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An Uncertainty Analysis for Carbon Quantification from Above-Ground Tree Biomass: Predicting Uncertainties in Allometric Models in Canada and Sweden

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An Uncertainty Analysis for Carbon Quantification from Above-Ground Tree Biomass: Predicting Uncertainties in Allometric Models in Canada and Sweden

By

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DECLARATION OF CO-AUTHORSHIP / PREVIOUS PUBLICATION

I. Co-Authorship

I hereby declare that this thesis incorporates material that is result of joint research. This thesis was completed under the supervision of Dr. Rajeev Ruparathna and Dr. Jerald Lalman from the University of Windsor (Windsor Ontario, Canada) and Dr. Shareq Mohd Nazir from the KTH Royal Institute of Technology (Stockholm, Sweden). In all cases, the key ideas, primary contributions, designs, data analysis, interpretation, and writing were performed by the author. The contributions of the co-authors were primarily provision of the research ideas, feedback throughout the experimental design, review of the results, participation in discussions, and the refinement and editing of the manuscript.

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This thesis includes 2 original papers that will be published/submitted for publication in peer reviewed journals, as follows:

Thesis Chapter	Publication Title/Full Citation	Publication Status
Chapter [3]	Simulation-Based Uncertainty Analysis Methodology for Carbon Quantification from Above-Ground Tree Biomass Allometric Models in Canada and Sweden	*In Preparation*

Chapter [4]	Evaluating the Effects of Model Uncertainties on Carbon Quantified from Above-Ground Tree Biomass Models: Adjustments and implications for methodological and political decision-making	*In Preparation*

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ABSTRACT

In compliance with international commitments to address the increasingly urgent need to reduce greenhouse gas (GHG) emissions, countries prepare national GHG inventories (NGHGI). NGHGIs include annual estimates of anthropogenic GHG emissions and removals. Reliable data in NGHGIs are essential for creating effective climate change policies and mitigation strategies, determining compliance with internationally agreed-upon targets, and tracking the sources and trends of GHG emissions and reductions. The above-ground biomass (AGB) carbon pool from the forestry sector is expected to contribute largely to carbon reductions; however, data for this sector is highly uncertain due to quantification challenges. These uncertainties have adversely impacted the reliability of the climate mitigation strategies and policies based on this data. AGB is quantified mainly by employing a Tier 3 approach involving allometric models derived from forest inventory data. A review of published literature indicated a need for research on the methods used to quantify model uncertainties and the effects of these uncertainties on carbon estimates from AGB. This research employs a simulation-based uncertainty analysis to quantify model uncertainties in carbon estimates from AGB allometric models. The literature, manuals, and R software were used to develop the uncertainty analysis. Alternative uncertainty analysis approaches were proposed to determine their effects on the uncertainty estimates. Case studies were performed for study areas in Canada and Sweden to determine the feasibility of the uncertainty analysis method when used in different countries. The results of this study demonstrated how model uncertainties can be quantified using the proposed uncertainty analysis method, and how estimates can be adjusted for uncertainties. The uncertainty estimates did not differ significantly from using the alternative uncertainty analysis methods. The main causes of model uncertainty for both case studies were due to measurement uncertainty in the model input variables and residual uncertainty. Recommendations were made on how uncertainties can be reduced by prioritizing methodological and data collection improvements in these areas. The effects of uncertainties on climate change mitigation strategies and methods to incorporate uncertainty information into climate change policies were assessed.

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LIST OF ABBREVIATIONS

AGB	:	Above-Ground Biomass
ArcGIS	:	Aeronautical Reconnaissance Coverage Geographic Information System
B.C.	:	British Columbia
CO_2	:	Carbon Dioxide
COP	:	Conference of Parties
Dbh	:	Diameter at Breast Height
FLNRO	:	Forest, Lands, and Natural Resource Operations
GHG	:	Greenhouse Gas
Ht	:	Canopy Height
IPCC	:	Intergovernmental Panel on Climate Change
LULUCF	:	Land-Use, Land-Use Change, and Forestry
MCS	:	Monte Carlo Simulation
NDC	:	Nationally Determined Contribution
NGHGI	:	National Greenhouse Gas Inventory
PDF	:	Probability Density Function
SLU	:	Swedish University of Agricultural Sciences
TACCC	:	Transparency, Accuracy, Completeness, Comparability, Consistency
UN	:	United Nations
UNFCCC	:	United Nations Framework Convention on Climate Change
VRI	:	Vegetation Resource Inventory
WMO	:	World Meteorological Organization

1.0 INTRODUCTION

1.1 Background and Problem Statement

Despite accords established at the United Nations (UN) Conference of Parties (COP), commitments to reduce greenhouse gas (GHG) emissions and stabilize global temperature rise have not been on track to limit global warming (COP26 Explained, 2021; UNEP, 2022). The Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment report emphasized the need for a rapid decline in GHG emissions, as climate resilient developments will become increasingly limited if global warming levels exceed 1.5℃ (IPCC, 2022). Many countries acknowledged the urgency for climate action through commitments to achieve net-zero emissions within the next few decades (van Soest et al., 2021). For example, the Canadian government plans to transition to net-zero GHG emissions by 2050, and the Swedish government by 2045 (Canadian Institute for Climate Choices, 2021; Government Offices of Sweden Ministry of the Environment and Energy, 2018). However, policymakers are concerned with the feasibility of planning for net-zero amidst uncertainties in GHG emission and removal data (Canadian Institute for Climate Choices, 2021).

In compliance with the UN Framework Convention on Climate Change (UNFCCC), participating countries prepare annual national GHG inventories (NGHGI) that include estimates of anthropogenic GHG emissions by sources and removals by sinks (Environment and Climate Change Canada, 2022; United Nations, 1992). Reliable data in NGHGIs are essential for creating effective climate change policies and mitigation strategies, determining compliance with internationally agreed-upon targets, and tracking the sources and trends of GHG emissions and reductions (Gillenwater et al., 2007; Lee et al., 2014, Polish Academy of Sciences, 2015). However, NGHGI data are associated with varying degrees of uncertainty (Fortin, 2021; Ritter et al., 2010).

Uncertainties in the land-use, land-use change, and forestry (LULUCF) sector are larger and more challenging to quantify in comparison to others sectors mainly due to the complexity of the processes involved in the GHG fluxes (Fortin, 2021; McGlynn et al., 2022; Ritter et al., 2010; United Nations, 1992). These uncertainties may result in challenges enacting appropriate mitigation measures, policies, and tracking GHG reduction progress. This may undermine the confidence of emission reduction claims, particularly for the forestry sector, which is expected to contribute largely to GHG reductions (McGlynn et al., 2022).

The forestry sector is an area of importance that can be used to mitigate climate change by increasing carbon dioxide removals from the atmosphere or halting the loss of carbon stock from the land (UNFCCC, 2020). The more stringent GHG reduction targets rely heavily on land-based mitigation options. Researchers have reported that one-third of GHG reductions needed to prevent the most severe consequences of climate change can be provided by the LULUCF sector (Shukla et al., 2020; UN-REDD Programme, 2022). Above-ground biomass (AGB) is an important carbon pool in forest ecosystems that most carbon estimates are derived from, as the extent of AGB determines current and future carbon storage capacities (Fu et al., 2017). The scope of this research will address uncertainties in large-area carbon quantification from AGB in the forestry sector, as the quantification methods employed on this scale are used to determine estimates for NGHGIs. AGB is most commonly quantified using allometric models calibrated from forest inventory data (Návar, 2010). However, measuring the effects of model uncertainties on carbon estimates from AGB is challenging, prompting the need for research related to uncertainty analysis methods (McRoberts and Westfall, 2014; Qin et al., 2021; Wayson et al., 2015).

Uncertainty analysis is an important tool that is required by the IPCC and designated as a good practice to improve the reliability of NGHGI estimates (Lee et al., 2020; Ritter et al., 2010). Uncertainty analysis assesses and documents the causes of uncertainty in individual estimates and the overall total (Paciornik et al., 2019). The information provided by uncertainty analysis can be used to prioritize methodological and data collection improvements (Paciornik et al., 2019). Quantifying uncertainty estimates requires analysts to have a scientific and technical understanding of the carbon fluxes and the quantification methods associated with the system, as uncertainty analysis only provides reliable results if properly implemented (Frey et al., 2006). Hence, there is a need to assess if the IPCC’s guidelines for reporting uncertainties in NGHGI’s are sufficient when accounting for model uncertainties for complex systems, such as the forestry sector.

1.1.2 Knowledge Gaps

A comprehensive literature review was conducted to: investigate the sources of uncertainty in carbon from AGB quantification and the methods used to quantify these uncertainties, review the IPCC guidelines for uncertainty analysis and identify areas where improvements may be needed, and review studies on uncertainty analysis methods to identify alternative methods that may improve the precision of uncertainty estimates. The scope of the research was established based on the following knowledge gaps identified through the literature review:

1. **Quantifying the Effects of Model Uncertainties:** Carbon emissions and removals from the forestry sector are challenging to quantify. Models calibrated from forest inventory data are commonly used in large-area estimation (Návar, 2010). However, model uncertainty is complex and in practice are rarely quantified (McRoberts and Westfall, 2016; Metsaranta et al., 2017). Based on existing research, there is a need for more studies on quantifying the effects of model uncertainty on carbon estimates from AGB.
2. **Guidance on Implementing Simulation-Based Uncertainty Analysis Methods:** The IPCC recommends using Monte Carlo Simulation (MCS) to quantify uncertainties in complex systems, such as the forestry sector, where large uncertainties are expected (Frey et al., 2006). However, few countries have implemented simulation based uncertainty analysis methods (Monni et al., 2007). By reviewing existing guidelines for MCS, this research suggests that more guidance is needed on how to employ this method when quantifying uncertainties in models involving complex algorithms.
3. **Comparison of Alternative Uncertainty Analysis Methods:** Despite the growing literature on uncertainty analysis methods, guidelines for the use of MCS have not been updated since 2006 (Paciornik et al., 2019). Additional research is needed to assess how alternative uncertainty analysis methods impact uncertainty estimates, and if an alternative method can improve the precision of estimates.
4. **Improved Documentation of Uncertainty Analysis Methods:** Quantifying uncertainty estimates must be comparable between countries for NGHGIs to be used for policy purposes and to determine compliance with international

commitments (Gillenwater et al., 2007). Improved documentation can assist countries to better understand and replicate procedures for uncertainty analysis. Additional work is needed to clearly outline the procedure used to quantify model uncertainties per TACCC reporting principles and assess how these methods apply to different countries.

1.1.3 Objectives

This research suggests that improvements can be made in how uncertainty analysis methods are used in NGHGIs when quantifying model uncertainties to increase the reliability of uncertainty estimates, improve implementation, and comply with TACCC reporting principles. This research will assess and quantify the uncertainties in carbon estimation from AGB allometric models used in the forestry sector. The uncertainty analysis method proposed can be used by countries to adopt and improve uncertainty quantification, and better understand the effects of uncertainties. The following objectives are proposed in order to achieve the overall objective:

1. Assess the causes and the types of uncertainties associated with carbon quantification from AGB in the forestry sector.
2. Review the IPCC guidelines for conducting uncertainty analysis used in NGHGIs. Identify alternative uncertainty analysis methods that may better define uncertainties compared to the methods recommended by the IPCC.
3. Develop a methodology to quantify uncertainties in carbon estimates from AGB.
4. Conduct case studies to investigate how uncertainties can be quantified in carbon estimates from AGB using different uncertainty analysis approaches.
5. Evaluate the impacts of these uncertainties on carbon quantification from AGB.

1.2 Methodology

The objectives are achieved by following the methodology outlined in Figure 1.1.

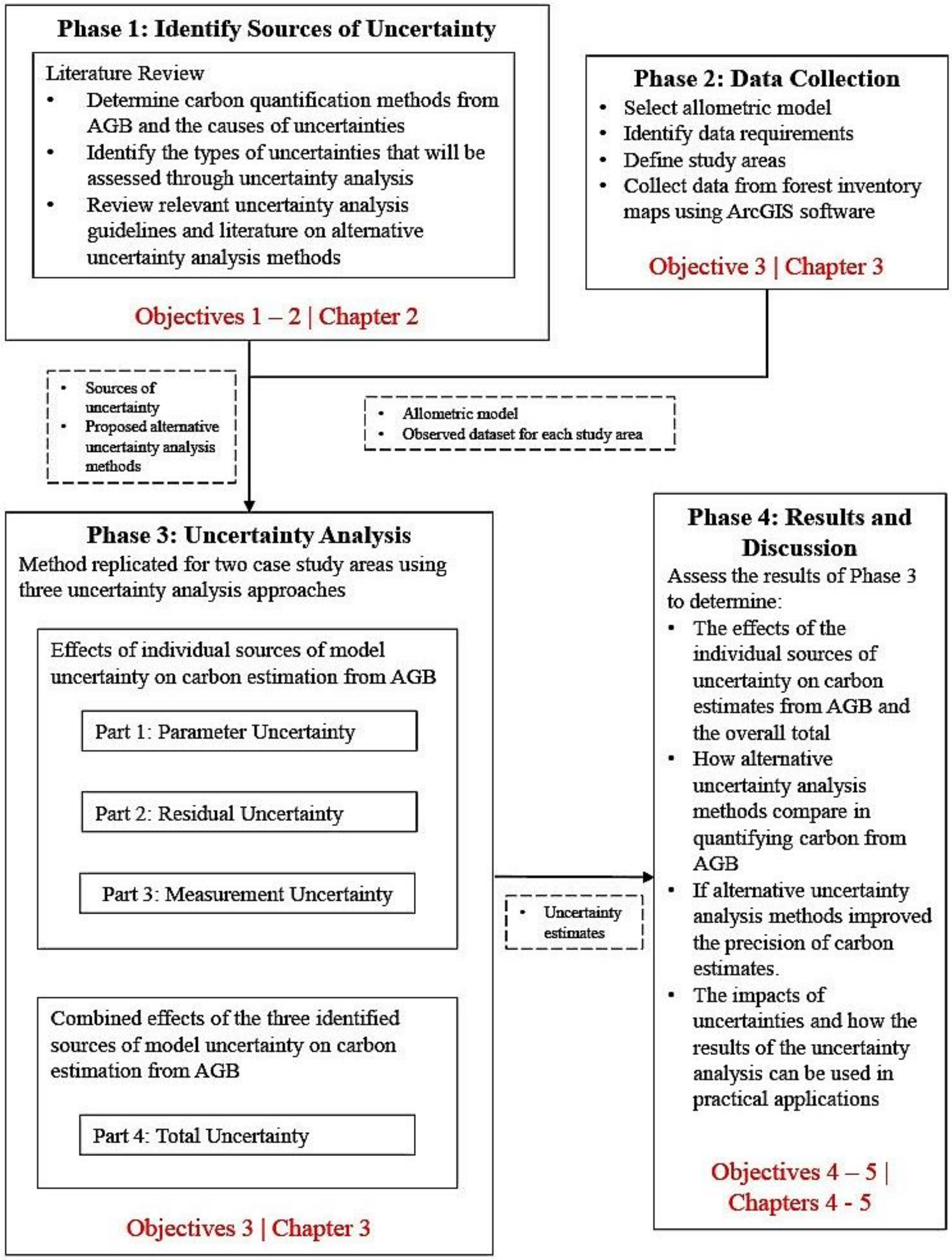

Figure 1.1 Overview of the research methodology

1.2.1 Phase 1: Identifying Uncertainties

Phase 1 consisted of an in-depth literature review which identified the challenges in quantifying carbon from AGB, and the associated sources of uncertainty. For large-area estimates used in NGHGIs, the most common method consists of deriving allometric models from forest inventory data that are obtained from direct measurements or remote sensing (Návar, 2010; Picard et al., 2012). The main sources of uncertainty in error analysis for forest inventories are from measurement, sampling, and model uncertainty (Cunia, 1965). Based on the literature, the scope of this study was to determine the causes and quantification of model uncertainty. The sources of model uncertainty are due to variances in model parameters, residual variance, and measurement error in the model input variables (Berger et al., 2014; Fu et al., 2017; McRoberts and Westfall, 2014, 2016; Qin et al., 2021). The uncertainty analysis procedure, including identifying alternative uncertainty analysis approaches, for analyzing uncertainties in carbon from AGB due to model uncertainty was formulated by reviewing guidelines from the IPCC and relevant literature. Phase 1 was concluded by identifying the sources of model uncertainties, and the proposed alternative uncertainty analysis approaches.

1.2.2 Phase 2: Data Collection

Phase 2 consisted of identifying the particular allometric model and the associated data needs. Case studies for an area in British Columbia (B.C.), Canada, and in Västernorrland County, Sweden, were proposed to determine the feasibility of the uncertainty analysis method when used in different countries. Data was collected from forest inventory maps. Phase 2 was concluded by constructing observed datasets for each of the study areas.

1.2.3 Phase 3: Uncertainty Analysis

Phase 3 consisted of a four-part uncertainty analysis. Parts 1 to 3 evaluated each individual source of model uncertainty and their effects on the estimation of carbon from AGB. Part 4 evaluated the combined effects of the sources of model uncertainty to calculate the overall effect on carbon from AGB quantification. The method was repeated for both study areas and for each of the alternative uncertainty analysis approaches identified in Phase 1.

1.2.4 Phase 4: Results and Discussion

Phase 4 consisted of assessing the results of the uncertainty analysis conducted in Phase 3. The results were compared to determine the effects of the individual sources of uncertainty on carbon estimates from AGB, and how results differed for the different study areas. This information was used to recommend methodological and data collection improvements in carbon quantification from AGB, and to assess the impacts of uncertainties on the creation of climate change mitigation strategies and policies. The alternative uncertainty analysis approaches were compared to determine how uncertainty estimates differed and if a method produced more precise estimates. This information was used to determine if recommendations could be made to the IPCC's guidelines for uncertainty analysis.

1.3 Thesis Organization

The thesis consists of five chapters with the following contents:

Chapter 1. Introduces the background, problem statement, and objectives of the research. The methodology followed to achieve the research objectives presented.

Chapter 2. Presents a comprehensive literature review that justifies the motivation for the research objectives.

Chapter 3. Describes the study systems and data collection methodology. An in-depth methodology of the four part uncertainty analysis method is presented.

Chapter 4. Presents the results of the uncertainty analysis conducted in Chapter 3. The results were interpreted to identify: (1) the main sources of uncertainty, (2) the effects of using alternative uncertainty analysis approaches, (3) the methodological and data collection improvements to reduce uncertainties, and (4) the effects of uncertainties on the creation of climate change mitigation strategies and policies.

Chapter 5. Summarizes the contributions of the research and discusses the limitations of the study and the opportunities for future work.

2.0 LITERATURE REVIEW

2.1 Introduction

Reliable greenhouse gas (GHG) emission and removal data in national GHG inventories (NGHGIs) are essential for planning climate action and policies. This research will investigate the causes and quantification methods for the uncertainties in carbon estimates from above-ground biomass (AGB). The following literature review will:

1. Discuss the need for GHG quantification and monitoring as it relates to current and foreseen challenges to climate change and existing global commitments.
2. Provide a background of GHG sources and sinks from the forestry sector to explain the significance of AGB quantification.
3. Discuss AGB quantification methods and the associated challenges contributing to uncertainties.
4. Identify sources of uncertainties in AGB quantification and review the literature on the methods used to quantify these uncertainties.
5. Review guidelines for uncertainty analysis provided by the Intergovernmental Panel on Climate Change (IPCC) to identify areas where improvements are needed.
6. Review the literature on alternative uncertainty analysis methods to identify methods that will be assessed in this study.

2.2 Overview of Greenhouse Gases and Climate Change

Climate change is one of the greatest challenges affecting many weather and climate extremes in every region across the globe (IPCC, 2021). The IPCC, established by the World Meteorological Organization (WMO) and the United Nations (UN) Environment, aims to provide authoritative and objective scientific and technical sources of information (IPCC, 2014b). According to reports by the IPCC, the scale of recent changes across the climate system as a whole and the present state of many aspects of the climate system are unprecedented over many centuries to many thousands of years (IPCC, 2021). Human influence has unequivocally contributed to atmospheric warming (IPCC, 2021). Anthropogenic GHG emissions have increased significantly since the pre-industrial era (IPCC, 2014b). GHGs absorb heat in the atmosphere and re-release is as infrared radiation back to the Earth’s surface (United Nations, 1992). Therefore, mean global temperature rise increases along with increases in the concentration of GHGs in the Earth's atmosphere (IPCC, 2014b). Climate change is a threat multiplier that will continue to impact human and natural systems, as the severity of adverse impacts is predicted to increase with increases in global temperatures (IPCC, 2018). The IPCC's Sixth Assessment Report found that climate resilient developments are increasingly limited if GHG emissions do not rapidly decline, especially if global warming levels exceeds 1.5˚C in the near-term (IPCC, 2022). Developments may not be possible in some regions and sub-regions if global warming levels exceed 2˚C (IPCC, 2022). Limiting climate change would require strong and sustained reductions in GHG emissions globally, including a decline of anthropogenic CO_2 emissions by approximately 45% from 2010 levels by 2030, reaching net zero by 2050, while also reducing net non-CO_2 radiative forcing (IPCC, 2018, 2021). This would require rapid and far-reaching transitions, prompting the need for strengthened global responses (IPCC, 2014, 2018).

2.3 A Brief History of Global Responses to Climate Change

The UN first recognized climate change as global concern at The Rio de Janeiro Earth Summit in 1992 (Council on Foreign Relations, 2022). The summit resulted in some of the first international agreements on climate change that would become the foundation for future accords, including the United Nations Framework Convention on Climate Change (UNFCCC) (Council on Foreign Relations, 2022). The UNFCCC acknowledges human activities have substantially increased atmospheric GHG emissions that have caused temperatures to rise in the Earth's surface and atmosphere, adversely affecting natural ecosystems and humankind. (United Nations, 1992). The UNFCCC calls for cooperation between all countries, and their participation in effective and appropriate international responses to climate change, with respect to the capabilities of individual countries (United Nations, 1992). This requires frequent meetings between ratifying countries, leading to the formation of the Conference of Parties (COP) (Council on Foreign Relations, 2022). The ultimate objective of the UNFCCC along with legal agreements adopted by the COP is to stabilize GHG concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system (United Nations, 1992). Strategies to mitigate climate change require accurate GHG emission and removal data that can be used to plan, analyze, validate, and at a global scale verify mitigation efforts while analyzing future scenarios (Ometto et al., 2014). Commitments in achieving this objective include the development of NGHGIs of anthropogenic emissions by sources and removals by sinks of all GHGs not controlled by the Montreal Protocol, using methodologies developed by the IPCC (IPCC, 1996; United Nations, 1992). However, as of 1994 the UNFCCC did not legally bind signatories to reduce GHG emissions, and no targets or timetables were established (Council on Foreign Relations, 2022).

The Kyoto Protocol in 1998, and the Paris Agreement in 2015 aimed to strengthen global response to climate change under the UNFCCC (UNFCCC, 2016; United Nations, 1998). The Kyoto Protocol was the first legally binding climate treaty: however, this protocol did not compel developing countries to take action (Council on Foreign Relations, 2022). The Paris Agreement is significant compared to previous accords, as it requires many countries to commit to common and ambitious efforts to combat climate change and adapt to its effects (Council on Foreign Relations, 2022; IPCC, 2014b; UNFCCC, 2016). This emphasizes the urgent need to maintain increases in the global average temperature well below 2℃ above pre-industrial levels while pursuing efforts to limit the temperature increase to 1.5℃ above pre-industrial levels (UNFCCC, 2016). Under the Paris Agreement, countries prepare, communicate, and maintain successive nationally determined contributions (NDCs) (United Nations, 2015). NDCs are a countries plan to achieve the goals of the Paris Agreement and may include strategies, actions, and mitigation targets for reducing GHG emissions (UNFCCC, 2021). NGHGIs are significant when setting and measuring the progress of each country's NDC, as well as supporting domestic climate policy development and evaluation (McGlynn et al., 2022). This is significant in decision making and adaptive governance to create common understanding and advance the effectiveness of policies (Shukla et al., 2020).

2.4 Carbon Sources and Sinks in the Forestry Sector

The forestry sector is an area of importance that can be used to mitigate climate change by increasing carbon removals from the atmosphere or halting the loss of carbon stock from land (UNFCCC, 2020). Forests are carbon sinks if more carbon is absorbed from the atmosphere than released (Natural Resources Canada, 2007). This can be achieved through carbon sequestration, a process in which carbon is removed from the atmosphere and stored into carbon pools (Ravin and Raine, 2007). Emissions can be decreased through conserving sinks, as a loss of carbon is equivalent to an emission (Bird et al., 2011). Additionally, the removal of carbon from the atmosphere through sinks can be considered as a negative emission (Bird et al., 2011). Due to the high mitigation potential the more stringent GHG reduction targets rely heavily on land-based mitigation options, as up to one-third of GHG reductions needed to prevent the most severe consequences of climate change can be provided by the land use, land-use change, and forestry (LULUCF) sector (UN-REDD Programme, 2022). Ninety percent of the second-generation of NDCs included the foretsry sector, and 57% referred specifically to forests as domestic options for GHG reduction (UNDP, 2021; UN-REDD Programme, 2022).

Although the forestry sector is able to remove carbon dioxide (CO_2) from the atmosphere, the main drawbacks are the potential loss of carbon and release of GHGs to the atmosphere as a result of human activities and natural disturbances (UNFCCC, 2020). Forests are sources of carbon if more carbon is released than absorbed (Natural Resources Canada, 2007). Carbon can be released through management practices, decay, disturbances (such as fires), and respiration (Natural Resources Canada, 2007; Salomón et al., 2017).

The net balance between carbon emissions and removals determines whether a forest is a carbon source or sink. However, this can be difficult to quantify due to the complexity of the processes involved in carbon flows, and the numerous factors that contribute to carbon stock changes.

2.4.1 Significance of Above-Ground Biomass as a Carbon Pool

The IPCC categorizes carbon stock changes according to the following three carbon pools: biomass (above-ground and below-ground biomass), dead organic matter (deadwood and litter), and soil organic matter (Paustian et al., 2006). AGB consists of biomass in all living vegetation above soil including, stems, branches, bark, seeds and foliage, making AGB the largest visible carbon pool in forest ecosystems (Aalde et al., 2006). Forest carbon stock estimates are mainly derived from AGB (Fu et al., 2017), making AGB an important variable for determining carbon sequestration in forest ecosystems, as the extent of AGB determines current and future carbon storage capacities.

The effects of human activities, natural disturbances, and climate change can have a rapid and large influence on carbon uptake through AGB, with the potential to convert many ecosystems that are currently carbon sinks into sources (Hoover and Smith, 2023; IPCC, 2022b; Li et al., 2022, 2020). This study will focus on assessing the uncertainties in AGB estimation, as reliable AGB estimates are crucial in quantifying and monitoring carbon stock changes in forests.

2.5 Uncertainties in Quantifying Carbon from Above-Ground Biomass

The methods and data used to quantify GHG emissions and removals employed by the IPCC is a three-tiered approach in which higher tiers have higher complexities (Michael et al., 2019). Tier 1 methods, the simplest approach, employs equations and default parameters (such as globally available emission factors) (Michael et al., 2019; Ogle et al., 2019). Tier 2 methods employ the same methods as Tier 1, only default data is replaced partially or entirely by country-specific data (Michael et al., 2019; Ogle et al., 2019). Tier 3 methods are advanced systems that use country specific data, measurements, and/or modeling (IPCC, 2003; Ogle et al., 2019). The IPCC guidelines provide minimal general guidance on Tier 3 methods, as measurements and models are tailored for specific national circumstances (Federici and Grassi, 2011). Therefore, the IPCC does not recommend or limit the selection of Tier 3 sampling schemes or modeling methods; but instead provides general guidance to assist in implementing Tier 3 methods (Ogle et al., 2019). Defining the quantification approach is important for managing the overall inventory uncertainty (UNFCCC, 2022). Although Tier 2 and 3 methods produce more reliable estimates, the complexities of these approaches introduce more potential sources of uncertainty. There is a need for uncertainty analysis methods that address the individual sources of uncertainty, and their impacts on the total uncertainty, to validate the reliability of emission estimates.

2.5.1 Carbon Quantification Methods from Above-Ground Biomass

The carbon content in all plants organisms is generally assumed to account for 50% of the total plant biomass (Kurz et al., 2009; Matthews, 1993; Morhart et al., 2016; Pretzsch, 2010). This assumption has been supported by several studies such as Pretzsch (2010) who suggested that carbon content can be calculated using volume tables, density and a general conversion factor. Matthews (1993) reviewed methods for the direct analysis of carbon, estimations for constituent compounds whose carbon contents are known, and estimation from destructive distillation data to identify the carbon content of trees. The results from these studies found that the carbon content tends to cluster around 49% to 51% with slight variations depending on tree species. In comparison, Matthews (1993) concluded that when considering uncertainty, assuming carbon content to be 50% of the total plant biomass is a reasonable assumption. The challenging aspect of measuring carbon content is the estimation of biomass.

Although the IPCC provides default parameters and methods to employ a Tier 1 quantification approach, the Tier 2 and 3 approaches are preferred because they provide more reliable estimates for relatively large fluxes in AGB, particularly on a national or large-scale where forest inventories are available (Aalde et al., 2006; Picard et al., 2012). Calculating AGB is most accurate when based on field measurements; however, sampling is costly, time-consuming, and destructive, making this method impractical for large scale estimation (Huynh et al., 2021; Li et al., 2020; Picard et al., 2012; Qin et al., 2021). The standard method of quantifying AGB is through the development and application of allometric models using forest inventory data (Návar, 2010). Allometric models use variables that are easily measured to make predictions for more challenging to measure variables, such as AGB (Návar, 2010; Picard et al., 2012). Models can be calibrated using measurements from remote sensing technology, such as high resolution satellite images, low resolution aerial photographs or sensors, in conjunction with field measurements to validate estimates (Picard et al., 2012). Remote sensing has become increasingly common, as this method is less time intensive, costly, destructive, and requires less manual work, while covering large areas, including inaccessible areas (Turton et al., 2022). On a national or large-scale, individual tree measurements are estimated as mean values within a plot, and plot-level estimates are averaged and expressed as a mean value per area (Fu et al., 2017; McRoberts and Westfall, 2016; Picard et al., 2012).

2.5.2 Sources of Uncertainty in Quantifying Carbon from Above-Ground Biomass

When referring to error analysis in forest inventories, many studies refer to Cunia's (1965) classification of the main sources as follows: measurement, sampling, and model uncertainty (Berger et al., 2014; Fu et al., 2017; Qin et al., 2019, 2021). The contributions of the different sources of uncertainty may differ for different study systems, and would need to be evaluated on a case-by-case basis. Assessing the individual sources of uncertainty and their overall impact on AGB estimation is essential for identifying and prioritizing methodological and data collection improvements. The following section will review published literature on the sources of uncertainties in AGB quantification to identify research needs and define the scope of this study.

Measurement error refers to the uncertainty in the forest inventory data that are used in AGB allometric models to predict carbon (Qin et al., 2019). Many factors contributing to measurement errors, include the influences of measurement methods, techniques, technology, and natural variations (McRoberts et al., 1994; Qin et al., 2019, 2021). For example, when remote sensing is employed the accuracy of measurements is affected by the efficiency of the technology used and the ability to differentiate forest types (Picard et al., 2012; Skovsgaard et al., 1998). Estimates can be hindered by cloud cover and are susceptible to saturated signals for certain vegetation types (Picard et al., 2012). For field measurements, errors may occur due to variations in the instruments used, divergences in tape placements when manually measuring, recording errors, and differences in sampling techniques and skills (Elzinga et al., 2005; McRoberts et al., 1994; Qin et al., 2019; Williams et al., 1994). Variations in measurements can occur naturally due to differences in a variable among a subject that would otherwise be considered similar (McRoberts et al., 1994). For example, a variation in tree diameter at breast height (Dbh) can occur naturally for a tree species but may appear as an outlier in an otherwise uniform dataset. Several studies have assessed the impacts of measurement errors due to differing quantification techniques and under various conditions (Elzinga et al., 2005; McRoberts et al., 1994; Persson et al., 2022; Westfall and Patterson, 2007; Williams et al., 1994). The effects of measurement errors on the uncertainty in carbon estimation from AGB are a less researched topic; however, this concern is becoming increasingly important in validating estimates. Accurately and precisely estimating the uncertainty in a response variable as a result of predictor variables is challenging according to work by Qin et al. (2019) and Wang et al. (2009). Berger et al. (2014) outlined a procedure to construct measurement error models from forest inventory data using a method by Hosmer and Lemeshow (1989). This method has been used in studies by Qin et al. (2019, 2021) and Shettles et al. (2015) to quantify measurement error in AGB estimation. Despite the research on this topic, very few generalizations are possible, as the effects of measurement error need to be assessed on a case-by-case basis (McRoberts and Westfall, 2016).

Sampling errors are the uncertainty caused by extrapolating data from sample plots distributed over an area to predict data for a larger unknown area (Breidenbach et al., 2014; Melo et al., 2018). Factors such as the sampling plot size, the sample size of the plots, and the heterogeneity of the landscape can affect sampling-related uncertainty (Qin et al., 2021). According to Berger et al. (2014), national forest inventories often consider only the uncertainty from sampling variability. Several studies have assessed the impacts of sampling error on AGB estimation, individually or in conjunction with modeling error (Breidenbach et al., 2014; Butt et al., 2013; Fu et al., 2017; Melo et al., 2018; Qin et al., 2021; Ståhl et al., 2014). Ståhl et al. (2014) has argued that the methods suggested in the IPCC's Good Practice Guidance for the LULUCF sector (IPCC, 2003) do not apply to sample surveys used in national forest inventories, and combining the effects of sampling and model errors is very complex, thus proposing a new uncertainty analysis method. Based on arguments by Ståhl et al. (2014), an alternative method was proposed by Fu et al. (2017). In comparison to work by Ståhl et al. (2014), Fu et al. (2017) proposal was more effective at separately quantifying sampling and modeling uncertainty with higher prediction accuracy. Fu et al. (2017) concluded that more studies should focus on reducing the effects of model error and improving model performance to reduce uncertainties and increase the accuracy of AGB predictions. Sampling errors have a considerable effect on the reliability of AGB estimates: however, based on existing research, methods to quantify this uncertainty source are well-defined, whereas there is a need for more studies on the effects of model errors.

