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Carbon Emissions Embodied in International Trade and Carbon Sequestration of Harvested Wood Products

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Carbon emissions embodied in international trade and carbon sequestration of harvested wood products

By

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Carbon emissions embodied in international trade and carbon sequestration of harvested wood products

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After timber harvesting, carbon in wood is transferred to products pool and remains entrapped for a considerable time. It is necessary to estimate this carbon flux in the harvested wood products (HWP); otherwise, carbon emission estimates of a country will be overestimated at the time of harvest. Furthermore, carbon estimates of the HWP must be assessed for uncertainties which need to be reduced as far as possible. Environmental implications might be associated with the HWP traded in the national and international markets. In the current context, there is a lack of economic-environmental studies that relate to the trade of HWP. The first part of this dissertation estimated the U.S. HWP contribution to carbon removals or emissions from 1990 to 2014 using the stock-change, production, atmospheric flow, and simple decay approaches. It concluded that the U.S. HWP stored carbon under all accounting approaches. Net annual carbon stored in the HWP, however, declined under all approaches from 1990 to 2014. The second part of the dissertation investigated uncertainty in the estimates of carbon stock in HWP using Monte Carlo simulation. A sensitivity analysis was also performed. Results showed that the net annual carbon accumulation in HWP was affected by uncertainty associated with input parameters. Carbon estimates in the HWP were most sensitive to uncertainty in the parameter for the carbon conversion factor for roundwood. The third part of the dissertation used a multi-regional input-output model to analyze embodied carbon emissions in the U.S. trade of HWP with its major trading partners – Brazil, Canada, China, Germany, Japan, Mexico, and Russia. Results demonstrated that the U.S. was a net importer of carbon emissions involving HWP. China was the major contributor of imported emissions, and Canada was the biggest recipient of the U.S. exported emissions. The consumption-based method had a higher emissions inventory in the HWP than the production-based method. Per-capita emissions in the HWP increased with an increase in per-capita GDP. These studies can be informative for policy makers in incorporating HWP in climate change mitigation and adaptation strategies, and in understanding the economic-environmental relationships of international trade of HWP.

DEDICATION

I dedicate this dissertation to my parents, Mr. Jeewan Hari Shrestha and Mrs. Chandra Laxmi Shrestha.

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CHAPTER I

GENERAL INTRODUCTION

1.1 Introduction

Reducing greenhouse gases, especially carbon dioxide (CO_2), and mitigating climate change have become important issues. Decades of research has established that forests play an effective and important role in mitigating climate change as they remove significant amounts of carbon from the atmosphere. After harvest, these carbon stocks in forests are transferred to harvested wood products (HWP) pools (both products in use and products discarded to landfills), and remain entrapped for a considerable period of time (Row & Phelps, 1996). Therefore, there is growing interest in analyzing the role of HWP in the global carbon cycle as a climate change mitigation strategy.

The carbon stock in HWP changes over time (Winjum, Brown, & Schlamadinger, 1998). In most of the countries carbon stored in the HWP is increasing as a result of increase in the harvest and increase in the products going to end uses with longer half-lives (Donlan, Skog, & Byrne, 2012; Skog, 2008). As such, excluding the HWP contribution in the national greenhouse gas inventories will significantly impact the emission estimates of a country. If carbon stored in HWP is not accounted for, then carbon emissions in the year of harvest might be overestimated (Smith, Heath, Skog, & Birdsey, 2006). Therefore, it is important to assess the carbon stored in HWP. Countries can estimate the HWP contribution to carbon removals or emissions using the stock-change, production, atmospheric flow, and simple decay approaches as adopted by the Intergovernmental Panel on Climate Change (IPCC).

For the U.S., studies have been conducted at the national and regional level to estimate the HWP contribution to carbon emissions or removals (Anderson et al., 2013; Skog, 2008). Some of these studies have used the stock-change, production, and atmospheric flow approaches, although most recent studies have focused on the production approach. However, none have used the simple decay approach. Comparison of estimates obtained from all four accounting approaches will provide insight into the suitable approach for estimating the U.S. HWP contribution to carbon removals or emissions.

At the global level, estimates of carbon stored in HWP vary considerably from 26 Mt (million metric tons) C per year to 139 Mt C per year (Winjum et al., 1998). Green, Avitabile, Farrell, and Byrne (2006) estimated the carbon stock in HWP for 2003 for Ireland to be 251 Mt C using production approach, and Donlan et al. (2012) estimated the carbon stock in HWP for Ireland for the same year using the same approach to be 268 Mt C. This shows that there is variation in the estimates of carbon stored in HWP at the global level as well as national level. This range or variation in the estimates is the result of uncertainty in the parameters (Green et al., 2006). Therefore, uncertainty in the parameters used in the model has an impact on the estimates of carbon stored in HWP.

The estimates must, therefore, be assessed for uncertainties which should be mitigated as much as possible (IPCC, 2003). Reliable uncertainty estimates are a tool for increasing the quality of the HWP contribution to carbon emissions or removals. 2006 IPCC guidelines described two approaches that can be used to analyze uncertainty. The first approach is based on error propagation and assumes that the relative ranges of uncertainty in emission factors are the same for the base year and the year of interest. The second approach is Monte Carlo simulation which is used for more detailed category-by-category assessment of uncertainty. Monte Carlo simulation has been commonly used in the literature to determine the uncertainty in the estimates of carbon stored in HWP (Donlan et al., 2012; Skog, 2008).

HWP traded in the international market play an important role in the estimation of a country's carbon sequestration (Ji, Yang, Nie, & Hong, 2013). The carbon accounting approaches have a great impact on the way countries regard their HWP's trade in the international market (Nabuurs & Sikkema, 2001). The trade of HWP in the international market is increasing as a result of globalization and open economies. For example, during the one year period from 2013 to 2014, the global trade of industrial roundwood, sawnwood, wood-based panels, paper and paperboard increased respectively by, 2, 4, 5, and 1 percent (FAO, 2016). During the physical transfer, carbon embodied in the HWP might have an environmental implication at the national and global level. In the current context, there is a lack of analysis on carbon emissions and transfer related to the international trade of HWP (Peters, Davis, & Andrew, 2012).

Therefore, the overall goal of this dissertation is to estimate, for the U.S., carbon content in the HWP and carbon embodied in the international trade of HWP. The overall goal is achieved by pursuing three specific objectives

1. Estimating and comparing carbon stored in the harvested wood products in the U.S. from 1990 to 2014 using the stock-change, production, atmospheric flow, and simple decay approaches.

2. Examining uncertainty in the estimates of carbon stock in the U.S. harvested wood products using Monte Carlo simulation and performing a variance-based sensitivity analysis of parameters contributing uncertainty.
3. Analyzing the embodied carbon emissions in the U.S. international trade of harvested wood products using multi-regional input-output model.

These three objectives are discussed in detail, respectively in Chapters II, III, and IV.

The findings from the first objective can provide information on the U.S. HWP as a component of carbon pool, i.e., whether or not the U.S. HWP acts as a carbon sink. This information will be helpful to policy makers in making decisions concerning the HWP as a strategy to reduce greenhouse gas emissions and mitigate climate change. The findings from the second objective can provide information on the uncertainty associated with the U.S. HWP carbon estimates and in determining the parameter that contributed most to the uncertainty in carbon estimates. This information will be helpful for researchers to improve the accuracy of the carbon estimates in HWP by reducing the error in those influential parameters. The findings from the third objective can provide information on the importance of considering carbon embodied in trade in emission mitigating agreements. It will also contribute to determining a fair allocation method for carbon responsibility, and encourage international cooperation among countries in reducing global carbon emissions.

CHAPTER II

CARBON ACCOUNTING OF HARVESTED WOOD PRODUCTS IN THE U.S.

(1990 – 2014)

2.1 Abstract

Carbon contained in the harvested wood products (HWP) pools, both in products in use and in products discarded in solid waste disposal sites, can remain entrapped for a considerable period of time depending on their end uses. HWP thus typically act as a carbon reservoir. It is necessary to estimate this carbon flux in the HWP, otherwise, carbon emission estimates of a country will be overestimated at the time of harvest. In this study, the HWP contribution to carbon removals or emissions in the U.S. from 1990 to 2014 was estimated using the stock-change[1], production[2], atmospheric flow[3], and simple decay[4] approaches. Methods were based on 2006 Intergovernmental Panel on Climate Change (IPCC) guidelines. Results indicated that average carbon removal estimates during the study period were highest for the stock-change approach (-127.8 Tg CO_2e), followed by the atmospheric flow approach (-117.4 Tg CO_2e), and the production and simple decay approaches (-102.8 Tg CO_2e). In 2014, the U.S. HWP contribution to carbon removals were -46.8, -54.4, -70.3, and -54.4 Tg CO_2e, respectively, for the stock-change, production, atmospheric flow, and simple decay approaches. Estimates of carbon

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[1] Estimates a net change in carbon stocks of HWP where they are consumed regardless of wood origin.
[2] Estimates a net change in carbon stocks of HWP where the wood is domestically produced.
[3] Estimates the flow of carbon between the atmosphere and HWP within a country.
[4] Estimates a net emissions or removals of carbon to and from the atmosphere.

stored in the HWP declined under all four approaches since 1990. In general, HWP in the U.S. act as a carbon sink from 1990 to 2014. Carbon estimates in the HWP varied according to the different approaches used. Estimates of carbon in the HWP will provide various incentives, such as use or trade of the HWP, to achieve policy goals. In addition, this information can be used to guide climate change mitigation and adaptation strategies.

Keywords: carbon sequestration, harvested wood products, stock-change approach, production approach, atmospheric flow approach, simple decay approach

2.2 Introduction

Harvested wood products (HWP) are the wood materials that leave harvest sites and are transformed into various commodities such as industrial roundwood, fuelwood, sawn wood, wood-based panels, paper and paperboard, and fiber furnish (UNFCCC, 2003). These HWP form an integral part of the global carbon cycle, and are considered to play an important role in mitigating emissions of greenhouse gases, especially carbon dioxide (CO_2), through carbon removals and storage (Leea, Lin, & Han, 2011).

The carbon stored in HWP remains for a considerable period of time depending on the end use of the products (Row & Phelps, 1996). For example, carbon stored in sawn wood can remain for almost 100 years, whereas carbon stored in paper products remains for less than five years (IPCC, 2006). In addition to the products in use, carbon is also entrapped in discarded HWP deposited in solid waste disposal sites (SWDS). Furthermore, HWP could be a considerable carbon pool which can be used as substitutes for energy intensive materials such as iron and steel (IPCC, 2003). HWP used for energy intensive materials could result in up to nine times less carbon emissions (Matthews & Robertson, 2002). Moreover, these wood products can be reused, recycled, disposed in landfill at the end of their service life (Malmsheimer et al., 2008). Thus, HWP can be directly or indirectly used to limit emissions of greenhouse gas to the atmosphere (Green & Byrne, 2004).

Previously, 1996 IPCC guidelines assumed that the carbon stocks in HWP do not change over time, and carbon is emitted immediately when a tree is harvested (UNFCCC, 2003). This default approach of IPCC assumed that the annual carbon inputs to the HWP reservoir equal outputs (IPCC, 2006), and hence did not account for the carbon stock in HWP. In general, this is not true, and carbon stored in HWP remains for the extended period of time. Some studies even showed that the amount of carbon in HWP is increasing as a result of an increase in harvest and products going to end uses with longer half-lives. For example, Pingoud, Perälä, Soimakallio, and Pussinen (2003) reported that the amount of carbon stored in HWP was increasing by 40 Mt C per year. They estimated that the total carbon stock in HWP doubled from 1500 to 3000 Mt C during the period from 1960 to 2000. Similarly, Donlan et al. (2012) found an increase in the net annual addition to carbon stocks in HWP in Ireland during the period from 1961 to 2009. Ji et al. (2013) also reported that the annual addition of the carbon stocks in HWP in China was increasing.

If the contribution to carbon stocks in HWP is not accounted for, then overestimation of carbon emissions to the atmosphere in the year of harvest will result (Smith et al., 2006). Recognizing the potential of HWP in carbon sequestration and its importance in the national greenhouse gas emission accounting, guidelines for estimating the fate of carbon from HWP were developed by IPCC. Accordingly, 2006 IPCC guidelines provide four accounting approaches from which a country can choose to report its HWP contribution (carbon changes in HWP) to annual agriculture, forestry, and land use (AFOLU) removals by sinks and emissions from sources. The estimates of additions of carbon in HWP or emissions associated with HWP help in making the national and international decisions and agreements on managing greenhouse gas emissions and sinks (IPCC, 2006).

The stock-change approach, production approach, atmospheric flow approach, and simple decay approach are four accounting approaches presented in 2006 IPCC guidelines that can be used to estimate the carbon in HWP. The first three approaches are commonly used in the literature (Ji et al., 2013; Leea et al., 2011; Skog, 2008). At the global level, these three approaches yield the same estimates of annual change in carbon in HWP (Hashimoto, Nose, Obara, & Moriguchi, 2002). In contrast, at the national level, the contribution of HWP in carbon emissions or removals differs depending upon the approaches chosen (Cowie, Pingoud, Robertson, & Schlamadinger, 2005). Pingoud et al. (2003) suggested that the same approach must be applied in all countries to avoid double counting or exclusion of emissions. However, disagreement exists on the common approach, as the implications of each accounting approach differ for different countries (Hashimoto, 2008; Lim, Brown, & Schlamadinger, 1999) . For instance, an importing country will support the stock-change approach as an import of products in this approach is considered to increase the carbon stock in that country (Tonosaki, 2009). In contrast, an exporting country will favor the production approach as exported carbon remains in the inventory of the producing country (Tonosaki, 2009).

Nevertheless, carbon stock in HWP changes over time, and the literature suggest that carbon stored in HWP is increasing. Thus, excluding the HWP contributions in national greenhouse gas inventories will significantly impact the emission estimates of a country. Therefore, it is important to assess and monitor the carbon stored in HWP. There are some studies that have estimated the HWP contribution to carbon emissions or removals in the U.S. (Anderson et al., 2013; Skog, 2008). However, none have compared the HWP carbon estimates using all four accounting approaches. This study estimated carbon sequestered in HWP in the U.S. from 1990 to 2014. Four established accounting approaches — the stock-change, production, atmospheric flow, and simple decay approaches were used to estimate the U.S. HWP contribution to carbon removals or emissions.

The stock-change and production approaches estimate a net change in carbon stocks in the products pools (i.e., products in use and products discarded to landfills), whereas the atmospheric flow and simple decay approaches estimate a net change in carbon stocks between products and the atmosphere. These four approaches differ in the way they define the system boundaries. The stock-change approach has a system boundary around a country, so imports of the HWP in that country are reported. The production approach has a system boundary around the wood that has grown in a particular country, so exports of the HWP to other countries are reported. The atmospheric flow and simple decay approaches have a system boundary between a country and the atmosphere, so that sum of all carbon fluxes to and from the atmosphere is counted.

The findings from this study can provide more information on the U.S. HWP as a component of carbon pool. It can also provide insight into the need for and importance of monitoring the contribution of the HWP carbon pools. In addition, the information can also be used in forest management decisions as additions of carbon to HWP pools are made through harvesting of forests. Findings can inform policy makers concerning the difference between alternative accounting approaches used. Which approach is chosen will have potential policy implications on incentives or disincentives to use and trade HWP. The information will also be helpful for governments in making decisions with regards to HWP as a strategy to reduce greenhouse gas emissions and mitigate climate change.

This study is organized as follows. Section 2.3 presents the literature related to carbon sequestration in HWP. The accounting approaches and HWP variables calculation methods are described in Section 2.4, followed by a description of the parameters required for this study and the sources in Section 2.5. The estimation results are presented in Section 2.6. Finally, the implications of results are discussed in Section 2.7.

2.3 Literature review

2.3.1 Sequestration of carbon in the harvested wood products

Several studies estimated the HWP contribution to carbon removals or emissions at the national and global level. For example, Winjum et al. (1998) developed the stock-change and atmospheric flow approaches to estimate the global carbon source-sink balance from forest harvesting and wood utilization for 1990 using the FAO databases. They estimated carbon stored in the HWP for developed and developing countries. The global carbon emission estimated by both the approaches was the same (980 Mt C). However, carbon emission estimates for developing and developed countries were different under the stock-change and atmospheric flow approaches. They concluded that the choice of method had potential policy implications on incentives or disincentives to use wood as a fuelwood and other commodities. Hashimoto et al. (2002) estimated the fate of carbon in wood products using stock-change and atmospheric flow approaches from 1990 to 1999. For all industrialized countries analyzed, they found a significant impact of accounting approaches on the net carbon emissions from wood products at the national level.

In 2006, IPCC published the detailed guidelines to estimate the HWP contribution to carbon removals or emissions under four accounting approaches − stock-change, production, atmospheric flow, and simple decay approaches. The guidelines explain ways to estimate key variables for tracking changes to the carbon stock in HWP in use and in SWDS. Following the guidelines and using carbon accounting approaches, several studies have quantified carbon sequestration in the HWP in different countries around the world. For example, Green et al. (2006) estimated and compared carbon stock in the HWP pool for the period 1961 to 2003 in Ireland. In 2003, the stock-change approach yield highest (375 Gg C per year) carbon accumulation in the HWP, followed by the production approach (271 Gg C per year) and the atmospheric flow approach (149 Gg C per year). They found that the carbon stock change increased in all approaches during the period from 1961 to 2003, indicating that the HWP in Ireland act as a carbon sink.

In another study, Dias, Louro, Arroja, and Capela (2007) estimated carbon accumulation in the HWP in Portugal from 1990-2000. Their objective was to contribute to the international debate on the choice of approaches for estimating the amount of carbon in HWP. Results showed that the carbon accumulation in HWP ranged between 112 to 1,016 Gg C per year. Among the three approaches, the atmospheric flow approach provided the highest estimates of carbon stored in the HWP because Portugal was the net exporter of carbon. This was followed by the production approach as the HWP exported from Portugal was produced mainly from domestically grown wood. The lowest estimates were under the stock-change approach. Also looking over a decade time span, Chen, Colombo, Ter-Mikaelian, and Heath (2008) projected carbon storage in the HWP from 2001 to 2010 in Ontario's Crown Forests using the production approach. They projected that the HWP in use and in landfills would both increase carbon sequestered by 3.6 Mt per year. They concluded that regular harvesting in forests would result in an increase in the HWP carbon sink.

In another multi-year study, Leea et al. (2011) estimated carbon emissions in the HWP in Taiwan from 1990 to 2008. This study, however, did not consider products in SWDS from domestic consumption and domestic harvest. The average HWP contribution for the stock-change, production, and atmospheric flow approaches were, respectively, 3.195 Tg, 0.412 Tg, and 10.632 Tg of CO_2 emissions. Under the stock-change approach, Taiwan HWP was a carbon reservoir. In contrast, under the production and atmospheric flow approaches Taiwan HWP serve as a CO_2 emitter. They also concluded that substituting HWP imports with increased domestic industrial roundwood production would lead to the HWP carbon sequestration under the production approach.

Donlan et al. (2012) estimated carbon storage in the HWP for Ireland from 1961 to 2009 using the production approach. There was an increase in annual net additions to the HWP carbon stocks, and this increase was due to increases in the domestic harvest of HWP. Likewise, Ji et al. (2013) estimated carbon sequestration and carbon flow in the HWP for China from 1961 to 2011. The average annual gains in the carbon stock were 10.6, 7.6, and 2.6 Mt C per year, respectively, under the stock-change, production, and atmospheric flow approaches. In addition, different approaches gave different estimates for China's annual contribution to carbon sequestration of HWP. Overall, they found that for China, the carbon stored in HWP was increasing continuously. Yang, Zhang, and Hong (2014) evaluated the carbon stock of HWP production in China from 1961 to 2012 using the stock-change approach and found that the carbon stock increased during the study period and in 2012 the carbon stock in HWP reached 888 million tons.

The above literature showed that for most countries, the HWP contribution was positive, meaning that HWP acts as a carbon sink storing a considerable amount of carbon. Studies also showed that the estimates of carbon stored in HWP differ according to different approaches used. Most of the studies used the stock-change, production, and atmospheric flow approaches. However, the simple decay approach has not been commonly used. Comparison of estimates obtained from all four approaches will provide insight into the suitable approach for accounting of the HWP contribution to carbon emissions or removals.

2.3.2 Studies related to the carbon stored in harvested wood products in the U.S.

Skog (2008) estimated the carbon stored in HWP from 1990 to 2005. The contribution to carbon removals under the stock-change, production and atmospheric flow approaches in 2005 were, respectively, 44 Mt C, 30 Mt C, and 31 Mt C. This range would offset 42 to 61 percent of carbon emissions from residential natural gas in 2005. During the period from 1990 to 2005, the HWP contribution to carbon removals under the production and atmospheric flow approaches declined. In contrast, during the same period of time, carbon stored in the HWP under the stock-change approach increased. The author concluded that the U.S. HWP contribution could be increased by increasing use of wood for longer lived products, increasing the use life of products, and decreasing landfill disposal of products that decay the most.

Similarly, the United States Department of Agriculture, USDA (2012) estimated carbon addition to the forests products in use and in landfills under the production approach for the U.S. Carbon stored in HWP in 2006 was around 29 Mt C. This accounted for about 17 percent of annual carbon addition to the forest ecosystems and offsets about 34 percent of carbon emissions by fossil fuel combustion in residential housing in the same year. However, the annual HWP contribution to carbon removals was less than that in 1990 because of a decrease in timber harvesting as well as replacement by imported products.

In the U.S., more recently, carbon stock and flux in the HWP has been estimated at the regional level to meet greenhouse gas monitoring commitments and climate change adaptation and mitigation objectives (Anderson et al., 2013; Butler et al., 2014a; Butler et al., 2014b; Loeffler et al., 2014a, 2014b, 2014c; Stockmann et al., 2014a, 2014b, 2014c). Estimates of carbon stored in the HWP have been studied in various regions of the United States Forest Service (USFS).

For example, Anderson et al. (2013) estimated HWP carbon storage from the USFS Northern region during the period from 1906 and 2010 and found the current HWP pools in this region to have a negative net annual carbon stock change. It means that the HWP pools act as a carbon source to the atmosphere. Similarly, Butler et al. (2014a) estimated carbon stored in HWP from the USFS Pacific Northwest region from 1909 to 2012 and found that there was a net loss of carbon stock in the HWP. Both these regions have a negative net annual stock change because the decay of the products harvested between the study periods exceeded additions of carbon to the HWP pool through harvest.

In contrast, Loeffler et al. (2014b) estimated carbon stored in HWP from the USFS Eastern region from 1911 to 2012 and found a positive net annual stock change in the HWP. It means that the HWP pools act as a sink for the atmospheric carbon. In the same way, Stockmann et al. (2014a) estimated carbon stored in HWP from the USFS Rocky Mountain region from 1906 to 2012 and found a positive net annual stock change in the HWP. Both of these regions have a positive net annual carbon stock change because additions of carbon to the HWP pools through harvest exceeded that of decay of the products harvested between study years.

Apart from the above studies, carbon stored in HWP in the other USFS regions has also been examined, such as Southwestern region (Butler et al., 2014b), Southern region (Loeffler et al., 2014a), Alaska region (Loeffler et al., 2014c), Intermountain region (Stockmann et al., 2014b), and Pacific Southwest region (Stockmann et al., 2014c). All of these studies conducted at the regional level have used IPCC production accounting approach to estimate annual changes in HWP pools. In all these regions, the results showed that the current net annual stock change in the HWP pool was negative.

2.4 Methodology

Estimates of the HWP contribution to carbon sinks and emissions were based on the methods described in 2006 IPCC guidelines. The HWP accounting approaches, variables used, and computational methods are described in the following sub-sections.

2.4.1 Harvested wood products accounting approaches

The stock-change approach estimates the annual carbon stock change in HWP within national boundaries (Dias et al., 2007), i.e. the net change in carbon stock of HWP is accounted for in the country where they are consumed regardless of origin (Winjum et al., 1998). The production approach estimates the annual change in carbon stock of HWP where the wood is domestically produced (Ji et al., 2013). In this approach, exported carbon stocks remain in the inventory of the exporting country, and any carbon stocks that cross a system boundary are not transferred from one country's inventory to another (IPCC, 2006).

The atmospheric flow approach estimates the flow of carbon between the atmosphere and HWP within a country (IPCC, 2006). Any carbon flows to the atmosphere from the oxidation or combustion of wood products are accounted for in the consuming country (Winjum et al., 1998). In practice, the carbon stock in this approach is identical to the carbon in HWP by the stock-change approach plus the net export of carbon in HWP. The simple decay approach estimates the net emissions or removals of carbon to and from the atmosphere. For this approach, all carbon release is reported by the country where the HWP is harvested (IPCC, 2006).

