown et al., 2005). Given that the architectural characteristics of the majority of the trees measured in the present study lie within the ranges mentioned above it is reasonable to assume that this allometric equation should provide reasonable estimates of AGWB for these pine-dominated woodlands. Lorey’s mean height (LMH), coefficient of variation (CV), and relative coefficient of variation (RCV) were calculated using equations 3.3., 3.4, and 3.5 respectively to characterise the variability of dbh, and total height around the arithmetic mean of the three PMGs.

\[
\text{LMH} = \frac{\sum h_i \times BA}{\sum BA} \quad (3.3)
\]
\[
\text{CV} = \frac{\sigma}{\mu} \quad (3.4)
\]
\[
\text{RCV} = \frac{CV}{\sqrt{n}} \times 100 \quad (3.5)
\]

Where BA is Basal Area in square metres, $\sigma$ is the standard deviation, $\mu$ is the arithmetic mean, and $n$ is the number of observations.
3.5. Results

3.5.1 Diameter at breast height

It is hypothesised that savanna woodlands under different protection and management regimes may produce significantly different diameter distributions. The range of the dbh distributions Whilst Fig.3.3A indicates a uni-modal distribution skewed to the right when the data from all areas are combined, when the data are subdivided into the different PMGs, three different distributions are revealed for UPR, PRPM and PRAM areas (Fig. 3.3B). Examining the larger dbh classes (i.e. mid-points ≥ 25cm), few large individuals are found within UPR areas (< 17% of trees/ha observed) while for PRAM and PRPM areas the number of bigger trees in a hectare is much higher (51 % and 48% of trees/ha respectively). The most frequent dbh class (Fig. 3.3B) is the 20 – 22cm class (approximately 18 trees /ha or 14% are in this class) for PRAM, compared to the 12 – 14cm dbh class for the UPR areas (63 trees /ha or 15%) and the 10 – 12cm class for the PRPM areas (15 trees /ha or 10%).

![Figures 3.1-3.3 showing dbh and total height distribution](image-url)

**FIGURE 3.3.** Number of individuals/ha plotted at the dbh class midpoint A (pooled data) and B (per PMG) and at the total height class midpoint C (pooled data) and D (per PMG). Boxplots summarising the data pooled and per PMG for total height (A) and dbh (B).
The boxplots in Fig. 3.3 E&F further illustrate that there is a higher mean value of dbh for the trees in the PRPM areas and a wider range of dbh values in comparison to the trees in UPR and PRAM groups.

### 3.5.2. Height

Total height data was available for only 88% of the trees measured (Fig. 3.3D), since tree height was not collected in Deep River. The range of total height measured is 0.58 – 26.80m. For all three PMGs, the height of most trees exceeds 10m (UPR: 92%, PRAM: 89% and PRPM: 86% exceedance). The predominant mean height of the 100 largest trees per hectare (pmh /ha) is 18.49m, 21.25m, and 18.83m for the UPR, PRAM and PRPM groups respectively; Lorey’s mean height for the same groups are 13.46m, 11.78m, and 14.38m respectively. A Kolmogorov-Smirnov test indicates that all three height distributions are significantly different from normal (p < 0.001). Although Fig.3.3F indicates that the mean total height between the PMGs is not visually different; the combination of the predominant mean height and Lorey’s height show that the PRPM areas have taller trees than UPR and PRAM areas.

### 3.5.3. Differences in diameter and tree height according to type of management

Due to their non-normal data distributions, the non-parametric Kruskal Wallis Rank ANOVA test was used to assess any differences in the diameters and heights observed between the three PMGs (table 3.2).

<table>
<thead>
<tr>
<th>Comparison</th>
<th>Diameter Diff of Ranks</th>
<th>Q</th>
<th>Total height Diff of Ranks</th>
<th>Q</th>
</tr>
</thead>
<tbody>
<tr>
<td>PRPM vs. UPR</td>
<td>1314.451</td>
<td>23.977</td>
<td>731.88</td>
<td>6.08</td>
</tr>
<tr>
<td>PRPM vs. PRAM</td>
<td>395.842</td>
<td>6.171</td>
<td>200.34</td>
<td>4.77</td>
</tr>
<tr>
<td>PRAM vs. UPR</td>
<td>918.609</td>
<td>15.600</td>
<td>531.53</td>
<td>4.47</td>
</tr>
</tbody>
</table>

Differences in the median values of dbh and in the total height were both statistically significant (P < 0.001). A post-ANOVA test (Dunn’s non-parametric method) indicated that both tree height and diameter were significantly different between woodlands with different types of management.
3.5.4. Variability of diameter and tree height

The variability around the mean for dbh and total height were examined using RCV. Table 3.3 presents results for the pooled data and for the data subdivided per PMG, whilst Fig 3.4 presents the RCVs for individual hectare plots in each PMG.

### Table 3.3: Descriptive statistics for diameter at breast height (cm) and total height (m) when data are pooled and when subdivided by different PMGs.

<table>
<thead>
<tr>
<th>DBH (cm)</th>
<th>n</th>
<th>Mean</th>
<th>Median</th>
<th>Mode</th>
<th>St. dev.</th>
<th>Min</th>
<th>Max</th>
<th>RCV</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>All</strong></td>
<td>6547</td>
<td>20.8</td>
<td>19.7</td>
<td>20</td>
<td>7.8</td>
<td>10</td>
<td>65.4</td>
<td>0.5</td>
</tr>
<tr>
<td><strong>UPR</strong></td>
<td>3030</td>
<td>18.1</td>
<td>17.5</td>
<td>13</td>
<td>5.6</td>
<td>10</td>
<td>62</td>
<td>0.6</td>
</tr>
<tr>
<td><strong>PRAM</strong></td>
<td>1561</td>
<td>21.4</td>
<td>20</td>
<td>20</td>
<td>6.3</td>
<td>10</td>
<td>48</td>
<td>0.7</td>
</tr>
<tr>
<td><strong>PRPM</strong></td>
<td>1956</td>
<td>24.5</td>
<td>24</td>
<td>12</td>
<td>9.9</td>
<td>10</td>
<td>65.4</td>
<td>0.9</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Total Height (m)</th>
<th>n</th>
<th>Mean</th>
<th>Median</th>
<th>Mode</th>
<th>St. dev.</th>
<th>Min</th>
<th>Max</th>
<th>RCV</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>All</strong></td>
<td>4950</td>
<td>12.5</td>
<td>12.5</td>
<td>13</td>
<td>3.5</td>
<td>0.6</td>
<td>26.8</td>
<td>0.4</td>
</tr>
<tr>
<td><strong>UPR</strong></td>
<td>2866</td>
<td>12.4</td>
<td>12.3</td>
<td>14</td>
<td>3</td>
<td>0.6</td>
<td>24.4</td>
<td>0.4</td>
</tr>
<tr>
<td><strong>PRAM</strong></td>
<td>152</td>
<td>11.2</td>
<td>11.2</td>
<td>13</td>
<td>2.3</td>
<td>3.7</td>
<td>15.6</td>
<td>1.6</td>
</tr>
<tr>
<td><strong>PRPM</strong></td>
<td>1932</td>
<td>12.9</td>
<td>13</td>
<td>14.5</td>
<td>4.2</td>
<td>2.2</td>
<td>26.8</td>
<td>0.7</td>
</tr>
</tbody>
</table>

FIGURE 3.4 RCV values (100% maximum) for diameter at breast height and total height between individual hectare sample plots belonging to different protection and management groups (A). (B) illustrates a generally positive relationship between variation in height and variation in dbh.

Overall the RCV expressed as percentage for both dbh and total height is very low (less than 5%) for all PMGs (table 3.3) and for the individual hectare plots (Fig. 3.4A), with dbh showing slightly more variability than height. The UPR areas show the lowest variability for dbh and total height whilst PRPM areas show slightly more variability. Total height is also slightly more variable in the PRPM areas. The RCV for diameter
breast height and total height were compared on a two axis plot (Fig. 3.4B), confirming that plots with more variability of dbh tend to also have more variability in total height.

3.5.5 Models of diameter distributions

Non-linear regression was used to fit both a single parameter power model and a single parameter exponential model to the observed distributions of dbh (table 3.4).

**TABLE 3.4** Power law scaling relationships as described by allometric theory fit most of the diameter distributions; however exponential models fit more closely to the data when regression parameters $r^2$, $F$ and standard error of estimate SEE are compared. Regression parameters are not presented for plots that models could not be fitted (i.e. 9 out of 20 hectare plots).

<table>
<thead>
<tr>
<th>PMG</th>
<th>Plot</th>
<th>N</th>
<th>Power law: $y = a \times x^b$</th>
<th>Exponential: $y = a \times e^{bx}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>$r^2$</td>
<td>$a$</td>
</tr>
<tr>
<td>Pooled</td>
<td>6547</td>
<td>0.64</td>
<td>540.61</td>
<td>-1.26</td>
</tr>
<tr>
<td>PMG</td>
<td></td>
<td>3030</td>
<td>0.64</td>
<td>2947.3</td>
</tr>
<tr>
<td>UPR</td>
<td>1561</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>PRAM</td>
<td>1956</td>
<td>0.68</td>
<td>217.75</td>
<td>-1.07</td>
</tr>
<tr>
<td>PRPM</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PRPM</td>
<td>9</td>
<td>174</td>
<td>0.88</td>
<td>1943.7</td>
</tr>
<tr>
<td>UPR</td>
<td>13</td>
<td>537</td>
<td>0.87</td>
<td>59807</td>
</tr>
<tr>
<td>PRPM</td>
<td>6</td>
<td>250</td>
<td>0.78</td>
<td>1412.4</td>
</tr>
<tr>
<td>UPR</td>
<td>14</td>
<td>688</td>
<td>0.85</td>
<td>19419</td>
</tr>
<tr>
<td>PRPM</td>
<td>10</td>
<td>177</td>
<td>0.76</td>
<td>1067</td>
</tr>
<tr>
<td>PRPM</td>
<td>17</td>
<td>202</td>
<td>0.75</td>
<td>903.07</td>
</tr>
<tr>
<td>PRPM</td>
<td>16</td>
<td>102</td>
<td>0.72</td>
<td>167.69</td>
</tr>
<tr>
<td>UPR</td>
<td>11</td>
<td>533</td>
<td>0.66</td>
<td>3878.3</td>
</tr>
<tr>
<td>PRPM</td>
<td>18</td>
<td>153</td>
<td>0.56</td>
<td>204.93</td>
</tr>
</tbody>
</table>

Note: In the power law and exponential equations, $y$ is the number of trees per hectare and $x$ is the dbh.

The models were fitted to the observations at three levels of aggregation: firstly with all data pooled, then for the trees within each PMG and finally models were fitted for each individual hectare plot if a fit could be obtained. When all data are pooled or grouped per PMG (table 3.4, upper), the exponential model as described by Meyer and Stevenson (1943) fits better as indicated by the regression report. When individual plots are used (table 3.4, lower), the power law commonly used in allometry only produces a closer fit in two cases (PRPM sample plots 9, 10), with the exponential model again producing lower standard errors for all the other plots.
3.5.6. Variations in biomass, basal area, and diameter evident at the plot scale

To examine differences in tree number density to BA, AGWB and mean dbh we used scatter plots (Fig.3.5). The plots contain 28 observations. 20 of these observations are derived from the 100x100m fixed-area plots in the PRAM, PRPM and UPR areas, while eight additional observations are obtained from cluster-plots, generated by randomly selecting and aggregating data from ten 0.1ha circular plots using the sampling grid shown on Fig. 3.1C. The cluster plot method enabled BA, AGWB and dbh observations collected from the Deep River area to be incorporated and compared at an equivalent level of aggregation to the data from the hectare plots in other locations. When compared visually (Fig. 3.5), the data collected from the different PMGS can be seen to cluster into different parts of the two dimensional space.

![Figure 3.5](image)

**FIGURE 3.5** AGWB /ha and BA/ha versus tree number density/ha for the three PMGs. Data points are a combination of fixed area and cluster plots. Error bars represent the standard error of the sum for AGWB and BA. Blue, red and green lines in (A) show the linear regression lines for each PMG.

The PRPM and PRAM data points appear closely grouped together in all three plots, while the UPR data points are more widely scattered. Fig 3.5A indicates that the greatest numbers of trees per hectare are found in UPR areas (432 trees/ha) followed by PRPM (163 trees/ha) and fewest in PRAM areas (132 trees/ha). In PRPM areas, the sample plots are shown to cover a relatively narrow range of AGWB and BA (80 – 100 t/ha and 8 – 10 m²/ha respectively) and to have a slightly wider range for the average dbh (22 – 28 cm).
Across all the UPR areas sampled, the values range more widely (25 – 85 t/ha, 4 – 15 m²/ha and 14 – 22cm for AGWB, BA and average dbh respectively) but the individual UPR plots contain less variation internally, as indicated by the smaller error bars. In PRAM areas the data points cluster consistently into the bottom left corner of each scatter plot; the only exception being the plot of average dbh (17 – 24cm).

From Fig. 3.5B we observe that the number of trees within a hectare of pine savanna woodland might be used to estimate the BA of that unit and in Fig. 3.5A we observe a possible positive relationship between AGWB and tree number density; this relationship appears to saturate for values of AGWB greater than 80 t/ha, with this appearance of saturation mostly created by the UPR data points. If we examine only the PRPM areas, AGWB/ha appears to continue to increase with increasing numbers of trees up to approximately 100 t/ha.

These trends hypothesised for AGWB and BA in relation to tree number density (Fig. 3.5A and Fig. 3.5B) was assessed using the Spearman rank order correlation (spearman’s roh, ρ). The Spearman’s roh is a non-parametric measure which is used in this chapter to assess the directionality and strength of the ranks. Results of the calculation showed that BA and tree density showed a strongly positive correlation (ρ=0.901, P<0.001), and that AGWB was also positively correlated with tree density (ρ=0.743, P<0.001).

3.5.7. Implications at the management of savanna woodlands

When taken together, these findings can support decision making about forest management in savanna areas. As in other parts of the world, forest managers in Belize are shifting from single-objective management of forests based on maximising timber yield, to more holistic approaches where the goal may involve finding a balance between timber extraction, carbon storage and biodiversity enhancement. The present study has shown that savanna woodlands differ in various structural attributes depending on the type of management applied.
In Fig. 3.6, the three polygons represent the three different types of protection and management by which the field data was grouped.

The vertices of the polygons are some structural attributes that a manager might use to assess a forest for objectives such as yield, carbon storage potential, structural complexity, or likely biodiversity of the forest habitat. The shapes and the different spaces occupied by the polygons graphically illustrate the differences found between the woodlands under differing types of protection or management. We observe that bringing unprotected areas under protection or active management may result in reduced tree density, whilst areas that are protected and passively managed have the highest above ground woody biomass per hectare, the highest variability in diameters and greatest number of larger trees, which are all woodland characteristics thought to favour biodiversity (Acker et al., 1998; Zenner and Hibbs, 2000).
3.6. Discussion

It was hypothesised that the structure of the savanna woodland areas (as observed through their dbh distributions, height, and population density) might differ depending on whether the woodlands had been passively protected or actively managed (PRAM and PRPM) or had no protection (UPR). Whilst it is not possible to factor out all differences other than forest management in a real world experiment, the comparison has validity in that these woodlands are relatively homogeneous (being dominated by more than 90% in each hectare by just one species - *Pinus caribaea*), and with all plots in the same clim8ate zone (Rubel and Kottek, 2010), on similar geological and geomorphological units (Wright *et al.*, 1958), and on soils originating from comparable-dystrophic coastal and palaeo-fluvial deposits (Furley, 2011). All these lowland woodlands were extensively logged for softwood timber until they came under protection or management in the early 1990s, and the protection and management regimes within the study PRAM and PRPM areas have remained the same for more than 15 years (Johnson, 1974; PfB, 2006; Linares, 2009). In contrast, the UPR areas have continued to experience random human pressures and in particular an increasing frequency of burning and logging during the same period.

3.6.1. Differences related to the types of management

Previously there was a presumption by land managers that all savanna woodlands throughout the Belize lowlands shared common properties and therefore could be treated as a single national population. The pooled dbh distribution portrays a national population composed mostly of juvenile pine (Fig 3.3A; Fig.3.3E; table 3.3) with high mortality rates at the higher dbh classes (dbh ≥ 22cm), but these characteristics of the pooled distribution were often not replicated in the individual plots.

When these pine woodlands are differentiated according to their type of protection or management, three characteristically different distributions are revealed (Fig. 3.3B, and Fig. 3.3D). Differences in both the diameter and total height of trees are observed between the three groups (Fig. 3.3B, and Fig. 3.3D) and shown to be significant
statistically (table 3.2) suggesting that the protection and management regime does significantly influence the woodland structure.

Areas which have been highly protected and passively managed (PRPM) for the last 20 years have experienced least pressure from human activities and appear to have developed most structural complexity. This is indicated in the data by a greater number of larger trees (dbh ≥ 40cm) (Fig. 3.3B) and by the models fitted, which predict a slower pace of loss for larger trees (table 3.4) in the PRPM areas. The distribution of the diameters in this group also suggests a more complex woodland structure than that found in the PRAM or UPR areas. The mean and RCV values for tree diameter and total tree height (Fig. 3.4, table 3.3) show that the greatest variability is found for the PRPM data set. The greater complexity of these woodlands may be attributed to the strong protection of the PRPM areas, with little thinning and no extraction, and the prescribed burning that allows the sapling population to increase while grasses which are highly competitive against tree saplings are kept controlled (Lamb, 1968; Farjon and Styles, 1997; Furley, 2010).

There were several indicators that the woodlands in the unprotected areas were experiencing the greatest disturbance. The mean dbh is much smaller in the unprotected areas than in the areas that are sustainably logged or protected, although interestingly the mean total height and Lorey’s mean height for pines was found to be similar across all three types of management (Fig. 3.3B). The various models fitted to the pooled diameter distributions (table 3.4) show that the exponential model, underpinned by theories of disturbance (Coomes et al., 2003), provides a better fit to the distribution of diameters than the power model, which is based upon an understanding of the biological factors that govern tree growth (West et al., 2009). When models were fitted to the dbh distributions, the models for the UPR areas generally had higher exponents than those fitted to the PRPM data, both for the data set for the whole PMG and also for the individual hectare plots within a group (table 3.4), indicating a trend for larger trees to be lost with a greater pace from UPR areas than from PRPM or PRAM areas. These observations are all indicative of greater pressure on the woodland in the unprotected areas.
Human pressure and natural disturbances are both generally considered to lead to a shift from a tree to grass cover in tropical savannas (House et al., 2003; Woollen et al., 2012; Furley, 2008). In apparent contrast, the evidence from this study suggests that in some UPR areas, where uncontrolled burning and other activities are most likely to happen, trees may be found in higher numbers and sometimes with higher AGWB and BA per hectare than in the protected and managed areas (Fig. 3.5A; Fig. 3.5B; Fig. 3.6). However, this finding need to be interpreted carefully, since the trees in the plots with highest number density were generally of low girth and were mostly juvenile. It is possible that pines in unprotected areas may be responding to the high understory mortality from frequent burning and competition for light resources by gaining height rather than adding girth, resulting in dense stands of thin, tall trees (Gignoux et al. 1997; Furley et. al., 2008; Frost and Robertson, 1985; Morrison, 1995).

As these trees mature, competition may lead to reduced numbers. Nevertheless, these dense stands observed in some unprotected areas appear to be a response to human pressure from cutting and burning, but where the pressure is not so intense that it leads to the removal of the woodland cover and its replacement by grass or scrub. The ways in which human pressure gives rise to these wide variations in tree numbers and biomass in these unprotected areas evidently requires further investigation.

3.7. Conclusions

Field measurements from approximately 6,500 individual trees have been analysed to produce the first systematic, quantitative description of pine savanna woodlands throughout their range in Belize, Central America. Roughly 40% (637km²) of these savannas have a woody component dominated by the Caribbean pine. These woodlands can be locally dense, occasionally reaching up to 700 trees per hectare with 60% canopy cover, and yielding a maximum biomass of around 100 t/ha, although 100-300 trees per hectare is much more typical. 95% of trees are between 9-16m in height (mean = 12.5m) have a dbh between 13-28 cm (mean = 21cm). The national distribution of diameters follows a reverse J-curve, suggesting a pine population composed mostly of juveniles and with fewer trees than expected in the larger dbh classes (>22cm). This
distribution was however dominated by the large number of trees from the unprotected areas, which are experiencing greatest pressure from human activities.

Subdividing the data according to the degree of protection from human activity illustrates the differences in tree numbers and structural complexity that these woodlands exhibit when they are managed for different purposes. Pine savanna areas that had been protected and were managed as extractive reserves exhibited the lowest numbers of individual trees (mean = 132 trees/ha) and lower values of above ground woody biomass (40-50 t/ha). Their distribution was typical of a forest managed for timber extraction, with a narrow range of diameters concentrated around the 20-22cm class favoured for pine lumber. Areas that had been protected from human pressure and managed passively without extraction also had relatively low numbers of trees (mean = 163 trees/ha) but the retention of bigger trees resulted in values of standing biomass at the higher end of the range (80-100 t/ha). These also formed more structurally complex pine stands, with a greater variety of tree girths, heights and a more open canopy cover which produced a habitat most favourable for plant and animal biodiversity. The unprotected woodlands lacked complexity of structure and an absence of larger trees makes them less preferable for sustainable logging or biodiversity conservation. Surprisingly, high tree numbers were found in some unprotected areas (mean = 432 trees/ha). These high biomass areas composed many tall, thin densely packed stems that may be a response to cutting and burning. In other unprotected areas, tree numbers and biomass were very low, leading to the conclusion that biomass in unprotected areas is very variable and the response of these woodlands to human pressure requires further investigation.

Overall, these findings indicate that different protection or management regimes can lead to different forest structures developing in pine woodlands within tropical lowland savannas. Of the three types of management examined, protection from human pressure combined with passive management involving prescribed burning to control wildfire appears to result in the greatest woodland complexity and inherent conservation value, as shown by the diameter distributions, the higher frequency of larger trees and the higher biomass observed in these areas.
References


Shackleton, C.M., Scholes, R.J., 2011. Above ground woody community attributes, biomass and carbon stocks along a rainfall gradient in the savannas of the central lowveld, South Africa. 77, 9-9.


Zisman, S., 1996. The Directory of Belizean Protected Areas and Sites of Nature Conservation Interest
Chapter Four

Estimation of Woody Biomass from ALOS PALSAR Imagery

4.1. Overview

Having established in chapter three the significance of protection and management for the growth of pine-dominated woodlands in the lowland savannas of Belize, in chapter 4 I am combining the protection and management information from chapter 3 and the ALOS PALSAR imagery to present a biomass retrieval approach and examine the influence of forest structure on the ALOS backscatter.

I use the semi-empirical water cloud model to describe the interaction between the SAR signal and vegetation and re-arrange the model to predict biomass. Estimations are made using the HV polarization SAR imagery collected by ALOS PALSAR during 2008 in combination with community woodland inventory data from pine savanna areas in Belize.

4.2 Author contributions – declaration

This chapter includes results and discussions from two publications;


For both articles Dimitrios G. Michelakis, Neil Stuart, and Iain H. Woodhouse devised the research; Dimitrios G. Michelakis, Neil Stuart, German Lopez, & Vinicio Linares collected the field data; Dimitrios G. Michelakis conducted the analysis; Dimitrios G. Michelakis wrote the article with assistance and revisions from all other authors.

**4.3 Introduction**

Although considered by many as a grassland dominated ecosystem, many of the world’s savannas comprise substantial woodland areas. As well as providing an economic resource to local populations, these woodlands also play a surprisingly significant role in global carbon sequestration processes (Scurlock & Hall, 1998) which require quantification under international agreements such as the United Nations initiative on Reducing Emissions from Deforestation and forest Degradation (UN-REDD) while also as biodiversity reserves under the United Nations convention on biological diversity (UNCBD). Consequently, land managers are turning to remote sensing as a cheaper and more rapid alternative to traditional forest inventory methods to enable effective monitoring of the woody component of savannas as a form of low density forest. For management purposes, previous workers suggest that satellite remote sensing should be used to predict biomass with errors within 20 t/ha for 80% of biomass estimates; but should not exceed 50 t/ha for biomass maps at the hectare spatial resolution (Hall* et al.*, 2011; Houghton* et al.*, 2009).

Satellite radar can play an important role in the remote measurement of forest biophysical parameters which have been shown to closely relate to biomass accumulation and biodiversity (Gibbs* et al.*, 2007). Synthetic aperture radar (SAR) data collected by
satellites using lower microwave frequencies such as L-band (1-2GHz) are one of the most widely used datasets in tropical areas, particularly during the last five years. This is due mainly to five reasons: 1) L-band frequencies have the ability to penetrate clouds and dense vegetation canopies since the elements of both are relatively small in comparison to the L-band wavelength (Woodhouse, 2006; Rosenqvist et al., 2003) 2) there is an established proportionality of the L-band backscattered intensity to biomass (Wu, 1987; Le Toan et al., 1992) the significant archive of radar data collected by the satellite L-band SAR sensor ALOS PALSAR between 2007-2012 (Rosenqvist et al., 2007) the wide range of methods that can be used with ALOS PALSAR data to derive biomass predictions (Hame et al., 2013; Wenjian et al., 2013; Englhart et al., 2012), and 5) the expectation of renewed global capability for, monitoring the same forest parameters using the forthcoming ALOS PALSAR 2 sensor and the NASA airborne UAVSAR system (Rosen et al., 2006).

Previous research has demonstrated the capability of the data collected by ALOS PALSAR to extract information about certain structural parameters (Kasischke et al., 1997; Wegmuller & Werner, 1997). These have included among others the amount and spatial distribution of above ground woody biomass (henceforth biomass) in savanna woodlands (Carreiras et al., 2013; Mitchard et al., 2013; Lucas & Armston, 2007; Mitchard et al., 2009; Mitchard et al., 2011; Ryan et al., 2012; Paradzayi et al., 2009), with the extracted information used to establish baseline inventories of forest and carbon stocks, using the derived biomass data for example for planning conservation-oriented actions, and for ecological monitoring of savanna areas (Mitchard et al., 2011; Ryan et al., 2012; Furley et al., 2010). Published research on African and Australian savannas has obtained strong correlations between ALOS PALSAR radar backscatter and field measurements of biomass using non-linear regression models (Mitchard et al., 2013; Lucas & Armston, 2007; Mitchard et al., 2009; Mitchard et al., 2011; Ryan et al., 2012); however these models were trained using solely the coefficient of
determination as a measure of good fit, neglecting the underlying principles of how radar is theorised to interact with vegetation canopies. These relationships have also been found to be less robust in other studies; as for example in (Cassells, et al. 2009) where very poor correlations between backscatter and biomass were recorded in African savannas. Although these poor correlations can be partially explained by factors such as the small numbers and areas of sample-plots used for collecting field data, by significant topographic relief or due to excessive prior precipitation (Newton et al., 2009), they can also be explained by differences in the vegetation structure and the degree of canopy closure in different woodlands, since both factors are also known to have a significant effect on the way radar backscatter interacts with areal units of vegetation (Robinson et al., 2013; Saatchi et al., 2011). In the Americas research has been undertaken to explore the capabilities of ALOS PALSAR for mapping land cover / land use in Brazilian savannas (Sano et al., 2010; Evans et al., 2010). Focusing specifically on Belize, researchers have examined the capability of using airborne radar imagery to identify woody subtypes of these savannas (Stuart et al., 2006) while Viergever et al., (2009) studied the sensitivity of airborne SAR backscatter at four wavelengths to biomass using interferometry. In both cases the relationships between tree structure and satellite radar backscatter were not explored. To our knowledge, this study is the first of its kind in Central and South America to explore the sensitivity, in particular, of ALOS PALSAR to forest structure.

The objectives of the study are to compare ALOS PALSAR backscatter data to biomass using: a) field measurements collected from sample plots in different pine dominated savanna sites distributed throughout the country of Belize and b) to evaluate the accuracy of modelling the backscatter response to biomass using a validation of a simple variation of the water cloud model (WCM) (Attema & Ulaby, 1978).
4.4 Materials and methods

4.4.1 The study site
The study was conducted in Belize, Central America with sites chosen from both protected and unprotected areas of the lowland savanna ecosystem. Lowland savanna covers approximately one tenth of the country (1750km² according to recent estimations by (Cameron et al., 2011; Meerman et al., 2011) and is characterized by gentle relief and seasonal flooding. The savanna woodlands are relatively homogeneous in their type with it being typical for a single pine species to dominate more than 90% of a hectare. All savanna woodlands in Belize occur within the same climate zone (Rubel & Kottek, 2010), on the same geological unit (Furley, 2011), and on mature coastal soil deposits (Wright, 1958). The main woody species are Pine (*Pinus caribaea*), and Oak (*Quercus oleoides*). In other areas scattered trees, palms, shrubs, and extensive grassland areas typical of the Neotropical savannas are also abundant (Bridgewater et al., 2012; Goodwin et al., 2013; Bridgewater, et al., 2002).

4.4.2 Ground truth data
In order to obtain a more comprehensive coverage of different savanna woodlands in Belize, and to sample the whole known range of biomass found in these woodlands, we examined previous studies conducted in the country (Viergever, 2009; Linares, 2009; Brown et al., 2005; Johnson & Chaffey, 1974), qualitative information from non-governmental organisations, and a visual interpretation of very high spatial resolution worldview imagery. The dbh ranges that were reported using these datasets are covered by the data collected by three field workers during four data collection campaigns between 2007 – 2012. These datasets are listed below and are represented graphical in Fig. 4.1:

(1) Dataset A includes 23 hectares of field data collected within pine dominated savanna areas between 2007 – 2011. Of this, 20 hectares were collected specifically for this study from 20 sample plots of 100m x 100m, between 2011-12.
These were established within pine woodlands under three different protection and management groups (PMGs) located throughout the north and central parts of Belize. Plot locations were chosen through purposive sampling, ensuring that the plots captured the full range of tree structures known to occur within savanna areas, within passively protected, and managed areas (PRPM), actively protected and managed areas (PRAM), and unprotected areas (UPR). Potential plot locations were first identified using Worldview II imagery and confirmed through personal communication with the local timber industry, local government and NGOs, and through direct observation. Three hectares from three rectangular sample plots (PRPM) of 167m x 60m were added to the above data which were extracted from a transect of 800m x 60m collected by Viergever, et al., (2009) in 2007. These sample plots targeted the lower range of tree number density (henceforth density) (0-100 trees/ha). In these low density savanna areas Viergever et al. (2009) commented that palm clumps (Acoelorrapha wrightii) may contribute significantly to the radar backscatter collected by a high resolution airborne
sensor (AIRSAR). We purposively excluded the areas that we confirmed contained only palm vegetation when using these data in our analysis. In the areas used, palms accounted for a small fraction of the vegetation and do not contribute significantly to the backscatter by visual inspection. For every tree with a diameter at breast height (henceforth dbh) larger than 10cm, the X, Y location and the dbh were measured, resulting in a total of 5391 trees measured in Dataset A.

**(2)** Dataset B includes 50 tree measurements collected in six 0.1ha circular sample plots and is a subset of a broader dataset which includes 1,390 tree measurements collected from 108 separate 0.1ha circular sample plots (17.84m radius), systematically distributed on a regular grid within the Deep River Forest Reserve (henceforth DR) in 2009 by Linares et al., (2009). These data were collected as part of a stocking inventory for sustainable forest management operations in the south of the country (PRAM). All 108 of the DR sample plots were visually inspected and compared to Worldview II data and only plots that clearly covered entire pine woodland areas were used. Data from the DR circular plots were also omitted whenever inspection of Worldview II imagery revealed there to be little or no woody vegetation present beyond the perimeter of the circular plot (Fig. 4.2).

**FIGURE 4.2 Use of WorldView data to create 44 virtual plots of 100m by 100m representative of lower biomass savanna woodlands in the Deep River Forest Reserve**

Finally 44 separate 0.1ha plots considered to have biomass similar to the surrounding hectare were used to estimate total biomass (t/ha). Six of these plots with values at the lower end of the biomass range (henceforth Dataset B) were used to supplement data set A and assisted the fitting of the backscatter-biomass model for areas with biomass less than 100 t/ha.
(3) Dataset V comprised the remaining 38 plots from the DR dataset, which were used for external validation.

(4) Dataset C comprised a further nine single hectare, square sample plots that were established randomly within open savanna areas where no woody vegetation was evident. This data set was used to model the backscatter: biomass relationship for areas with very low values of woody biomass.

Fig. 4.3 summarises the size, the purpose and the constituency of each of these four data sets schematically.

FIGURE 4.3 Schematic representation of datasets used. Datasets B and V are subsets of DR. Sizes in circles represent differences in areal size.

For all trees with a dbh ≥ 10cm in data sets A, B, and V, the biomass for each tree was estimated using the allometric equations developed specifically for *Pinus caribaea* and *Quercus oleoides* in Belize by (Viergever et al., 2009; Brown et al., 2005) expressed in equations (4.1) and (4.2):

\[
\text{Biomass}_{\text{Kg}} = 0.0407 \times \text{diameter}^{2.4323} \tag{4.1}
\]

\[
\text{Biomass}_{\text{Kg}} = \left(0.5 + \frac{25000 \times \text{diameter}^{2.5}}{\text{dbh}^{2.5} + 246872}\right) \times 2 \tag{4.2}
\]

The part of the equation within the brackets in (5.2) estimates the carbon stock in kilograms. The factor of two is used as indicated in IPCC, (2006) to estimate the amount of biomass per tree. These allometric equations were developed using destructive
Dimitrios Michelakis

sampling within savanna woodland in a protected area, which is also where 12 of the square plots measured in this study are located. The ground data for the development of the allometric equation were collected during 2002 and 2003 by harvesting 53 individual pine trees and saplings in the RBCMA with their dbh ranging from 1.0 – 52.4 cm (Brown et al., 2005). In this study, the biomass estimations per tree using allometric equations (1), and (2) were then up scaled to estimates per hectare, by summing the individual tree biomasses (henceforth total biomass).

4.4.3 Satellite Data

Two level 1.0 ALOS PALSAR (CEOS format) FBD polarization (HH and HV) scenes (Table 4.1) covering the fieldwork locations, collected during the wet season in 2008, were obtained through the Japanese Aerospace Exploration Agency (JAXA).