In practice, model uncertainties are rarely quantified (McRoberts and Westfall, 2016; Metsaranta et al., 2017). Model error refers to the uncertainty caused by the deficiency of the AGB allometric model to predict carbon (Qin et al., 2021). Model uncertainties arise mainly due to the choice of the allometric model, the values of the predictor variables, residual variability, and model parameter estimates (McRoberts and Westfall, 2014; Qin et al., 2021). Carbon from AGB is commonly quantified from existing generalized allometric models when local models are unavailable, but these rarely include an assessment of uncertainty and guidance for the appropriate application, particularly when the models used were derived decades ago (Wayson et al., 2015). Assessing model uncertainty becomes challenging when there is a lack of information about the model fit statistics (i.e., fit parameters' confidence intervals, R2, n, etc.) and the original raw data used to derive these models (Wayson et al., 2015). Although Wayson et al. (2015) proposed a method to generate pseudo-data from incomplete fit statistics to assess parameter uncertainty, they recommend using this method only if there are no other possible options to recover information for the allometric models used. Rather than assessing the uncertainty in existing models, studies by McRoberts and Westfall (2016) and Qin et al. (2021) demonstrated how to derive allometric models for a study area and quantify the associated model uncertainty. Due to the challenges in recovering fit statistics for existing allometric models, the work in this thesis will follow a similar procedure. Several studies have compared the performance of different forms of allometric models when predicting AGB (Balbinot et al., 2018; Fradette et al., 2021; Mensah et al., 2017; Mugasha et al., 2016; Qin et al., 2021; Sadono et al., 2021; Segura et al., 2006; Shettles et al., 2015). Conclusions from these studies will be used to select the form of the allometric model: therefore, the uncertainty from model misspecification will not be assessed in this study. McRoberts and Westfall (2014) confirmed that all parameters in AGB models are influenced by measurement errors that should be considered when assessing the uncertainty in AGB predictions. Therefore, measurement error will be assessed as it relates to the uncertainty in the model input variables.

Although Qin et al. (2021) emphasized that AGB has been widely investigated, further studies are required to determine which uncertainties contribute the most to overall errors. The contribution of uncertainty sources differ between countries due to differences in measurements, input variables, and methods (Qin et al., 2021). This study will contribute to research on uncertainties in carbon estimates from AGB by demonstrating a procedure to quantify model uncertainties from allometric models. The results can be used to identify and prioritize methodological improvements. Model uncertainties for study areas in Canada and Sweden will be assessed to demonstrate how this procedure can be employed in different countries and how the contributions from sources of uncertainty differ.

2.6 Uncertainty Analysis Methods

Uncertainty analysis is an important tool that can be used to produce a quantitative estimate of the interval of a measured value within which the true value with a given confidence is expected to reside (Wells, 1992). The information provided by uncertainty analysis can be used to determine the reliability of estimates, and prioritize methodological and data collection improvements (Paciornik et al., 2019).

Uncertainty analysis methods that are most commonly used based on IPCC recommendations are propagation of error and Monte Carlo Simulation (MCS) (Paciornik et al., 2019). As shown in Table 2.1, there are many benefits to MCS in comparison to error propagation. MCS can handle both simple and complex models in which correlations may occur and uncertainties may differ for different years, resulting in more detailed and reliable analysis.

Table 2.1 Comparison of the Uncertainty Analysis Approaches Recommended by the IPCC

Approach 1: Error Propagation	**Approach 2: Monte Carlo Simulation**
Works well if uncertainties are relatively small, symmetric and follow normal distribution	Works well if uncertainties are large, follow a non-normal distribution, involve complicated algorithms, and vary over time
Standard Deviation/Mean < 0.3	Detailed category-by-category assessment method
Simple Approach • Assessment can be completed using a spreadsheet and simple equations provided in the IPCC guidelines	Complex Approach • Assessment requires specialized software • Requires shape of probability density function (PDF), however; identifying which function best fits a set of data can be difficult
Difficult to assess correlations	Able to assess varying degrees of correlation

Sources: (Frey et al., 2006; Grassi et al., 2016; Paciornik et al., 2019; Tanabe, 2016)

In practice MCS should be used for Tier 2 and 3 quantification methods, particularly for complex systems in the LULUCF sector where large uncertainties are expected (Frey et al., 2006). However, this is not always the case. Within the past decade, simulation-based uncertainty analysis methods have only been implemented in some countries. For example, in the European Union only 8 countries use MCS for uncertainty estimates (Monni et al., 2007). This is likely due to implementation challenges such as high data requirements, the time needed to conduct simulations, and the complexity of the model and results (Fauser et al., 2012; Molina-Castro, 2022; Monni et al., 2007).

Quantifying uncertainty estimated using MCS requires analysts to have a scientific and technical understanding of GHG fluxes and the quantification methods associated with the system, as MCS only provides reliable results if properly implemented (Frey et al., 2006). However, the guidelines provided by the IPCC are very general. The IPCC's 2006 Guidelines for National Greenhouse Gas Inventories Volume 1 Chapter 3 on Uncertainties, the Good Practice Guidance and Uncertainty Management in National Greenhouse Gas Inventories Chapter 6 "Quantifying Uncertainties in Practice" and the Good Practice Guidance for Land Use, Land-Use Change and Forestry Chapter 5 "Cross-Cutting Issues" provide similar guidance for MCS. This process consists of specifying uncertainties in input variables, constructing probability density functions (PDFs), and using readily available statistical software packages to conduct simulations and calculate uncertainties (Frey et al., 2006; IPCC, 2001a; Paciornik et al., 2003). An example of this process is shown in Figure 2.1.

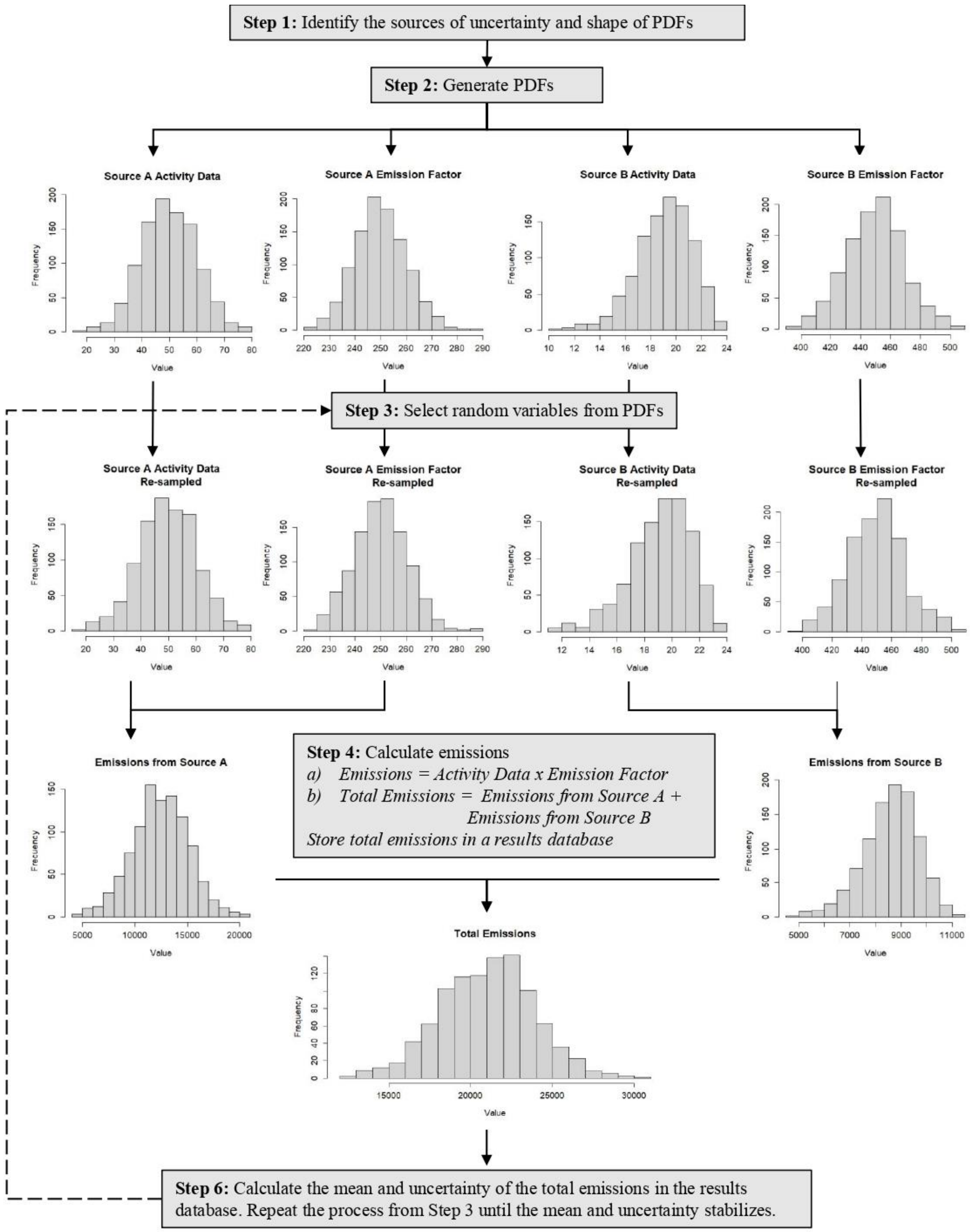

Figure 2.1 Example of Monte Carlo method for uncertainty analysis in GHG quantification. Information source: (Frey et al., 2006)

The IPCC does not provide guidance on how to implement this approach when accounting for model uncertainties that involve complex algorithms. For example, when calculating the uncertainty in model parameters, the model is re-fit, and parameters are re-calculated for each iteration after varying the input data. Most commercially available software packages follow a simple procedure similar to the procedure shown in Figure 2.1. However, this procedure and may not be capable of processing the method required to calculate model uncertainties. The IPCC recommends conceptualizing model uncertainties by (1) qualitatively discussing the implications of uncertainties in estimates obtained by the model; (2) comparing the model results with independent data to verify the accuracy of results; (3) comparing the results of the model to the results of alternative models; and (4) providing estimates based on expert judgment (Frey et al., 2006). No amendments were made to guidelines related to uncertainties associated with models and methods for MCS in the 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (Paciornik et al., 2019). Limited guidance is provided on how to quantitatively assess model uncertainties. Point (2) faces limitations in data availability as models for AGB are mainly used to represent large areas for which measurements can be challenging to obtain and may also be subject to uncertainties, and point (3) would only provide information on how a model compares to another model that may also be uncertain, rather than accounting for the uncertainties in the individual model. These guidelines are insufficient when quantifying model uncertainties using simulation-based uncertainty analysis methods and research is needed to demonstrate how to quantify uncertainties for models involving complex algorithms.

Individual countries are responsible for ensuring that uncertainty analysis methods are documented by following the TACCC reporting principles (Goodwin et al., 2019). These principles ensure the reporting of NGHGIs are transparent, accurate, complete, comparable, and consistent between countries (UNFCCC, 2022). However, numerous challenges exist in implementing consistent methods across different countries, especially when the methods used are not well documented. Very few countries report uncertainties systematically (IPCC, 2001b). Quantifying uncertainty estimates must be comparable between countries for NGHGIs to be used for policy purposes and to determine compliance with international commitments (Gillenwater et al., 2007). There is a need to clearly outline the procedure used to quantify model uncertainties as per the TACCC reporting principles and assess how these methods apply to different countries.

Another criticism is a conflict between IPCC guidelines and the latest peer reviewed literature (Yona et al., 2022). Despite the growing literature on the topic of uncertainty analysis methods, guidelines for using MCS have not been updated since 2006 (Paciornik et al., 2019). One possible explanation is the IPCC does not want to recommend alternative uncertainty analysis methods that may be less well-tested when compared to MCS (Yona et al., 2022). Incorporating recent information into existing guidelines require more research to validate alternative uncertainty analysis approaches or improvements to MCS. Literature comparing alternative uncertainty analysis methods to those recommended by the IPCC were reviewed in Table 2.2. Many of the studies presented in Table 2.2 compared the precision of the uncertainty estimates quantified using different uncertainty analysis approaches to determine a preferred approach. Since the true value of the uncertainty estimates are unknown, the accuracy cannot be compared. However, the precision of the estimates, which refers to the closeness between estimates, is compared mainly in terms of variance (Fortin, 2021). In some studies, factors such as the number of simulations and the assumptions required were accounted for when determining the preferred uncertainty analysis approach.

Table 2.2 Alternative Uncertainty Analysis Methods used in Literature

Source	**Sector**	**Uncertainty Analysis Methods**											
		MCS	**Propagation-based**	**Naïve**	**MCS W/ CTV**	**Goodman' s Estimator**	**Bootstrap**	**Block Bootstrap**	**LHS**	**Bayesian**	**RPEM**	**HPEM**	**Fuzzy Theory**
(Fortin, 2021)	GHG (Biomass & Peat)	X	X	X		**X**							
(Lee et al., 2020)	GHG (Agriculture)	X					**X**						
(Lee et al., 2017)	GHG (Agriculture)	X						**X**					
(Yu et al., 2001)	Rainfall runoff-model	X							**X**		X	X	
(Park et al., 2019)	GHG (Agriculture)	X			**X**								
(Camacho et al., 2015)	Hydraulic & Hydrodynamic Model	X								X			
(Doctor et al., 1988)	Groundwater Flow Model	X							**X**				
(Romano et al., 2004)	Air Emission Data	X					X						X
(Salway, 2010)	GHG (All Sectors)	**X**	**X**				**X**		**X**				
(Fauser et al., 2012)	GHG (All Sectors excl. LULUCF)	**X**	X										
(Garcia-Alfonso and Cordova-Esparza, 2018)	Camera Calibration Model	X							**X**				
(Kim and Bahadory-Jahromi, 2017)	Building Simulation Model	X											**X**
(McCandles and Gustafson, 2017)	Heart Failure Data	X								**X**			

Conclusions based on the comparison shown in Table 2.2 are described in the following statements. In most cases, an alternative uncertainty analysis approach was preferred in comparison to MCS, except for disagreements reported by Salway (2010) and Frauser et al. (2012). The comparison by Salway (2010) found that MCS performed similarly to the LHS and Bootstrap methods. According to Salway (2010) and Frauser et al. (2012) MCS was preferred compared to error propagation. However, these findings lacked consistency. For example, Camacho et al. (2015) reported no significant difference between MCS and Bayesian methods: however, McCandless and Gustafson (2017) reported Bayesian as the preferred method. Lee et al. (2020) found bootstrapping to be preferred when compared to MCS: however, Salway (2010) and Romano et al. (2004) found the results for both methods to be similar. An important note to consider is that each comparison was for one or a few study systems, with different quantification methods and limited data points. To assess the effects of alternative uncertainty analysis methods on the estimated uncertainties, uncertainty analysis methods incorporating MCS, bootstrap, and Bayesian bootstrap will be investigated in this thesis.

2.6.1 Monte Carlo Simulation

For decades, Monte Carlo methods have been commonly and successfully used to predict uncertainties (Johansen, 2010). Contrary to the usual problem of statistics, rather than estimating random quantities in a deterministic manner, MCS employs random quantities to establish deterministic estimates (Johansen, 2010). This procedure is performed by defining input domains, such as probability density functions (PDFs), for the sources of uncertainty (Hayes, 2011; Shreider et al., 1966). PDFs can be derived from repeatedly measuring a process, theoretical arguments, and/or expert judgment (Hayes, 2011). Using the principles of statistical interference random numbers are generated from these PDFs and used to establish approximations for an unknown quantity (Hayes, 2011; Johansen, 2010).

The theoretical justification for establishing the MCS procedure works can be explained by evaluating the integral shown in Equation 2.1, which represents the expectation of the function $h(x)$ of the random variable X, under the probability density

$f(x)$, in which χ is the input domain from where the random variable takes its value (Hayes, 2011; Robert and Casella, 2004a).

$$\mathbb{E}_f[h(X)] = \int h(x)f(x)\, dx \tag{2.1}$$

A Monte Carlo estimate is determined from repeatedly sampling random numbers x_j from the distribution $f(x)$, and using the sampled dataset x_j to calculate a value for $h(x_j)$, in which $h(x_j)$ is a possible outcome of the function $h(x)$ (Hayes, 2011). For each iteration in which this process is completed an average value of $h(x_j)$ is calculated according to Equation 2.2 (Robert and Casella, 2004a).

$$\bar{h}_n = \frac{1}{n} \sum_{\mathrm{j=1}}^{\mathrm{n}} \mathrm{h(x_j)} \tag{2.2}$$

The most elementary Monte Carlo method is justified by employing two theorems (Johansen, 2010). According to the Strong Law of Large Numbers, $\bar{h}_n$ converges to $\mathbb{E}_f[h(X)]$, and based on the Central Limit Theorem, if h^2 has finite expectation under f, $\bar{h}_n$ converges in distribution to a normal distribution centered at $\mathbb{E}_f[h(X)]$ with variance v_n that can be calculated using Equation 2.3 (Johansen, 2010; Robert and Casella, 2004a).

$$v_n = \frac{1}{n^2} \sum_{j=1}^{n} \left[h(x_j) - \bar{h}_m\right]^2 \tag{2.3}$$

A major limitation to implementing MCS is the high data requirement, which if not met is substituted by making assumptions in the place of empirical information (Ferson, 2008). The issue of identifying the type of PDF can be challenging (Frey et al., 2006). According to studies that quantified uncertainties related to allometric models, this shape of the PDFs were assumed, presumably from expert judgment or past studies (Berger et al., 2014; McRoberts and Westfall, 2016; Qin et al., 2021). Depending on the type of distribution, statistical parameters such as the minimum, maximum, standard deviations, and/or mean of a dataset, are used to generate PDFs. Therefore, PDFs do not take into account variations in datasets, but instead generate values based on the shape of the distribution. In many cases, several PDFs will accurately fit a dataset within a given probability limit, however; different PDFs can significantly change the outcome of an uncertainty analysis (Frey et al., 2006). The assumptions considered in selecting the type of the PDFs can significantly impact the predicted uncertainty. The alternative uncertainty analysis methods investigated in this thesis will incorporate different statistical re-sampling methods into MCS that place less dependence on PDFs, thus requiring fewer assumptions.

2.6.2 Bootstrap

Bootstrap methods were introduced by Efron (1979) as a method to estimate the statistical properties of a parameter of interest θ given a random sample $X = (X_1, X_2, \dots, X_n)$ from an unknown distribution F by re-sampling the observed dataset X. More precisely, according to Equation 2.4, assume the property of interest is $\theta(F)$, which can be calculated using the function $h(x)$ where $x_i = X_i$ are values from the unknown distribution F (Robert and Casella, 2004b).

$$\theta(F) = \int h(x) dF(x) \tag{2.4}$$

Using bootstrap methods, random samples $X^{*i} = (X_1^*, X_2^*, \dots, X_n^*)$ are taken with replacement from the observed dataset X resulting in a distribution F_n (Efron, 1979; Efron and Gong, 1983; Robert and Casella, 2004b). Using the re-sampled dataset X^{*i} an estimate for $\theta(F_n)$ can be calculated using Equation 2.5 (Robert and Casella, 2004b).

$$\theta(F_n) = \int h(x) dF_n(x) \tag{2.5}$$

This method is justified by the Glivenko-Cantelli Theorem that guarantees the sup-norm convergence of F_n to F, thus guaranteeing that $\theta(F_n)$ is a consistent estimator of $\theta(F)$ (Robert and Casella, 2004b). This estimate becomes more accurate by simulating this approach, for example by using MCS (Efron, 1979; Robert and Casella, 2004b).

Bootstrapping differs from MCS as values are selected from an observed dataset rather than a specified PDF. This can be advantageous as bootstrapping is capable of accounting for variations in the dataset. However, this also places a high dependence on the observed dataset, which can be a limitation depending on the reliability of the observed dataset, especially when the observed data is a sample meant to represent a larger unknown population.

2.6.3 Bayesian Bootstrap

Bayesian methods are derived from Bayes Theorem proposed by Bayes (1763). The theorem explains the probability of an event occurring based on prior knowledge of the conditions associated with the event (Joyce, 2021; K. Hackenberger, 2019). The Bayesian bootstrap method introduced by Rubin (1981) is the Bayesian analogue of the bootstrap, capable of incorporating information on the distribution F from previous simulations (Hjort, 1991). Bayesian bootstrap differs from bootstrap as each Bayesian bootstrap replication generates a posterior probability for each X_i^* re-sampled from the observed dataset $X = (X_1, X_2, \dots, X_n)$ (Rubin, 1981). Posterior probabilities are probabilities assigned after the acquisition of new data (Weirich, 2011). For example, prior to re-sampling each value in the dataset X has a posterior probability of zero. After an iteration of re-sampling each value X_i^* selected during re-sampling has a posterior probability based on the number of times each value was selected, whereas values that were not selected have a posterior probability of zero (Rubin, 1981). Therefore, in the next iteration values are more likely to be selected during re-sampling according to prior knowledge of the posterior probabilities from the previous iterations.

Rubin (1981) suggests the advantages of Bayesian bootstrap over the bootstrap relate to the resulting inferences between the parameters. Bayesian bootstrap generates likelihood statements rather than frequency statements about statistics under assumed values for parameters. Bayesian bootstrap can be considered an 'informative extension' of the bootstrap that smooths out outside data points (Hjort, 1991). However, there is a lack of research comparing the results of Bayesian bootstrap and bootstrap concerning data re-sampling or uses in estimating error.

2.7 Summary

This chapter reviewed the need for accurate and reliable GHG emission and removal data in NGHGI. AGB from the forestry sector is an area of importance when quantifying carbon, but is often associated with high degrees of uncertainty due to the complexity of the tier 3 quantification methods employed. Based on literature, there is a need for research on quantifying the effects of model uncertainty. However, the research in this thesis argues that IPCC guidelines for simulation-based uncertainty analysis methods (such as MCS) are insufficient when accounting for model uncertainty. A lack of guidance may result in challenges implementing consistent methods across countries. Furthermore, alternative uncertainty analysis approaches may predict more precise uncertainty estimates. The knowledge gaps identified through this chapter justify the objectives of this research outlined in Chapter 1.

3.0 SIMULATION-BASED UNCERTAINTY ANALYSIS METHODOLOGY FOR CARBON QUANTIFICATION FROM ABOVE-GROUND TREE BIOMASS ALLOMETRIC MODELS IN CANADA AND SWEDEN

3.1 Introduction

This research will examine improvements to the Intergovernmental Panel on Climate Change (IPCC) guidelines for simulation-based uncertainty analysis methods. Improved documentation can assist in applying consistent uncertainty analysis methods between countries and improve the understanding and reliability of emission estimates. The objectives of this chapter are as follows: to outline the methodology employed to quantify model uncertainties in carbon estimates from above-ground biomass (AGB) allometric models. The sources of model uncertainties are due to model parameter uncertainty, model residual variance, and measurement uncertainty for model input variables: diameter at breast height (Dbh) and canopy height (Ht) (McRoberts and Westfall, 2014; Qin et al., 2021). Methods to incorporate the following alternative uncertainty analysis approaches will be assessed: Monte Carlo Simulation (MCS), MCS with bootstrap, and MCS with Bayesian bootstrap. The feasibility of the proposed methodology when used in different countries will be assessed by conducting a case study in British Columbia (B.C.), Canada and in Västernorrland County, Sweden.

3.2 Above-Ground Biomass Allometric Model

The standard method of quantifying AGB is through the development and application of allometric models (Návar, 2010). Allometry relates the measurement of one easily measurable variable to a more difficult to quantify variable (Návar, 2010; Vorster et al., 2020). Allometric models are statistically parameterized with measured tree data in which effect or independent variables (e.g. Dbh, bole base, Ht, wood specific gravity, etc.) and the response or dependent variable (volume, dry foliage, branch, bole and/or total AGB) for a number of trees are fit to a model by estimating parameters (βs and αs) (Návar, 2010; Picard et al., 2012). Allometric models are commonly in the form of Equation 3.1 (McRoberts and Westfall, 2014; Picard et al., 2012).

$$Y = \beta_0 X_1^{\beta_1} \times X_2^{\beta_2} \times \ldots \times X_p^{\beta_p} \times \varepsilon \tag{3.1}$$

In Equation 3.1, Y is the response or dependent variable, X is the effect or independent variable, and ε is a random residual error that can be estimated from the Gaussian distribution (0,1) (McRoberts and Westfall, 2014, 2016; Picard et al., 2012). The most common forms of this model used for a wide range of forest ecosystems and species globally involve Dbh alone or with Ht as the independent variables and AGB as the dependent variable (Fradette et al., 2021). For example, this model can be written in the forms of Equations 3.2, 3.3, and 3.4.

$$AGB_i = \beta_0 {Dbh_i}^{\beta_1} + \varepsilon_i \tag{3.2}$$

$$AGB_i = \beta_0 \left({Dbh_i}^2 Ht_i\right)^{\beta_1} + \varepsilon_i \tag{3.3}$$

$$AGB_i = \beta_0 (Dbh_i)^{\beta_1} (Ht_i)^{\beta_2} + \varepsilon_i \tag{3.4}$$

Several studies that evaluated and compared the performance of different model forms concluded that in consideration of challenges in measuring tree data, Equation 3.2 is robust enough to provide reliable predictions. However, models with additional independent variables are more precise and have a lower degree of uncertainty (Balbinot et al., 2018; Fradette et al., 2021; Mensah et al., 2017; Mugasha et al., 2016; Qin et al., 2021; Sadono et al., 2021; Segura et al., 2006). Due to the challenges in obtaining measurements for multiple independent variables, Equation 3.4 is the preferred model (Fradette et al., 2021) and, will be used in this thesis to obtain precise estimate of AGB and the resulting impacts of model uncertainties including uncertainties in measurements from both Dbh and Ht.

Equation 3.4 can be expressed in a linear form by applying the natural logarithmic (ln) transformation to both sides of the equation, resulting in the reformulated model shown in Equation 3.5 (McRoberts and Westfall, 2016; Picard et al., 2012).

$$\ln(AGB_i) = \alpha_0 + \alpha_1 \times \ln(Dbh_i) + \alpha_2 \times \ln(Ht_i) + {\varepsilon_i}' \tag{3.5}$$

Equation 3.5 simplifies the estimation of model parameters and removes heteroskedasticity, thus eliminating the need for weighted regressions (McRoberts and

Westfall, 2016). According to McRoberts and Westfall (2016), Equation 3.6 is obtained by converting the model to the original scale.

$$\widehat{AGB}_i = \exp\left[\alpha_0 + \alpha_1 \times ln(Dbh_i) + \alpha_2 \times ln(Ht_i) + \frac{\hat{\sigma}_\varepsilon}{2}\right] \quad (3.6)$$

The term $\frac{\hat{\sigma}_\varepsilon}{2}$ represents half the residual standard deviation on the ln-ln scale, and is the correction factor that compensates for the bias that arises from transforming the equation from the ln-ln scale to the original scale (Baskerville, 1972; McRoberts and Westfall, 2016).

3.2.1 Model Fitting

The AGB model was fitted and validated following a manual by Picard et al. (2012) using the linearized form shown in Equation 3.5 and forest inventory data. The model was evaluated according to the following statistical parameters.

The p value is commonly used to explain the statistical significance of the relationship between independent variables and the dependent variable (Thiese et al., 2016). The p value tests the hypothesis that the independent variables do not affect the dependent variable, in which a p value > 0.05 indicates that there is strong evidence against this hypothesis (Thiese et al., 2016). However, several studies have criticized the interpretation of the p value and indicated that numerous factors (such as sample size, bias, and random error) negatively impact the p value. (Di Leo and Sardanelli, 2020; Dorey, 2010; Thiese et al., 2016).

The R^2 value is calculated to explain the quality of the fit. The R^2 value measures the variance of the sample accounted for by the model relative to the total sample variance, in which a value closer to 1 indicates a better fit (Brown et al., 1989). However, the interpretation of R^2 has limitations and is not recommended as a reliable criterion for selecting the shape of a model, as higher R^2 values may be the result of model over-parameterization to a specific dataset (Picard et al., 2012).

Although the R^2 value and the p value provide important statistical information describing the model, based on the previously mentioned criticisms, these parameters was not used to validate the fit of the model. Instead the method reported by Picard et al. (2012) was used.

Fitting the model is concluded when the following conditions are satisfied: (1) The residuals are independent, (2) The residuals follow a normal distribution, and (3) The residuals variances are constant (Picard et al., 2012). The independence of the residuals can be assumed when the sampling plan is robust (Picard et al., 2012). The hypotheses that the residuals are normally distributed and independent were tested by visual inspection. By graphing the empirical quantiles of the residuals against the theoretical quantiles a near straight line indicates that the residuals are normally distributed (Picard et al., 2012). By graphing the residual values against the fitted values a cluster of points that show no particular trend or structure indicates that the variance of the residuals are constant (Picard et al., 2012).

3.3 Description of Study Areas

To assess and compare the applicability of the uncertainty analysis method for different countries model uncertainties were evaluated for one study area in B.C., Canada, and the other in Västernorrland County, Sweden. These areas were selected as this research is a collaboration between institutes in Canada and Sweden: however, this methodology can be employed in other areas and countries where similar forest inventories are available.

3.3.1 Study Area 1

Study Area 1 is in the Petitot Plain Ecosection in northeastern B.C., Canada. The area includes approximately 12,365 ha of land consisting of riparian habitats, wetlands, and upland forests (BC Parks, 2001; Demarchi, 2011), located at the northern end of the Thinahtea protected area, as shown in Figure 3.1[1]. The forest types are mainly boreal white and black spruce but also contain trembling aspen, lodgepole pine, tamarack, paper birch, and balsam poplar.

[1] 'Maps throughout this research were created using ArcGIS® software by Esri. ArcGIS® and ArcMap™ are the intellectual property of Esri and are used herein under license. Copyright © Esri. All rights reserved. For more information about Esri® software, please visit www.esri.com.'

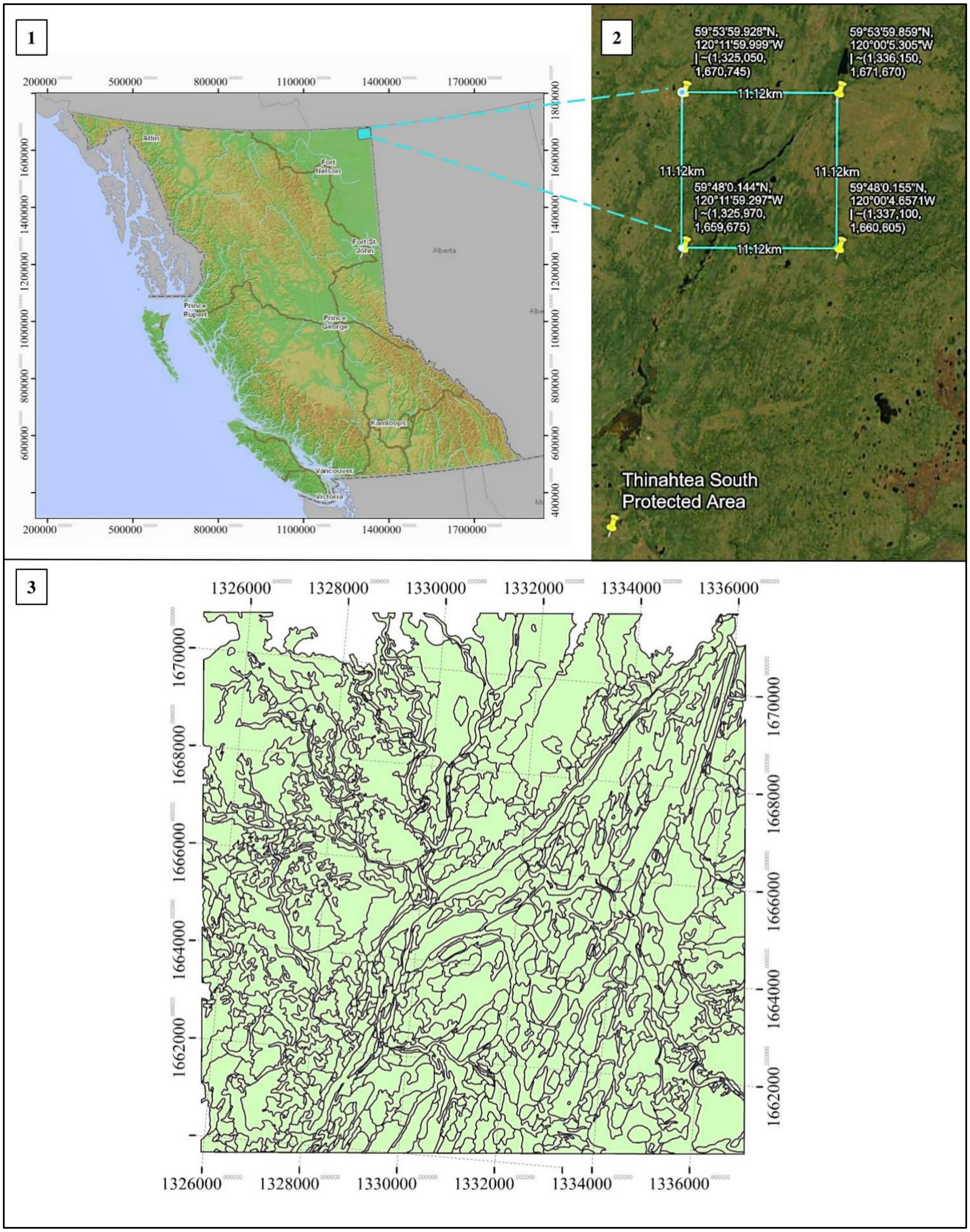

Figure 3.1 Study area 1 in B.C., Canada. (1) Provincial view (ESRI, 2018). (2) Satellite view (ESRI, 2009a). (3) View of polygons within the study area (BC, Canada Study Area, 2023).