Estimating the HWP contribution based on four approaches

The HWP contribution to annual carbon removal, which is equal to the annual change in carbon stock in HWP (Ji et al., 2013), can be obtained either using carbon stock change variables or carbon release variables. The HWP contribution to annual carbon removals by the stock-change (SC_t), production (P_t), atmospheric flow (AF_t), and simple decay (SD_t) approaches in Tg C yr^{-1} were estimated as shown respectively, in Equations 2.1, 2.2, 2.3, and 2.4.

$$SC_t = \Delta C_{DC,IU,t} + \Delta C_{DC,SW,t} \qquad 2.1$$

$$P_t = \Delta C_{DH,IU,t} + \Delta C_{DH,SW,t} \qquad 2.2$$

$$AF_t = \Delta C_{DC,IU,t} + \Delta C_{DC,SW,t} + P_{EX,t} - P_{IM,t} \qquad 2.3$$

$$SD_t = H_t - \uparrow C_{DH,t} \qquad 2.4$$

HWP variables $\Delta C_{DC,IU,t}$, $\Delta C_{DC,SW,t}$, $\Delta C_{DH,IU,t}$, $\Delta C_{DH,SW,t}$, $P_{EX,t}$, $P_{IM,t}$, H_t, and $\uparrow C_{DH,t}$ are described below. The HWP contribution computed using four approaches as mentioned above were multiplied by the factor -44/12 to convert the contribution amount to Tg CO_2 yr^{-1}. The negative value represents carbon stored in the HWP.

2.4.2 Harvested wood products variables

According to the 2006 IPCC guidelines, to estimate the HWP contribution under any of four accounting approaches, a set of annual HWP variables (described below) needs to be estimated. The HWP carbon pool includes both the products in use (IU) and products that have been discarded to solid waste disposal sites (SWDS). The HWP categories include solid wood products and paper products. The required variables and methods to compute these variables are described below.

a) Variable 1A $\left(\Delta C_{DC,IU,t}\right)$ is the annual change in carbon stock in products in use from domestic consumption (*DC*) (Tg C yr^{-1}). Here, products mean both solidwood and paper products. Variable 1A was estimated as shown in Equations 2.5 and 2.6.

$$C_{DC,IU,t} = \sum_{i=1}^{2}\left(e^{-k_i}C_{DC,IU,i,t-1} + \frac{1-e^{-k_i}}{k_i}I_{DC,IU,i,t-1}\right) \tag*{2.5}$$

$$\Delta C_{DC,IU,t} = C_{DC,IU,t} - C_{DC,IU,t-1} \tag*{2.6}$$

where, t is a year; $C_{DC,IU,t}$ is the carbon stock in products in use from domestic consumption in the year t (Tg C yr^{-1}). For the year 1900, carbon stock is assumed to be zero (i.e. $C_{DC,IU,1900} = 0$). The subscript $i = 1$ refers to solidwood products and $i = 2$ refers to paper products. Here, k is the decay constant rate (yr^{-1}) for solidwood products (k_1) and paper products (k_2) (Table 2.1). Similarly, $I_{DC,IU,i,t}$ is the carbon inflow to solidwood or paper products (Tg C yr^{-1}).

For solidwood products (i.e., $i = 1$),

$$I_{DC,IU,1,t} = a_1\left(\sum_{n=1}^{2}\left(Q_{p,n} + Q_{I,n} - Q_{E,n}\right)\right) + a_2\left(B_P + B_I - B_E\right) \tag*{2.7}$$

where, a_1 is the carbon conversion factor for sawnwood and other industrial roundwood; a_2 is the carbon conversion factor for wood based panels. The subscript $n = 1$ refers to sawnwood and $n = 2$ refers to other industrial roundwood. $Q_{p,n}$ is the annual production of sawnwood or other industrial roundwood; $Q_{I,n}$ is the annual import of sawnwood or other industrial roundwood; and $Q_{E,n}$ is the annual export of sawnwood or other industrial roundwood. Similarly, B_p is the annual production of wood-based panels; B_I is the annual import of wood based panels; and B_E is the annual export of wood-based panels.

For paper products (i.e., $i = 2$),

$$I_{DC,IU,2,t} = a_3\left(J_P + J_I - J_E\right) \qquad 2.8$$

where, a_3 is the carbon conversion factor for paper and paperboard; J_p, J_I, and J_E are respectively, production, imports, and exports of paper and paperboard.

b) Variable 1B $\left(\Delta C_{DC,SW,t}\right)$ is the annual carbon stock change of domestically consumed solid wood and paper products disposed of in SWDS (Tg C yr^{-1}). Two types of SWDS were considered – open dumps and managed landfill. Solidwood and paper waste from municipal solid waste (MSW) and industrial waste were considered. Both methane (CH_4) and CO_2 emissions from SWDS were calculated. Basic steps include –

i) Amount of methane generated and emitted from SWDS

The amount of methane generated from SWDS was estimated based on the First Order Decay (FOD) method. The FOD model is built on an exponential factor. The calculation was based on the amount of Decomposable Degradable Organic Carbon (DDOC) in the waste deposited. To estimate the amount of methane generated from SWDS, first, the amount of DDOC $\left(DD_{m,t}\right)$ for municipal paper, wood waste, or industrial waste was each estimated from the waste disposal data as shown in Equation 2.9.

$$DD_{m,t} = W_{m,t} d_m \left(df\right) X \qquad 2.9$$

where, the subscript $m = 1,2,3$ respectively, refers to paper waste, wood waste, or industrial waste; W_t is the amount of waste deposited in SWDS in year t (Tg). d is the Degradable Organic Carbon (DOC) in the year of deposition for municipal paper waste $\left(d_1\right)$, municipal wood waste $\left(d_2\right)$, and industrial waste $\left(d_3\right)$ discarded in a landfill (Tg

C/Tg waste) (Table 2.1). Similarly, df is the fraction of DOC that decomposed under anaerobic condition. $X\left(=f_1Z_d+f_2Z_l\right)$ is the Methane Correction Factor (MCF), which is taken as the weighted average of that disposed in dumps and managed landfill; f_1 is the MCF for dumps, f_2 is MCF for managed landfill, Z_d is the percentage of waste going to dumps, and Z_l is the percentage of waste going to managed landfill.

Then, the amount of DDOC accumulated ($D_{a,m,t}$) and the amount of DDOC decomposed ($D_{d,m,t}$) in the SWDS for municipal paper waste or wood waste or industrial waste were estimated as shown in Equations 2.10 and 2.11, respectively.

$$D_{a,m,t}=DD_{m,t}+D_{a,m,t-1}e^{-j_m} \qquad 2.10$$

$$D_{d,m,t}=D_{a,m,t-1}(1-e^{-j_m}) \qquad 2.11$$

where, j refers to decay constant rate for paper products in MSW$\left(j_1\right)$, wood products in MSW$\left(j_2\right)$, or products in industrial waste $\left(j_3\right)$ (Table 2.1).

Finally, the total methane generated $\left(M_{g,t}\right)$ and the amount of methane emitted $\left(M_{e,t}\right)$ from SWDS is estimated as shown in Equations 2.12 and 2.13, respectively. The methane emitted from SWDS is calculated by subtracting the methane recovered in the gas collection system and oxidized to carbon dioxide in the cover layer from the amount of methane generated. Here, it is assumed that the methane is not recovered and that 10% of the generated methane is oxidized to carbon dioxide near the surface of the landfill (RTI, 2010).

$$M_{g,t} = \sum_{m=1}^{3} D_{d,m,t} F\left(16/12\right) \qquad 2.12$$

$$M_{e,t} = M_{g,t}(1-OX)21 \qquad 2.13$$

where, F is the fraction of CH_4, by volume, in generated landfill gas; and $16/12$ is the molecular weight ratio CH_4 / C; OX is the oxidation factor. The factor 21 is the global warming potential (GWP) of methane which converts the amount of methane emitted into carbon dioxide equivalent (CO_2e).

ii) Amount of CO_2 (C_t) emitted from SWDS

CO_2 emissions for landfills without gas collection systems was calculated from the methane generated as

$$C_t = M_{g,t}\left(\frac{1-F}{F} + OX\right)(44/16) \qquad 2.14$$

where, $44/16$ is the ratio of molecular weight of CO_2 to molecular weight of CH_4, and the other factors are as described before.

iii) The annual change in carbon stock in products disposed of in SWDS $\left(\Delta C_{DC,SW,t}\right)$ was estimated as

$$C_{DC,SW,t} = \left(\sum_{T=1900}^{t} W_{m,T} D_m (1-Df)X\right) - \left(M_{e,t} + C_t\right)\left(12/44\right) \qquad 2.15$$

$$\Delta C_{DC,SW,t} = C_{DC,SW,t} - C_{DC,SW,t-1} \qquad 2.16$$

where, $C_{DC,SW,t}$ is the total carbon stock in products disposed of in SWDS (Tg C yr^{-1}).

$W_{m,T}$, D_m, Df , X , $M_{e,t}$, and C_t are same parameters as described before. The factor $12/44$ is the molecular weight of carbon / molecular weight of CO_2. The term in first parentheses gives the amount of carbon accumulated in products disposed of in SWDS.

c) Variable 2A $\left(\Delta C_{DH,IU,t}\right)$ is the annual change in carbon stock in products in use from domestic harvest (Tg C yr^{-1}). Like variable 1A, the products here include both solidwood and paper products. Variable 2A was computed as

$$C_{DH,IU,t} = \sum_{i=1}^{2}\left(e^{-k_i} C_{DH,IU,i,t-1} + \frac{1-e^{-k_i}}{k_i} I_{DH,IU,i,t-1}\right) \qquad 2.17$$

$$\Delta C_{DH,IU,t} = C_{DH,IU,t} - C_{DH,IU,t-1} \qquad 2.18$$

where, $C_{DH,IU,t}$ is the carbon stock in products in use from domestic harvest at year t (Tg C yr^{-1}). For the year 1900, carbon stock was assumed to be zero (i.e. $C_{DH,IU,1900} = 0$). Similarly, $I_{DH,IU,i,t}$ is the carbon in inflow to solidwood or paper products and estimated as shown in Equations 2.19 and 2.20, respectively.

For solidwood products, $I_{DH,IU,1,t} = K\left(a_1\left(\sum_{n=1}^{2} Q_{p,n}\right) + a_2 B_P\right)$ 2.19

For paper products, $I_{DH,IU,2,t} = K\left(a_3 J_P\right)$ 2.20

where, $K = \left(\frac{N_p}{N_P + N_I - N_E + T_I - T_E + V_I - V_E}\right)$; N_P, N_I, and N_E are the industrial roundwood production, imports, and exports, respectively; T_I and T_E are the wood chips and particles imports and exports, respectively; V_I and V_E are the wood residues imports and exports, respectively. The other factors are the same as that described for variable 1A.

d) Variable 2B $\left(\Delta C_{DH,SW,t}\right)$ is the annual carbon stock change of HWP in SWDS from domestic harvest (Tg C yr^{-1}) and was computed as presented in Equation 2.21.

$$\Delta C_{DH,SW,t} = \Delta C_{DC,SW,t} \times \left[1 - \frac{I_w}{I_w + N_P} \right] \qquad 2.21$$

where, $I_w \left(= L_I + B_I + J_I + G_I + N_I + T_I + V_I \right)$ is the imported wood materials; L_I is the sawnwood imports; G_I is the wood pulp and recovered paper imports. The other notations are as described in earlier section.

e) Variable 3 $\left(P_{IM,t} \right)$ is the carbon in annual import of HWP (Tg C yr^{-1}) and was computed as shown in Equation 2.22.

$$P_{IM,t} = a_1 \left(T_I + V_I + L_I \right) + a_2 B_I + a_3 \left(J_I + G_I \right) + a_4 U_I + a_1 b R_I \qquad 2.22$$

where, a_4 is the carbon conversion factor for wood charcoal; U_1 is the imports of wood charcoal; b is the bark ratio for roundwood; and R_I is the roundwood import.

f) Variable 4 $\left(P_{EX,t} \right)$ is the carbon in annual export of HWP (Tg C yr^{-1}) and was estimated as shown in Equation 2.23.

$$P_{EX,t} = a_1 \left(T_E + V_E + L_E \right) + a_2 B_E + a_3 \left(J_E + G_E \right) + a_4 U_E + a_1 b R_E \qquad 2.23$$

where, U_E is the export of wood charcoal; and R_E is the roundwood export.

g) Variable 5 $\left(H_t \right)$ is the carbon in annual harvest of HWP (Tg C yr^{-1}) estimated as

$$H_t = a_1 b R_P \qquad 2.24$$

where, R_P is the annual roundwood production.

h) Variable 7 $\left(\uparrow C_{DH,t} \right)$ is the annual release of carbon to the atmosphere from domestic harvest of HWP (Tg C yr^{-1}) computed as

$$\uparrow C_{DH,t} = H_t - \Delta C_{DH,IU,t} - \Delta C_{DH,SW,t} \qquad 2.25$$

All the variables in Equation 2.25 are as defined earlier.

2.5 Parameters and data sources

The data required for this study include harvested wood products (solid wood and paper products) production and trade (exports and imports) data, carbon conversion factors for wood and paper products, decay rate constant for solidwood and paper products, amount of wood and paper products waste going to municipal solid waste (MSW) disposal sites, amount of waste going to industrial SWDS, oxidation factor at both MSW and industrial SWDS, degradable organic carbon, fraction of DOC decomposed, and decay rate constant for paper and wood waste in MSW and industrial landfill, and fraction by volume of methane in landfill gas. The sources of these data are presented in Table 2.1. The uncertainty might be associated with using some default data and parameters. For example, parameter decay rate for solidwood and paper products from the products in use pool has uncertainty of ± 50 percent (IPCC, 2006). It is important to make the best possible estimates of net carbon stored in the HWP, and for this uncertainty in the carbon estimates as a result of uncertainty in input data and parameters must be assessed. Chapter III of this dissertation thus analyzes the uncertainty in the HWP carbon estimates obtained in this chapter.

These required data for the study were obtained from the literature and existing databases. The data for production and trade of harvested wood products were taken from the FAOSTAT databases of Forestry for the U.S. The descriptive statistics of production, imports, and exports of wood products are reported in Table 2.2. The summary statistics showed that the production of roundwood varies from 121,120 to 509,319 thousand cubic meters. Similarly, the mean of roundwood import was 2,243, fluctuating from 218 to 4,057 thousand cubic meters. The mean of roundwood export was 7,005 and ranged from 1,102 to 22,647 thousand cubic meters. The statistics for other wood products can be described in a similar way.

The carbon conversion factors for various wood and paper products are presented in Table 2.1. The decay rate constant for solidwood products and paper products were respectively, 0.023 and 0.231 yr^{-1} (IPCC, 2006). Two types of landfills were considered, open dumps and managed landfill. The percentage of waste going to open dumps prior to 1980 was taken to be 94%, and that for managed landfill was 6% (RTI, 2010). The methane correction factor (MCF) for open dumps and managed landfill were respectively, 0.6 and 1 (IPCC, 2006). The DOC for paper and wood waste in MSW landfills, paper waste in an industrial landfill, and decay rate values are presented in Table 2.1. It was assumed that 10% of the methane generated is oxidized to carbon dioxide near the surface of the landfill (RTI, 2010). The fraction of methane generated in gas was 0.5, and the fraction of DOC degraded was 0.5 (RTI, 2010).

The percentage of wood and paper products disposed in landfills from the year 1960 to 2013 were compiled from U.S. EPA reports that were published from 1995 to 2013 (USEPA, 1997, 2001, 2006, 2010, 2015). The data for the year 2014 was forecasted. These reports do not have data between the years 1961-1969, 1971-1979, and 1981-1989. A linear interpolation was used for these years.

Figure 2.1 shows the amount of solidwood and paper products discarded in MSW landfill. The paper products discarded in landfill showed a general downward trend, whereas the solidwood products discarded in the landfill were more or less stable during the study period from 1990 to 2014. During the same period, the amount of solid wood products discarded to landfill increased by 1.9 Tg, whereas the amount of paper products decreased by 23.8 Tg. The decrease in the amount of paper products discarded in SWDS during this period was because of the increase in the recovery of paper waste going to the landfills, such as recycling of waste paper and combustion with energy recovery. Overall, the tonnage of paper waste landfilled declined over time by the greater amount and the decline was sharp in 2009. In this year, the amount of paper waste disposed of in SWDS after recovery was 7.8 Tg less than that in the previous year. In contrast to the paper waste, the tonnage of wood waste landfilled increased over time.

2.6 Results

2.6.1 Carbon estimates in the harvested wood products variables

Additions to carbon stock in the HWP variables were estimated on an annual basis from 1990 to 2014. The annual estimates of the HWP variables are presented in Table 2.3. Variables 1A, 1B, 2A, and 2B track the additions to and removals from the pools of products in use and products held in SWDS. Variable 3 represents the annual flow of carbon in imports of the wood and paper products. Similarly, Variable 4 represents the carbon stock in annual exports of the wood and paper products. Variable 5 gives the annual carbon stock in the domestic harvest. Variable 7 represents the annual release of carbon to the atmosphere from HWP that came from the domestic harvest. Variables 1A and 1B were used to estimate the HWP contribution under the stock-change approach, whereas variables 2A and 2B were used to estimate the HWP contribution under the production approach. Similarly, variables 1A, 1B, and 5 were used to estimate the HWP contribution under the atmospheric flow approach. Variables 5 and 7 were used to estimate the HWP contribution under the simple decay approach.

Variable 1A - annual change in carbon stock in products in use from the domestic consumption

Results for variable 1A indicated that total carbon stocks in the HWP in use from domestic consumption increased from 1990 to 2014. However, the net annual increase in carbon stock decreased during the same time period, meaning that total carbon stored in the HWP pools in use in the inventory year was lower than the previous year. The annual addition of carbon stock in the products in use was 33 Tg C in 1990 which decreased to 4.9 Tg C in 2014. Change in carbon stocks during the same period averaged to 24.3 Tg C per year. The annual addition to HWP carbon stock in the products in use peaked in 2006 and was 40.6 Tg C, and reached its minimum in 2010 and was -10.7 Tg C. In the 1990s, the annual addition of carbon in the products in use increased from 33 Tg C in 1990 to 35.4 Tg C in 1999, with some inter-annual variability. During this period, the net change in carbon stock was minimum in 1992 with the addition of 23.3 Tg C. In the 2000s, the annual addition of carbon stock decreased from 38.9 Tg C in 2000 to 6.5 Tg C in 2009. This period had the overall highest annual addition of carbon stock in the products in use that was in 2006. In the 2010s, the net change in carbon stocks moved from positive to negative, 2010 being marked as the largest reduction in carbon stock. During this period, some negative values were seen (Table 2.3), and these negative values indicated that the HWP in use became a net source of the atmospheric carbon. From 2010 to 2012, there was net annual emission of carbon from the products in use to the atmosphere.

Variable 1B – annual carbon stock change of domestically consumed products in SWDS

The total carbon stocks in SWDS from the domestic consumption increased from 1990 to 2014. However, the net annual addition of carbon stock in SWDS decreased during the same period. The beginning of the study period i.e., 1990 showed the annual addition of carbon stock to be 10.9 Tg C which decreased to 7.9 Tg C in 2014. The annual addition averaged to 9.21 Tg C during the study period. The highest annual carbon addition to the products discarded was 11.3 Tg C in 1994. The minimum change in carbon stock in SWDS was 7.4 Tg C in 2009, 2011 and 2012. Results showed that in the 2010s, annual addition of carbon was lower compared to that in the 1990s and 2000s. All the values (net carbon additions) for the variable 1B were positive (Table 2.3) indicating that the products in SWDS were a net sink of the atmospheric carbon.

Comparison between variables 1A and 1B

Decrease in the net annual carbon stock was most prominent in variable 1A (products in use) as compared to variable 1B (products in SWDS). From 1990 to 2014, the net change in annual addition of carbon stock decreased by 28.1 Tg C in variable 1A, whereas it only decreased by 3 Tg C in variable 1B. In contrast, the average annual addition of carbon stock was higher in variable 1A (24.3 Tg C) as compared to that of variable 1B (9.21 Tg C) during the study period. The net addition of carbon in the products in use exceeded that in the products in SWDS from 1990 to 2008. However, the additions to the products in use were exceeded by carbon additions to the products discarded in SWDS since 2009. The annual addition of carbon in products in SWDS is almost constant after 2009. The annual addition of carbon in the products in use were somewhat fluctuating with sharp decline in 2010. In contrast, the trend showed that the net change in carbon stock in products in SWDS were mostly stable during the study period.

Variable 2A- annual change in carbon stock in products in use from the domestic harvest

Results showed that the carbon stock in HWP in use from the domestic harvest increased from 1990 to 2014. In contrast, the annual addition of carbon stock to products in use from the domestic harvest decreased from 31.1 Tg C in 1990 to 7.8 Tg C in 2014. The net change in carbon stock averaged to 18.82 Tg C with a peak stock change in 1992 (addition of 32.4 Tg C) and a minimum stock change in 2010 (addition of -6.8 Tg C). As described earlier, the negative value in 2010 means the products in use from the domestic harvest were a net carbon emitter to the atmosphere. The first sharp decline in the net carbon addition in the products in use was in 1992, when carbon stock declined by 6.2 Tg C from the previous year. With a series of increase-decrease patterns, the net annual addition of carbon stock declined sharply in the year 2010, when the carbon stock in HWP decreased by 13.3 Tg C from the previous year and became negative. After 2010, the annual addition of carbon stock increased and became positive again in 2012.

Variable 2B- annual carbon stock change in products in SWDS from the domestic harvest

For variable 2B, the total carbon stocks in HWP in SWDS from the domestic harvest increased from 1990 to 2014. However, the net annual addition of carbon stock decreased. The net change in carbon stock averaged to 8.12 Tg C, with the highest addition in 1994 of 10.1 Tg C and lowest in 2009, 2011, and 2012 of about 6.7 Tg C. The annual addition of carbon was 10 Tg C in 1990, which decreased to 7 Tg C in 2014. All carbon estimates were positive indicating that the products in SWDS from the domestic harvest were a net sink of carbon from the atmosphere.

Comparison between variables 2A and 2B

Comparing variable 2A (products in use) and 2B (products in SWDS), decrease in the net addition of carbon stock was more prominent in variable 2A than variable 2B. The net addition of annual carbon stock decreased by 23.3 Tg C in variable 2A, whereas that decreased by 3 Tg C in variable 2B. In contrast, the average annual addition of carbon stock from 1990 to 2014 was higher in variable 2A (18.82 Tg C) as compared to that of variable 2B (8.12 Tg C). The net addition of carbon in variable 2A exceeded that in variable 2B from 1990 to 2008. However, the additions to the products in use were exceeded by carbon additions to products discarded in SWDS since 2009. The annual additions of carbon in the products in use were relatively fluctuating with an overall sharp decline and becoming negative in 2010. In contrast, the trend showed that the net changes in carbon stock in products in SWDS were rather flat during the study period.

Comparison between variables 1A and 2A, and between variables 1B and 2B

Variable 1A, i.e. products in use from the domestic consumption, and variable 2A, i.e. products in use from the domestic harvest, showed a similar trend during the study period. In both variables, net carbon addition to the product pools showed a series of increase-decrease pattern and hit the minimum and negative value in 2010, after which it started increasing and became positive in 2014. However, the average annual addition of carbon stock in variable 1A was 5.48 Tg C more than that in variable 2A. The annual addition of carbon stock in variable 1A peaked in 2006 (towards the middle of the study period), and in variable 2A peaked in 1992 (towards the beginning of the study period).

Variable 1B, i.e. products in SWDS from the domestic consumption, and variable 2B, i.e. products in SWDS from the domestic harvest, showed a similar pattern. Although there was decrease in the net additions of carbon stocks in both the variables, they were mostly stable during the study period. However, the annual average addition of carbon stock in variable 1B was more than that in variable 2B. In 2014, the estimates of net carbon stock change in variable 1A, 1B, 2A, and 2B were positive, indicating that the products in use and products discarded in SWDS from the domestic consumption and domestic harvest all act as a carbon sink.