TABLE 4.1 ALOS PALSAR data acquired over the study sites

<table>
<thead>
<tr>
<th>Scene Id</th>
<th>Mode</th>
<th>Incidence angle (deg)</th>
<th>Acquisition Time Centre Image (UTC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALPSRP142970330</td>
<td>Fine Beam Dual Polarisation (HH / HV)</td>
<td>34.3</td>
<td>30/09/2008 - 04:29:43</td>
</tr>
<tr>
<td>ALPSRP138740330</td>
<td></td>
<td></td>
<td>01/09/2008 - 04:31:01</td>
</tr>
</tbody>
</table>

These scenes (henceforth I, II) were processed to level 1.1 single look complex images (SLC) using the Modular SAR processor developed by GAMMA. Only the HV polarisation was used in this study due to its superior recorded sensitivity to biomass and the minimal impact on the signal resulting from soil moisture variation (Dubois et al., 1995; Sarabandi & Ulaby, 1992). The calibration factor used for the HV polarisation was -58.30 dB as established in Lucas et al., (2007). The SLC images were then converted to multi-look intensity images (MLI) and transformed to geo-coded images (level 1.5) using the differential interferometry geocoding module (DIFF&GEO) of GAMMA software and a SRTM dataset (90m pixel spacing) for Belize. The level 1.5 scenes are four-look imagery with 13 metre pixel spacing displaying backscatter intensity. By visually inspecting the processed SAR imagery we observed that the size of some individual tree crowns was significantly larger than these pixel elements (Small, 1998) and so the pixel size was increased further by aggregating adjacent neighbourhoods of pixels using a 2x2 window and arithmetically averaging their
backscatter in the power domain to create values at 26m pixel spacing. This multi looking technique was also used to remove speckle noise (Laur et al., 1997). The backscatter intensity for each pixel was extracted and averaged using the sample plot edges and transformed to decibels as shown in equation (4.3) showing the definition of Normalised radar Cross Section $\sigma_{HV}^0$

$$\sigma_{HV}^0 dB = 10 \times \log_{10} (\sigma_{HV}^0 \text{power units})$$ (4.3)

Values of $\sigma_{HV}^0$ henceforth referred to as backscatter were then extracted from the ALOS data corresponding to the ground biomass measurements estimated from plot data.

### 4.4.4 Fitting a Water Cloud Model to Examine the Backscatter Biomass Relationship

The statistical analysis performed in this study seeks to establish a relationship between ALOS PALSAR backscatter and biomass estimates derived from field measurements of all trees in one hectare sample plots. The analysis performed in Michelakis et al, (2013) showed this plot size to be appropriate for estimating biomass using ALOS PALSAR backscatter. Pearson’s and Spearman’s correlation coefficients are used to assess any linear or monotonic relationships indicated by the radar theory using equations (4.4) and (4.5):

$$r_p = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2 \sum_{i=1}^{n}(Y_i - \bar{Y})^2}}$$  (4.4)

$$r_s = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2 \sum_{i=1}^{n}(Y_i - \bar{Y})^2}}$$  (4.5)

where $n$ is number of samples, $X_i$, $\bar{X}$, $Y_i$, and $\bar{Y}$ are raw values and the corresponding averages and $y_i$, $\bar{y}$ are the transformed values. Spearman’s rho is calculated using the ranks of the AGWB and BA data. We incorporate a simple form of the WCM as described by Attema & Ulaby, (1978) and Graham & Harris, (2003). This general form of equation, but without an explicit derivation from radar theory, has been used.
previously to relate L-band backscatter to biomass in savanna woodlands (Mitchard et al., 2013; Mitchard et al., 2009; Mitchard et al., 2011).

4.4.4.1 The semi-empirical Water Cloud Model

The water cloud model (WCM) was first introduced by (Attema & Ulaby, 1978) for the study of the interaction between radar energy and vegetated surfaces. It represents the above ground vegetation canopy as a simplistic structure featuring a relatively homogeneous volume consisting of canopy components and air (Graham & Harris, 2003; Prevot et al., 1993; Magnusson et al., 2007). The canopy components are represented by homogeneous spherical scatterers which mimic the structure of a “water cloud”. The WCM was created to model the attenuation of a radar signal with depth through a vegetated canopy in the absence of a stem component. The simplest expression of the WCM takes the following form (He et al., 2014; Kweon et al., 2014):

$$\sigma^0 = \sigma^0_{\text{veg}} + \tau^2 \times \sigma^0_{\text{soil}}$$ (5.6)

Where $\sigma^0$ represents the total backscatter measured by the radar sensor, $\sigma^0_{\text{soil}}$ and $\sigma^0_{\text{veg}}$ represent the backscattered radiation from the soil and the vegetation canopy respectively. $\tau^2$ represents the two-way attenuation of the radar backscatter resulting from interaction with vegetation. For a certain incidence angle ($\theta$) the $\tau^2$ can be written as in equation 4.7.

$$\tau^2 = e^{\left(\frac{-2B\times Wc}{\cos \theta}\right)}$$ (4.7)

where B and Wc represent an empirical parameter and the water content of the vegetation canopy respectively.

$$\sigma^0_{\text{veg}} = A \times \cos \theta \left(1 - \tau^2\right)$$ (4.8)
\[ \sigma_{\text{soil}}^0 = C + D \times m_s \] (4.9)

\[ \sigma^0 = A \times \cos \theta \times \left(1 - e^{-\left(\frac{2 \times B \times w_c}{\cos \theta}\right)}\right) + (C + D_{ms}) \times e^{-\left(\frac{2 \times B \times w_c}{\cos \theta}\right)} \] (4.10)

A, B, C and D are empirical parameters, \( w_c \) represents the water content of the canopy and \( m_s \) represents the soil moisture. Other studies such as Mitchard et al., (2013), Mitchard et al., (2009) and Mitchard et al., (2011) have used a general exponential model similar to equation (5.10) to establish the sensitivity of ALOS PALSAR backscatter to woody biomass, but have not established the physical basis for applying this model as we do here. It is also commonly found in the following form:

\[ \sigma^0 = \sigma_{\text{veg}}^0 \times \left(1 - e^{-C \times \text{Biomass}}\right) + \sigma_{\text{soil}}^0 \] (4.11)

where \( \gamma \) represents an empirical coefficient that can be estimated using ground truth data and ALOS PALSAR backscatter data. It is possible for every positive real number (b) to be written as in equation (5.12)

\[ b = e^k, \ k \in \mathbb{R}, \ b \in \mathbb{A}, \ A = \{x \in \mathbb{R} | x \geq 0\} \] (4.12)

Where in this case, \( b = e^{-\gamma \times \text{Biomass}} \), \( k \) is a real number, \( \mathbb{R} \) is the set of all real numbers, and \( x \) is a non-negative real number. Equation (4.11) can then be written as in equation (5.12):

\[ \sigma^0 = \sigma_{\text{veg}}^0 \times \left(1 - e^{-\gamma \times \text{Biomass}}\right) + \sigma_{\text{soil}}^0 \] (4.13)

where \( \gamma \) represents the same parameter as in (4.11). Fitting and calculation of the empirical coefficients is performed on equation (4.13) (henceforth known as the forward model) in addition to non-linear least squares regression. The forward model was then rearranged to estimate biomass, as shown in equation (4.14):

\[ \text{Biomass} = \log_{\gamma} \left( \frac{\sigma_{\text{soil}}^0 - \sigma_{\text{soil}}^0 + \sigma_{\text{veg}}^0}{\sigma_{\text{veg}}^0} \right) \] (4.14)
Using the re-arranged forward model to estimate biomass may lead to infinite or negative values when $\sigma^0 \leq \sigma_{\text{soil}}^0$ or $\sigma^0 \geq \sigma_{\text{veg}}^0$ respectively (Magnusson et al., 2007; Peregon & Yamagata, 2013). In this study we followed the example shown in Askne et al., 2003 by assigning the highest biomass observed in the field to all values calculated to be infinite. To the values calculated as negative a value of zero biomass was assigned.

4.4.4.2 Validation of the biomass predictions

Datasets A, B, and C were used during model training to ensure that backscatter values were obtained from multiple ground targets representing the entire range of biomass found within the pine savanna woodlands throughout Belize. Two validation processes were conducted, which we refer to as an internal and an external validation (Fig. 4.4).

![Flowchart of the data sets created and analysis steps](image-url)
We used the training datasets A, B, and C to internally validate the fit of the model to the data. We then used dataset V as an independent data set, not used to develop the model, to externally validate it. For both internal and external validation we report the Root Mean Squared Error (RMSE) with inputs of the field-observed and radar-predicted biomass (henceforth predicted biomass).

4.5 Results and Discussion

To explore whether the relationship between the backscatter and AGWB varied according to the size of the ground area within which the AGWB was calculated, each original one hectare sample plot in datasets A and C was subdivided into two, four and ten subplots of 0.5, 0.25 and 0.1ha producing 48, 96 and 240 subplots for each subdivision respectively (Fig. 4.5A). AGWB was then calculated for each subplot of 0.5ha, 0.25ha and 0.1ha by spatially identifying the trees falling within each subplot. Standardized values of AGWB (t/ha) were then calculated for each of the three subplot data sets. The complete dataset B was used in the 0.1ha scale of analysis, but data from only eight of the 0.1ha sample plots from dataset B were used in the one hectare scale of analysis.

FIGURE 4.5 HV intensity (dB) plotted against above ground woody biomass derived by field plots of (A) one hectare (B) 0.5ha (C) 0.25 ha and (D) 0.1ha.
Data from the 0.1ha circular plots from dataset B were omitted whenever inspection of Worldview II imagery revealed there was little or no woody vegetation present beyond the perimeter of the circular plot (Fig. 4.5B right). Eight 0.1 ha plots which were considered to have an AGWB similar to the surrounding hectare was used to estimate values for AGWB (t/ha) for correlation to the backscatter at the one hectare scale. Spearman’s rank correlation coefficient (ρ), number of observations and probability of the statistical dependence being random (p) between backscatter and AGWB were calculated using the software Sigmaplot 12.0 for each of the four spatial scales.

Fig. 4.5 indicates strong statistical dependence between sigma nought ($^0\sigma_{HV}$) and AGWB (t/ha) when using a field plot size of one hectare (16 pixels), 0.5ha (eight pixels) and 0.25ha (four pixels) for averaging the backscatter. Backscatter is increasing monotonically with AGWB in all four cases. The statistical dependency of the relationship decreases exponentially ($r^2 = 0.98$, $p = 0.005$, $F = 173.27$) when less pixels within field sample plots are used for averaging the backscatter. The statistical dependency between $^0\sigma_{HV}$ and AGWB at the 0.1ha scale is the weakest ($\rho = 0.56$) but still reveals a monotonic relationship between the two variables and a low probability the relationship being random ($p = 0.001$).

4.5.1. Field Data

The training datasets A, B, and C produced total biomass estimates ranging from 0 t/ha to 101.65 t/ha (Table 4.2). This was expected as a consequence of the targeted sampling strategy which used local knowledge and interpretation of existing maps and optical imagery to ensure covering the known range of pine savanna tree biomass in Belize. The data from the field plots used to develop the model are summarized in Table 4.2 which also includes the mean backscatter for each plot sensed by ALOS PALSAR. For the validation dataset (dataset V, not included in Table 4.2), the range of the total biomass was slightly lower (3.8 t/ha to 71.8 t/ha). This lower range of total biomass is mainly a response to the sustainable extractive logging that takes place in DR.

In Fig.4.6 (a) it is apparent that total biomass is linearly correlated to total basal area and in Fig.4.6 (d) non-linearly to density. This is expected in resource-limited ecosystems such as savannas as shown in Peregon & Yamagata, (2013) and Askne et
(2003), and justifies our use of tree numbers as a simple field method for establishing plots for sampling different ranges of total biomass.

### TABLE 4.2. Total and mean values of field data collected on the study sites. The data are sorted by increasing total biomass

<table>
<thead>
<tr>
<th>Plot</th>
<th>Dataset</th>
<th>PMG</th>
<th>Density (trees/ha)</th>
<th>Mean dbh (cm)</th>
<th>Min dbh (cm)</th>
<th>Max dbh (cm)</th>
<th>SEM dbh (cm)</th>
<th>Total Basal Area (m²/ha)</th>
<th>Total Biomass (t/ha)</th>
<th>dbHVD (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1001</td>
<td>C</td>
<td>PRPM</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-24.88</td>
</tr>
<tr>
<td>1002</td>
<td>C</td>
<td>PRPM</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-23.7</td>
</tr>
<tr>
<td>1003</td>
<td>C</td>
<td>UPR</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-24.58</td>
</tr>
<tr>
<td>1004</td>
<td>C</td>
<td>UPR</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-22.37</td>
</tr>
<tr>
<td>1005</td>
<td>C</td>
<td>UPR</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-25.24</td>
</tr>
<tr>
<td>1006</td>
<td>C</td>
<td>UPR</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-24.95</td>
</tr>
<tr>
<td>1007</td>
<td>C</td>
<td>PRAM</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-22.89</td>
</tr>
<tr>
<td>1008</td>
<td>C</td>
<td>UPR</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-24.7</td>
</tr>
<tr>
<td>1009</td>
<td>C</td>
<td>PRAM</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>-26.51</td>
</tr>
<tr>
<td>502</td>
<td>B</td>
<td>PRAM</td>
<td>20</td>
<td>21</td>
<td>18.00</td>
<td>24.00</td>
<td>3.00</td>
<td>0.71</td>
<td>4.49</td>
<td>-19.56</td>
</tr>
<tr>
<td>504</td>
<td>B</td>
<td>PRAM</td>
<td>30</td>
<td>20</td>
<td>18.00</td>
<td>22.00</td>
<td>1.15</td>
<td>0.95</td>
<td>5.67</td>
<td>-21.49</td>
</tr>
<tr>
<td>299</td>
<td>B</td>
<td>PRAM</td>
<td>80</td>
<td>18</td>
<td>14.00</td>
<td>26.00</td>
<td>1.64</td>
<td>2.15</td>
<td>12.80</td>
<td>-19.93</td>
</tr>
<tr>
<td>475</td>
<td>B</td>
<td>PRAM</td>
<td>80</td>
<td>18.5</td>
<td>14.00</td>
<td>26.00</td>
<td>1.29</td>
<td>2.22</td>
<td>13.04</td>
<td>-21.19</td>
</tr>
<tr>
<td>411</td>
<td>B</td>
<td>PRAM</td>
<td>200</td>
<td>16.2</td>
<td>10.00</td>
<td>24.00</td>
<td>0.93</td>
<td>4.38</td>
<td>23.97</td>
<td>-17.31</td>
</tr>
<tr>
<td>3</td>
<td>A</td>
<td>UPR</td>
<td>123</td>
<td>19.85</td>
<td>10.00</td>
<td>36.70</td>
<td>0.53</td>
<td>4.15</td>
<td>27.93</td>
<td>-18.29</td>
</tr>
<tr>
<td>22</td>
<td>A</td>
<td>PRPM</td>
<td>50</td>
<td>24.26</td>
<td>10.40</td>
<td>131.80</td>
<td>2.58</td>
<td>3.60</td>
<td>28.70</td>
<td>-16.34</td>
</tr>
<tr>
<td>2</td>
<td>A</td>
<td>PRAM</td>
<td>171</td>
<td>21.65</td>
<td>10.00</td>
<td>48.00</td>
<td>0.44</td>
<td>6.73</td>
<td>47.99</td>
<td>-16.22</td>
</tr>
<tr>
<td>16</td>
<td>A</td>
<td>PRPM</td>
<td>102</td>
<td>24.77</td>
<td>10.00</td>
<td>47.20</td>
<td>1.04</td>
<td>5.78</td>
<td>53.27</td>
<td>-17.36</td>
</tr>
<tr>
<td>23</td>
<td>A</td>
<td>PRPM</td>
<td>65</td>
<td>31.75</td>
<td>10.20</td>
<td>104.40</td>
<td>1.88</td>
<td>6.29</td>
<td>55.64</td>
<td>-15.11</td>
</tr>
<tr>
<td>20</td>
<td>A</td>
<td>PRPM</td>
<td>97</td>
<td>26.22</td>
<td>10.00</td>
<td>65.40</td>
<td>1.13</td>
<td>6.17</td>
<td>56.87</td>
<td>-14.94</td>
</tr>
<tr>
<td>19</td>
<td>A</td>
<td>PRPM</td>
<td>112</td>
<td>26.62</td>
<td>10.10</td>
<td>50.40</td>
<td>0.86</td>
<td>6.95</td>
<td>60.63</td>
<td>-15.53</td>
</tr>
<tr>
<td>21</td>
<td>A</td>
<td>PRPM</td>
<td>119</td>
<td>25.14</td>
<td>10.50</td>
<td>62.00</td>
<td>0.97</td>
<td>6.94</td>
<td>60.76</td>
<td>-16.61</td>
</tr>
<tr>
<td>598</td>
<td>B</td>
<td>PRAM</td>
<td>90</td>
<td>31.3</td>
<td>24.00</td>
<td>38.00</td>
<td>1.73</td>
<td>7.11</td>
<td>62.85</td>
<td>-15.29</td>
</tr>
<tr>
<td>13</td>
<td>A</td>
<td>UPR</td>
<td>567</td>
<td>15.52</td>
<td>10.00</td>
<td>45.50</td>
<td>0.21</td>
<td>11.86</td>
<td>68.11</td>
<td>-15.98</td>
</tr>
<tr>
<td>18</td>
<td>A</td>
<td>PRPM</td>
<td>153</td>
<td>24.36</td>
<td>10.00</td>
<td>53.80</td>
<td>0.75</td>
<td>8.17</td>
<td>72.83</td>
<td>-15.73</td>
</tr>
<tr>
<td>4</td>
<td>A</td>
<td>UPR</td>
<td>345</td>
<td>20.03</td>
<td>10.00</td>
<td>35.80</td>
<td>0.29</td>
<td>11.65</td>
<td>79.31</td>
<td>-13.07</td>
</tr>
<tr>
<td>5</td>
<td>A</td>
<td>PRPM</td>
<td>127</td>
<td>28.23</td>
<td>10.90</td>
<td>50.00</td>
<td>0.84</td>
<td>8.85</td>
<td>82.50</td>
<td>-16.3</td>
</tr>
<tr>
<td>10</td>
<td>A</td>
<td>PRPM</td>
<td>163</td>
<td>24.2</td>
<td>10.00</td>
<td>51.00</td>
<td>0.86</td>
<td>9.05</td>
<td>82.72</td>
<td>-13.36</td>
</tr>
<tr>
<td>8</td>
<td>A</td>
<td>PRPM</td>
<td>151</td>
<td>26.82</td>
<td>10.00</td>
<td>53.00</td>
<td>0.75</td>
<td>9.54</td>
<td>84.21</td>
<td>-12.65</td>
</tr>
<tr>
<td>9</td>
<td>A</td>
<td>PRPM</td>
<td>197</td>
<td>22.51</td>
<td>10.00</td>
<td>50.00</td>
<td>0.79</td>
<td>9.75</td>
<td>85.68</td>
<td>-14.16</td>
</tr>
<tr>
<td>7</td>
<td>A</td>
<td>PRPM</td>
<td>173</td>
<td>24.79</td>
<td>10.00</td>
<td>64.00</td>
<td>0.78</td>
<td>9.79</td>
<td>85.95</td>
<td>-13.68</td>
</tr>
<tr>
<td>14</td>
<td>A</td>
<td>UPR</td>
<td>680</td>
<td>16.27</td>
<td>10.00</td>
<td>42.00</td>
<td>0.18</td>
<td>15.29</td>
<td>86.91</td>
<td>-15.42</td>
</tr>
<tr>
<td>11</td>
<td>A</td>
<td>UPR</td>
<td>568</td>
<td>17.57</td>
<td>10.00</td>
<td>39.40</td>
<td>0.19</td>
<td>14.77</td>
<td>87.43</td>
<td>-15.89</td>
</tr>
<tr>
<td>12</td>
<td>A</td>
<td>PRPM</td>
<td>239</td>
<td>24.26</td>
<td>10.40</td>
<td>43.00</td>
<td>0.38</td>
<td>11.69</td>
<td>88.03</td>
<td>-12.47</td>
</tr>
<tr>
<td>1</td>
<td>A</td>
<td>UPR</td>
<td>258</td>
<td>23.85</td>
<td>10.00</td>
<td>39.50</td>
<td>0.32</td>
<td>12.07</td>
<td>88.29</td>
<td>-13.37</td>
</tr>
<tr>
<td>17</td>
<td>A</td>
<td>PRPM</td>
<td>202</td>
<td>23.09</td>
<td>10.00</td>
<td>52.30</td>
<td>0.69</td>
<td>9.97</td>
<td>90.89</td>
<td>-13.78</td>
</tr>
<tr>
<td>6</td>
<td>A</td>
<td>PRPM</td>
<td>240</td>
<td>22.59</td>
<td>10.00</td>
<td>49.00</td>
<td>0.66</td>
<td>11.55</td>
<td>96.99</td>
<td>-12.72</td>
</tr>
<tr>
<td>15</td>
<td>A</td>
<td>UPR</td>
<td>489</td>
<td>19.4</td>
<td>10.00</td>
<td>62.00</td>
<td>0.24</td>
<td>15.55</td>
<td>101.65</td>
<td>-13.51</td>
</tr>
</tbody>
</table>
FIGURE 4.6 Total biomass values for the plot samples in UPR, PRPM, and PRAM areas plotted against (a) total basal area, and (b) mean dbh. Density values for UPR, PRPM, and PRAM areas as a function of total basal area (c), total biomass (d). Widths of the circles represent in (a), (c), and (d) the standard error of the mean for the dbh measured within each sample plot (cm), and in (b) the number of trees measured within each sample plot. In (e) the dbh distributions for the three PMGs are shown.
In both cases the correlation with total biomass appears stronger for the lower basal areas and lower densities. The Pearson correlation coefficient estimates a value of \( r_p = 0.97, P < 0.0001 \) suggesting that the two variables increase linearly with respect to one another. The correlation between density and total biomass as shown in Fig. 4.5(d) was also assessed using Spearman’s rank correlation coefficient \( r_s = 0.778, P < 0.0001 \) illustrating a positive monotonic relationship between the two variables. Nevertheless, visual inspection of Fig. 4.6(a) reveals for the higher values of total basal area, a cluster of six points which are identified in UPR areas (table 5.2, plots 1, 4, 11, 13, 14, 15) that appear to deviate significantly from the linearity to total biomass observed in the lower basal area plots (i.e. \( \leq 11 \text{ m}^2/\text{ha} \)). These six plots are the most homogeneous in our dataset as regards their dbh \( (0.18\text{cm} \leq \text{standard error of the mean (SEM dbh)} \leq 0.38\text{cm}) \) in comparison to the rest of the plots \( (\text{SEM dbh} \geq 0.5\text{cm}) \) which implies more variability. This is consistent with theoretical work which suggests that homogeneity in a dbh distribution may cause the normally linear relationship found between total basal area and total biomass to break (Chiba, 1998). No correlation was found between total biomass, and mean dbh per sample plot in these woodlands (Fig. 4.6(b)). However, taken together Fig. 4.6(b), and Fig. 4.6(e) indicates that protection and management has an impact on the growth of these woodlands. For example, within UPR areas total biomass is stored in many juvenile trees, in contrast to PRPM areas where a similar amount of total biomass is stored within a smaller number of larger trees.

4.5.2 Backscatter relationships to vegetation structure

In Fig. 4.7 significant positive monotonic relationships are shown between backscatter and total biomass \( (r_s = 0.91, P < 0.001) \), total basal area \( (r_s = 0.88, P < 0.001) \) and density \( (r_s = 0.80, P < 0.0001) \), while a weaker but highly significant relationship was found between backscatter and mean dbh \( (r_s = 0.68, P < 0.001) \). The reason why backscatter is more strongly correlated with biomass rather than basal area is possibly due to the strong correlation revealed from the field data between biomass and both basal area (Fig. 4.6(a)) and density (Fig. 4.6(d)).

The sensitivity of biomass to structural variations would suggest that if backscatter is correlated strongly with biomass then backscatter displays a clear sensitivity to the structural makeup of the forest. With the backscatter being a dataset sensitive to the
structure of vegetated areas, the backscatter is expected to show a stronger correlation to that structural attribute whether that be basal area, mean dbh or density. Fig. 4.6 (d) provides some insight into how the backscattered signal tends to increase with increasing mean dbh within the differently managed woodland areas. The way in which backscatter values increase with dbh seems to vary considerably between the three different woodland types. It is also interesting to note that a similar grouping of the plots by management regime was observed in Fig. 4.5 (b) when total biomass was plotted against the mean dbh.

![Graphs showing backscatter values for different attributes](image)

**FIGURE 4.7** Backscatter values for: (a) total biomass, (b) total basal area, (c) Density, and (d) mean dbh. The width of the circles represent in (a) the standard error of the mean dbh, and in (b), (c), (d) the number of trees per hectare. The dotted rectangular box within bubble plot (a) is used to indicate the exact number of UPR observations found in the delineated space because these observations are not easily differentiated visually.

The datasets used in this study also show that the backscatter relationships to both total basal area and total biomass appear to be unstable at higher ranges of total biomass (≥ 80 t/ha) as shown in Fig. 4.7(b) and total basal area (≥ 12 m²/ha) in Fig. 4.7 (c). There are three possible explanations for this result: 1) The canopy cover may be assumed to be increasing with increasing total biomass, and thus as described in the WCM the
backscatter $\sigma^0$ would be expected to decrease because of increasing attenuation in $\sigma^0_{veg}$; 2) it is possible that the deterioration of the backscatter – total biomass sensitivity at the higher biomass ranges may relate to the weakening correlation between total biomass and density evidenced in Fig. 4.6(d) above 80 t/ha, 3) the weaker backscatter-biomass relationship at higher total biomass may also be understood through an observation from the fieldwork that the some of the high biomass plots had quite contrasting structures and large variation in tree numbers resulting from the different management activities or growth conditions.

In Fig. 4.7(a), for example, the decreasing backscatter observed for tree number densities above 400 trees/ha is produced entirely by data points observed within the UPR sample plots; as discussed previously, these plots are the least heterogeneous, with small values of SEMdbh and fewer big trees than PRPM areas (Fig. 4.6 (e)). These same UPR points are observed to also deviate from the otherwise generally monotonic backscatter-total biomass and backscatter-total basal area trends (Fig. 4.7(b), (c)).

Approximately 80% of the high biomass – backscatter data points (Fig. 4.7(b)) were collected within passively managed pine savanna areas (PRPM) in which most of the total biomass is contained within a few large trees and where there is a more variable forest structure even at the hectare scale (Fig. 4.6 (e)). These woodlands are more open and have relatively low canopy cover, with many woodland gaps. Despite the generally lower densities, a strong correlation still exists in these woodlands between density and total biomass.

In contrast, a small number of other sample plots with high biomass are in unprotected areas where the biomass is stored within a much larger number of trees within a hectare (Fig. 4.6(e)), creating less variable pine savannas with a more closed and uniform canopy. These contrasting management regimes produce woodlands with similar total biomass and similar total basal areas but very different densities.

4.5.3. SAR modelling and Validation

Fig. 4.8(a) shows the fitting of the non-linear forward model, equation (5.13), accompanied by the model predictions of biomass, Fig. 4.8(b), (c), and (d).
The coefficient of determination ($R^2=0.92$) shows that the water cloud model line approximates the data points well while the regression passed all statistical tests (PRESS, Durbin-Watson statistic, a Shapiro-Wilk normality test, and the constant variance test). The standard error of estimate (SSE) which shows the disperse of the errors of the prediction is $1.28\, \text{dB}$. This shows that backscatter is a good predictor of biomass. The estimated coefficients with their standard errors for the forward model as defined in (5.13) are $\sigma^0_{\text{veg}} = 10.40 \pm 0.40$, $\sigma^0_{\text{soil}} = -24.06 \pm 0.65$ and $\gamma = 0.96 \pm 0.007$. The small standard errors show that these coefficients are appropriate for the dataset used. Five estimates were computed as negative or infinite and their values were set to the highest total biomass observed in the training dataset (101.67 t/ha) or zero total biomass if an infinite or negative biomass value was calculated respectively.

We assessed the performance of the model through an internal and external validation using the training Datasets A, B, and C in the first case ($N = 38$) and Dataset V in the
second (N = 38). The performance of the model for both validation processes is shown in Fig. 4.8(b) and Fig. 4.8(d) for the internal and external validations respectively. The RMSE of the biomass estimation for the internal validation using 38 training observations was recorded as 25.11 t/ha while a polynomial regression equation of the form \( y = \alpha \times x + \beta \) was also fitted (\( R^2=0.70, F=84.42, P < 0.0001 \)). We observed that the predicted biomass values at the higher end of the biomass range were extremely over-estimated. When biomass values larger than 80 t/ha are removed the performance of the model greatly improves with an RMSE of 11.30 t/ha and a polynomial fit with statistics \( R^2=0.88, F=180.08, \) and \( P < 0.0001 \), see Fig. 4.8(c), and Fig. 4.10.

FIGURE 4.9 Residuals are plotted against the biomass predicted from the adapted water cloud model using validation dataset (i.e. Dataset V).

FIGURE 4.10 Errors in predicted biomass from the adapted water cloud model are plotted against the total biomass measured on the ground, with two dashed lines showing the biomass error allowed for a) at least 80% of the predictions (20 t/ha), and b) none of the predictions (50 t/ha). Accuracy criteria suggested by Hall et al., (2011), and Houghton et al., (2009) for forest management activities.
Dataset V, which has a biomass range at the lower end of the training dataset (0-80 t/ha) was used in an external validation process. The results show a low RMSE of 13.36 t/ha and a polynomial fit with descriptive statistics $R^2 = 0.54$, $F = 41.37$, and $P < 0.0001$. The external validation dataset passed a constant variance test ($P = 0.62$) while the residuals vs. the predicted biomass are shown in Fig. 4.9. For the external validation, the errors in the predicted biomass for the individual sample plots (Fig. 4.10), ranged from 0-29 t/ha (100% of predictions ≤ 50 t/ha), while for 85% of our predictions the errors were below 20 t/ha. Evaluated against the accuracy criteria proposed by Hall et al., (2011) and Houghton et al., (2009) these results appear promising, with the method delivering the accuracy required for forest management activities in the actively managed PRAM areas.

Empirical backscatter-total biomass relationships using spaceborne L-band in low biomass tropical savanna woodlands (e.g. maximum total biomass ≤ 100 t/ha) found in Africa are reported with lower $R^2$ for the model fitting, and higher RMSE for biomass prediction to that found in the adapted WCM, and the external validation here [e.g. $R^2 \leq 0.76$, and RMSE = 19.2 t/ha in Mitchard et al., (2009), $R^2 = 0.86$, and RMSE = 24 t/ha in Mitchard et al., (2011), $R^2 = 0.49$, and RMSE = 17.4 t/ha in Ryan et al., (2012)]. In the present study the comparable values are $R^2 = 0.92$, and RMSE = 11.3 t/ha. The differences in $R^2$, and RMSE are probably due to the lower total biomass range of the PRAM areas for the external validation, and that 90% of the vegetation is Pine. In comparison, airborne Light Detection and Ranging (LiDAR) predicts biomass with an RMSE from 11.6 t/ha to 18.4 t/ha in an example in savannas of eastern South Africa (Colgan et al., 2012).

4.5.4. Saturation

Visually, the curve produced by the forward model in this study (Fig. 4.8a)), does not show a typical saturation-like response before 100 t/ha as found in studies such as Viergever, et al., (2009), Watanabe et al., (2004), and Santos et al., (2002). In this study we estimated the saturation point for the forward model, equation (13), using the
gradient of the curve (Watanabe et al., 2006; Larson & Edwards, 2013). For this analysis we used the derivative of equation (13) and the backscatter value of 0.01 dB as similarly used in (Watanabe et al., 2006). The gradient of the forward model could then be calculated using equations 5.15 and 5.16.

\[ f'(\text{biomass}) = \delta \sigma_0 / \delta \text{biomass} = ax^b \ln b \]  

(5.15)

\[ f'(\text{biomass}) = 0.01 \text{dB} \]  

(5.16)

Results show that the radar backscatter provides useful information regarding biomass change up to a maximum of 106 t/ha. This saturation point is significantly higher than others reported in similar studies such as Viergever et al., (2009), Imhoff, (1995) and Watanabe et al., (2004) but agree with findings reported in Lucas et al., (2007), Mitchard et al., (2009), Mitchard et al., (2011) and Watanabe et al., (2004). We argue that the nature of our study areas play a key role in these findings. The significant features being that more than 90% of the vegetation is pine, and thus it is suggested that the saturation point increases due to the long and thin woody canopy elements such as branches and twigs (Woodhouse, 2006) and significantly through the existence of a strong correlation between density with total basal area and total biomass (Fig.5.6 (c),(d)). These are assumed to play a key role in the continuing backscatter increase beyond the typical saturation points reported in other studies using L-band SAR (i.e. 50-100 t/ha) (Watanabe et al., 2004). It also alludes to the impact of forest structure on backscatter saturation proposed in Woodhouse, (2006) and Brolly & Woodhouse, (2012).

**4.6. Conclusion**

This study has focused on the development of a biomass retrieval approach for pine savanna woodland using L-Band ALOS PALSAR satellite SAR data. An adapted WCM was combined with field data collected at the hectare scale to train a semi-empirical model. This data included dbh, basal area, and number densities per hectare. Biomass values for the field plots were calculated using allometric equations based on dbh.
We have found that ALOS PALSAR (HV) backscatter is sensitive to biomass when used in an adapted WCM, across pine-dominated savanna sites differing significantly in their vegetation structure due to protection and management regimes. The internal validation of the model using Datasets A, B, and C showed that PALSAR HV backscatter data have the potential to predict biomass with useful accuracy in the exhibited savanna environment of 0-100 t/ha with a mean RMSE of around 25 t/ha. This may be satisfactory for baseline inventories of woodland cover, coarse screening for carbon assessments (i.e. per protected area) and to map woodland density as a proxy for biodiversity in certain conservation initiatives. A generally high level of correlation was exhibited between the radar backscatter and the estimates of biomass calculated through field measurements and allometry for the woodland areas used to develop the equation. External validation of the model using independent field data from a sustainably managed pine savanna area with biomass generally below 50 t/ha, showed that the model actually produced more accurate estimates (to within 11 t/ha) at this lower range, which are particularly useful for establishing baselines and monitoring stocks and regeneration in such areas. The acceptable accuracy of the predictions (100% of predicted biomass below 50 t/ha, and 85% of biomass predictions below 20 t/ha) in the protected area where the external validation was conducted show that ALOS PALSAR can be used to produce biomass maps at fine spatial scale (i.e. 1ha) to support forest management.