3.3.2 Study Area 2

Study Area 2 is in the High Coast region in Västernorrland County, Sweden. The area includes approximately 10,000 ha of land consisting of mountainous terrain, wetlands, and forests (Poutanen and Steffen, 2015; “Sweden’s National Parks,” 2023), surrounding the Skuleskogen National Park, as shown in Figure 3.2. The forest types are mainly Norway spruce and Scots pine but also contain birch, contorta, and other hardwoods.

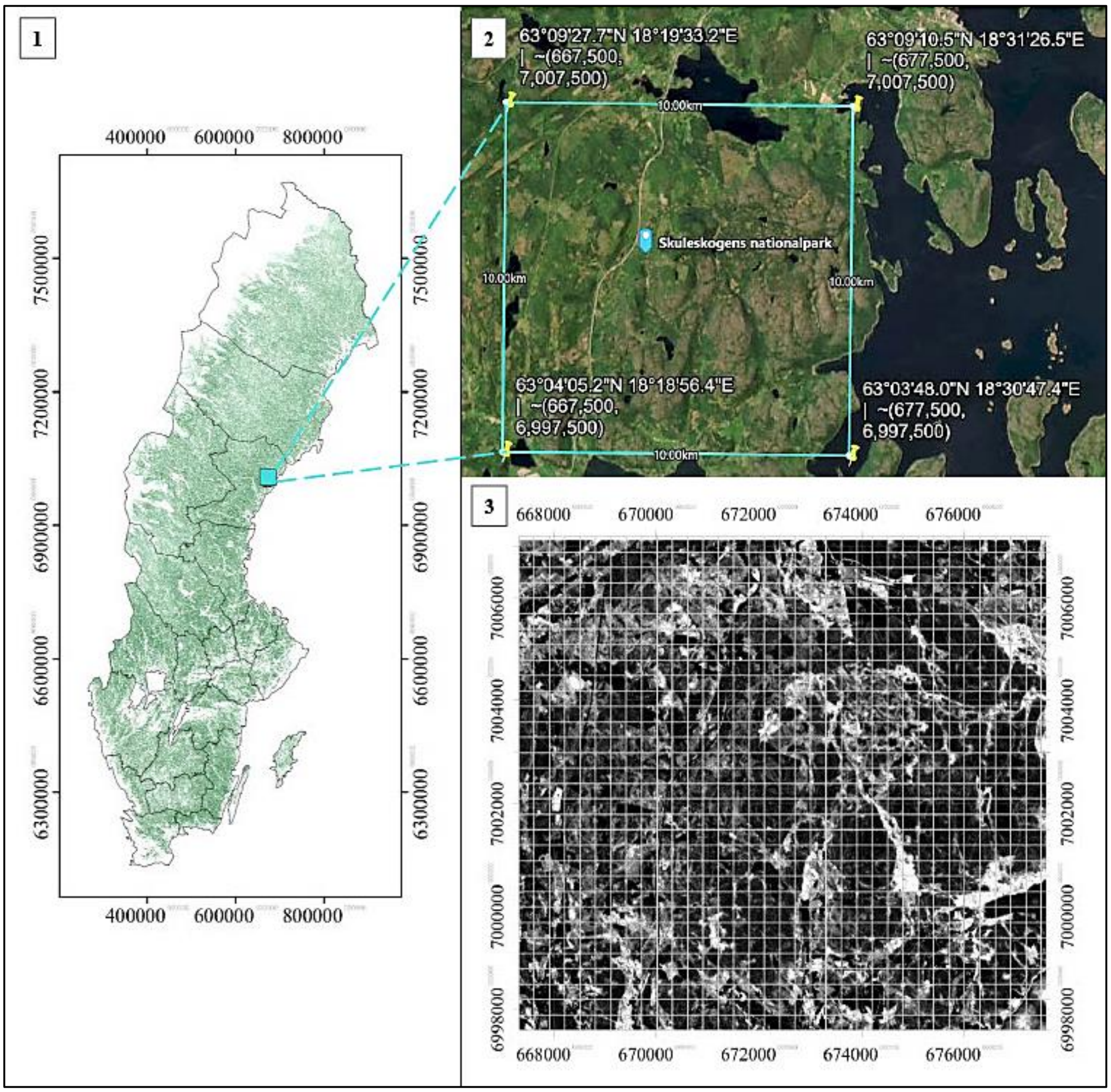

Figure 3.2 Study area 2 in Västernorrland County, Sweden. (1) Country view (Sweden Forest Volume, 2023). (2) Satellite view (ESRI, 2009b). (3) View of polygons within the study area (Västernorrland County, Sweden Study Area, 2023)

3.4 Data Collection

To calibrate the AGB models, geospatial forest inventory datasets were collected using ArcMap version 10.8.2 (ESRI, 2023). These datasets are referred to as the observed datasets. The following sections describe the data collection procedures for each study area.

3.4.1 Study Area 1

Data was collected at the provincial level from the government of British Columbia's Vegetation Resource Inventory (VRI), which is compiled and maintained as required by the Ministry of Forests, Lands and Natural Resource Operations (FLNRO) Forest Inventory Strategic Plan (FLNRO, 2013). The VRI is a photo-based, two-phased vegetation inventory. In the first phase, aerial photographs are used to estimate vegetation characteristics (FLNRO, 2022a). Land is delineated into polygons according to these characteristics. In the second phase, ground sampling is used to verify the accuracy of the photo estimates (FLNRO, 2022a).

Polygons for non-vegetated areas or with missing data were eliminated and 580 polygons were available for this study. The average polygon area was approximately 12.0 ha, the average basal area was approximately 21.0 m^2/ ha, and the average number of live stems per polygon was 1195. Data for the mean Dbh, Ht, and AGB per polygon was collected.

The Dbh was based on a 13.5 cm utilization was expressed in cm for each polygon (VRI Relational Data Dictionary (version 5.0), 2019). The Dbh was calculated based on the basal area and the number of live stems, resulting in an estimate that assign greater weighting to trees that occupy a larger basal area (FLNRO, 2022a; Kivari et al., 2011). Data for the mean projected Ht weighted by basal area and expressed in metres was available for the leading and second species for each polygon (VRI Relational Data Dictionary (version 5.0), 2019). For the remaining species, the commonly used Chapman-Richards height-diameter model using parameters from Huang et al. (1992) and Peng et al. (2001) were used to predict the average tree height per species for each polygon. The weighted mean Ht for all trees within a polygon were calculated using weights based on the percentage of the basal area each species occupied. Data for AGB included the biomass in the whole stem, branches, bark, and foliage for all species per polygon on a utilization of 4.0 cm expressed as tonnes/ha (VRI Relational Data Dictionary (version 5.0), 2019). Work by McRoberts and Westfall (2014) reported that not much is gained by using species-specific models for large area AGB estimates. Hence a single non-species-specific allometric model was derived for each study area. Therefore, the Dbh, Ht, and AGB values were not aggregated according to the tree species.

3.4.2 Study Area 2

Date collected from the 2015 SLU Forest Map was obtained from the Swedish University of Agricultural Sciences (SLU) Division of Forest Remote Sensing at the Department of Forest Resource Management. SLU, the official Swedish provider of forest statistics, is responsible for the Swedish National Forest Inventory (Wallerman et al., 2021). The SLU Forest Map is produced from co-processing field data from the Swedish NFI, satellite images, and surface models (Wallerman et al., 2021).

The SLU Forest Map is based on raster data in which the grid cell sizes are 12.5 m x 12.5 m (SLU, 2021). For this study, the data was aggregated into 300 m x 300 m (9.0 ha) grid cells to reduce the computer memory requirements and the time needed to run the model. This resulted in 1120 grid cells. The average basal area was approximately 19.2 m^2/ha and the average number of live stems per grid cell was 561. Data for the mean Dbh, Ht, and AGB per polygon was collected.

Similarly to section 2.2.1, the Dbh was expressed in cm for each grid cell; however, there was no Dbh limit. The mean Ht for all species greater than 3.0 m was weighted according to the basal area and expressed in metres for each grid cell (SLU, 2021). Data for AGB included the biomass in the trunk of the tree excluding the stump, the branches, and the tops for all species per grid cells expressed as ton TS/ha (SLU, 2021).

3.5 Uncertainty Calculation

Simulations of the uncertainty analysis were concluded when the mean and uncertainty of the parameter for which the uncertainty is being assessed stabilized. Similar to approaches by McRoberts and Westfall (2016) and Qin et al. (2021) the mean and variance over replications were calculated following Rubin (1987). The mean over replications $\bar{\mu}_{AGB}$ was calculated based on the mean AGB for the entire study area $\overline{AGB}_k$ for each replication k.

$$\bar{\mu}_{AGB} = \frac{1}{n}\sum_{k=1}^{n}\overline{AGB}_k \tag{3.7}$$

The variance of $\bar{\mu}_{AGB}$ was calculated by combining the mean variance between simulations W_1 and the mean variance within-simulation W_2.

$$Var(\bar{\mu}_{AGB}) = \left(1 + \frac{1}{n}\right) \times W_1 + W_2 \tag{3.8}$$

$$W_1 = \frac{1}{n-1}\sum_{k=1}^{n}(\bar{\mu}_P - \overline{AGB}_k)^2 \tag{3.9}$$

$$W_2 = \frac{1}{n-1}Var(\overline{AGB}_k) \tag{3.10}$$

The relative uncertainty R_{AGB} was calculated from the standard error $SE(\bar{\mu}_{AGB})$.

$$SE(\bar{\mu}_{AGB}) = \sqrt{Var(\bar{\mu}_P)} \tag{3.11}$$

$$R_{AGB} = \frac{SE(\bar{\mu}_{AGB})}{\bar{\mu}_{AGB}} \times 100\% \tag{3.12}$$

The procedure described in this section calculates the mean and relative uncertainty of AGB estimates. As discussed in Chapter 2 Section 2.5.1, when considering uncertainty it is reasonable to assume the carbon content to be 50% of the AGB (Matthews, 1993). Therefore, it was assumed that there was no added uncertainty by applying a 50% conversion factor to calculate the carbon content of AGB. Hence the relative uncertainty of AGB is equal to the relative uncertainty of carbon from AGB.

3.6 Statistical Software

All statistical analysis and modelling were performed using R version 4.2.2 (R Core Team, 2023), and extension packages were downloaded from CRAN. The package *boot*, written by Canty and Ripley (2022) based on functions from Davidson and Hinkley (1997), was used for the bootstrap analysis. The package *bayesboot*, written by Bååth (2018) was used for the implementation of the Bayesian bootstrap described in Rubin (1981).

3.7 Simulating Uncertainty in Above-Ground Biomass Models

This thesis aims to assess the effects of model uncertainties on carbon estimation from AGB from the following sources: model parameter uncertainty, model residual variance, and measurement uncertainty for model input variables Dbh and Ht. The proposed uncertainty analysis investigated how model uncertainties can be quantified considering three sources of model uncertainties. Parts I to III evaluated each individual source of model uncertainty and their effects on the estimation of carbon from AGB. Part IV discussed the method employed to conduct uncertainty analysis considering each source of model uncertainty in order to calculate the overall effects of model uncertainty on carbon from AGB quantification. To investigate how the results differ between countries, the study areas considered were in Canada and Sweden. The results from the following approaches assessed the effects of alternative uncertainty analysis methods on the estimated uncertainties. Approach 1 uses MCS by assuming the shapes of PDFs; 2 uses bootstrap re-sampling with MCS; and 3 uses Bayesian bootstrap re-sampling with MCS. Each section of the methodology was repeated for both study areas and the three approaches.

3.7.1 Part I: Parameter Uncertainty

MCS and statistical re-sampling can simulate the sampling process of a dataset to generate multiple pseudo-datasets. The variances of the model parameters were estimated by repeatedly refitting the model to randomly sampled pseudo-datasets in order to obtain a distribution of possible model parameters. The proposed method follows a similar procedure as Wayson et al. (2015) and McRoberts and Westfall (2016). The procedure shown in Figure 3.3 was used to calculate the uncertainty in model parameters.

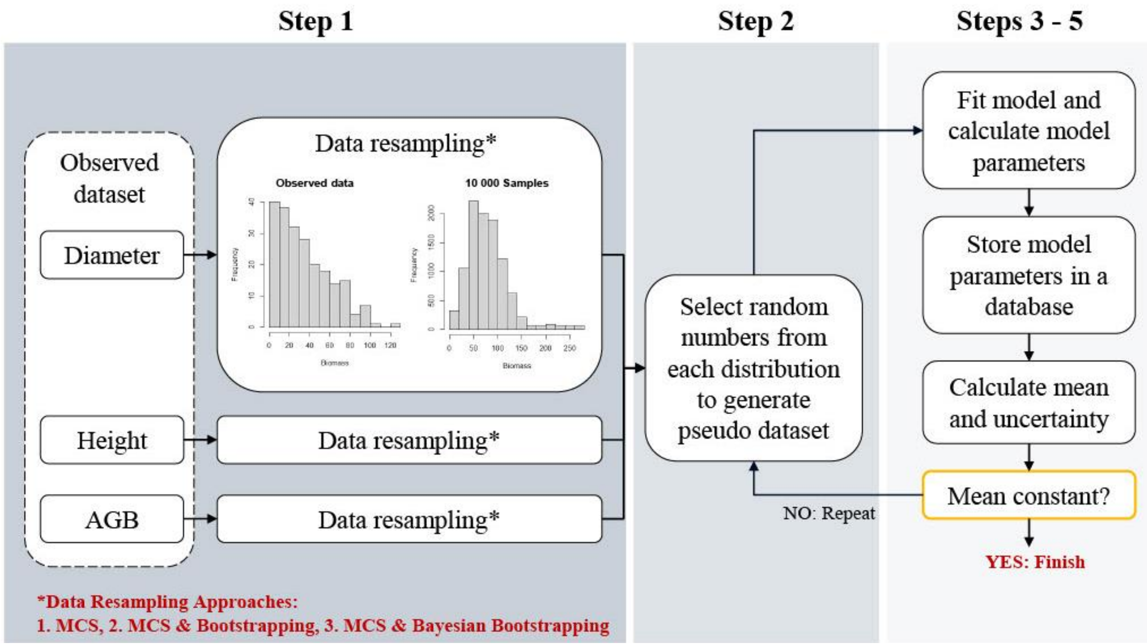

Figure 3.3 Method to calculate uncertainty in model parameters

Step 1. Values for AGB, Dbh, and Ht from the observed dataset were aggregated into 20 classes and each class contained at least 30 values.

a. Approach 1: Values in each class were assumed to have a uniform distribution based on studies by Qin et al. (2021) and Wayson et al. (2015). Each variable was randomly re-sampled according to the assumed distribution until a pseudo-dataset containing 10,000 values was generated.
b. Approach 2: Values in each class were resampled using bootstrap resampling until a pseudo-dataset containing 10,000 values was generated.
c. Approach 3: Values in each class were resampled using Bayesian bootstrap resampling until a pseudo-dataset containing 10,000 values was generated.

Step 2. Random values were sampled from the pseudo-datasets until the original sample size of the observed dataset was achieved.

Step 3. The AGB model was fit to these random values and the model parameters were calculated and stored in a database.

Step 4. Following the method described in Chapter 3 Section 3.5, the mean and relative uncertainty for each of the parameters was calculated.

Step 5. Steps 2 – 4 were repeated until the mean and uncertainty stabilized.

The procedure shown in Figure 3.4 was used to calculate the uncertainty in AGB as a result of parameter uncertainty.

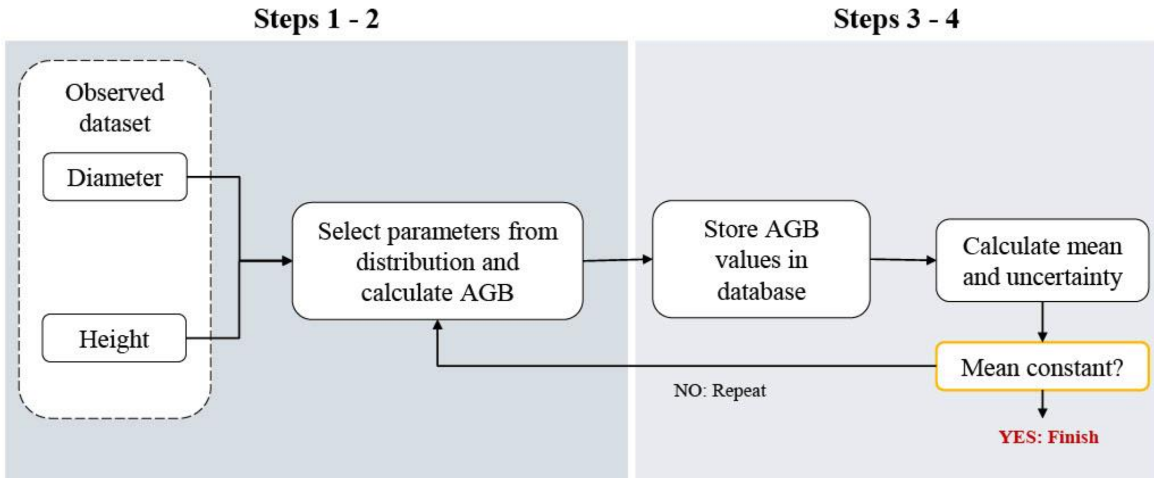

Figure 3.4 Method to calculate uncertainty in AGB due to parameter uncertainty

Step 1. A distribution of parameters was obtained from the database described in previous procedure (Step 3). A set of parameters were randomly selected for the AGB model.

Step 2. Values for Dbh and Ht from the observed dataset, and the parameters selected in Step 1, were used to calculate an estimate for AGB . Calculated values were stored in a database.

Step 3. The mean and uncertainty of the AGB estimates in the database were calculated using the method described in Chapter 3 Section 3.5.

Step 4. Steps 1 – 3 were repeated until the mean and uncertainty for the AGB estimates stabilized.

3.7.2 Part II: Residual Uncertainty

The residual error is the result of the differences between the observed value of the dependent variable and the predicted value calculated from the model (Triyason et al., 2015). For this study, the observed value was the AGB from the observed dataset, and the predicted value was the $\widehat{AGB}$ generated by the AGB model on the original scale based on Equation 3.6. The proposed method followed a similar procedure reported by Qin et al. (2021) and McRoberts and Westfall (2016); however, Qin et al. (2021) assumed the residual error model that relates the standard deviation of residuals σ_g and the mean predicted $\overline{\widehat{AGB}}$ to be linear, but McRoberts and Westfall (2016) described this relationship using a power model. In this thesis, several forms of this model were examined, and the investigation demonstrated a second-order polynomial best fit this relationship. The procedure shown in Figure 3.5 was used to derive the residual error model.

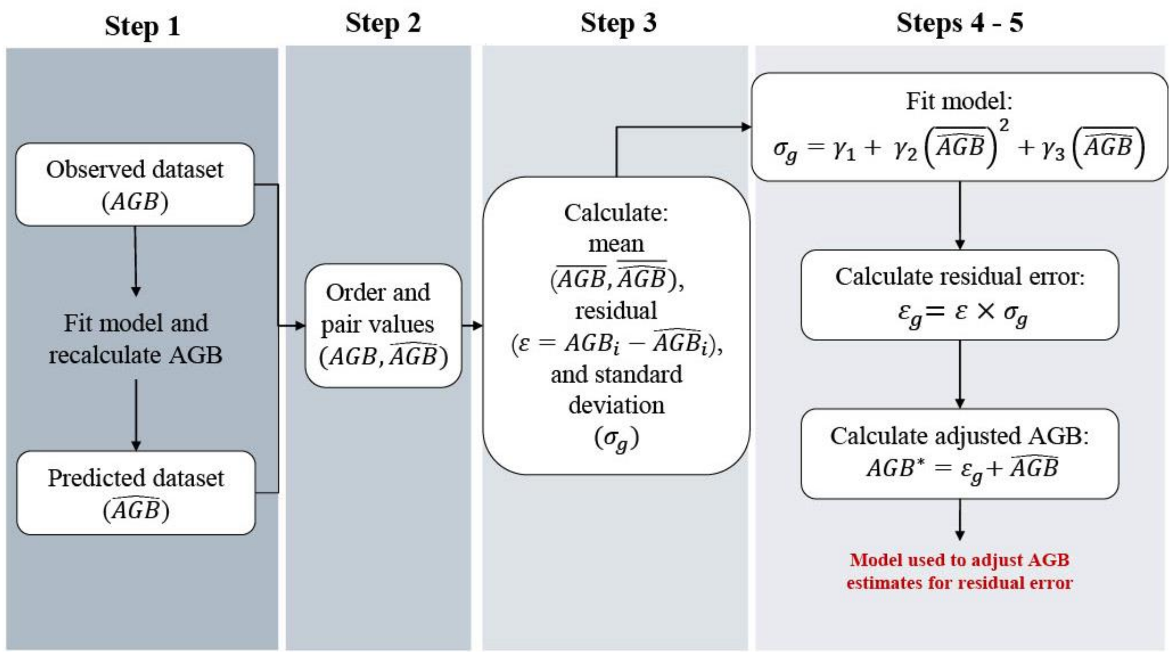

Figure 3.5 Method to derive the residual error model

Step 1. The model was fitted using the observed dataset and AGB values were re-calculated from this model using the independent variables of the observed dataset. The AGB values from the observed dataset are referred to as AGB and the AGB values predicted from the model are referred to as $\widehat{AGB}$.

Step 2. $\widehat{AGB}$ and the corresponding AGB values were paired and arranged in ascending order with respect to $\widehat{AGB}$. These values were aggregated into classes containing 20 values.

Step 3. For each class, the following parameters were calculated:

a. The mean of the observed $(\overline{AGB})$ and predicted $\overline{(\widehat{AGB})}$ values.
b. The residual for each pair $\varepsilon = AGB_i - \widehat{AGB}_i$.
c. The standard deviation of the residuals (σ_g).

Step 4. The relationship between σ_g and $\overline{\widehat{AGB}}$ was represented using Equation 3.13:

$$\sigma_g = \gamma_1 + \gamma_2 \left(\overline{\widehat{AGB}}\right)^2 + \gamma_2 \left(\overline{\widehat{AGB}}\right) \tag{3.13}$$

Using the values calculated in Step 2, the model parameters γ_1, γ_2, γ_3 were estimated.

Step 5. AGB^* represents the AGB adjusted for residual error that can be calculated using Equation 3.14:

$$AGB^* = \widehat{AGB} + \left(\varepsilon \times \sigma_g\right) \tag{3.14}$$

In which ε is a random residual error that follows a Gaussian distribution (0,1) in which $|\varepsilon| < 1.96$ assuming a 95% confidence interval (McRoberts and Westfall, 2016). With respect to Approaches 1, 2, and 3, ε is sampled from the assumed distribution, by bootstrapping, or by Bayesian bootstrapping the distribution.

The procedure shown in Figure 3.6 was used to calculate the uncertainty in AGB as a result of residual uncertainty.

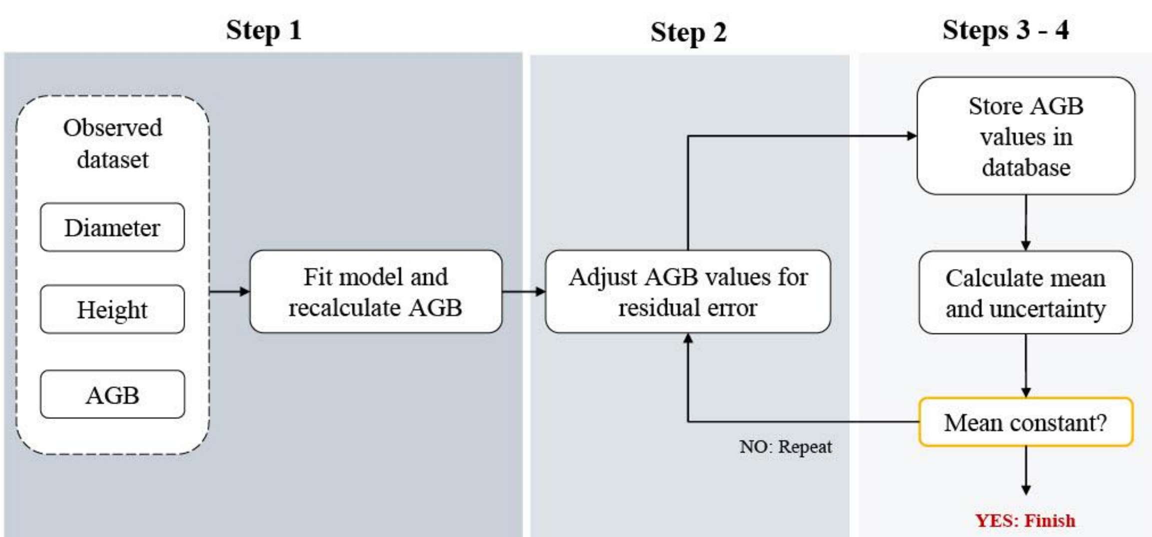

Figure 3.6 Method to calculate uncertainty in AGB due to residual uncertainty

Step 1. The AGB model was fit using the observed dataset and AGB values were re-calculated from this model using the independent variables of the observed dataset.

Step 2. Using Equations 3.13 and 3.14, the calculated values of AGB were adjusted for residual error. The adjusted AGB values were stored in a database.

Step 3. The mean and uncertainty of the AGB estimates in the database were calculated using the method described in Chapter 3 Section 3.5.

Step 4. Steps 2 – 3 were repeated until the mean and uncertainty for the AGB estimates stabilized.

3.7.3 Part III: Measurement Uncertainty

The measurement error is the result of uncertainties in the input variables for the model and the resulting impacts on the AGB estimates (Berger et al., 2014). The proposed method followed the procedure described in Berger et al. (2014) to derive measurement error models for Dbh measurements that relates the standard deviation of the measurement differences σ_M^{Dbh} and the mean of the measurements $\overline{Dbh}$. Studies by Berger et al. (2021) and Qin et al. (2019, 2021) assumed this relationship to be linear. However, Berger et al. (2014) emphasized that linearity is merely an approximation using a non-linear regression model that results in similar but larger results. In this thesis, several forms of this model were examined, and the investigation demonstrated a second-order polynomial best fit this relationship. The procedure shown in Figure 3.7 was used to derive the measurement error model for Dbh measurements.

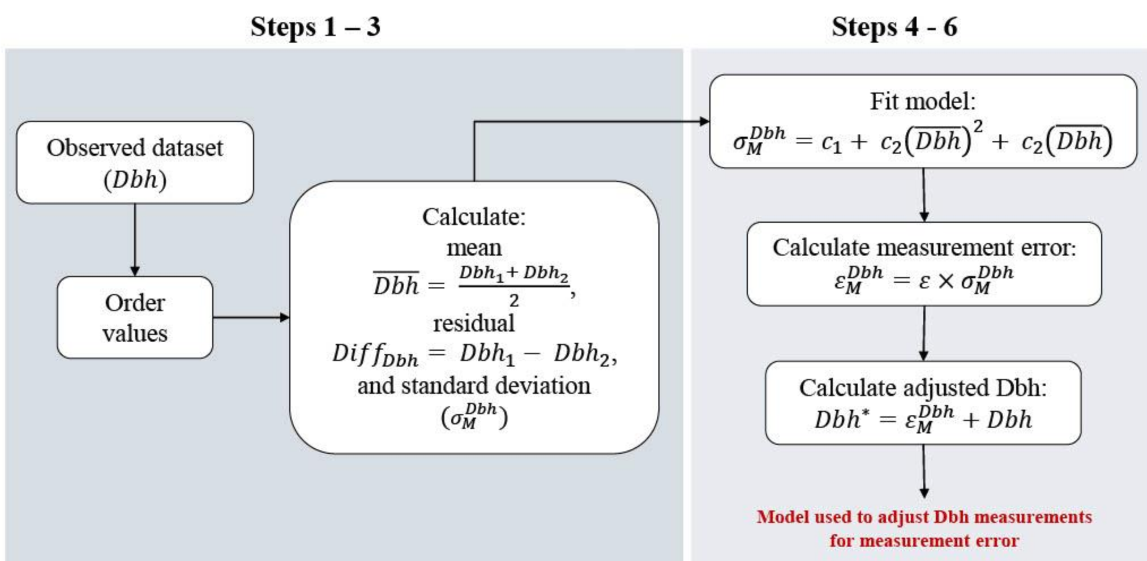

Figure 3.7 Method to derive Dbh measurement uncertainty model

Step 1. Dbh measurement values were arranged in ascending order. For every two values the mean $\overline{Dbh} = \frac{Dbh_1 + Dbh_2}{2}$ and the difference $Diff_{Dbh} = Dbh_1 - Dbh_2$ was calculated where Dbh_1 was the first value and Dbh_2 was the second value.

Step 2. The $\overline{Dbh}$ and the corresponding $Diff_{Dbh}$ values were grouped into classes containing 20 values.

Step 3. For each class, the standard deviation of $Diff_{Dbh}$ was calculated (σ_M^{Dbh}).

Step 4. The relationship between σ_g and $\overline{Dbh}$ was represented using Equation 3.15:

$$\sigma_M^{Dbh} = c_1 + c_2\left(\overline{Dbh}\right)^2 + c_2\left(\overline{Dbh}\right) \tag{3.15}$$

Using the values calculated in Step 2 and 3, the model parameters c_1, c_2, and c_3 were calculated.

Step 5. Due to large variations in Dbh measurements in the observed dataset, the significance of outliers was tested and two outliers were eliminated using Dixon's Q-test.

Step 6. Dbh^* represents the Dbh adjusted for measurement error that can be calculated using Equation 3.16:

$$Dbh^* = Dbh + \left(\varepsilon \times \sigma_M^{Dbh}\right) \tag{3.16}$$

In which ε is a random residual error that follows a Gaussian distribution (0,1) in which $|\varepsilon| < 1.96$ assuming a 95% confidence interval (McRoberts and Westfall, 2016). With respect to Approaches 1, 2, and 3, ε is sampled from the assumed distribution, by bootstrapping, or by Bayesian bootstrapping the distribution.

Estimates for errors in Ht measurements followed a similar procedure reported by McRoberts and Westfall (2014) and Qin et al. (2021). The minimum tolerances for Ht measurements was 15% according to the B.C. government's Vegetation Resources Inventory Photo Interpretation Quality Assurance Procedures and Standards (version 4.6) (FLNRO, 2022b), and 12% according to the quality reported for the 2015 SLU Forest Map (SLU, 2021). Measurement uncertainty is commonly assumed to follow a Gaussian distribution with mean 0 and standard deviation equal to $\sigma = \frac{X-\mu}{Z}$ (Berger et al., 2014;

McRoberts and Westfall, 2016; Qin et al., 2021; Shettles et al., 2015). Following the procedure described by McRoberts and Westfall (2016), the standard deviation for Ht measurement error for study areas 1 and 2 can be calculated according to Equations 3.17 and 3.18 respectively.

$$\sigma_M^{Ht} = \frac{x - \mu}{z} = \frac{0.15 \times Ht}{1.440} \tag{3.17}$$

$$\sigma_M^{Ht} = \frac{x - \mu}{z} = \frac{0.12 \times Ht}{1.554} \tag{3.18}$$

Ht^* represents the Ht adjusted for measurement error that can be calculated using Equation 3.19:

$$Ht^* = Ht + (\varepsilon \times \sigma_M^{Ht}) \tag{3.19}$$

In which ε is a random residual error that follows a Gaussian distribution (0,1) in which $|\varepsilon| < 1.96$ assuming a 95% confidence interval. With respect to Approaches 1, 2, and 3, ε is sampled from the assumed distribution, by bootstrapping, or by Bayesian bootstrapping the distribution.

The procedure shown in Figure 3.8 was used to calculate the uncertainty in AGB as a result of measurement uncertainty.

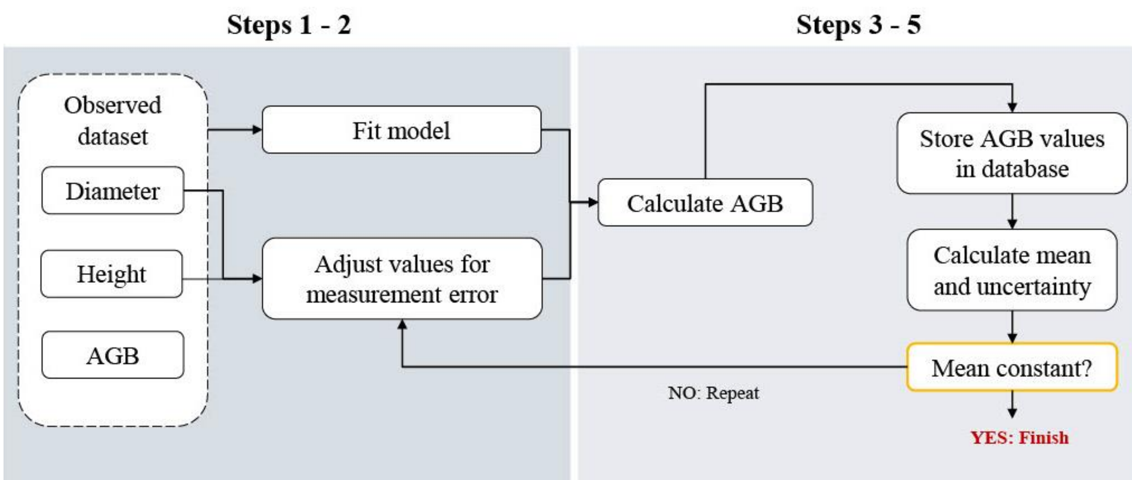

Figure 3.8 Method to calculate uncertainty in AGB due to measurement uncertainty

Step 1. The AGB model was fit using the observed dataset and AGB.