Variable 3 – carbon in annual imports of the harvested wood products

The annual carbon stock in imports of the wood and paper products in 1990 and 2014 were respectively, 20.7 Tg C and 22.3 Tg C. Therefore, there was a net increase of 1.6 Tg C in the carbon stocks in the products pools during the study period. The average carbon stock in imports was 26.6 Tg C per year. Carbon stock in imports declined in 1991 by 1.9 Tg C after which it started increasing and reached 32.4 Tg C in 1999. During the 2000s, the carbon stock in imports reached both the highest (41.6 Tg C) and lowest (17.6 Tg C) values, respectively, in the years 2004 and 2009. Following a series of increase from 1992 to 2004, carbon stock in imports started decreasing until it reached a minimum in 2009. In 2010, annual carbon stock in imports increased by 1.4 Tg C, and the following year, it again decreased by 0.3 Tg C. From 2012 to 2014, the carbon stock in imports increased by 3 Tg C.

Variable 4 – carbon in annual exports of the harvested wood products

Results indicated that annual carbon stock in exports of the wood and paper products increased slightly (0.4 Tg C) from 1990 to 2014, with minor fluctuation. The average annual carbon stock in exports was 23.9 Tg C. The annual carbon stock reached its minimum in 2009 with an estimate of 21 Tg C, after which it increased and peaked in

2013 with an estimate of 28.9 Tg C. In 2014, the carbon stock in exports dropped slightly (0.2 Tg C) from its previous year.

Variable 5 – carbon in annual harvest of the wood products

The results for variable 5 showed that the annual carbon stock due to the domestic harvest of wood products declined during the period from 1990 to 2014. The decline was greatest in the year 2009 where the addition was 186 Tg C. Overall, the annual carbon stock in domestic harvest in 2014 was 62 Tg C less than that in 1990.

Variable 7 – annual release of carbon to the atmosphere from the domestic harvest

The trend results for variable 7 showed that the annual release of carbon to the atmosphere from the wood products harvest decreased during the study period by 36 Tg C. The average carbon release from 1990 to 2014 was 211.1 Tg C. The annual carbon release was highest in the year 1990 with 244.1 Tg C and lowest in 2009 with 173.1 Tg C.

2.6.2 Domestic harvest trends

The harvested wood products output trend (Tg C) is shown in Figure 2.2. From 1990 to 2014, production averaged to 247.6 Tg C per year. The annual HWP production was 285.2 Tg C in 1990 which declined to 223.3 Tg C in 2014. The production in 1990 was the maximum production during the study period. From 1990 to 2005, the HWP production averaged to 262.63 Tg C per year, before beginning a downward trend and hitting the minimum in 2009 of 186.2 Tg C. From 1990 to 2005, the production showed inter-annual variability with lowest production in 2002 of 250.9 Tg C. The annual HWP harvest began to grow, starting at the minimum in 2009, with fluctuation in the year 2012, where it showed decrease in the production.

2.6.3 Harvested wood products contribution to carbon removals or emissions under accounting approaches

The HWP contribution to carbon emissions or removals under four accounting (stock-change, production, atmospheric flow, and simple decay) approaches, as recommended by 2006 IPCC guidelines, are presented in Table 2.4. The negative sign in the estimates in Table 2.4 represent the net annual removals of carbon from the atmosphere, and the positive sign in the estimates represent the net annual emissions of carbon into the atmosphere. In the other words, the negative estimate indicates that the HWP contribution is positive (i.e., HWP act as a carbon sink) and positive estimate indicates the HWP contribution is negative (i.e., HWP act as a carbon source).

For the stock-change approach, the net annual HWP carbon accumulation decreased by 114 Tg CO_2e during the time period from 1990 to 2014. The average accumulation was -127 Tg CO_2e per year, meaning that the HWP stored 127 Tg CO_2e annually from 1990 to 2014. In the 1990s, the net annual carbon stored in the HWP increased from -160.8 Tg CO_2e in 1990 to -169.8 Tg CO_2e in 1999, with a series of fluctuations in between. In contrast, in the 2000s, the net annual carbon stored in the HWP decreased from -180.8 Tg CO_2e in 2000 to -51.1 Tg CO_2e in 2009. The net annual carbon accumulation in HWP peaked in the year 2006 accounting -184.7 Tg CO_2e. Since then, carbon stored in HWP declined and in the beginning of the 2010s, reached the lowest value. In 2010, the carbon stored in HWP was 10.3 Tg CO_2e, which means the HWP were a net source of carbon emissions to the atmosphere. Carbon stored in HWP declined by 195 between 2006 (highest estimate) and 2010 (lowest estimate). From the year, 2010, the HWP contribution to carbon removals increased, and in 2014 it was -47 Tg CO_2e. This represents the increase of 57.1 Tg CO_2e from the lowest estimate in 2010.

Overall, except in the year 2010, the HWP contributions under the stock-change approach were positive, i.e. there were net removals of carbon from the atmosphere from 1990 to 2014.

Similar to the stock-change approach, the HWP contribution to carbon removals under atmospheric flow approach also declined from 1990 to 2014 by 118.4 Tg CO_2e. The average accumulation of carbon in HWP was -117.4 Tg CO_2e. In the 1990s, the net annual accumulation of carbon decreased from -188.7 Tg CO_2e in 1990 to -145.4 Tg CO_2e in 1999. The year 1990 represented the highest estimated HWP contribution to carbon removals under the atmospheric flow approach. The annual carbon stored in HWP decreased by 87.6 Tg CO_2e from 2000 to 2009, however there has been an increase in carbon accumulation in the years between 2005 and 2007. During the 2000s, the decline was greatest between 2008 and 2009 when carbon stored in HWP declined by 53.8 Tg CO_2e. Similar to the stock-change approach, the HWP contribution to carbon removals was lowest in 2010 accounting -7.4 Tg CO_2e. In contrast to stock-change approach, the HWP contribution was positive in that year. Carbon stored in the HWP declined by 113.9 between 1990 (highest estimate) and 2010 (lowest estimate). Carbon stored in the HWP increased after 2010 and in 2014 it was -70.3 Tg CO_2e. This represented 62.9 Tg CO_2e increased from the lowest estimate in 2010. Overall, the HWP contributions under the atmospheric flow approach were positive, i.e. HWP act as CO_2e removals from 1990 to 2014.

Results under the production approach indicated that the annual carbon accumulation in HWP decreased from -150.8 Tg CO_2e in 1990 to -54.4 Tg CO_2e in 2014. The average carbon stored in HWP was -102.8 Tg CO_2e per year. The HWP contribution under the production approach followed a path similar to that under the atmospheric flow approach. In the 1990s, the carbon accumulation in HWP declined by 21.1 Tg CO_2e. 1990 was the year in which carbon estimate in the HWP reached at its peak, similar to that of the atmospheric flow approach. From 2000 to 2009, carbon stored in the HWP decreased by 88.2 Tg CO_2e. Like the stock-change and atmospheric flow approaches, carbon stored in the HWP was at a minimum in 2010 with -1.4 Tg CO_2e. The carbon stored in HWP declined by 112.6 between 1990 (highest estimate) and 2010 (lowest estimate). In contrast, the carbon accumulation in HWP increased after 2010, and in 2014 it was -54.4 Tg CO_2e. This represented 53 Tg CO_2e increase from the lowest estimate in 2010. Overall, the HWP contributions under the production approach were positive, i.e. HWP act as carbon sink from 1990 to 2014.

The HWP CO_2 estimates under the simple decay approach behave in the similar way as that of other three approaches. The estimates were exactly the same as that under the production approach. The results indicated that the HWP contribution to CO_2 removals declined from 1990 to 2014 by 96.4 Tg CO_2e. The carbon stored in HWP was highest in 1990 with -150.8 Tg CO_2e and lowest in 2010 with -1.4 Tg CO_2e. Overall, the HWP contributions under the simple decay approach were positive.

2.6.4 Comparison of net annual carbon estimates among four accounting approaches

Results indicated that the HWP contribution estimates differ among some of the approaches used. However, the HWP contribution estimates were identical for the production and simple decay approaches. Over the period from 1990 to 2014, the estimated average annual HWP carbon accumulation was highest for the stock-change approach (-127.8 Tg CO_2e), followed by the atmospheric flow approach (-117.4 Tg CO_2e), and the production and simple decay approaches (-102.8 Tg CO_2e). The annual carbon accumulation in HWP was highest for the atmospheric flow approach from 1990 to 1992 and 2009 to 2014, whereas it was highest for the stock-change approach from 1993 to 2008. The annual carbon estimates under the production and simple decay approaches were lowest for most of the years, except for the years from 2010 to 2014 during which carbon estimates were lowest for the stock-change approach. For 2014, the HWP contribution to carbon removals was highest for the atmospheric flow approach (-70.3 Tg CO_2e), followed by the production and simple decay approaches (-54.4 Tg CO_2e) and the stock-change approach (-46.8 Tg CO_2e). Between 1990 and 2014, the difference in carbon stored in HWP was highest in the atmospheric flow approach (118.4 Tg CO_2e), followed by the stock-change approach (114 Tg CO_2e) and the production and simple decay approaches (96.4 Tg CO_2e).

For all of the four approaches, there were several periods during the study timeframe with fluctuations of HWP contribution above and below the prior year estimates. Except for the stock-change approach in 2010, the HWP contributions were positive, i.e. there were net accumulations of carbon in HWP. For all of the approaches, the net annual HWP carbon accumulation was lowest in the year 2010 (Table 2.4). However, for the stock-change approach, the carbon stored in HWP peaked in 2006, whereas for other three approaches, the carbon stored in HWP peaked in the year 1990.

2.7 Conclusion and discussion

Forests capture carbon from the atmosphere and store a significant amount of that carbon in their biomass. When forests are harvested, a portion of carbon is stored in

HWP. This study estimated the carbon stored in the U.S. HWP from 1990 to 2014. The methods were based on 2006 IPCC guidelines. Several variables were defined and estimated accordingly. Based on these variables, four accounting approaches, stock-change, atmospheric flow, production, and simple decay approaches, were used to estimate the HWP contribution to carbon removals or emissions.

Based on the results, conclusions can be made that, depending on the approaches used, there is a considerable difference in the estimates of carbon accumulation in the U.S. HWP. This result was similar to other studies that estimated carbon stored in the HWP according to different approaches (Dias et al., 2007; Hashimoto et al., 2002; Ji et al., 2013; Leea et al., 2011; Skog, 2008; Winjum et al., 1998). The variation in the estimates is because these approaches have different system boundaries for carbon sequestration and emissions in wood products between producers and consumers. The estimates under the production approach and the simple decay approach were, however, the same. This might be because both these approaches depend on the amount of annual harvest of the wood products.

The average annual estimate of carbon accumulation in HWP was highest for the stock-change approach, followed by the atmospheric flow approach, and production and simple decay approaches. This result was consistent with the results from Skog (2008) for the U.S. This result was, however, different from Dias et al. (2007), where the HWP contribution was highest for the atmospheric flow approach, followed by the production and stock-change approaches, and from Ji et al. (2013), where the carbon stored in HWP was highest for the stock change approach, followed by the production and atmospheric flow approaches.

It can be concluded that HWP in the U.S. act as a carbon reservoir under all the accounting approaches from 1990 to 2014, except for the stock-change approach in 2010. The HWP contribution to carbon removals under all the approaches declined sharply from the late-2000s until it reached its lowest value in 2010. During this period, the harvest level declined resulting in less carbon entering into the HWP pools (Figure 2.2). The decrease in the domestic harvest might be due to dramatic changes in the economy during the same period. For instance, 2007 to 2009 was marked as a period of great recession in the U.S. economy. During this period, both the housing market and the consumption of paper and paperboard declined, impacting the overall forest products industry (Dahal, Henderson, & Munn, 2015).

Carbon sequestration in HWP increased beyond the year 2010 under all the accounting approaches. The harvest level rose resulting in more carbon entering into the HWP pools. The net increase in the HWP carbon stock after 2010 under the stock-change approach may be due to a net increase in the products in use. Additions of the HWP to SWDS have remained roughly constant (Figure 2.1). Under the atmospheric flow approach, the net increase in the carbon stock may be because of a decrease in the amount of net imports. The net increase in carbon stock under the production approach may be due to an increase in domestic harvest and net additions to the products in use. The net increase of carbon stock under the simple decay approach may be due to an increase in domestic harvest of products.

Each of the four accounting approaches provides various incentives to achieve different policy goals (Hashimoto, 2008). For example, the stock-change and atmospheric flow approaches provide incentives for the long-term storage of biomass into wood products such as material use. The production approach provides an incentive for the long-term storage of biomass into domestic wood products excluding imported wood products. The stock-change approach, production approach, and simple decay approach would provide incentives for the use of wood products for energy. In addition, the stock-change approach gives an incentive to import HWP and a disincentive to export HWP (Tonosaki, 2009). This is because the stock-change approach regards exported HWP as a carbon loss and imported HWP as a carbon gain. However, the production approach gives an incentive to export, and the atmospheric flow approach gives an incentive to export and a disincentive to import. The choice of accounting approaches would thus impact the international trade in wood products, which in turn will affect the forest management activities and forest products industry in a country (Tonosaki, 2009). In general, the net-importing countries will support the stock-change approach, whereas the net-exporting countries will support either production or atmospheric flow or simple decay approaches.

This clearly shows that there are trade-offs between alternative approaches used to estimate the HWP carbon stock. Therefore, choice of accounting method has potential policy implications on incentive or disincentives to use and trade HWP. The suitable approaches for a particular policy goal might pose problems for other policy goals. For example, there might be a conflict between the domestic use of wood and conservation of forests, use of imported HWP and forest conservation in exporting countries, or conflict among enhancement of carbon stock in a landfill, products recycling, increasing life of products, and forest conservation (Hashimoto, 2008). Keeping all these in mind, the accounting approach that is best compatible with the policy goals should be adopted.

These approaches, however, do not account for carbon fluxes associated with the substitution of products such as substitution of HWP for metal or concrete. Nor do these approaches account for carbon fluxes associated with the substitution of fossil fuels for bioenergy, which is one of the most researched areas in the current context. In addition, these approaches do not account for carbon emissions associated with the HWP such as carbon emissions from fossil fuels used in transportation and manufacturing of the HWP. To get a complete picture of the HWP contribution to carbon removals and emissions, all these carbon fluxes and emissions need to be taken into account. This can be the direction for the future research.

Nevertheless, HWP are important carbon pools and help sequester a considerable amount of carbon. Total carbon stock and carbon stock change in HWP should be monitored over time, because HWP are an important component in making country-level inventories of GHG emissions. In addition, the contribution of HWP to carbon removals or emissions should also be estimated at the smaller land management units. Policy makers should consider HWP in decision making associated with carbon monitoring, and climate change mitigation and adaptation strategies.

Table 2.1 Parameters and sources for estimating carbon in the U.S. HWP

Symbol	Description	Value	Source
a_1	carbon conversion factor for roundwood, sawnwood, chip and particles, other industrial roundwood, and wood residues	0.0000005	IPCC (2006)
a_2	carbon conversion factor for wood based panels	0.000000295	IPCC (2006)
a_3	carbon conversion factor for paper and paperboard, and wood pulp and recovered paper	0.00000045	IPCC (2006)
a_4	carbon conversion factor for wood charcoal	0.000000765	IPCC (2006)
b	bark ratio	1.12	IPCC (2006)
k_1	decay rate for solidwood	0.0231	IPCC (2006)
k_2	decay rate for paper products	0.231	IPCC (2006)
d_1	degradable organic carbon for paper waste in municipal solid waste	0.4	RTI (2010)
d_2	degradable organic carbon for wood waste in municipal solid waste	0.43	RTI (2010)
d_3	degradable organic carbon in industrial waste	0.2	RTI (2010)
df	fraction of DOC decomposed	0.5	RTI (2010)
j_1	decay rate for paper waste in municipal solid waste	0.05	RTI (2010)
j_2	decay rate for wood waste in MSW	0.025	RTI (2010)
j_3	decay rate for industrial waste	0.03	RTI (2010)
f_1	methane correction factor for dumps	0.6	IPCC (2006)
f_2	methane correction factor for managed landfills	1	IPCC (2006)
F	fraction of methane	0.5	RTI (2010)
ox	oxidation factor	0.1	RTI (2010)

Table 2.2 Descriptive statistics for the production and trade data of HWP (1000 units)

Symbol	Description	Unit	Mean	St Dev	Min	Max
R_p	Roundwood production	m^3	293,532	122,055	121,121	509,319
R_I	Roundwood import	m^3	2,243	846	219	4,057
R_E	Roundwood export	m^3	7,005	6,422	1,102	22,647
L_P	Sawnwood production	m^3	55,309	20,885	24,275	97,020
L_I	Sawnwood import	m^3	12,802	10,777	3,106	43,992
L_E	Sawnwood export	m^3	2,497	2,108	576	8,451
B_P	Wood based panel production	m^3	18,926	14,011	4,528	45,801
B_I	Wood based panel import	m^3	3,324	4,830	319	21,077
B_E	Wood based panel export	m^3	812	1,123	18	3,253
J_P	Paper and paperboard production	mt	41,052	25,241	12,856	88,670
J_I	Paper and paperboard import	mt	6,565	4,277	2,131	17,513
J_E	Paper and paperboard export	mt	3,021	3,523	401	12,122
G_I	Wood pulp and recovered paper import	mt	2,236	2,458	192	6,964
G_E	Wood pulp and recovered paper import	mt	5,257	5,892	593	18,605
N_P	Industrial roundwood production	m^3	253,890	106,127	103,803	427,200
N_I	Industrial roundwood import	m^3	2,208	877	219	4,057
N_E	Industrial roundwood export	m^3	6,962	6,389	1,102	22,647
O_P	Other industrial roundwood production	m^3	11,696	2,741	7,091	16,964
O_I	Other industrial roundwood import	m^3	390	314	0	1,508
O_E	Other industrial roundwood export	m^3	99	197	0	911
T_I	Chip and particles import	m^3	329	442	0	1,406
T_E	Chip and particles export	m^3	2,271	2,977	0	9,848
U_I	Wood charcoal import	mt	17	18	4	88
U_E	Wood charcoal export	mt	8	10	0	34
V_I	Wood residues import	m^3	300	212	94	1,021
V_E	Wood residues export	m^3	39	127	0	850

Table 2.3 Estimated annual carbon in the harvested wood products variables (Tg C)

Year	Var1A	Var1B	Var2A	Var2B	Var3	Var4	Var5	Var7
1990	33.0	10.9	31.1	10.0	20.7	28.3	285.2	244.1
1991	31.3	8.6	32.4	7.9	18.8	28.6	275.1	234.7
1992	23.3	10.7	26.2	9.8	20.6	26.9	270.9	234.9
1993	28.4	11.0	28.4	9.9	23.4	23.2	263.6	225.3
1994	32.3	11.3	28.0	10.1	25.3	23.9	264.9	226.8
1995	36.4	10.7	30.7	9.5	26.9	25.5	263.1	222.9
1996	36.0	9.9	29.8	8.8	27.4	25.8	258.2	219.6
1997	35.0	10.5	28.3	9.3	29.2	25.7	260.0	222.4
1998	38.3	10.5	30.3	9.3	30.4	25.9	263.1	223.5
1999	35.4	10.9	25.9	9.5	32.4	25.8	262.8	227.4
2000	38.9	10.4	28.2	9.0	33.8	25.7	261.3	224.1
2001	36.1	10.1	24.7	8.7	34.3	23.3	251.5	218.2
2002	30.2	10.3	17.3	8.8	36.2	22.2	250.9	224.7
2003	33.0	9.9	18.4	8.4	36.8	21.1	251.2	224.4
2004	31.9	10.5	16.5	8.7	41.6	22.1	258.6	233.3
2005	39.6	9.8	20.8	8.2	41.5	22.1	261.7	232.7
2006	40.6	9.8	22.9	8.2	39.3	22.0	255.9	224.9
2007	35.7	9.2	20.4	7.9	32.3	23.8	238.1	209.7
2008	23.4	9.1	15.9	8.1	24.0	23.6	213.1	189.1
2009	6.5	7.4	6.5	6.7	17.6	21.0	186.2	173.1
2010	-10.7	7.9	-6.8	7.1	19.0	23.8	210.9	210.5
2011	-5.1	7.4	-1.2	6.7	18.7	25.4	221.3	215.7
2012	-2.7	7.4	1.8	6.7	19.3	28.7	217.0	208.5
2013	0.1	7.6	5.0	6.8	21.0	28.9	222.2	210.4
2014	4.9	7.9	7.8	7.0	22.3	28.7	223.3	208.4

Note: Var1A – annual change in stock of HWP in use from consumption $\left(\Delta C_{DC,IU,t}\right)$; Var1B – annual change in stock of HWP in SWDS from consumption $\left(\Delta C_{DC,SW,t}\right)$; Var2A – annual change in stock of HWP in use produced from domestic harvest $\left(\Delta C_{DH,IU,t}\right)$; Var2B – annual change in stock of HWP in SWDS produced from domestic harvest $\left(\Delta C_{DH,SW,t}\right)$; Var3 – annual imports of wood, and paper products plus wood fuel, pulp, recovered paper, roundwood, wood chips $\left(P_{IM,t}\right)$; Var4 – annual exports of wood, and paper products plus wood fuel, pulp, recovered paper, roundwood, wood chips $\left(P_{EX,t}\right)$; Var5 – annual domestic harvest $\left(H_t\right)$; Var7 – annual release of carbon to the atmosphere from HWP including fuelwood where wood came from domestic harvest from products in use and products in SWDS $\left(\uparrow C_{DH,t}\right)$.

Table 2.4 Annual HWP carbon sequestration or emissions under accounting approaches (Tg CO_2e)

Year	Stock-change	Production	Atmospheric flow	Simple decay
1990	-160.8	-150.8	-188.7	-150.8
1991	-146.5	-148	-182.7	-148
1992	-124.9	-132.1	-148.2	-132.1
1993	-144.4	-140.5	-143.8	-140.5
1994	-159.7	-139.8	-154.5	-139.8
1995	-172.4	-147.3	-167.1	-147.3
1996	-168.3	-141.4	-162.4	-141.4
1997	-166.8	-137.8	-154.2	-137.8
1998	-179.2	-145.1	-162.7	-145.1
1999	-169.8	-129.7	-145.4	-129.7
2000	-180.8	-136.5	-151.3	-136.5
2001	-169.3	-122.2	-129.2	-122.2
2002	-148.5	-95.8	-97.3	-95.8
2003	-157.2	-98.1	-99.5	-98.1
2004	-155.3	-92.7	-83.7	-92.7
2005	-180.8	-106.5	-109.8	-106.5
2006	-184.7	-114	-121.3	-114
2007	-164.6	-104	-133.6	-104
2008	-119.1	-87.8	-117.5	-87.8
2009	-51.1	-48.3	-63.7	-48.3
2010	10.3	-1.4	-7.4	-1.4
2011	-8.5	-20.3	-33.1	-20.3
2012	-17.3	-31.2	-51.8	-31.2
2013	-27.9	-43.2	-57	-43.2
2014	-46.8	-54.4	-70.3	-54.4

Note: The negative values indicate the net carbon sequestration in harvested wood products and the positive value indicate the net carbon emissions from harvested wood products.

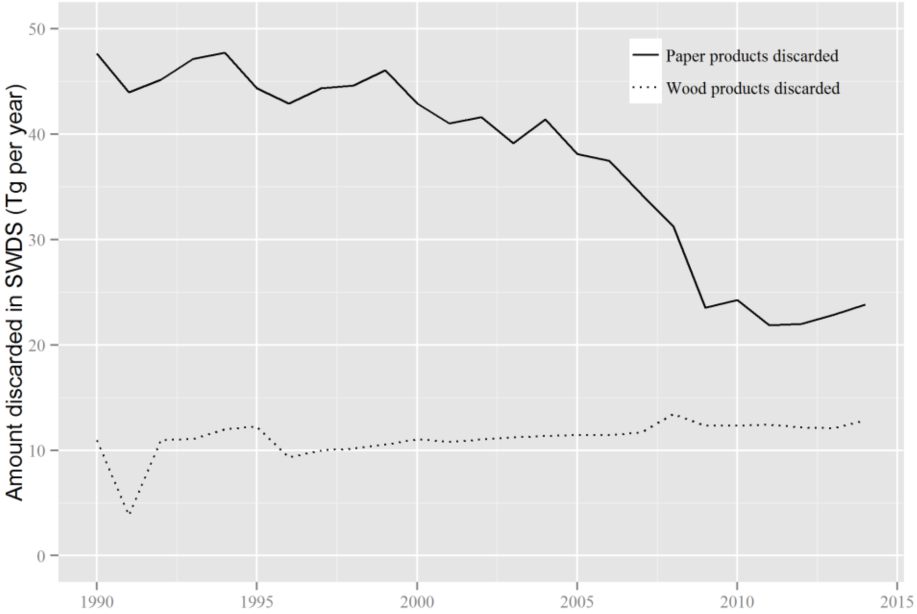

Figure 2.1 Amount of paper products and solid wood products discarded (Tg per year) in solid waste disposal sites from 1990 to 2014.