Although the plot data collected on the ground sampled the full known range of the biomass values found in pine savanna areas in Belize, the range of biomass predicted from the backscatter has a much wider range than the field observations. The model fitted in this study estimates from zero to infinite values of biomass and although the analysis of saturation provides guidance about the upper usable limit of the model predictions, further work is needed to understand the drivers of this behaviour and to constrain the model.

We recall that radar backscatter is not a direct measure of biomass and is not viewed as such in this study. It is suggested that the interaction of backscatter with tropical savanna vegetation needs to be further investigated using L-band data collected during both dry and wet seasons to understand if these relationships vary seasonally. A strong
and significant relationship was established here using the WCM between radar backscatter and biomass, while the combination of density and the homogeneity of some of these woodlands have been found to have the greatest influence upon the backscattered L-band signal.

Finally, we note that four ALOS PALSAR scenes cover all the pine savanna woodlands found in the country of Belize (~645km²), suggesting that the utilization of these radar data can be an economically viable means to map and monitor the biomass of these savanna woodlands, providing a valuable tool for REDD+ projects. The importance of mapping woody biomass with sufficient accuracy, and use these biomass maps to detect change through a range of short-term temporal scales (i.e. quarterly or annually) and strategic temporal scales (i.e. 3-year and 5-year intervals) have been identified as two of the key parameters for the inclusion of Earth observation data and techniques in detecting areas that have been deforested or degraded to support REDD+ and MRV activities. The encouraging results that were derived in this chapter, using the WCM technique and ALOS PALSAR data collected during the wet season, enhances the already established scientific consensus that L-band radar data may be used to predict and map biomass in tropical savannas. The technique should be further investigated using a combination of archived data collected by ALOS PALSAR from 2009 to 2012 or new data collected by ALOS PALSAR-2, and new or archived field datasets to predict AGWB and to create biomass maps for different periods in time and different seasons (i.e. dry / wet). The new calibrated water cloud models could then be used to create biomass maps for the time that the ALOS PALSAR data were collected, which could in turn be used to assess biomass change for the different time periods that the WCM were calibrated.

The model that we have described here is now being applied to generate a fine scale (100m) mapping of biomass zones for the savannas of Belize which will supplement coarser scale global biomass estimates from satellite remote sensing, and enhance existing national and sub-national scale maps of savanna woodlands in Belize.
References


Chapter Five

Local Scale Mapping of Biomass Using ALOS PALSAR

5.1. Overview

The establishment of ALOS PALSAR in chapter four as a possible means for predicting above ground woody biomass (AGWB) in the lowland savannas of Belize enables the creation of biomass maps to support forest managers with the prospect of more detailed and locally accurate information for measuring, reporting, and verification activities in contexts such as sustainable forest management (SFM), carbon stock assessments, and ecological studies of forest growth and change. In chapter five I make an attempt to use the method developed in chapter five for estimating AGWB at fine scales and compare these AGWB estimates to coarser resolution global biomass maps.

In this study, I apply the locally validated method established in chapter four for estimating (AGWB) from ALOS PALSAR data to produce an AGWB map for the lowland pine savannas of Belize at a spatial resolution of 100 m. The 100m mapping is used to estimate the representative AGWB quantities found in the main woody savanna subtypes, which were previously mapped thematically, and to compare these 100m AGWB estimates to global biomass maps at 500m and 1000m spatial resolutions respectively.

5.2 Author Contributions - declaration

This chapter has been published at the open-access journal “Forests”, full citation and title: Michelakis D, Stuart N, Lopez G, Linares V, Woodhouse IH, (2014) ‘Local-Scale
Mapping of Biomass in Tropical Lowland Pine Savannas Using ALOS PALSAR’.

Author contributions: Dimitrios G. Michelakis, Neil Stuart, and Iain H. Woodhouse devised the research; Dimitrios G. Michelakis, Neil Stuart, German Lopez, & Vinicio Linares collected the field data; Dimitrios G. Michelakis conducted the analysis; Dimitrios G. Michelakis wrote the article with assistance and revisions from all other authors.

5.3. Introduction

5.3.1. Why map tropical savannas at more local scales?

Savannas are an important component of global vegetation, covering approximately 18% of the Earth’s land surface (Grace *et al.*, 2006). The woody component of savannas can be variable (Ratnam *et al.*, 2011) however many woody savannas can be characterized as forests according to the FAO definition (FAO, 2010). The woody component is of major significance for storing biomass (Furley, 2010; Castro & Kauffman, 1998), supporting biodiversity (Felipe *et al.*, 2006), and sustaining the local hydrological cycle (Klink & Machado, 2005). A growing recognition of the value of natural carbon stores, and the intention to reduce emissions caused by deforestation and forest degradation (FAO, 2005) are encouraging developing countries to protect and manage these tropical forest ecosystems more sustainably.

Wooded areas within savannas are increasingly pressured by human intervention, leading to unsustainable management practices. In the Neotropics, key threats are the continuing expansion of agriculture and pasture (Ratter *et al.*, 1997; Silva & Bates, 2002) as well as over frequent logging and burning (Frost & Robertson, 1985; Hannan *et al.*, 2008), which has resulted in the reducing extent and health of this ecosystem (Lehmann, 2010; Bond, 2008).

With these pressures changes degrading both the biodiversity and economic value of savanna woodlands, techniques are urgently needed to measure, map, and monitor the
woody component reliably and produce this information at appropriate scales to support conservation and management actions. Maps of above ground woody biomass (AGWB), if they are sufficiently detailed, can assist conservation managers, practitioners and policy makers to formulate specific practices (e.g. thinning, fire control, seedling regeneration, biodiversity surveys e.t.c.) that are appropriate for woodland patches within the broader savanna areas they are managing (Gibbs *et al.*, 2007; Silva *et al.*, 2011).

Many countries presently lack a capacity to produce their own local maps of forest biomass and so must rely on existing biomass maps founded upon broader regional and global datasets. Although providing a consistent approach to estimation of biomass differences over areas of hundreds of square kilometers, we contend that the resolution of these global data sets (typically 500m or 1000m) is often too coarse for quantifying and monitoring the distribution of woody biomass within areas of 10,000 ha or less, which are common sizes for protected areas or forest reserves, particularly in smaller countries.

In this article we use the example of pine woodlands in Belize, for which a locally modelled relationship between ground measured biomass and satellite sensed radar backscatter from ALOS has recently been established and validated, to explore potential forestry applications for finer scale biomass mapping produced using this data. Specifically, we address the following objectives:

- Mapping the AGWB of over 50% of the lowland savanna woodlands of Belize at 100m resolution, using this locally modelled relationship between the satellite radar backscatter and observations of biomass from an extensive national inventory of forest plots.

- Analyzing the resulting AGWB map to quantify for the first time the variation in AGWB across the different woodland savannas within the country and exploring how this might provide forest managers with enhanced information about the nature and locality of different woodland components, compared to previous qualitative thematic mapping using the UNESCO land cover classification system.
Examining, within a pilot study area of approximately 933 km$^2$, whether the biomass map produced at 100m might enable differences in biomass to be observed between forest areas that are being protected or sustainably managed, compared to unprotected forest areas.

For two specific protected areas of Belize covered by the new 100m mapping, assessing if this finer scale mapping of biomass produces biomass estimates that accord more closely with ground measurements of biomass in these protected areas than estimates based on AGWB values extracted for the same areas from pan-tropical biomass data sets at 500m and 1000m resolution produced by Baccini et al., (2012) and Saatchi et al., (2011).

5.3.2. Mapping of savanna woodlands with active satellite Earth observation

New advances in the mapping of biomass by active satellite Earth observation (EO) have greatly facilitated efforts to characterize savanna ecosystems at multiple scales. Using the archive of the Advanced Land Observing satellite (ALOS) Phased Array type L-band Synthetic Aperture radar (PALSAR) satellite data collected from 2007 – 2009, the Japanese Aerospace Exploration Agency (JAXA) produced the first 50m global forest / non-forest map (Zeng et al., 2014) to support activities for the United Nations-Reducing Emissions from Deforestation and Degradation (UN-REDD+). Jet Propulsion Laboratory (JPL) in collaboration with JAXA created a regional mosaic of ALOS PALSAR imagery for wide ground swaths (~350Km) to assist ecosystem assessments in the Americas. Recent research has shown that ALOS PALSAR data are suitable for classifying vegetation types and assessing carbon stocks at regional scales (Shimada et al., 2010). In Baccini et al., (2012) and Saatchi et al., (2011) satellite LiDAR measurements collected by ICESAT GLAS and a diversity of optical satellite EO were used in combination with field measurements to create pan-tropical carbon stock maps with the explicit intent of assisting tropical countries to monitor and report their carbon stocks for UN-REDD+ projects at national and sub-national scales (i.e. 10000ha). In Africa, De Grandi et al., (2011) created an ALOS PALSAR mosaic at 100m spatial resolution to be used, among other applications, to map deforestation and
agricultural encroachment upon the forest-savanna boundary. In their study within savanna landscapes (Mitchard et al., 2009) identified strong relationships between AGWB and radar backscatter sensed by ALOS PALSAR, concluding that the approach was necessary and sufficient for monitoring and reporting of biomass baselines for REDD+ projects, and Ryan et al., (2012) similarly found ALOS PALSAR images to assist in quantifying deforestation at small scales in savanna woodlands in Mozambique. In Australia, Lucas & Armston, (2007) stressed the value of ALOS PALSAR data for quantifying the contribution of the woody component of tropical savannas to regional carbon stocks.

There is thus a growing body of evidence derived by studies conducted in tropical savannas supporting the technique of deriving biomass maps from L-band data collected by ALOS PALSAR, with the majority of the work to date conducted in African and Australian savannas. The wide availability of L-band data (up until 2011) and new L-band data acquisitions from operational ALOS PALSAR-2 (launched in 2014), and future missions such as the SAAtélite Argentino de Observación Microondas (SAOCOM), and NASA’s airborne Unmanned Aerial Vehicle (UAV) SAR makes it an attractive data source for wide area biomass monitoring. However, finer scale biomass mapping using L-band SAR data relies on establishing a strong and consistent relationship between the backscattered signal and biomass measurements collected in the field in each locality. The relationship between biomass and backscatter is known to vary for different woodlands and to be influenced by local topographic and climatic conditions which, for example, affect the attenuation of the signal (Woodhouse et al., 2012). For these reasons, some attempts to create fine scale biomass maps from ALOS PALSAR data have not been successful. For example, Cassells et al., (2009) were not able to map AGWB in savanna woodlands sufficiently accurately in Malawi because of substantial topographic relief in the study area, combined with heterogeneity of the woody component.
5.3.3. The use of more detailed mapping of woody biomass in savannas

Work is now progressing beyond dichotomous mapping of forest versus savanna, to create finer scale mapping of biomass differences within savanna landscapes. This is often driven by the need to create baseline carbon stock maps and to monitor changes in biomass as part of reporting requirements of REDD+ projects. Although radar techniques are well established for mapping biomass in more uniform forest plantations, such as those in temperate and boreal regions, forest managers and researchers are raising questions whether coarse resolution (i.e. 500m, and 1000m pixel resolution) mapping from EO data is adequate for tasks such as primary production planning or forest stock mapping in more heterogeneous woody environments, such as tropical savannas. For example, Jantz et al., (2014) used the 500m biomass maps produced by Baccini et al., (2012) to plan corridors to connect together broadleaf forest areas and have suggested that a similar method could be used to identify conservation corridors in lower biomass ecosystems. Whilst the AGWB maps produced by Baccini et al., (2012) and Saatchi et al., (2011) may be used to meet regional scale emissions reporting requirements or for preliminary estimation of national carbon stocks when no finer scale information is available, these maps need to be validated against local forest stock surveys or AGWB maps from higher resolution satellite imagery when these are available.

Beyond the present focus on carbon stocks, there is wider interest in how finer scale spatial information about biomass in savanna woodlands can inform work in forest management and forest ecology. Biogeographers and forest ecologists studying shifts in savanna-forest boundaries can use finer scale information to detect changes in the relative balance between woody vegetation and grasses more rapidly, whilst finer scale data allows them to understand the relative importance of human activities compared to climatic changes as factors influencing local shifts (Banfai et al., 2005; Hennenberg et al., 2006; House et al., 2003; Woollen et al., 2012; Furley et al., 2008; Furley, 2010). AGWB estimates derived from ALOS PALSAR may enable scientists to explore and monitor these dynamic phenomena and processes in more depth. There is also interest
in using finer scale biomass mapping to monitor regeneration and growth in low
density woodlands. For example, ALOS PALSAR data have been combined with
Landsat data by Lucas et al., (2006) and Clewley et al., (2012) to characterize re-growth
in open Brigalow woodlands in Australia to assist management strategies such as
thinning and weed control, illustrating practical management actions that can be
supported by this finer scale information.

5.4. Experimental Section

5.4.1. Description of the lowland savanna ecosystem

This study is conducted within the lowland areas of Belize (Fig. 5.1A) which comprise
approximately 1754 km² of savanna landscape (Bridgewater et al., 2012) (Fig. 5.1B).
These areas are the most northern Neotropical savannas (Bridgewater et al., 2002)
which represent the second most extensive savanna vegetation formation within the
America Neotropics (Mistry, 2000). In this analysis we focus on mapping the above
ground woody biomass (AGWB) of woody savannas which are recognized for their
importance in carbon sequestration due to the presence of pine trees (Furley et al.,
1999). Pine (Pinus caribaea var. hondurensis) forms low density wood clusters (10% -
~65% canopy cover) within the savanna landscape, while other woody vegetation, such
as Palms (Acoelorraphe wrightii) and shrubs (Byrsonima crassifolia), are often evident
and usually scattered through the grass landscape (Goodwin et al., 2013).

The national ecosystems map of Belize classifies the lowland savannas into three
UNESCO classes (Fig. 5.1C, and Fig. 5.1D). Here we examine the: a) ‘short-grass
savannas with dense trees or shrubs – [UNESCO code: VA2a (1/2)] (Fig. 5.2A&C), and
b) short-grass savannas with scattered trees and/or shrubs [UNESCO code: VA2a (1)
(2)] (Fig. 5.2B&D). Pine woodlands occur in both these vegetation zones and the local
density of the tree cover in relation to other shrubs and grasses has until now been
interpreted qualitatively as the basis for allocating most savanna land into one or the
other of these classes (Meerman & Sabido, 2001). The climate in Belize is subtropical
to tropical with an average annual precipitation around 1500mm in the northern parts
of the country and 3800mm in the south. In Fig. 5.3 the annual mean precipitation is shown per month using data collected in three weather stations of the Belize National Meteorological Service and a rainfall monitoring product which is based on derived by the Global Precipitation Climatology Centre (GPCC).

5.4.2. ALOS PALSAR data

Two Fine Beam Dual polarization (FBD) ALOS PALSAR datasets (Level 1.0) covering approximately 55% (933.46 km²) of the lowland savanna ecosystem in Belize were collected during the wet season in September, 2008 (Fig 5.1B, I&II). The radar data that were used in this study included only the Horizontal-Vertical polarization (HV) because of their sensitivity to biomass. The HV data were pre-processed at the Aberystwyth University from level 1.0 to single look complex (SLC) images using the Modular SAR processor in GAMMA software while a calibration factor of -58.30 decibels (dB) was used. Subsequently the SLC images were multi-looked and geo-coded to level 1.5 using the differential interferometry geocoding module (DIFF & GEO) which is also included in GAMMA software.

The resulting four look images (pixel spacing ≈ 13m) were further processed to reduce speckle by aggregating neighborhoods of adjacent pixels [2x2] and arithmetically averaging the radar intensity at the power domain (Michelakis et al., 2014; Michelakis et al., 2009). The final radar product has a pixel-spacing of 26m and data represent the normalized radar cross-section \( \sigma_{dB}^0 \) where dB is decibels. The total extent of the lowland savanna has been mapped by previous projects (Bridgewater et al., 2012) and that map is used to constrain the biomass mapping from the ALOS data to within the savanna extents.

The total study area is 933.46 km² (Fig. 5.1, C&D) and is comprised by approximately 345 km² of lowland savannas with sparse trees or shrubs (VA2a (1/2) [51% of total VA2a (1/2)], and 588 km² of lowland savannas with dense trees or shrubs (VA2a (1) (2) [58% of total VA2a (1) (2)]. Although the ALOS PALSAR data were acquired during the wet season, the rainfall estimates of the Tropical Rainfall Measurement Mission
LOCAL SCALE MAPPING OF BIOMASS USING ALOS PALSAR (product 3B42V7) for the radar data acquisition dates (+/- three days) within the study area shows that the mean rainfall is very low in both ALOS PALSAR images (~15 mm).

FIGURE 5.1 (A) Belize in the region of Central America, (B) Footprints of the ALOS PALSAR and the national ecosystems map based on UNESCO classes and (C&D) the lowland savanna areas in the ALOS PALSAR scenes. Light gray areas indicate the extent of protected areas with lowland savannas. RBCMA stands for Rio Bravo Conservation and Management Area.

FIGURE 5.2 Representative photographs of lowland savanna areas with dense trees or shrubs – VA2a (1/2) (A, C) and sparse trees and/or shrubs – VA2a (1) (2) (B, D).
/ day for Image I, and ~9 mm / day for Image II). When comparing visually these precipitation estimates to the mean dry season gauged precipitation data acquired in the two weather stations falling within the ALOS PALSAR image extents (Fig. 5.3) we find that the precipitation estimates from the TRMM during the ALOS PALSAR data acquisition are lower than the mean precipitation estimates from the TRMM or ground weather stations found during the dry season in the same areas, and thus the have more confidence for using these ALOS PALSAR imagery which were collected during the wet season for AGWB estimation.

![Graph showing monthly precipitation](image)

**FIGURE 5.3** illustrating the wet and dry seasonality in Belize. Two major precipitation spikes are observed in June and October while September also appears to be a rainy month.

### 5.4.3. Biomass Mapping Using ALOS PALSAR and Semi-Empirical Modelling

Biomass mapping was achieved by adapting a forward parametric model which is based on a semi-empirical Water Cloud Model (WCM) (Michelakis et al., 2014; Michelakis et al., 2013; Attema & Ulaby, 1978) to derive a mathematical relationship between the backscattered intensity of the radar signal ($\sigma_{pp}^0$), where pp corresponds to emitted and received polarization of the radar signal, and the biomass ($AGWB$) calculated from ground surveys of 6457 trees collected over 32.6 hectares of savanna woodlands throughout Belize.

In the WCM, the AGWB is represented as a relatively homogeneous above ground volume which consists of canopy components and air (Michelakis et al., 2014; Michelakis et al., 2013; Attema & Ulaby, 1978); the canopy components are assumed
to be relatively homogeneous spherical scatterers, which mimic a water cloud. Mathematically the parametric forward model describing the WCM usually takes the form of equation 5.1 to perform fitting, non-linear least squares regression and calculation of the empirical coefficients $\sigma_{\text{veg}}^0$, $\sigma_{\text{soil}}^0$, and $\gamma$ which are dependent on the structure of the woodlands. The regression equation is then re-arranged to estimate biomass as shown in equation 5.2 (Michelakis et al., 2014).

$$\sigma_{\text{total}}^0 = \sigma_{\text{veg}}^0 \times (1- \gamma^{\text{Biomass}}) + \sigma_{\text{soil}}^0$$

(5.1)

$$\text{Biomass} = \log \gamma \left( \frac{\sigma_{\text{soil}}^0 - \sigma_{\text{soil}}^0 + \sigma_{\text{veg}}^0}{\sigma_{\text{veg}}^0} \right)$$

(5.2)

In equation 5.2 $\sigma_{\text{total}}^0$ represents the total backscattered intensity of the radar signal collected by ALOS PALSAR and $\sigma_{\text{veg}}^0$ is the fraction of the total backscattered intensity due to radar-vegetation interaction and $\sigma_{\text{soil}}^0$ due to bare soil interaction. An AGWB training dataset which was collected on the ground in four different years 2006, 2011, 2012, and 2013 (table 5.1), and the ALOS PALSAR imagery (HV polarization) was used in Michelakis et al. (2014) to undertake non-linear regression analysis to show that the HV intensity of the radar backscatter can be predicted in relation to the AGWB with an $R^2 = 0.92$ (Fig. 5.5A).

<table>
<thead>
<tr>
<th>Datasets</th>
<th>Plot size (ha)</th>
<th>AGWB (t / ha)</th>
<th>Density (Trees / ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Range</td>
<td>Mean</td>
<td>St. Dev.</td>
</tr>
<tr>
<td>Training</td>
<td>32 $\times$ 1 $\times$ 6 $\times$ 0.1</td>
<td>0-101.6</td>
<td>47.3</td>
</tr>
<tr>
<td>Validation</td>
<td>38 $\times$ 0.1</td>
<td>1-72</td>
<td>39.5</td>
</tr>
</tbody>
</table>

Although the satellite data were collected in 2008 the slow growth rate of Caribbean pine even in better sites in Belize as recorded by Johnson & Chaffey, (1974) (0.4 cm ≤ dbh ≤ 1 cm) allows us to use these field measurements in the development of the WCM. The semi-empirical model fitted in this study is shown in equation 5.3. Using an external validation dataset (table 5.1), AGWB estimates were assessed demonstrating that AGWB can be predicted on the ground with a Root Mean Squared Error (RMSE)
~ 13.5 t/ha, while 85% of the AGWB estimates were found to have an error of less than 20 t/ha (Michelakis et al., 2014).

\[
\sigma^0 = 10.40 \times (1 - 0.96^{\text{Biomass}}) - 24.06
\]  

(5.3)

To assess the AGWB map created using the ALOS PALSAR data and the semi-empirical WCM an evaluation of the estimation accuracy was conducted using the validation dataset (table 5.1) for the lower biomass range (i.e. \( \leq 75 \) t/ha) and the training dataset (table 5.1) for the higher biomass range (i.e. \( \geq 75 \) t/ha). The training dataset was used to assess the higher biomass range predictions due to lack of high biomass observations in the validation dataset. The Relative Root Mean Squared Error (RRMSE) was separately calculated for seven biomass classes with 15 t/ha intervals (i.e. 0-15, 15 – 30, 30 – 45, 45 – 60, 60 – 75, 75-90, and 90 – 105 t/ha) using equation 5.4. Where RMSE and \( \bar{\text{AGWB}} \) are the Root Mean Squared Error and the mean observed AGWB within each biomass class.

\[
\text{RRMSE (\%) =} \left( 100 \times \frac{\text{RMSE}}{\bar{\text{AGWB}}} \right)
\]  

(5.4)

FIGURE 5.4 (A) The non-linear regression model fitted (solid line) using the training dataset from table 1 and ALOS PALSAR HV imagery, and (B) the histogram of both AGWB datasets (training and external validation). Note the zero AGWB points in scatterplot (A) which were collected on the ground using a global navigation satellite system (GNSS) device on areas with no woody vegetation to sample the backscatter in these areas.
A concern with the mathematical formulation in equation 5.3 is that negative or infinite values of biomass can be predicted (Magnusson et al., 2007; Peregon & Yamagata, 2013). To constrain estimates to realistic values the method by Askne et al., (2003) was used, and in this case any cells with infinite values were assigned the highest value of biomass actually measured in the field (101.65 t/ha), whilst any cells with negative estimates of biomass were assigned a value of zero. Askne et al. (2003) argue that limiting the prediction to the biomass levels observed in the field may have an effect on the retrieval accuracy of the developed model; however this poses a limiting factor when during the calibration of the model the field data are derived from different volume, or in this case biomass, groups. For example in their study Askne et al. (2003) developed a backscatter-volume regression model to predict the total volume found in each of the 42 stands within a Swedish forest. The field data that were used in Askne et al. (2003) comprised stands of multiple tree species (i.e. Spruce, Pine, and Birch) with volumes ranging from 0 to ~340 m$^3$/ha. The 42 stands were divided in two groups of 21 stands each, both including a similar set of stem volumes with the only difference being the maximum observed volume within the groups (i.e. 275 m$^3$/ha for the first group, and ~340 m$^3$/ha for the second group). Askne et al., (2003) argue that if a backscatter-volume model was calibrated using the data from the first group (i.e. max. ~275 m$^3$/ha) the retrieval accuracy of the models would degrade if the observed volumes in the second group were used. In this chapter as well chapter six we constrain the retrieval model using the methodology from Askne et al., (2003) because no previous field studies conducted in savanna woodlands in Belize such as from Viergever et al., (2009); Linares, (2009); Michelakis et al., (2014); Brown et al., (2005) and Johnson & Chaffey, (1974) have measured AGWB in these savanna woodlands above 101.65 t/ha, so we feel confident to use this value as our realistic upper limit for this case study.

Although a recent study from Tanase et al., (2014) has shown that parametric forward models show higher errors than other approaches there are five reasons that a semi-
empirical WCM is employed in this study: (a) The semi-empirical model is grounded in the physical basis of how the backscattered intensity of the radar is expected to interact with vegetation targets in contrast to more statistical driven approaches such as backward models, (b) the use of non-parametric models such as machine learning algorithms could not be implemented in this research because of the lack of the significant data amounts that are needed [for example Carreiras et al., (2013) used more than 50 data samples for biomass mapping using decision trees classifiers], (c) the WCM accounts for the low canopy cover nature of the savanna woodlands (10% - 65%) by using a weighting area fill factor \[ (1 - e^{-\gamma \times AGWB}) \] in the vegetation backscatter (Tanase et al., 2014), (d) the WCM varies as it interacts with vegetation of different biomass, and supplements and extends upon previous quantitative analysis of radar backscatter as a surrogate measure of biomass (Michelakis et al., 2014; Michelakis et al., 2013; Attema & Ulaby, 1978), and (e) the biomass estimation results can be comparable to future research using methods that are based to other forward models in contrast to solely statistical approaches.

5.4.4 Consistency of Biomass Estimate of two Protected Areas

We used the inverted WCM (eq. 2) described in the previous section and the ALOS PALSAR data covering two of the country’s largest savanna woodlands (RBCMA, and Deep River protected area) to estimate the mean AGWB for the whole protected areas extent, and compared these with AGWB estimates calculated from previously published data (Linares, 2009; Brown et al., 2005). These two protected areas are both over 10,000ha and their locations and extents are suitable for sub-national scale UN-REDD+ projects Baccini et al., (2012).

In RBCMA Brown et al. (2005) estimated mean carbon stock of 13.1 tC/ha for approximately 10,000ha of savanna by developing new allometric equations which predicted biomass carbon using tree attributes as independent variables that could be easily measured from aerial images. To develop the allometric equations Brown et al., (2005) used an extensive ground dataset which was collected by the destructive
sampling of 51 pine trees, and then 77 image sample plots were used in three dimensional very high spatial resolution aerial imagery to assist with the remote measurement of the tree attributes which were used to estimate carbon stocks. To convert carbon stock to biomass we multiplied by a factor of two (carbon is 50% of biomass) (Schlesinger, 1997) calculating a mean AGWB of 26.2 t/ha for RBCMA. In Deep River (DR), to estimate AGWB for approximately 3500ha of savanna woodlands (31.60 t/ha), we used 62 circular sample plots (0.1ha), which were not used during the WCM training and only 18 out of the 62 were used in the external validation of the WCM, in the denser woodland areas originally collected by (Linares, 2009) to support plans for sustainable timber extraction (table 5.2).

To derive the mean AGWB value for these savanna woodlands, for each tree the AGWB was estimated using the allometric equations (eq. 5&6) developed by Brown et al., (2005) in RBCMA, where dbh is the diameter at breast height (1.3m), and biomass is dry above ground woody biomass in kilograms. More than 30% (2190 trees) of the field data measurements that were used in this study were collected within RBCMA and more than 95% of the tree dbh measurements are within the range sampled by Brown et al. (2005) (1-52.4cm). The AGWB/ha was estimated for each 0.1ha sample plot by summing the AGWB of individual trees, and multiplying the sum by a factor of 10 to extrapolate to the hectare.

Having obtained these ‘ground truth’ estimates of mean AGWB/ha for both protected areas, we then multiplied these up by the area of the RBCMA and the denser woodland areas of DR and compared these totals to those obtained by using a GIS to aggregate cells from the 100m biomass map within the boundaries of the RBCMA and DR respectively.

**TABLE 5.2. Summary of the plots which were collected in the denser woodland areas of (DR).**

<table>
<thead>
<tr>
<th>Data</th>
<th>Plot size (ha)</th>
<th>AGWB (t / ha)</th>
<th>Density (Trees / ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Range Mean St. Dev.</td>
<td>Range Mean St. Dev.</td>
</tr>
<tr>
<td>DR</td>
<td>62×0.1</td>
<td>2.25–76.19 31.60 17.78</td>
<td>20–350 121 70.40</td>
</tr>
</tbody>
</table>

\[
\text{Pine Biomass}_{Kg} = 0.0407 \times \text{dbh}^{2.4323} \tag{5.5}
\]
5.4.5. Classification of savannas by protection and management type

Approximately 25% of the lowland savannas in Belize is under some form of protection (Bridgewater et al., 2012) and has been characterized as category Ia, II, IV, or VI according to the IUCN classification system (Dudley, 2008). Using information acquired from land managers and published management plans (Linares, 2009; Mcloughlin et al., 2012; Mcloughlin et al., 2013; Mcloughlin et al., 2013; Programme for Belize, 2006) we examined the influence of land management in various protected savanna woodlands by comparing the biomass quantities predicted by our model. In unprotected savanna woodlands the possibility of a management plan cannot be excluded however it was not possible to acquire management information for these savanna woodlands thus the unprotected areas are considered as not managed in this study. To allow the influence of both passive and active management to be explored, as well as the binary ‘protected-unprotected’ dichotomy, we subdivided the study area into three protection and management groups using the information acquired by managers and the published management plans.

Approximately 40km² of savanna woodlands found within the RBCMA and in the Bladen nature reserve were characterized as highly protected and passively managed areas (henceforth PRPM). These areas have been managed mostly to promote biodiversity (Mcloughlin et al., 2012; Mcloughlin et al., 2013; Mcloughlin et al., 2013) while they have been classified as ‘strict nature reserve, Ia’ and ‘Habitat/Species Management Area, IV’ by the IUCN. Similarly, some 118 km² of savanna woodlands found in Manatee and DR forest reserves were grouped as protected and actively managed (PRAM) areas, where timber is extracted sustainably (Linares, 2009) and both have been classified as ‘Protected area with sustainable use of natural resources, VI’ by the IUCN. Further areas totaling approximately 595 km² of savanna woodlands with no protection designations were identified as unprotected (UPR) areas. The remaining 185km² of protected areas for which we could not obtain reliable information about their management were not included in this analysis. Using GIS, we then overlaid the
new biomass map upon the three forest management groups and calculated the biomass in mean AGWB/ha for each of the three areas.

5.4.6. **Comparing the new mapping with national level carbon stock maps from pan-tropical data sets**

To conduct a comparison with our local biomass map (Michelakis Biomass Estimates henceforth MBE100), two national level carbon stock maps were acquired for Belize. These were the pan-tropical national level carbon stock dataset (Baccini Biomass Estimates, henceforth BBE500) produced by Baccini et al., (2012), and the benchmark national carbon data (Saatchi Biomass Estimates, henceforth SBE1000) produced by Saatchi et al., (2011). Both datasets are stored in single tagged image format file (*.tiff) representing the above ground carbon density of above ground live woody vegetation. These gridded values were predicted using data collected by a range of EO sensors such as the ICESAT GLAS, MODIS, and the Shuttle radar Topography Mission (SRTM) in non-parametric spatial modelling processes. Baccini et al. (2012) used the random forest algorithm to produce the BBE500 product and Saatchi et al. (2011) used the Maximum Entropy Modeling (MaXEnt) algorithm for the SBE1000 product (Saatchi et al., 2011). The BBE500 data were downloaded from the Woods Hole Research Centre (WHRC) website (Woods Hole Research Centre, 2012) with pixel size of 463.31m × 463.31m, and the SBE1000 data were downloaded by the web resource in Saatchi, (2014) with a pixel size of 910.89m × 910.89m.

To enable a cell-by-cell comparison at the 500m and 1000m scale using ANOVA and to produce percentage difference maps, we reduced the resolution of the MBE100 data to 500m and 1000m, and the BBE500 data from Woods Hole Research Centre (2014) to 1000m (table 5.3). We compared MBE100 to both BBE500 and BBE1000, to enable in the first instance a more direct comparison to the pantropical national carbon stock map, using the spatial resolution defined by Baccini et al., (2012) and at the former instance to compare all three carbon maps at the coarser resolution (i.e. 1000m defined by Saatchi et al., (2011)). The data meaning for each reduced resolution pixel is the
arithmetic mean of all the increased resolution pixel values which were contained within the extent of each the new reduced resolution pixel. To assess the differences between our local biomass estimates and these national carbon stock estimates, within the boundaries of our study area we aggregated and averaged the grid values of our MBE100 data set using a window size of $5 \times 5$ and $10 \times 10$ to create reduced resolution rasters (MBE$_{500}$, and MBE$_{1000}$ respectively) (table 5.3).