Step 2. Using Equations 3.16 and 3.17, the model input variables were adjusted for measurement error.

Step 3. Values for AGB were calculated using the values from Steps 1 and 2. Calculated values were stored in a database.

Step 4. The mean and uncertainty of the AGB estimates in the database were calculated using the method described in Chapter 3 Section 3.5.

Step 5. Steps 2 – 5 were repeated until the mean and uncertainty for the AGB estimates stabilize.

3.7.4 Part IV: Overall Uncertainty Analysis

The following uncertainty analysis method shown in Figure 3.9 was used to calculate the overall model uncertainty resulting from model parameter uncertainty, model residual variance, and measurement uncertainty for model input variables Dbh and Ht.

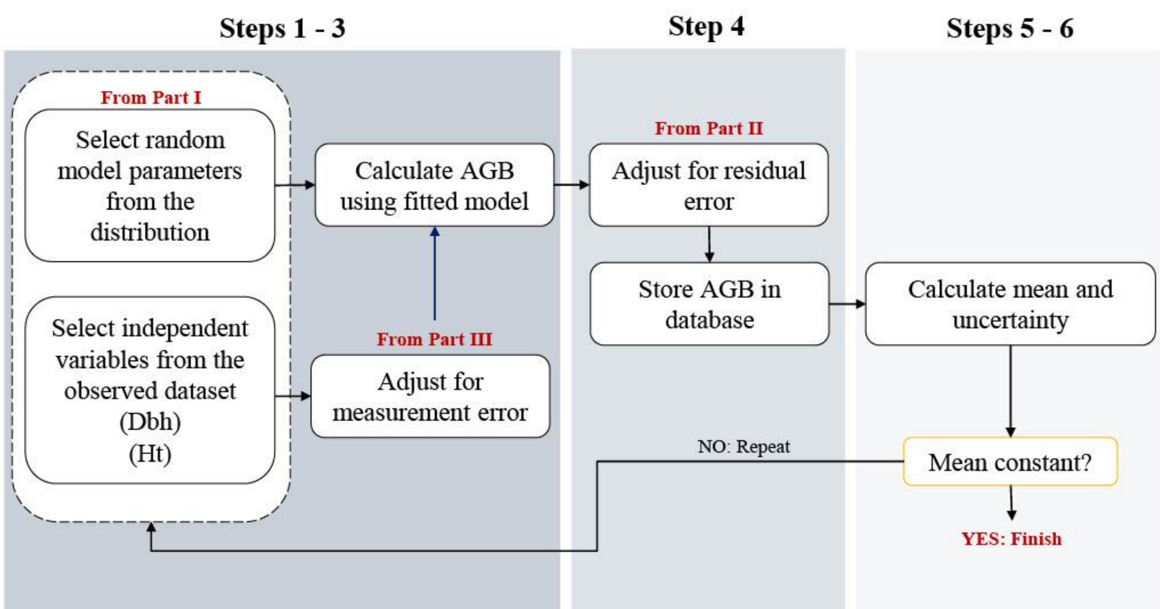

Figure 3.9 Overall model uncertainty method

Step 1. Values for the model input variables Dbh and Ht were selected from the observed dataset. These values were adjusted for measurement error following the method described in Part III.

Step 2. Model parameters were randomly generated from the distributions created in Part I for each respective approach.

Step 3. Using the AGB model (Equation 3.6), the values simulated in Steps 1 and 2 were used to calculate a value for AGB.

Step 4. The value of AGB calculated in Step 3 was adjusted for residual error following the method described in Part II. The adjusted AGB value was stored in a database.

Step 5. The mean and uncertainty of the AGB estimates in the database were calculated using the method described in Chapter 3 Section 4.0.

Step 6. Steps 2 – 6 were repeated until the mean and uncertainty for the AGB estimates stabilize.

3.8 Summary

This chapter presented the methodology for the simulation-based uncertainty analysis that can be employed to quantify model uncertainties in carbon estimates from AGB due to: model parameter uncertainty, model residual variance, and measurement uncertainty for model input variables: diameter at breast height (Dbh) and canopy height (Ht). The procedure is summarized in Figure 3.10.

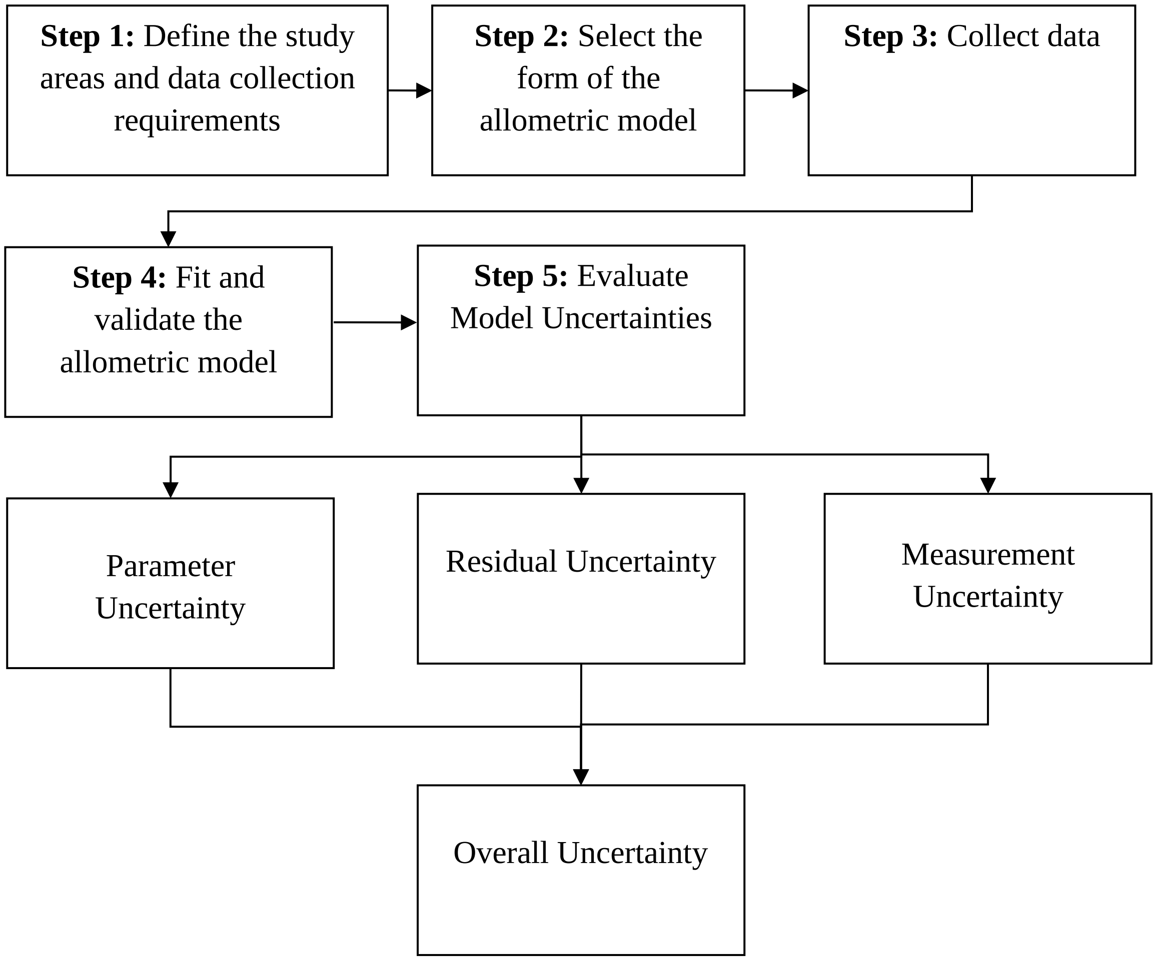

Figure 3.10 Summary of the uncertainty analysis methodology

4.0 EVALUATING THE EFFECTS OF MODEL UNCERTAINTIES ON CARBON QUANTIFIED FROM ABOVE-GROUND BIOMASS MODELS: ADJUSTMENTS AND IMPLICATIONS FOR METHODOLOGICAL AND POLITICAL DECISION-MAKING

4.1 Introduction

Case studies were conducted to demonstrate how the uncertainty analysis methodology proposed in Chapter 3 was employed to estimate model uncertainties in carbon quantification from above-ground biomass (AGB) allometric models. Case study 1 used forest inventory data for an area in British Columbia (B.C.), Canada, and case study 2 in Västernorrland County, Sweden. The main sources of model uncertainty were due to the following: model parameter uncertainty, model residual variance, and measurement uncertainty for model input variables: diameter at breast height (Dbh) and canopy height (Ht) (McRoberts and Westfall, 2014; Qin et al., 2021). Uncertainty estimates were quantified for the following uncertainty analysis approaches: Monte Carlo Simulation (MCS), MCS with bootstrap, and MCS with Bayesian bootstrap. The objectives of the case studies were to indicate how the different sources contribute to the overall model uncertainty and how alternative uncertainty analysis approaches affect the uncertainty estimates. These results were used to adjust the carbon estimates for model uncertainty.

4.2 Above-Ground Biomass Allometric Model Fitting

For case study 1, the model fitted to the observed data shown in Equation 4.1 resulted in a residual standard deviation of $\hat{\sigma}_{\varepsilon}$ = 0.62, a p value less than 2.20 × (10^{-16}) indicating that the model was highly significant, and an R^2 = 0.69.

$$AGB_i = 0.228 \times (Dbh_i)^{-1.397}(H_i)^{3.688} \tag{4.1}$$

For case study 2, the model fit to the observed data shown in Equation 4.2 resulted in a residual standard deviation of $\hat{\sigma}_{\varepsilon}$ = 0.11, a p value less than 2.20 × (10^{-16}) indicating that the model was highly significant, and an R^2 = 0.96.

$$AGB_i = 6.898 \times (Dbh_i)^{-1.956}(H_i)^{3.247} \tag{4.2}$$

The relationship between the predicted and observed AGB values described by equations 4.1 and 4.2 are shown in Figure 4.1. The conditions discussed in Chapter 3 Section 1.1 were tested to validate the model fit. For both case studies, visual inspection concluded that the residuals were normally distributed and the variance of the residuals was constant. The graphs used to validate the conditions are available in Appendix A.

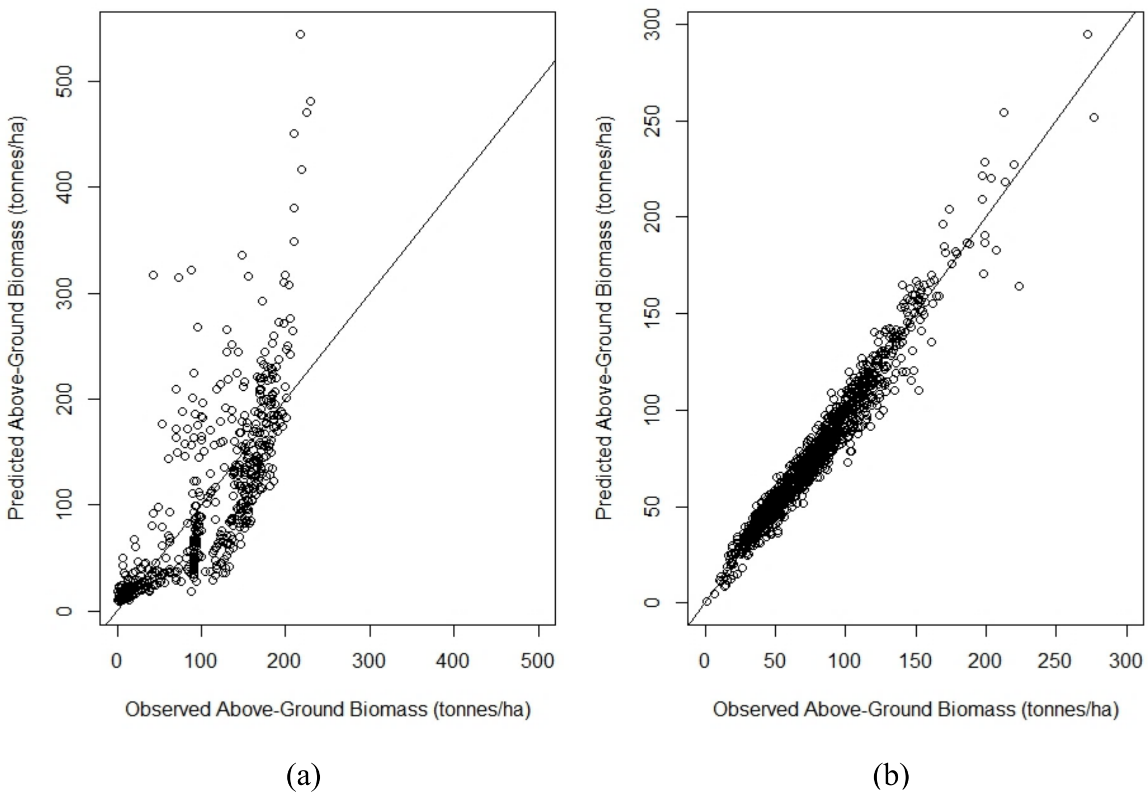

Figure 4.1 The relationship between the predicted and observed AGB described by (a) Equation 4.1, and (b) Equation 4.2

It is evident that Equation 4.2 derived for case study 2 resulted in more accurate predictions compared to Equation 4.1 derived for case study 1. Both case studies were observed for similarly sized areas that each implemented extensive data collection and validation procedures. The differences in the models may be due to natural variations in the observed datasets or the deficiency of the model form to mimic the system's behavior. By comparing the data used for both case studies, differences in the technology or sampling strategies used may have resulted in improved data quality in case study 2. For example, case study 2 contained more data as the grid cells used for sampling were smaller, resulting in a more comprehensive depiction of the study area.

The following sections will discuss the uncertainties associated with the derived AGB models when estimating carbon for both case studies.

4.3 Case Study 1: Uncertainty Analysis

This section reviews the results of the four-part uncertainty analysis for case study 1 in BC, Canada. The three uncertainty analysis approaches investigated resulted in the same conclusions. Histograms depicting the distribution of the pseudo-data generated from the three approaches for both case studies are available in Appendix B. Measurement errors had the most significant impact on carbon quantification from AGB, followed by model residual variance, which had similar uncertainties. Although the individual model parameters were highly uncertain, this did not have a significant impact on carbon quantification.

4.3.1 Parameter Uncertainty

Figures 4.2, 4.3, and 4.4 show the uncertainty in the individual model parameters based on the form of the model shown by Equation 3.6 in Chapter 3 Section 3.1. For the three approaches investigated, the parameter "ao" had the highest relative uncertainty (57.1%, 24.6%, and 29.0%), followed by "a1" (10.9%, 12.5%, and 13.9%), and "a2" (4.8%, 6.4%, and 6.9%). However, as shown in Figure 4.5, these uncertainties did not significantly impact the carbon estimation from the AGB model. The predicted mean carbon from each approach was 67.2, 70.7, and 69.8 tonnes/ha. The associated relative uncertainty due to parameter uncertainty was 2.1%, 3.6%, and 3.7%. By adjusting for uncertainty, the mean value of carbon would be between 65.8 to 68.6 tonnes/ha, 68.1 to 73.3 tonnes/ha, and 67.3 to 72.4 tonnes/ha for each approach.

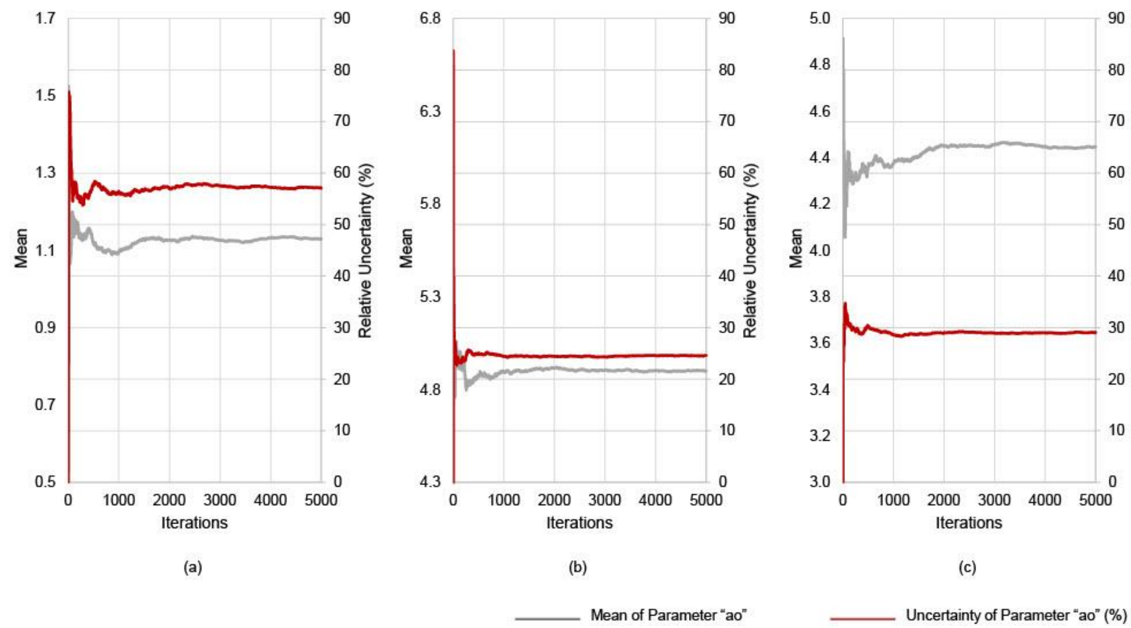

Figure 4.2 Simulated uncertainty for parameter "ao" in Equation 3.6 using (a) approach 1: MCS, (b) approach 2: bootstrap and MCS, and (c) approach 3: Bayesian bootstrap and MCS

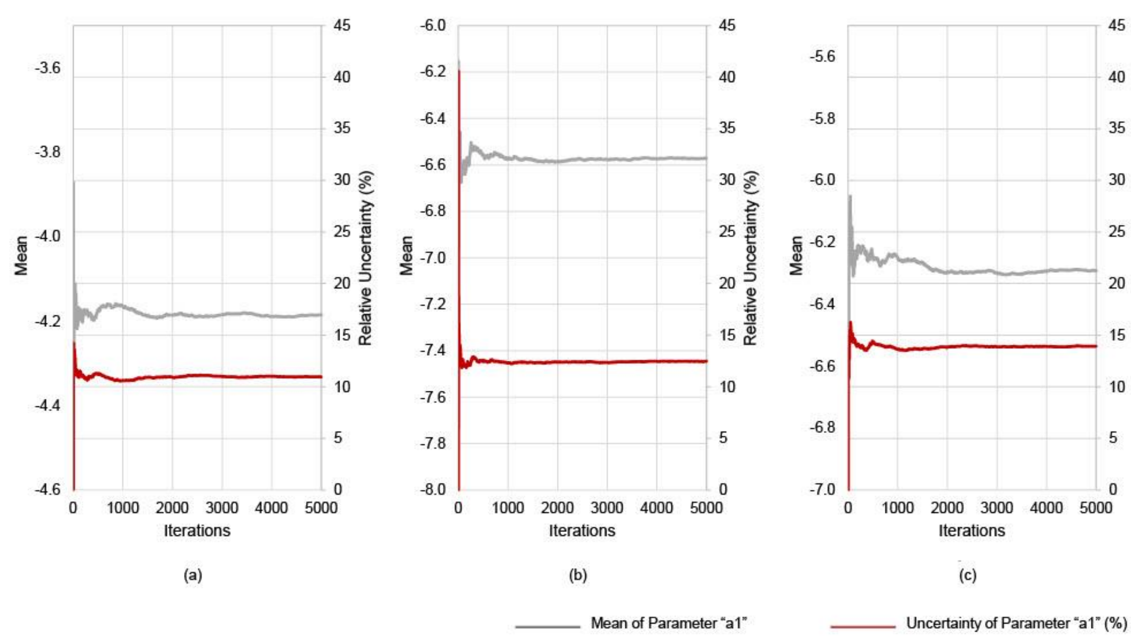

Figure 4.3 Simulated uncertainty for parameter "a1" in Equation 3.6 using (a) approach 1: MCS, (b) approach 2: bootstrap and MCS, and (c) approach 3: Bayesian bootstrap and MCS

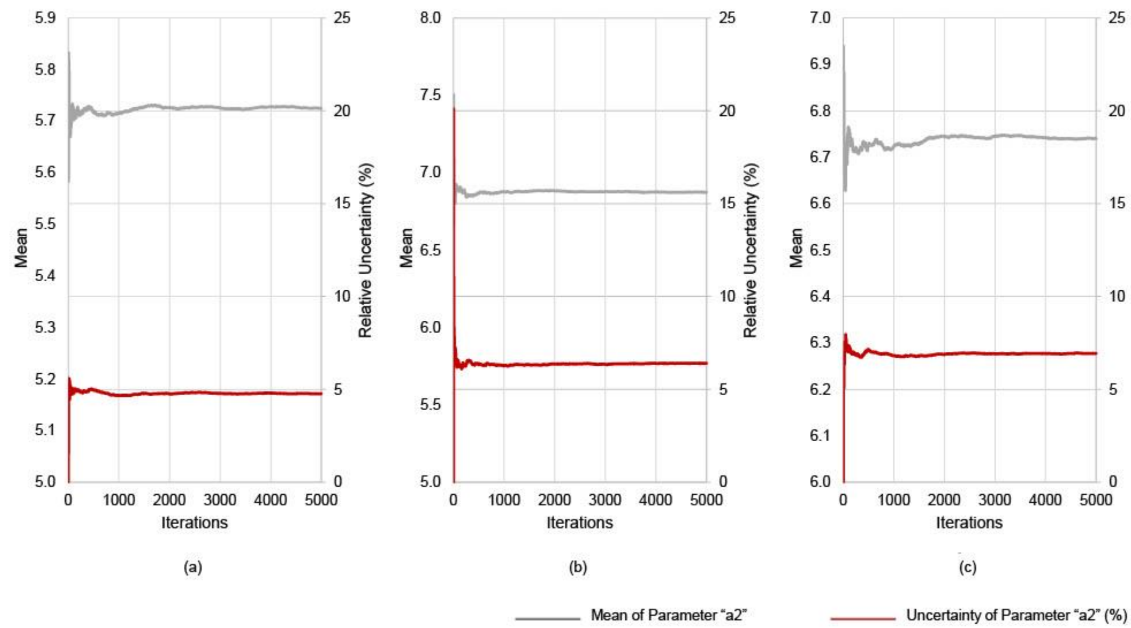

Figure 4.4 Simulated uncertainty for parameter "a2" in Equation 3.6 using (a) approach 1: MCS, (b) approach 2: bootstrap and MCS, and (c) approach 3: Bayesian bootstrap and MCS

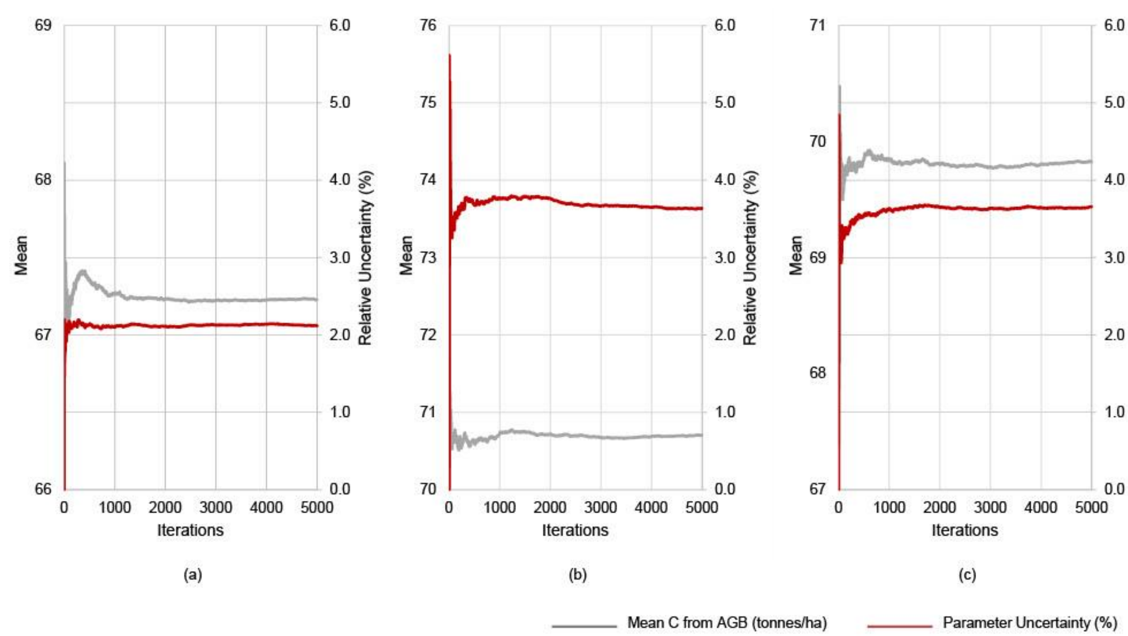

Figure 4.5 Simulated uncertainty in carbon from AGB due to variances in model parameters using (a) approach 1: MCS, (b) approach 2: bootstrap and MCS, and (c) approach 3: Bayesian bootstrap and MCS

4.3.2 Residual Uncertainty

The residual error model shown in Equation 4-3 resulted in an $R^2 = 0.57$.

$$\sigma_g = 21.2 + (30.0 \times 10^{-5}) \times \left(\overline{\widehat{AGB}}\right)^2 + (3.21 \times 10^{-2}) \times \left(\overline{\widehat{AGB}}\right) \tag{4.3}$$

The alternative models investigated for are shown in Appendix C. As shown in Figure 4.6, residual variance had a significant impact on carbon quantification from the AGB model. The predicted mean carbon from each approach was 53.9, 54.2, and 53.7 tonnes/ha. The associated relative uncertainty due to residual uncertainty was 24.2%, 24.1%, and 24.0%. By adjusting for uncertainty, the mean value of carbon would be between 41.2 to 67.2 tonnes/ha, 41.1 to 67.3 tonnes/ha, and 40.8 to 66.6 tonnes/ha for each approach.

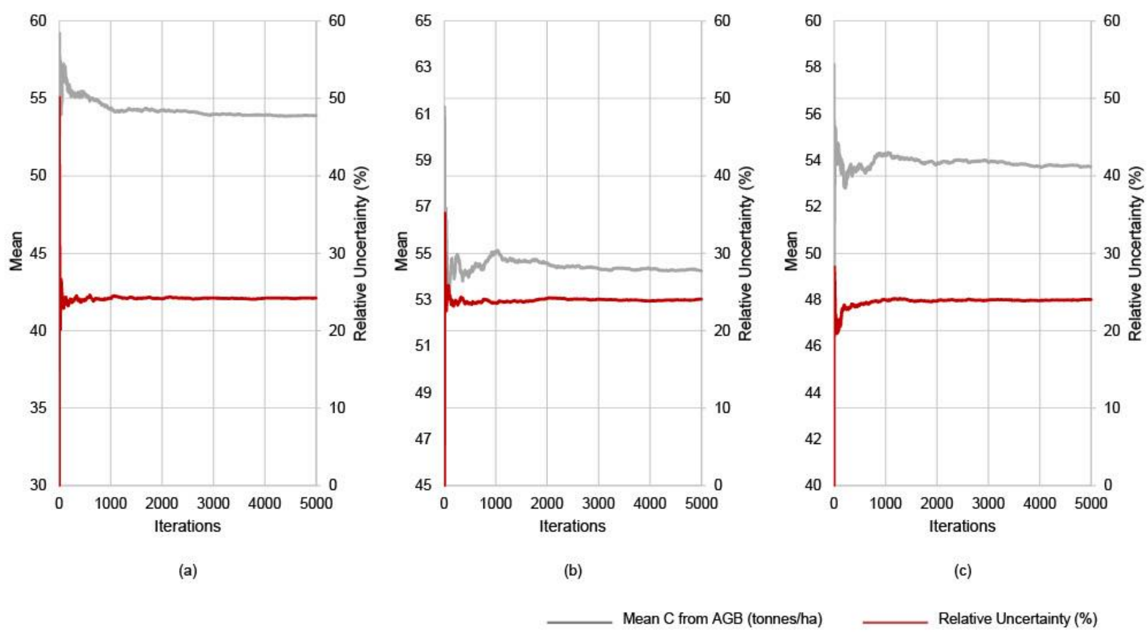

Figure 4.6 Simulated uncertainty in carbon from AGB due to residual variances using (a) approach 1: MCS, (b) approach 2: bootstrap and MCS, and (c) approach 3: Bayesian bootstrap and MCS

4.3.3 Measurement Uncertainty

The Dbh measurement error model shown in Equation 4.4 resulted in an $R^2 = 0.66$.

$$\sigma_M^{Dbh} = 0.24 + (90.0 \times 10^{-5}) \times \left(\overline{Dbh}\right)^2 + (2.91 \times 10^{-2}) \times \left(\overline{Dbh}\right) \tag{4.4}$$

The alternative models investigated are shown in Appendix D. As shown in Figure 4.7, measurement errors in the model input variables contributed the most to the uncertainty in carbon from the AGB model. The predicted mean carbon from each approach was 56.8, 55.8, and 56.4 tonnes/ha. The associated relative uncertainty due to measurement uncertainty was 32.5%, 33.2%, and 32.8%. By adjusting for uncertainty, the mean value of carbon would be between 38.3 to 75.3 tonnes/ha, 37.3 to 74.3 tonnes/ha, and 37.9 to 74.9 tonnes/ha for each approach.

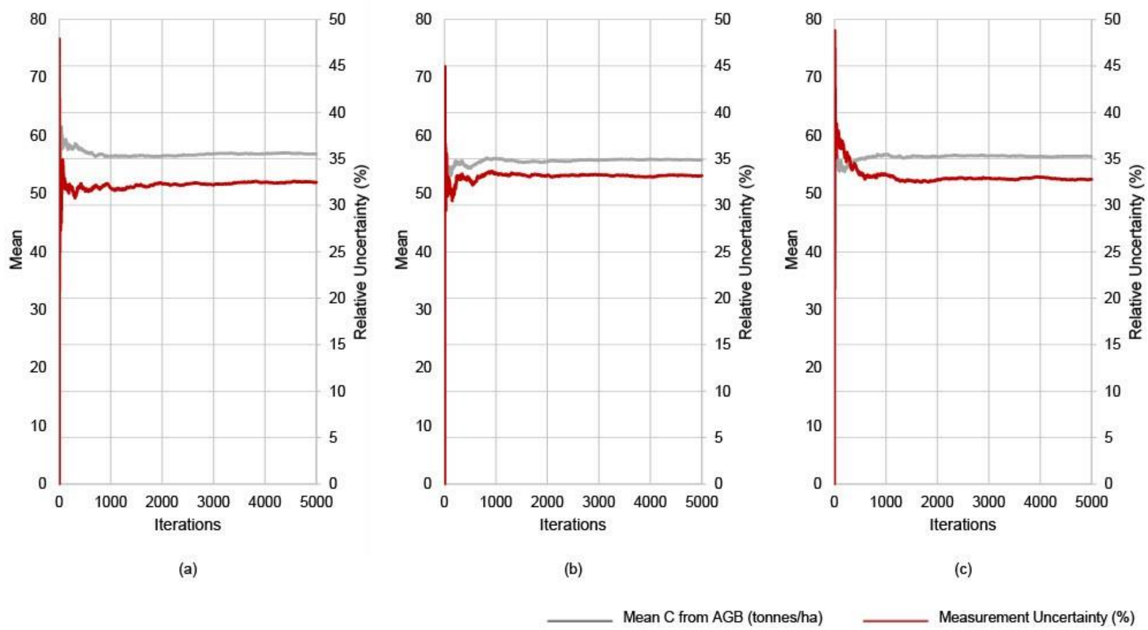

Figure 4.7 Simulated uncertainty in carbon from AGB due to measurement error in model input variables using (a) approach 1: MCS, (b) approach 2: bootstrap and MCS, and (c) approach 3: Bayesian bootstrap and MCS

4.3.4 Total Uncertainty

Figure 4.8 shows the results of the overall uncertainty in the carbon estimates from AGB due to the following sources of model uncertainties: model parameter uncertainty, model residual variance, and measurement uncertainty for model input variables. The observed mean carbon for study area 1 was approximately 54.4 tonnes/ha. The predicted carbon from the AGB model and the associated uncertainty for each approach was approximately 75.4 tonnes/ha (56.4% uncertain), 81.7 tonnes/ha (69.2% uncertain), and 80.6 tonnes/ha (80.6% uncertain). By adjusting for uncertainty, the mean value of carbon would be between 32.9 to 118 tonnes/ha, 25.2 to 138 tonnes/ha, and 26.1 to 135 tonnes/ha for each approach.