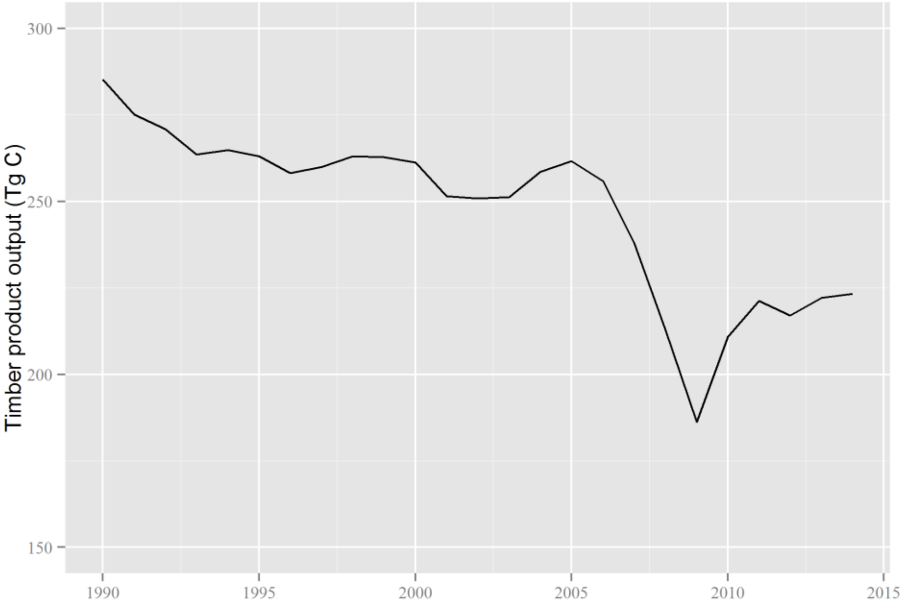

Figure 2.2 Trend showing annual domestic harvest (Tg C) in the U.S. from 1990 to 2014.

CHAPTER III

MONTE CARLO UNCERTAINTY ANALYSIS OF THE U.S. HARVESTED WOOD PRODUCTS CARBON ESTIMATES

3.1 Abstract

Sequestering carbon in harvested wood products (HWP) is one of the strategies to reduce greenhouse gas emissions and to mitigate climate change. It is important to make the best possible estimates of net carbon stored in HWP. However, there is variation in carbon estimates as a result of uncertainty in input data and parameters used. This study quantified uncertainty in the estimates of carbon stored in the U.S. HWP from 1990 to 2014 under the stock-change, production, atmospheric flow, and simple decay approaches using Monte Carlo simulation. In addition, variance-based sensitivity analysis was also conducted. For 2014, Monte Carlo analysis resulted in an uncertainty range in the carbon estimates of -0.7 to +0.94 percent in the stock-change approach, -0.98 to +0.79 percent in the production and simple decay approaches, and ±0.75 percent in the atmospheric flow approach. Uncertainty in the trend was estimated at 72.56, 65, 63, and 65 percent, respectively, for the stock-change, production, atmospheric flow, and simple decay approaches. Results for sensitivity analysis indicated that under all four approaches, the parameter which had the greatest influence in the carbon estimates in HWP was carbon conversion factor for roundwood, sawnwood, chip and particles, other industrial roundwood, and wood residues. In contrast, under all accounting approaches,

the parameter decay rate for industrial waste had no contribution to the uncertainty in carbon estimates. The information can be used as a tool for increasing accuracy of the HWP carbon estimates by improving the most influential parameters in the carbon estimates.

Keywords: uncertainty, sensitivity analysis, Monte Carlo simulation, harvested wood products

3.2 Introduction

Global concentrations of greenhouse gases in the atmosphere are rising. Thus, global warming and climate change are the critical issues in today’s world. Reducing greenhouse gas emissions, especially carbon dioxide, has become an important environmental policy at the national and international level. It is crucial and necessary to estimate the amount of carbon flux between the atmosphere and ecosystem. Also, strategies for mitigating the global climate change require accurate estimates of the emissions of greenhouse gases. This will not only help in identifying the major carbon sink, but also guide the national and international policy and management efforts (Leea et al., 2011; Woodbury, Smith, & Heath, 2007). In addition, it will help improve the understanding of the global carbon cycle.

Sequestering carbon in harvested wood products (HWP) is regarded as one of the strategies to reduce carbon emissions to the atmosphere and mitigate climate change (Dias et al., 2007; Hashimoto et al., 2002). HWP such as furniture and wood buildings can store carbon for decades thus, delaying the release of carbon back into the atmosphere. Similarly, wood products discarded in landfills at the end of their service life, decay slowly thus, reducing carbon emissions in the atmosphere. Both wood products in use and wood products discarded in solid waste disposal sites store a considerable amount of carbon. It is important to make the best possible estimates of the net carbon stored in HWP pools, in order to accurately track carbon stocks and flows in the HWP (Ji et al., 2013). The HWP contribution to carbon emissions or removals has been discussed in Chapter II.

Studies have shown that there is variation in the estimates of carbon stored in HWP at the global level as well as national level. For example, at the global level, the carbon estimates stored in HWP vary considerably from 26 Mt C per year to 139 Mt C per year (Winjum et al., 1998). Similarly, Green et al. (2006) estimated carbon stock in the HWP for 2003 in Ireland using the production approach to be 251 Mt C, and Donlan et al. (2012) estimated carbon stocks in the HWP for the same year using same approach in Ireland to be 268 Mt C. This range or variation in the estimates is the result of uncertainty in input parameters (Green et al., 2006). This uncertainty will in turn impact the estimates of carbon stored in HWP. Therefore, the estimates of HWP contribution to carbon removals or emissions at the national and global level must be assessed for uncertainties (IPCC, 2006) and should be reduced as far as possible (Dias et al., 2007).

Reliable uncertainty estimates are a tool for increasing the quality of the HWP contribution to carbon emissions or removals. In addition, sensitivity analysis will help identify the parameters that impacted the HWP carbon estimates the most. Therefore, more critical sources of parameters in analysis can be identified by evaluating the relative importance of the input parameters in contributing to uncertainty in carbon estimates in HWP. Identified parameters can then be improved to increase the quality of carbon estimates, which increase the accuracy of the carbon stocks in HWP. Thus, the purpose of uncertainty and sensitivity analysis is to determine quantitative uncertainty associated with the estimates of HWP contribution.

2006 IPCC guidelines described two approaches that can be used to analyze the uncertainty. The first approach is based on error propagation and assumes that the relative ranges of uncertainty in emission factors are the same for base year and year of interest. The second approach is Monte Carlo simulation which is used for more detailed category-by-category assessment of uncertainty. Monte Carlo simulation has been commonly used in the literature to determine the uncertainty in estimates of carbon stored in HWP (Dias et al., 2007; Donlan et al., 2012; Green et al., 2006; Skog, 2008).

The objective of this study is to analyze uncertainty in the carbon stored in the U.S. HWP under four accounting approaches – stock-change, production, atmospheric flow, and simple decay approaches, from 1990 to 2014. In addition, uncertainty in the carbon estimate in HWP variables was also determined. The carbon estimates that were determined in Chapter II were used. Based on the literature, uncertain parameters were identified and probability functions were assigned to them. Uncertainty in the estimates of carbon was then determined using Monte Carlo simulation with 50,000 iterations. The results of uncertainty analysis were represented in terms of 95 percent confidence interval.

In addition, variance-based sensitivity analysis was performed to determine the parameters that contributed most to the uncertainty of carbon estimates in HWP under four accounting approaches for the year 2014. This type of sensitivity analysis quantifies the contribution of each uncertain parameter to total variance of the output. The results were presented in terms of the first order sensitivity indices for each parameter. The sensitivity index will show the importance of influence of each parameter in the carbon estimates in HWP. The findings from this study can help researchers to identify the parameters that need to be improved to increase the quality of carbon estimates in HWP.

The literature on uncertainty analysis, sensitivity analysis, and Monte Carlo simulation will be discussed in Section 3.3. The method of determining uncertainty in the carbon stored in HWP using Monte Carlo simulation and parameters sensitivity indices will be illustrated in Section 3.4, followed by data and parameter sources in Section 3.5. Results are reported in Section 3.6. Finally, the implications of the results will be discussed in Section 3.7.

3.3 Literature review

3.3.1 Uncertainty analysis

Uncertainty refers to lack of knowledge about specific factors, parameters, or models. The existence of uncertainty is often mentioned as a crucial limitation for clear interpretation of the estimate results (Sonnemann, Schuhmacher, & Castells, 2003). A quantitative measure of uncertainty constitutes an important contribution to evaluation of inventory quality. As a result, appropriate uncertainty estimates of output results are gaining importance in every field. For example, Meier (1997) reported uncertainty for the life cycle assessment of waste gas purification systems in the chemical industry. Sonnemann et al. (2003) measured the uncertainties in the life cycle study on waste incineration in Spain. Similarly, Heath and Smith (2000) estimated uncertainty in national-level carbon budget for the U.S. and found that the corresponding true mean carbon stock estimate was within approximately 5 percent of the reported mean value at the 80 percent confidence level. Woodbury et al. (2007) quantified uncertainty in the U.S.

national-level forest carbon budgets for the period from 1990 to 1999. They estimated true mean net carbon flux to be within 15 percent of the reported mean at the 80 percent confidence level. Heath, Smith, Skog, Nowak, and Woodall (2011) performed uncertainty analysis in flux estimate for forest carbon stocks. Estimation of uncertainty in the national greenhouse gas inventories have become a part of the 2006 IPCC guidelines (Winiwarter & Rypdal, 2001).

Uncertainty in the estimates of output arises from uncertainty in the parameters used. Generally, many parameters are needed whether it is for estimation of the amount of carbon stored in the HWP pools (such as decay rates, carbon conversion factors, and proportion of wood that goes to landfill) or any life cycle studies. Often these input data cannot be determined precisely. In practice, most of the input parameters are not known exactly (Winiwarter & Rypdal, 2001). The values of parameters have mostly been determined as best estimates from research and the literature. Thus, there arises the parameter uncertainty. The uncertainty of these parameters causes uncertainty in the outcome of the study. The common sources of parameter uncertainty are empirical inaccuracy (imprecise measurements), unrepresentative (incomplete or outdated measurements), and lack of data (no measurements) (Sonnemann et al., 2003).

3.3.2 Monte Carlo simulation for uncertainty analysis

Monte Carlo simulation has been commonly used to examine uncertainty in the outcome. It was devised as an experimental probabilistic method to solve difficult deterministic problems since computers can easily simulate a large number of experimental trials that have random outcomes (Papadopoulos & Yeung, 2001). Monte Carlo method is a viable statistical tool for analyzing uncertainty in the outcome. It uses statistical sampling techniques to obtain a probabilistic approximation to the solution of a model. The basic goal of Monte Carlo simulation is to characterize, quantitatively, the uncertainty in the estimates of the study (IPCC, 2006). The other goal is to identify key sources of uncertainty and to quantify the relative contribution of these sources to the overall variance and range of model results (IPCC, 2006).

Monte Carlo method has many advantages over other methods for the estimation of uncertainty. Specifically, this method is relatively simple to implement and is gaining acceptance in all fields (Papadopoulos & Yeung, 2001). When applied to uncertainty estimation, random numbers are used to randomly sample parameters' uncertainty space (Papadopoulos & Yeung, 2001). Similarly, it is suitable for detailed category-by-category assessment of uncertainty, particularly where uncertainties are large, distribution is non-normal, the algorithms are complex functions and/or there are correlations between some of the activity sets, emissions factors, or both (IPCC, 2006). In addition, it can deal with probability density functions of any physically possible shape and width, as well as handling varying degrees of correlation (IPCC, 2006).

Moreover, Monte Carlo analysis can be applied to a simple models (e.g., emission inventories that are the sum of sources and sinks, each of which is estimated using multiplicative factors) as well as complex models (e.g., the first order decay for CH_4 from landfills) (IPCC, 2006). The basic steps in this method are selection of essential parameters, assigning probability distributions to the selected parameters, simulation, and interpretation of the results (Sonnemann et al., 2003). The results are basically interpreted in terms of the mean, standard deviation, 95 percent confidence interval, and histograms (IPCC, 2006).

3.3.3 Sensitivity analysis

Sensitivity analysis is performed to determine the parameters responsible for the observed uncertainty in the output. There are two approaches of sensitivity analysis that have been proposed in the literature – qualitative approach and quantitative approach. Both the approaches allow classification of the parameters into a hierarchy with respect to the importance of their influence on the output (Kiebre, Anstett-Collin, & Basset, 2011). In addition, quantitative approach also provides means of quantification of each parameter influence and thus, is more constructive compared to qualitative approach (Kiebre et al., 2011).

The quantitative approach is further classified into local and global approaches. Local approach determines the impact of a small parameter variation around a nominal value. The impact of the local approach is determined by calculating partial derivative of the output function versus the corresponding parameter at the nominal value (Kiebre et al., 2011). Global approach determines impacts of parameter in entire range of variation. Therefore, this approach is based on the analysis of the output variance. The ratio of contribution of the individual parameter to the total variance of output is calculated. This will provide the results for the contribution of each parameter.

3.3.4 Uncertainty and sensitivity analysis of harvested wood products

Several studies have quantified uncertainty in the HWP carbon stock estimates. For example, Skog, Pingoud, and Smith (2004) found that the estimates change in carbon in HWP for the U.S. was most sensitive to uncertainty in the production data for solid wood products, carbon conversion factor, and the proportion of products in solid waste disposal sites, whereas service life of products had limited effect. For Ireland, Green et al.

(2006) showed that uncertainty in the carbon removal estimates of HWP ranged from ±31 to ± 48 percent respectively, for the atmospheric flow and production approaches. The model was found to be most sensitive to the change in decay rates and dry weight of wood products. In a study by Dias et al. (2007) for Portugal, uncertainty in the carbon accumulated in HWP for the stock-change, production, and atmospheric flow approaches were respectively, ±23, ±20, and ±12 percent. The major sources of uncertainty were production and trade data of HWP, decay rate, fraction of HWP to landfills, and dry weight conversion factor. They concluded that efforts should be made to reduce uncertainty within those parameters.

In another study, Skog (2008) identified 13 sources of uncertainty in estimating the HWP contribution of carbon removals for the U.S. Results suggested that the 90 percent confidence interval for the HWP contribution estimates was within -23 to +19 percent for the production and stock-change approaches and -20 to +16 percent for the atmospheric flow approach. Likewise, Donlan et al. (2012) performed parameter uncertainty assessment on the estimated carbon stock in HWP for Ireland under the production approach. They found that the 90 percent confidence interval range as percent of the carbon stock change in HWP was between -20 and +19 percent.

In all the studies that estimated uncertainty in the carbon estimates in HWP, Monte Carlo simulation has been used. The literature suggests that uncertainty in the parameters or data input affects the estimates of carbon stored in harvested wood products. The most common sources of variables or uncertainty found in the literature are carbon conversion factors, proportion of wood products in solid waste disposal sites, and decay rates of wood products.

3.4 Methodology

3.4.1 Monte Carlo simulation for uncertainty analysis in the harvested wood products carbon estimates

Monte Carlo method is convenient method for formulating uncertainty analysis (Pingoud et al., 2003) thus, is commonly used in the literature to quantify uncertainty in the estimates of carbon stored in HWP (Dias et al., 2007; Green et al., 2006; Skog, 2008). Therefore, for this study, uncertainty in the net carbon estimates of HWP for the U.S. from 1990 to 2014 is quantified using Monte Carlo method. The carbon estimates were calculated using stock-change, production, atmospheric flow, and simple decay approaches in Chapter II. In addition, the simulation was also used to depict uncertainty in the estimates of HWP variables (as referred in 2006 IPCC guidelines) — variable 1A, variable 1B, variable 2A, variable 2B, variable 3, variable 4, variable 5, and variable 7. Refer Chapter II for description of the HWP variables. Uncertainties in trends were also analyzed based on statistical analysis of the differences between the base year and the target year. Uncertainties were given in percent with respect to the mean difference or in percent points to the mean base year estimates.

First, sources of uncertainty in the input variables were identified. These sources were identified based on the literature (Dias et al., 2007; Skog, 2008) and as per recommended by 2006 IPCC guidelines. The sources of uncertainty in the input variables are presented in Table 3.1. The uncertain parameters were – carbon conversion factor for solidwood and paper products, amount of solidwood and paper products going to landfills, decay rate of HWP in use and in solid waste disposal sites, decay rate of solid, paper and industrial waste in landfill, and methane correction factor for dumps and managed landfills.

The key requirements of Monte Carlo simulation are the specification of probability density functions that reasonably represent each model input for which the uncertainty is quantified (IPCC, 2006). Probability density function describes the range and relative likelihood of possible values. 2006 IPCC guidelines describe commonly used five types of probability density functions — normal distribution, lognormal distribution, uniform distribution, triangular distribution, and fractile distribution. Thus, the uncertainty of each input parameter involved in the calculations was defined in the form of a probability density function. The probability density function for each input uncertain parameter was based on the literature.

Two types of probability density functions were used in this study – normal and triangular. The distributions are also assumed to be independent of one another. Basically, normal distribution is appropriate when the range of uncertainty is small and the uncertainty around the input parameter is expected to be symmetrical (Dias et al., 2007). For the triangular distribution, the uncertainty was defined in relation to the upper and lower limits of the probability density function. The normal probability density function was represented by the mean and the standard deviation. For triangular distribution, minimum, mode, and maximum values are required. For this study, carbon conversion factor for solidwood and paper products is assumed to have normal probability density function, and the rest were considered to have triangular probability density functions (see Table 3.1).

Once the uncertainties surrounding input data were quantified as probability distribution functions, a Monte Carlo simulation was conducted. In the context of Monte Carlo analysis, simulation is the process of approximating the output of a model through the repetitive random application of a model's algorithm (IPCC, 2006). The principle of Monte Carlo simulation is to perform the inventory calculation many times by the computer, each time with the uncertain factors or parameters chosen randomly within the distribution on uncertainties specified by the user (IPCC, 2006).

Thus, a series of sample values were randomly selected from their distributions, and the corresponding results were calculated. Monte Carlo simulation is a numerical method and hence, the precision of the results improves as the number of iterations is increased. For example, Dias et al. (2007) performed 5,000 iterations in their study. The number of iterations can be determined either by setting the number of model runs, a priori, such as 10,000 and allowing the simulation to continue until reaching the set number, or by allowing the mean to reach a relatively stable point before terminating the simulation (IPCC, 2006). For this study, the procedure was repeated 50,000 times to numerically simulate the effects of the random probability density functions selection on the estimates.

In general, Monte Carlo simulation includes four steps. Step one includes estimation of parameters and their associated probability density functions. Step two includes a selection of input values which are the estimates applied in the inventory calculation. This is the start of the iterations. For each input data item, a number is randomly selected from the probability density function of that variable. Step three is to estimate emissions and removals. The variables selected in Step 2 are used to estimate annual emissions and removals based on input values. Step four includes the iteration and monitoring of results. The calculation from Step three is stored, and the process is repeated from Step two. The results from the repetitions are used to calculate the mean and confidence limits.

3.4.2 Sensitivity analysis of uncertain parameters

In addition to estimating uncertainty in the carbon stored in HWP, sensitivity analysis of individual input parameters was also conducted. Sensitivity analysis was conducted to determine the parameters which have the greatest influence on the estimates of HWP contribution to carbon removals. These parameters were responsible for the uncertainty in the estimates of carbon under four accounting approaches – stock-change, production, atmospheric flow, and simple decay approaches. The quality of the carbon estimates under each of the approaches can be increased by reducing the error in the identified most influential parameters. In addition, the parameters that have little or no influence in the carbon estimates of HWP were also identified. These parameters can be set at their nominal values with no significant effect on the estimates of carbon stored in HWP.

The output, i.e., carbon estimates and the uncertain parameters were considered to have a relation as shown in Equation 3.1.

$$y = f\left(x_1, x_2, \ldots\ldots, \mathrm{x_n}\right) \qquad 3.1$$

where, $y \in R$ represents the output or the carbon estimates under four accounting approaches; $x_i \in R,\ i = 1, \ldots, \mathrm{n}$ are the uncertain parameters. Parameters considered in this study and their distributions are presented in Table 3.1 and has been described in the earlier section, for this study, $n = 11$. The parameter x_i, which has the greatest influence on the output was identified by performing the sensitivity analysis in the Equation 3.1.

The sensitivity of output to an individual input parameters was estimated using the first order sensitivity index of each parameter as shown in Equation 3.2.

$$S_i = \frac{V(y \mid x_i)}{V(y)} \qquad 3.2$$

where, S_i is the sensitivity index of the parameter x_i; $V(y \mid x_i)$ is the conditional variance of y, i.e., variance of y due to x_i; and $V(y)$ is the total variance of y. Therefore, sensitivity index is the ratio of the variance of output (carbon estimates of the HWP) due to individual uncertain parameters and the total variance of output.

The first order sensitivity index S_i measure indicates the relative importance of an individual parameter x_i in driving uncertainty in the output parameter y, i.e. carbon estimates of HWP. To compute the first order sensitivity index for every parameter x_i, Monte Carlo simulation has to be run n times varying one parameter at a time. Here, n is the number of iterations in the simulation which was performed 50,000 times. The variance of the output was calculated for each of the simulation. In addition, simulation in which all parameters were allowed to vary was performed. The value of the first order sensitivity index S_i lies between 0 and 1. If the value is closer to 1, then it means that the parameter x_i contributes more to the total variance of y.

3.5 Parameters

Table 3.1 shows the parameters that were considered to contribute uncertainty in the HWP carbon estimates. The parameters were – carbon conversion factor for roundwood, sawnwood, chip and particles, other industrial roundwood, and wood residues (referred as a_1 in this study); carbon conversion factor for wood-based panels (a_2); carbon conversion factor for paper and paperboard, and wood pulp and recovered paper (a_3); carbon conversion factor for wood charcoal (a_4); decay rate for solidwood (k_1); decay rate for paper products (k_2); decay rate for paper waste in municipal solid waste (MSW) (j_1); decay rate for wood waste in MSW (j_2); decay rate for industrial waste (j_3); methane correction factor for dumps (f_1); methane correction factor for managed landfills (f_2). The values and sources of these parameters have been described in Chapter II. Table 3.1 also shows the probability density function for each of the input parameters. Parameters a_1, a_2, a_3, and a_4 were assumed to have normal probability density function and were represented by mean and standard deviation. Rest of the parameters k_1, k_2, j_1, j_2, j_3, f_1, and f_2 were assumed to have triangular distribution and were represented by minimum, mode, and maximum values.

3.6 Results

3.6.1 Uncertainty results for the carbon estimates in harvested wood products variables

Results for the uncertainty analysis using Monte Carlo simulation for the net carbon estimates in HWP variables and approaches are presented in Table 3.2 to 3.5. The results are represented in terms of simulated mean and the 95 percent confidence interval. The 95 percent confidence interval has a 95 percent probability of enclosing the true value.

The simulation means obtained from the simulation of the harvested wood products variable estimation are shown in Table 3.2. The results showed that the simulation means for variable 1A during the period from 1990 to 2014 ranged from -2.5

Tg C in 2012 to 40.71 Tg C in 2006. That for variable 1B ranged from 6.16 Tg C in 2011 to 9.74 Tg C in 1994. During the same time frame, for variable 2A the simulation mean ranged from -0.99 Tg C to 32.5 Tg C, and that for variable 2B ranged from 5.6 Tg C to 8.73 Tg C. From 1990 to 2014, the simulation mean for variable 3 ranged from 17.56 Tg C in 2009 to 41.5 Tg C in 2004, and that for variable 4 ranged from 21.01 Tg C in 2009 to 28.6 in 2013. The simulation mean for variable 5 ranged from 185.71 Tg C to 284.44 Tg C. Finally, the simulation mean for variable 7 ranged from 173.42 Tg C in 2009 to 244.60 Tg C in 1990.