**TABLE 5.3 Local and pantropical datasets used for comparison and summary of the data and methods used to derive the biomass maps.**

<table>
<thead>
<tr>
<th>Biomass map</th>
<th>EO data used</th>
<th>Algorithm</th>
<th>Pixel size (m)</th>
<th>Reduced resolution (m)</th>
<th>Compared to:</th>
</tr>
</thead>
<tbody>
<tr>
<td>MBE$_{500}$</td>
<td>ALOS PALSAR</td>
<td>Semi-empirical Water Cloud Model</td>
<td>100</td>
<td>500 1000</td>
<td>BBE$<em>{500}$ BBE$</em>{1000}$ SBE$_{1000}$</td>
</tr>
<tr>
<td>BBE$_{500}$</td>
<td>ICESAT GLAS MODIS BDRF SRTM</td>
<td>RandomForests</td>
<td>500</td>
<td>1000</td>
<td>MBE$<em>{500}$ SBE$</em>{1000}$</td>
</tr>
<tr>
<td>SBE$_{1000}$</td>
<td>ICESAT GLAS MODIS LAI/NDVI/VCT SRTM QUICKSAT</td>
<td>MaxEnt</td>
<td>1000</td>
<td>-</td>
<td>MBE$<em>{1000}$ BBE$</em>{1000}$</td>
</tr>
</tbody>
</table>

To perform AGWB comparisons between our reduced resolution AGWB estimates and BBE$_{500}$ and SBE$_{1000}$ estimates we calculated the percentage differences (eq. 5.7) per pixel and per protected areas (i.e. DR and RBCMA). To assess the difference between mean biomass estimations for the whole protected areas, percentage errors were calculated (eq. 5.8). In equation 5.7 AGWB$_1$ and AGWB$_2$ refer to (a) the AGWB values in each individual pixel of the compared datasets (e.g. MBE$_{500}$ vs BBE$_{500}$) or (b) the mean AGWB values derived using all biomass pixels of the compared datasets within the extent of a protected area. In equation 5.8 AGWB$_{reference}$ corresponds to the locally derived mean AGWB value for the woody savannas using field data in DR (table 5.2) or to the derived mean AGWB calculated by Brown _et al._, (2005) in BCMA. In eq. 5.8 AGWB$_{estimated}$ refers to the AGWB estimates based on the MBE, BBE, and SBE maps.

\[
\text{Percentage Difference} = \frac{|\text{AGWB}_1 - \text{AGWB}_2|}{0.5 \times (\text{AGWB}_1 + \text{AGWB}_2)} \times 100 \quad (5.7)
\]
Percentage Error = \left| \frac{\text{AGWB}_{\text{reference}} - \text{AGWB}_{\text{estimated}}}{\text{AGWB}_{\text{reference}}} \right| \times 100 \quad (5.8)

5.5. Results and Discussion

5.5.1. Evaluating the new biomass map against field data and previous ground surveys

Using the semi-empirical model developed by Michelakis et al., (2014) we create a 100m biomass map (MBE\textsubscript{100}) for the whole study area (Fig 5.5, A&B).

FIGURE 5.5 AGWB estimates (MBE\textsubscript{100}) derived by ALOS PALSAR scenes I, and II for (A) north Belize (scene I), and (B) south Belize (scene II), overlaid on protected areas boundaries (light grey polygons with dashed lines as boundaries) that contain savannas.
For the one half of the total savanna area of the RBCMA that is covered by the ALOS PALSAR scene, we estimate mean AGWB based on 3632 pixels from MBE\textsubscript{100} to be 29.55±0.84 t/ha, where the 95% confidence interval is reported with ±, and for the denser woodland areas sensed in the DR forest reserve (Fig. 5.1D) 38.03±0.92 t/ha based on 3105 pixels. On average, slightly higher biomass values (mean AGWB = 24.18±0.24 t/ha) were mapped within the boundaries of all the protected areas in the study area compared to values mapped in other areas which are considered unprotected (23.29±0.19 t/ha). Although a Mann-Whitney U test shows that there is a difference between the two biomass distributions (i.e. protected areas vs. unprotected areas, P < 0.050), the dispersion of biomass values in Fig. 5.6C appear similar for both groups. Perhaps surprisingly, this suggests that protection in general does not lead to substantially higher values of mean AGWB/ha in these woodlands.

To explore this finding further, in Fig. 5.6D only the biomass values mapped within two types of protected areas are presented, those which are passively managed (PRPM) and those which are actively managed (PRAM); these are compared again to values mapped in unprotected areas (UPR).

![Box plots](image.png)

FIGURE 5.6 ALOS PALSAR derived AGWB/ha estimates for A) the study area (933km\textsuperscript{2}), B) the two UNESCO savanna land cover classes, C) protected versus unprotected areas, and D) the protected areas with active management (PRAM), passive management (PRPM), and unprotected areas (UPR). In each case N represents the number of pixels (104m x104m) from the biomass map falling within each of the groupings.
The visual differences in biomass are now more evident, and although the differences of the median values for PRAM, PRPM, and UPR are again small, they are more significant (Kruskal Wallis\textsuperscript{24} one way ANOVA, P < 0.001). Specifically results from the post-hoc Dunn’s method, indicate that all three protection and management groups differ from each other (P<0.05) while the groups that differ more and less to each other are PRPM and UPR (difference on ranks~4558), and PRAM and UPR (difference of rank~1541) respectively.

The protected areas which are passively managed (PRPM) with fire control and conservation management are estimated to have a mean AGWB of approximately 29.5±0.85 t/ha and a higher variability of biomass values in comparison to protected areas that are actively managed for extractive logging (PRAM); for these latter areas AGWB is estimated at approximately 24.3±0.41 t/ha and the variability in the biomass values is lower. One possible explanation for this difference is that larger trees are commonly retained in biodiversity reserves but are usually harvested before reaching such a size in forest reserves (Linares, 2009).

5.5.2 Using the Map to Characterize AGWB in the Lowland Savannas of Belize

Visual interpretation of the AGWB maps (Fig. 5.5A&B) indicates that the study areas are dominated by low mean AGWB/ha (0-30 t/ha). Analysis of the data shows that over 90% of the mean AGWB/ha values are below 60 t/ha with less than 10% of the residual values predicted in the upper range from 60 t/ha to 101.65 t/ha (Fig. 5.6A). The results obtained show that when AGWB is summed within the areas of the two UNESCO savanna classes mapped, each class produces almost the same total AGWB [VA2a (1) (2): 1.00Mt, and VA2a (1/2): 0.99Mt]; however the less dense UNESCO class VA2a (1) (2) covers some two-thirds of the study area. In Fig. 5.6C the denser VA2a (1/2) class is shown to contain significantly higher mean values of AGWB/ha (~32±0.27 t/ha in comparison to ~19±0.16 t/ha), a difference which is statistically significant.

\textsuperscript{24} A Kruskal Wallis one way ANOVA technique was used because the biomass data failed the normality test Kolmogorov-Smirnov (P < 0.001) indicating that the biomass data varies significantly from the pattern expected if the data was drawn from a population with a normal distribution.
(Mann-Whitney U statistic, $P < 0.001$). The observed higher mean biomass found in VA2a (1/2) can be explained by the denser woody component being more extensively found in this class; in general increasing number of trees/ha has been found to produce increased mean AGWB/ha in these savanna woodlands (Michelakis et al., 2014), and in other tropical savannas that are resource limited (Cassells et al., 2009). AGWB values estimated within the VA2a (1/2) vegetation class also showed a greater standard deviation (24.65 t/ha in comparison to 18.57 t/ha). Taken together these findings suggest that the less extensive VA2a (1/2) areas may be important to focus upon for carbon sequestration and, if they also have greater structural diversity, they may also be suitable for biodiversity conservation initiatives.

The RRMSE$^{25}$ and the average estimated bias between the AGWB that was predicted by the WCM and the AGWB estimated using the training and the validation dataset for each of the seven AGWB classes mentioned in section 5.4.3 are shown in table 5.4.

<table>
<thead>
<tr>
<th>AGWB Class (t/ha)</th>
<th>Number of AGWB Observations</th>
<th>Average AGWB Observed (t/ha)</th>
<th>RMSE (t/ha)</th>
<th>RRMSE (%)</th>
<th>Number of MBE100 pixels</th>
<th>Average</th>
<th>Max</th>
<th>80th perc.</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-15</td>
<td>4 (V)</td>
<td>10.84</td>
<td>14.2</td>
<td>131</td>
<td>35425</td>
<td>6.75</td>
<td>19.64</td>
<td>14.21</td>
</tr>
<tr>
<td>15-30</td>
<td>8 (V)</td>
<td>20.60</td>
<td>16.02</td>
<td>78</td>
<td>22758</td>
<td>17.21</td>
<td>23.40</td>
<td>20.67</td>
</tr>
<tr>
<td>30-45</td>
<td>11 (V)</td>
<td>38.88</td>
<td>7.43</td>
<td>19</td>
<td>13774</td>
<td>6.96</td>
<td>8.55</td>
<td>7.79</td>
</tr>
<tr>
<td>45-60</td>
<td>9 (V)</td>
<td>51.98</td>
<td>15.13</td>
<td>29</td>
<td>6247</td>
<td>14.93</td>
<td>17.40</td>
<td>16.48</td>
</tr>
<tr>
<td>60-75</td>
<td>6 (V)</td>
<td>66.30</td>
<td>14.62</td>
<td>22</td>
<td>3014</td>
<td>14.66</td>
<td>16.50</td>
<td>15.64</td>
</tr>
<tr>
<td>75 – 90</td>
<td>10 (T)</td>
<td>85.10</td>
<td>43.8</td>
<td>51.47</td>
<td>1489</td>
<td>42.00</td>
<td>45.90</td>
<td>43.86</td>
</tr>
<tr>
<td>90 – 105</td>
<td>3 (T)</td>
<td>96.51</td>
<td>25.58</td>
<td>26.51</td>
<td>1567</td>
<td>26.81</td>
<td>27.45</td>
<td>27.45</td>
</tr>
</tbody>
</table>

$^{25}$ In this thesis I am assessing the accuracy of the AGWB predictions by calculating the bias between the predicted AGWB and the calculated AGWB using a training and a validation dataset and the RMSE, and the RRMSE. However, I acknowledge that the underlying overall uncertainties which are described by systematic and random errors of measurement and estimation are important and should be examined in future work.
FIGURE 5.7. Bias estimates for MBE\textsubscript{100} derived by ALOS PALSAR for (A) north Belize (scene I), and (B) south Belize (scene II), overlaid on protected areas boundaries (light grey polygons with dashed lines as boundaries) that contain savannas.

5.5.3. Comparison of the local map estimates with pan-tropical carbon stock maps

The reduced resolution rasters MBE\textsubscript{500}, and MBE\textsubscript{1000} derived in section 5.4.6 contain pixels with the arithmetic mean of the input pixels (MBE\textsubscript{100}) that were included. Based on 4616 pixels (pixel size 500m) it is evident from Fig. 5.8A that BBE\textsubscript{500} predicts significantly higher mean AGWB/ha for the whole study area than MBE\textsubscript{500} (~88±1.21 t/ha vs. ~24±0.632 t/ha; percentage diff. = +115.50%), while the SBE\textsubscript{1000} AGWB estimation (~95±2.86 t/ha) is higher than both the BBE\textsubscript{1000} and MBE\textsubscript{1000} (~88±2.50 t/ha and ~24±1.28 t/ha respectively) based on 1096 pixels (Fig. 5.8B) of 1000m pixel size (percentage diff. = +8.2% and +121% respectively). Visual comparison of the percentage difference maps (Fig. 5.9) suggests that the 500m and 1000m biomass maps yield different and higher biomass estimates compared to those from aggregating our 100m estimates while the comparison of the box plots (Fig. 5.8 A and B) also support that MBE, BBE, and SBE show differences in their biomass distribution. The relatively
FIGURE 5.8. Differences between biomass maps for (A) 500m, and (B) 1000m resolution.

FIGURE 5.9 Percentage differences as calculated from equation 5 per 1000m pixel for the comparisons between (A and D) MBE1000 vs BBE1000, (B and E) MBE1000 vs SBE1000, (C and F) BBE1000 vs SBE1000 for northern and southern Belizean savannas within the ALOS PALSAR scenes. In histogram (G) we show the distribution of the percentage differences pixel-wise for each biomass map comparison group, and in scatterplot (H) we show the relationship between the percentage difference for each pixel and the biomass estimated for the same pixel using the MBE1000 maps.
similar magnitudes of the estimates for the two pan-tropical carbon maps produced by Baccini et al., (2012) and Saatchi et al., (2011) is expected, since they have used very similar EO data and allometric equations to derive biomass estimations, with the main difference being only the machine learning algorithm used (Random Forest, versus MaxEnt respectively).

Whilst the above comparison was done for the entire study area to maximize the data volume included, we also compared the estimates from the different biomass maps for the RBCMA and DR areas, since these are more typical of the areas of interest to land managers in Belize. We found that the carbon stock maps created for RBCMA and DR using data from Baccini et al., (2012) and Saatchi et al., (2011) at 1 km spatial resolution again produced significant overestimation of the mean AGWB/ha compared to local reference values from the field surveys described earlier. Percentage errors were 277% and 319% for BBE\textsubscript{1000} and SBE\textsubscript{1000} respectively in the RBCMA, and 302% and 298% for BBE\textsubscript{1000} and SBE\textsubscript{1000} respectively in DR. In contrast, upscaling our finer scale AGWB estimations in both the RBCMA and DR did not produce large overestimation compared to the same local reference values (+8.1% and +4.5% respectively for MBE\textsubscript{500} and 10.7% and 0.04% for the MBE\textsubscript{1000}). These findings confirm the need for caution when using biomass estimations produced from satellite EO (Hill et al., 2013) at coarse resolution for quantifying AGWB locally. These results support earlier findings in savanna woodlands in Mozambique where considerable differences in mean AGWB were observed between a biomass maps produced locally by Baccini et al. (2012) and maps produced by Ryan et al., (2012). Generally, these estimates of AGWB by our local method (~ 26 t/ha) and by the pan-tropical data sets (~ 90 t/ha) need to be considered in the context of the ranges of above ground biomass that are estimated for woody savannas in other parts of the world. According to a review of observations by Grace et al., (2006) the highest values of biomass observed in savannas have been in Northern Australia (~ 67.2 t/ha)(Chen et al., 2003), while in South and Central America the highest biomass values recorded have been observed in Brazilian cerrado vegetation (~31.8 t/ha) (Abdala et al., 1998). This leads to the suggestion that the pan-tropical
carbon maps may be over-estimating AGWB in savanna areas, and this suggestion will need to be explored more rigorously as more field based estimates of biomass are collated from other savanna woodlands.

5.6 Conclusions

This study has shown that ALOS PALSAR radar data can be used with semi-empirical modelling to produce estimates of AGWB/ha for the woody component of tropical savannas at a spatial resolution of 100m. When these pixel estimates are aggregated within the extents of two protected areas of approximately 10,000 ha, the satellite derived biomass maps agree to within 12% and 20% respectively with estimates obtained from local forest survey data, and from biomass estimated from airborne very high spatial resolution imagery, suggesting that this method has sufficient accuracy to be used for reporting biomass estimates for sub-national extents.

Over 90% of the woodlands mapped in Belize are estimated to have an AGWB less than 60 t/ha and the average woody biomass of these savannas is estimated at ~23.5 t/ha. Overlaying the results upon previous thematic mapping of national land cover allows us to assign a representative mean biomass value of ~32 t/ha to UNESCO savanna class VA2a (1/2) (‘short-grass savannas with dense trees or shrubs’”) which clearly separates it from the ‘short-grass savannas with scattered trees and/or shrubs’ VA2a (1) (2) land cover variant (~18 t/ha). This is the first quantitative assessment of the difference in the woody component between these two land cover classes and this information significantly enhances the value of the existing land cover map for forest managers.

A two-way comparison of the mean AGWB values mapped for all protected versus all unprotected areas in the study area showed a small gain in biomass within protected areas; subdividing the protected areas further revealed higher AGWB values (~30 t/ha) were being estimated for passively managed biodiversity reserves than for the extractive forest reserves (~25 t/ha).

The comparison of our AGWB estimate to the pan-tropical carbon stock maps produced by Baccini et al. (2012), and Saatchi et al. (2011) shows that the three biomass
estimates are not consistent, and with both pan-tropical data sets significantly overestimating AGWB when compared to estimations based on more localized backscatter-biomass relationships constrained by forest survey data. It must be noted that although in this research large sample plots were used (i.e. one hectare) to calibrate the ALOS PALSAR imagery assisting with the reduction of the systematic bias observed by Réjou-Méchain et al. (2014), and a range of protection and management areas were used to collect the field data to further reduce the introduction of systematic biases it wasn’t possible to quantify the total systematic bias that was introduced during the development of the method used (Hill et al., 2013) in this research.

A recent FAO forestry article published a new approach to estimating forest cover loss [26]. This evidence from this study suggests that the pan-tropical carbon stock maps overestimate the biomass of savanna woodlands in Belize at the national level and are also less suited for exploring differences in AGWB at the sub-national scale, for example for monitoring biomass differences within and between the country’s protected areas.
References


Zeng, T., Dong, X., Quegan, S., Hu, C., Uryu Y. (2014) Regional tropical deforestation detection using ALOS PALSAR 50m mosaics in Riau province, Indonesia, Electronics Letters, 50, 547-54
CONCLUSION & RECOMMENDATIONS

6.1. Thesis contributions

This research has demonstrated how active satellite EO and field measurements can be combined to characterise the extent and diversity of woody structure, and to predict the above ground woody biomass of the pine-dominated savannas of lowland Belize.

To restate, the main objectives were to:

1. Describe quantitatively the structure of the lowland pine-dominated savanna woodlands and to understand if these characteristics are similar or different for woodlands under different types of protection and management.

2. Investigate the sensitivity of satellite microwave EO collected by ALOS PALSAR to AGWB as measured by field survey in these woodlands.

3. Develop and validate a statistical model to predict AGWB from ALOS PALSAR backscatter intensity data, and examine any effects of woodland structure upon the backscatter signal.

4. Produce and evaluate the first fine-scale mapping of AGWB (i.e. 1ha spatial resolution) within the savanna woodlands of Belize using the prediction model developed in (3).
The thesis contributes to a growing literature which critically examines the capability of active satellite EO to support prediction and mapping of AGWB in different types of tropical mixed woodlands. The three main achievements of this thesis can be summarised as:

- This thesis produced the first comprehensive quantitative assessment of the structure of pine dominated savanna woodlands growing under different protection and management regimes in Belize. This is important because although field observations have been analysed in the past to produce quantitative descriptions of pine savannas in particular parts of Belize, previous studies have conceptual limitations in that (i) most previous studies have been very localised, for example Viergever et al., (2008) and Stuart et al., (2006) only studied woodlands in the well protected area of the Rio Bravo, focusing on the denser woodland areas of greatest economic value, leading to questions about the applicability of the findings to a wider range of savanna woodland structures, (ii) the woodland sites studied previously have all been protected under the same management regime and in particular, there have been no reported vegetation studies in unprotected areas (iii) some earlier studies used pan-tropical rather than locally derived and verified allometric equations to estimate tree or stand biomass, This thesis addresses these limitations by:
  - **(A)** Drawing the sample field plots much more widely geographically across the country and sampling the full range of tree densities known to exist in Belize (i.e. from 50 up to 700 trees/ha).
  - **(B)** Defining more clearly the type of protection and management for the woodland in each sample plot by using a-priori qualitative and quantitative information to classify the human activities taking place in each area.
  - **(C)** Examining quantitative differences in vegetation structure in each sample plot by analysing the diameter and the total height distributions of trees per plot, and
  - **(D)** Estimating the above-ground woody biomass in each sample plot using locally derived allometric equations.

- The thesis has developed and tested the use of ALOS PALSAR for prediction of AGWB in the lowland pine savanna ecosystem. By showing that different woodland structures develop under different types of management and that backscatter responds
differently (i.e. predicts AGWB differently) in woodlands with these different structures I have demonstrated, that it is necessary to have a-priori knowledge of the human activities taking place within forested areas (e.g. whether they are protected or unprotected) in order to accurately constrain estimates of biomass, either when one is making remote observations using radar or when carrying out a visual assessment of tree numbers in the field.

- This thesis has demonstrated for a typical area of the lowland savannas of Belize where a commonly used method of active forest management is being undertaken (i.e. sustainable logging) that the ALOS PALSAR backscatter data can estimate biomass with sufficient accuracy to support forest management activities at local scales (i.e. down to one hectare scale, with error ≤ 20 t/ha). Comparing this local mapping to previous widely available global biomass predictions I have shown an improvement in AGWB estimation compared to these pre-existing maps, demonstrating that the method developed here is more suitable for creating sub-national biomass maps (i.e. ≤ 10000ha) designed to support local sustainable forest management (SFM) and REDD+ MRV activities.

### 6.2 Summary of Findings

The focus of this thesis was the use of active satellite EO to support AGWB prediction in savanna woodlands since AGWB is frequently used to provide information about forest structure in SFM and REDD+ MRV activities and was shown to be related to stocking measures such as tree number density and basal area in these woodlands.

This thesis demonstrated that radar satellite observations from ALOS PALSAR can characterise AGWB in these woodlands in a way that accords consistently with comprehensive field measurements obtained throughout the country of Belize. Each of the four objectives listed in section 7.1 was addressed by a separate chapter of the thesis and so the principal findings from each chapter are now summarised below to demonstrate that each objective was achieved.
6.2.1 Chapter 3 – Accepted subject to minor revision: Caribbean Journal of Science

This chapter addresses objective (1):

“Describe quantitatively the structure of the lowland pine-dominated savanna woodlands and understand if these characteristics are similar or different for woodlands under different types of protection and management.”

The study found that the lowland pine savannas in Belize are dominated by juvenile individuals (50% of trees have a DBH ≤ 20cm). Although tree density is typically ~240 trees/ha, in a few areas density can reach 680 trees/ha, producing maximum AGWB of 100 t/ha and BA of up to 15 m²/ha.

The pine-dominated savanna areas throughout Belize differ significantly in their tree number densities, BA, and AGWB. The woodlands in unprotected areas (UPR) were found to be on average more dense (mean tree number density ~ 432 trees/ha) than the woodlands in protected areas where activities such as selective logging, fire management and biodiversity management were practiced (PRPM: 163 trees/ha) or in forest reserves which are actively managed for sustainable timber extraction (PRAM: 132 trees/ha respectively). The data showed that savanna woodlands in unprotected areas (UPR) had less internal (i.e. within hectare sample plot) variation in AGWB. In some UPR areas, woodlands were found to contain unexpectedly high amounts of AGWB, stored in a large number of juvenile trees. In contrast, within protected areas similar high quantities of AGWB are stored in fewer trees and in a wider range of tree sizes.

These findings are important for the following reasons:

(A) It suggests that protecting and managing tropical savanna woodlands creates forest structures that can produce high AGWB per hectare. This is because of the variation in vegetation structure created (i.e. biomass is stored in a wider range of tree sizes). The knowledge about the biomass that can be stored and the timber volumes available in these woodlands can assist land managers to make decisions about alternative uses for different woodlands areas (e.g. their relative suitability for conservation initiatives,
timber extraction or other activities which have the capacity to promote other ecosystem services).

(B) The strong positive correlation between AGWB and the structural attributes of number density and BA found all the plots (i.e. under all types of management) suggests that resource limitations upon biomass production (e.g. limited nutrient availability) are a common feature of all these woodlands and are not mitigated by forest protection (i.e. higher AGWB is not found in protected areas compared to unprotected areas). Rather it appears that it is the number of trees within a hectare that is driving the quantity of AGWB present. An important practical implication for land managers is that counting the number of trees within an area will enable them to make an initial estimate of AGWB. This consistent relationship between tree number density and AGWB is used further to understand and develop the relationship between the radar backscatter and the biomass prediction in these woodlands.

6.2.2 Chapter 4 – This chapter integrates the results and discussions of two published articles (a) at the IEEE International Geoscience and Remote Sensing Symposium, 2013 and (b) at the IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2015

This chapter addresses objective (2) and (3):

“Investigate the sensitivity of satellite microwave EO collected by ALOS PALSAR to AGWB in these woodlands.”

Chapter 4 showed that a strong statistical relationship between ALOS PALSAR backscatter data (L-HV) and AGWB can be developed and used to predict AGWB. The relationship is found to be stronger when the field data used to estimate AGWB were collected using a sample plot size of one hectare; subdividing these plots into 0.1ha, 0.25ha, and 0.5ha sub-plots led to the strength of the relationship decreasing exponentially (r² = 0.98, p = 0.005, F = 173.27) with decreasing sample plot size. The weakening relationship may be attributed to the smaller number of ALOS PALSAR pixels used to create the statistical relationship and the increasing structural variability apparent with smaller sample plot sizes.
The main practical implication of this chapter is that for many REDD + MRV activities where AGWB needs to be quantified over wide areas using ALOS PALSAR it will be preferable to collect forest inventory data using sample plots of one hectare size in order to enable a stronger statistical relationship to be fitted to the L-band radar data.

Taking the results of the woodland structural analyses from chapter 3 together with the findings in chapter 4 led the author to conclude that:

(A) The greater variability of vegetation structure observed at smaller sample sizes (i.e. < 0.5ha) is one possible factor contributing to the weaker statistical dependence between backscatter and AGWB when smaller field plots are used to create the relationship.

(B) In order to develop a model which will utilise ALOS PALSAR backscatter in conjunction with the ground vegetation measurements for reliable biomass prediction and mapping, the forest structures within each hectare sample plot used in this chapter (i.e. in Fig. 4.5A) have to be examined further. For example, the DBH distributions for each of the individual hectare sample plots (i.e. each of the observations plotted in Fig. 4.5) need to be analysed to understand which elements of forest structure are driving the response of the radar backscatter to increasing AGWB. This was pursued in Chapter 5.

Chapter four also addresses Objective (3):

"Develop and validate a statistical model to predict AGWB from ALOS PALSAR backscatter intensity data, and examine any effects of woodland structure upon the backscatter signal."

Three of the most important achievements of this chapter were:

(A) The development of the adapted semi-empirical model ($R^2=0.92$) for the prediction of AGWB in these savanna pine woodlands using a training dataset ($n = 38$) and with the predictive accuracy estimated ($\text{RMSE} = 13.8$ t/ha) using a validation dataset ($n = 38$).
CONCLUSION & RECOMMENDATIONS

(B) Examining further the findings from chapter 4(B), I showed that forest vegetation structure, as expressed by the variability of the DBH distributions seems to affect the L-HV signal. The reduced variability in DBH that was found to occur with increased tree number density above a certain threshold (~400 trees/ha) and a concurrent increase in both AGWB and BA above 80 t/ha and 12 m²/ha respectively are two factors that may explain the backscattered signal actually decreasing slightly in these denser plots.

(C) I found that the saturation point for predicting AGWB using the L-band backscatter is approximately 106 t/ha. Although similar values have been observed in other studies using ALOS PALSAR data in African and Australian savannas; lower saturation points (i.e. 50-100 t/ha) using L-band data are also typical. In this study, I suggest that the saturation point is positively influenced by three factors: (i) the thin and long elements (e.g. twigs and branches) of the dominant pine vegetation (~90% of field observations), with more than 90% of the biomass stored within the stem, allowing the L-band microwave signal to penetrate deeper into the woodland canopy minimizing the effects of saturation due to canopy element interactions, (ii) because the backscatter signal is driven by the strong relationships between tree number density and AGWB and BA (Fig. 4.6c and Fig. 4.6d), and (iii) the effective inclusion of a variety of different forest structures (i.e. different levels of within-plot variability of DBH – table 4.2) into the regression model that was developed, as a result of including plot data from different protection and management regimes (i.e. UPR, PRAM, and PRPM – Fig. 4.7a and Fig.4.7b). These three factors have all previously been hypothesized to have increased backscatter beyond lower saturation points using L-band data from other SAR systems (i.e. ≤ 50 t/ha) (Woodhouse et al., 2012; Brolly & Woodhouse, 2013).

This increased saturation point allows AGWB to be predicted with high accuracy for a significant amount of the savanna woodlands in Belize, enabling AGWB maps to be produced that can be used to support management of these woodlands for protected and extractive SFM areas across the country at fine spatial scales (more than 85% of AGWB predictions had an error of less than 20 t/ha). The field observations made in this research as well as previous work indicate that the range of the AGWB in these
woodlands does not exceed 105 t/ha, and that most (~80%) areas have considerably less than this (i.e. ≤ 80 t/ha).

6.2.3 Chapter 5– Published: Special Issue on Applications of Remote Sensing to Forestry, 2014

This chapter addresses objective (4):

“Produce and evaluate the first fine-scale mapping of AGWB (i.e. 1ha) within the savanna woodlands of Belize using the prediction model developed in objective (3)”

In this chapter the semi-empirical model developed in chapter 5 is applied to produce the first fine scale maps (100m resolution) of AGWB for a test area encompassing more than 50% of the total lowland savanna landscape of Belize. This fine scale mapping is designed to support SFM and REDD+ MRV activities in two selected protected areas within the footprints of the ALOS scenes (i.e. RBCMA and Deep River FR). A general case is then built for finer scale mapping of AGWB rather than obtaining biomass predictions for areas from existing global Earth observation datasets.

The results obtained showed that the AGWB predictions mapped out at 100m resolution and aggregated within the extents of dense tree savanna in the Deep River forest reserve agreed closely (≤20% difference) with biomass estimates obtained independently from a comprehensive set of field measurements made within the same area. When the new estimates were mapped out within the savannas of the RBCMA, these also produced a total AGWB value that agreed closely with biomass estimates that had been obtained previously for the same area by using local allometric equations and mapping from very high spatial resolution 3-dimensional aerial imagery (12.8% percent difference). In contrast, when these locally modelled predictions of biomass were compared to AGWB estimates for the same geographical areas that had been derived from global EO data sets, significant overestimations occurred (up to ~320%) using the coarser scale products.

The results of this chapter are significant because they illustrate:
(A) That ALOS PALSAR backscatter can be used to measure and report AGWB at finer scales than previously and for different types of protected areas - those which are managed either for timber extraction (Deep River) or biodiversity (RBCMA).

(B) These estimates quantify for the first time the typical values and the spatial variations in biomass found across the savanna woodlands, and enable this detailed variation to be mapped in Belize. As chapter 6 showed, these estimates can then be aggregated within a given ground area to estimate, for example, the total biomass and its distribution within a given protected area. This information usefully supplements Belize’s national ecosystems mapping of savannas, which uses a more qualitative UNESCO land cover classification, enabling representative values of the mean woody biomass to be assigned to each of the thematic savanna classes (~32 t/ha for the ‘short-grass savannas with dense trees or shrubs’ class and ~18 t/ha for the ‘short-grass savannas with scattered trees and/or shrubs’ class). The ability to produce biomass estimates at a finer scale provides an information asset for land managers and policy makers who need to quantify biomass within specific areas; for example, it enables them to assess the potential of certain forest stands for extractive use or alternatively for protection as carbon stores. Land managers know that different areas are more suitable for uses such as SFM or for biodiversity conservation and this finer granularity of mapping can allow them to map and designate the type of forest management to be practiced in different zones.

(C) The findings suggest that it may not be effective to use existing global data sets of AGWB for sub-national (i.e. ≤ 10000ha) and national AGWB prediction for purposes such as REDD+ MRV activities, delineating SFM compartments or protected areas zoning. For example, using the Baccini et al. (2012) or Saatchi et al. (2011) products for estimating standing biomass in the Deep River Forest Reserve would overestimate AGWB, with the consequence that areas might be chosen which are not in fact yielding enough timber volume either for SFM or for carbon sequestration, leading to a possible failure of a business case. As a further illustration, the biomass mapping products from Baccini et al., (2012) and Saatchi et al., (2011) are too coarse for zoning the savanna areas of the RBCMA into multiple use compartments, as is required by their management plan. The managed pine stands in the RBCMA vary in extent from 45-
180ha (SmartWood, 2005); only one or two pixels at most could be used for assessing the biomass of a stand using the Saatchi et al., (2011) data and 2-4 pixels using the Baccini et al., (2012) data, with ‘edge effects’ likely to affect the accuracy of the estimates in both cases. Although the coarse biomass mapping products created by Saatchi and Baccini are useful for national biomass assessments, these practical examples show that to support management decisions in many small-medium sized protected areas, finer scale biomass mapping is needed.

### 6.2.4 Calibration and Validation using different sample plot sizes

It must be noted that although in chapter four an external validation dataset was used to perform an accuracy assessment for AGWB prediction using the semi-empirical WCM; the training and validation datasets had different sample plot sizes and shapes (i.e. 1ha square plots and 0.1ha circular plots respectively). The author recommends that the same sample plot size is used for the training and validation datasets to assess the accuracy of a prediction model and also that the validation sample plots are selected randomly, if they are part of a larger pool of samples such as in this thesis (i.e. 38 sample plots selected out of a grand total of 108 sample plots within a savanna).

Although the author made an attempt to find and acquire one hectare pine savanna data for validation purposes, the in-country search and literature research showed that the field data collection component of this thesis is the only one in Belize that has collected observations for the pine savannas in the country at the one hectare sample plot size. The validation data (i.e. 38×0.1ha) that were collected in Deep River and were used in this thesis in chapters four and five are part of an extended pine savanna data collection campaign (Linares, 2009) which had been designed to fit the aims of a forest inventory (i.e. the extrapolation of observations collected within as many locations as possible within the Deep River Forest Reserve). This is why the data were collected from Linares, (2009) using a point grid covering a large geographical extent of the study area. However this forest inventory method does not aim to establish the sample plots within woodlands which share within plot and outside plot woodland cover, but aims to establish a sample plot where pine woodland exists. This means that surely all the sample plots will have some pine woodland within their geographical extent; however
outside their geographical extent there may be none or very little which means that the sample plot may not be representative of the surrounding area (e.g. the surrounding hectare).

This becomes problematic when making an attempt to use the field inventory data as a validation dataset to assess the WCM calibration, and the AGWB map in chapters four and five since there is need to identify sample plots that their geographical extent can be extrapolated to (a) include as many SAR pixels as possible from the ALOS PALSAR imagery (i.e. 16 pixels which translates to one hectare on the ground), due to the SAR data collection ambiguity as described in chapter two, and (b) to make sure that the observed data collected within the 0.1ha sample plots (i.e. tree density, canopy cover, biomass etc.) are representative of the surrounding hectare outside the sample plot geographical extent and can be compared to the SAR backscatter collected by ALOS PALSAR described in (a). To ensure this, the author used the methodology described in chapters five and six where VHR WorldView data were used to visually identify the 0.1ha sample plots (out of the 108×0.1ha) which would be able to fulfil the above criteria (i.e. a, b). This technique is novel and it can supplement existing techniques for field inventory data pooling assuming that the VHR contains little cloud, which is challenging in many tropical countries; however the author also recognises that the technique lacks statistical integrity since an observer may criticise the fact that the validation sample plots have not been selected randomly either using random numbers or from an unbiased user.

### 6.3 Recommendations and suggestions for further work

The findings of this research lead me to suggest recommendations for forest managers that intend to use satellite data to predict AGWB in the context of continuous monitoring, policy makers who intend to include savanna woodlands in climate change adaptation contexts such as REDD+ and the research community who will further explore L-band satellite data for AGWB prediction in tropical woodlands.

#### 6.3.1 Recommendations for forest managers

The finding that the ALOS PALSAR backscatter data predicted AGWB in savanna woodlands with relatively satisfactory accuracies (i.e. 85% of predictions had prediction
errors of less than 20 t/ha), suggests that forest managers may begin exploring this method of monitoring carbon stocks over the extent of their conservation areas or forest reserves and for sustainable forest management and MRV activities in contexts such as REDD+. For example, the L-HV backscatter relationship to AGWB developed here could be used for monitoring carbon stocks in several protected areas across Belize, including both strict conservation areas and extractive forest reserves, where biomass is generally ~50 t/ha and does not exceed 100 t/ha, such as in the Deep River Forest Reserve, Payne’s Creek National Park, and the Crooked Tree Wildlife Sanctuary.