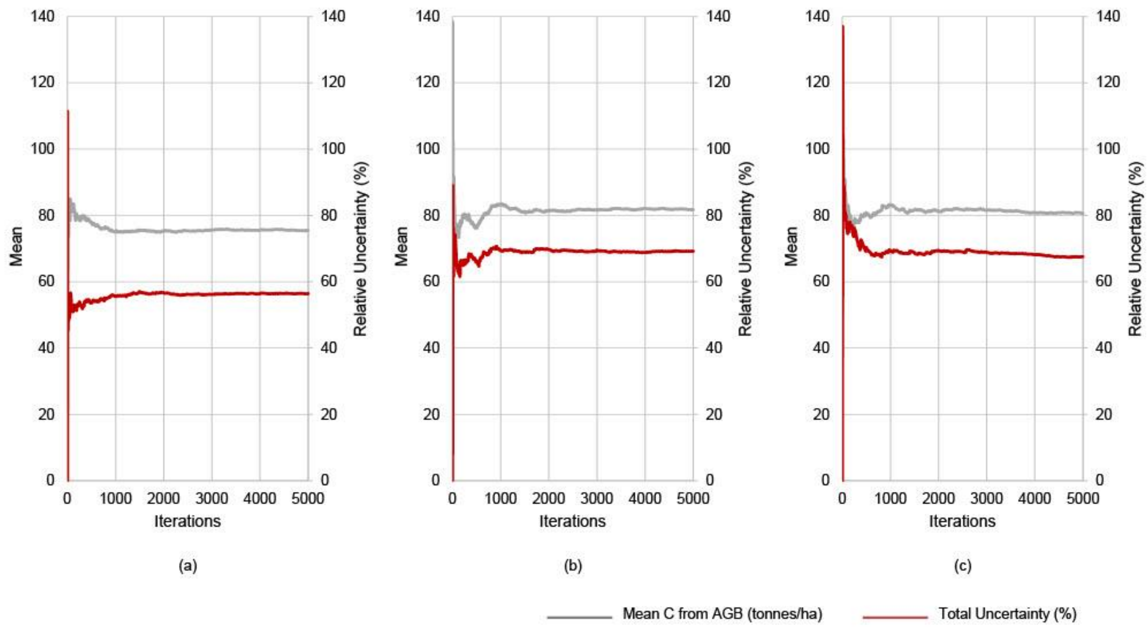

Figure 4.8 Overall simulated uncertainty in carbon from AGB using (a) approach 1: MCS, (b) approach 2: bootstrap and MCS, and (c) approach 3: Bayesian bootstrap and MCS

4.4 Case Study 2: Uncertainty Analysis

This section will review the results of the four-part uncertainty analysis for case study 2 in Västernorrland County, Sweden. The results of case study 2 were similar to that of case study 1. The three uncertainty analysis approach resulted in the same conclusions: measurement errors had the most significant impact on carbon quantification from AGB, followed by model residual variance, and parameter uncertainty was insignificant.

4.4.1 Parameter Uncertainty

Figures 4.9, 4.10, and 4.11 show the uncertainty in the individual model parameters based on the form of the model shown by Equation 3.6 in Chapter 3 Section 3.1. For the three approaches investigated, the relative uncertainty of parameter "ao" was 18.7%, 48.2%, and 55.7%, "a1" was 29.9%, 49.9%, and 45.3%, and "a2" was 20.7%, 32.3%, and 39.5%.

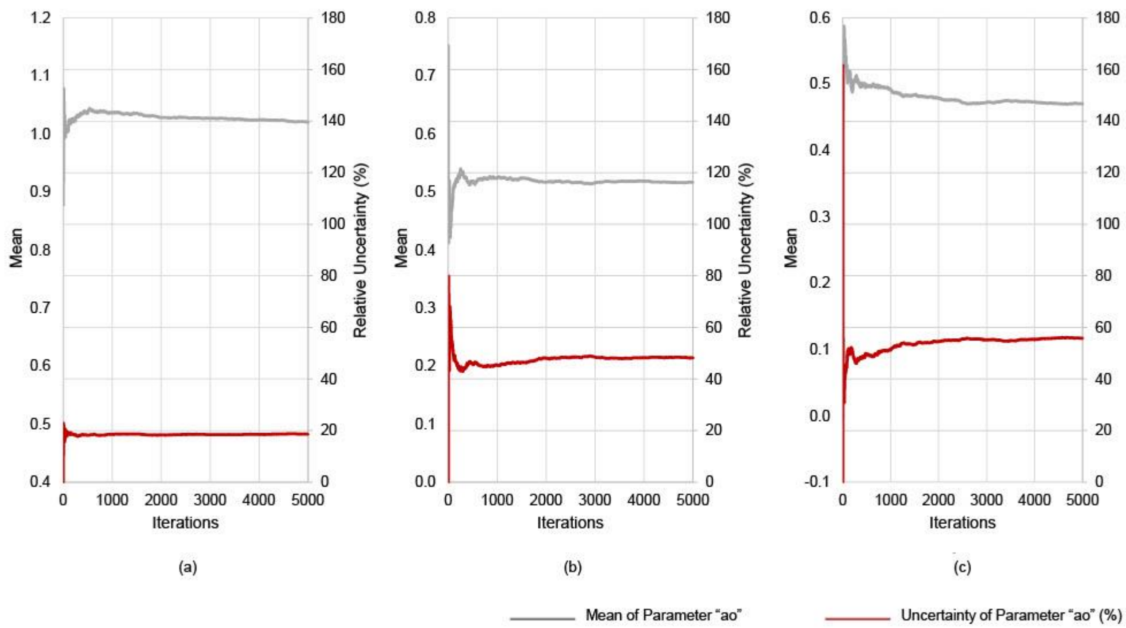

Figure 4.9 Simulated uncertainty for parameter "ao" in Equation 3.6 using (a) approach 1: MCS, (b) approach 2: bootstrap and MCS, and (c) approach 3: Bayesian bootstrap and MCS

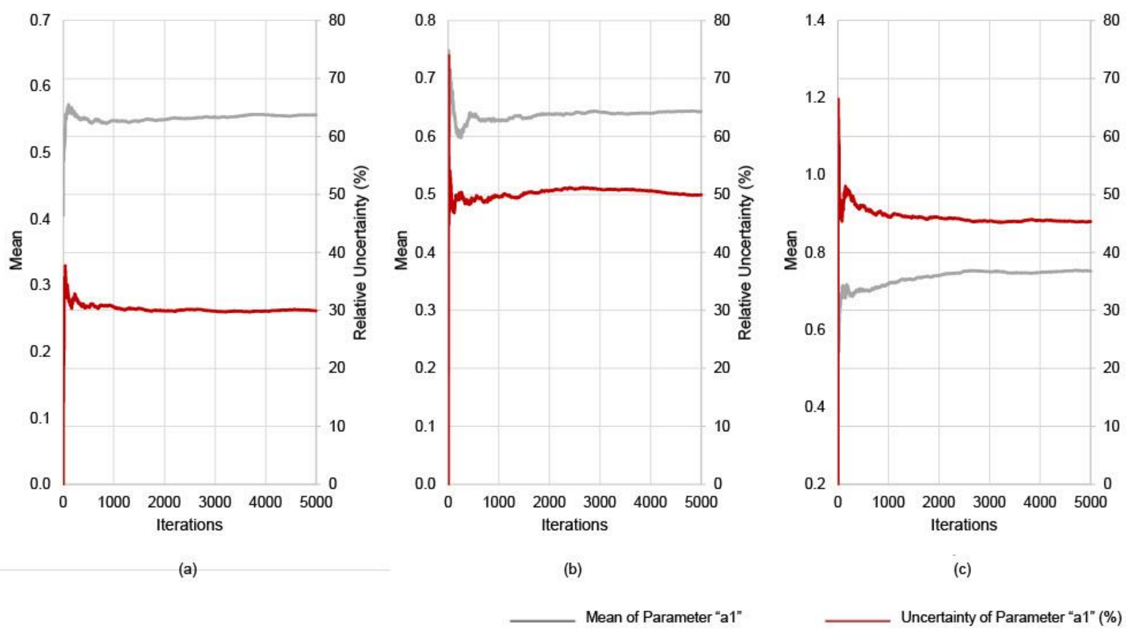

Figure 4.10 Simulated uncertainty for parameter "a1" in Equation 3.6 using (a) approach 1: MCS, (b) approach 2: bootstrap and MCS, and (c) approach 3: Bayesian bootstrap and MCS

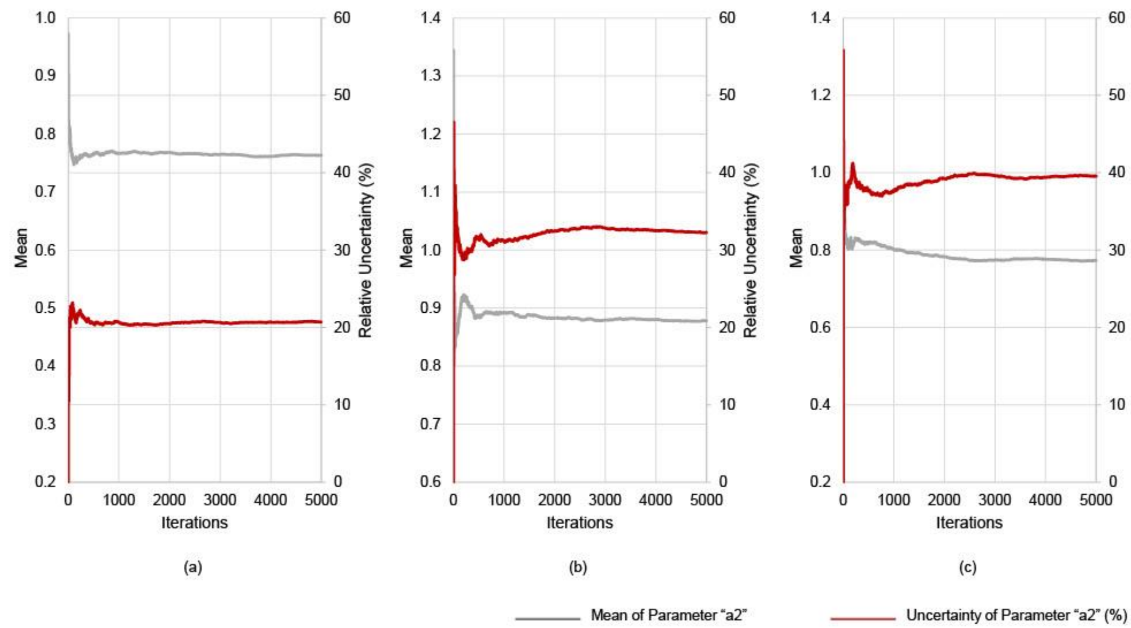

Figure 4.11 Simulated uncertainty for parameter "a2" in Equation 3.6 using (a) approach 1: MCS, (b) approach 2: bootstrap and MCS, and (c) approach 3: Bayesian bootstrap and MCS

As shown in Figure 4.12, these uncertainties did not significantly impact the carbon estimation from AGB. The predicted mean carbon from each approach was 38.2, 38.6, and 38.6 tonnes/ha. The associated relative uncertainty due to parameter uncertainty was 0.6%, 0.4%, and 0.6%. By adjusting for uncertainty, the mean value of carbon would be between 38.0 to 38.4 tonnes/ha for approach 1 and 38.4 to 38.8 tonnes/ha for approaches 2 and 3.

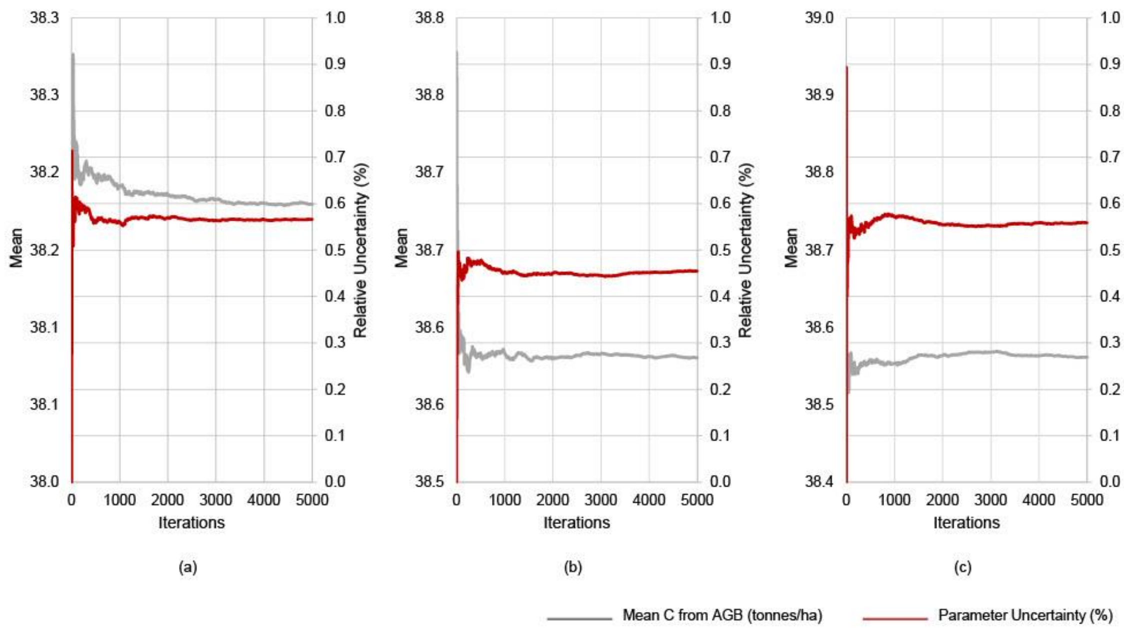

Figure 4.12 Simulated uncertainty in carbon from AGB due to variances in model parameters using (a) approach 1: MCS, (b) approach 2: bootstrap and MCS, and (c) approach 3: Bayesian bootstrap and MCS

4.4.2 Residual Uncertainty

The residual error model shown in Equation 4.5 resulted in an R^2 = 0.68.

$$\sigma_g = 3.77 + (20.0 \times 10^{-5}) \times \left(\overline{\widehat{AGB}}\right)^2 + (2.39 \times 10^{-2}) \times \left(\overline{\widehat{AGB}}\right) \tag{4.5}$$

The alternative models investigated are shown in Appendix C. As shown in Figure 4.13, the predicted mean carbon from each approach was 38.9 tonnes/ha. The associated relative uncertainty due to residual uncertainty was 8.1% for approach 1, and 8.0% for approaches 2 and 3. By adjusting for uncertainty, the mean value of carbon would be between 35.7 to 42.0 tonnes/ha for approach 1 and 35.8 to 42.0 tonnes/ha for approaches 2 and 3.

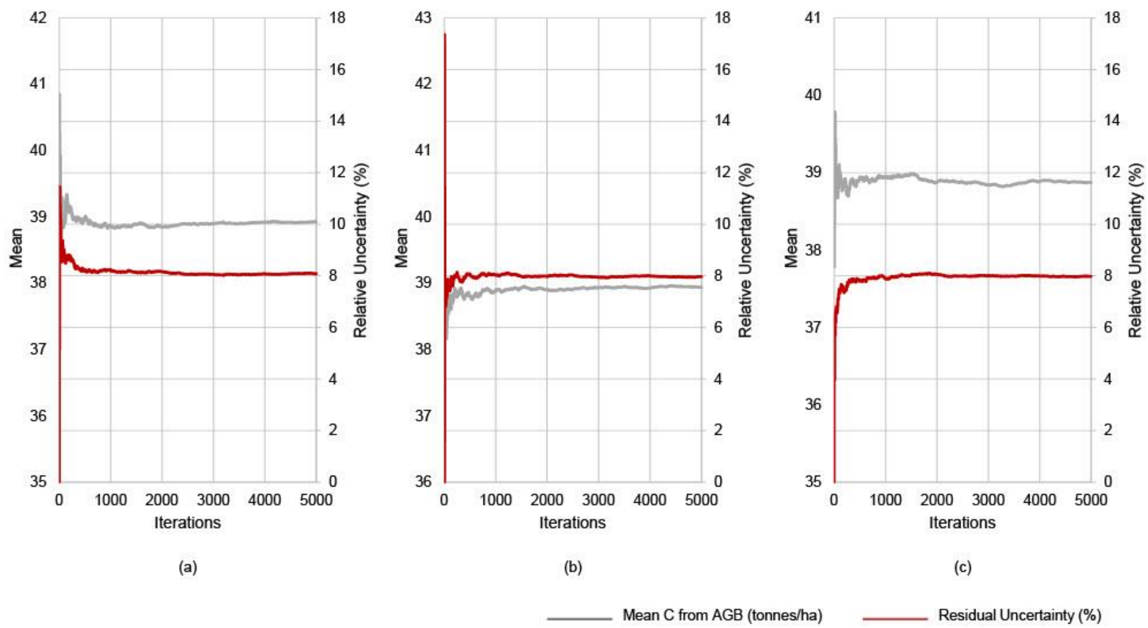

Figure 4.13 Simulated uncertainty in carbon from AGB due to residual variances using (a) approach 1: MCS, (b) approach 2: bootstrap and MCS, and (c) approach 3: Bayesian bootstrap and MCS

4.4.3 Measurement Uncertainty

The Dbh measurement error model shown in Equation 4.6 resulted in an $R^2 = 0.74$.

$$\sigma_M^{Dbh} = 0.16 + (70.0 \times 10^{-5}) \times \left(\overline{Dbh}\right)^2 + (2.15 \times 10^{-2}) \times \left(\overline{Dbh}\right) \quad (4.6)$$

The alternative models investigated are shown in Appendix D. As shown in Figure 4.14, measurement errors in the model input variables contributed the most to the uncertainty in carbon from the AGB model. The predicted mean carbon from each approach was 40.0, 40.1, and 40.5 tonnes/ha. The associated relative uncertainty due to measurement uncertainty was 28.6%, 27.9%, and 29.3%. By adjusting for uncertainty, the mean value of carbon would be between 28.6 to 51.4 tonnes/ha, 28.9 to 51.3 tonnes/ha, and 28.6 to 52.4 tonnes/ha for each approach.

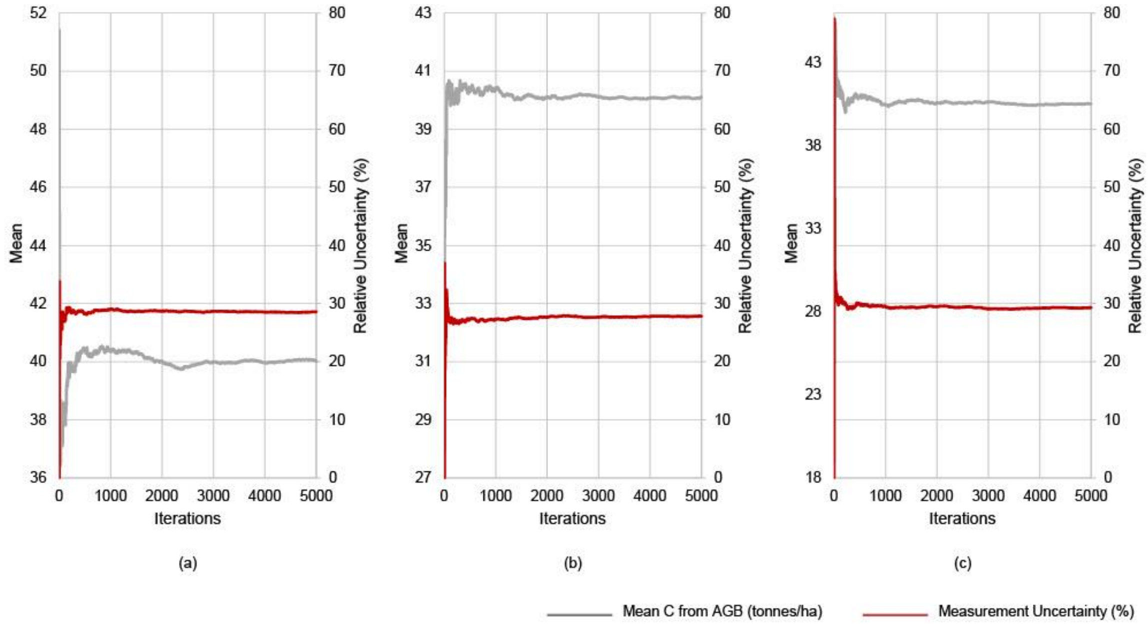

Figure 4.14 Simulated uncertainty in carbon from AGB due to measurement error in model input variables using (a) approach 1: MCS, (b) approach 2: bootstrap and MCS, and (c) approach 3: Bayesian bootstrap and MCS

4.4.4 Total Uncertainty

Figure 4.15 shows the results of the overall uncertainty in the carbon estimates from AGB due to the following sources of model uncertainties: model parameter uncertainty, model residual variance, and measurement uncertainty for model input variables. The observed mean carbon for study area 1 was approximately 39.1 tonnes/ha. The predicted carbon from the AGB model and the associated uncertainty for each approach was approximately 38.1 tonnes/ha (10.7% uncertain), 38.6 tonnes/ha (11.4% uncertain), and 38.6 tonnes/ha (11.1% uncertain). By adjusting for uncertainty, the mean value of carbon would be between 34.0 to 42.2 tonnes/ha, 34.2 to 43.0 tonnes/ha, and 34.3 to 42.9 tonnes/ha for each approach.

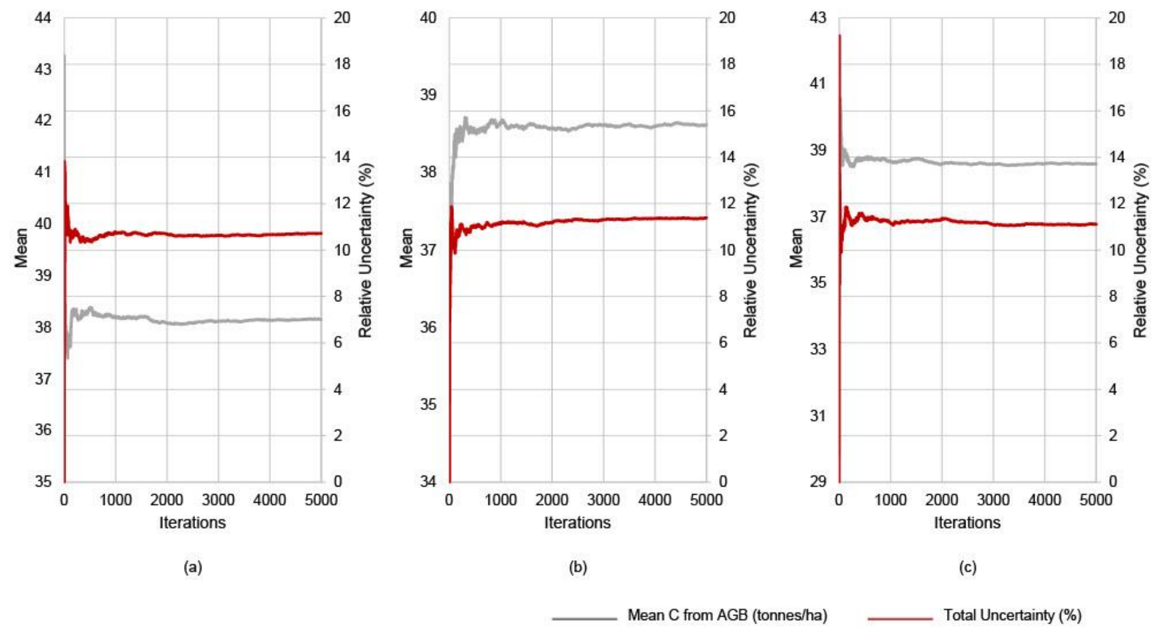

Figure 4.15 Overall simulated uncertainty in carbon from AGB using (a) approach 1: MCS, (b) approach 2: bootstrap and MCS, and (c) approach 3: Bayesian bootstrap and MCS

4.5 Comparison of Results

Case Studies 1 and 2 assessed the effects of model uncertainties on carbon estimation from AGB from the following sources: model parameter uncertainty, model residual variance, and measurement uncertainty for model input variables Dbh and Ht. The results of both case studies are summarized in Table 4.1.

The contributions of the individual sources of uncertainty to the overall model uncertainty were consistent for both case studies. The measurement errors for the model input variables were the largest source of uncertainty, followed by the model residual variance. The relative uncertainty due to variances in model parameters was the smallest source of uncertainty.

The effects of using alternative uncertainty analysis approaches on the uncertainty estimates were negligible in most cases, as each approach resulted in similar estimates.

Table 4.1 Summary of Results for Case Studies 1 and 2

Case Study	Uncertainty Source	Approach 1			Approach 2			Approach 3		
		Mean C from AGB (tonnes/ha)	Uncertainty (tonnes/ha, %)	Variance	Mean C from AGB (tonnes/ha)	Uncertainty (tonnes/ha, %)	Variance	Mean C from AGB (tonnes/ha)	Uncertainty (tonnes/ha, %)	Variance
Case Study 1	Model Parameters	67.2	(±1.4, 2.1)	81.3 (10^{-1})	70.7	(±2.5, 3.6)	26.5	69.8	(±2.6, 3.7)	29.3
	Model Residual Variance	53.9	(±13.0, 24.2)	68.1 (10)	54.2	(±13.1, 24.1)	68.3 (10)	53.7	(±12.9, 24.0)	67.2 (10)
	Model Input Measurements	56.8	(±18.5, 32.5)	13.6 (10^2)	55.8	(±18.5, 33.2)	13.7 (10^2)	56.4	(±18.5, 32.8)	13.7 (10^2)
	Overall	75.4	(±42.5, 56.4)	72.4 (10^2)	81.7	(±56.5, 69.2)	12.8 (10^3)	80.6	(±54.5, 67.5)	12.8 (10^3)
Case Study 2	Model Parameters	38.2	(±0.2, 0.6)	18.7 (10^{-2})	38.6	(±0.1, 0.4)	12.3 (10^{-2})	38.6	(±0.2, 0.6)	18.6 (10^{-2})
	Model Residual Variance	38.9	(±3.1, 8.1)	39.7	38.9	(±3.1, 8.0)	38.5	38.9	(±3.1, 8.0)	38.5
	Model Input Measurements	40.0	(±11.4, 28.6)	52.4 (10)	40.1	(±11.2, 27.9)	49.9 (10)	40.5	(±11.9, 29.3)	56.4 (10)
	Overall	38.1	(±4.1, 10.7)	66.8	38.6	(±4.40, 11.4)	77.4	38.6	(±4.3, 11.1)	73.6

4.6 Effects of Implementing Alternative Uncertainty Analysis Approaches

This thesis suggests that the IPCC's guidelines for MCS are insufficient when quantifying uncertainties for models that involve complex algorithms. By researching literature related to uncertainties in allometric models, the procedure outlined Chapter 3 demonstrated a method that can be used to quantify model uncertainties for carbon quantification from AGB. To assess the effects of alternative uncertainty analysis methods on the estimated uncertainties, the following approaches were proposed: Approach 1 used MCS by assuming the shapes of PDFs; 2 used bootstrap re-sampling with MCS; and 3 used Bayesian bootstrap re-sampling with MCS. The results of this thesis found that for both case studies there were no significant differences by quantifying uncertainties using the alternative approaches. Each approach resulted in similar carbon estimates and the associated uncertainties, resulting in a difference of less than 2.0% for each uncertainty source in both case studies, with the exception of the overall uncertainty calculated for case study 1 in which this difference was less than 13.0%. The variance was measured to assess the precision of the carbon estimates due to the difference sources of uncertainty. In most cases there was no significant difference in precision for both case studies, with the exception of the carbon estimated taking into account parameter uncertainty and the overall uncertainty for case study 1, in which variance differed by a value of 21.2 and 556 between approach 1 and approaches 2 and 3. However, despite the differences in precision, all results converged to similar estimates after 5,000 simulations, therefore any lack of precision did not significantly impact carbon estimates from AGB, or estimates of uncertainty. The results of this study conclude that no recommendations are made according to the alternative approaches assessed in this study.

4.7 Evaluation and Applications of the Predicted Uncertainties

The information provided by the uncertainty analysis can be used to determine the reliability of carbon estimates from AGB, and prioritize methodological and data collection improvements (Paciornik et al., 2019). This section aims to discuss (1) how the results of this study compare to similar assessments; (2) the impacts of uncertainties on carbon from AGB quantification methods; and (3) the affects of uncertainties on the creation of climate change policies and mitigation strategies.

4.7.1 Comparison to Similar Assessments

Contributions of the individual sources of uncertainty to the overall uncertainty differed in comparison to similar studies:

- This thesis followed similar methodologies reported by McRoberts and Westfall (2016) and Qin et al. (2021). However, these studies concluded the effects of model uncertainty were mainly due to the uncertainty in parameter and residual variance, noting that higher parameter uncertainty resulted in increased residual variance.
- Breidenbach et al. (2014), Chen et al. (2015), and Persson et al. (2022) followed a different methodology. Breidenbach et al. (2014) and Chen et al. (2015) reported findings similar to McRoberts and Westfall (2016), and Qin et al. (2021). Persson et al. (2022) described residual uncertainties were large, whereas measurement and parameter uncertainty were negligeable

However, due to methodological differences, Breidenbach et al. (2014) and Chen et al. (2015) assumed that some measurement values were without errors or assessed measurement values as they relate to variances in model parameters and residuals but not as an individual source of error.

The results of this thesis emphasize the importance of assessing the effects of measurement errors on model uncertainty. Shettles et al. (2015) concluded that uncertainty in AGB prediction is underestimated if measurement errors are not considered when quantifying model uncertainty, and Qin et al. (2019) concluded that model outputs may not be representative if measurement errors are not considered. Persson et al. (2022) explained measurement errors should be assessed as they relate to model uncertainty, as the magnitude of measurement errors may be inflated through the model. Furthermore, measurement variances may be larger depending on individual forest inventories, emphasizing the importance of assessing uncertainties on a case-by-case basis (Persson et al., 2022).

Measurement errors in national forest inventories are often assumed to be error-free. Magnussen and Russo (2012) quantified the uncertainty in photo-interpreted data in Canada's National Forest Inventory. Magnussen and Russo (2012) found that the uncertainty ranged from 0% to 36.0%, which is consistent with the approximately 33.0% measurement error quantified in case study 1. SLU (2021) predicted the uncertainty in the SLU Forest map to be 12.0% for height and 16.0% for diameter. The results of case study 2 predicted a higher value of 28.5% uncertain.

Based on this comparison, generalizations that apply to all study systems cannot be made. Evaluating the effects of the individual sources of uncertainty on carbon quantification from AGB allometric models should be assessed on a case-by-case basis, as the contributions to the overall uncertainty from each source can differ among study systems due to variations in the quantification approaches used. For example, several factors including the difference in the choice of the allometric model, the amount and quality of the data obtained, the sampling procedures and standards implemented by the data compilers, and the representativeness and natural variability in the study area may result in different sources of uncertainty being more prevalent than others.

4.7.2 Impacts of Uncertainties on Quantification Methods

Assessing the individual sources of uncertainties can be used to identify areas in which methodological and data collection improvements in carbon quantification from AGB are needed (Paciornik et al., 2019). In this study, the largest source of uncertainty was due to measurement errors. Factors that impact the reliability of measurements include sampling techniques, equipment, and skills when directly measuring samples, and the efficiency of technology and the allocation sampling plots when using remote sensing (McRoberts et al., 1994; Picard et al., 2012; Skovsgaard et al., 1998). However, even if improvements are implemented, measurement errors can still occur (Elzinga et al., 2005; Qin et al., 2021). The need for research on how proposed improvements affect uncertainties and the associated economic trade-offs remains outstanding.

Increasing the sample size can improve the accuracy of the model (Chen et al., 2016; Qin et al., 2021). This can be seen by comparing the results of case studies 1 and 2. Both case studies were conducted in similar areas (12,365 and 10,000 ha); however, case study 1 had 580 mean values per polygon (each polygon containing 1195 live stems), and case study 2 had 1120 mean values per polygon (each polygon containing 561 live stems). The average polygon area was significantly less in case study 2 (12.5 m x 12.5 m or ~15.6

x 10^{-3} ha) compared to case study 1 (~12.0 ha), resulting in a larger sample size. The model fit was improved in case study 2, and the variances in model parameters and residuals was less by approximately 2.6% and 16.1%. However, increasing the sample size can be technically and economically challenging (Persson et al., 2022; Qin et al., 2021). In AGB quantification, increasing the plot size is equivalent to accumulating more trees, hence larger plot sizes result in lower residual error (Picard et al., 2015). Alternatively, AGB models that incorporate more predictor variables tend to produce more reliable estimates, resulting in lower variances in parameters and residuals; however, studies have found that incorporating additional variables did not significantly improve estimates and were not worth the high cost of obtaining representative measurements for additional predictor variables (Balbinot et al., 2018; Fradette et al., 2021; Mensah et al., 2017; Mugasha et al., 2016; Picard et al., 2015; Qin et al., 2021; Sadono et al., 2021; Segura et al., 2006).

Evaluating the improvements to carbon quantification from AGB is a complicated process that involves evaluating the technical and economic trade-offs with respect to the capabilities of individual study areas. Future research may focus on the costs and benefits of modifying quantification methods to reduce uncertainties.

4.7.3 Impacts of Uncertainties on Climate Change Policy Creation

There are numerous applications requiring reliable data in National Greenhouse Gas Inventories (NGHGIs), including the creation of climate change policies (Gillenwater et al., 2007). However, this data is associated with high uncertainty, particularly in the forestry sector, prompting the need for research on how uncertainty information can be incorporated in practical applications (Gillenwater et al., 2007; Ulvdal et al., 2023).