Results of the 95 percent confidence interval obtained from the Monte Carlo simulation for the HWP variables carbon estimates are presented in Table 3.3. The 95 percent confidence interval for variable 1A for 1990 ranged from 32.69 Tg C to 33.35 Tg C, with a mean value of 33.2 Tg C. This is equivalent to an uncertainty of -1.2 and + 0.6 percent. Similarly, the 95 percent confidence interval for variable 1A for 2014 ranged from 4.97 Tg C to 5.18 Tg C, with a mean value of 5.08 Tg C. This is equivalent to an uncertainty of -1.9 and +1.88 percent. Likewise, the 95 percent confidence interval for variable 1B for 1990 ranged from 9.39 Tg C to 9.45 Tg C. With the mean of 9.42 Tg C, this is equivalent to an uncertainty of +/-0.32 percent. Similarly, for 2014, the probability range was from 6.56 Tg C to 6.60 Tg C. This is equivalent to an uncertainty of +/-0.30 percent.

The 95 percent confidence interval for variable 2A for 1990 ranged from 30.90 Tg C to 31.491 Tg C, with a mean value of 31.2 Tg C. This is equivalent to a +/- 0.98 percent difference from the mean. For variable 2A for the year 2014, the 95 percent confidence interval ranged from 7.88 Tg C to 8.11 Tg C, with a mean of 7.99 Tg C. This is equivalent to an uncertainty of -1.25 to +1.34 percent. Similarly, for variable 2B for the year 1990, the 95 percent probability ranged from 8.62 Tg C to 8.67 Tg C. This resulted in the uncertainty of -0.34 to +0.23 percent. For the year 2014, the 95 percent confidence interval ranged from 5.86 Tg C to 5.90 Tg C with the mean of 5.88 Tg C. This correspond to the uncertainty of +/-0.34 percent.

In the same way, the 95 percent confidence interval for variable 3 for 1990 ranged from 20.50 Tg C to 20.84 Tg C, with a difference from the mean of -0.97 to +0.67 percent. That for 2014 ranged from 22.15 Tg C to 22.48 Tg C, with a difference from the mean of -0.9 to +0.8 percent. The 95 percent confidence interval for variable 4 for 1990 ranged from 27.97 Tg C to 28.54 Tg C, with the difference from the mean of -1.07 to +0.94 percent. Similarly, for 2014, the 95 percent confidence interval for variable 4 ranged from 28.52 Tg C to 28.94 Tg C, with the difference from the mean equivalent to +/- 0.7 percent.

Likewise, the 95 percent confidence interval for variable 5 for 1990 ranged from 280.54 Tg C to 288.34 Tg C, with the difference from mean equivalent to +/- 1.4 percent. For 2014, the range was from 219.61 Tg C to 225.71 Tg C, with the difference from mean equivalent to -1.4 percent to +1.3 percent. Finally, the 95 percent confidence interval for variable 7 ranged from 240.99 Tg C to 248.22 Tg C, with the difference from mean equivalent to +/- 1.4 percent. For 2014, it ranged from 205.83 Tg C to 211.74 Tg C, with the difference from mean equivalent to -1.45 percent to +1.37 percent.

Uncertainty range of the HWP variables for other years can be described in a similar way from Tables 3.2 and 3.3. The results indicated small uncertainty range in all the variables. The 95 percent confidence interval for these variables ranged from +/-0.30

to +1.37 percent. For 1990, variables 5 and 7 have the highest uncertainty among all the other variables. This was followed by variable 4, variable 2A, variable 1A, variable 3, variable 2B, and variable 1B. For 2014, the highest uncertainty was for variable 1A. This was followed by variable 7, variable 5, variable 2A, variable 3, variable 4, variable 2B, and variable 1B. Taking into account different year changed the uncertainty of different variables. However, variable 1B was least uncertain in both the years.

3.6.2 Uncertainty results for the carbon estimates in harvested wood products under accounting approaches

Table 3.4 and 3.5 shows the mean and 95 percent confidence intervals obtained from Monte Carlo simulation of the HWP carbon estimates under four approaches. For the stock change approach, the results indicated that the net sequestered carbon in the year 1990 was -155.6 Tg C with the uncertainty range of -0.78 to +0.8 percent, which correspond to the 95 percent probability range of -156.9 Tg C to 154.4 Tg C. Similarly, for 2014, the mean carbon estimates for the stock change approach was -42.7 Tg C with the uncertainty range of -0.70 to +0.94 percent. Based upon the total base year and final year in the study period, the average uncertainty in trend was 72.56 percent decrease in the carbon sequestered from 1990 to 2014.

For the production approach, the results indicated that the net sequestered carbon in 1990 was -146.1 Tg C with an uncertainty of +/- 0.75 percent, which correspond to the 95 percent probability range of -147.2 Tg C to -145.0 Tg C. For 2014, the mean of the HWP carbon estimate was -50.9 Tg C. The 95 percent confidence interval lower and upper bounds were respectively, -51.3 Tg C and -50.4 Tg C. This correspond to the uncertainty in the estimates of -0.98 to +0.79 percent. The uncertainty trend showed the net decrease in carbon estimates of 65 percent from 1990 to 2014.

Similarly, for the atmospheric flow approach, the results indicated that the mean of carbon estimate in HWP for 1990 was -183.4 Tg C. The corresponding 95 percent confidence interval ranged from -185.1 Tg C to -181.8 Tg C. This showed that the resulting uncertainty in the atmospheric approach for 1990 ranged from -0.87 to +0.92 percent. Similarly, for 2014, the mean of carbon estimates was -66.3 Tg C, which correspond to the 95 percent probability range of -66.8 Tg C to -65.8 Tg C. This resulted in the uncertainty of +/- 0.75 percent. The uncertainty in the trend showed the net decrease in carbon estimates of 63 percent from 1990 to 2014.

Finally, for the simple decay approach, the mean estimate of carbon stored in HWP for the year 1990 was -146.1 Tg C. The 95 percent confidence interval for the same year was -147.2 Tg C to -145 Tg C. This corresponds to the uncertainty of +/-0.75 percent. For the year 2014, the mean estimate was -50.9 Tg C. The uncertainty ranged from -0.98 to +0.78 percent. This corresponds to the 95 percent confidence interval of -51.3 Tg C to -50.4 Tg C. The results for the simple decay approach were the same as that of the production approach. Similarly, the uncertainty in the trend showed the net decrease in carbon estimates of 65 percent from the year 1990 to 2014.

Results indicated that the uncertainty ranges in all the approaches were very small at most 2 percent. The 95 percent confidence interval for four accounting approaches for the carbon estimates in HWP ranged from -0.7 percent to +0.99 percent. Though, small comparing the results, in the year 1990, the uncertainty in the atmospheric flow approach was highest, followed by the stock-change approach, and the production and simple decay approaches. However, in the year 2014, the uncertainty in the production approach was highest among the four approaches considered in this study. This was followed by the stock-change approach and the atmospheric flow approach.

3.6.3 Sensitivity indices of the influential parameters in the carbon estimates of harvested wood products

The first order sensitivity indices of parameters for the HWP carbon estimates under each of the accounting approaches for 2014 are presented in Table 3.6. The results indicated that for the stock-change approach, the sensitivity index of parameter a_1 (carbon conversion factor for roundwood, sawnwood, chip and particles, other industrial roundwood, and wood residues) was highest (0.52) compared to the sensitivity index of other parameters. Hence, the parameter a_1 was the most influential parameter in the estimates of carbon in HWP under the stock-change approach, meaning parameter a_1 resulted in the greater uncertainty in the carbon stored in HWP.

Similarly, parameter k_1 (decay rate for solidwood) was the second most influential parameter contributing uncertainty in the estimates of carbon in HWP under the stock-change approach. The first order sensitivity index of parameter k_1 was 0.15. The result also showed that parameters a_4 (carbon conversion factor for wood charcoal) and j_3 (decay rate for industrial waste) had sensitivity indices equal to 0. Therefore, these parameters did not contribute to uncertainty in the estimates of carbon stored in HWP under the stock-change approach. All the other parameters had sensitivity index below 0.1, therefore had little influence on the carbon estimates.

The results indicated that the sensitivity index of parameter a_1 was highest among the other parameters for the production approach and was equal to 0.72. Therefore, like the stock-change approach, a_1 was the most influential parameter in the carbon estimate in HWP under the production approach. The parameter k_1 which had the first order sensitivity index of 0.09 was the second most influential parameter contributing to uncertainty in the estimates of carbon stock under the production approach. In contrast, the parameters a_4, j_3, and f_1 (methane correction factor for dumps) did not have any influence in the HWP carbon estimates as the sensitivity index of these parameters were zero. All the other parameters had sensitivity index below 0.1, therefore, had little influence in the carbon estimates. The results under the simple decay approach were same as that under production approach.

For the atmospheric flow approach, the first-order sensitivity index was highest for parameter $a_1$and was equal to 0.73. This was followed by parameter k_1 whose index was equal to 0.10. Therefore, a_1 and k_1 were the first and second most influential parameters contributing to uncertainty in the estimates of carbon in HWP under the atmospheric flow approach. In contrast, parameters j_3 and f_1 had no influence on the carbon estimates in HWP as the sensitivity indices of these parameters were zero. All the other parameters had little influence in the estimates of carbon in HWP, and their sensitivity indices were below 0.1.

The results of sensitivity analysis were similar under all the accounting approaches. In all four approaches, parameter a_1 had the highest sensitivity index indicating it to be the most influential parameter responsible for uncertainty in the carbon estimates. Similarly, in all four approaches, parameter j_3 had zero sensitivity index indicating that it did not contribute to uncertainty in the carbon estimates.

Under the stock-change, production, and simple decay approaches, parameter a_4 had zero sensitivity index, whereas under the atmospheric flow approach this parameter had little influence on the carbon estimates. Parameter f_1 had zero sensitivity index under the production, atmospheric flow, and simple decay approaches, whereas this parameter had little influence on the carbon estimates under the stock-change approach.

Among four accounting approaches, sensitivity index of most of the parameters were highest for the stock-change approach and lowest for the production and simple decay approaches. For example, parameters a_2 (carbon conversion factor for wood based panels), a_3 (carbon conversion factor for paper and paperboard, and wood pulp and recovered paper), k_1 (decay rate for solidwood), k_2 (decay rate for paper products), j_1 (decay rate for paper waste in municipal solid waste), f_1 (methane correction factor for dumps), and f_2 (methane correction factor for managed landfills) were most responsible for uncertainty in the estimates of carbon in HWP under the stock-change approach and least influential for carbon estimates under the production approach. In contrast, parameters a_1 (carbon conversion factor for roundwood, sawnwood, chips and particles, other industrial roundwood, and wood residues) and j_2 (decay rate for industrial waste) were responsible more for uncertainty in the estimates of HWP under the atmospheric flow approach and least influential for estimates under the stock-change approach.

3.7 Conclusion and discussion

This study quantified uncertainty in the carbon estimates of HWP obtained under four accounting approaches – stock-change, production, atmospheric flow, and simple decay approaches from 1990 to 2014 in Chapter II. Uncertainty was also estimated for the HWP variables. Monte Carlo simulation was used with 50,000 iterations. In addition, a sensitivity analysis was also performed to determine parameters that have the greatest and least or no influence on the carbon estimates in HWP under four accounting approaches for 2014. The results of uncertainty were presented in terms of 95 percent of the confidence interval. The results of the sensitivity analysis were presented in terms of first order sensitivity indices for each uncertain parameters selected for the study.

For both the variables and approaches, uncertainty range was very small. For the HWP variables, the highest range was around 4 percent, whereas, for approaches, the highest uncertainty range was around 2 percent. For the HWP variables, uncertainty ranged from +/- 0.03 percent to +1.37 percent. For 1990, the variables with the highest uncertainty were variables 5 and 7, and that with the lowest uncertainty was variable 1B. For 2014, the highest uncertainty was for variable 1A, and the lowest uncertainty was for variable 1B. For approaches, the uncertainty ranged from -0.7 to +0.99 percent. For 1990, the highest uncertainty was for the atmospheric flow approach, and the lowest uncertainty was for the production and simple decay approaches. Similarly, for the year 2014, the highest uncertainty was for the production and simple decay approach and the lowest uncertainty was for the atmospheric flow approach.

Compared to the other similar studies, the uncertainty range for the approaches were small in this study indicating the low uncertainty in the carbon estimates. For example, in Green et al. (2006), the uncertainty estimates associated with each approach ranged from 31 percent to 48 percent. In Dias et al. (2007), the relative amplitude of the 95 percent confidence interval in the period 1990 to 2000 ranged from 46 percent (uncertainty of +/- 23 percent) to 182 percent (uncertainty of -89 and +93 percent) for the stock-change approach, from 24 percent (uncertainty of +/-12 percent) to 75percent (uncertainty of -48 and +27 percent) for the atmospheric flow approach, and from 45 percent (uncertainty of -25 and +20 percent) to 65 percent (uncertainty of -38 and +27 percent) for the production approach. Similarly, in Dias, Louro, Arroja, and Capela (2009) relative amplitude of the 95 percent confidence interval obtained by this method ranged from 42 percent (uncertainty of -27 percent and +15 percent) to 52 percent (uncertainty of -30 percent and 22 percent). In another study Skog (2008), the 90 percent confidence intervals for the five HWP variables for 2005 ranged from +/- 10 percent to + 25 percent and – 24 percent.

The results of sensitivity analysis indicated that under all four accounting approaches, the parameter which had the greatest influence in the carbon estimates in HWP was carbon conversion factor for roundwood, sawnwood, chip and particles, other industrial roundwood, and wood residues. In contrast, under all the accounting approaches, the parameter decay rate for industrial waste had no contribution to uncertainty in the carbon estimates in HWP.

Studies showed that the results of carbon accumulation in HWP were affected by uncertainty associated with the input parameters. There are a number of policy orientated consequences that derive from the magnitude of uncertainties in the carbon estimates as well as uncertainties in trends (Winiwarter & Rypdal, 2001). For example, a high uncertainty in the estimates may pose problems in designing effective mitigation strategies (Rypdal & Winiwarter, 2001). Thus, it is important to further reduce uncertainty in the input parameters. It can be done by identifying the most influential parameters that have the greatest contribution to uncertainty in the HWP carbon estimates. The identified parameters need to be improved to increase the quality of carbon estimates in HWP. Improvements can be made using country specific data, as much as possible (IPCC, 2006). This will give a more comprehensive picture of the potential of the U.S. HWP in sequestering carbon.

Table 3.1 Uncertain parameters in the HWP carbon estimates and their probability density functions

Sources of uncertainties	Symbol	PDF	Mean	SD	Min	Mode	Max
Carbon conversion factor for roundwood, sawnwood, chip and particles, other industrial roundwood, and wood residues	a_1	Normal	0.0000005	0.00000078			
Carbon conversion factor for wood based panels	a_2	Normal	0.00000029	0.00000018			
Carbon conversion factor for paper and paperboard, and wood pulp and recovered paper	a_3	Normal	0.00000045	0.00000027			
Carbon conversion factor for wood charcoal	a_4	Normal	0.00000077	0.0000005			
Decay rate for solidwood	k_1	Triangular			0.01	0.02	0.04
Decay rate for paper products	k_2	Triangular			0.11	0.23	0.37
Decay rate for paper waste in MSW	j_1	Triangular			0.03	0.05	0.08
Decay rate for wood waste in MSW	j_2	Triangular			0.01	0.03	0.04
Decay rate for industrial waste	j_3	Triangular			0.02	0.03	0.05
Methane correction factor for dumps	f_1	Triangular			0.03	0.6	0.09
Methane correction factor for managed landfills	f_2	Triangular			0.05	1	1.5

Table 3.2 Means obtained from Monte Carlo simulation of the HWP variables

Year	Simulation Mean							
	Var 1A	Var 1B	Var 2A	Var 2B	Var 3	Var 4	Var 5	Var 7
1990	33.02	9.42	31.20	8.65	20.67	28.25	284.44	244.60
1991	31.40	7.50	32.50	6.90	18.77	28.60	274.36	234.96
1992	23.40	9.22	26.30	8.41	20.56	26.89	270.19	235.48
1993	28.46	9.48	28.47	8.56	23.37	23.23	262.89	225.86
1994	32.37	9.74	28.09	8.73	25.27	23.84	264.22	227.40
1995	36.42	9.22	30.76	8.22	26.86	25.44	262.39	223.41
1996	36.06	8.54	29.85	7.58	27.35	25.75	257.50	220.07
1997	35.07	9.00	28.41	7.94	29.15	25.72	259.26	222.92
1998	38.40	9.05	30.42	7.96	30.35	25.87	262.34	223.96
1999	35.47	9.39	25.97	8.18	32.41	25.75	262.10	227.95
2000	39.03	8.93	28.35	7.74	33.77	25.74	260.56	224.47
2001	36.19	8.64	24.81	7.42	34.24	23.33	250.82	218.58
2001	36.19	8.64	24.81	7.42	34.24	23.33	250.82	218.58
2003	33.10	8.45	18.55	7.17	36.76	21.06	250.48	224.76
2004	32.00	8.93	16.69	7.46	41.62	22.11	257.87	233.72
2005	39.67	8.35	21.01	7.01	41.50	22.15	261.00	232.98
2006	40.71	8.32	23.01	7.01	39.23	21.96	255.25	225.23
2007	35.76	7.85	20.59	6.75	32.25	23.81	237.42	210.09
2008	23.47	7.73	16.04	6.83	24.01	23.58	212.51	189.64
2009	6.65	6.26	6.67	5.62	17.56	21.01	185.71	173.42
2010	-10.49	6.57	-6.57	5.95	18.95	23.76	210.31	210.92
2011	-4.84	6.16	-0.99	5.62	18.65	25.36	220.68	216.05
2012	-2.50	6.17	1.97	5.60	19.25	28.66	216.42	208.85
2013	0.26	6.29	5.17	5.66	20.99	28.93	221.61	210.78
2014	5.08	6.58	7.99	5.88	22.31	28.73	222.66	208.79

Note: Var1A – annual change in stock of HWP in use from consumption; Var1B – annual change in stock of HWP in SWDS from consumption; Var2A – annual change in stock of HWP in use produced from domestic harvest; Var2B – annual change in stock of HWP in SWDS produced from domestic harvest; Var3 – annual imports of wood, and paper products plus wood fuel, pulp, recovered paper, roundwood, wood chips; Var4 – annual exports of wood, and paper products plus wood fuel, pulp, recovered paper, roundwood, wood chips; Var5 – annual domestic harvest; Var7 – annual release of carbon to the atmosphere from HWP including fuelwood where wood came from domestic harvest from products in use and products in SWDS.

Table 3.3 The 95 percent confidence intervals obtained from Monte Carlo simulation of the HWP variables estimation

Year	95% Confidence Interval															
	Variable 1A		Variable 1B		Variable 2A		Variable 2B		Variable 3		Variable 4		Variable 5		Variable 7	
	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
1990	32.69	33.35	9.39	9.45	30.90	31.49	8.62	8.67	20.50	20.84	27.97	28.54	280.54	288.34	240.99	248.22
1991	31.08	31.71	7.48	7.53	32.19	32.81	6.87	6.92	18.61	18.92	28.32	28.87	270.60	278.12	231.50	238.42
1992	23.17	23.64	9.19	9.24	26.06	26.54	8.39	8.44	20.39	20.73	26.65	27.14	266.49	273.90	232.00	238.95
1993	28.17	28.74	9.45	9.51	28.20	28.73	8.53	8.59	23.17	23.57	23.03	23.42	259.28	266.49	222.51	229.21
1994	32.05	32.69	9.71	9.77	27.82	28.36	8.70	8.76	25.06	25.49	23.65	24.03	260.60	267.84	224.03	230.76
1995	36.06	36.78	9.19	9.25	30.47	31.05	8.19	8.24	26.63	27.08	25.24	25.64	258.79	265.99	220.10	226.73
1996	35.71	36.41	8.51	8.57	29.58	30.12	7.55	7.60	27.12	27.58	25.56	25.94	253.97	261.03	216.80	223.35
1997	34.71	35.43	8.97	9.02	28.14	28.67	7.91	7.96	28.91	29.39	25.53	25.90	255.71	262.82	219.62	226.21
1998	38.03	38.77	9.03	9.08	30.14	30.70	7.93	7.98	30.10	30.60	25.67	26.08	258.75	265.94	220.64	227.29
1999	35.13	35.80	9.36	9.41	25.74	26.21	8.15	8.20	32.15	32.67	25.55	25.96	258.51	265.69	224.58	231.32
2000	38.68	39.38	8.90	8.96	28.10	28.60	7.72	7.76	33.50	34.04	25.54	25.93	256.98	264.13	221.14	227.80
2001	35.85	36.53	8.61	8.66	24.58	25.05	7.40	7.45	33.96	34.51	23.15	23.50	247.38	254.26	215.36	221.80
2001	35.88	36.50	8.61	8.66	24.62	25.01	7.40	7.45	33.95	34.53	23.17	23.49	247.39	254.25	215.33	221.83
2003	32.76	33.43	8.43	8.48	18.35	18.75	7.15	7.20	36.46	37.05	20.92	21.21	247.05	253.92	221.52	228.01
2004	31.68	32.32	8.91	8.96	16.52	16.87	7.44	7.48	41.27	41.96	21.96	22.26	254.33	261.41	230.35	237.09
2005	39.27	40.06	8.32	8.38	20.79	21.23	6.99	7.03	41.16	41.85	22.00	22.30	257.42	264.58	229.61	236.35
2006	40.29	41.12	8.30	8.35	22.77	23.25	6.99	7.03	38.92	39.55	21.82	22.11	251.75	258.75	221.96	228.50
2007	35.41	36.11	7.83	7.88	20.38	20.79	6.73	6.77	31.99	32.50	23.65	23.96	234.17	240.68	207.03	213.15
2008	23.23	23.72	7.71	7.76	15.88	16.20	6.81	6.85	23.83	24.19	23.42	23.74	209.59	215.42	186.87	192.40
2009	6.55	6.76	6.24	6.28	6.58	6.75	5.61	5.64	17.43	17.68	20.86	21.15	183.16	188.26	170.93	175.91
2010	-10.61	-10.36	6.55	6.59	-6.66	-6.47	5.93	5.97	18.82	19.08	23.60	23.92	207.42	213.19	207.97	213.88
2011	-4.93	-4.75	6.14	6.18	-1.06	-0.93	5.60	5.64	18.52	18.78	25.19	25.54	217.65	223.70	212.99	219.11
2012	-2.57	-2.43	6.16	6.19	1.91	2.03	5.58	5.61	19.11	19.38	28.45	28.87	213.45	219.38	205.90	211.80
2013	0.19	0.33	6.27	6.31	5.09	5.25	5.65	5.68	20.84	21.15	28.72	29.14	218.57	224.65	207.80	213.76
2014	4.97	5.18	6.56	6.60	7.88	8.11	5.86	5.90	22.15	22.48	28.52	28.94	219.61	225.71	205.83	211.74

Table 3.4 Means obtained from Monte Carlo simulation of the HWP approaches

Year	Simulation Mean			
	Stock-change	Production	Atmospheric-flow	Simple decay
1990	-155.6	-146.1	-183.4	-146.1
1991	-142.6	-144.4	-178.7	-144.4
1992	-119.6	-127.3	-142.8	-127.3
1993	-139.1	-135.8	-138.6	-135.8
1994	-154.4	-135.0	-149.1	-135.0
1995	-167.3	-142.9	-162.2	-142.9
1996	-163.5	-137.2	-157.7	-137.2
1997	-161.6	-133.3	-149.0	-133.3
1998	-174.0	-140.7	-157.6	-140.7
1999	-164.5	-125.2	-140.1	-125.2
2000	-175.9	-132.3	-146.4	-132.3
2001	-164.4	-118.2	-124.4	-118.2
2002	-143.4	-91.7	-92.3	-91.7
2003	-152.4	-94.3	-94.8	-94.3
2004	-150.1	-88.6	-78.6	-88.6
2005	-176.1	-102.7	-105.1	-102.7
2006	-179.8	-110.1	-116.4	-110.1
2007	-159.9	-100.2	-129.0	-100.2
2008	-114.4	-83.9	-112.9	-83.9
2009	-47.4	-45.1	-60.0	-45.1
2010	14.4	2.3	-3.3	2.3
2011	-4.8	-17.0	-29.4	-17.0
2012	-13.5	-27.8	-48.0	-27.8
2013	-24.0	-39.7	-53.1	-39.7
2014	-42.7	-50.9	-66.3	-50.9

Table 3.5 The 95 percent confidence intervals from Monte Carlo simulation of the HWP approaches