As an illustration, the biomass mapping using L-HV and very high spatial resolution imagery collected by WorldView could be used to establish a permanent grid of sample plots within Deep River where the radar derived AGWB estimates (at one hectare resolution) have been found to match closely with measurements from the small area plots currently used for monitoring forest practices in Deep River (0.1ha). A permanent sampling grid would be used to achieve two goals: (A) using the permanent grid in combination with the archived ALOS PALSAR data to establish a historical baseline (i.e. project the changes in biomass before the implementation of any REDD+ projects) and (B) to support future monitoring and mapping of woody biomass change by using field measurements from the permanent grid to calibrate an updated semi-empirical model using forthcoming ALOS PALSAR-2 imagery.

Establishing a link between L-band radar data and AGWB also creates the opportunity for studies to monitor change in the extent and distribution of woody savannas in Belize over longer time periods, using previous forestry mapping. For example, as part of an economic forest assessment in 1974, extensive forest inventory measurements (DBH) were taken in pine savanna woodlands in the southern coastal savannas, and a detailed map was created of the different densities of pine throughout the southern coastal plains of Belize (Johnson and Chaffey, 1974). The extent of these maps covering the Deep River (DR) and Payne’s Creek (PNCP) areas were recently digitised by Katsigiannis, (2014) and so provide historical baseline geographical information that could be used in with the new biomass mapping developed by this author to estimate
changes in pine woodland density in different areas across the Deep River and Payne’s Creek National Park over 40 years.

Monitoring biomass in protected areas for shorter and more recent periods of time could be achieved by acquiring data from the new ALOS PALSAR-2 satellite sensor. To take advantage of this data for monitoring I recommend the establishment of permanent one hectare sample plots in various protected areas. For this method to be most effective, field data observations would also need updating so they are approximately contemporaneous with the ALOS PALSAR -2 scene acquisitions. A network of permanent plots would also be needed or on-going monitoring and to establish and monitoring forest carbon baselines.

6.3.2 Recommendations for further research

6.3.2.1 Assessing consistency over time of L-HV backscatter for AGWB estimation and seasonal influences

For developing the backscatter-AGWB relationships within this ecosystem it has been beneficial that pine-dominated savannas occur in plains where topography is gentle and thus there is less significant negative contribution of relief, as explained in chapter 2, upon the backscattered signal collected by the radar sensor. However, this gentle relief in combination with the patchy nature of pine-dominated stands in the grassland landscape may increase the backscattered radiation signal under two specific conditions:

(A) During the wet season when the ground is inundated, ‘double-bounce’ of the radar backscatter may produce erroneously high backscatter values which may reduce the accuracy of the AGWB predictions.

(B) When a pine stand next to an open grassland area acts as a ‘corner reflector’ the radiation backscattered from these forest edges will increase; in both these cases, the likely result would be for the radar method to overestimate AGWB in comparison to values estimated from field measurements.

The volume of ALOS PALSAR data that we acquired from the NASA-ASF, which were collected during drier seasons, were not sufficient to examine these effects in this
thesis; however there will be an opportunity with the new ALOS PALSAR-2 sensor, and possibly SAOCOM in the near future for new acquisitions in order to test the reliability of the AGWB predictions with L-band backscatter in different seasons, providing that field data can also be collected in the test areas of radar data acquisition.

6.3.2.2 AGWB prediction using L-HV in other protected areas

The practical capability of ALOS PALSAR to predict AGWB and to support woodland management in the Deep River forest reserve has been demonstrated in this research. More extensive validation of the method should now be conducted in different forest areas and in other actively (PRAM) or passively (PRPM) managed protected areas, using additional field data collected at the same time as the remote sensing data collection to minimize effects of temporal differences. This will allow researchers to field test the method in other protected areas, with the results building further understanding of the repeatability and the bias of biomass estimation in this ecosystem.

To give a specific example in the ecologically and economically important Rio Bravo Conservation and Management Area (RBCMA), where a sufficient amount of pine-dominated savanna woodlands exist (i.e. ~10000ha) to support a small-scale REDD+ project, additional hectare sample plots (i.e. 15×1ha) should be established. This is because of three reasons which are supported by the evidence found in chapter 5 and chapter 6:

(A) In protected and passively managed areas (PRPM) such as the RBCMA, the savanna woodlands show more within-plot structural variation than was evident in either the other protected (e.g. PRAM) or the unprotected (UPR) areas.

(B) It may be the case that it is the increasing biomass or an increasing uniformity of tree girth, (as was found in the UPR areas but not observed in PRPM areas) that may be driving the backscatter – biomass relationship to saturate. However this may not be the case and saturation might not occur so readily if increasing within-plot biomass is not associated with the decreasing structural variability, as observed in PRPM.

(C) In the higher biomass ranges (i.e. 75 t/ha ≤ biomass ≤ 90 t/ha) which is typical of RBCMA as observed in this study, the AGWB predictions using the ALOS PALSAR
imagery show increased estimated bias than was evident in lower biomass ranges (i.e. 30 t/ha < AGWB < 75 t/ha) which was observed in other protected areas (i.e. DR) in this study.

These cases are precisely what the field data collected in this thesis showed to be occurring in the PRPM areas such as the RBCMA. To explore this further the field sampling effort in RBCMA needs to focus on (1) the lower biomass range (biomass ≤ 30 t/ha), compared to the full biomass range that was sampled in this thesis (0 t/ha ≤ biomass ≤ 105 t/ha), and (2) the upper middle biomass range (60 t/ha ≤ biomass ≤ 80 t/ha) in order to create a backscatter: biomass relationship for this protected area alone.

The aim of this thesis to establish a nationwide mapping capability required sampling across the country and within different protection and management regimes and unprotected areas to build a national relationship between radar backscatter and biomass. Although RBCMA was relatively well sampled, new sample plots at the lower ranges of biomass (i.e. ≤ 30 t/ha) and 60-80 t/ha would allow a complete range to be explored within this important protected area, where the management creates specific structurally diverse formations for which I believe the backscatter may saturate at higher values. The additional field data will supplement the 11×1ha field data were collected in this thesis, allowing researchers to develop a semi-empirical biomass prediction model specifically for PRPM forest structures.

6.3.2.3 Contribution of other high and very high spatial resolution optical data to supplement ground measurements

High and very high spatial resolution (VHR) data collected by SPOT and WorldView were used to identify pine-dominated savanna areas, and to assist in validating AGWB predictions and identifying locations for siting representative ground sample plots. These optical datasets were examined visually in combination with the savanna ecosystems map to ensure that all pine-dominated stands sampled on the ground were in either the ‘VA2a (1/2)’ and ‘VA2a (1) (2)’ UNESCO vegetation classes which describe ‘short-grass savannas with dense trees or shrubs’, and ‘short-grass savannas with scattered trees and/or shrubs’ respectively. This systematic use of radar and optical EO data ensured that these two UNESCO classes were both well sampled and this enabled the biomass of each of these two classes and the amount of the internal
variability in biomass within these two classes to be reliably quantified. Satellite optical EO data are still widely used for land use planning and zoning in many parts of the world; however when the combination of radar and optical data are used together, the radar data provide additional information about woody biomass which can be used to further subdivide or assess thematic areas.

The optical data was also very useful in this study for ensuring that the pine-dominated stands which the radar was interacting with were always larger than one hectare. The increased spectral resolution of WorldView II (including Near Infrared, and Red Edge bands), and the panchromatic band (0.5m pixel size) assisted significantly in differentiating the pine vegetation from other savanna vegetation such as palmetto, oaks, and low vegetation such as shrubs. Using the combination of SPOT and WorldView data I found that it was possible to identify visually pine-dominated savanna areas, to count individual tree crowns or groups of adjacent tree crowns. This increased certainty that the backscatter was from the intended ground targets and was not being confounded or intercepted by interactions with other vegetation structures. The optical and radar imagery from this analysis could be used for further research into how the radar signal interactions with savanna vegetation and particularly how the backscatter signal varies at the fine scale, according to changes in canopy cover, tree number density and tree spacing.

6.3.2.4 Further research specific to savanna woodlands in Belize

Further research characterising the woody cover in this savanna ecosystem could also focus on:

- The inclusion of field data about other woody vegetation such as oak stands and palmetto stands that are also found in the lowland savanna landscape. In this study we focused only on the pine-dominated areas due to their economic and social importance to the local population and timber industry. This would further enhance the capacity that this thesis created towards creating a complete biomass inventory for these savanna areas.
- Additional field data collection in those protected areas (e.g. RBCMA, Deep River, and Payne’s Creek) which may be favoured for conservation initiatives or
carbon sequestration in the future. These protected areas are important and should be enhanced with new field data acquisitions because the amount of savanna woodlands is significant (≥ 5000ha) making them potential candidates for small-scale REDD+ projects, and to study the effects of management practices including prescribed burning and pine seedling regeneration (Walker et al., 2009; Linares, 2009). In total 25.8 hectares of field data have been collected in RBCMA and Deep River in the context of this thesis and by collating data from previous research conducted by Viergever et al., (2008) and Linares (2009). These sample plot measurements however will need to be updated and the number of plots extended in order to examine the capacity of L-band HV to monitor biomass with high accuracies in particular PAs.

- Other satellite radar bands (i.e. C-band) collected by sensors such as the recent Sentinel-1A launched by ESA and RADARSAT-1/2 should be explored to enhance monitoring of woody biomass change. For example C-band data have been found by Viergever et al., (2008) to provide useful information on the presence of woody canopy cover in the lowland savannas of Belize. The continuity of C-band data that the Sentinel-1 constellation will provide (with legacy data provided from ERS-1 and ENVISAT) in combination with the increased temporal resolution of the Sentinel-1 constellation (~6 days in tropical areas, after the launch of Sentinel-1B in 2016 or in combination with RADARSAT-1/2), could provide the means to monitor the effects of seasonality in radar backscatter and quantify changes in woody vegetation over specified times periods or after particular events such as fires or hurricanes.

Two significant findings of this research that might be a start for further investigations were (A) the possible effect of vegetation structure as a driver of the radar backscatter as demonstrated in chapter 5 and summarised in section 7.3.2.2, and (B) the high saturation point found in these savanna areas (~105 t/ha) as summarised in section 7.2.3 up to which the L-band data can provide reliable information for AGWB prediction. To further examine the validity of these findings, a backscatter vs. biomass relationship should be developed for each of the three PMGs separately. This will show if the saturation point found in this study (i.e. ~105 t/ha) is found repeatedly and consistently for different PMGs and hence for different woodland structures and provide further insights of how the vegetation structure drives the radar backscatter in
different woodlands, with different styles of protection and management and hence forest structure.

### 6.3.3 Recommendations to policy makers & advisers

Satellite EO is increasingly used to map carbon stocks under different international agendas and to support SFM. A key challenge on the policy side is to encourage the development of EO science and policy collaborations that reflect policy needs in an operational manner. This section stresses recommendations to address this challenge.

- **Strengthen the strategic discussion**
  
  A continuous dialogue between scientific bodies that have demonstrated the capability of satellite EO to support environmental protection and management (i.e. The University of Belize Environmental Research Institute or the school of Geosciences at the University of Edinburgh) and policy advisers (i.e. the Forest Department of Belize (FD), the Protected Areas Conservation Trust (PACT), and the Association of Protected Area Management Organisations (APAMO)) can contribute to ensuring the effective distribution and update of current knowledge for environmental protection and management. For example this thesis has reinforced the capacity of active satellite EO such as ALOS PALSAR to predict and map biomass in savanna woodlands showing that methods first developed in Africa and Australia can be adapted to predict AGWB in savannas woodlands of Belize. The biomass map created in chapter 6 is an example of a new product that can assist policy advisers to make more informed and localised decisions about the savanna areas that are carbon rich or have enough structural variability to promote biodiversity. This can be readily integrated up to support the making of national policies and priorities for land use, including conservation areas and key biodiversity areas (KBA). For instance, the Global Environment Facility (GEF) and World Bank (WB) are funding parts of the strategic protection and management of KBAs in Belize. The goals of this strategy include the investment of resources into Belizean communities living near forests and woodlands to involve them in protection activities including the application of SFM and sustainable land management (SLM) techniques (World Bank, 2012). The biomass map created in chapter 6 can support these components either by using the carbon stock map in the field to supplement local
communities’ knowledge of the areas to support protection, SFM and SLM in KBAs, or by informing policy makers and the funding bodies (i.e. GEF and WB) on the quantities of carbon stocks, and using the biomass map and the methodology developed in chapter 5 to create a new biomass map using new ALOS PALSAR-2 imagery to monitor the effectiveness of these projects.

As part of the Belizean National Protected Areas System (NPAPSP), policy makers such as APAMO and PACT have identified an extensive network of protected areas in the country while the strategic goals of NPAPSP are to enhance management of protected areas by 2030. However, a significant number of PAs in Belize are less well-managed (e.g. Forest Reserves which account for ~13% of total number of protected areas) because of lack of resources and personnel. Although funding from the WB and GEF will be invested in enhancing personnel in the Forest department to enable more effective management of FRs (World Bank, 2012) the method that I developed in this research and the mapping products could assist the new personnel to support forest management by monitoring carbon stocks.

- **Recognise that EO methods still require extensive field data resources**

The value of the method that was developed in this thesis to predict and map biomass in the savanna woodlands of Belize, may be limited if the field component is under-resourced. The main activity that needs support is the establishment of a permanent national woodland inventory. The inventory could for example, aim to sample significantly more woody component found in the lowland savannas [e.g. VA2a (1) (2) and VA2a (1/2)]. To maximise use of the data collected and data security, I suggest that sample plots are located in selected protected areas which are protected and managed using active or passive management (e.g. priorities might be Deep River, Rio Bravo Conservation and Management Area, Payne’s Creek, and the Crooked Tree Wildlife Sanctuary). Data should be collected at the one hectare spatial scale. This is a time-consuming and resource intensive activity but achieving additional sampling of the savanna woodlands in the above four protected areas (area ~263ha) will provide statistically significant information for a carbon baseline, which is required to assess whether savanna woodlands should be included for future REDD+ support. The biomass map created in chapter 6 could inform sample plot placement, so that a more
comprehensive biomass range and PAs range can be sampled, in comparison to this thesis. Further field sampling would allow the influence of tree structural variability within savanna woodlands, and its revealed effects on the radar backscatter, to be explored further.

The field data that were collected in this thesis (20 × 1 ha or ~8% of the 263 ha estimated above) will be donated to the Forest department of Belize to supplement the already published data by Viergever et al. (2008) in an attempt to reduce the resource consumption; the Forest department of Belize has already planned to re-establish up to 40 hectare in broadleaf forests to support sustainable forest management and carbon monitoring (Cho et al., 2013), and I recommend that the same protocols be adopted in the savanna woodlands.

- **Identify other active satellite data sources to support carbon stocks assessment**
  There is an extensive archive of satellite L-band data starting in 1992 with JAXA JERS-1, and continuing with ALOS PALSAR, while the continuity that will be provided by ALOS PALSAR 2 (launched in June 2014) and the new L-band satellite (SAOCOM) from Argentina (estimated launch, 2015) are further satellite sensors with potential for the prediction and monitoring of AGWB. Understanding of the sensitivity of satellite L-band data to AGWB that was achieved in this thesis can assist researchers working with data from present and future L-band satellite missions to develop more reliable means for the assessment of initial carbon baselines in the context of REDD+. For example, by using these active satellite Earth observations, policy advisers can make an initial estimate of the woody cover present within an area and hence its potential for a carbon sequestration project, before making more precise carbon stocks measurements as advised by protocols and standards (e.g. VCS).

- **Recognise the value of combining satellite optical & active methods**
  This study has shown that a combination of Earth observation approaches (e.g. satellite optical and satellite active) will be more effective than using only active satellite EO in this ecosystem. The actively sensed data (i.e. ALOS PALSAR) should continue to be
supplemented with optical imagery (i.e. from LANDSAT, WORLDVIEW, or SPOT) and the new SENTINEL-2 to assess vegetation cover such as savanna subtypes visually and to assist with the establishment of the permanent forest inventory grid proposed in this section.
References


APPENDICES
APPENDIX ONE

TECHNICAL FEASIBILITY ARTICLE PRESENTED AND PUBLISHED AT THE INTERNATIONAL GEOSCIENCE AND REMOTE SENSING SYMPOSIUM (IGARSS, 2013)

This article is part of chapter four
ESTABLISHING THE SENSITIVITY OF ALOS PALSAR TO ABOVE GROUND WOODY BIOMASS: A CASE STUDY IN THE PINE SAVANNAS OF BELIZE, CENTRAL AMERICA

Dimitrios G. Michailakis, Neil Stuurt, Iain H. Woodhouse, German Lopez, Vincenzo Linares

School of Geosciences, University of Edinburgh, EH9 3XP, UK
Environmental Research Institute, University of Belize, P.O. Box 340, Belize

ABSTRACT

Despite their conservation value, the drier wooded areas within tropical savannas are experiencing unsustainable management and anthropogenic pressures. Satellite radar Earth observation is a possible method for supporting forest protection and management in these areas. The aim of this study is to establish the ability of ALOS PALSAR for providing biomass estimates in savanna pine woodlands in Belize. A strong monotropic statistical dependence has been found between the ALOS PALSAR backscatter and above ground woody biomass using field data collected at 1 ha, 0.5 ha, and 0.25 ha and a weak monotropic statistical dependence has been found using field data collected at 0.1 ha.

Index Terms— Forestry, Radar Remote Sensing, Biomass, North America

1. INTRODUCTION

Although considered by many as a grassland-dominated ecosystem, many world savannas contain substantial areas of woodland. As well as providing an economic resource to local populations, these woodlands also have significance for carbon sequestration under international agreements such as UN-REDD and as biodiversity reserves under the UN-CBD [1]. Consequently, land managers are turning to remote sensing for monitoring the woody component of savannas as a form of low density forest. Previous research has demonstrated the capability of synthetic aperture radar (SAR) to extract information about certain structural parameters such as stocking density and the spatial distribution of above ground woody biomass (hereafter AGWB) in savanna woodlands [2-4], with the information obtained used for establishing baseline inventories of forest and carbon stocks, for planning conservation-oriented actions and for ecological monitoring of savanna areas over time [5].

Some researchers in African and Australian savannas have obtained strong correlations between radar backscatter and field measurements of AGWB using non-linear regression models [6, 7]. These relationships are not always found however; others working in Africa have obtained very poor correlations between backscatter and biomass [8]. A few workers have begun to explore the capabilities of ALOS PALSAR for mapping land cover / land use in Brazilian savannas [9, 10] and exploring the sensitivity of PALSAR data to AGWB. Vierow et al. [11] studied the sensitivity of airborne SAR backscatter at four wavelengths to AGWB using interferometry in a detailed study of one woody savanna in Belize, but similar relationships between tree structure data and satellite radar backscatter have not been explored. To our knowledge, this is the first study in the Americas exploring the sensitivity of ALOS PALSAR to AGWB. We compare field data collected from plots in different pine dominated savannas at sites well distributed throughout the country with the backscattered microwave radiation collected by ALOS PALSAR in the L-band (λ = 23.62 cm).

3. METHODOLOGY

3.1. Study area

The study was conducted in Belize, Central America which lies between 15°52' and 18°30'N and between 87°58' to 90°13'W and focused on protected and unprotected areas of the lowland savanna biome. Lowland savanna covers an area of 1750 km² which is approximately one tenth of the country and is characterized by gentle topography and seasonal flooding. The main woody vegetation consists of Pine (Pinus caribaea); oak (Quercus velutina); other scattered trees and shrubs and extensive grassland areas typical of the Neotropical savanna are also locally abundant [12].

3.2. Field measurements

25.8 hectares of field data were collected within pine dominated savanna areas between 2009 – 2011 (fig. 1). Of this, 15 hectares (hereafter dataset A) was collected specifically for this study in 2011-12 from 15 sample plots of 100m x 100m. These were established within a variety of different pine woodland areas located throughout the north and central parts of Belize. Plot locations were chosen by
purposive sampling, ensuring that the plots captured the full range of tree densities known to occur within savanna areas; potential plot locations were first identified using Worldview II imagery and then confirmed by personal communications with the local timber industry, local government and NGOs and by direct observation. For every tree, the X, Y location and the diameter at breast height (hereafter dbh) was measured, resulting in a total of 4,496 trees measured in dataset A.

This dataset was then supplemented by a second dataset of 1,290 tree measurements for which dbh had been measured in the Deep River Forest Reserve in 2009 as part of a stocking inventory for sustainable forest management operations in this area in the south of the country. These measurements, henceforth dataset B, were collected using 0.1ha circular sample plots (17.84m radius), systematically distributed on a regular grid. All plots were inspected and compared to Worldview II data and only plots that clearly were entirely covering pine woodland areas were used. Dataset B was used not simply to increase the volume of ground data, but to provide a more comprehensive geographical coverage by including more data from the south of the country and from locations where ground access is difficult. For all trees in data sets A and B, the AGWB for each tree was estimated using allometric equations developed specifically for Pinus caribaea in Belize [11]. In addition to these data collected from forested areas, a further nine one hectare square sample plots were established randomly within other open savanna areas where no woody vegetation was evident (henceforth dataset C).

3.3. Satellite data

Two level 1.1. ALOS PALSAR fine beam dual polarization (FBD) scenes which had been collected during the wet season in 2008, covering the fieldwork locations, were obtained through the Japanese Aerospace Exploration Agency (JAXA). The images (henceforth LI, II) were multi-looked, proceded and radiometrically normalised and calibrated using GAMMA software and the calibration factors provided by JAXA. The level 1.5 scenes are four-look imagery with approximately 1.3 meter pixel spacing and power intensity backscatter as the data values. The imagery was further processed to reduce speckle, by aggregating neighboring pixels using a 2x2 window and arithmetically averaging their backscatter in the power domain and storing the average into the new pixel created (2m pixel spacing). The power-intensity backscatter for each pixel was then extracted and averaged using the sample plot edges and were then transformed to decibels using equation 5 (dB) = 10 × log10 (DN) using ENVI / IFL. Sigma-naught backscatter values were then extracted from the ALOS data corresponding to the ground for which AGWB was

![Figure 1](image1.png) Map showing the study area, the lowland savanna ecosystem and the ALOS PALSAR data footprints, and detail of the sampling in three areas

![Figure 2](image2.png) Low density pine woodlands within the savanna landscape in Belize

<table>
<thead>
<tr>
<th>Dataset</th>
<th>No. Plots (N)</th>
<th>No. Trees (n)</th>
<th>Plot size (ha)</th>
<th>Average AGWB (Mg/ha²)</th>
<th>ALOS Image</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>15</td>
<td>4300</td>
<td>1</td>
<td>32.73</td>
<td>I and II</td>
</tr>
<tr>
<td>B</td>
<td>118</td>
<td>1390</td>
<td>0.1</td>
<td>33.36</td>
<td>II</td>
</tr>
<tr>
<td>C</td>
<td>9</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>I and II</td>
</tr>
</tbody>
</table>

Table 1. Summary of the field measurements

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Date Collected (MM/YY)</th>
<th>Incidence Angle at Centre Swath (degree)</th>
<th>Looks</th>
<th>Product</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>01/03/2008</td>
<td>39.19</td>
<td>4</td>
<td>FBD</td>
</tr>
<tr>
<td>II</td>
<td>30/09/2008</td>
<td>39.00</td>
<td>4</td>
<td>FBD</td>
</tr>
</tbody>
</table>

Table 2. Attributes of the ALOS PALSAR images used estimated from the plot data.
Figure 3. Extract of ALOS PALSAR HV pixels within savanna areas and corresponding histograms.

3.4 Statistical analysis

To explore whether the relationship between $\sigma_0$ backscatter and AGWB varied according to the size of the ground area within which the AGWB was calculated, each original one hectare sample plot in datasets A and C was subdivided into two, four and ten subplots of 0.5, 0.25 and 0.1ha producing 48, 96 and 240 subplots for each subdivision respectively (fig. 4A). AGWB was then calculated for each subplot of 0.5ha, 0.25ha and 0.1ha by spatially identifying the trees falling within each subplot. Standardized values of AGWB in Mg ha$^{-1}$ were then calculated for each of the three subplot data sets. The complete dataset B was used in the 0.1ha scale of analysis, but data from only eight of the 0.1ha sample plots from dataset B were used in the one hectare scale of analysis.

Data from the 0.1ha circular plots from dataset B were omitted whenever inspection of Worldview II imagery revealed there was little or no woody vegetation present beyond the perimeter of the circular plot (fig. 4B right). Eight 0.1ha plots which were considered to have an AGWB similar to the surrounding hectare was used to estimate values for AGWB ha$^{-1}$ for correlation to the $\sigma_0$ at the one hectare scale. Spearman’s rank correlation coefficient (p), number of observations and probability of the statistical dependence being random (p) between $\sigma_0$ and AGWB were calculated using the software SigmaPlot 12.0 for each of the four spatial scales.

4. RESULTS

Results (fig. 5) indicate strong statistical dependence between sigma nought ($\sigma_0$) and AGWB (Mg) when using a field plot size of one hectare (16 pixels), 0.5ha (eight pixels) and 0.25ha (four pixels) for averaging the $\sigma_0$. Backscatter is increasing monotonically with AGWB in all four cases. The statistical dependency of the relationship decreases exponentially ($r^2 = 0.98$, $p = 0.005$, $F = 173.27$) when less pixels within field sample plots are used for averaging the backscatter. The statistical dependency between $\sigma_0$ and AGWB at the 0.1ha scale is the weakest ($r^2=0.56$) but still reveals a monotonic relationship between the two variables and a low probability the relationship being random ($p = 2 \times 10^{-3}$).

5. DISCUSSION AND CONCLUSION

The use of backscatter data collected by ALOS PALSAR as a possible predictor for AGWB in the low density pine savanna woodlands in Belize is clearly supported by the current findings. This study supports the results of other workers in tropical savannas in Africa and Australia and suggests that in these pine woodlands the appropriate sample size for estimating AGWB using L-HV is one hectare. The reasons that the significance of the relationship between the two variables is reducing with smaller field plot area may be because reduced number of pixels used to calculate the average value of the radar backscatter (1-4 pixels) may fail to capture the increased within-plot structural variability evident at these smaller field plot sizes. It may also be that the area coverage of the trees are a main driver of both, AGWB and radar backscatter.
Figure 5. HV intensity (dB) plotted against above-ground woody biomass derived by field plots of A) one hectare B) 0.2ha C) 0.22 ha and D) 0.1ha.

More work needs to be done to better understand the interactions of the ALOS PALSAR backscatter data and AGWB and other structural attributes such as basal area and dbh when field data is aggregated in different spatial scales. This work is now under development using ALOS PALSAR backscatter data collected during dry periods and new field data collected in 2013.

6. ACKNOWLEDGEMENTS

This work is supported by an ERDF Scholarship from the resources of O.P. (Education and Lifelong Learning), European Social Fund (ESF) and the NSRF 2007–2013, by the School of Geosciences of the University of Edinburgh and the Centenary Research Fund. We are grateful to the Darwin Initiative project “Savanna Ecosystem Assessment / Belize 2009 – 2012 and the Environmental Research Institute of the University of Belfast for providing logistical help and resources for the collection of the field data. We wish to thank Plant Action for providing the satellite data for identifying the field data collection sites.

7. REFERENCES


APPENDIX TWO


This article is part of chapter four
Estimation of Woody Biomass of Pine Savanna Woodlands From ALOS PALSAR Imagery

Dimitrios Michelakis, Neil Stuart, Matthew Brophy, Member, IEEE, Iain H. Woodhouse, Member, IEEE, German Lopez, and Vinicio Linares

Abstract—We present an adapted woody biomass retrieval approach for tropical savanna areas appropriate for use with satellite acquired L-band SAR imagery. We use the semiparametric water cloud model to describe the interaction between the SAR signal and vegetation and re-arrange the model to predict biomass. Estimations are made using dual polarization SAR imagery collected by ALOS PALSAR during 2006 in combination with community woodland inventory data from pine savanna areas in Brazil. Estimation accuracy is assessed internally by the fit of the model to the ground training data, and then validated against an independent external database, quality controlled using WorldView II imagery. The internal validation shows a biomass estimation with an RMSE of 25 t/ha and a coefficient of determination R² of 0.70, while the external validation indicates an RMSE of 13 t/ha with R² of 0.53. This approach to biomass estimation appears to be most influenced by the plots with higher tree numbers and where the trees were more homogenous. The existence of many similar sized individual in those plots influence the SAR backscatter and is predicted to be the cause of the elevated level of saturation found in this study (> 100% /1/00) with complete saturation predicted as a result of number density increases, and concurrently increasing back areas, both not exclusively dependent on biomass.

Index Terms—Carbon, forestry, radar imaging, satellite applications, synthetic aperture radar (SAR).  

1. INTRODUCTION

ALTHOUGH considered by many as a grassland dominated ecosystem, many of the world’s savannas comprise substantial woodland areas. As well as providing an economic resource to local populations, these woodlands also play a surprisingly significant role in global carbon sequestration processes [1], which require quantification under international agreements such as the United Nations initiative on Reducing Emissions from Deforestation and Forest Degradation (UN-REDD) while also as biodiversity reserves under the United Nations convention on biological diversity (UNCBD). Consequently, land managers are turning to remote sensing as a cheaper and more rapid alternative to traditional forest inventory methods to enable effective monitoring of the woody component of savannas as a form of low density forest. For management purposes, previous works suggest that satellite remote sensing should be used to predict biomass with errors within 20 t/ha for 80% of biomass estimates, but should not exceed 50 t/ha for biomass maps at the hectare spatial resolution [2, 3]. Satellite radar can play an important role in the remote measurement of forest bio-physical parameters which have been shown to closely relate to biomass accumulation and biodiversity [4]. Synthetic aperture radar (SAR) data collected by satellites using lower microwave frequencies such as L-band (1–2 GHz) are one of the most widely used datasets in tropical areas, particularly during the last 5 years. This due mainly to five reasons: 1) L-band frequencies have the ability to penetrate clouds and dense vegetation canopies since the elements of both are relatively small in comparison to the L-band wavelength [5, 6]; 2) there is an established proportionality of the L-band backscatter intensity to biomass [7, 8]; 3) the significant archive of radar data collected by the satellite L-band SAR sensor ALOS PALSAR between 2007 and 2012 [9, 4] the wide range of methods that can be used with ALOS PALSAR data to derive biomass predictions [10–12] and 5) the expectation of renewed global capability for monitoring the same forest parameters using the foregoing ALOS PALSAR sensor and the NASA airborne CANSAR system [13].

Previous research has demonstrated the capability of the data collected by ALOS PALSAR to extract information about certain structural parameters [14, 15]. These have included among others the amount and spatial distribution of above ground woody biomass (hereafter biomass) in savanna woodlands [16–22], with the retrieved information used to establish baseline inventories of forest and carbon stocks, using the derived biomass data, e.g., for planning conservation-oriented actions, and for ecological monitoring of savanna areas [20, 21, 23]. Published research on African and Australian savannas has obtained strong correlations between ALOS PALSAR radar backscatter and field measurements of biomass using non-linear regression models [17–21]; however, these models were trained using solely the coefficient of determination as a measure of good fit, neglecting the underlying principles of how radar is theorised to interact with vegetation canopies. These
relationships have also been found to be less robust in other studies, e.g., in [24], where very poor correlations between backscatter and biomass were recorded in African savannas. Although these poor correlations can be partially explained by factors such as the small numbers and sizes of sample plots used for collecting field data, by significant topographic relief or due to excessive prior precipitation [25], they can also be explained by differences in the vegetation structure [26], [27]. In the U.S., research has been undertaken to explore the capabilities of ALOS PALSAR for mapping land cover/land use in Brazilian savannas [28], [29].

Focusing specifically on Belize, researchers have examined the capability of using airborne radar imagery to identify woody subtypes of these savannas [30], while [31] studied the sensitivity of airborne SAR backscatter at four wavelengths to biomass using interferometry. In both cases, the relationships between tree structure and satellite radar backscatter were not explored. To our knowledge, this study is the first of its kind in Central and South America to explore the sensitivity, in particular, of ALOS PALSAR to forest structure.

The objectives of the study are to compare ALOS PALSAR backscatter data to biomass using: 1) field measurements collected from sample plots in different pine dominated savanna sites distributed throughout the country of Belize and 2) to evaluate the accuracy of modeling the backscatter response to biomass using a validation of a simple variation of the water cloud model (WCM) [32].

II. MATERIALS AND METHODS

A. Study Site

The study was conducted in Belize, Central America with sites chosen from both protected and unprotected areas of the lowland savanna ecosystem. Lowland savannas cover approximately one-tenth of the country (1750 km²) according to recent estimations by Camiran et al. [33] and Mooreman [34], and is characterized by gentle relief and seasonal flooding. The savanna woodlands are relatively homogeneous in their type with it being typical for a single pine species to dominate more than 90% of a hectare. All savanna woodlands in Belize occur within the same climate zone [35], on the same geological unit [36], and on mature coastal soil deposits [37]. The main woody species are pine (Pinus caribaea) and oak (Quercus mexicana). In other areas, scattered trees, palms, shrubs, and extensive grassland areas typical of the Neotropical savannas are also abundant [38]-[40].

B. Ground Truth Data

In order to obtain a more comprehensive coverage of different savanna woodlands in Belize, and to sample the whole known range of biomass found in these woodlands, we examined previous studies conducted in the country [31], [41]-[43], qualitative information from nongovernmental organizations, and a visual interpretation of very high spatial resolution worldview imagery. The dbh ranges that were reported using these datasets are covered by the data collected by three field workers during four data collection campaigns between 2007 and 2012. These datasets are listed below.

1) Dataset A includes 25 ha of field data collected within pine dominated savanna areas between 2007 and 2012 (Fig. 1). Of this, 20 ha were collected specifically for this study from 20 sample plots of 100 × 100 m, between 2011 and 2012. These were established within pine woodlands under three different protection and management regimes (PMRs) located throughout the north and central parts of Belize. Plot locations were chosen through purposive sampling, ensuring that the plots captured the full range of tree structures known to occur within savanna areas, within passively protected, and managed areas (PRPM), actively protected and managed areas (PRAM), and unprotected areas (UPA).