Considering case study 1, a report by Skene and Polanyi (2021) published by the National Resource Defense Council in Canada criticized the government for excluding large uncertainties in forest carbon estimates from policy decisions. The report explains that current accounting and regulating practices misrepresent the actual carbon cost of industrial logging and wood products, allowing certain industries to emit more carbon without repercussions, thus undervaluing the benefits of protecting existing forests (Skene and Polanyi, 2021). A potential solution requires basing policies on worse-case projections predicted from the high range of uncertainty estimates (Skene and Polanyi, 2021).

Considering case study 2, a study by Knaggård (2014) reported that scientific uncertainty played a very marginal role in the creation of Swedish climate change policies from 1975 to 2007. The article explains a need for methods to translate scientific uncertainties to political applications, as most policies were made according to knowledge of what was politically possible, rather than desirable from a scientific perspective (Knaggård, 2014).

Uncertainty estimates within the forestry sector are rarely applied in the decision making process (de Pellegrin Llorente et al., 2023). Enhanced efforts in communicating the theoretical framework for uncertainty analysis can lead to an increased understanding of uncertainties between researchers and policymakers, which can assist in incorporating uncertainty information into policies (de Pellegrin Llorente et al., 2023). Another method involves adjusting emission estimates in NGHGIs to include uncertainty information (Gillenwater et al., 2007). As a result, policies would be implemented based on the worst-case projection. For example, Chapter 4 Section 4.3 presents intervals for the emission estimates within which the true value is expected to reside. Adjusting emission estimates for uncertainty would require reporting the upper bound of the interval as the true value. Future research may focus on the feasibility and resulting political and economic impacts of incorporating uncertainties in climate change policies.

4.7.4 Impacts of Uncertainties on Climate Change Mitigation Strategies

Due to the high mitigation potential, ninety percent of the second-generation of nationally determined contributions (NDCs) included the forestry sector, and 57% referred specifically to forests as domestic options for greenhouse has (GHG) reduction (UNDP, 2021; UN-REDD Programme, 2022). However, GHG reductions can be overestimated if uncertainties are not accounted for.

Emission trading under the Kyoto Protocol is an example of a mitigation strategy with uncertain reliability in reducing GHGs. Emission trading allows companies or individuals to offset GHG emissions by purchasing carbon credits from entities that remove or reduce GHGs (UNDP, 2022). Trading in carbon credits is predicted to reduce the cost of implementing NDCs by more than half by 2030 (Edmonds et al., 2019). However, forestry projects employed to generate carbon credits have long been considered unreliable due to the high uncertainties associated with forest carbon quantification (IPCC, 2014a; van der Gaast et al., 2016). Furthermore, Article 6 of the Paris Agreement (2015) allows mitigation outcomes towards NDCs to be transferred internationally. Research reported by van der Gaast et al. (2016) concluded that improved carbon accounting in the forestry sector can enhance the scope and feasibility of the related NDCs. Proper accounting is an important requirement to ensure consistency and comparability when trading carbon credits between countries.

The outcomes of this thesis can be used to improve the quantification of uncertainties in carbon accounting, which can be used when determining the reliability of carbon estimates. However, further work is needed on how to incorporate uncertainty information in carbon estimates when developing NDCs.

4.8 Summary

Case studies 1 and 2 demonstrated the application of the uncertainty analysis methodology outlined in Chapter 3. The results of the uncertainty analysis were used to assess the effects of model uncertainties on carbon estimation from AGB from the following sources: model parameter uncertainty, model residual variance, and measurement uncertainty for model input variables Dbh and Ht. Contributions from the individual sources of uncertainty to the overall model uncertainty were consistent for both case studies. The measurement errors for the model input variables were the largest source of uncertainty, followed by the model residual variance, and model parameters were the smallest source of uncertainty. There was no significant difference in the carbon estimates or the associated uncertainty from using the different uncertainty analysis approaches. By comparing the results to similar studies, few generalizations can be made that apply to all study systems. The significance of different sources of uncertainty can differ between study systems, thus emphasizing the importance of evaluating uncertainty on a case-by-case basis. Assessing the individual sources of uncertainty can be used to prioritize methodological and data collection improvements. In this study, measurement and residual variances were the largest sources of uncertainty, and improvements that may reduce these uncertainties were proposed. Uncertainty information within the forestry sector is rarely applied in climate change decision-making, resulting in challenges regulating emissions.

Studies that assessed methods to incorporate this information into climate change policies recommended enhancing efforts to communicate the theoretical framework for uncertainty analysis to improve the understanding of uncertainties. Another method involves adjusting emission estimates to include uncertainty information so that policies are based on worst-case projections.

5.0 CONCLUSIONS

5.1 Summary, Conclusions, and Contributions

This thesis contributes to the understanding and implementation of uncertainty analysis methods used to quantify model uncertainties in carbon estimates from above-ground biomass (AGB) due to the following sources: model parameter uncertainty, model residual variance, and measurement uncertainty for model input variables: diameter at breast height (Dbh) and canopy height (Ht). A summary of the contributions and conclusions for each of the research objectives are shown in Table 5.1.

Chapter 2 reviewed the need for accurate and reliable greenhouse gas (GHG) emission and removal data in national GHG inventories (NGHGIs), particularly for AGB in the forestry sector. AGB is expected to contribute largely to GHG reductions; but contains highly uncertain estimates. It was determined that further studies are needed on quantifying the effects of model uncertainties in carbon estimation from AGB. Furthermore, this research reported a lack of guidance pertaining to the methods recommended by the Intergovernmental Panel on Climate Change (IPCC) for simulation-based uncertainty analysis methods that accounts for model uncertainty.

Chapter 3 proposed a simulation-based uncertainty analysis method for quantifying model uncertainties in AGB allometric models derived from forest inventory data. This method assessed the uncertainty as a result of the individual sources and the overall total. Uncertainty analysis approaches were proposed to assess the affects of using alternative approaches on uncertainty estimates. Approach 1 used Monte Carlo Simulation (MCS) by assuming the shapes of probability density functions; 2 used bootstrap re-sampling with MCS; and 3 used Bayesian bootstrap re-sampling with MCS.

Chapter 4 employed the uncertainty analysis methodology discussed in Chapter 3 for a study area in British Columbia (B.C.), Canada and in Västernorrland County, Sweden. The effects of the sources of uncertainty on carbon estimates from AGB were reported and estimates were adjusted to account for uncertainty. In both case studies, the measurement errors for the model input variables were the largest source of uncertainty, followed by the model residual variance, and model parameters were the smallest source of uncertainty.

There was no significant difference in the carbon estimates or the associated uncertainty from using the different uncertainty analysis approaches investigated. This chapter discussed how uncertainty estimates can be used to prioritize methodological and data collection improvements, and the impacts of uncertainties on climate change policies and mitigation strategies.

This thesis contributes a comprehensive guide for countries to follow when quantifying model uncertainties in carbon estimates from AGB allometric models using simulation-based uncertainty analysis. This is significant, as reliable carbon estimates in NGHGIs are essential for creating effective climate change policies and mitigation strategies, determining compliance with internationally agreed-upon targets, and tracking the sources and trends of GHG emissions and reductions.

This research demonstrates how the results of the uncertainty analysis can be interpreted and how estimates can be adjusted for uncertainty. It is important to assess the uncertainties in individual estimates on a case-by-case basis to determine areas in which methodological and data collection improvements may be needed to reduce uncertainties. The results of this research indicate that reducing measurement errors in forest inventory data had the highest potential to reduce uncertainties in carbon estimates from AGB. This could be achieved by improving sampling techniques, equipment, and skills when directly measuring samples, and the efficiency of technology and the allocation sampling plots when using remote sensing.

Rarely incorporating uncertainty information into practical applications undermines the confidence and effectiveness of climate change policies and mitigation strategies, resulting in the mismanagement of GHG emissions. To assist in incorporating uncertainty information into climate change decision-making: this research recommends improving the understanding of uncertainties by enhancing the communication of the theoretical framework for uncertainty analysis, similar to the methodology demonstrated in Chapter 3. Additionally, climate policies may be based on emission estimates that are adjusted for uncertainty, as demonstrated in Chapter 4, so that policies are based on worst-case projections, thus utilizing more reliable predictions of carbon from AGB.

Table 5.1 Summary of Contributions and Conclusions

Phase	Sub-Objective	Contribution/Conclusion
Phase 1: Literature Review	1. Assess the types and sources of uncertainties associated with carbon quantification from AGB in the forestry sector 2. Review the IPCC guidelines for conducting uncertainty analysis used in NGHGIs. Identify alternative uncertainty analysis methods that may better define uncertainties compared to the methods recommended by the IPCC	• Types of uncertainty: sampling, model & measurement • Sources of model uncertainty: model misspecification, parameters, residuals, and measurements in input data • Lack of guidance from the IPCC on simulation-based uncertainty analysis for model uncertainty • Effects of alternative uncertainty analysis methods on uncertainty methods were inconclusive in literature • In many cases alternative methods were better than MCS: however, further research is needed on this topic to evaluate the effects in different study systems
Phase 2: Data Collection **Phase 3:** Uncertainty Analysis	3. Develop a methodology to quantify uncertainties in carbon estimates from AGB	• Contributes a guide to assist countries in quantifying uncertainties in carbon quantified from AGB allometric models when using different uncertainty analysis approaches
Phase 4: Results and Discussion	4. Conduct case studies to investigate how uncertainties can be quantified in carbon estimates from AGB using different uncertainty analysis approaches. 5. Evaluate the impacts of these uncertainties on carbon quantification from AGB	• Demonstrates how the methodology outlined in Phases 2 and 3 can be applied to different countries, and how results can be interpreted and adjusted for uncertainties • Evaluated the impacts of uncertainties when prioritizing methodological and data collection improvements, and planning climate change policies and mitigation strategies

5.2 Limitations and Future Work

The following lists limitations encountered as the research progressed and the adjustments made to mitigate the effects. Recommendations are made to assist future work.

5.2.1 Uncertainty Types

The scope of the project was narrowed to focus on model uncertainties due to following sources: variances in model parameters, model residual variance, and measurement errors for model input variables Dbh and Ht. However, there are several sources of uncertainty, some of which may affect other sources. The amount of uncertainty sources was a limiting factor in this study as the scale of the project would significantly increase by considering more sources. The scope of the project was justified in Chapter 2 Sections 2.5.2 by reviewing literature on the sources of uncertainties in carbon quantification from AGB allometric models. However, this review only consisted of the quantitative sources of uncertainty. Qualitative sources of uncertainty are an important, but significantly under researched topic. To address this need, it is recommended that future work assesses the uncertainties due to the following sources: (1) uncertainties in classifying the source of GHG emissions and removals (direct human-induced, indirect human-induced, or natural), (2) uncertainties in using different land definitions between countries, (3) uncertainties in delineating land areas according to the managed land proxy (MLP), (4) and uncertainties in omitting unmanaged lands from reporting in NGHGIs (IPCC, 2006; IPCC, 2009; Michael et al., 2019; Ogle et al., 2018).

5.2.2 Methodological Uncertainties

The results of the uncertainty analysis may include uncertainties that arise due to methodological decisions. In Chapter 3 Sections 3.7.2 and 3.7.3, error models were derived to quantify the uncertainties due to measurement errors in the input variable Dbh and residual variance. However, different studies assumed different shapes for these error models (Berger et al., 2014; McRoberts and Westfall, 2016; Qin et al., 2021). The effects of this uncertainty was mitigated by selecting the shape of the error model by investigating the shapes of alternative models. This resulted in some R^2 values being less than 0.70. Although these methods are well defined in literature, future work is needed to validate the shape of the error models.

5.2.3 Data Availability

The accuracy of the model in predicting carbon from AGB is dependent on the amount and quality of data obtained. Validating the allometric model using field measurements would improve the accuracy (Picard et al., 2012). However, in this study only forest inventory measurements were available. These measurements were mainly derived from remote sensing and verified using ground sampling (FLNRO, 2022a; Wallerman et al., 2021). Although the data availability was limited, based on the standards implemented in compiling the forest inventories, it was assumed that this data was accurate enough to construct the allometric models.

5.2.3 Incorporating Uncertainties in Practical Applications

Based on the discussion provided in Chapter 4, the following research needs were identified to assist in implementing this research into practical applications. Assessing the sources of uncertainties can be used to identify and prioritize the need for methodological and data collection improvements. However, due to the complexities of quantifying carbon from AGB, research is needed assess the associated technical and economic trade-offs of the proposed changes to quantification methods. Recommendations were made to incorporate uncertainty information into policies; however, the associated political and economic impacts would need to be assessed. Lastly, there is a research need to incorporate the uncertainties in the creation and implementation of NDCs in order to advance effective and reliable climate change mitigation strategies.

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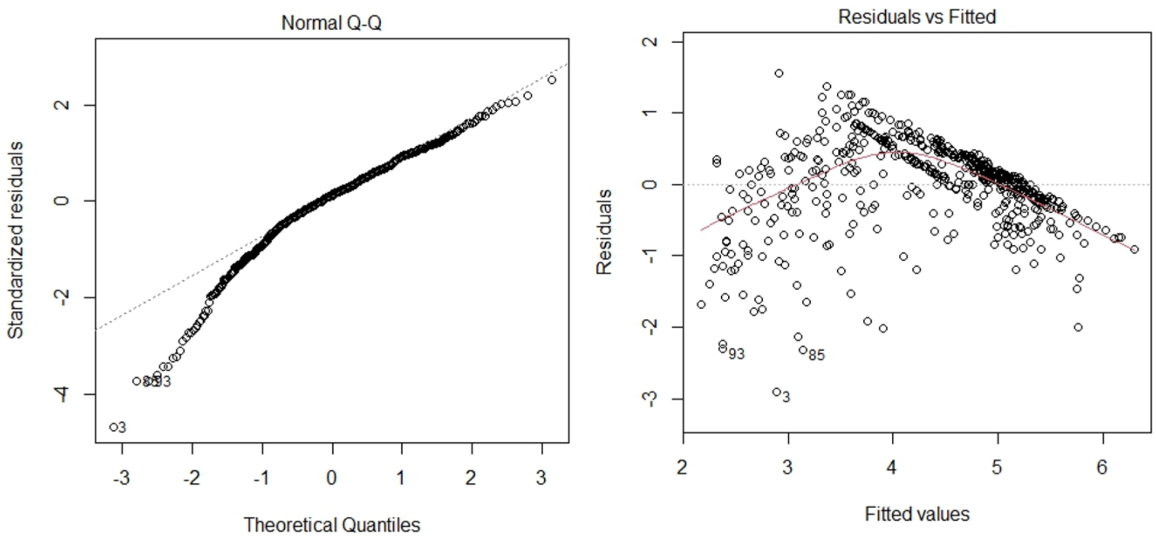
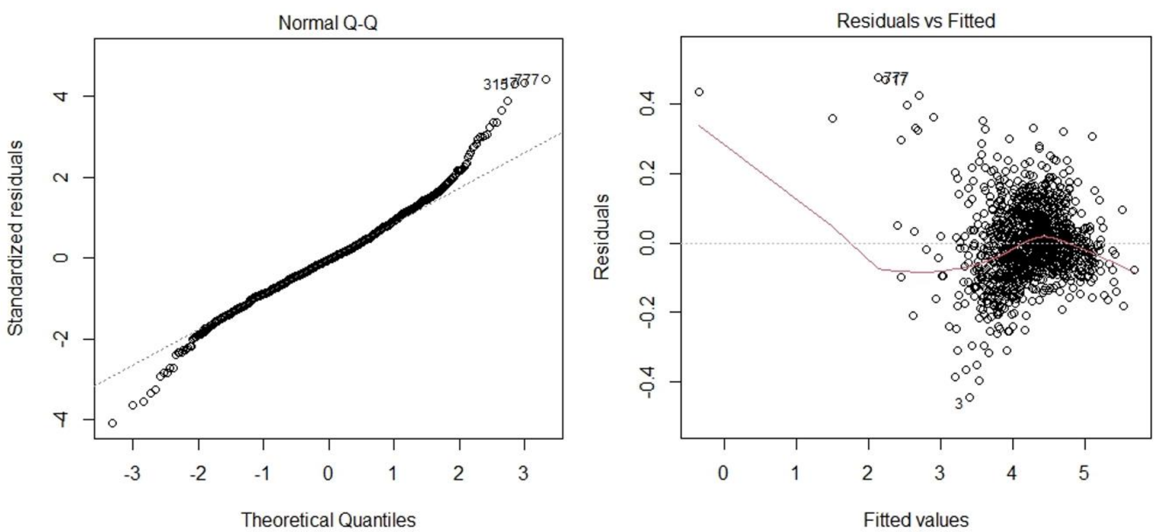
APPENDIX A: MODEL FITTING RESULTS



(a) (b)

Figure A.1 Model fitting results for case study1 hypothesis test: (a) quantile - quantile plot (b) residuals plotted against fitted values



(a) (b)

Figure A.2 Model fitting results for case study 2 hypothesis test: (a) quantile - quantile plot (b) residuals plotted against fitted values

APPENDIX B: HISTOGRAMS OF THE OBSERVED DATA AND THE PSEUDO-DATA

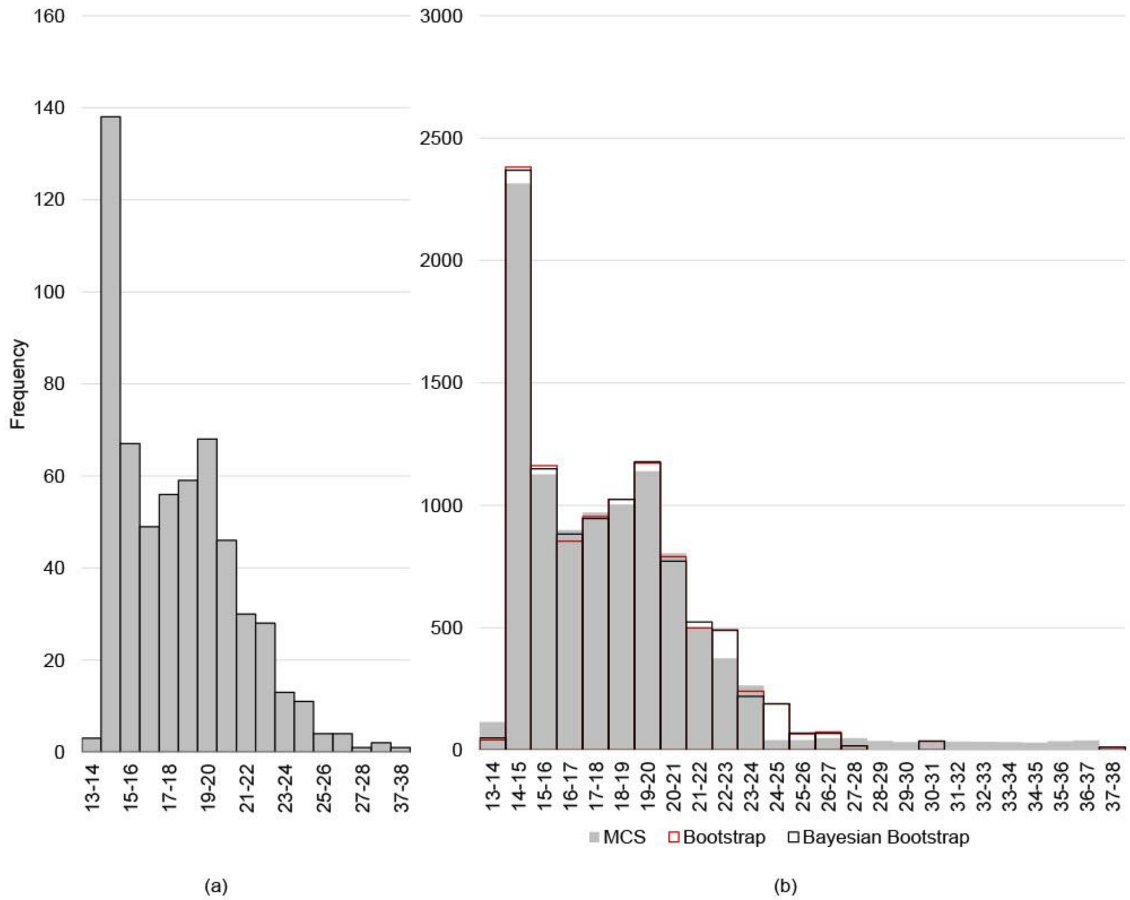


Figure B.1 Case study 1: Dbh histograms for (a) the observed dataset and (b) the pseudo-data generated from approach 1: MCS, approach 2: bootstrap and MCS, and approach 3: Bayesian bootstrap and MCS

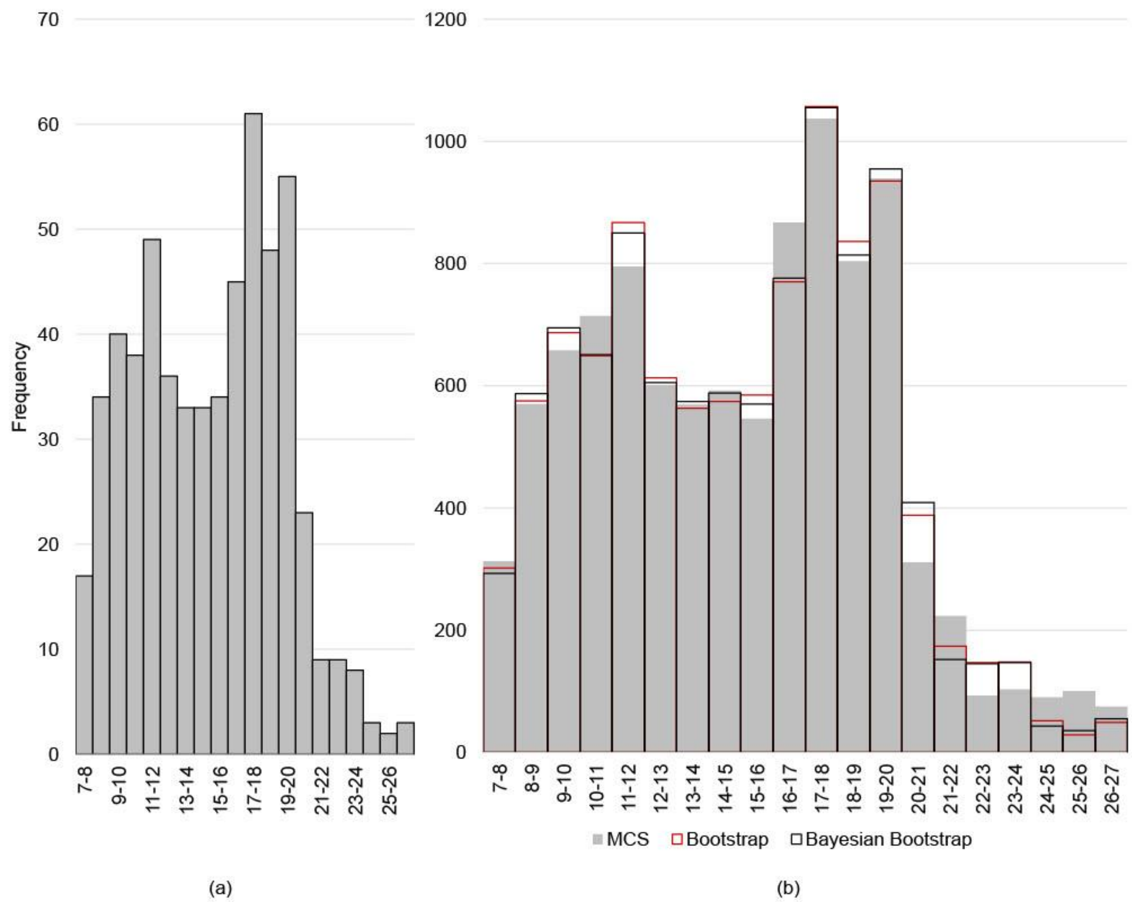


Figure B.2 Case study 1: Ht histograms for (a) the observed dataset and (b) the pseudo-data generated from approach 1: MCS, approach 2: bootstrap and MCS, and approach 3: Bayesian bootstrap and MCS

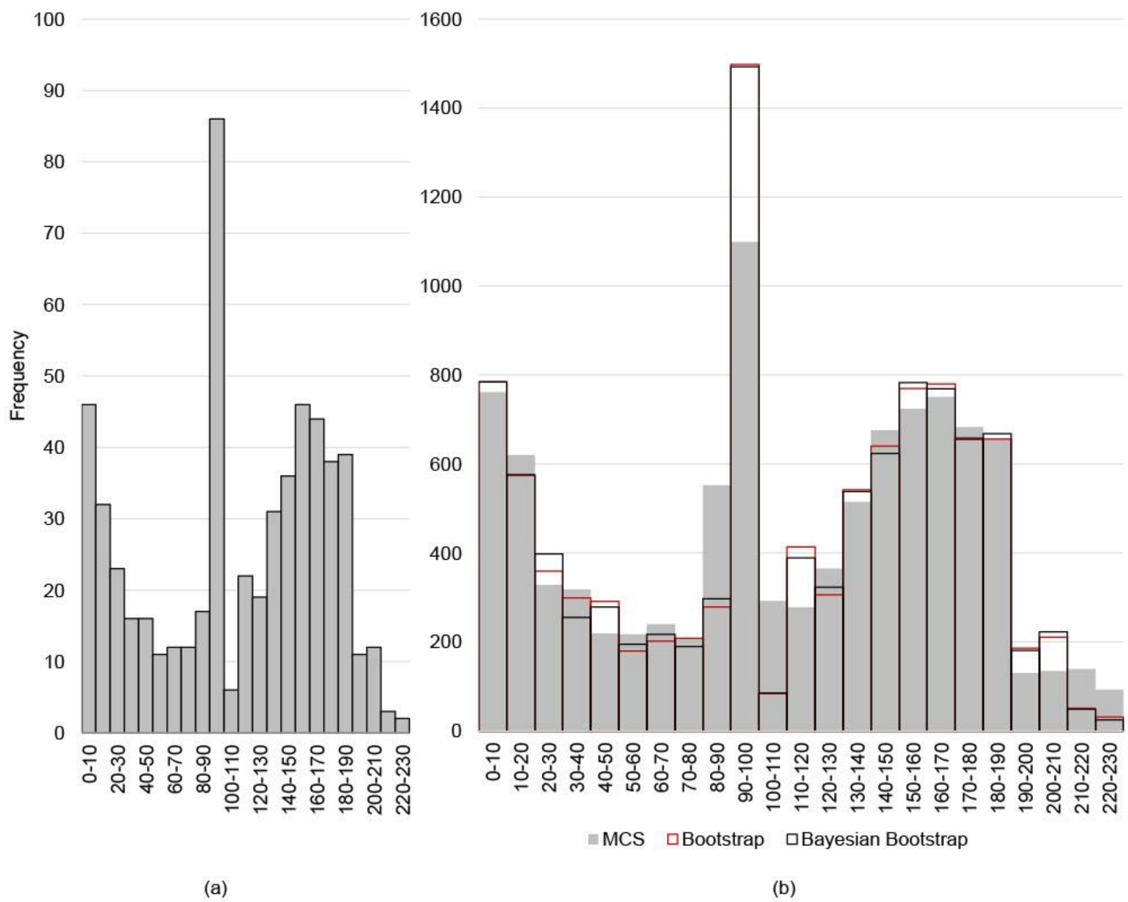


Figure B.3 Case study 1: AGB histograms for (a) the observed dataset and (b) the pseudo-data generated from approach 1: MCS, approach 2: bootstrap and MCS, and approach 3: Bayesian bootstrap and MCS

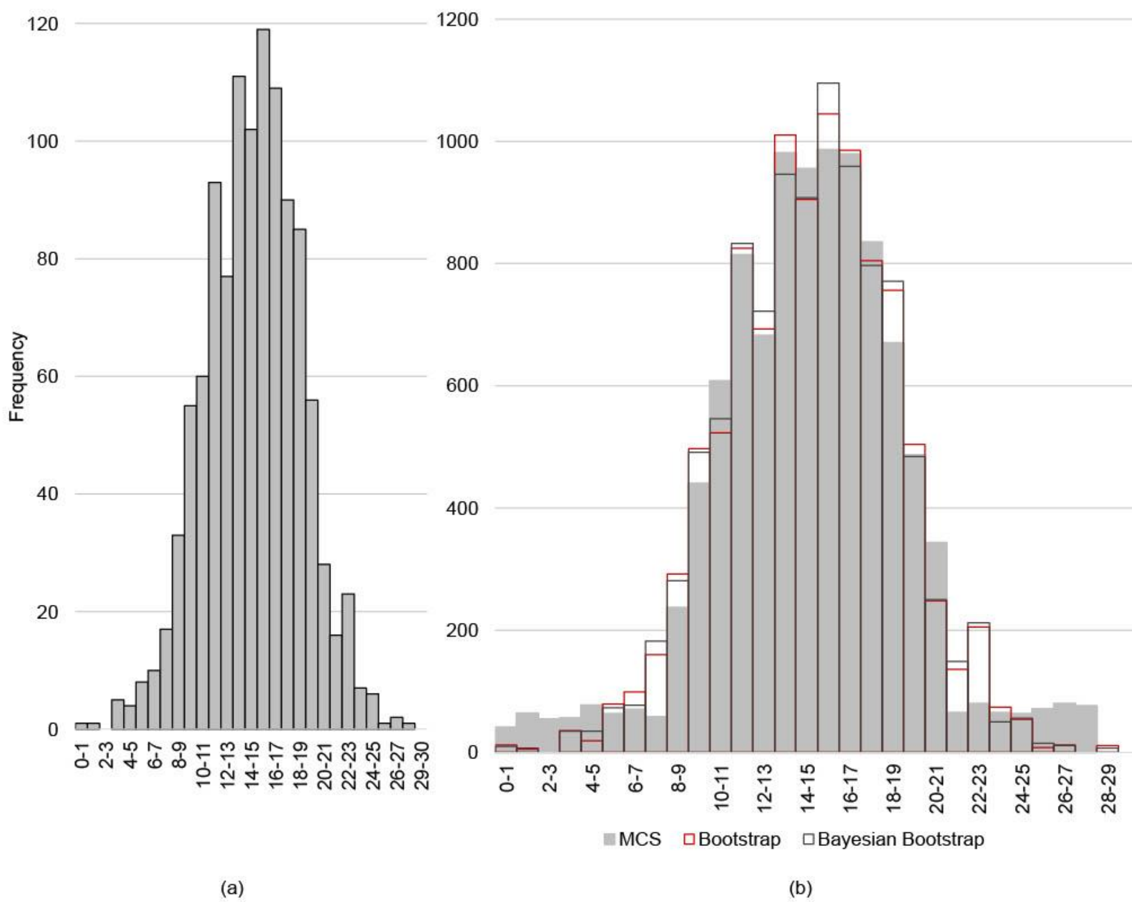


Figure B.4 Case study 2: Dbh histograms for (a) the observed dataset and (b) the pseudo-data generated from approach 1: MCS, approach 2: bootstrap and MCS, and approach 3: Bayesian bootstrap and MCS

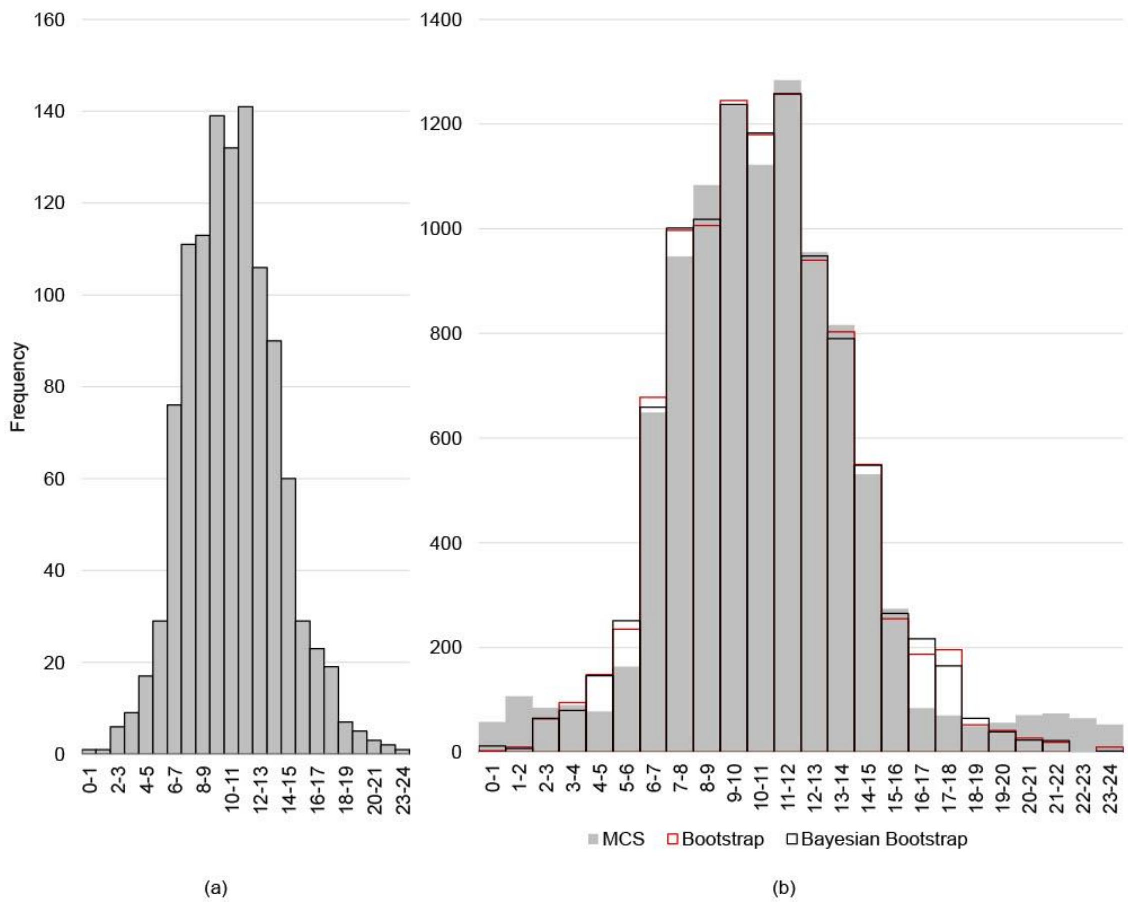


Figure B.5 Case study 2: Ht histograms for (a) the observed dataset and (b) the pseudo-data generated from approach 1: MCS, approach 2: bootstrap and MCS, and approach 3: Bayesian bootstrap and MCS