Year	95% Confidence Interval							
	Stock-change		Production		Atmospheric-flow		Simple decay	
	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
1990	-156.9	-154.4	-147.2	-145.0	-185.1	-181.8	-147.2	-145.0
1991	-143.8	-141.5	-145.6	-143.3	-180.3	-177.1	-145.6	-143.3
1992	-120.5	-118.7	-128.2	-126.4	-143.9	-141.7	-128.2	-126.4
1993	-140.2	-138.1	-136.7	-134.8	-139.6	-137.6	-136.7	-134.8
1994	-155.6	-153.2	-136.0	-134.0	-150.2	-148.0	-136.0	-134.0
1995	-168.7	-166.0	-144.0	-141.8	-163.4	-160.9	-144.0	-141.8
1996	-164.8	-162.3	-138.2	-136.3	-158.8	-156.5	-138.2	-136.3
1997	-162.9	-160.3	-134.3	-132.3	-150.1	-147.9	-134.3	-132.3
1998	-175.4	-172.6	-141.8	-139.7	-158.8	-156.4	-141.8	-139.7
1999	-165.7	-163.2	-126.1	-124.4	-141.1	-139.1	-126.1	-124.4
2000	-177.2	-174.5	-133.2	-131.4	-147.4	-145.4	-133.2	-131.4
2001	-165.6	-163.1	-119.1	-117.4	-125.2	-123.5	-119.1	-117.4
2002	-144.5	-142.2	-92.4	-91.0	-92.9	-91.6	-92.4	-91.0
2003	-153.6	-151.1	-95.1	-93.6	-95.5	-94.1	-95.1	-93.6
2004	-151.3	-148.9	-89.2	-87.9	-79.0	-78.1	-89.2	-87.9
2005	-177.5	-174.6	-103.5	-101.9	-105.8	-104.4	-103.5	-101.9
2006	-181.3	-178.3	-111.0	-109.2	-117.3	-115.6	-111.0	-109.2
2007	-161.2	-158.6	-101.0	-99.5	-129.9	-128.1	-101.0	-99.5
2008	-115.3	-113.5	-84.5	-83.3	-113.7	-112.0	-84.5	-83.3
2009	-47.7	-47.0	-45.4	-44.8	-60.4	-59.6	-45.4	-44.8
2010	13.9	14.8	1.9	2.6	-3.6	-2.9	1.9	2.6
2011	-5.2	-4.5	-17.2	-16.7	-29.7	-29.1	-17.2	-16.7
2012	-13.7	-13.2	-28.0	-27.5	-48.3	-47.7	-28.0	-27.5
2013	-24.3	-23.8	-40.0	-39.4	-53.5	-52.8	-40.0	-39.4
2014	-43.1	-42.4	-51.3	-50.4	-66.8	-65.8	-51.3	-50.4

Table 3.6 Sensitivity indices of parameters for the carbon estimates in HWP under different accounting approaches for 2014

Parameters	Symbol	Stock-change	Production	Atmospheric flow	Simple decay
Carbon conversion factor for roundwood, sawnwood, chip and particles, other industrial roundwood, and wood residues	a_1	0.52	0.72	0.73	0.72
Carbon conversion factor for wood based panels	a_2	0.02	0.01	0.00	0.01
Carbon conversion factor for paper and paper board, and wood pulp and recovered paper	a_3	0.03	0.01	0.01	0.01
Carbon conversion factor for wood charcoal	a_4	0	0	0.00	0
Decay rate for solidwood	k_1	0.15	0.09	0.11	0.09
Decay rate for paper products	k_2	0.00	0.00	0.00	0.00
Decay rate for paper waste in MSW	j_1	0.00	0.00	0.00	0.00
Decay rate for wood waste in MSW	j_2	0.00	0.00	0.00	0.00
Decay rate for industrial waste	j_3	0	0	0	0
Methane correction factor for dumps	f_1	0.00	0	0	0
Methane correction factor for managed landfills	f_2	0.04	0.03	0.03	0.03

CHAPTER IV

CARBON EMISSIONS EMBODIED IN THE U.S. INTERNATIONAL TRADE OF HARVESTED WOOD PRODUCTS

4.1 Abstract

Quantifying the environmental impacts of international trade of general goods and services has gained significant attention. However, there still lack the economic-environmental studies related to international trade of harvested wood products. This study estimated carbon emissions embodied in the international trade of harvested wood products for 2011 using multi-regional input-output method. U.S. and its major trading partners Brazil, Canada, China, Germany, Japan, Mexico, and Russia, were considered for the study. Results showed that the U.S. was a net importer of 4.64 Mt of carbon emissions, which represented 9.07 percent of total emissions on the consumption basis. Total imported carbon from the U.S.'s trading partners was 8.30 Mt which accounted for 16.23 percent of total emissions, and the total exported carbon from the U.S. to its trading partners was 3.66 Mt which accounted for 7.15 percent of total emissions. The majority of embodied carbon in imports was contributed by China (23.89 percent). Canada was the biggest recipient of exported emissions of the U.S. (36.04 percent). Estimating embodied emissions under the production-based accounting would have decreased the emission inventory of the U.S. Wood and products of wood and cork industry (sector 20), and pulp, paper, paper printing and publishing industry (sector 21t22) were both net importers of carbon emissions for the U.S. The latter contributed more to the imported carbon emissions in the U.S. Direct carbon emissions, carbon emissions under the consumer responsibility, and carbon emissions embodied in the trade of sectors 20 and 21t22 were significant and correlated with the gross domestic product. Findings can provide policy makers consider carbon embodied in trade in domestic emission mitigating agreements. On the global level, findings can contribute in determining the fair allocation method of carbon responsibility in reducing carbon emissions, and help encourage the international cooperation among the countries.

Keywords: carbon emissions embodied, international trade, multi-regional input-output model, consumption-based emissions, production-based emissions

4.2 Introduction

International trade of general goods and services has increased gradually as countries have become rapidly integrated with each other into an open economy (Lee, 2011). On one hand, international trade leads to the economic development of a country and on the flip side, it causes unintended and unwanted environmental problems and pressures (Saikku, Soimakallio, & Pingoud, 2012). The most studied environmental pressure as a result of international trade is carbon dioxide (CO_2) emissions (Strømman, Hertwich, & Duchin, 2009). For example, there were around 5.3 Gt of CO_2 emissions embodied in the international trade among 87 countries in 2001 (Peters & Hertwich, 2008).

The externalities related to the trade of goods and services are not reflected in the price of products. In addition, carbon embodied in internationally traded commodities can have considerable influence on the national balance of greenhouse gas. Increasing exports of the products in a country increases the energy consumption and carbon emissions in that country, while opposite holds when the products are imported into that country. Many national greenhouse gas policies are grounded on controlling emissions by reducing domestic greenhouse gas emissions. This ignores the importance of carbon embodied in the international trade flows. Wyckoff and Roop (1994) argued that policies developed on this basis may not be effective if domestic consumption is highly being contributed by imports of commodities.

If the emission policies are based only on the domestic markets, then developed or industrialized countries would reduce their domestic emissions by importing carbon-intensive goods from developing or other countries (Machado, Schaeffer, & Worrell, 2001), and transfer their carbon emissions to developing countries (Schaeffer & de Sá, 1996), resulting in carbon leakage (Lenzen, 1998). To avoid such leakage between the countries, carbon embodied in the international trade should be considered in emission mitigation agreements (Khrushch, 1996). This type of study is important as it would help understand the emission drivers (Le Quéré, Raupach, Canadell, & Marland, 2009), and policy applications at the national and global level. In addition, trade might serve as an abatement control (Subak, 1995), and might have positive impacts on the environment (Beghin, Bowland, Dessus, Roland-Holst, & Mensbrugghe, 2002; Strutt & Anderson, 2000), thus reducing the global carbon emissions. For example, trade between Japan and Canada reduced emissions in both the countries (Hayami & Nakamura, 2002).

Therefore, environmental pollution, especially carbon emission, embodied in traded goods and services is becoming increasingly important (Peters & Hertwich, 2008), and gaining attention among researchers, society, and policy makers. There is a fairly substantial and growing literature that have attempted to estimate carbon emissions as a result of international trade of general goods and services (Ackerman, Ishikawa, & Suga, 2007; Li & Hewitt, 2008; Lin & Sun, 2010). Most studies have focused on commodities such as primary metals, construction, chemical, and non-metallic mineral products or all commodities collectively. In the current context, there is a lack of analysis on carbon emissions and transfer related to the trade of harvested wood products (Peters et al., 2012). None of the studies in the U.S. have focused on carbon emissions from the international trade of harvested wood products. This clearly shows that there exists a knowledge gap in this field.

Therefore, this study aims at partially fulfilling this research gap by analyzing the embodied carbon emissions in the U.S. international trade of harvested wood products for the year 2011. In addition, the consumption-based carbon emissions of harvested wood products were compared with that of the production-based emissions. Finally, per-capita carbon emissions of the harvested wood products were compared against per-capita gross domestic product (GDP). The U.S. is the world's largest importer and producer, and the second largest exporter of wood products. In 2013, it was the second largest carbon emitter with per-capita emissions being 16.5 t CO_2 (USEPA, 2016). Brazil, Canada, China, Japan, Germany, Mexico, and Russia were the major trading partners of the U.S. selected for this study. Multi-regional input-output (MRIO) method was used to analyze the economic-environmental effects of the wood products trade among the U.S. and its trading partners. The most recent 2011 MRIO table from the World Input-Output Database (WIOD) was used for the analysis. This table consisted of 35 economic sectors which were aggregated into 15 economic sectors.

Findings from this study can provide insight into the importance of carbon emissions embodied in the international trade flows of wood products for the U.S. and its trading partners. It can also help governments to develop effective policy to reduce emission inventory from the trade of wood products. In addition, findings can help policy makers understand the emissions drivers. This study will also contribute to determining the fair allocation method of carbon responsibility, which ultimately will encourage international cooperation among the countries in reducing carbon emissions.

Section 4.3 presents the literature for carbon emissions embodied in trade and input-output analysis. Section 4.4 presents the multi-regional input-output model and methods for calculation of emission embodied in trade. Section 4.5 presents the data required for this study and the sources from where the data were obtained. Section 4.6 presents the results for the trade balance of embodied emissions. Section 4.7 presents the general conclusions of the study.

4.3 Literature review

Carbon embodied in imports and exports of goods and services has gained widespread concern. For example, Schaeffer and de Sá (1996) estimated the carbon embodied in Brazilian exports and imports from 1970 to 1993, and found that the total carbon emission in trade was 8.3 Mt of carbon. Carvalho, Santiago, and Perobelli (2013) found that the main trade activities of Minas Gerais were carbon intensive. More recently, Ren, Yuan, Ma, and Chen (2014) found that China's growing trade surplus was one of the important reasons for the rapidly rising carbon emissions.

In addition to a single-country assessment, there is a growing interest in analyzing embodied emissions in bilateral trade, i.e. trade between two countries. As such, Hayami and Nakamura (2002) studied carbon emission and trade between Japan and Canada, and found that their bilateral trade reduced emissions in both of the countries. This study showed the positive impacts of trade on the environment. X. Liu, Ishikawa, Wang, Dong, and Liu (2010) showed that carbon emission in China was reduced and that in Japan was increased as a result of trade between these two countries. This type of bilateral trade studies helps the participating countries to identify whether a country is a net importer (or exporter) of carbon emissions from (or to) another country. In addition, it will help to determine whether or not the overall carbon emissions can be reduced from such trade.

A wide range of studies also seek to identify carbon emissions incorporated in the international trade among multiple countries. Such multi-country analysis allows the representation of more complex interactions between countries. Peters and Hertwich (2008) estimated that 21.5 percent of the global carbon emissions were embodied in the international trade among 87 countries in 2001. Similarly, Nakano et al. (2009) suggested that globally, about 860 and 1550 Mt of carbon emissions were resulted, respectively, from the trade among non-Organization for Economic Co-operation and Development (OECD) and OECD countries. They concluded that an increase in the global trade intensity would increase the impact of embodied emissions.

A common finding from most of the studies is that carbon emissions embodied in the international trade of goods and services is significant, and that major developed countries such as Canada, the U.S., and Australia are a net carbon importers. In most cases, the international trade results in an increase of the global greenhouse gas emissions (Peters, Minx, Weber, & Edenhofer, 2011).

4.3.1 Production-based and consumption-based accounting

Production-based accounting method is the one in which carbon emission generated is attributed to a country where the goods are produced, regardless of where they are consumed. Thus, this accounting process ignores the emissions impact of consumption of the goods, and producers are responsible for the carbon emissions from the production of goods and services. This might put an unfair burden on the countries whose economy is export oriented. A production-based carbon emission inventory may lead to carbon leakage (L. Liu & Ma, 2011). Instead of producing carbon-intensive goods, a country can import these goods from other countries to cut its own emissions. Production-based accounting does not distinguish exports and the domestic consumption, and hence carbon emissions from the production of goods that are exported to foreign countries are treated as domestic emissions. This might influence the ability to meet the national carbon emission reduction target (Munksgaard & Pedersen, 2001).

On the other hand, a consumption-based accounting estimates the emissions occurring from economic consumption within a country. In this accounting method, consumers are responsible for carbon emissions from the production of goods and services. It can eliminate carbon leakage and give a balanced picture of carbon emission responsibilities (L. Liu & Ma, 2011). Consumption-based accounting can be considered as the trade adjusted version of the production-based accounting estimates. Thus, consumption-based emission inventory takes the production-based emission inventory but deducts the emissions embodied in exports and add the emissions embodied in imports (Rodrigues, Domingos, & Marques, 2010).

4.3.2 Input-Output (I-O) analysis

The input-output model has been used in many studies to investigate economic-environmental relationship and to track the carbon embodied in the national and international trade of goods and services (Wier, 1998; Wright, 1974). I-O analysis theorized and developed by economist Wassily (Leontief, 1936), represents monetary transactions between supply chains in mathematical form (Ren et al., 2014). It was then extended to interregional and international trade applications by Isard (1951), Chenery (1953), and Moses (1955). The application of I-O analysis to environmental problems dates back to the 1970s. Walter (1973) made an early attempt to examine the pollution content of the U.S. trade. In another study, Fieleke (1974) determined the U.S. trade deficit in embodied energy. Similarly, Bourque (1981) estimated embodied energy trade balance between Washington State and the rest of the U.S. Since then a number of studies have been carried out using I-O approach to analyze the environmental impact of international trade. The advantage of using I-O based approaches is that they allow the quantification of responsibility according to different principles i.e. not only the producer and consumer responsibility accounts can be estimated (Munksgaard & Pedersen, 2001) but also any share of responsibility can be quantified with such a framework (Gallego & Lenzen, 2005).

A large literature throughout the world can be found that has used I-O model to evaluate the impact of trade of commodities on carbon emissions. For example, (Druckman & Jackson, 2009) estimated CO_2 emissions embodied in trade between 1990 and 2004 for the UK. In addition, I-O analysis has also been used in analyzing the carbon emissions embodied in bilateral and multi-lateral trades. Shimoda, Watanabe, Ye, and

Fujikawa (2008) calculated environmental loads (energy and CO_2 emissions) associated with the trade flows between nine countries of Asia-Pacific region and the U.S. from 1985 to 2000. McGregor, Swales, and Turner (2008) analyzed embodied carbon in interregional trade flows between Scotland and the rest of the UK.

4.3.3 Single-regional I-O (SRIO) and multi-regional I-O (MRIO) analysis

Both single-region I-O (SRIO) and multi-region I-O (MRIO) models have been applied in the literature. The SRIO model treats imports as either exogenous (Schaeffer & de Sá, 1996) or endogenous (Lenzen, 1998). It assumes that the foreign commodities are produced with the same technology as the domestic ones (Machado et al., 2001; Sánchez-Chóliz & Duarte, 2004). This assumption, however, is not true in reality. Generally, imports to a country come from a number of different countries with high discrepancies in technology (Gemechu, Butnar, Llop, Castells, & Sonnemann, 2014). This assumption may thus lead to the error into the CO_2 multipliers and CO_2 embodiments in internationally traded goods and services (Lenzen, 1998; Shui & Harriss, 2006). In addition to this, SRIO models do not capture feedback effects (Wiedmann, Lenzen, Turner, & Barrett, 2007).

On the premises of avoiding errors due to the same technology assumption in SRIO model, the MRIO approach emerged as the best alternative. MRIO model differentiates the production technology of imported products from domestic ones. Most literature argue that MRIO is the most appropriate and accurate method for analyzing environmental problems associated with the international trade (Minx et al., 2009; Su & Ang, 2011, 2014; Wiedmann et al., 2007). The other advantage of MRIO analysis is that it can represent the entire global economic structure, including all trade linkages, and can also be used to analyze large bundles of goods simultaneously (Peters, 2010).

4.3.4 Emissions embodied in the U.S.'s trade

Emissions embodied in imports and exports of general goods and services of the U.S. have been analyzed in many studies. For example, Shui and Harriss (2006) found that the global CO_2 emissions increased by 720 Mt because of the trade between the U.S. and China. Weber and Matthews (2007) used I-O model to analyze the environmental effects of changes in the U.S. trade structure and volume from 1997 to 2004. Norman, Charpentier, and MacLean (2007) examined emissions as a result of trade between Canada and the U.S. Ackerman et al. (2007) analyzed carbon emissions embodied in the trade between Japan and the U.S. Most of these studies have shown that the U.S. is a net importer of CO_2 emissions.

4.3.5 Carbon emission embodied in the international trade of harvested wood products

The trade of harvested wood products, like other general goods and services, in the international market is increasing as a result of globalization and open economies. For example, during the one year period from 2013 to 2014, the global trade of industrial roundwood, sawnwood, wood-based panels, paper and paperboard increased, respectively by 2, 4, 5, and 1 percent (FAO, 2016). During imports and exports, carbon embodied in the harvested wood products might have an environmental implication at the national and global level.

Only a few studies have also incorporated the trade of harvested wood products in their analysis along with other goods and services. Peters et al. (2012) analyzed the carbon physically presented in harvested wood products in the international trade of 112 countries in 2004 using multi-regional input-output (MRIO) model. They used Global Trade Analysis Project (GTAP) database to allocate emissions to each country and estimated global carbon emissions traded through the harvested wood products to be 148 Mt of carbon. Machado et al. (2001) estimated carbon embodied in the international trade of Brazil and took pulp and paper as one of the commodities. They found the pulp and paper commodity to be a net exporter of 0.77 Mt of carbon.

4.4 Methodology

MRIO model was used to analyze carbon emissions and transfer related to the U.S.'s international trade and domestic emission inventory of the harvested wood products. MRIO is a widely used method for estimating embodied carbon. It has the ability to account for different technologies associated with different countries' products. It also provides accurate information on the displacement of carbon emissions through trade (Tian, Chang, Lin, & Tanikawa, 2014).

4.4.1 Input-Output (I-O) framework

The general I-O framework that gives the total output of an economy is given by Equation 4.1. The output of each sector can be either used as the intermediate input for another sector or as final consumption (or final demand).

$$x = Ax + y \tag{4.1}$$

where, (x) is the total output of an economy; Ax is the sum of the intermediate consumption; A is the economy's direct requirement matrix which integrates both the domestic and imported inputs and also referred to as the matrix of production technology or direct use coefficient. y is the final consumption or total net demand on the economy. The final consumption (y) comprises both demand on domestic production and exports and imports. It includes numerous components, such as household, gross fixed capital formation, non-profit organizations serving households, government, and changes in inventories and valuables.

For m-region multi-regional case, where each of m countries imports from every other country, to inter-industry demand and final demand, the extended I-O can be expressed as shown in Equation 4.2.

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ \vdots \\ x_m \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1m} \\ A_{21} & A_{22} & \cdots & A_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ A_{m1} & A_{m2} & \cdots & A_{mm} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ \vdots \\ x_m \end{bmatrix} + \begin{bmatrix} y_{11} & y_{21} & \cdots & y_{m1} \\ y_{12} & y_{22} & \cdots & y_{m2} \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ y_{1m} & y_{2m} & \cdots & y_{mm} \end{bmatrix} l \qquad 4.2$$

Here, $(x_1 \ x_2 \cdots x_m)'$ is the vector of sectoral gross output for all the m regions (or countries). A_{rs} is a $k \times k$ matrix and represents the intermediate trade flow from region r to region s; and k is the number of sectors. If $r = s$, then it represents the domestic flows. Thus, the diagonal matrices of compound A represent domestic inter-industry requirements, and the off-diagonal elements represent the inter-industry requirements of traded products. The components of A_{rs} matrices were normalized to sectoral gross output. Each element in A_{rs}, $a_{ij} = \frac{x_{ij}}{x_j}$, where, a_{ij} denotes the direct inputs from the sector i in region r needed for a sector j in region s to produce one unit of output; x_{ij} inputs from sector i to sector j, and x_j is total output of sector j. y_{rs} represents the final demand in region s for products from region r, i.e., exports of final products from r to s. y_{rr} is the final demand of country r supplied by domestic industries. The vector l is an all ones-column vector of dimensions n. The product of the matrix of final demands by the vector l results in a column vector of total final demands y.

Multi-directional trade flow is considered instead of the unidirectional trade flow assumptions. Multi-directional trade flow means that the domestic economy trades with all the other countries and other regions also trade among each other. Unidirectional trade flow assumes that the domestic country trades with all of its trading partners, but these trading partners do not trade among each other.

Using the linearity assumptions of I-O analysis in Equation 4.1, the total output of the domestic economy can be determined as

$$x = (I - A)^{-1} y \qquad 4.3$$

where, I is an identity matrix; $(I - A)^{-1}$ represents the Leontief inverse matrix. The elements of Leontief inverse matrix in the multi-regional framework represent the total, direct, and indirect unit input requirements of each sector in each region for intermediates from each sector in each region. The columns of the Leontief inverse matrix show the unit input requirements, direct and indirect, from all other countries, generated by one unit of output.

4.4.2 Emission embodied in international trade and final consumption

The direct emission intensity vector (e) of production processes within a sector for each region is determined as in Equation 4.4. This gives the carbon emissions per unit of production of each sector in each region.

$$e = \frac{f_j}{x_j} \tag{4.4}$$

where, f_j is the vector of direct carbon emissions generated by each sector j. The direct carbon emissions generated by each sector in each country were obtained from Genty, Arto, and Neuwahl (2012) and are presented in Table 4.2.

The carbon emissions (E) associated with final demand in country s emitted in the industry i in country r, is estimated as shown in Equation 4.5 and the extended form is presented in Equation 4.6.

$$E = \hat{e}\left(I - A\right)^{-1} y \tag{4.5}$$

$$\begin{bmatrix} E_{11} & E_{12} & \cdots & E_{1m} \\ E_{21} & E_{22} & \cdots & E_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ E_{m1} & E_{m2} & \cdots & E_{mm} \end{bmatrix} = \begin{bmatrix} \hat{e}_1 & 0 & \cdots & 0 \\ 0 & \hat{e}_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \hat{e}_m \end{bmatrix} \begin{bmatrix} I - A_{11} & -A_{12} & \cdots & -A_{1m} \\ -A_{21} & I - A_{22} & \cdots & -A_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ -A_{m1} & -A_{m2} & \cdots & I - A_{mm} \end{bmatrix}^{-1} \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1m} \\ y_{21} & y_{22} & \cdots & y_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ y_{m1} & y_{m2} & \cdots & y_{mm} \end{bmatrix} \tag{4.6}$$

where, E_{rs} represents the emissions produced in country r by industry associated with final demand of country s; $\hat{e}_r$ is a diagonalized vector of industry-specific emission intensities for country r; y_{rs} is the demand of country s for final products produced by country r.

The carbon emissions can be estimated based on the consumption and production basis. The consumption-based method allocates emissions to those countries where the goods and services are eventually consumed. In contrast, in the production-based method, the carbon emissions are allocated no matter what the origin of production inputs or the final use of the production generated. The consumption-based emission of country r is calculated as the sum of column r in the matrix E presented in Equation 4.6. Similarly, the production-based emission is calculated as row sums of matrix E presented in Equation 4.6.

Total carbon emissions embodied in exports (EE) and imports (EI) is estimated as in Equations 4.7 and 4.8, respectively.

$$EE = \sum_{s,r \neq s} E_{rs} \qquad 4.7$$

$$EI = \sum_{s,r \neq s} E_{sr} \qquad 4.8$$

The balance of emissions embodied in international trade (BEET) is obtained as shown in Equation 4.9.

$$BEET = EE - EI \qquad 4.9$$

If BEET is positive, there is an emission surplus, so a country exports more pollution to other countries than imported from other countries in the trade (L. Liu & Ma, 2011). If the BEET is negative, there is an emission deficit, i.e., a country imports more pollution from other countries.