Potential plot locations were first identified using Worldview II imagery and confirmed through personal communication with the local timber industry, local government, and NGOs, and through direct observation. Three hectares from three rectangular sample plots (PRPM) of 167 m × 60 m were added to the above data which were extracted from a transect of 800 m × 60 m collected by Wingrove et al. [31] in 2007. These sample plots targeted the lower range of tree number density (henceforth density) (0–100 trees/ha). In these low-density savanna areas Wingrove et al. in [31] commented that palm clumps (Accoerisperma sp.) may contribute significantly to the radar backscatter collected by a high resolution airborne sensor (AirSAR). We purposefully excluded the areas that we confirmed contained only palm vegetation when using these data in our analysis. In the areas used, palms accounted for a small fraction of the vegetation and do not contribute significantly to the backscatter by visual inspection. For every tree with a diameter at breast height (henceforth dbh) larger than 10 cm, the X, Y location and the dbh were measured, resulting in a total of 5391 trees measured in dataset A.

2) Dataset B includes 50 trees measurements collected in six 0.1 ha circular sample plots and is a subset of a broader dataset which includes 1390 trees measurements collected from 108 separate 0.1 ha circular sample plots (17.84 m radius), systematically distributed on a regular grid within the Deep River Forest Reserve (henceforth DR) in 2009 by Linaran [41]. These data were collected as part of a stocking inventory for sustainable forest management operations in the south of the country (PRAM). All 108 of the DR sample plots were visually inspected and compared to Worldview II data and only plots that clearly covered entire pine woodland areas were used. Data from the DR circular plots were also omitted whenever inspection of Worldview II imagery revealed there to be little or no woody vegetation present beyond the perimeter of the circular plot (Fig. 2). Finally, 44 separate 0.1 ha plots considered to have biomass similar to the surrounding hectare were used to estimate total biomass (t/ha). Six of these plots with values at the lower end of the biomass range (henceforth dataset B) were used to supplement dataset A.
and assisted the fitting of the backscatter-biomass model for areas with biomass less than 100 daa.
3) Dataset V comprised the remaining 38 plots from the DR dataset, which were used for external validation.
4) Dataset C comprised a further nine single hectare, square sample plots that were established randomly within open savannah areas where no woody vegetation was evident. This dataset was used to model the backscatter-biomass relationship for areas with very low values of woody biomass.

Fig. 3 summarizes the size, the purpose, and the consistency of each of these four datasets schematically.

For all trees with a dbh ≥ 10 cm in datasets A, B, and V, the biomass for each tree was estimated using the allometric equations developed specifically for *Pinus caribaea* and *Quercus oblongata* in Belize by Brown et al. [42] and Vierheger et al. [31], expressed as

$$\text{Biomass}_{\text{dx}} = 0.007 \times \text{diameter}^{2.453}$$

(1)

$$\text{Biomass}_{\text{dx}} = \left( 0.5 + \frac{25000 \times \text{diameter}^{2.5}}{dbh^{2.5} + 216872} \right) \times 2.$$  

(2)
### TABLE I
ALOS PALSAR DATA ACQUIRED OVER THE STUDY SITES

<table>
<thead>
<tr>
<th>Scene Id</th>
<th>Mode</th>
<th>Incidence (deg)</th>
<th>Acquisition Time (UTC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALOPS20100701010</td>
<td>PBD</td>
<td>34.3</td>
<td>2009-07-01 00:00:00-2009-07-01 23:59:59</td>
</tr>
<tr>
<td>ALOPS20100701010</td>
<td>PBD</td>
<td>24.3</td>
<td>2009-07-01 00:00:00-2009-07-01 23:59:59</td>
</tr>
</tbody>
</table>

The part of the equation within the brackets in (2) estimates the carbon stock in kilograms. The factor of two is used as indicated in [44] to estimate the amount of biomass per tree. These allometric equations (R² = 0.99) were developed using destructive sampling within savanna woodland in a protected area, where 12 of the square plots measured in this study are located. The ground data for the development of the allometric equation were collected during 2002 and 2005 by harvesting 55 individual tree trees and saplings in the RBecaMA with their diameter ranging from 1.0 to 52.4 cm. [44]. In this study, the biomass estimations per tree using allometric equations (1) and (2) were then up scaled to estimates per hectare, by summing the individual tree biomass (henceforth total biomass).

### C. Satellite Data

Two level-1 ALOS PALSAR (CTOS, forma) PBD polarization (HH and HV) scenes (Table I) covering the fieldwork locations, collected during the wet season in 2008, were obtained through the Japanese Aerospace Exploration Agency (JAXA). These scenes (henceforth L1B) were processed to level 1.1 single look complex (SLC) images using the modular SAR processor developed by GAMMA. Only the HV polarization was used in this study due to its superior recorded sensitivity to biomass and the minimal impact on the signal resulting from soil moisture variation [45, 46]. The calibration factor used for the HV polarization was 1.53-36.3 dB as established in [47]. The SLC images were then converted to multiLook intensity images (MLIs) and transformed to geo-coded images (level 1.5) using the differential interferometric geocoding module (DIFFIGEO) of GAMMA software and a SRTM dataset (90-m pixel spacing) for Belize. The level 1.5 scenes are four-look imagery with 13-m pixel spacing displaying backscatter intensity. By visually inspecting the processed SAR imagery we observed that the size of some individual tree crowns was significantly larger than these pixel elements [48] and so the pixel size was increased further by aggregating adjacent neighbourhoods of pixels using a 3 x 3 window and arithmetically averaging their backscatter in the power domain to create values at 25-m pixel spacing. This multilooking technique was also used to remove speckle noise [49]. The backscatter intensity for each pixel was extracted and averaged using the sample plot edges and transformed to decibels as shown in (3) showing the definition of normalized radar cross section $\sigma^0_{HV}$.

$$\sigma^0_{HV} = 10 \times \log_{10} \left( \frac{P_{HV}}{\rho_{HV} \cdot \cos(\theta) \cdot \bar{n}} \right)$$

Values of $\sigma^0_{HV}$ henceforth referred to as backscatter were then extracted from the ALOS data corresponding to the ground biomass measurements estimated from plot data.

### III. FITTING A WCM TO EXAMINE THE BACKSCATTER-BIOMASS RELATIONSHIP

The statistical analysis performed in this study seeks to establish a relationship between ALOS PALSAR backscatter and biomass estimates derived from field measurements of all trees in 1 ha sample plots. The analysis performed in [50] showed this plot size to be appropriate for estimating biomass using ALOS PALSAR backscatter. Pearson’s and Spearman’s correlation coefficients are used to assess any linear or monotonic relationships indicated by the radar theory in [44] and [51].

$$r_p = \frac{\sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n} (X_i - \bar{X})^2 \sum_{i=1}^{n} (Y_i - \bar{Y})^2}}$$

$$r_s = \frac{\sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n} (X_i - \bar{X})^2 \sum_{i=1}^{n} (Y_i - \bar{Y})^2}}$$

where $n$ is the number of samples, $X_i$, $X$, $Y_i$, and $Y$ are the raw values and the corresponding averages and $r_p$, $r_s$ are the transformed values. We incorporate a simple form of the WCM as described by Atchuan and Ulaby [32] and Graham and Harris [51]. This general form of equation, but without an explicit derivation from radar theory, has been previously to relate L-band backscatter to biomass in savanna woodlands [17, 19, 20]. The overall workflow, including the datasets used to fit and validate the WCM in this study, is summarized graphically in Fig. 4.

### A. Semiempirical Water Cloud Model

The WCM was first introduced by Atchuan and Ulaby [32] for the study of the interaction between radar energy and vegetated surfaces. It represents the ground vegetation canopy as a symmetrical structure featuring a relatively homogenous volume consisting of canopy components and air [51, 53]. The canopy components are represented by homogeneous spherical scatterers which mimic the structure of a “water cloud.” The WCM was created to model the attenuation of a radar signal with depth through a vegetated canopy in the absence of a stem component. The simplest expression of the WCM for a certain incidence angle $\theta$ takes the following form:

$$\sigma^0 \sim \sigma^0_{null} + t^2 \times \sigma^0_{int}$$

$$\sigma^0_{int} = A \cos \theta (1 - \sigma^2)$$

$$\sigma^0_{null} = C + D \times n$$

$$\sigma^0 = A \cos \theta (1 - \sigma^2) + \sigma^0_{null}$$

where $\sigma^2$ represents the total backscatter measured by the radar sensor, $\sigma^0_{null}$ and $\sigma^0_{int}$ represent the backscattered radiation from the soil and the vegetation canopy, respectively. $t^2$ represents the two-way attenuation of the radar backscatter resulting from interaction with vegetation, A, B, C, and D are empirical constants.
parameters, \( w_c \) represents the water content of the canopy, and \( w_m \) represents the soil moisture. Other studies such as [17], [19], and [20] have used a general exponential model similar to (10) to establish the sensitivity of ALOS PALSAR backscatter to woody biomass, but have not established the physical basis for applying this model as we do here. It is also commonly found in the following form:

\[
\sigma_0^D = \sigma_{0,\text{avg}} + \left( 1 - e^{-\gamma \text{ Biomass}} \right) \sigma_{0,\text{avg}} \cdot \gamma
\]  

where \( \gamma \) represents an empirical coefficient that can be estimated using ground truth data and ALOS PALSAR backscatter data. It is possible for every positive real number \( b \) to be written as

\[
b = c \cdot e^a, \quad c, e^a, A \in \mathbb{R}, \quad c \in \mathbb{R}^+ \geq 0 
\]

where in this case, \( b = e^{c \cdot \text{ Biomass}} \). \( c \) is a real number, \( \mathbb{R} \) is the set of all real numbers, and \( c \) is a nonnegative real number. Equation (11) can then be transformed to provide the definition shown as

\[
\sigma_0^D = \sigma_{0,\text{avg}} + \left( 1 - e^{-\gamma \text{ Biomass}} \right) \sigma_{0,\text{avg}} \cdot \gamma
\]

where \( \gamma \) represents the same parameter as in (11). Fitting and calculation of the empirical coefficients is performed on (13) (henceforth known as the forward model) in addition to nonlinear least squares regression. The forward model was then rearranged to estimate biomass as

\[
\text{Biomass} = \log_{10} \left( \frac{\sigma_{\text{main}} - \sigma_0^D}{\sigma_{0,\text{avg}}} \right) 
\]

Using the re-arranged forward model to estimate biomass may lead to infinite or negative values when \( \sigma_0^D \leq \sigma_{\text{main}} \) or \( \sigma_0^D \geq \sigma_{0,\text{avg}} \), respectively. [53], [54]. In this study, we followed the example shown in [55] by assigning the highest biomass observed in the field to all values calculated to be infinite. To the values calculated as negative a value of zero biomass was assigned.

B. Validation and Uncertainty of the Biomass Predictions

Datasets A, B, and C were used during model training to ensure that backscatter values were obtained from multiple ground targets representing the entire range of biomass found within the pine savanna woodlands throughout Belize. Two validation processes were conducted, which we refer to as an internal and an external validation. We used the training datasets A, B, and C to internally validate the fit of the model to the data. We then used dataset V as an independent dataset, not used to develop the model, to externally validate it. For both internal and external validation, we report the root mean squared error (RMSE) with inputs of the field-oberved and radar-predicted biomass (henceforth predicted biomass).

IV. RESULTS AND DISCUSSION

A. Field Data

The training datasets A, B, and C produced total biomass estimates ranging from 0 to 101.65 t/ha. This was expected as a consequence of the targeted sampling strategy which used local knowledge and interpretation of existing maps and optical imagery to ensure covering the known range of pine savanna tree biomass in Belize. The data from the field plots used to develop the model are summarized in Table II which also includes the mean backscatter for each plot sensed by ALOS PALSAR. For the validation dataset (dataset V, not included in Table II), the range of the total biomass was slightly lower (3.8–71.8 t/ha). This lower range of total biomass is mainly a response to the sustainable extractive logging that takes place in IDR.

In Fig. 5(a), it is apparent that total biomass is linearly correlated to total basal area and in Fig. 5(d) nonlinearly with density. This is expected in resource-limited ecosystems such as savannas as shown in [54] and [55], and justifies our use of tree numbers as a simple field method for establishing plots for sampling different ranges of total biomass. In both cases, the correlation with total biomass appears stronger for the lower basal areas and lower densities. The Pearson correlation coefficient estimates a value of \( r_p = 0.97, P < 0.0001 \) suggesting that the two variables increase linearly with respect to one another. The correlation between density and total biomass as
shown in Fig. 5(d) was also assessed using Spearman’s rank correlation coefficient ($r_s = 0.778$, $P < 0.0001$) illustrating a positive monotonic relationship between the two variables. Nevertheless, visual inspection of Fig. 5(a) reveals for the higher values of total basal area, a cluster of six points which are identified in UPR areas (Table II, plots 1, 4, 11, 13, 14, 15) that appear to deviate significantly from the linearity to total biomass observed in the lower basal area plots (i.e., $≤ 11m^2/ha$). These six plots are the most homogenous in our dataset as regards their dbh (0.18m ≤ standard error of the mean (SEDBH) ≤ 0.38cm) in comparison to the rest of the plots (SEDBH ≥ 0.5cm) which implies more variability. This is consistent with theoretical work which suggests that homogeneity in a dbh distribution may cause the normally linear relationship found between total basal area and total biomass to break [56]. No correlation was found between total biomass, and mean dbh per sample plot in these woodlands (Fig. 5(b)). However, taken together Fig. 5(b) and (c) indicates that prescription and management has an impact on the growth of these woodlands. For example, within UPR areas total biomass is stored in many juvenile trees, in contrast to PRPM areas where a similar amount of total biomass is stored within a smaller number of larger trees.

### Backscatter Relationships to Vegetation Structure

In Fig. 6, significant positive monotonic relationships are shown between backscatter and total biomass ($r_s = 0.91$, $P < 0.0001$), total basal area ($r_s = 0.88$, $P < 0.0001$), and density ($r_s = 0.90$, $P < 0.0001$), while a much less significant relationship was found between backscatter and mean dbh ($r_s = 0.68$, $P < 0.0001$). The reason why backscatter is more strongly
correlated with biomass rather than basal area in possibly due to the strong correlation revealed from the field data between biomass and both basal area [Fig. 5(a)] and density [Fig. 5(d)]. The sensitivity of biomass to structural variations would suggest that if backscatter is correlated strongly with biomass then backscatter displays a clear sensitivity in the structural makeup of the forest. With the backscatter being a dataset sensitive to the structure of vegetated areas, the backscatter is expected to show a stronger correlation to that structural attribute whether that be basal area, mean dbh or density. Fig. 6(d) provides some insight into how the backscattered signal tends to increase with increasing mean dbh within the differently managed woodland areas. The way in which backscatter values increase with dbh seems to vary considerably between the three different woodland types. It is also interesting to note that a similar grouping of the plots by management regime was observed in Fig. 5(b) when total biomass was plotted against the mean dbh.

The datasets used in this study also show that the backscatter relationships to both total basal area and total biomass appear to be sensitive at higher rates of total biomass (>80 Mtha) as shown in Fig. 6(b) and total basal area (>120 m²/ha) in Fig. 6(c).

There are three possible explanations for this result: 1) the canopy cover may be assumed to be increasing with increasing total biomass and thus as described in the WCM the backscatter would be expected to decrease because of increasing attenuation in $\sigma_u^0$; 2) it is possible that the degradation of the backscatter—total biomass sensitivity at the higher biomass ranges may relate to the weakening correlation between total biomass and density evidenced in Fig. 5(d) above 80 Mtha; 3) the weaker backscatter-biomass relationship at higher total biomass may also be understood through an observation from the fieldwork that the same of the high biomass plots had quite contrasting structures and large variation in tree numbers resulting from the different management activities or growth conditions.

In Fig. 6(c), the decreasing backscatter observed for tree number densities above 400 trees/ha is produced entirely by data points observed within the UPR sample plots; as discussed previously, these plots are the least heterogeneous, with small values of SU_MDA, and fewer big trees than PPRM areas [Fig. 5(c)]. These same UPR points are observed to also deviate from the otherwise generally monotonic backscatter-total biomass and backscatter-total basal area trends [Fig. 6(b) and (c)].

Approximately 80% of the high biomass—backscatter data points [Fig. 6(b)] were collected within passively managed pine savanna areas (PSSM) in which most of the total biomass is contained within a few large trees and where there is a more variable forest structure even at the hectare scale [Fig. 5(e)]. These woodlands are more open and have relatively low canopy cover, with many woodland gaps. Despite the generally lower densities, a strong correlation still exists in these woodlands between density and total biomass. In contrast, a small number of other sample plots with high biomass are in unprotected areas where the biomass is stored within a much larger number.
of trees within a hectare (Fig. 5e)], creating less variable pine savannah with a more closed and uniform canopy. These contrasting management regimes produce woodlands with similar total biomass and similar total basal areas but very different densities.

C. SAM Modeling and Validation

Fig. 7(a) shows the fitting of the nonlinear forward model (15) accomplished by the model predictions of biomass (Fig. 7b-d). The coefficient of determination ($R^2 = 0.92$) shows that the WCM line approximates the data points well while the regression passed all statistical tests (SPSS, Durbin-Watson statistic, a Shapiro-Wilk normality test, and the constant variance test). The standard error of estimate (SSE) which shows the disperse of the errors of the prediction is 1.28 dB. This shows that backscatter is a good predictor of biomass. The estimated coefficients with their standard errors for the forward model as defined in (13) are $\sigma_0^2 = 10.40 \pm 0.80$, $\sigma_\tau^2 = 21.06 \pm 0.66$, and $\gamma = 0.96 \pm 0.07$. The small standard errors show that these coefficients are appropriate for the dataset used. Five estimates were compiled as negative or infinite and their values were set to the highest total biomass observed in the training dataset (101.67 t/ha) or zero total biomass if an infinite or negative biomass value was calculated, respectively.

We assessed the performance of the model through an internal and external validation using the training datasets A, B, and C in the first case ($N = 38$) and dataset V in the second ($N = 38$). The performance of the model for both validation processes is shown in Fig. 7(b) and (d) for the internal and external validations, respectively. The RMSE of the biomass estimation for the internal validation using 38 training observations was recorded as 25.11 t/ha while a polynomial regression equation of the form $y = a \times x + b$ was also fitted ($R^2 = 0.70$, $F = 84.42$, $P < 0.0001$). We observed that the predicted biomass values at the higher end of the biomass range were extremely over estimated. When biomass values larger than 80 t/ha are removed, the performance of the model greatly improves with an $R^2$ of 0.70 and a polynomial fit with statistics $R^2 = 0.58$, $F = 180.08$, and $P < 0.0001$, see Figs. 7(c) and 8. Dataset V, which has a biomass range at the lower end of the training dataset (0–80 t/ha), was used in an external validation process. Results show a low RMSE of 13.36 t/ha and a polynomial fit with descriptive statistics $R^2 = 0.54$, $F = 43.37$, and $P < 0.0001$. For the external validation, the errors in the predicted biomass for the individual sample plots (Fig. 8), ranged from 0 to 29 t/ha (100% of predictions ≤50 t/ha), while for 85% of our predictions the errors were below 20 t/ha. Evaluated against the accuracy criteria proposed by Hall et al. [2] and Houghton et al. [3], these results appear promising, with the method delivering the accuracy required for forest management activities in the actively managed PRAM areas.

Empirical backscatter-total biomass relationships using spaceborne L-band low biomass tropical savanna woodlands (e.g., maximum total biomass ≤100 t/ha) found in Africa are reported with lower $R^2$ for the model fitting, and higher RMSE for biomass prediction than found in the adapted WCM, and the external validation here (e.g., $R^2 \leq 0.76$, and RMSE = 19.2 t/ha in [10], $R^2 = 0.86$, and RMSE = 24.8 t/ha in [20], $R^2 = 0.79$, and RMSE = 17.4 t/ha in [21]). In the present study, the comparable values are $R^2 = 0.92$, and RMSE = 11.2 t/ha. The differences in $R^2$, and RMSE are probably due to the lower total biomass range of the PRAM areas for the external validation, and that 90% of the vegetation is Pine. In comparison, airborne Light Detection and Ranging (LIDAR) predicts biomass with an RMSE from 11.6 to 18.4 t/ha in an example of savanna of eastern South Africa [57].

D. Saturation

Usually, the curve produced by the forward model in this study (Fig. 7a) does not show a typical saturation-like response before 100 t/ha as found in studies such as [31] and [58], allowed (or at least 80% of the predictions (20 t/ha, and (2) none of the predictions (50 t/ha). Accuracy criteria suggested by Hall et al. [2] and Houghton et al. [3] for forest management activities [9]. In this study, we estimated the saturation point for the forward model (13), using the gradient of the curve [69, 61]. For this analysis, we used the derivative of (13) and
the backscatter value of 0.01 dB as similarly used in [69]. The gradient of the forward model could then be calculated as

$$f(biomass) = \frac{\partial \sigma}{\partial biomass} = a + b \cdot biomass \cdot \ln b$$

$$f(\text{biomass}) = 0.01 \text{ dB}$$

Results show that the radar backscatter provides useful information regarding biomass change up to a maximum of 10 t/ha. This saturation point is significantly higher than others reported in similar studies such as [31], [62], and [58] but agree with findings reported in [18], [19], [20], and [58]. We argue that the nature of our study area plays a key role in these findings. The significant features being that more than 90% of the vegetation is pine, and thus it is suggested that the saturation point increases due to the long and thin woody canopy elements such as branches and twigs [63] and significantly through the existence of a strong correlation between density with total basal area and total biomass (Fig. 5(c) and 6(d)). These are assumed to play a key role in the continuing backscatter increase beyond the typical saturation points reported in other studies using L-band SAR (i.e., 50–100 t/ha) [58]. It also alludes to the impact of forest structure on backscatter saturation proposed in [64] and [65].

V. Conclusion

This study has focused on the development of a biomass retrieval approach for pine savanna woodland using L-band ALOS PALSAR satellite SAR data. An adapted WCM was combined with field data collected at the hectare scale to train a semiparametric model. This data included dbh, basal area, and number densities per hectare. Biomass values for the field plots were calculated using allometric equations based on dbh.

We have found that ALOS PALSAR (HV) backscatter is sensitive to biomass when used in an adapted WCM, across pine-dominated savanna sites differing significantly in their vegetation structure due to PMSs. The internal validation of the model using datasets A, B, and C showed that PALSAR HV backscatter data have the potential to predict biomass with useful accuracy in the exhibited savanna environment of 0–10 t/ha with a mean RMS of a σ = 25 t/ha. This may be satisfactory for baseline inventories of woodland cover, coarse screening for carbon assessments (i.e., per protected area) and to map woodland density as a proxy for biodiversity in certain conservation initiatives. A generally high level of correlation was exhibited between the radar backscatter and the estimates of biomass calculated through field measurements and allometry for the woodland areas used to develop the equation. External validation of the model using independent field data from a sustainably managed pine savanna area with biomass generally below 50 t/ha showed that the model actually produced more accurate estimates (to within 11 t/ha) at this lower range, which are particularly useful for establishing baselines and monitoring stocks and regeneration in such areas. The acceptable accuracy of the predictions (100% of predicted biomass below 50 t/ha, and 85% of biomass predictions below 20 t/ha) to the protected area where the external validation was conducted show that ALOS PALSAR can be used to produce biomass maps at fine spatial scale (i.e., 1 ha) to support forest management.

Although the plot data collected on the ground sampled the full known range of the biomass values found in pine savanna areas in Belize, the range of biomass predicted from the backscatter has a much wider range than the field observations. The model fitted in this study estimates from zero to infinite values of biomass and although the analysis of saturation provides guidance about the upper usable limit of the model predictions, further work is needed to understand the drivers of this behavior and to constrain the model.

We recall that radar backscatter is not a direct measure of biomass and is not viewed as such in this study. It is suggested that the interaction of backscatter with tropical savanna vegetation needs to be further investigated using L-band data collected during both dry and wet seasons to understand if these relationships vary seasonally. A strong and significant relationship was established here using the WCM between radar backscatter and biomass, while the combination of density and the homogeneity of some of these woodlands have been found to have the greatest influence upon the backscattered L-band signal.

Finally, we note that four ALOS PALSAR scenes cover all the pine savanna woodlands found in the country of Belize (~6454 km²), suggesting that the utilization of these radar data can be an economically viable means to map and monitor the biomass of these savanna woodlands, providing a valuable tool for REDD+ projects. The model that we have described here is now being applied to generate a fine scale (10 m) mapping of biomass zones for the savannas of Belize which will supplement coarser scale global biomass estimates from satellite remote sensing, and enhance existing national and sub-national scale maps of savannas woodlands in Belize.

ACKNOWLEDGMENT

The authors are grateful to the Darwin Initiative project “Savanna Ecosystem Assessment/Belize 2009–2012” and the Environmental Research Institute of the University of Belize for providing logistical support to complete the field data. They wish to thank Planet Action for providing the satellite data for identifying the field data collection sites. They would like to thank the two anonymous reviewers for their comments, which we believe improved this paper.

REFERENCES

Dimitrios Michelakis


After working in the commercial sector for 2 years, he returned to the University of Edinburgh to pursue his Ph.D. degree in radar remote sensing in 2010. From 2011 to 2013, he held a Research Associate position with the University of Maryland, College Park, MD, U.S.A., before becoming a Lecturer in geography/remote sensing with the University of Birmingham in 2015. His research interests include active remote sensing, modeling, and sensor fusion particularly in the field of environmental science.

Lain H. Woodhouse (M’95) received the B.S. degree in physics from the University of Edinburgh, Edinburgh, U.K., and the M.S. degree in remote sensing and image processing from the University of Dundee, Dundee, U.K., in 1989 and 1990, respectively.

Following a period with the Mentor Research Center, Lincoln, U.K., working on radar system design, he then received the Ph.D. degree in atmospheric remote sensing from De Montfort University, Edinburgh, U.K.

Since 1999, he has been a Lecturer with the School of Geography, University of Edinburgh, and has made Professor of Applied Earth Observation in 2013. His research interests include active remote sensing of vegetation and are currently focusing on the African dry tropics, with a special emphasis on Malawi.

In 2008, he co-founded Ecometrics, a climate management company, and in 2012, he co-founded Carbonery, a forest survey company. He is the author of the book Introduction to Microwave Remote Sensing (Taylor and Francis, 2009) and Twenty Seven Chapters on Remote Sensing (Spackman Press, 2013).

German Lopez was born in Belmop, 1980. He received the B.Sc. degree in biology from the University of Belize, Belize, Belize, in 2006. He is now pursuing the M.Sc. degree in environmental forestry from the University of Burgos, Burgos, U.K.

After working for 5 years in the private sector, he was employed in 2019 at a Junior Researcher with a water management project funded by the MRC government. He obtained forest inventory skills and training by attending tropical forestry courses in Belmop, Costa Rica, and El Salvador.

Vladimir Leires was born in Guamau, 1979. He received the B.S. degree in forestry from FUNDAÇAO Universidade, Brasilia, the Master of Environmental Management from the Yale School of Forestry and Environmental Studies, New Haven, CT, USA, and the M.B.A. from Tuas Nusosa Business School, Tilburg, the Netherlands, in 2007 and 2009, respectively.

From 2009 to 2013, he has worked in sustainable forest management and community-based forestry enterprise strengthening in many Latin American countries. For the last few years, he has been working on closing the existing gap between small and medium enterprises and the financial sector.

Niel Stuart received the B.Sc. degree in geography from the University of Leeds, Leeds, U.K., in 1985 and the Ph.D. degree in geographical information science from the Leeds University, in 1990.

Since 1989, he has been a Lecturer with the School of Geography, University of Edinburgh, Edinburgh, U.K., and is a former Director of their internationally renowned Masters program in GIS. He has worked extensively in Belize since first-flying out coastal transect surveys there in 1990. He recently directed a major research and capacity building program for that country from 2009 to 2012 funded by the U.K. Government’s Darwin Initiative.
APPENDIX THREE

PUBLISHED ARTICLE AT THE JOURNAL MDPI FORESTS (2014)

This article is chapter five
Local-Scale Mapping of Biomass in Tropical Lowland Pine Savannas Using ALOS PALSAR

Dimitrios Michelakis 1,2, Neil Stuart 1, German Lopez 3, Vinicio Linares 2 and Iain H. Woodhouse 1

1 School of Geosciences, College of Science and Engineering, University of Edinburgh, Edinburgh, EH9 3XP, UK; E-Mails: ns@staffmail.ed.ac.uk (N.S.); i.h.woodhouse@ed.ac.uk (I.H.W.)
2 School of Environment Natural Resources and Geography, Bangor University, Bangor, LL57 2UW UK; E-Mail: glopez@ub.edu.bz
3 Forestry, Entrepreneurship, Finance and Corporate Social Responsibility, Greater New York City Area, USA; E-Mail: avlin14@gmail.com

4 Author to whom correspondence should be addressed; E-Mail: dimmihel@gmail.com; Tel.: +44-131-650-9046; Fax: +44-131-650-2524.

Received: 3 April 2014; in revised form: 8 September 2014 / Accepted: 22 September 2014 / Published: 25 September 2014

Abstract: Fine-scale biomass maps offer forest managers the prospect of more detailed and locally accurate information for measuring, reporting and verification activities in contexts, such as sustainable forest management, carbon stock assessments and ecological studies of forest growth and change. In this study, we apply a locally validated method for estimating aboveground woody biomass (AGWB) from Advanced Land Observing Satellite (ALOS) Phased Array-type L-band Synthetic Aperture Radar (PALSAR) data to produce an AGWB map for the lowland pine savannas of Belize at a spatial resolution of 100 m. Over 90% of these woodlands are predicted to have an AGWB below 60 tha⁻¹, with the average woody biomass of these savannas estimated at 23.5 tha⁻¹. By overlaying these spatial estimates upon previous thematic mapping of national land cover, we derive representative average biomass values of ~32 tha⁻¹ and ~18 tha⁻¹ for the previously qualitative classes of “denser” and “less dense” tree savannas. The predicted average biomass, from the mapping for savannas woodlands occurring within two of Belize’s larger protected areas, agree closely with previous biomass estimates for these areas based on ground surveys and forest inventories (error ≤20%). However, biomass estimates derived for these protected areas from two biomass maps produced at coarser resolutions (500 m and 1000 m) from global datasets overestimated biomass (errors ≥275% in each dataset).
The finer scale biomass mapping of both protected and unprotected areas provides evidence to suggest that protection has a positive effect upon woody biomass, with the mean AGWB higher in areas protected and managed for biodiversity (protected and passively managed (PRPM), 29.5 t ha\(^{-1}\)) compared to unprotected areas (UPR, 23.29 t ha\(^{-1}\)). These findings suggest that where sufficient ground data exists to build a reliable local relationship to radar backscatter, the more detailed biomass mapping that can be produced from ALOS and similar satellite data at resolutions of ~100 m provides more accurate and spatially detailed information that is more appropriate for supporting the management of forested areas of ~10,000 ha than biomass maps that can be produced from lower resolution, but freely available global data sets.

**Keywords:** savanna woodlands; Earth observation; ALOS PALSAR; biomass map; conservation planning; Belize

1. Introduction

1.1. Why Map Tropical Savannas at More Local Scales?

Savannas are an important component of global vegetation, covering approximately 18% of the Earth’s land surface [1]. The woody component of savannas can be variable [2]; however, many woody savannas can be characterized as forests according to the FAO definition [3]. The woody component is of major significance for storing biomass [4,5], supporting biodiversity [6] and sustaining the local hydrological cycle [7]. A growing recognition of the value of natural carbon stores and the intention to reduce emissions caused by deforestation and forest degradation [8] are encouraging developing countries to protect and manage these tropical forest ecosystems more sustainably.

Wooded areas within savannas are increasingly pressured by human intervention, leading to unsustainable management practices. In the Neotropics, key threats are the continuing expansion of agriculture and pasture [9,10], as well as overly frequent logging and burning [11,12], which have resulted in the reduced extent and health of this ecosystem [13,14].

With these pressures degrading both the biodiversity and economic value of savanna woodlands, techniques are urgently needed to measure, map and monitor the woody component reliably and to produce this information at appropriate scales to support conservation and management actions. Maps of aboveground woody biomass (AGWB), if sufficiently detailed, can assist conservation managers, practitioners and policy makers to formulate specific practices (e.g., thinning, fire control, seedling regeneration, biodiversity surveys, etc.) that are appropriate for woodland patches within broader savanna areas [15,16].

Many countries presently lack the capacity to produce their own local maps of forest biomass and, so, must rely on existing biomass maps founded upon broader regional and global datasets. Although providing a consistent approach to estimation of biomass differences over areas of hundreds of square kilometres, we contend that the resolution of these global data sets (typically 500 m or 1000 m) is often
too coarse for quantifying and monitoring the distribution of woody biomass within areas of 10,000 ha or less, which are common sizes for protected areas or forest reserves, particularly in smaller countries.

In this paper, we use the example of pine woodlands in Belize, for which a locally modelled relationship between ground measured biomass and satellite sensed radar backscatter from PALSAR has been established and validated, to explore finer scale biomass mapping to support potential forestry applications. Specifically, we address the following objectives:

- Mapping the AGWB of over 50% of the lowland savanna woodlands of Belize at 100-m resolution, using a locally modelled relationship between the satellite radar backscatter and observations of biomass from an extensive national inventory of forest plots.
- Analysing the resulting AGWB map to quantify for the first time the variation in AGWB across the different woodland savannas within the country and exploring how this might provide forest managers with enhanced information about the nature and locality of different woodland components, compared to previous qualitative thematic mapping using the UNESCO land cover classification system.
- Examining, within a pilot study area of approximately 933 km², whether the biomass map produced at 100 m might enable differences in biomass to be observed between forest areas that are being protected or sustainably managed, compared to unprotected forest areas.
- For two specific protected areas of Belize, assessing if this finer scale mapping produces biomass estimates that accord more closely with ground measurements of biomass than estimates based on biomass values extracted from pantropical biomass data sets at 500-m and 1000-m resolution produced by [17,18].