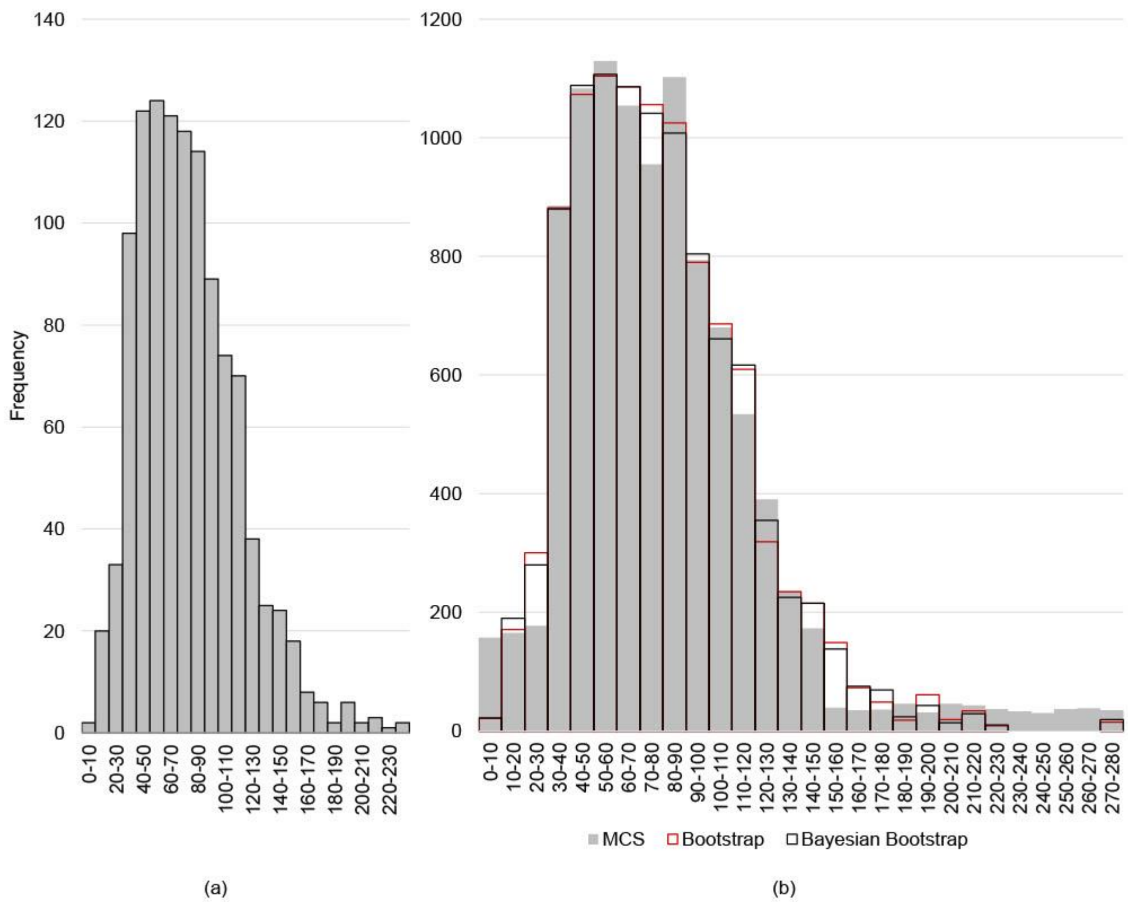


Figure B.6 Case study 2: AGB histograms for (a) the observed dataset and (b) the pseudo-data generated from approach 1: MCS, approach 2: bootstrap and MCS, and approach 3: Bayesian bootstrap and MCS