4.4.3 Emission embodied in final demand by each sector (or industry)

To analyze the emissions embodied in the consumption of country s by final demand industry, instead of having column vectors of y_{rs} , demand matrix consisting of matrix blocks that are made off diagonalized vectors $\hat{y}_{rs}$ needs to be created, and the resulting final demand matrix is as shown in Equation 4.10.

$$\hat{y}_{rs} = \begin{bmatrix} \hat{y}_{rs}^{1} & 0 & \cdots & \cdots & 0 \\ 0 & \hat{y}_{rs}^{2} & \cdots & \cdots & 0 \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ 0 & 0 & \cdots & \cdots & \hat{y}_{rs}^{k} \end{bmatrix} \text{and } \hat{Y} = \begin{bmatrix} \hat{y}_{11} & \hat{y}_{12} & \cdots & \cdots & \hat{y}_{1m} \\ \hat{y}_{21} & \hat{y}_{22} & \cdots & \cdots & \hat{y}_{2m} \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ \hat{y}_{m1} & \hat{y}_{m2} & \cdots & \cdots & \hat{y}_{mm} \end{bmatrix} \qquad 4.10$$

The resulting matrix for the emissions embodied in final demand by each industry is presented in Equation 4.11.

$$\begin{bmatrix} E_{11} & E_{12} & \cdots & E_{1m} \\ E_{21} & E_{22} & \cdots & E_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ E_{m1} & E_{m2} & \cdots & E_{mm} \end{bmatrix} = \begin{bmatrix} \hat{e}_1 & 0 & \cdots & 0 \\ 0 & \hat{e}_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \hat{e}_m \end{bmatrix} \begin{bmatrix} I-A_{11} & -A_{12} & \cdots & -A_{1m} \\ -A_{21} & I-A_{22} & \cdots & -A_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ -A_{m1} & -A_{m2} & \cdots & I-A_{mm} \end{bmatrix}^{-1} \begin{bmatrix} \hat{y}_{11} & \hat{y}_{12} & \cdots & \hat{y}_{1m} \\ \hat{y}_{21} & \hat{y}_{22} & \cdots & \hat{y}_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ \hat{y}_{m1} & \hat{y}_{m2} & \cdots & \hat{y}_{mm} \end{bmatrix} \qquad 4.11$$

where, $E^{ij}{}_{rs}$ is carbon emitted in industry i in country r, when producing final products of industry j consumed in country s.

4.4.4 Responsibilities versus gross domestic products (GDP)

GDP is a commonly used metric of economic welfare. It is defined as domestic final consumption plus exports minus imports. It is equivalent to gross domestic income, which is the primary input of the I-O model. The relation between GDP and emissions were examined for the U.S. and its trading countries. The GDP was compared with direct carbon emissions, carbon emissions under consumer responsibility, and carbon emissions for wood and paper products.

Per-capita emissions for each country were compared against per-capita GDP. Both were taken in log-log scale, and the data were described by a power-law of the type $y = ax^{b}$, where y refers to per-capita direct emissions and x refers to per-capita GDP; a

and b are coefficients. The coefficient b is the elasticity of emissions with respect to GDP. If coefficients a and b are positive, then it implies that an increase in GDP is associated with an increase in all types of emissions.

4.5 Data and sources

The data required for this study are an input-output table where total inputs to each economic sector are equal to the total outputs of that sector, and direct environmental impacts associated with each sector. From the World Input-Output Database (WIOD) the most recent 2011 MRIO table was obtained which consists of 35 economic sectors and 40 regions (Timmer, Dietzenbacher, Los, Stehrer, & Vries, 2015). The production, import, and export data were all obtained from the MRIO table. The 40 regions modeled in WIOD are classified into three groups according to their classification by the Monetary Fund — developed economies, emerging countries, and developing countries (Zhang & Peng, 2016).

For this study, 35 economic sectors were aggregated into 15 sectors. The sectors and the codes are presented in Table 4.1. The sector classification is based on the NACE (European Classification of Economic Activities) rev 1 classifications (Timmer et al., 2015). Eight regions were selected including the U.S. and all the other regions were aggregated into rest of the world category. The regions selected as the trading partners of the U.S. were Brazil, Canada, China, Germany, Japan, Mexico, and Russia. The selection of trading partners was based on trade volume of the wood products with U.S. (USITC, 2015). Canada is the U.S.'s leading trading partner for the wood products, and accounted for 45 percent of the U.S. imports and 25 percent of the U.S. exports of the products (USITC, 2015). China is the U.S.'s second largest trading partner for the wood products, accounting for 21 percent of imports and 18 percent of the U.S. exports (USITC, 2015). The other major export markets and import suppliers are Brazil, Germany, Japan, Mexico, and Russia (USITC, 2015). Canada, Germany, Japan, and U.S. are developed economies, whereas Brazil, China, Mexico, and Russia are the emerging countries according to WIOD classification. The GDP data for 2011 in billion US $ and population in millions for each of the selected country were obtained from the WorldBank (n.d.).

The direct carbon emissions generated by each sectors in each countries (f_j in Equation 4.4 in the Methodology section) were obtained from Genty et al. (2012) and are presented in Table 4.2. The direct emissions are an environmental indicator as most carbon emissions are generated to produce goods and services. The data showed that total carbon emission of 15 sectors in the U.S. was 1804 Mt CO_2. Compared to its trading partners, the U.S. is ranked second most carbon emitter, China being the first with total emissions of 1915 Mt CO_2. The direct carbon emission from Brazil is 193 Mt CO_2, which is lowest among the selected countries. Looking at the sector 20 i.e., wood and products of wood and cork (hereafter wood products sector), the direct carbon emissions of the U.S. is 14.53 Mt CO_2, which is the largest volume compared with its trading partners. Likewise, for the sector 21t22 i.e., pulp, paper, paper printing and publishing (hereafter paper products sector), the direct carbon emissions is highest for the U.S. (61.3 Mt CO_2) compared to the other selected countries. The emissions from wood products sector (sector 20) is lowest for the Brazil (0.39 Mt CO_2), and from paper products sector (sector 21t22) is lowest for Russia (1.52 Mt CO_2).

4.6 Results

4.6.1 Multilateral trade balance for embodied carbon emissions

Table 4.3 shows the multilateral trade balance for embodied carbon emissions in the international trade of harvested wood products for the U.S. and its major trading partners based on the consumer responsibility. The column in the Table 4.3 represents the carbon embodied in trade from a consuming country and the row represents the carbon emissions embodied in trade from a producing region.

The results showed that the total carbon emission under the consumer responsibility was 95.29 Mt CO_2. The carbon embodied in multilateral trade of the U.S. and its trading partners was 20.46 Mt CO_2. This accounted for 21.47 percent of their total emissions. Based on the consumer responsibility, the total emissions was highest for the U.S. (51.13 Mt CO_2), followed by Germany (7.15 Mt CO_2), China (5.29 Mt CO_2), Canada (5.10 Mt CO_2), Brazil (3.53 Mt CO_2), Japan (3.36 Mt CO_2), Russia (3.29 Mt CO_2), and Mexico (2.52 Mt CO_2). The rest of the world had total emissions of 13.97 Mt CO_2.

The embodied emissions in the imports ranged from 0.26 Mt CO_2 for Russia to 8.30 Mt CO_2 for the U.S. The embodied emissions in imports were highest for the U.S., followed by Germany, Canada, Japan, Brazil, China, Mexico, and Russia. The rest of the world had total embodied emissions in imports of 3.52 Mt CO_2. For the U.S. carbon emissions from imports represented the share of 16.23 percent in the total carbon emissions under the consumption-based accounting. Comparing all the countries, the share of embodied carbon in imports of the harvested wood products in the national emissions (total emissions) ranged from 7.93 percent for Russia to 37.96 percent for

Canada. The share of embodied emissions in imports in the total national emissions was lowest for the U.S. compared to its trading partners, except for Russia. Similarly, the share of carbon emissions in imports in total trade of the U.S. and its trading partners was highest for the U.S. (40.57 percent) and lowest for Russia (1.27 percent).

The results indicated that China was the largest source of embodied carbon in the national carbon accounting of the U.S. About 1.98 Mt CO_2 embodied in imports from China was accounted for in the U.S. Similarly, Canada was the second largest source of embodied carbon emissions in the national carbon account of the U.S. The total of 1.66 Mt CO_2 embodied in the imports from Canada was accounted for in the U.S. The embodied carbon emissions in the trade of harvested wood products from Brazil (0.13 Mt CO_2) represented the lowest share in the national carbon emission accounting of the U.S. The rest of the world contributed about 2.86 Mt CO_2 to total accounting of carbon emissions from the harvested wood products for the U.S. based on the consumer responsibility.

For the trading partners Brazil, Canada, China, Germany, and Mexico, the U.S. was the largest source of embodied carbon in the harvested wood products. Around 1.32 Mt CO_2 embodied carbon in the national emissions in Canada was contributed by the U.S. Similarly, embodied carbon contributes of the U.S. to the national CO_2 emissions of Brazil, China, Germany, and Mexico were, respectively, 0.14, 0.19, 0.44, and 0.51Mt CO_2. For other countries, Japan, Russia, and rest of the world, China contributed to the largest share of embodied carbon emissions.

4.6.2 Consumption-based and production-based emissions

Comparison of the consumption-based and production-based emissions for the U.S. and its trading countries are shown in Figure 4.1. The overall total emissions based on the consumer responsibility and producer responsibility were equal (95.29 Mt CO_2). However, each country's total emissions estimates were different under the two responsibilities. For example, total emission for the U.S. under the consumption-based responsibility was 51.13 Mt $CO_{2,}$ and under the production-based responsibility the total emissions was 46.49 Mt CO_2. This showed that when emission estimates were estimated under the consuming responsibility, the emission inventory of the U.S. products were higher as compared to estimates under the producer responsibility. The difference in carbon emissions under the production-based and consumption-based accounting was around 10.4 percent.

Similar to the U.S., its trading partners Brazil, Germany, Japan, and Mexico had higher emission inventories when emissions are accounted based on the consuming responsibility. The percentage difference was highest for Brazil (24.68 percent). In contrast, the U.S trading partners, Canada, China, and Russia had lower emission inventories when consumption-based emissions accounting was used. The percentage difference of emissions between the consumption-based and production-based accounting was highest for China whose emission estimates were lowered by 3.31 Mt CO_2 when the consumption-based accounting was used instead of the production-based accounting.

The results for the rest of the world showed similar pattern as that of China, Canada, and Russia. Overall, the difference in total emissions under the consumption-based and production-based accounting ranged from -3.31 Mt CO_2 for China to 4.64 Mt

CO_2 for the U.S. In terms of percentage change of responsibility difference, the changes ranged from -38.56 percent for China to 24.68 percent for Brazil.

4.6.3 Trade balance of embodied carbon based on consumer responsibility

Bilateral trade balances of embodied carbon of the U.S. and its trading partners are shown in Table 4.4. The U.S. imported a total of 8.30 Mt CO_2 from its trading partners and exported a total of 3.66 Mt CO_2 to its trading partners. In 2011, the U.S. was a net importer of 4.64 Mt CO_2 from its trading partners. These emissions account for 9.07 percent of total emissions and 55.90 percent of total imported carbon in the U.S. Trading partners Brazil, Germany, Japan, and Mexico had emission deficits of respectively, 0.70, 1.14, 0.36, and 0.25 Mt CO_2. In contrast, Canada, China, and Russia have net emission surpluses of 0.04, 3.32, and 1.24 Mt CO_2, respectively. The rest of the world had an emission surplus of 2.49 Mt CO_2.

The results for bilateral trade between the U.S. and trading partners showed that, except for Brazil and Mexico, the U.S. had a net emission deficit with all other countries in terms of embodied carbon. With Brazil and Mexico, there was net emission balance of 0.01and 0.08 Mt $CO_{2,}$ respectively. The emission deficit was highest with China. The carbon emission in imports of harvested wood products from China to the U.S. was 1.98 Mt $CO_{2,}$ whereas the carbon emissions exported to China from the U.S. was 0.19 Mt $CO_{2.}$ Hence, there was a net deficit of 1.79 Mt CO_2 in the U.S. with China. Similarly, Russia was the second largest contributor of net carbon emissions (0.45 Mt CO2) in imports to the U.S., followed by Canada (0.34 Mt CO_2), Japan (0.07 Mt CO_2), and Germany (0.04 Mt CO_2). The trade deficit with rest of the world was 2.02 Mt CO_2.

For bilateral trade between other countries, the results indicated that except with Russia, China had trade surplus with all other countries which summed to 3.32 Mt CO_2. The highest surplus contributor was the U.S. which accounted almost 54.42 percent. Similarly, Russia had the trade surplus with all the countries, and like China, the highest contributor of surplus was the U.S. (36.29 percent). The results indicated that China was the largest source of embodied carbon in the total emissions account of most of the countries, including the U.S.

4.6.4 Sectoral balance of embodied emissions in trade

This section describes the results for the carbon emissions embodied in final demand trade by sectors. This study focused on the harvested wood products hence only the results for two sectors were presented here — wood and products of wood and cork sector (sector 20, referred as wood products), and pulp, paper, paper printing and publishing sector (sector 21t22, referred as paper products). The results for multilateral trade balance of wood products sector (sector 20) is presented in Table 4.5. The total emission in the U.S. from this sector was 4.05 Mt CO_2 which accounted for 7.92 percent emissions in total national emissions of harvested wood products in the U.S. The emissions embodied in imports from trading partners accounted to 0.85 Mt CO_2 which presented a share of 20.98 percent in the total emissions for this sector and 10.24 percent in the total emissions embodied in imports.

The results for multilateral trade balance of paper products sector (sector 21t22) is presented in Table 4.6. The total emission in the U.S. from this sector was 47.09 Mt CO_2 which accounted 92.09 percent emissions in the total national emissions of harvested wood products in the U.S. The emissions embodied in imports from trading partners accounts to 7.45 Mt CO_2 which presents a share of 15.82 percent in the total emissions for this sector and 89.75 percent in the total emissions embodied in imports.

Embodied carbon in imports from and exports to, the trading partners of the U.S. and net trade balance for wood products sector is shown in Figure 4.2. The total imported emissions from the U.S.'s trading partners and rest of the world was 0.85 Mt CO_2, and the total exported carbon emissions from the U.S. to its trading partners and rest of the world was 0.41 Mt CO_2. Overall, the results indicated that in 2011, wood products sector was net importer of 0.44 Mt CO_2 in the U.S.

Among the trading partners, China was the highest contributor of the embodied emissions (0.33 Mt CO_2) in the imports to the U.S., followed by Canada (0.11 Mt CO_2). The rest of the world contributed to 0.28 Mt CO_2 emissions in the U.S. In contrast, Brazil was the least contributor of embodied emissions (0.01 Mt CO_2) in imports to the U.S.

In terms of exported emissions from the U.S. to its trading partners, Canada received the highest portion of carbon emissions (0.09 Mt CO_2) and Russia received the lowest embodied carbon (0.002 Mt CO_2). Overall, the balance of emission embodied in trade of wood products sector show that the U.S. had trade deficit of 0.56 Mt CO_2 with its trading partners such as Brazil, Canada, China, Russia, and rest of the world. The emission deficit was highest with China and lowest with Brazil. In contrast, the U.S. had trade surplus of 0.12 Mt CO_2 with Germany, Japan, and Mexico. The surplus was highest with Japan and lowest with Mexico.

Figure 4.3 shows the result for embodied carbon in imports from and exports to, the trading partners of U.S. for paper products sector. The total imported emissions from trading partners to the U.S. summed to 7.45 Mt CO_2, whereas the total exported emissions from the U.S. to its trading partners summed to 3.24 Mt CO_2. Overall, the results indicated that like wood products sector, the paper products sector was net importer of 4.21 Mt CO_2 in the U.S.

Among the trading partners, the U.S. imported the great majority of embodied emissions from China (1.65 Mt CO_2) and least from Brazil (0.12 Mt CO_2). Canada was the second most contributors of imported emissions (1.55 Mt CO_2) in the U.S. through paper products sector. Similarly, for the exported emissions, the U.S. exported majority of its emissions to Canada (1.23 Mt CO_2) and least to Russia (0.02 Mt CO_2). The results for paper products sector for imported and exported emissions in regard to the U.S. were similar to that of wood products sector. The balance of emission embodied in trade of paper products sector show that the U.S. had an emission deficit with all its trading partners except Brazil and Mexico. The emission deficit was highest with China (1.52 Mt CO_2) and lowest with Germany (0.08 Mt CO_2).

4.6.5 Per-capita emissions as a function of per-capita gross domestic product

The results for per-capita emissions with respect to per-capita GDP are presented in Table 4.7 and Figures 4.4 – 4.7. Figure 4.4 shows the results for per-capita direct carbon emissions (t CO_2) against per-capita gross domestic product ($) for the U.S. and its trading partners. The result indicated that the direct carbon emission from the harvested wood products in each country was significantly correlated with economic growth of that country ($R^2 = 0.67$ and p-value = 0.012 at 0.05 level of significance). The results showed that the direct carbon emissions from the harvested wood products increased with economic growth of that country, with an elasticity, E = 0.884. This indicated that for a one percent increase in GDP, the direct carbon emissions increased by

0.884. The elasticity was smaller than one which implied that an additional unit of GDP will lead to less than one additional unit of carbon emissions. The figure shows that the U.S., Canada, Japan, and Germany are clustered at the right and China, Mexico, Russia, and Brazil are clustered at the left. The U.S., Canada, Japan, and Germany have more or less similar per-capita GDP and per-capita emissions which were higher than other countries.

Similarly, the result for per-capita carbon emissions on the consumer responsibility (t CO2) against per-capita GDP is presented in Figure 4.5. Similar to the relationship between direct carbon emissions and GDP, the results indicated that the carbon emissions under the consumer responsibility was significantly correlated with GDP ($R^2 = 0.78$ and p-value = 0.0034 at 0.05 level of significance). Elasticity, E = 1.24 which means that doubling GDP increases carbon emissions of harvested wood products under the carbon responsibility by 1.24 percent. The elasticity was greater than one which implied that an additional unit of GDP will lead to more than one additional unit of carbon emissions. The figure shows that the U.S., Canada, Germany, and Japan were clustered at the right where as China is at the left. All other countries (Mexico, Brazil, and Russia) were clustered at the center.

Figure 4.6 and Figure 4.7 show the results for per-capita total carbon emissions under the consumption-based accounting as a function of GDP per-capita in wood products (sector 20) and paper products (sector 21t22) sectors, respectively. The relationship between wood products related carbon emissions and the national income growth exhibit significant correlation ($R^2 = 0.66$ and p-value = 0.014). The elasticity with economic growth, E = 1.16, suggesting that as a result of economic growth of a country, wood products related carbon emissions will increase by 1.16 percent. The relationship between paper products related carbon emissions and economic growth was correlated and was significant. The elasticity was 1.28, which is steeper as compared to that of the wood products sectors. In both the figures, the U.S., Canada, Germany, and Japan were clustered at the right. The cluster on the right was the group of economies with higher per capita GDP values.

4.7 Conclusion and discussion

Reducing greenhouse gas emissions has become the issues in international trade and politics because of globalization. This study estimated carbon emissions embodied in the trade of harvested wood products of the U.S. with its major trading partners such as Brazil, Canada, China, Germany, Japan, Mexico, and Russia. Multi-regional input-output model was used to estimate domestic carbon emission and the carbon emissions in imports and exports of harvested wood products for the year 2011, the most recent year available data. Production-based carbon emissions and consumption-based emissions were compared. In addition, the per-capita emissions were compared against the per-capita GDP for the U.S. and its trading partners.

From the results, it can be concluded that the U.S. was a net importer of 4.64 Mt CO_2 in the harvested wood products, accounting for 9.07 percent of total emissions and 55.90 percent of total imported carbon. The U.S. imported a total of 8.30 Mt of carbon emissions from its trading partners and exported 3.66 Mt of carbon emissions to its trading partners. The carbon emissions from the imports of China were highest and that of Brazil was lowest. In terms of carbon embodied in exports, Canada and Russia was respectively, the biggest and smallest recipient of exported emissions of the U.S.

Similar to many other studies (Fernández-Amador, Francois, & Tomberger, 2016; Pang, Yan, & Wu, n.d.; Zhang & Peng, 2016), carbon emissions estimates of the U.S. and its trading partners varied under the production and consumption-based methods. It can be concluded that for the U.S., estimating carbon emissions of the harvested wood products under consuming responsibility instead of producing responsibility increased the emissions inventory. This may be because the U.S. is one of the largest net-importer of harvested wood products. From its seven trading partners and rest of the world (in this study), the U.S. imports net 2598 million (in US $). Similar to the U.S., its trading partners, Brazil, Germany, Japan, and Mexico had higher carbon emissions inventory on using consuming responsibility. For its trading partners, Canada, China, and Russia, and rest of the world, the total carbon emissions estimates decreased when the consumption-based accounting was used instead of the production-based accounting.

The results also indicated that wood products sector (sector 20) and paper products sector (sector 21t22) in the U.S. were both net importers of embodied carbon emissions. The net imported emission of paper products sector was higher as compared to wood products sector. Among the trading partners of U.S, the imported emissions were highest with China, second being Canada for both of the industries. Similarly, the exported emissions from the U.S. were highest to Canada and lowest to Russia for both of the industries. Likewise, the trade deficit was highest with China for both the industries. Trading partners, Germany, Japan, and Mexico provided a surplus to the U.S. for the wood products sectors. In contrast, Germany and Japan provided emission deficit to the U.S. for the paper products sector. In the same way, Brazil which was trade deficit for the U.S. for wood products sector was trade surplus for paper products sector.

It can be concluded that per-capita direct carbon emissions, carbon emissions under consumer responsibility, carbon emissions embodied in wood and paper products sectors increased with increase in per-capita gross domestic product. The elasticity for per-capita direct carbon emissions against per-capita GDP was lowest compared to carbon emissions under consumer responsibility and carbon emissions in wood and paper products sectors. The elasticity of the paper products sector was steeper as compared to that of the wood products sector. The U.S. and its trading partners were clustered into groups according to the higher and lower per-capita GDP.

Several implications can be drawn from the results. To be effective, the emission mitigation policy should be based on both domestic emissions and emissions from the trade of harvested wood products. Changing trading partners in the open economy can make a change in the profile of embodied carbon. U.S. is more dependent on imports of harvested wood products and thus could reduce its carbon emissions under the consumption-based accounting by reducing the imports of harvested wood products from the countries like China. In contrast, U.S. has emission surplus with emerging country Mexico and thus can increase trade with Mexico. Looking separately at the sectors, wood products sector (sector 20) and paper products sector (sector 21t22), the findings can help understand the net carbon emission drivers. The net carbon emission in imports of paper products sector is more than that of wood products sector. Hence, policy options should address in reducing emissions embodied in trade from paper products sector (sector 21t22).

Production-based accounting model considers carbon emissions from domestic production including production for export, whereas consumption-based accounting model considers the carbon emissions caused by domestic consumption including emissions in countries producing the imported commodities. Canada, China, and Russia had greater advantage when consumption-based accounting was used. For the U.S. or other net importers, accounting carbon embodied in trade under production-based method could avoid a fraction of carbon emissions by using exported products from its trading partners.

The United Nations Framework Convention on Climate Change (UNFCCC) allocates the national carbon emissions based on the production-based method (Zhang & Peng, 2016). Therefore, developed economies are maintaining or reducing their emissions by increasing imports from emerging or developing countries. As a result, there has been the issue of carbon leakage. If the emissions allocation is based on consumption-based method, then the emission imports are attributed to importing country. This in turn has the capacity to reduce carbon leakage. Accounting under consumption-based method to measure carbon emissions is more precise as compared to the production-based method that ignores carbon offsetting in exported products. Therefore, the allocation of carbon responsibility and the relevant policy implications related to carbon leakage must be reconsidered. To increase the international cooperation in reducing global greenhouse gas emissions, the allocation of carbon responsibility should be fair.

However, the net carbon importers like the U.S. might not accept the consumption-based method and the net carbon exporters like China might face a bias with the production-based method. Shared producer and consumer responsibility could be more appropriate or promising way to allocate emission responsibility (Pang et al., n.d.;

Zhang & Peng, 2016). Producers and consumers both have an influence on the amount of carbon emissions as they produce or consume. Shared production and consumption based allocation schemes could provide a direct incentive for both the producers and consumers to reduce carbon emissions. Estimating carbon emissions embodied in trade of harvested wood products under shared responsibility can be directions for research in future.