1.2. Mapping of Savanna Woodlands with Active Satellite Earth Observation

New advances in the mapping of biomass by active sensors have greatly facilitated efforts to characterize savanna ecosystems at multiple scales. Using the archive of the Advanced Land Observing satellite (ALOS) Phased Array-type L-band Synthetic Aperture Radar (PALSAR) satellite data collected from 2007–2009, the Japanese Aerospace Exploration Agency (JAXA) produced the first 50-m global forest/non-forest map [19] to support activities for the United Nations-Reducing Emissions from Deforestation and Degradation (UN-REDD+), while the Jet Propulsion Laboratory (JPL) in collaboration with JAXA created a regional mosaic of ALOS PALSAR imagery for wide ground swaths (~150 km) to assist ecosystem assessments in the Americas. Recent research has shown that ALOS PALSAR data are suitable for classifying vegetation types and assessing carbon stocks at regional scales [20]. In [17,18], satellite LiDAR measurements collected by Ice, Cloud, and land Elevation/Geoscience Laser Altimeter System (ICESAT GLAS), and a diversity of optical spaceborne sensors were used in combination with field measurements to create pantropical carbon stock maps with the explicit intent of assisting tropical countries with monitoring and reporting of their carbon stocks for UN-REDD+ projects at national and sub-national scales (i.e., 10,000 ha). In Africa, [21] created an ALOS PALSAR mosaic at 100-m spatial resolution to be used, among other applications, to map deforestation and agricultural encroachment upon the forest-savanna boundary. In their study within savanna landscapes, [22] identified strong relationships between AGWB and radar backscatter sensed by ALOS PALSAR, concluding that the approach was necessary and sufficient for monitoring
and reporting of biomass baselines for REDD+ projects, and [23] similarly found ALOS PALSAR images to assist in quantifying deforestation at small scales in savanna woodlands in Mozambique. In Australia, [24] stressed the value of ALOS PALSAR data for quantifying the contribution of the woody component of tropical savannas to regional carbon stocks.

There is thus a growing body of evidence derived by studies conducted in tropical savannas supporting the technique of deriving biomass maps from L-band data collected by ALOS PALSAR, with the majority of the work to date conducted in African and Australian savannas. The wide availability of L-band data (up until 2011) and new L-band data acquisitions from operational ALOS PALSAR-2 (launched in 2014), as well as future spaceborne and airborne missions, such as the Satélite Argentino de Observación Microondas (SAOCOM) and NASA’s airborne Unmanned Aerial Vehicle (UAV) SAR, makes it an attractive data source for wide and local area biomass monitoring. However, finer scale biomass mapping using L-band SAR data relies on establishing a strong and consistent relationship between the backscattered signal and biomass measurements collected in the field in each locality. The relationship between biomass and backscatter is known to vary for different woodlands and to be influenced by local topographic and climatic conditions, which, for example, affect the attenuation of the signal [25]. For these reasons, some attempts to create fine-scale biomass maps from ALOS PALSAR data have not been successful. For example, [26] were not able to map AGWB in savanna woodlands sufficiently accurately in Malawi, because of substantial topographic relief in the study area, combined with the heterogeneity of the woody component.

1.3. The Use of More Detailed Mapping of Woody Biomass in Savannas

Work is now progressing beyond dichotomous mapping of forest versus savanna, to create finer scale mapping of biomass differences within savanna landscapes. This is often driven by the need to create baseline carbon stock maps and to monitor changes in biomass as part of the reporting requirements of REDD+ projects. Although radar techniques are well established for mapping biomass in more uniform forest plantations, such as those in temperate and boreal regions, forest managers and researchers are raising questions about whether coarse resolution (i.e., 500-m and 1000-m pixel resolution) mapping from EO data is adequate for tasks, such as primary production planning or forest stock mapping, in more heterogeneous woody environments, such as tropical savannas. For example, Junitz et al. in [27] used the 500-m biomass maps produced by [17] to plan corridors to connect together broadleaf forest areas and have suggested that a similar method could be used to identify conservation corridors in lower biomass ecosystems. Whilst the AGWB maps produced by [17,18] may be used to meet regional-scale emissions reporting requirements or for preliminary estimation of national carbon stocks when no finer scale information is available, these maps need to be validated against local forest stock surveys or AGWB maps from higher resolution satellite imagery when these are available.

Beyond the present focus on carbon stocks, there is wider interest in how finer scale spatial information about biomass in savanna woodlands can inform work in forest management and forest ecology. Biogeographers and forest ecologists studying shifts in savanna-forest boundaries can use finer scale information to detect changes in the relative balance between woody vegetation and grasses more rapidly, whilst finer scale data allows them to understand the relative importance of human
activities compared to climatic changes as factors influencing local shifts [4,28–33]. AGWB estimates derived from ALOS PALSAR may enable scientists to explore and monitor these dynamic phenomena and processes in more depth. There is also interest in using finer scale biomass mapping to monitor regeneration and growth in low density woodlands. For example, ALOS PALSAR data have been combined with Landsat data by [34,35] to characterize re-growth in open Brigalow woodlands in Australia to assist management strategies, such as thinning and weed control, illustrating practical management actions that can be supported by this finer scale information.

2. Experimental Section

2.1. Description of the Lowland Savanna Ecosystem

This study is conducted within the lowland areas of Belize (Figure 1A), which comprise approximately 1754 km² of savanna landscape [36] (Figure 1B). These areas are the most northern Neotropical savannas [37], which represent the second most extensive savanna vegetation formation within the America Neotropics [38]. In this analysis, we focus on mapping the aboveground woody biomass (AGWB) of woody savannas, which are recognized for their importance in carbon sequestration due to the presence of pine trees [39]. Pine (Pinus caribaea var. hondurensis) forms low density wood clusters (10%—65% canopy cover) within the savanna landscape, while other woody vegetation, such as Palms (Acoclorrhapha wrightii) and shrubs (Byrsonima crassifolia), are often evident and usually scattered through the grass landscape [40].

Figure 1. (A) Belize in the region of Central America; (B) footprints of the ALOS PALSAR and the national ecosystems map based on UNESCO classes; and (C,D) the lowland savanna areas in the ALOS PALSAR scenes: light grey areas indicate the extent of protected areas with lowland savannas; RBCMA stands for Río Bravo Conservation and Management Area.
The national ecosystems map of Belize classifies the lowland savannas into three UNESCO classes (Figure 1C and Figure 1D). Here, we examine the: (1) short-grass savannas with dense trees or shrubs (UNESCO code: VA2a (1/2)) (Figure 2A,C); and (2) short-grass savannas with scattered trees and/or shrubs (UNESCO code: VA2a (1) (2)) (Figure 2B,D). Pine woodlands occur in both of these vegetation zones, and the local density of the tree cover in relation to other shrubs and grasses has until now been interpreted qualitatively as the basis for allocating most savanna land into one or the other of these classes [41]. The climate in Belize is subtropical to tropical with an average annual precipitation of around 1500 mm in the northern parts of the country and 3800 mm in the south. In Figure 3, the annual mean precipitation is shown per month using data collected in three weather stations of the Belize National Meteorological Service and a rainfall monitoring product, which is based on derived data from the Global Precipitation Climatology Centre (GPCC).

**Figure 2.** Representative photographs of lowland savanna areas with dense trees or shrubs (VA2a (1/2)) (A,C); and sparse trees and/or shrubs (VA2a (1) (2)) (B,D).

**Figure 3.** Illustrating the wet and dry seasonality in Belize; two major precipitation spikes are observed in June and October, while September also appears to be a rainy month.
2.2. ALOS PALSAR Data

Two fine beam dual polarization (FBD) ALOS PALSAR datasets (Level 1.0) covering approximately 55% (933.46 km²) of the lowland savanna ecosystem in Belize were collected during the wet season in September, 2008 (Figure 1B, II). The radar data that were used in this study included only the horizontal-vertical polarization (HV), because of their sensitivity to biomass found for the same areas used in this study in [42,43]. The HV data were pre-processed at Aberystwyth University from raw data to single look complex (SLC) images using the Modular SAR processor in GAMMA software, while a calibration factor of −58.30 decibels (dB) was used. Subsequently, the SLC images were multi-looked and geo-coded to precision images (PRI) using the differential interferometry geocoding module (DIFF and GEO), which is also included in GAMMA. The resulting four look images (pixel spacing = 13 m) were further processed to reduce speckle by aggregating neighbourhoods of adjacent pixels (2 × 2) and arithmetically averaging the radar intensity at the power domain [42,43]. The final radar product has a pixel-spacing of 26 m, and data represent the normalized radar cross-section ($\sigma^0_{db}$), where dB is decibels. The total extent of the lowland savanna has been mapped by previous projects [36], and that map is used to constrain the biomass mapping from the ALOS data to within the savanna extents.

The total study area is 933.46 km² (Figure 1, C,D) and is comprised of approximately 345 km² of lowland savannas with sparse trees or shrubs (VA2a (1/2)) (51% of total VA2a (1/2)) and 588 km² of lowland savannas with dense trees or shrubs (VA2a (1) (2)) (58% of total VA2a (1) (2)).

Although the ALOS PALSAR data were acquired during the wet season, the rainfall estimates of the Tropical Rainfall Measurement Mission (Product 3B42V7) for the radar data acquisition dates (±/− three days) within the study area shows that the mean rainfall is very low in both ALOS PALSAR images (~15 mm/day for Image I and ~9 mm/day for Image II). When comparing these mean precipitation estimates to the mean dry season gauged precipitation data acquired in the two weather stations falling within the ALOS PALSAR image extents (Figure 3), we have more confidence for using this ALOS PALSAR imagery, which was collected during the wet season for AGWB estimation.


Biomass mapping was achieved by adapting a forward parametric model, which is based on a semi-empirical water cloud model (WCM) [42–44] to derive a mathematical relationship between the backscattered intensity of the radar signal ($\sigma^0_{pp}$), where $pp$ corresponds to emitted and received polarization of the radar signal and the biomass (AGWB) calculated from ground surveys of 6,457 trees collected over 32.6 hectares of savanna woodlands throughout Belize.

In the WCM, the AGWB is represented as a relatively homogeneous aboveground volume, which consists of canopy components and air [42,44]; the canopy components are assumed to be relatively homogeneous spherical scatterers, which mimic a water cloud. Mathematically, the parametric forward model describing the WCM usually takes the form of Equation (1) to perform fitting, non-linear least squares regression and calculation of the empirical coefficients $\sigma^0_{deg}$, $\sigma^0_{vhi}$ and $y$, which are dependent on the structure of the woodlands. The regression equation is then re-arranged to estimate biomass as shown in Equation (2) [42].
In Equation (2), \( \sigma_{\text{total}}^0 \) represents the total backscattered intensity of the radar signal collected by ALOS PALSAR, \( \sigma_{\text{seg}}^0 \) is the fraction of the total backscattered intensity due to radar-vegetation interaction and \( \sigma_{\text{soil}}^0 \) is due to bare soil interaction.

Using this WCM (Equation (1)), an AGWB training dataset, which was collected on the ground in four different years, 2006, 2011, 2012 and 2013 (Table 1), and the ALOS PALSAR imagery (HV polarization), Michelakis et al. in [42] undertook non-linear regression analysis to show that the HV intensity of the radar backscatter can be predicted in relation to the AGWB with an \( R^2 = 0.92 \) (Figure 4A).

**Figure 4.** (A) The non-linear regression model fitted (solid line) using the training dataset from Table 1 and ALOS PALSAR HV imagery; and (B) the histogram of both aboveground woody biomass (AGWB) datasets (training and external validation); note the zero AGWB points in scatterplot (A), which were collected on the ground using a global navigation satellite system (GNSS) device on areas with no woody vegetation to sample the backscatter in these areas.

**Table 1.** Training and external validation AGWB datasets that were used in the non-linear regression fitting and the validation of the WCM; these datasets are described in [42].

<table>
<thead>
<tr>
<th>Datasets</th>
<th>Plot size (ha)</th>
<th>AGWB (tha(^{-1})) Range</th>
<th>Density (Trees ha(^{-1})) Range</th>
<th>BA (m(^2)ha(^{-1})) Range</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Mean St. Dev.</td>
<td>Mean St. Dev.</td>
<td>Mean St. Dev.</td>
</tr>
<tr>
<td>Training</td>
<td>32 (\times) 1/6 (\times) 0.1</td>
<td>0–101.6 47.3 37.1</td>
<td>0–680 155 171.7</td>
<td>0–15.3 6.15 5.0</td>
</tr>
<tr>
<td>Validation</td>
<td>38 (\times) 0.1</td>
<td>1–72 39.5 19.4</td>
<td>20–350 145 75.1</td>
<td>0–11.0 5.7 2.6</td>
</tr>
</tbody>
</table>

Although the satellite data were collected in 2008, the slow growth rate of Caribbean pine, even in better sites in Belize as recorded by [45] (0.4 cm \(\leq\) dbh \(\leq\) 1 cm), allows us to use these field measurements in the development of the WCM. The semi-empirical model fitted in this study is shown
in Equation (3). Using an external validation dataset (Table 1), AGWB estimates were assessed demonstrating that AGWB can be predicted on the ground with a root mean squared error (RMSE) ~ 13.5 tha\(^{-1}\), while 80% of the AGWB estimates were found to have an error of less than 20 tha\(^{-1}\) [42].

\[
\sigma_{\text{RMSE}}^2 = 10.40 \times \left(1 - e^{-0.96 \times AGWB}\right) - \frac{24.06}{1 - e^{-0.96 \times AGWB}}
\]  

(3)

To assess the uncertainty of the AGWB map created using the ALOS PALSAR data and the semi-empirical WCM, an evaluation of the estimation accuracy was conducted using the validation dataset (Table 1) for the lower biomass range (i.e., ≤75 tha\(^{-1}\)) and the training dataset (Table 1) for the higher biomass range (i.e., ≥75 tha\(^{-1}\)). The training dataset was used for estimating uncertainty in the higher biomass range due to the lack of high biomass observations in the validation dataset. The relative root mean squared error (RRMSE) was separately calculated for seven biomass classes with 15 tha\(^{-1}\) intervals (i.e., 0–15, 15–30, 30–45, 45–60, 60–75, 75–90 and 90–105 tha\(^{-1}\)) using Equation (4).

\[
RRMSE (%) = \left(\frac{100 \times \text{RMSE}}{\text{AGWB}}\right)
\]  

(4)

where RMSE and AGWB are the root mean squared error and the mean observed AGWB within each biomass class.

A concern with the mathematical formulation in Equation (2) is that negative or infinite values of biomass can be predicted [46–48]. To constrain estimates to realistic values, any cells with infinite values were assigned the highest value of biomass actually measured in the field (101.65 tha\(^{-1}\)), whilst any cells with negative estimates of biomass were assigned a value of zero. No previous field studies conducted in savanna woodlands in Belize by [45,49–52] have measured AGWB in these savanna woodlands above 101.65 tha\(^{-1}\), so we feel confident using this value as our realistic upper limit for this case study.

Although a recent study from [53] has shown that parametric forward models show higher errors than other approaches, there are five reasons that a semi-empirical WCM is employed in this study: (1) The semi-empirical model is grounded in the physical basis of how the backscattered intensity of the radar is expected to interact with vegetation targets in contrast to more statistically driven approaches, such as backward models; (2) the use of non-parametric models, such as machine learning algorithms, could not be implemented in this research, because of the lack of the significant data amounts that are needed (for example, [54] used more than 50 data samples for biomass mapping using decision trees classifiers); (3) the WCM accounts for the low canopy cover nature of the savanna woodlands (10%–65%) by using a weighting area fill factor \((1 - e^{-\gamma \times AGWB})\) in the vegetation backscatter [53]; (4) the WCM varies as it interacts with vegetation of different biomass and supplements and extends upon previous quantitative analysis of radar backscatter as a surrogate measure of biomass [42,44]; and (5) the biomass estimation results can be comparable to future research using methods that are based on other forward models in contrast to solely statistical approaches.
2.4. Deriving Ground-Based Estimates of AGWB for Two Protected Areas

We used the inverted WCM (Equation (2)) described in the previous section and the ALOS PALSAR data covering two of the country’s largest savanna woodlands (Rio Bravo Conservation and Management Area (RBCMA) and Deep River protected area) to estimate the mean AGWB for the whole protected area extent and compared these with AGWB estimates calculated from previously published data [50,52]. These two protected areas are both over 10,000 ha and are typical locations and extents for sub-national scale UN-REDD+ projects [17].

In RBCMA, Brown et al. in [52] estimated mean carbon stock of 13.1 tC ha⁻¹ for approximately 10,000 ha of savanna by developing new allometric equations, which predicted biomass carbon using tree attributes as independent variables that could be easily measured from aerial images. To develop the allometric equations, Brown et al. used an extensive ground dataset, which was collected by the destructive sampling of 51 pine trees, and then 77 image sample plots were used in three-dimensional very high spatial resolution aerial imagery to assist with the remote measurement of the tree attributes, which were used to estimate carbon stocks. To convert the carbon stock estimation by Brown et al. to biomass, we multiplied by a factor of two [55] (carbon is 50% of biomass), calculating a mean AGWB of 26.2 t ha⁻¹ for RBCMA. In Deep River (DR), to estimate AGWB for approximately 3500 ha of savanna woodlands (31.60 tC ha⁻¹), we used 62 circular sample plots (0.1 ha), which were not used during the WCM training, and only 18 out of the 62 were used in the external validation of the WCM, in the denser woodland areas originally collected by [50] to support plans for sustainable timber extraction (Table 2).

Table 2. Summary of the plots that were collected in the denser woodland areas of Deep River (DR).

<table>
<thead>
<tr>
<th>Data Region</th>
<th>AGWB (t ha⁻¹)</th>
<th>Density (Trees ha⁻¹)</th>
<th>BA (m² ha⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Data</td>
<td>Plot size (ha)</td>
<td>Range</td>
</tr>
<tr>
<td>DR</td>
<td>62 x 0.1</td>
<td>2.25–76.19</td>
<td>31.60</td>
</tr>
</tbody>
</table>

To derive the mean AGWB value for both RBCMA and DR, for each tree, the AGWB was estimated using the allometric equations (Equations (5) and (6)) developed by [52] in RBCMA, where dbh is the diameter at breast height (1.3 m) and biomass is dry aboveground woody biomass in kilograms. More than 30% (2190 trees) of the field data measurements that are used in this study were collected within RBCMA, and more than 95% of the tree dbh measurements are within the range sampled by [52] (1–52.4 cm). The AGWB ha⁻¹ was estimated for each 0.1 ha sample plot by summing the AGWB of individual trees and multiplying the sum by a factor of 10 to extrapolate to the hectare.

Having obtained these “ground truth” estimates of mean AGWB ha⁻¹ for both protected areas, we then multiplied these up by the area of the RBCMA and the denser woodland areas of DR and compared these totals to those obtained by using a GIS to aggregate cells from the 100-m biomass map within the boundaries of the RBCMA and DR, respectively.

\[
\text{Pine Biomass}_{AGWB} = 0.0407 \times \text{dbh}^{2.423}
\]  

(5)
\[ Oak\ Biomass_{OB} = \left( 0.5 + \frac{25,000 \times \text{dbh}^{2.5}}{\text{dbh}^{2.5} + 246,872} \right) \times 2 \] (6)

2.5. Classification of Savannahs by Protection and Management Type

Approximately 25% of the lowland savannas in Belize are under some form of protection [36] and have been characterized as Category Ia, II, IV or VI, according to the International Union for Conservation of Nature (IUCN) classification system [56]. Using information acquired from land managers and published management plans [50,57–60], we examined the influence of land management in various protected savanna woodlands by comparing the biomass quantities predicted by our model. In unprotected savanna woodlands, the possibility of a management plan cannot be excluded. However, it was not possible to acquire management information for these savanna woodlands; thus, the unprotected areas are considered as not managed in this study. To allow the influence of both passive and active management to be explored, as well as the binary “protected-unprotected” dichotomy, we subdivided the study area into three protection and management groups using the information acquired by managers and the published management plans.

Approximately 40 km² of savanna woodlands found within the RBCMA and in the Bladen nature reserve were characterized as highly protected and passively managed areas (hereafter, PRPM). These areas have been managed mostly to promote biodiversity [57–60], while they have been classified as “strict nature reserve, Ia” and “habitat/species management area, IV” by the IUCN. Similarly, some 118 km² of savanna woodlands found in the Manatee and DR forest reserves were grouped as protected and actively managed (PRAM) areas, where timber is extracted sustainably [50], and both have been classified as “protected area with sustainable use of natural resources, VI” by the IUCN. Further areas, totalling approximately 395 km² of savanna woodlands, with no protection designations, were identified as unprotected (UPR) areas. The remaining 185 km² of protected areas for which we could not obtain reliable information about their management were not included in this analysis. Using GIS, we then overlaid the new biomass map upon the three forest management groups and calculated the biomass in mean AGWB ha⁻¹ for each of the three areas.

2.6. Comparing the New Mapping with National Level Carbon Stock Maps from Pantropical Data Sets

To conduct a comparison with our local biomass map (Michelakis biomass estimates henceforth MBE₁₀₀), two national-level carbon stock maps were acquired for Belize. These were the pantropical national-level carbon stock dataset (Baccini biomass estimates, henceforth BBE₂₀₀) produced by [17] and the benchmark national carbon data (Saatchi biomass estimates, henceforth SBE₁₀₀) produced by [18]. Both datasets are stored in a single tagged image format file (*.tiff) representing the aboveground carbon density of aboveground live woody vegetation. These gridded values were predicted using data collected by a range of EO sensors, such as the ICESAT GLAS, MODIS and the Shuttle Radar Topography Mission (SRTM) in non-parametric spatial modelling processes. Baccini et al. used in [17] the RandomForest algorithm to produce the BBE₂₀₀ product, and Saatchi et al. in [18] used the Maximum Entropy (MaxEnt) modelling algorithm for the SBE₁₀₀ product [18]. The BBE₂₀₀ data were downloaded from the Woods Hole Research Centre (WHRC)
website [61] with a pixel size of 463.31 m × 463.31 m, and the SBE1600 data were downloaded by [62] with a pixel size of 910.89 m × 910.89 m.

To enable a cell-by-cell comparison between MBE100, BBE500, and SBE1000 at the 500-m and 1000-m scale using ANOVA and to produce percentage difference maps, we reduced the resolution of the MBE100 data to 500 m and 1000 m, and the BBE500 data from [61] to 1000 m (Table 3). We compared MBE100 to both BBE500 and BBE1000, to enable, in the first instance, a more direct comparison to the pantropical national carbon stock, using the spatial resolution defined by Baccini et al., and at the former instance, to compare all three carbon maps at the coarser resolution (i.e., 1000 m defined by Saatchi et al.). The data meaning for each reduced resolution pixel is the arithmetic mean of all the increased resolution pixel values, which were contained within the extent of each new reduced resolution pixel. To assess the differences between our local biomass estimates and these national carbon stock estimates, within the boundaries of our study area, we aggregated and averaged the grid values of our MBE100 data set using a window size of 5 × 5 and 10 × 10 to create reduced resolution rasters (MBE500, and MBE1000, respectively).

Table 3. Local and pantropical datasets used for comparison and summary of the data and methods used to derive the biomass maps; MBE, Michelakis biomass estimates; BBE, Baccini biomass estimates; SBE, Saatchi biomass estimates.

<table>
<thead>
<tr>
<th>Biomass map</th>
<th>EO data used</th>
<th>Algorithm</th>
<th>Pixel size (m)</th>
<th>Reduced resolution (m)</th>
<th>Compared to</th>
</tr>
</thead>
<tbody>
<tr>
<td>MBE100</td>
<td>ALOS PALSAR</td>
<td>Semi-empirical water cloud model</td>
<td>100</td>
<td>500</td>
<td>BBE500, BBE1000, SBE1000</td>
</tr>
<tr>
<td>BBE500</td>
<td>ICESAT GLAS MODIS Bidirectional Reflectance Distribution Function BDRF SRTM</td>
<td>RandomForests</td>
<td>500</td>
<td>1000</td>
<td>MBE100, SBE1000</td>
</tr>
<tr>
<td>SBE1000</td>
<td>ICESAT GLAS MODIS LAI/NDVI/Vegetation Continuous Fields VCT SRTM QUICKSAT</td>
<td>MaxEnt</td>
<td>1000</td>
<td>-</td>
<td>MBE1000, BBE1000</td>
</tr>
</tbody>
</table>

To perform AGWB comparisons between our reduced resolution AGWB estimates and BBE500 and SBE1000 estimates, we calculated the percentage differences (Equation (7)) per pixel and per protected areas (i.e., DR and RBMCA). To assess the difference between mean biomass estimations for the whole protected areas, percentage errors were calculated (Equation (8)).

In Equation (7), AGWBb and AGWb refer to (1) the AGWB values in each individual pixel of the compared datasets (e.g., MBE100 vs. BBE500) or (2) the mean AGWB values derived using all biomass pixels of the compared datasets within the extent of a protected area. In Equation (8), AGWBReference corresponds to the locally derived mean AGWB value for the woody savannas using field data in DR (Table 2) or to the derived mean AGWB calculated by [52] in BCMA. In Equation (8), AGWBstimated refers to the AGWB estimates based on the MBE, BBE and SBE maps.
3. Results and Discussion

3.1. Evaluating the AGWB of the Lowland Savannas per Protection and Management

Using the semi-empirical model developed by [42], we create a 100-m biomass map (MBE100) for the whole study area (Figure 5A,B). For the half of the total savanna area of the RBCMA that is covered by the ALOS PALSAR scene, we estimate mean AGWB based on 3,632 pixels from MBE100 to be 29.55 ± 0.84 t/ha, where the 95% confidence interval is reported with ±, and for the denser woodland areas sensed in the DR forest reserve (Figure 1D), 38.03 ± 0.92 t/ha based on 3105 pixels. On average, slightly higher biomass values (mean AGWB = 24.18 ± 0.24 t/ha) were mapped within the boundaries of all of the protected areas in the study area compared to values mapped in other areas, which are considered unprotected (23.29 ± 0.19 t/ha). Although this small difference in biomass is statistically significant (Mann-Whitney U-test, p < 0.050), the dispersion of biomass values in Figure 6C appears similar for both groups. Perhaps surprisingly, this suggests that protection in general does not lead to substantially higher values of mean AGWB ha⁻¹ in these woodlands.

Figure 5. AGWB estimates (MBE100) derived by ALOS PALSAR Scenes I, and II for (A) north Belize (Scene I) and (B) south Belize (Scene II), overlaid on protected areas boundaries (light grey polygons with dashed lines as boundaries) that contain savannas.
To explore this finding further, in Figure 6D, only the biomass values mapped within two types of protected areas are presented: those which are passively managed (PRPM) and those which are actively managed (PRAM); these are compared again to values mapped in unprotected areas (UPR). Differences in biomass are now more evident, and although the differences are again small, they are more significant (Kruskal–Wallis one-way ANOVA, \( p < 0.001 \)). The protected areas that are passively managed (PRPM) with fire control and conservation management are estimated to have a mean AGWB of approximately 29.5 ± 0.85 \( \text{tha}^{-1} \) and a higher variability of biomass values in comparison to protected areas that are actively managed for extractive logging (PRAM); for these latter areas, AGWB is estimated at approximately 24.3 ± 0.41 \( \text{tha}^{-1} \), and the variability in the biomass values is lower. One possible explanation for this difference is that larger trees are commonly retained in biodiversity reserves, but are usually harvested before reaching such a size in forest reserves [50].

**Figure 6.** ALOS PALSAR-derived AGWB \( \text{ha}^{-1} \) estimates for (A) the study area (933 km\(^2\)), (B) the two UNESCO savanna land cover classes, (C) protected versus unprotected areas and (D) the protected areas with active management (PRAM), passive management (PRPM) and unprotected areas (UPR); in each case, \( N \) represents the number of pixels (104 m \( \times \) 104 m) from the biomass map falling within each of the groupings.

### 3.2. Using the Map to Characterize AGWB in the Lowland Savannas of Belize

Visual interpretation of the AGWB map (Figure 5A,B) indicates that the study areas are dominated by low mean AGWB \( \text{ha}^{-1} \) (0–30 \( \text{tha}^{-1} \)). Analysis of the data shows that over 90% of the pixels show AGWB below 60 \( \text{tha}^{-1} \), with less than 10% of the remaining values predicted in the upper range from 60 \( \text{tha}^{-1} \) to 101.65 \( \text{tha}^{-1} \) (Figure 6A). The results obtained show that when AGWB is summed within the areas of the two UNESCO savanna classes mapped, each class produces almost the same total AGWB (VA2a (1/2): 1.00 Mt; and VA2a (1/2): 0.99 Mt); however, the less dense UNESCO class VA2a (1) (2) covers some two-thirds of the study area. In Figure 6B, the denser VA2a (1/2) class is shown to contain significantly higher mean values of AGWB \( \text{ha}^{-1} \) (\( \sim 32 \pm 0.27 \text{tha}^{-1} \) in comparison to \( \sim 19 \pm 0.16 \text{tha}^{-1} \)), a difference that is statistically significant (Mann–Whitney \( U \) statistic, \( p < 0.001 \)).
The observed higher mean biomass found in VA2a (1/2) can be explained by the denser woody component being more extensively found in this class; in general, increasing number of trees ha\(^{-1}\) has been found to produce increased mean AGWB ha\(^{-1}\) in these savanna woodlands [42] and in other tropical savannas that are resource limited [26]. AGWB values estimated within the VA2a (1/2) vegetation class also showed a greater standard deviation (24.65 tha\(^{-1}\) in comparison to 18.57 tha\(^{-1}\)). Taken together, these findings suggest that the less extensive VA2a (1/2) areas may be important to focus upon for carbon sequestration, and if they also have greater structural diversity, they may also be suitable for biodiversity conservation initiatives.

The RRMSE and the average estimated uncertainty of the AGWB mapping for each of the seven AGWB classes mentioned in Section 2.3 are shown in Table 4. The RRMSE for the lower AGWB classes (0–15 tha\(^{-1}\) and 15–30 tha\(^{-1}\)) is considerably higher (113% and 78% respectively) in contrast to the RRMSE calculated (19%–52%) for the higher AGWB classes (30–105 tha\(^{-1}\)). Although the lower AGWB classes show considerable average uncertainty estimates (6.75 tha\(^{-1}\) and 17.21 tha\(^{-1}\)), 80% of the uncertainty estimates for the MBE\(_{100}\) pixels (Figure 7) are lower or close to 20 tha\(^{-1}\) (Table 4).

**Figure 7.** Uncertainty estimates for MBE\(_{100}\) derived by ALOS PALSAR for (A) north Belize (Scene I) and (B) south Belize (Scene II), overlaid on protected area boundaries (light grey polygons with dashed lines as boundaries) that contain savannas.
Table 4. Estimated uncertainty values and their basic description per AGWB class; letters T and V indicate the dataset that was used in the RMSE and average AGWB calculations (i.e., T, training, or V, validation); note that 13 observations of AGWB (i.e., ≥ 75 tha⁻¹) are used from the training dataset to calculate uncertainty for the higher AGWB classes.

<table>
<thead>
<tr>
<th>AGWB Class (tha⁻¹)</th>
<th>Number of AGWB Observations</th>
<th>Average AGWB Observed (tha⁻¹)</th>
<th>RMSE (tha⁻¹)</th>
<th>RRMSE (%)</th>
<th>Number of MBE500 Pixels</th>
<th>Average (tha⁻¹)</th>
<th>Max (tha⁻¹)</th>
<th>80th Percentile (tha⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0–15</td>
<td>4 (V)</td>
<td>10.84</td>
<td>14.2</td>
<td>131</td>
<td>35,425</td>
<td>6.75</td>
<td>19.64</td>
<td>14.21</td>
</tr>
<tr>
<td>15–30</td>
<td>8 (V)</td>
<td>20.60</td>
<td>16.02</td>
<td>78</td>
<td>22,758</td>
<td>17.21</td>
<td>23.40</td>
<td>20.67</td>
</tr>
<tr>
<td>30–45</td>
<td>11 (V)</td>
<td>38.88</td>
<td>7.43</td>
<td>19</td>
<td>13,774</td>
<td>6.96</td>
<td>8.55</td>
<td>7.79</td>
</tr>
<tr>
<td>45–60</td>
<td>9 (V)</td>
<td>51.98</td>
<td>15.13</td>
<td>29</td>
<td>6247</td>
<td>14.93</td>
<td>17.40</td>
<td>16.48</td>
</tr>
<tr>
<td>60–75</td>
<td>6 (V)</td>
<td>66.30</td>
<td>14.62</td>
<td>22</td>
<td>3014</td>
<td>14.66</td>
<td>16.50</td>
<td>15.64</td>
</tr>
<tr>
<td>75–90</td>
<td>10 (T)</td>
<td>85.10</td>
<td>43.8</td>
<td>51.47</td>
<td>1489</td>
<td>42.00</td>
<td>45.90</td>
<td>43.86</td>
</tr>
<tr>
<td>90–105</td>
<td>3 (T)</td>
<td>96.51</td>
<td>25.58</td>
<td>26.51</td>
<td>1567</td>
<td>26.81</td>
<td>27.45</td>
<td>27.45</td>
</tr>
</tbody>
</table>

3.3. Comparison of the Local Map Estimates with Pantropical Carbon Stock Maps

The reduced resolution rasters MBE500 and MBE1000 derived in Section 2.6 contain pixels with the arithmetic mean of the input pixels (MBE1000). Based on 4616 pixels (pixel size: 500 m), it is evident from Figure 8A that BBE500 predicts significantly higher mean AGWB ha⁻¹ for the whole study area than MBE500 (~88 ± 1.21 tha⁻¹ vs. ~24 ± 0.632 tha⁻¹; percentage difference = +115.50%).

Figure 8. Differences between biomass maps for (A) 500-m and (B) 1000-m resolution.

Based on 1096 pixels of 1000-m pixel size (Figure 8B), the SBE1000 AGWB estimation (~95 ± 2.86 tha⁻¹) is higher than both the BBE1000 and MBE1000 (~88 ± 2.50 tha⁻¹ and ~24 ± 1.28 tha⁻¹, respectively) (percentage diff. = +8.2% and +121%, respectively). A Kruskal–Wallis ANOVA test (p ≤ 0.001) and percentage difference maps (Figure 9A–F) using pixel-by-pixel comparisons confirm that the 500-m and 1000-m biomass maps yield significantly different and higher biomass estimates compared to those from aggregating our 100-m estimates (p ≤ 0.001). The relatively similar magnitudes of the estimates for the two pantropical carbon maps produced by [17,18] is expected (Figure 9 C,F), since they have used very similar EO data and allometric equations to derive biomass...
estimations, with the main difference being only the machine learning algorithm used (RandomForests, versus MaxEnt, respectively).

**Figure 9.** Percentage differences as calculated from Equation (7) per 1000-m pixel for the comparisons between (A, D) MBE1000 vs. BBE1000, (B, E) MBE1000 vs. SBE1000 and (C, F) BBE1000 vs. SBE1000 for northern and southern Belizean savannas within the ALOS PALSAR scenes; in histogram (G), we show the distribution of the percentage differences pixel-wise for each biomass map comparison group, and in scatterplot (H), we show the relationship between the percentage difference for each pixel and the biomass estimated for the same pixel using the MBE1000 maps.