APPENDIX C: INVESTIGATED RESIDUAL ERROR MODELS

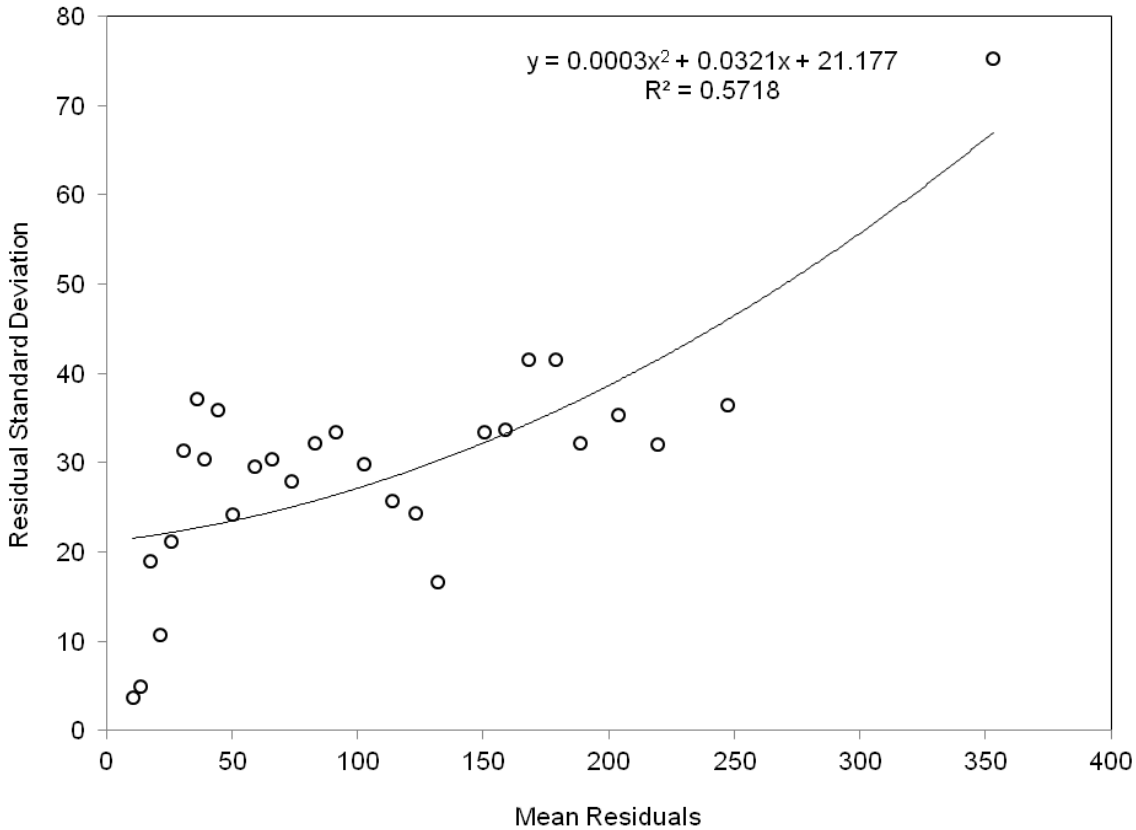


Figure C.1 Case study 1 residual error model: second-order polynomial model

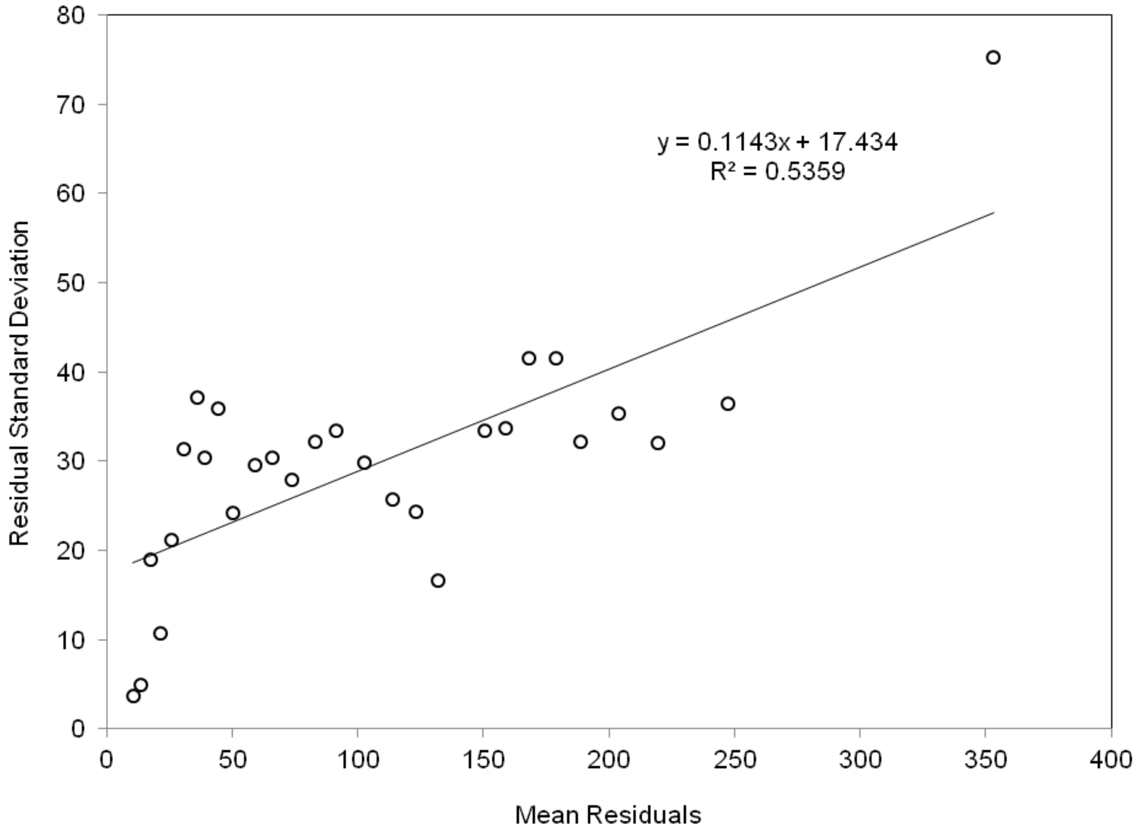


Figure C.2 Case study 1 residual error model: linear model

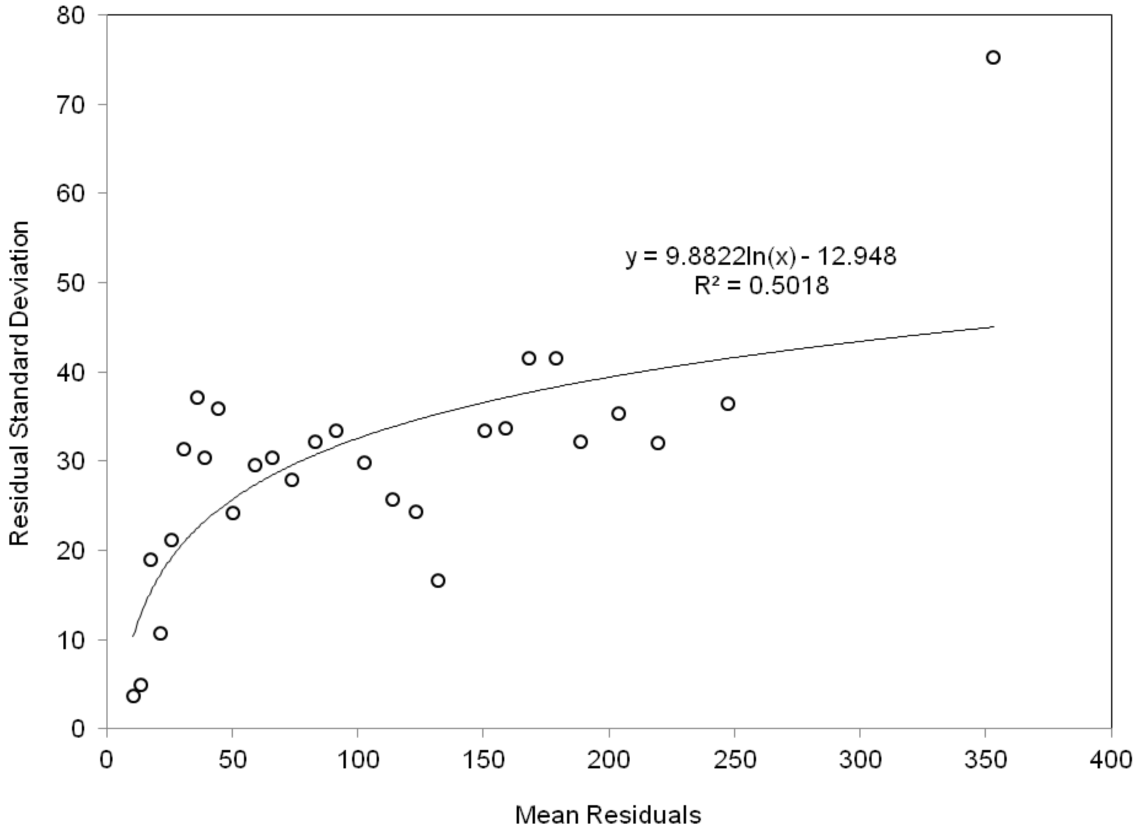


Figure C.3 Case study 1 residual error model: logarithmic model

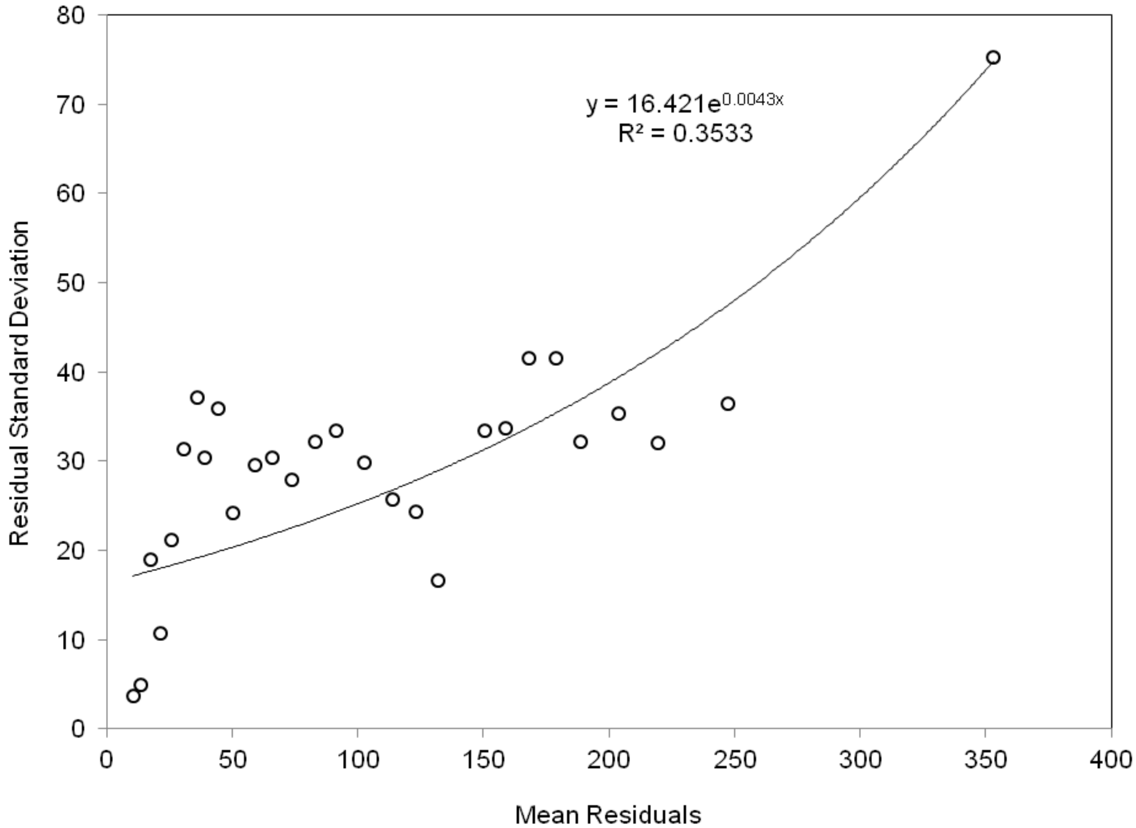


Figure C.4 Case study 1 residual error model: exponential model

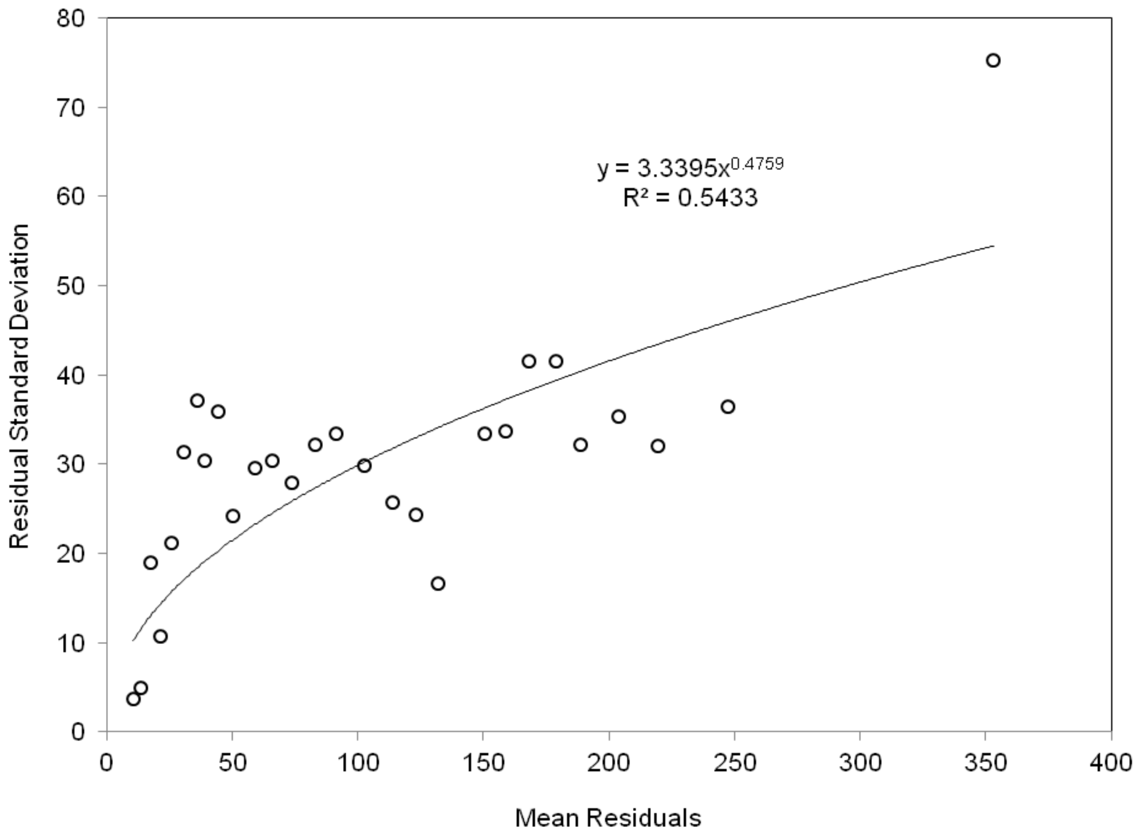


Figure C.5 Case study 1 residual error model: power model

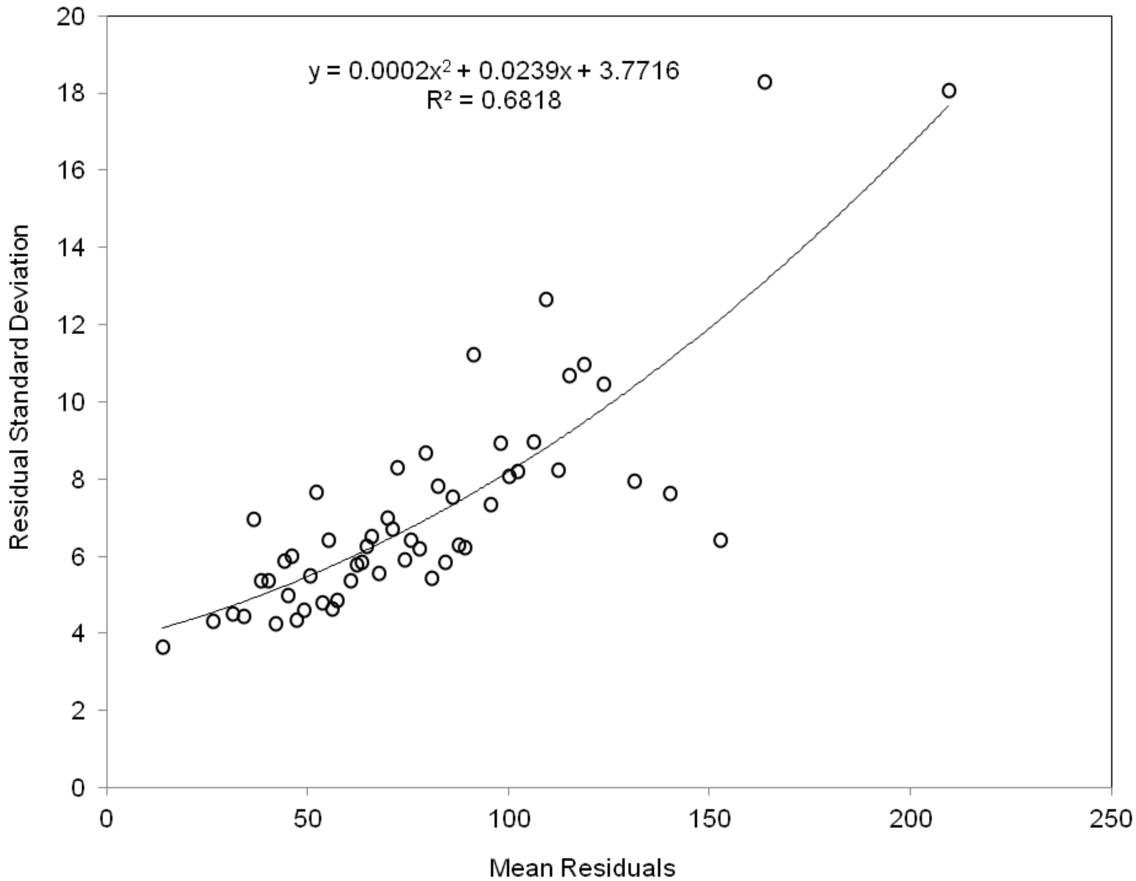


Figure C.6 Case study *2* residual error model: second-order polynomial model

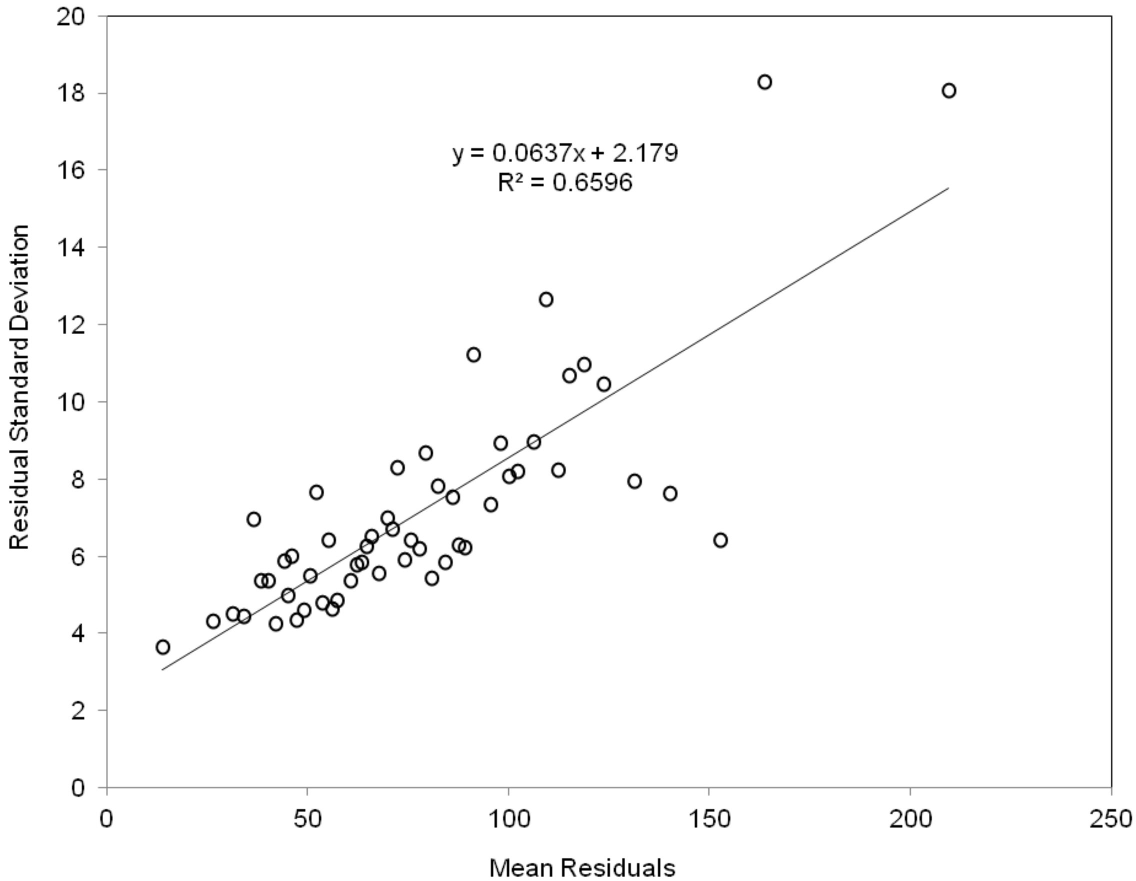


Figure C.7 Case study 2 residual error model: linear model

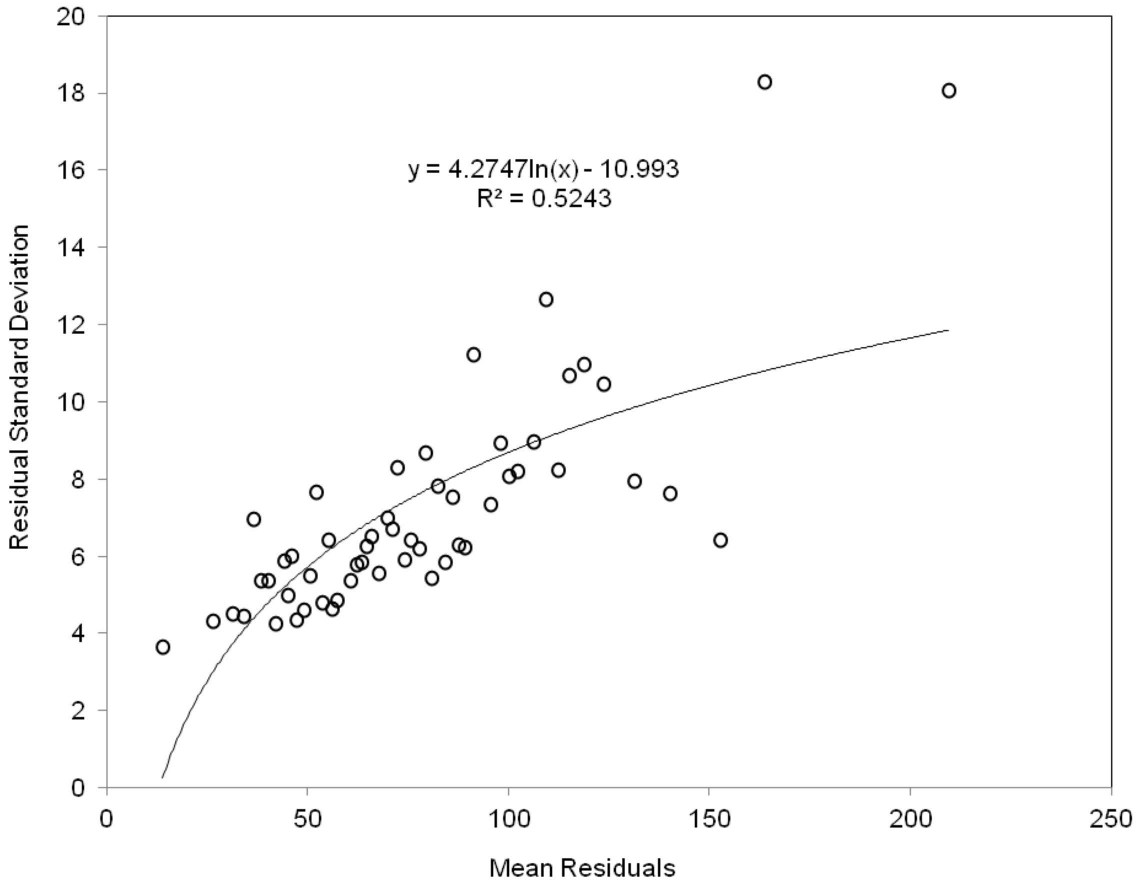


Figure C.8 Case study 2 residual error model: logarithmic model

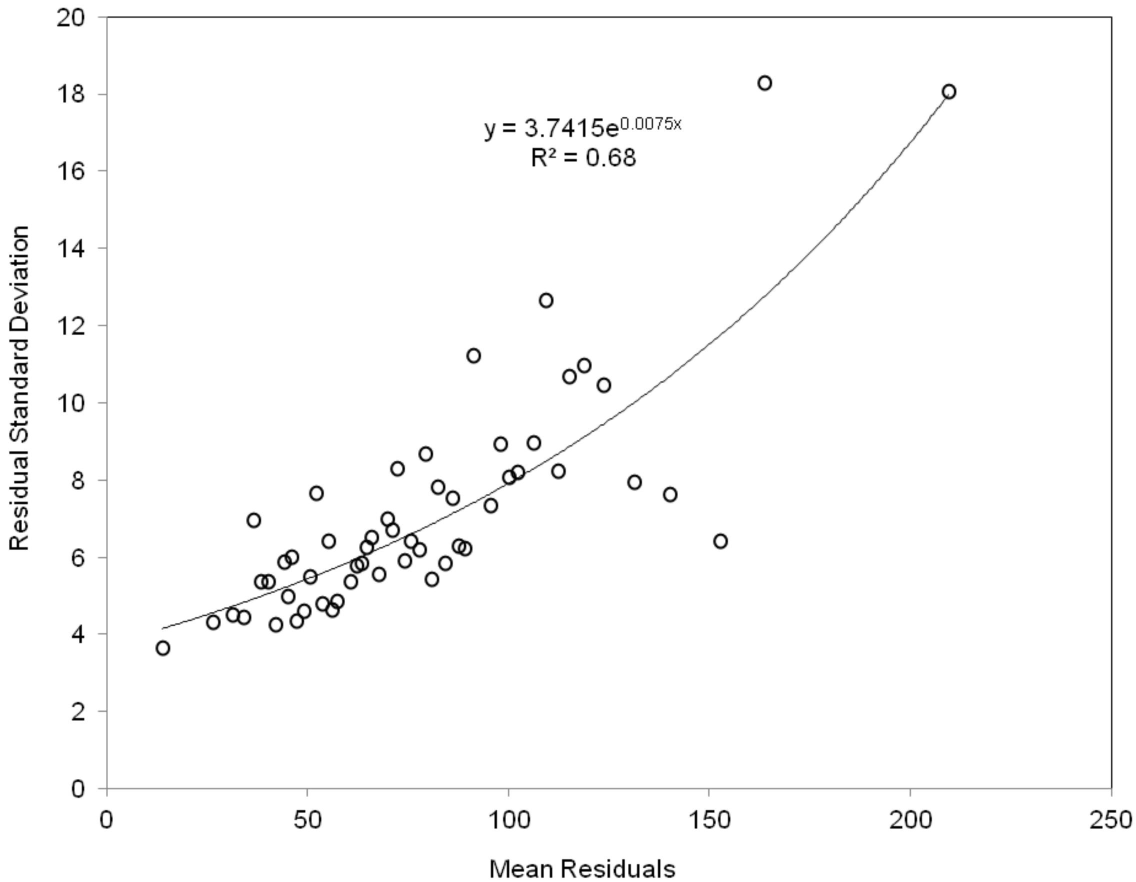


Figure C.9 Case study 2 residual error model: exponential model

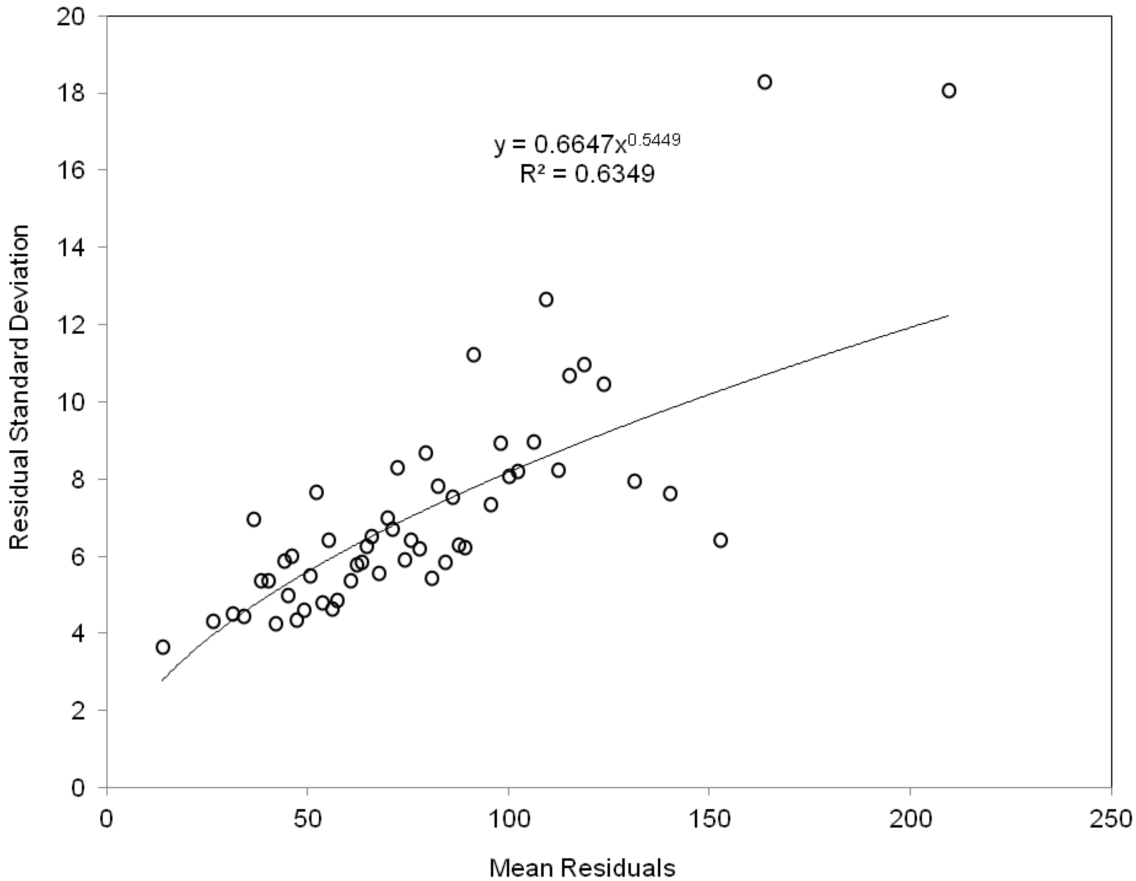


Figure C.10 Case study 2 residual error model: power model

APPENDIX D: INVESTIGATED DBH MEASUREMENT ERROR MODELS

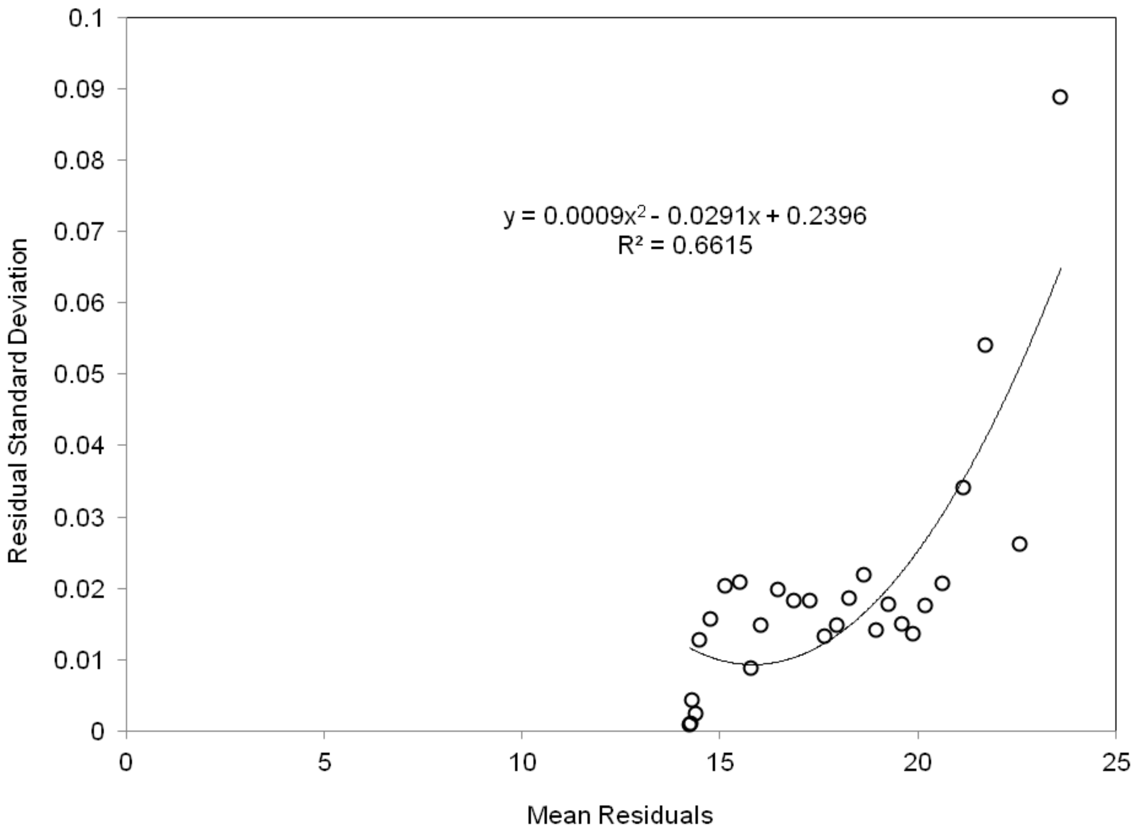


Figure D.1 Case study 1 measurement error model: second-order polynomial model

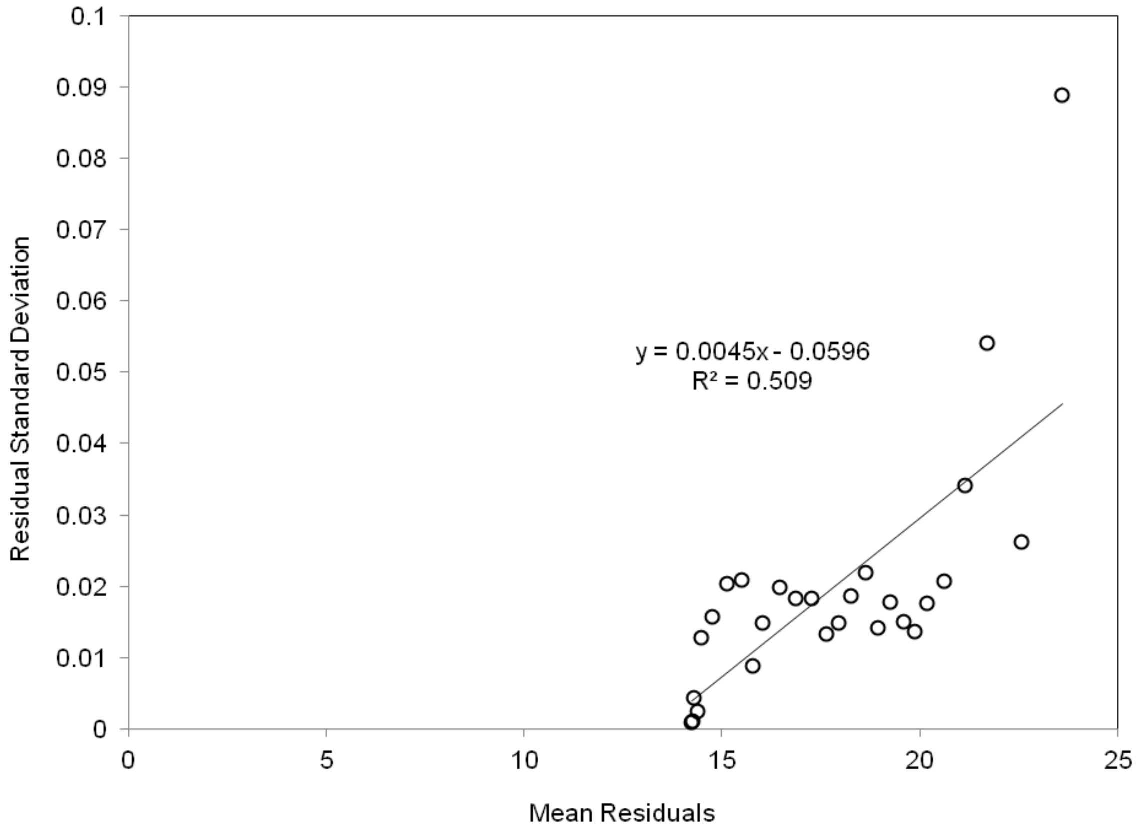


Figure D.2 Case study 1 measurement error model: linear model

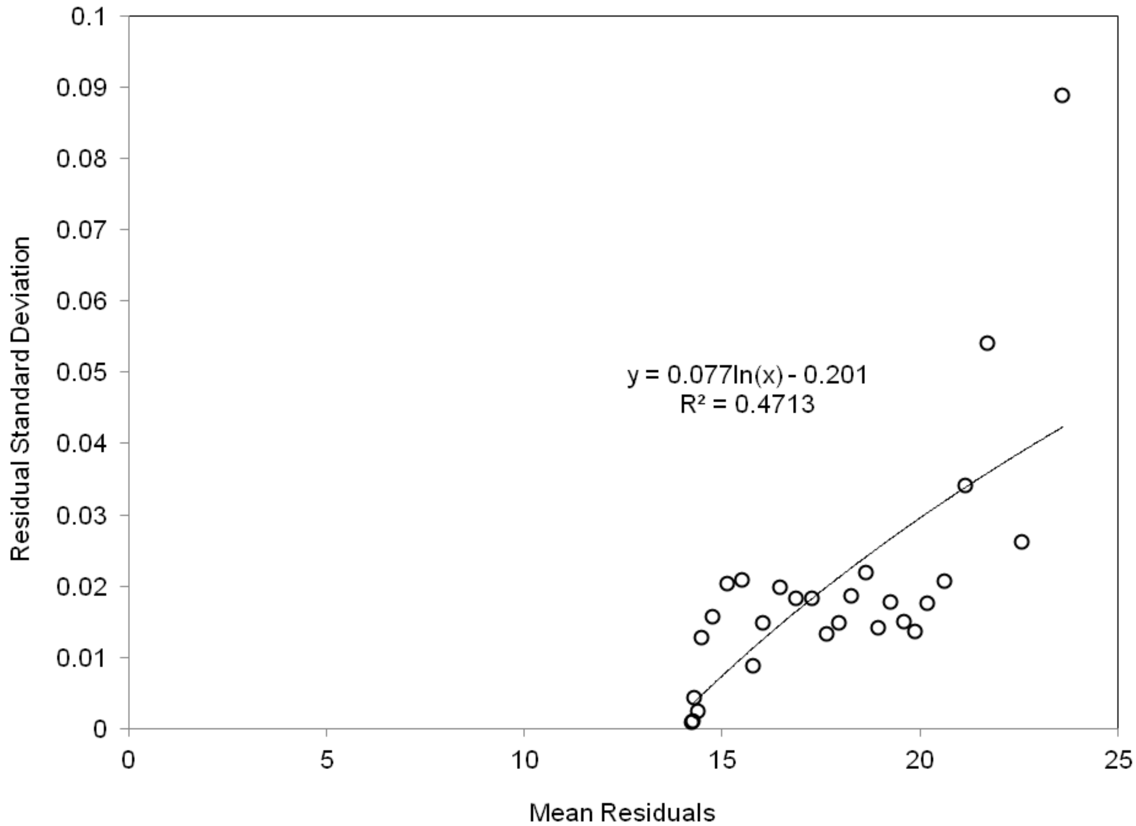


Figure D.3 Case study 1 measurement error model: logarithmic model

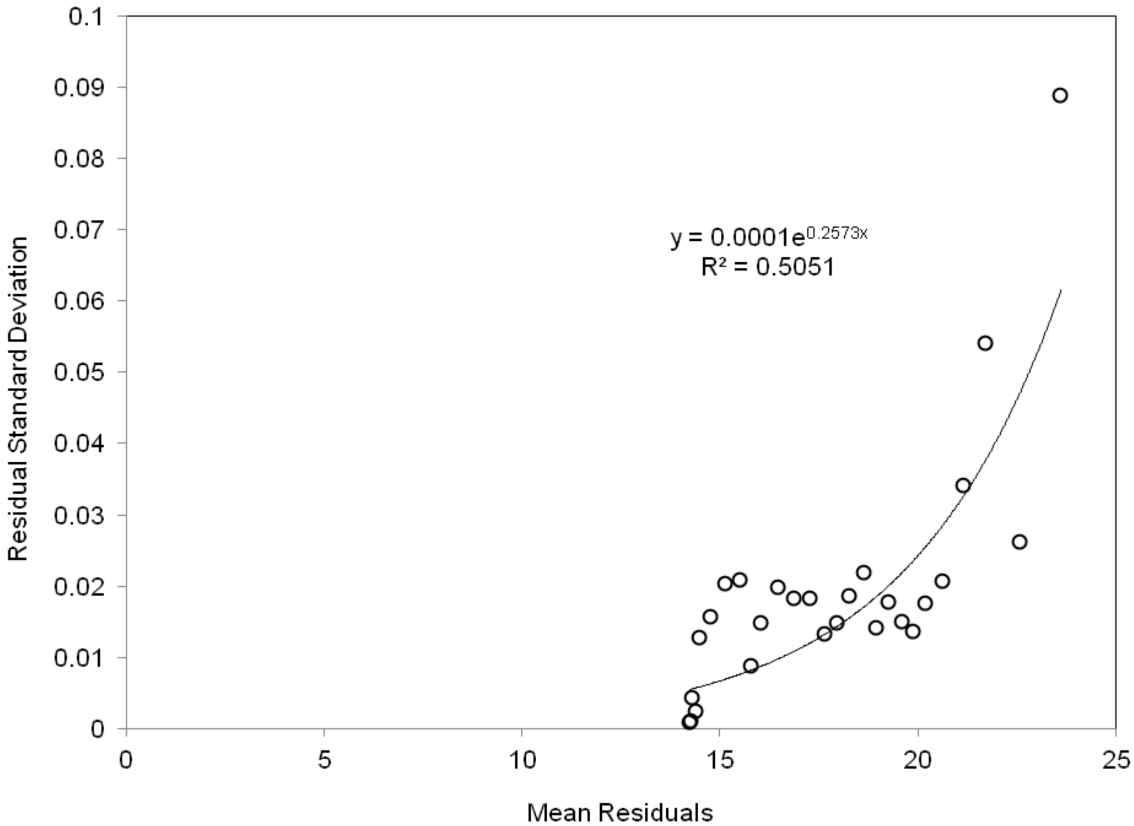


Figure D.4 Case study 1 measurement error model: exponential model

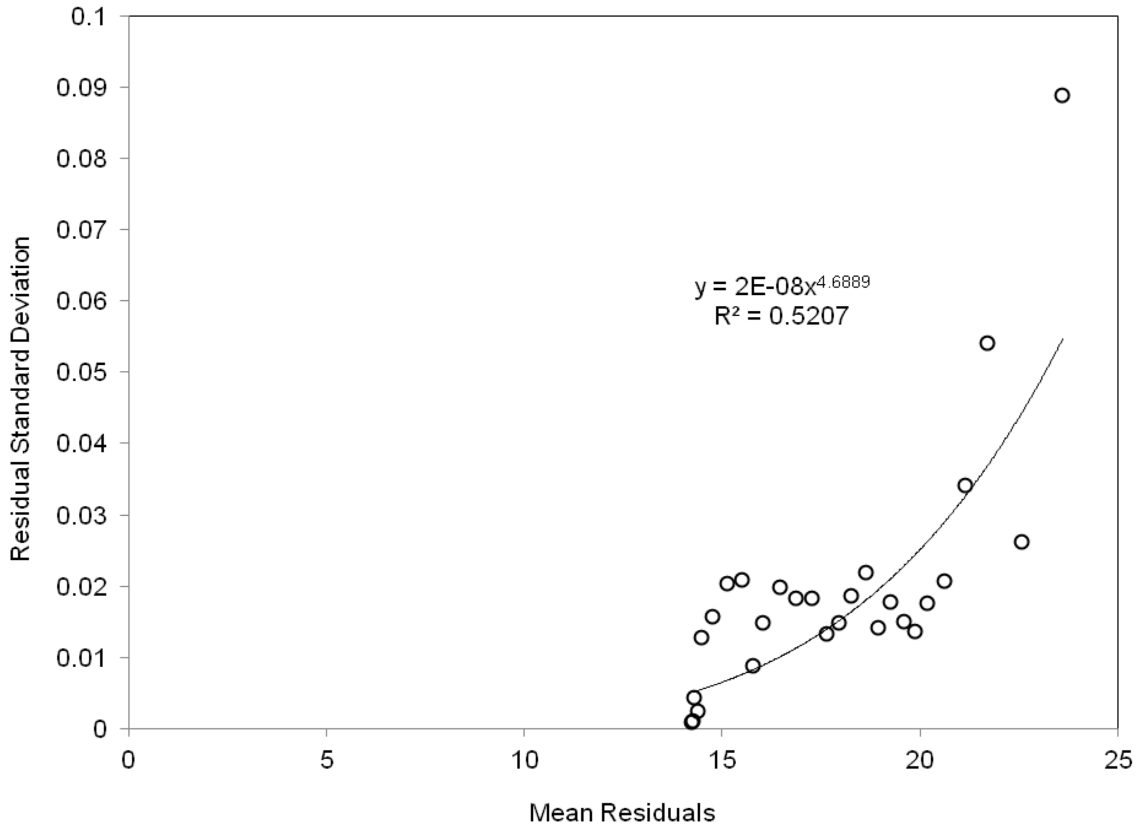


Figure D.5 Case study 1 measurement error model: power model

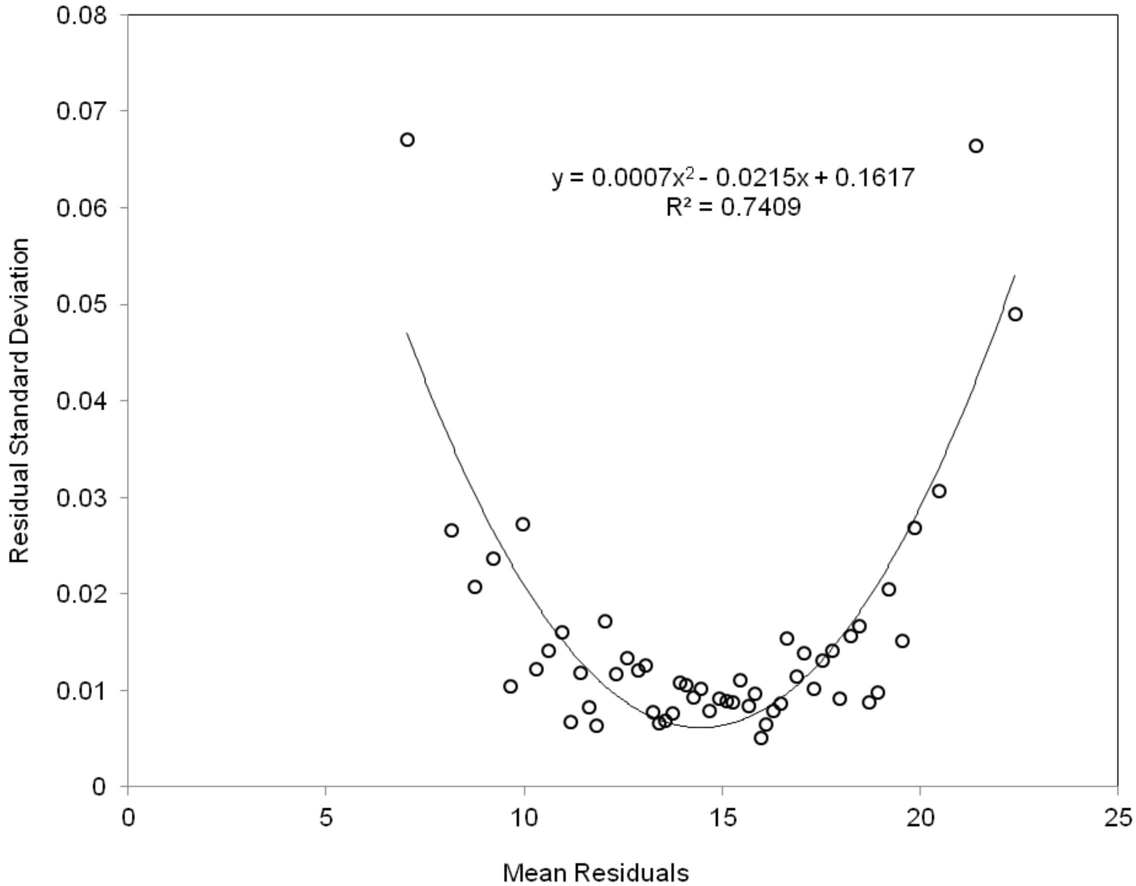


Figure D.6 Case study 2 measurement error model: second-order polynomial model

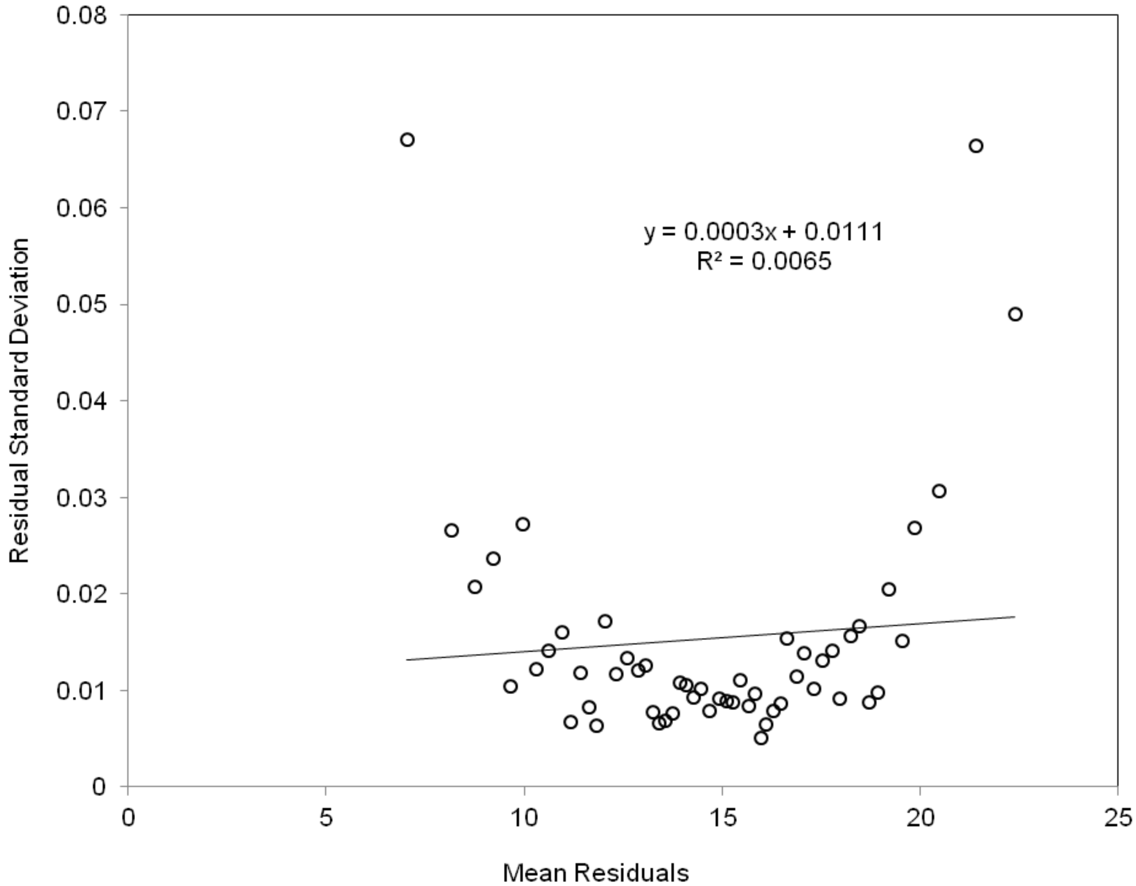


Figure D.7 Case study 2 measurement error model: linear model

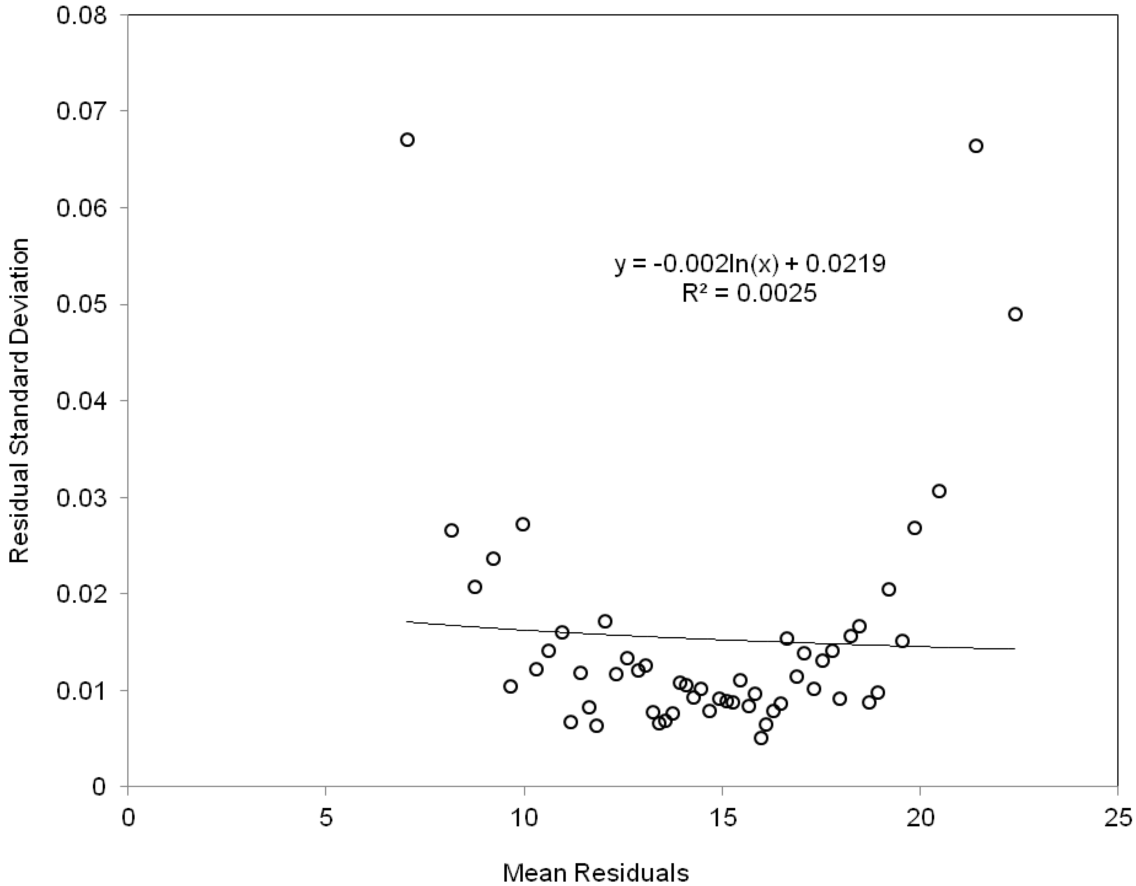


Figure D.8 Case study 2 measurement error model: logarithmic model

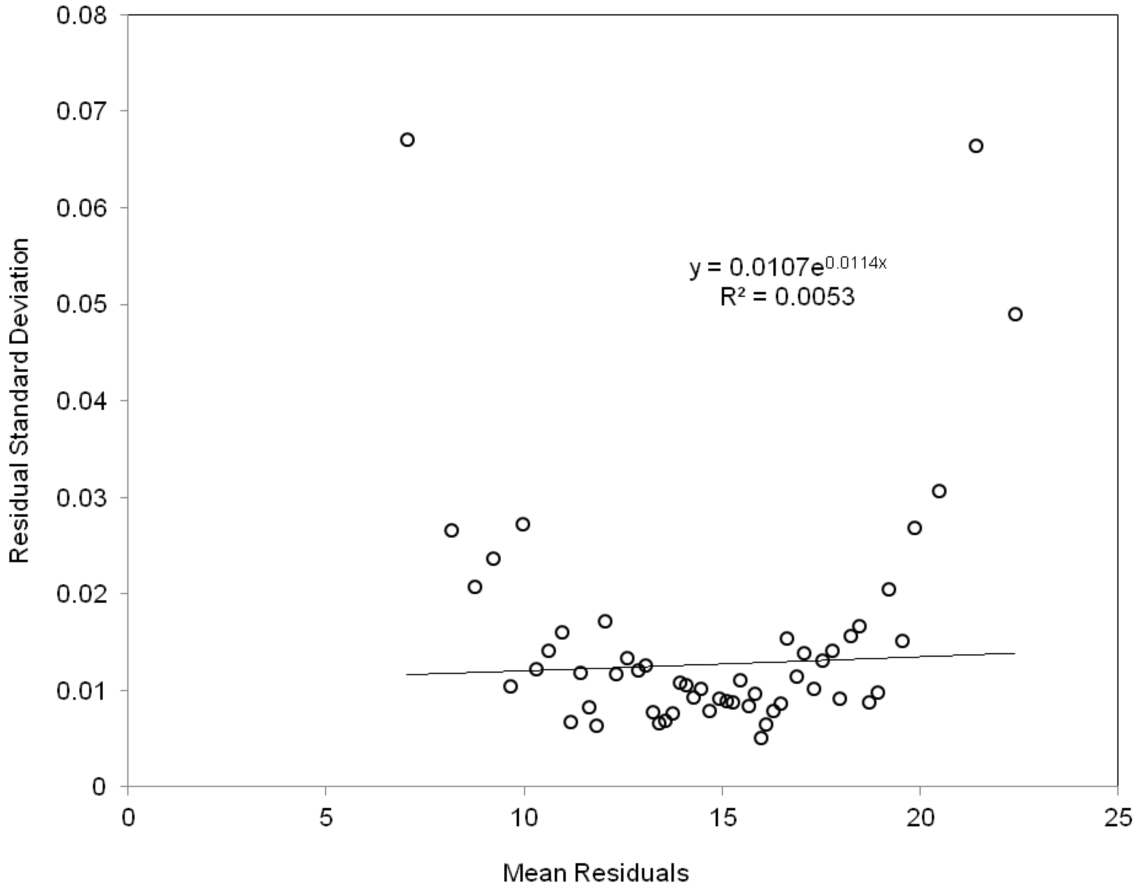


Figure D.9 Case study 2 measurement error model: exponential model

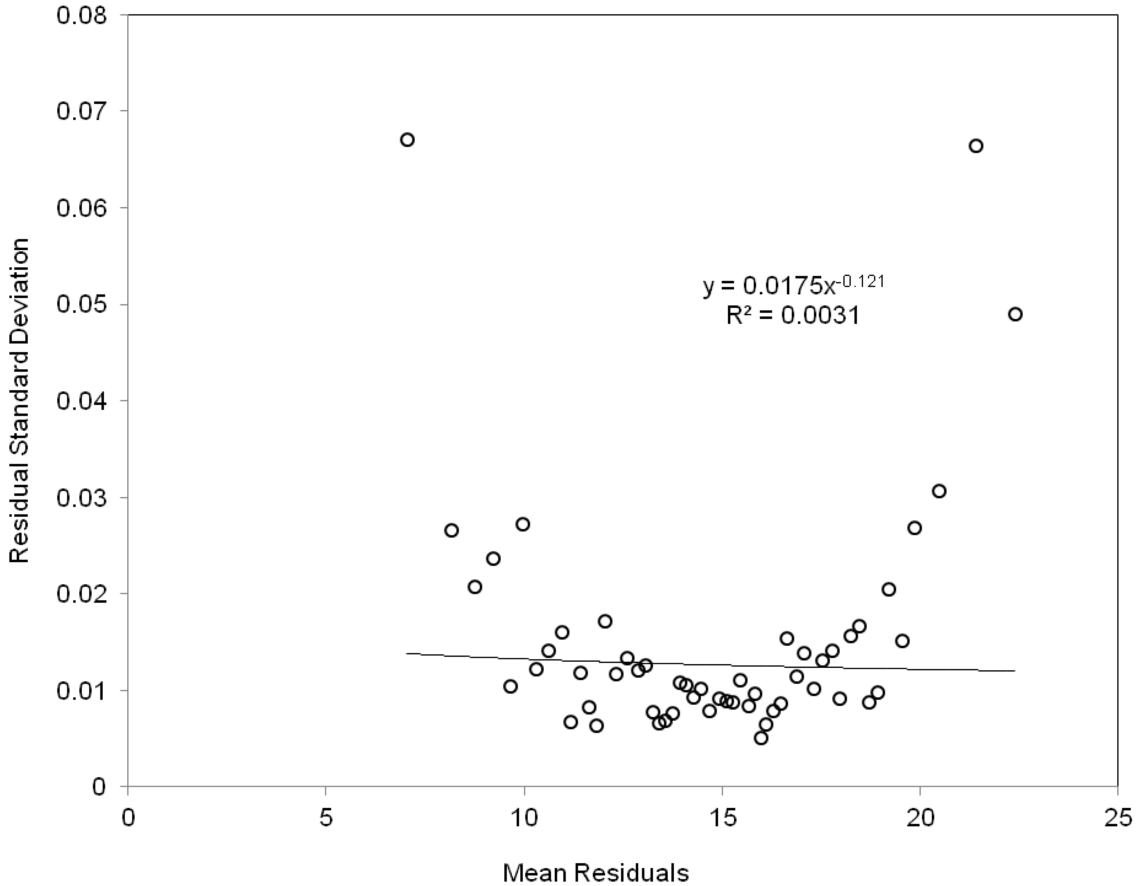


Figure D.10 Case study 2 measurement error model: power model

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