Whilst the above comparison was done for the entire study area to maximize the data volume included, we also compared the estimates from the different biomass maps for the RBCMA and DR
areas, since these are more typical of the areas of interest to land managers in Belize. We found that the carbon stock maps created for RBCMA and DR using data from [17,18] at 1-km spatial resolution again produced significant overestimation of the mean AGWB ha\(^{-1}\) compared to local reference values from the field surveys described earlier. Percentage errors were 277% and 319% for BBE\(_{100}\) and SBE\(_{100}\), respectively, in the RBCMA and 302% and 298% for BBE\(_{100}\) and SBE\(_{100}\), respectively, in DR. In contrast, upscaling our finer scale AGWB estimations in both the RBCMA and DR did not produce large overestimation compared to the same local reference values (+8.1% and +4.5%, respectively, for MBE\(_{100}\) and 10.7% and 0.04% for the MBE\(_{100}\)). Similar findings are observed in [63], where Hill et al. find considerable differences in mean AGWB by comparing between the biomass maps produced by [23] and [17] for a small study area in Mozambique (~1160 km\(^2\)), which is dominated by Miombo woodlands (mean AGWB ~35.6–38.4 tha\(^{-1}\) found in [23] vs. 102.4 tha\(^{-1}\) found in [17]). These findings confirm the need for caution when using biomass estimations produced from satellite EO [63] at coarse resolution for quantifying AGWB locally.

Generally, these estimates of AGWB by our local method (~26 tha\(^{-1}\)) and by the pantropical data sets (~90 tha\(^{-1}\)) need to be considered in the context of the ranges of aboveground biomass that are estimated for woody savannas in other parts of the world. According to a review of observations by [1], the highest values of biomass observed in savannas have been in Northern Australia (~67.2 tha\(^{-1}\)) [64], while in South and Central America, the highest biomass values recorded have been observed in Brazilian cerrado vegetation (~31.8 tha\(^{-1}\)) [65]. This leads to the suggestion that the pantropical carbon maps may be overestimating AGWB in savanna areas, and this suggestion will need to be explored more rigorously as more field-based estimates of biomass are collated from other savanna woodlands.

4. Conclusions

This study has shown that ALOS PALSAR radar data can be used with semi-empirical modelling to produce estimates of AGWB ha\(^{-1}\) for the woody component of tropical savannas at a spatial resolution of 100 m. When these pixel estimates are aggregated within the extents of two protected areas of approximately 10,000 ha, the satellite-derived biomass maps agree to within 12% and 20%, respectively, of the estimates obtained from local forest survey data and from biomass estimated from airborne very high spatial resolution imagery, suggesting that this method has sufficient accuracy to be used for reporting biomass estimates for sub-national extents.

Over 90% of the woodlands mapped in Belize are estimated to have an AGWB less than 60 tha\(^{-1}\), and the average woody biomass of these savannas is estimated at ~23.5 tha\(^{-1}\). Overlaying the results upon previous thematic mapping of national land cover allows us to assign a representative mean biomass value of ~32 tha\(^{-1}\) to UNESCO savanna class VA2a (1/2) ("denser tree savanna"), which clearly separates it from the "less dense" VA2a (1) (2) land cover variant (~18 tha\(^{-1}\)). This is the first quantitative assessment of the difference in the woody component between these two land cover classes, and this information significantly enhances the value of the existing land cover map for forest managers.

A two-way comparison of the mean AGWB values mapped for all protected versus all unprotected areas in the study area showed a small gain in biomass within protected areas; further subdivision of
the protected areas revealed higher AGWB values (~30 tha⁻¹) for passively managed biodiversity reserves than for the extractive forest reserves (~25 tha⁻¹).

The comparison of our AGWB estimate to the pantropical carbon stock maps produced by Baccini et al. in [17] and Sautchi et al. in [18] shows that the three biomass estimates are not consistent, with both pantropical data sets significantly overestimating AGWB when compared to estimations based on more localized backscatter-biomass relationships constrained by forest survey data. The evidence from this study suggests that the pantropical carbon stock maps overestimate the biomass of savanna woodlands in Belize at the national level and are also less suited for exploring differences in AGWB at the sub-national scale, for example for monitoring biomass differences within and between the country’s protected areas.

Acknowledgments

This work is supported by a Hellenic Scholarships Foundation (IKY) Scholarship from the resources of Operational Programme (O.P.) “Education and Lifelong Learning”, the European Social Fund (ESF) and the National Strategic Reference Framework (NSRF) 2007–2013, as well as by the School of Geosciences of the University of Edinburgh. We are grateful to the Darwin Initiative project, “Savannah Ecosystem Assessment/Belize 2009–2012, and the Environmental Research Institute of the University of Belize for providing logistical help and resources for the collection of the field data. We wish to thank Planet Action for providing the satellite data used to identify the field data collection sites and the Institute of Geography Centenary Fund for providing part of the funding for the fieldwork component. We are particularly grateful to the forestry team of the NGO “Programme for Belize” and the students of the MSc in Plant Taxonomy organized by the Royal Botanical Gardens of Edinburgh for their assistance with collecting field data in the Rio Bravo Conservation and Management Area. We wish to thank the four anonymous reviewers for their constructive suggestions, which significantly improved this manuscript.

Author Contributions

Dimitrios Michelakis, Neil Stuart and Iain H. Woodhouse conceived and designed the experiments; Dimitrios Michelakis performed the experiments and analyzed the data; German Lopez and Vinicio Linare contributed reagents/materials/analysis tools; Dimitrios Michelakis wrote the paper.

Conflicts of Interest

The authors declare no conflict of interest.

References and Notes


56. Dudley, N. *Guidelines for Applying Protected Areas Management Categories*; IUCN: Gland, Switzerland, 2008; p. 86.


© 2014 by the authors; licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution license (http://creativecommons.org/licenses/by/3.0/).
APPENDIX FOUR

COMMENTED SCRIPT DESCRIBING THE SAR PROCESSING FROM LEVEL 1.0 (RAW) TO LEVEL 1.1 (SLC) USING THE FACILITIES OF GAMMA SOFTWARE, FOR THE SCENE ‘ALPSRP138740310’.
#!/bin/csh
#
# Script to process RAW ALOS data to Level 1_1
# Created by Joao Carreiras
# Modified by Dan Clewley 01/02/10 to run single scene only
# Modified by Dan Clewley 16/02/10 as template for BatchGamma.py
# From this point forward is just the processing from 1.0 (raw) to 1.1 (SLC).
#
# 1st, generation of the SAR sensor parameter file, and MSP parameter file.
PALSAR_proc LED-ALPSRP138740310-H1.0_A
alpsha_138740310_34_163887_1092008_bd_lev1.hh.sar.par
palpsba_138740310_34_163887_1092008_bd_lev1.hh.slc.par IMG-HH-
ALPSRP138740310-H1.0_A
alpsha_138740310_34_163887_1092008_bd_lev1.hh.raw 0 0
PALSAR_proc LED-ALPSRP138740310-H1.0_A
alpsha_138740310_34_163887_1092008_bd_lev1.hv.sar.par
palpsba_138740310_34_163887_1092008_bd_lev1.hv.slc.par IMG-HV-
ALPSRP138740310-H1.0_A
alpsha_138740310_34_163887_1092008_bd_lev1.hv.raw 0 1

# 2nd, generation of the calibration file and update of the SAR sensor parameter file using the external calibration file.
PALSAR_antpat alpsha_138740310_34_163887_1092008_bd_lev1.hh.sar.par
palpsba_138740310_34_163887_1092008_bd_lev1.hh.slc.par
/usr/local/GAMMA_20080630/MSP_v11.5/sensors/palsar_ant_20061024.dat
alpsha_138740310_34_163887_1092008_bd_lev1.hh.PALSAR_antpat_MSP.dat
- 0 0
PALSAR_antpat alpsha_138740310_34_163887_1092008_bd_lev1.hh.sar.par
palpsba_138740310_34_163887_1092008_bd_lev1.hh.slc.par
/usr/local/GAMMA_20080630/MSP_v11.5/sensors/palsar_ant_20061024.dat
alpsha_138740310_34_163887_1092008_bd_lev1.hh.PALSAR_antpat_MSP.dat
- 0 1

# 3rd, determine the Doppler ambiguity.
dop_mlcc alpsha_138740310_34_163887_1092008_bd_lev1.hh.sar.par
palpsba_138740310_34_163887_1092008_bd_lev1.hh.slc.par
alpsha_138740310_34_163887_1092008_bd_lev1 hh.raw
alpsha_138740310_34_163887_1092008_bd_lev1 hh.mlcc
dop_mlcc alpsha_138740310_34_163887_1092008_bd_lev1.hv.sar.par
palpsba_138740310_34_163887_1092008_bd_lev1 hv.slc.par
alpsha_138740310_34_163887_1092008_bd_lev1 hv.raw
alpsha_138740310_34_163887_1092008_bd_lev1 hv.mlcc

# 4th, estimation of Doppler centroid. The different polarisations present different start times. For this reason, estimation of the Doppler centroid is done for one polarisation (e.g., HH), and the Doppler centroid and effective velocity are copied to the parameter file of the other polarisation. In this way, all the images will have the same geometry and phase reference, i.e., they will all overlap. For this, use the program "doppler" first on the master polarisation (e.g., HH) and then the program "set_value" to update the MSP processing parameter files of the other polarisation.
doppler alpsha_138740310_34_163887_1092008_bd_lev1.hh.sar.par
palpsba_138740310_34_163887_1092008_bd_lev1 hh.slc.par
alpsha_138740310_34_163887_1092008_bd_lev1 hh.raw
alpsha_138740310_34_163887_1092008_bd_lev1 hh.dop
set a1 = `grep doppler_polynomial
palpsba_138740310_34_163887_1092008_bd_lvl1.hh.slc.par |cut -d : -f 1 --complement`
set_value palpsba_138740310_34_163887_1092008_bd_lvl1.hv.slc.par
"doppler_polynomial" "$a1" 0

# 5th, range compression.
pre_rc alpsba_138740310_34_163887_1092008_bd_lvl1.hh.sar
alpsba_138740310_34_163887_1092008_bd_lvl1.hh.slc.par
alpsba_138740310_34_163887_1092008_bd_lvl1.hh.raw
alpsba_138740310_34_163887_1092008_bd_lvl1.hh.rc

pre_rc alpsba_138740310_34_163887_1092008_bd_lvl1.hv.sar.par
alpsba_138740310_34_163887_1092008_bd_lvl1.hv.slc.par
alpsba_138740310_34_163887_1092008_bd_lvl1.hv.slc.par
alpsba_138740310_34_163887_1092008_bd_lvl1.hv.slc.par
alpsba_138740310_34_163887_1092008_bd_lvl1.hv.raw
alpsba_138740310_34_163887_1092008_bd_lvl1.hv.rc

set a2 = `grep sensor_velocity_vector
palpsba_138740310_34_163887_1092008_bd_lvl1.hh.slc.par |cut -d : -f 1 --complement`
set_value palpsba_138740310_34_163887_1092008_bd_lvl1.hv.slc.par
"sensor_velocity_vector" "$a2" 0

# 6th, estimate autofocus (twice) for one polarisation (e.g., HH) and copy the effective velocity to the other MSP parameter file, so that all polarisation channels will be identical.
autof alpsba_138740310_34_163887_1092008_bd_lvl1.hh.sar.par
alpsba_138740310_34_163887_1092008_bd_lvl1.hh.slc.par
alpsba_138740310_34_163887_1092008_bd_lvl1.hh.slc.par
alpsba_138740310_34_163887_1092008_bd_lvl1.hh.slc.par

autof alpsba_138740310_34_163887_1092008_bd_lvl1.hv.sar.par
alpsba_138740310_34_163887_1092008_bd_lvl1.hv.slc.par
alpsba_138740310_34_163887_1092008_bd_lvl1.hv.slc.par
alpsba_138740310_34_163887_1092008_bd_lvl1.hv.slc.par

# 7th, azimuth compression.
az_proc alpsba_138740310_34_163887_1092008_bd_lvl1.hh.sar.par
alpsba_138740310_34_163887_1092008_bd_lvl1.hh.slc.par
alpsba_138740310_34_163887_1092008_bd_lvl1.hh.slc.par
alpsba_138740310_34_163887_1092008_bd_lvl1.hh.slc.par

az_proc alpsba_138740310_34_163887_1092008_bd_lvl1.hv.sar.par
alpsba_138740310_34_163887_1092008_bd_lvl1.hv.slc.par
alpsba_138740310_34_163887_1092008_bd_lvl1.hv.slc.par
alpsba_138740310_34_163887_1092008_bd_lvl1.hv.slc.par

# 8th, generating the ISP parameter files.
par_MSP alpsba_138740310_34_163887_1092008_bd_lvl1.hh.sar.par
alpsba_138740310_34_163887_1092008_bd_lvl1.hh.slc.par
alpsba_138740310_34_163887_1092008_bd_lvl1.hh.slc.par
alpsba_138740310_34_163887_1092008_bd_lvl1.hh.slc.par

par_MSP alpsba_138740310_34_163887_1092008_bd_lvl1.hv.sar.par
alpsba_138740310_34_163887_1092008_bd_lvl1.hv.slc.par
alpsba_138740310_34_163887_1092008_bd_lvl1.hv.slc.par
alpsba_138740310_34_163887_1092008_bd_lvl1.hv.slc.par

# 9th, generating a file with the SLC extents.
SLC_corners alpsba_138740310_34_163887_1092008_bd_lvl1.hh.slc.par >
alpsba_138740310_34_163887_1092008_bd_lvl1.hh.slc.corners
SLC_corners alpsba_138740310_34_163887_1092008_bd_lev1.hv.slc.par > alpsba_138740310_34_163887_1092008_bd_lev1.hv.slc.corners

# 10th, generating SUN raster image of SLC intensity images. First, we need to get the number of samples in the SLC image

```bash
set rs = `grep range_pixels palpsba_138740310_34_163887_1092008_bd_lev1.hh.slc.par | cut -d : -f 1 --complement`
```

# and now we generate the SUN raster images (*.ras), averaged 10x in range and 10x in azimuth.

```bash
rasSLC alpsba_138740310_34_163887_1092008_bd_lev1.hh.slc "$rs" -- 10 10
rasSLC alpsba_138740310_34_163887_1092008_bd_lev1.hv.slc "$rs" -- 10 10
```

# Remove raw data

```bash
rm *ALPSRP*
rm *.rc
rm *.raw
```
APPENDIX FIVE

COMMENTED SCRIPT DESCRIBING THE SAR PROCESSING FROM LEVEL 1.1 (SLC) DATA (HH & HV) TO LEVEL 1.5 USING THE FACILITIES OF GAMMA SOFTWARE, FOR THE SCENE ‘ALPSRP138740310’.
#! /bin/csh
# Script to geocode ALOS SLC data
# Created by Joao Carreiras
# Modified by Dan Clewley 01/02/10 to run single scene only
# Modified by Dan Clewley 16/02/10 as template for BatchGamma.py
# The files that must be present are:
# - the DEM file, in big endian format, short integer, in the
  # projection we want the SAR to be geocoded to;
# - the DEM parameter file;
# - a default offset text file called "diff_par_in".
# The first step is to create a Multi-Look Image (MLI) from the SLC
# data. The number of looks in range and azimuth was set above.
# These are one look in range and five looks in azimuth.

multi_look alpsba_138740310_34_163887_1092008_bd_lev1.hh.slc
alpsba_138740310_34_163887_1092008_bd_lev1.hh.slc.par
alpsba_138740310_34_163887_1092008_bd_lev1.hh.mli
alpsba_138740310_34_163887_1092008_bd_lev1.hh.mli.par 1 5
multi_look alpsba_138740310_34_163887_1092008_bd_lev1 hv.slc
alpsba_138740310_34_163887_1092008_bd_lev1 hv.slc.par
alpsba_138740310_34_163887_1092008_bd_lev1 hv.mli
alpsba_138740310_34_163887_1092008_bd_lev1 hv.mli.par 1 5

# The second step is to generate a initial lookup table (LUT), that
# will tell us for each pixel of the DEM image which is the
# corresponding pixel in the SAR image. The file
# "galpsba_138740310_34_163887_1092008_bd_lev1 dem.par" contains all
# the parameters for the geocoded SAR data.

gc_map alpsba_138740310_34_163887_1092008_bd_lev1 hh.mli.par -
/data/ALOS/Belize/SRTM/SRTM_Belize ieee dem_par
/data/ALOS/Belize/SRTM/SRTM_Belize DEM.ieee
galpsba_138740310_34_163887_1092008 bd lev1 ddem.par
alpsba_138740310_34_163887_1092008 bd lev1 dem
alpsba_138740310_34_163887_1092008 bd lev1 rough geo to rdc 7 7
alpsba_138740310_34_163887_1092008 bd lev1 sim sar --
alpsba_138740310_34_163887_1092008 bd lev1 inc --
alpsba_138740310_34_163887_1092008 bd lev1 pix

# The third step is to refine the initial LUT, as the one produced
# in a previous step has locational errors and needs to be refined.
# Several procedures are needed to refine the LUT. a) We need to
# transform the region simulated SAR image from map to SAR geometry.
# To get the number of columns"(width) of the simulated SAR image in
# map geometry we can use, e.g., the command "grep width
galpsba_138740310_34_163887_1092008 bd lev1 dem.par". To get the
# number of samples of the simulated SAR image in SAR geometry we can
# use, e.g., the command "grep range samples
galpsba_138740310_34_163887_1092008 bd lev1 hh mli.par". For the
# resampling we can choose several methods, in this case we use
# nearest neighbour, and several image formats, in this case we choose
# float.

set w1 = `grep width
galpsba_138740310_34_163887_1092008 bd lev1 dem.par |cut -d : -f 1 --complement`
set rs1 = `grep range samples
galpsba_138740310_34_163887_1092008 bd lev1 hh mli.par |cut -d : -f 1 --complement`
To compute the offsets between the simulated SAR image and the actual SAR we apply a procedure similar to the co-registration of two SLC images for interferometry. First of all we need to generate a file (text file) in which the offsets will be stored (diff_par_in). To start with we accept all default values. As this command runs interactively, create a text file with the required values and then pass it to the command. In this case we will create first a file called "diff_par_in" with the required values, which is this case are the defaults:

```
#scene title: ?????
# range, azimuth offsets of image-2 relative to image-1 (samples):
#  0  0
# enter number of offset measurements in range, azimuth:  16  16
# search window sizes (32, 64, 128...) (range, azimuth):  256  256
# minimum matching SNR (nominal=6.5):      7.000
create_diff_par
alpsba_138740310_34_163887_1092008_bd_lev1.hh.mli.par -
 alpsba_138740310_34_163887_1092008_bd_lev1.sim.sar.sar
alpsba_138740310_34_163887_1092008_bd_lev1.diff_par 1 <
/media/ALOS/GAMMA/Essential_Files/diff_par_in
```

First guess of offsets (not required, but helpful in some cases). If the two images have small contrast, "init_offsetm" might lead to a wrong estimate of the constant offsets. It is therefore recommended to use this command with care.

```
init_offsetm alpsba_138740310_34_163887_1092008_bd_lev1.hh.mli
alpsba_138740310_34_163887_1092008_bd_lev1.sim.sar.sar
alpsba_138740310_34_163887_1092008_bd_lev1.diff_par >
alpsba_138740310_34_163887_1092008_bd_lev1.geocode_error.txt
```

Second, to find the local offsets we take windows all over the images and in each we compute the offset in range and azimuth by correlating the intensities. For the offset computation we apply a several-step procedure. The sequence offset_pwrm offset_fitm shall be run as many times as possible, playing with number of windows and window size.

```
offset_pwrm alpsba_138740310_34_163887_1092008_bd_lev1.hh.mli
alpsba_138740310_34_163887_1092008_bd_lev1.sim.sar.sar
alpsba_138740310_34_163887_1092008_bd_lev1.diff_par
galpsba_138740310_34_163887_1092008_bd_lev1_offs_hh
galpsba_138740310_34_163887_1092008_bd_lev1_snr_hh 128 128
galpsba_138740310_34_163887_1092008_bd_lev1_offsets_hh 8 32
offset_fitm galpsba_138740310_34_163887_1092008_bd_lev1_offs_hh
galpsba_138740310_34_163887_1092008_bd_lev1_snr_hh
alpsba_138740310_34_163887_1092008_bd_lev1.diff_par
alpsba_138740310_34_163887_1092008_bd_lev1.geocode_error.txt
```

```
offset_pwrm alpsba_138740310_34_163887_1092008_bd_lev1.hh.mli
alpsba_138740310_34_163887_1092008_bd_lev1.sim.sar.sar
alpsba_138740310_34_163887_1092008_bd_lev1.diff_par
galpsba_138740310_34_163887_1092008_bd_lev1_offs_hh
galpsba_138740310_34_163887_1092008_bd_lev1_snr_hh 128 128
galpsba_138740310_34_163887_1092008_bd_lev1_offsets_hh 16 64
```
offset_fitm galpsba_138740310_34_163887_1092008_bd_lev1_offs_hh
galpsba_138740310_34_163887_1092008_bd_lev1_snr_hh
galpsba_138740310_34_163887_1092008_bd_lev1.diff_par
galpsba_138740310_34_163887_1092008_bd_lev1.coffs_hh
galpsba_138740310_34_163887_1092008_bd_lev1_offsets_hh
alpsba_138740310_34_163887_1092008_bd_lev1_snr_hh
alpsba_138740310_34_163887_1092008_bd_lev1.diff_par
alpsba_138740310_34_163887_1092008_bd_lev1.coffs_hh
alpsba_138740310_34_163887_1092008_bd_lev1_coffs_hh
alpsba_138740310_34_163887_1092008_bd_lev1_coffsets_hh
alpsba_138740310_34_163887_1092008_bd_lev1.geocode_error.txt

# To refine the lookup table based on the offset polynomial. The new
refined lookup table (*.geo_to_rdc) contains now at each pixel (i.e.
map position) the correct position of a pixel in the SAR image. The
value "$w1" refers to the number of columns of the SAR image in map
geometry.
gc_map_fine
galpsba_138740310_34_163887_1092008_bd_lev1.rough.geo_to_rdc "$w1"
galpsba_138740310_34_163887_1092008_bd_lev1.diff_par
galpsba_138740310_34_163887_1092008_bd_lev1.geo_to_rdc 0

# Finally, to geocode the MLI images.
geocode_back alpsba_138740310_34_163887_1092008_bd_lev1.hh.mli
"$rs1" galpsba_138740310_34_163887_1092008_bd_lev1.geo_to_rdc
alpsba_138740310_34_163887_1092008_bd_lev1.hh.utm "$w1"
geocode_back alpsba_138740310_34_163887_1092008_bd_lev1.hv.mli
"$rs1" galpsba_138740310_34_163887_1092008_bd_lev1.geo_to_rdc
alpsba_138740310_34_163887_1092008_bd_lev1.hv.utm "$w1"

# Generate the SUN raster file (*.ras) for the MLI geocoded image.
raspwr alpsba_138740310_34_163887_1092008_bd_lev1.hh.utm "$w1" - -
10 10
raspwr alpsba_138740310_34_163887_1092008_bd_lev1.hv.utm "$w1" - -
10 10

# Remove files that are no longer needed
rm *.env
rm *.slc
rm *.slc.par
rm *.mli
rm *.mli.par
rm *.rough.geo_to_rdc
rm *.sar
rm *.dem
APPENDIX SIX

NAME AND DESCRIPTION OF THE EM SPECTRAL BANDS THAT ARE COLLECTED BY THE SPOT AND WORLDVIEW SENSORS ACCOMPANIED BY THE SPATIAL RESOLUTION FOR EACH BAND.
<table>
<thead>
<tr>
<th>Sensor</th>
<th>electromagnetic spectrum name</th>
<th>pixel size (m)</th>
<th>spectral bands (μm)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>SPOT 5</strong></td>
<td>Panchromatic</td>
<td>2.5 m or 5</td>
<td>0.48 - 0.71</td>
</tr>
<tr>
<td></td>
<td>B1: green</td>
<td>10</td>
<td>0.50 - 0.59</td>
</tr>
<tr>
<td></td>
<td>B2: red</td>
<td>10</td>
<td>0.61 - 0.68</td>
</tr>
<tr>
<td></td>
<td>B3: near infrared</td>
<td>10</td>
<td>0.78 - 0.89</td>
</tr>
<tr>
<td></td>
<td>B4: mid infrared</td>
<td>20</td>
<td>1.58 - 1.75</td>
</tr>
<tr>
<td><strong>WorldView I (WV-1)</strong></td>
<td>Panchromatic</td>
<td>0.5</td>
<td>0.397-0.905</td>
</tr>
<tr>
<td></td>
<td>Panchromatic</td>
<td>0.5</td>
<td>0.447 - 0.808</td>
</tr>
<tr>
<td></td>
<td>Coastal</td>
<td>2</td>
<td>0.396 - 0.458</td>
</tr>
<tr>
<td></td>
<td>Blue</td>
<td>2</td>
<td>0.442 - 0.515</td>
</tr>
<tr>
<td></td>
<td>Green</td>
<td>2</td>
<td>0.506 - 0.586</td>
</tr>
<tr>
<td></td>
<td>Yellow</td>
<td>2</td>
<td>0.584 - 0.632</td>
</tr>
<tr>
<td></td>
<td>Red</td>
<td>2</td>
<td>0.624 - 0.694</td>
</tr>
<tr>
<td></td>
<td>Red Edge</td>
<td>2</td>
<td>0.699 - 0.749</td>
</tr>
<tr>
<td></td>
<td>Near-IR1</td>
<td>2</td>
<td>0.765 - 0.901</td>
</tr>
<tr>
<td></td>
<td>Near-IR2</td>
<td>2</td>
<td>0.856 - 1.043</td>
</tr>
</tbody>
</table>
APPENDIX SEVEN

<table>
<thead>
<tr>
<th>Scene Name</th>
<th>Date Collected (Cycle 22)</th>
<th>Incidence angle Off-Nadir</th>
<th>Azimuth Size of Product</th>
<th>PALSAR Product</th>
<th>Datum and Projection</th>
<th>Number of Looks Level 1.5</th>
<th>Pixel Size Level 1.5</th>
<th>Data Meaning Level 1.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASPLSBA138740300</td>
<td>01/09/2008</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ASPLSBA138740310</td>
<td>01/09/2008</td>
<td></td>
<td></td>
<td>Fine Beam Dual (FBD)</td>
<td>NAD 27 UTM 16</td>
<td>4</td>
<td>12.6m</td>
<td>Power Intensity</td>
</tr>
<tr>
<td>ASPLSBA140490330</td>
<td>13/09/2008</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ASPLSBA140490340</td>
<td>13/09/2008</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ASPLSBA140490350</td>
<td>13/09/2008</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ASPLSBA141220320</td>
<td>18/09/2008</td>
<td>34.3</td>
<td>70Km</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ASPLSBA142970310</td>
<td>30/09/2008</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ASPLSBA142970330</td>
<td>30/09/2008</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ASPLSBA142970340</td>
<td>30/09/2008</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
APPENDIX EIGHT

ALOS PALSAR DATA ACQUIRED BY THE NASA ALASKA SATELLITE FACILITY
<table>
<thead>
<tr>
<th>Scene Name</th>
<th>Date Collected</th>
<th>PALSAR Product</th>
<th>Datum and Projection</th>
<th>Incidence Angle Off-Nadir</th>
<th>Azimuth Size of Product</th>
<th>Number of looks Level 1.5</th>
<th>Pixel size Level 1.5</th>
<th>Data Meaning Level 1.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALPSRP122840330</td>
<td>15/05/2008</td>
<td>Fine Beam Dual (FBD)</td>
<td>WGS84</td>
<td>4</td>
<td></td>
<td></td>
<td>12.5m</td>
<td>Power Intensity</td>
</tr>
<tr>
<td>ALPSRP136260330</td>
<td>15/08/2008</td>
<td>Fine Beam Dual (FBD)</td>
<td>WGS84</td>
<td>4</td>
<td></td>
<td></td>
<td>12.5m</td>
<td>Power Intensity</td>
</tr>
<tr>
<td>ALPSRP142970330</td>
<td>30/09/2008</td>
<td>Fine Beam Dual (FBD)</td>
<td>WGS84</td>
<td>4</td>
<td></td>
<td></td>
<td>12.5m</td>
<td>Power Intensity</td>
</tr>
<tr>
<td>ALPSRP230200330</td>
<td>21/05/2010</td>
<td>Fine Beam Dual (FBD)</td>
<td>WGS84</td>
<td>4</td>
<td></td>
<td></td>
<td>12.5m</td>
<td>Power Intensity</td>
</tr>
<tr>
<td>ALPSRP259520330</td>
<td>08/12/2010</td>
<td>Fine Beam Dual (FBD)</td>
<td>WGS84</td>
<td>4</td>
<td></td>
<td></td>
<td>12.5m</td>
<td>Power Intensity</td>
</tr>
<tr>
<td>ALPSRP270460330</td>
<td>21/02/2011</td>
<td>Fine Beam Single (FBS) HH</td>
<td>WGS84</td>
<td>34.3</td>
<td>70Km</td>
<td></td>
<td>Power Intensity</td>
<td></td>
</tr>
<tr>
<td>ALPSRP278553280</td>
<td>17/04/2011</td>
<td>Fine Beam Single (FBS) HH</td>
<td>WGS84</td>
<td>34.3</td>
<td>70Km</td>
<td></td>
<td>Power Intensity</td>
<td></td>
</tr>
<tr>
<td>ALPSRP278553290</td>
<td>17/04/2011</td>
<td>Fine Beam Single (FBS) HH</td>
<td>WGS84</td>
<td>34.3</td>
<td>70Km</td>
<td></td>
<td>Power Intensity</td>
<td></td>
</tr>
<tr>
<td>ALPSRP278553300</td>
<td>17/04/2011</td>
<td>Fine Beam Single (FBS) HH</td>
<td>WGS84</td>
<td>34.3</td>
<td>70Km</td>
<td></td>
<td>Power Intensity</td>
<td></td>
</tr>
<tr>
<td>ALPSRP263750320</td>
<td>01/06/2011</td>
<td>Fine Beam Single (FBS) HH</td>
<td>WGS84</td>
<td>34.3</td>
<td>70Km</td>
<td></td>
<td>Power Intensity</td>
<td></td>
</tr>
<tr>
<td>ALPSRP263750330</td>
<td>01/06/2011</td>
<td>Fine Beam Single (FBS) HH</td>
<td>WGS84</td>
<td>34.3</td>
<td>70Km</td>
<td></td>
<td>Power Intensity</td>
<td></td>
</tr>
<tr>
<td>ALPSRP263750340</td>
<td>01/06/2011</td>
<td>Fine Beam Single (FBS) HH</td>
<td>WGS84</td>
<td>34.3</td>
<td>70Km</td>
<td></td>
<td>Power Intensity</td>
<td></td>
</tr>
<tr>
<td>ALPSRP219260310</td>
<td>07/03/2010</td>
<td>Fine Beam Single (FBS) HH</td>
<td>WGS84</td>
<td>34.3</td>
<td>70Km</td>
<td></td>
<td>Power Intensity</td>
<td></td>
</tr>
<tr>
<td>ALPSRP223490330</td>
<td>05/04/2010</td>
<td>Fine Beam Single (FBS) HH</td>
<td>WGS84</td>
<td>34.3</td>
<td>70Km</td>
<td></td>
<td>Power Intensity</td>
<td></td>
</tr>
<tr>
<td>ALPSRP223490330</td>
<td>05/04/2010</td>
<td>Fine Beam Single (FBS) HH</td>
<td>WGS84</td>
<td>34.3</td>
<td>70Km</td>
<td></td>
<td>Power Intensity</td>
<td></td>
</tr>
<tr>
<td>ALPSRP223490330</td>
<td>05/04/2010</td>
<td>Fine Beam Single (FBS) HH</td>
<td>WGS84</td>
<td>34.3</td>
<td>70Km</td>
<td></td>
<td>Power Intensity</td>
<td></td>
</tr>
<tr>
<td>ALPSRP223490330</td>
<td>05/04/2010</td>
<td>Fine Beam Single (FBS) HH</td>
<td>WGS84</td>
<td>34.3</td>
<td>70Km</td>
<td></td>
<td>Power Intensity</td>
<td></td>
</tr>
<tr>
<td>ALPSRP223490330</td>
<td>05/04/2010</td>
<td>Fine Beam Single (FBS) HH</td>
<td>WGS84</td>
<td>34.3</td>
<td>70Km</td>
<td></td>
<td>Power Intensity</td>
<td></td>
</tr>
<tr>
<td>ALPSRP248213320</td>
<td>21/09/2010</td>
<td>Fine Beam Polarimetric (PLR)</td>
<td>WGS84</td>
<td>21.5</td>
<td>30Km</td>
<td></td>
<td>Power Intensity</td>
<td></td>
</tr>
<tr>
<td>ALPSRP248213320</td>
<td>21/09/2010</td>
<td>Fine Beam Polarimetric (PLR)</td>
<td>WGS84</td>
<td>21.5</td>
<td>30Km</td>
<td></td>
<td>Power Intensity</td>
<td></td>
</tr>
<tr>
<td>ALPSRP248213320</td>
<td>21/09/2010</td>
<td>Fine Beam Polarimetric (PLR)</td>
<td>WGS84</td>
<td>21.5</td>
<td>30Km</td>
<td></td>
<td>Power Intensity</td>
<td></td>
</tr>
<tr>
<td>ALPSRP248213320</td>
<td>21/09/2010</td>
<td>Fine Beam Polarimetric (PLR)</td>
<td>WGS84</td>
<td>21.5</td>
<td>30Km</td>
<td></td>
<td>Power Intensity</td>
<td></td>
</tr>
<tr>
<td>ALPSRP248213320</td>
<td>21/09/2010</td>
<td>Fine Beam Polarimetric (PLR)</td>
<td>WGS84</td>
<td>21.5</td>
<td>30Km</td>
<td></td>
<td>Power Intensity</td>
<td></td>
</tr>
<tr>
<td>ALPSRP248213320</td>
<td>21/09/2010</td>
<td>Fine Beam Polarimetric (PLR)</td>
<td>WGS84</td>
<td>21.5</td>
<td>30Km</td>
<td></td>
<td>Power Intensity</td>
<td></td>
</tr>
</tbody>
</table>