Carbon emissions in the trade of harvested wood products among U.S. and its trading partners can be decomposed into emissions embodied in the trade of final products, emissions embodied in direct trade of intermediate products, and emissions embodied in indirect trade of intermediate products (Zhang & Peng, 2016). Decomposing trade into these three categories might help understand the impact of international production fragmentation on carbon emissions (Zhang & Peng, 2016). This study has not looked at such decomposition. Therefore, this can be directions for research in future.

Table 4.1 Sector and sector codes based on the world input-output database

Sector	Sector code
Wood and products of wood and cork	20
Pulp, paper, paper printing and publishing	21t22
Coke, refined petroleum and nuclear fuel	23
Chemicals and chemical products; Rubber and plastics	24t25
Basic metals and fabricated metal	27t28
Manufacturing and recycling	36t37
Wholesale, commission, and retail sale; repair of household goods	51t52
Transport (inland, water, and air)	60t62
Post and telecommunications	64
Real estate business	70t74
Agriculture, hunting, forestry and fishing	AtB
Mining and quarrying	C
Construction	F
Financial intermediation	J
Services	LtO

Note – sector 20 (i.e., wood and products of wood and cork) in this study is referred as wood products; sector 21t22 (i.e., pulp, paper, paper printing and publishing) in this study is referred as paper products. Here, 21t22 means 21 to 22.

Table 4.2 Direct carbon emissions (Mt CO_2) generated by each sector in the U.S. and its trading partners in the year 2011

Sector code	US	Brazil	Canada	China	Germany	Japan	Mexico	Russia	ROW
20	14.5	0.4	2.9	12.0	0.9	1.7	0.4	1.8	2.7
21t22	61.3	4.0	4.6	52.0	7.4	11.9	3.1	1.5	11.8
23	186.4	17.8	32.9	100.9	18.4	27.8	31.1	64.3	182.0
24t25	138.5	17.0	16.3	292.7	33.6	54.1	11.1	58.7	522.9
27t28	101.1	28.0	24.2	628.3	48.0	110.8	14.1	177.1	191.0
36t37	3.7	0.7	1.2	5.6	0.8	2.3	3.0	0.5	123.7
51t52	109.6	7.4	20.7	15.5	14.9	28.7	11.5	10.0	79.8
60t62	404.2	45.6	51.0	276.4	46.5	131.6	34.2	124.7	617.8
64	31.4	2.4	5.3	5.8	7.0	2.9	2.1	2.0	24.6
70t74	113.3	5.1	14.8	30.0	18.9	19.6	6.3	8.3	67.6
AtB	50.2	25.4	8.4	118.1	7.2	13.3	20.8	24.4	142.4
C	111.0	17.1	76.9	195.5	5.0	22.1	28.5	95.4	194.3
F	41.8	3.8	8.7	71.4	7.8	26.1	11.7	7.5	42.3
J	30.5	0.5	6.9	3.2	2.2	3.5	0.9	1.6	17.3
LtO	406.6	18.4	46.5	107.2	23.4	71.6	16.9	29.5	231.5
Total	1804.0	193.4	321.3	1914.7	242.0	528.0	195.7	607.3	2451.8

Note: ROW is the rest of the world

Table 4.3 Multilateral trade balance of embodied carbon based on the consumer responsibility (Mt CO_2)

Country	U.S.	Brazil	Canada	China	Germany	Japan	Mexico	Russia	ROW
U.S.	42.83	0.14	1.32	0.19	0.44	0.21	0.51	0.02	0.84
Brazil	0.13	2.51	0.01	0.02	0.05	0.01	0.01	0.00	0.08
Canada	1.66	0.04	3.16	0.03	0.06	0.04	0.04	0.00	0.10
China	1.98	0.14	0.21	4.30	0.39	0.45	0.09	0.07	0.96
Germany	0.48	0.04	0.04	0.02	4.74	0.02	0.02	0.03	0.60
Japan	0.28	0.02	0.02	0.06	0.06	2.16	0.01	0.01	0.38
Mexico	0.43	0.01	0.04	0.01	0.01	0.00	1.68	0.00	0.09
Russia	0.47	0.08	0.03	0.11	0.23	0.08	0.02	3.03	0.47
ROW	2.86	0.54	0.26	0.55	1.16	0.39	0.14	0.12	10.39
Total emissions (Consumer responsibility)	51.13	3.53	5.10	5.29	7.15	3.36	2.52	3.29	13.92
Emissions in imports	8.30	1.01	1.94	0.98	2.41	1.20	0.84	0.26	3.52
Share of embodied emissions (%)	16.23	28.75	37.96	18.56	33.69	35.71	33.22	7.93	25.32

Note: ROW is the rest of the world

Table 4.4 Net imports and exports of embodied carbon based on the consumer responsibility (Mt CO_2)

Country	U.S.	Brazil	Canada	China	Germany	Japan	Mexico	Russia	ROW
U.S.	0.00	0.01	-0.34	-1.80	-0.04	-0.07	0.08	-0.45	-2.02
Brazil	-0.01	0.00	-0.03	-0.12	0.01	-0.01	0.00	-0.08	-0.45
Canada	0.34	0.03	0.00	-0.18	0.03	0.02	0.00	-0.03	-0.16
China	1.80	0.12	0.18	0.00	0.37	0.40	0.08	-0.03	0.40
Germany	0.04	-0.01	-0.03	-0.37	0.00	-0.04	0.01	-0.19	-0.56
Japan	0.07	0.01	-0.02	-0.40	0.04	0.00	0.01	-0.07	-0.01
Mexico	-0.08	0.00	0.00	-0.08	-0.01	-0.01	0.00	-0.02	-0.05
Russia	0.45	0.08	0.03	0.03	0.19	0.07	0.02	0.00	0.35
ROW	2.02	0.45	0.16	-0.40	0.56	0.01	0.05	-0.35	0.00
Trade balance	4.64	0.70	-0.04	-3.32	1.14	0.36	0.25	-1.24	-2.49

Note: ROW is the rest of the world

Table 4.5 Multilateral trade balance of embodied carbon for wood products sector (sector 20) based on the consumer responsibility (Mt CO_2)

	U.S.	Brazil	Canada	China	Germany	Japan	Mexico	Russia	ROW
U.S.	3.19	0.00	0.09	0.05	0.06	0.07	0.08	0.00	0.07
Brazil	0.01	0.07	0.00	0.01	0.01	0.01	0.00	0.00	0.01
Canada	0.11	0.00	0.54	0.02	0.01	0.02	0.01	0.00	0.01
China	0.33	0.01	0.05	1.96	0.13	0.29	0.01	0.03	0.20
Germany	0.02	0.00	0.00	0.01	0.62	0.01	0.00	0.00	0.04
Japan	0.02	0.00	0.00	0.02	0.02	1.04	0.00	0.00	0.06
Mexico	0.04	0.00	0.01	0.00	0.00	0.00	0.36	0.00	0.00
Russia	0.05	0.00	0.01	0.06	0.07	0.06	0.00	0.48	0.08
ROW	0.28	0.02	0.05	0.27	0.30	0.22	0.03	0.02	1.08

Table 4.6 Multilateral trade balance of embodied carbon for paper products sector (sector 21t22) based on the consumer responsibility (Mt CO_2)

	U.S.	Brazil	Canada	China	Germany	Japan	Mexico	Russia	ROW
U.S.	39.64	0.14	1.23	0.13	0.39	0.14	0.43	0.02	0.77
Brazil	0.12	2.45	0.01	0.01	0.04	0.00	0.01	0.00	0.08
Canada	1.55	0.04	2.63	0.02	0.05	0.02	0.03	0.00	0.09
China	1.65	0.13	0.17	2.35	0.26	0.17	0.07	0.04	0.76
Germany	0.47	0.04	0.03	0.01	4.12	0.01	0.02	0.03	0.56
Japan	0.26	0.02	0.02	0.04	0.04	1.12	0.01	0.01	0.31
Mexico	0.39	0.01	0.03	0.00	0.01	0.00	1.32	0.00	0.09
Russia	0.43	0.08	0.03	0.05	0.16	0.02	0.02	2.55	0.39
ROW	2.58	0.52	0.22	0.28	0.86	0.16	0.11	0.10	9.32

Note: ROW is the rest of the world

Table 4.7 Elasticity of per-capita emissions (for direct, consumption-based accounting, wood products sector, and paper products sector) with respect to per-capita GDP for the U.S. and its trading partners.

	DE	EEC	EEC-WP	EEC-PP
Elasticity(E)	0.88	1.24	1.16	1.28
R^2	0.67	0.78	0.66	0.67
p-value	0.012	0.0034	0.014	0.013

Note: DE – direct emissions; EEC – emissions embodied under consumption-based accounting; EEC-WP – emissions embodied for wood, products of wood, and cork sector (sector 20); EEC-PP – emissions embodied for pulp, paper, paper printing and publishing sector (sector 21t22).

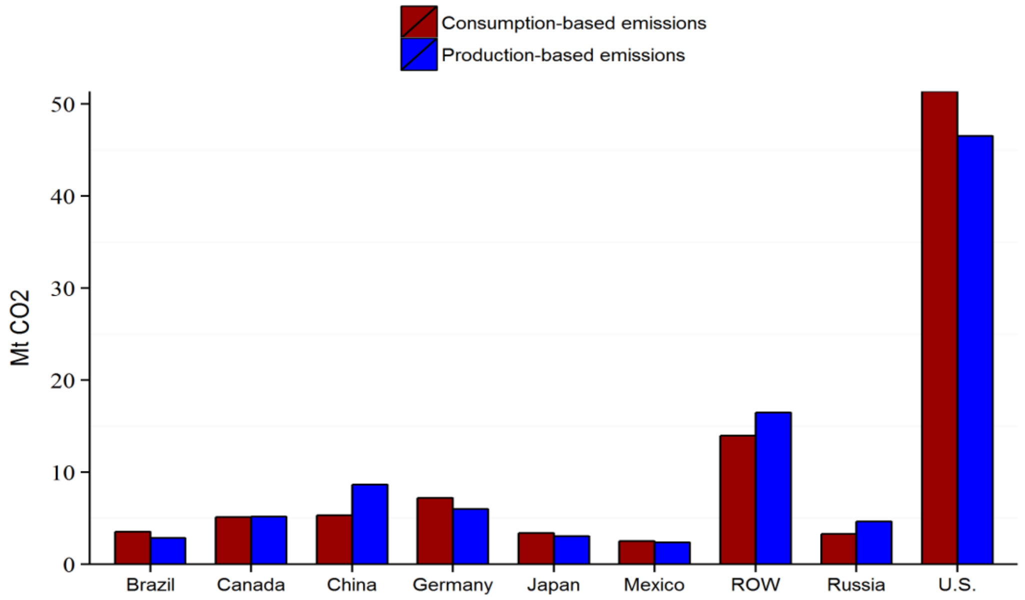

Figure 4.1 Consumption-based and production-based emission inventories of the U.S. and its trading partners

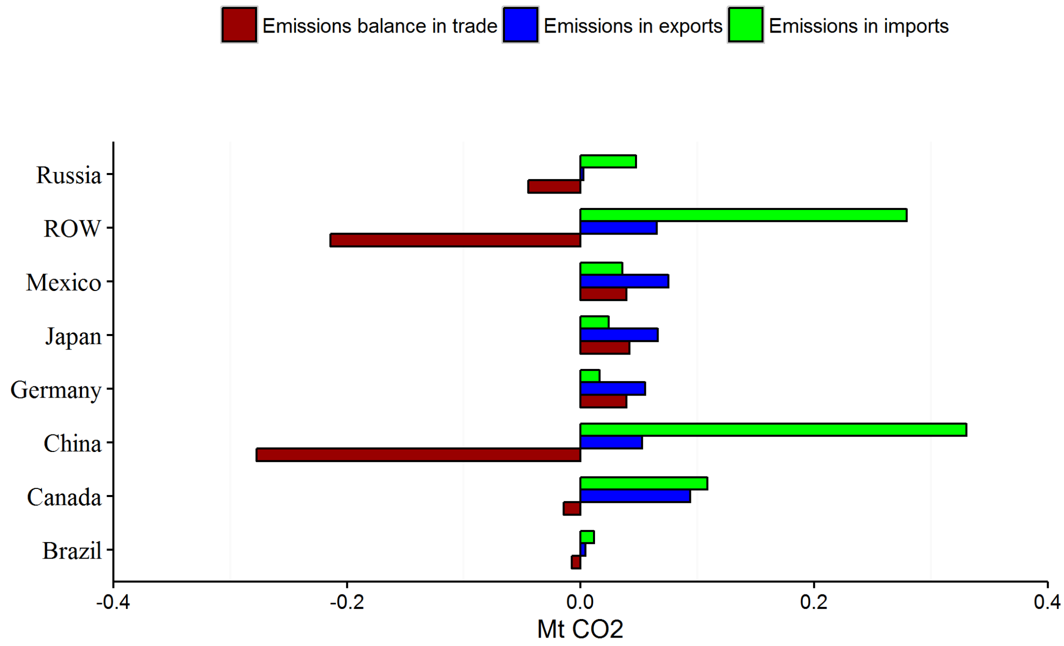

Figure 4.2 Embodied carbon in imports and exports of sector 20 (wood products) from and to trading partners of the U.S.

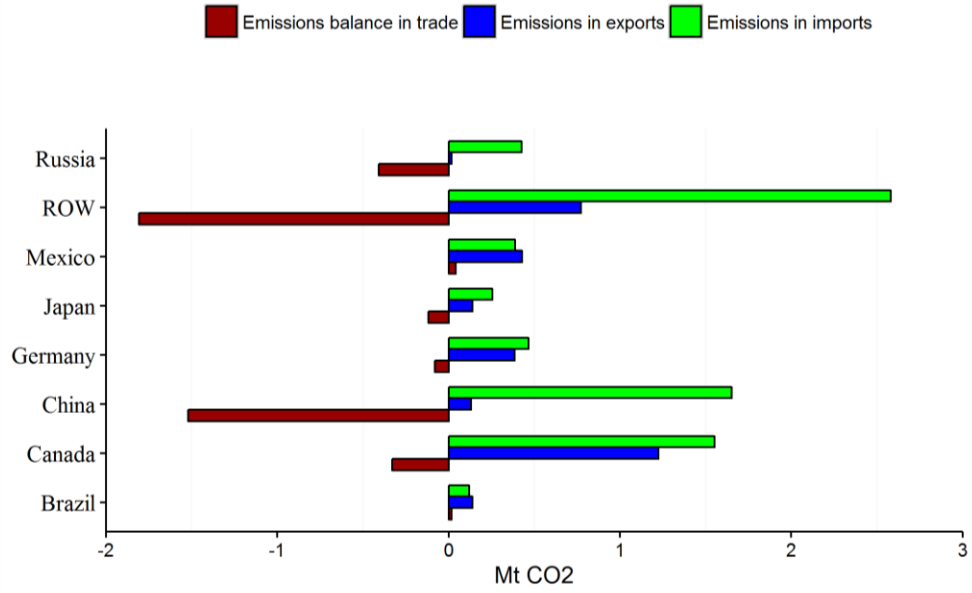

Figure 4.3 Embodied carbon in imports and exports of sector 21t22 (paper products) from and to trading partners of the U.S.

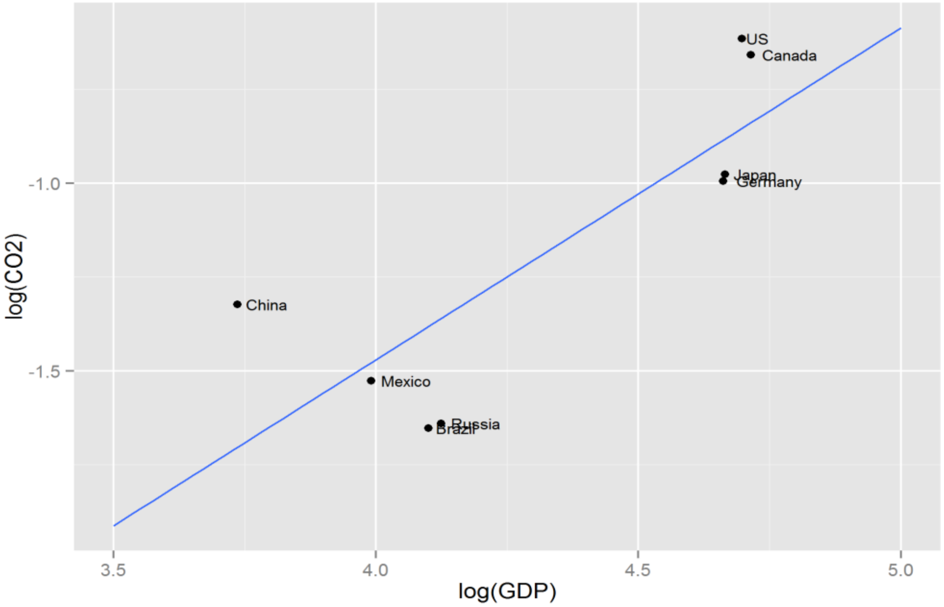

Figure 4.4 Per-capita carbon emissions (t CO_2) as a function of per-capita GDP ($) in 2011 for the U.S. and its trading partners.

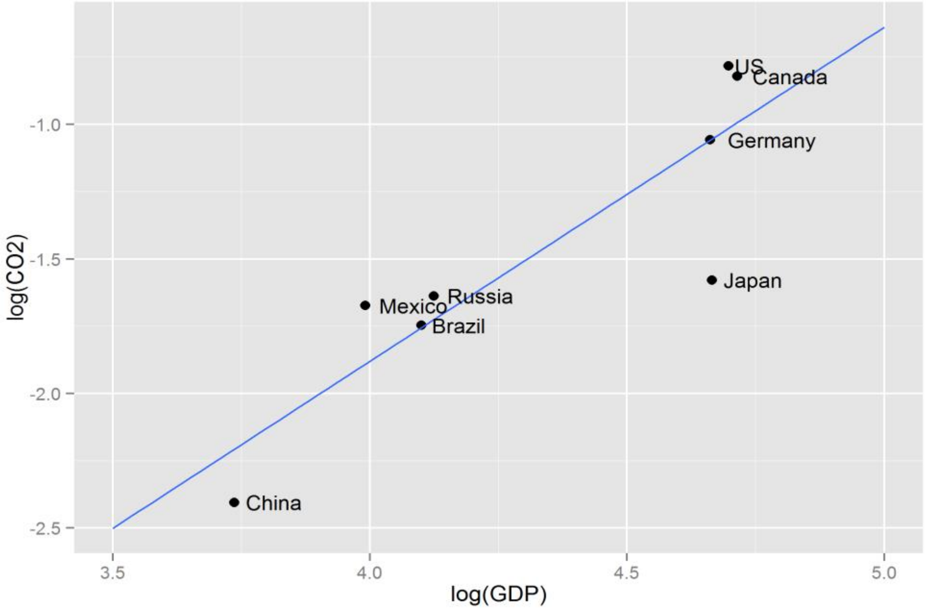

Figure 4.5 Per-capita emissions under consumer responsibility (t CO_2) as a function of per-capita GDP ($) in 2011 for the U.S. and its trading partners

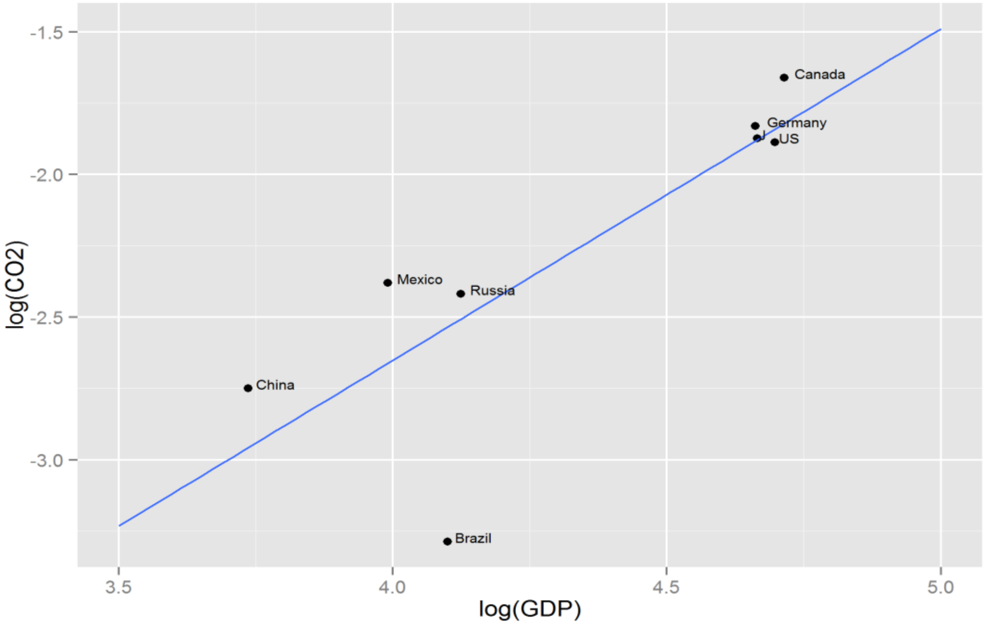

Figure 4.6 Per-capita carbon emissions (t CO_2) in wood products sector (sector 20) as a function of per-capita GDP in the U.S. and its trading partners.

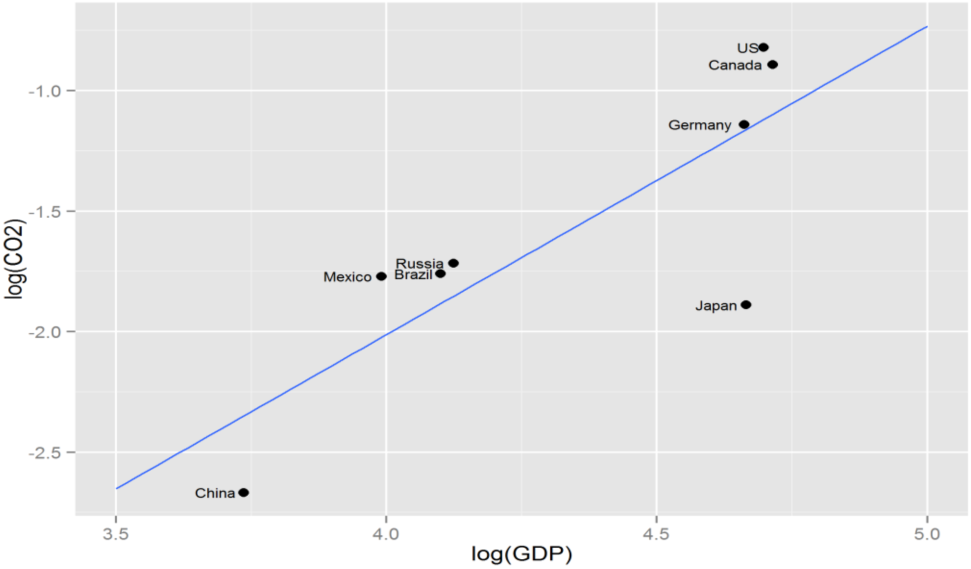

Figure 4.7 Per-capita carbon emissions (t CO_2) in paper products sector (sector 21t22) as a function of per-capita GDP ($) in the U.S. and its trading partners.

CHAPTER V

CONCLUSIONS

Reducing greenhouse gases and mitigating climate change have become important issues. Carbon in forests after harvesting is transferred into wood products pools. Therefore, HWP are considered to play an important role in mitigating climate change by delaying carbon emissions into the atmosphere. Nevertheless, international trade of HWP as a result of globalization has resulted in embodied carbon emissions. This dissertation estimated carbon content in the HWP and carbon emissions embodied in the international trade of HWP for the U.S. The overall objective was achieved by pursuing three specific objectives as described in Chapter II, Chapter III, and Chapter IV.

Chapter II estimated the carbon stored in HWP in the U.S. from 1990 to 2014. The computational method was based on 2006 IPCC guidelines. Several variables were defined and estimated according to the guidelines. Based on these variables, four accounting approaches – stock-change, production, atmospheric flow, and simple decay approaches were used to estimate the U.S. HWP contribution to carbon removals or emissions. The results showed that the U.S. HWP act as a carbon reservoir under all accounting approaches during the study period, except for the stock-change approach in 2010. The net annual carbon stock change in HWP under all accounting approaches declined from 1990 to 2014. The estimates of carbon stored in HWP varied according to different accounting approaches used, except for the production and simple decay approaches. On average, the annual HWP contribution to carbon removals was highest for the stock-change approach, followed by the atmospheric flow, and the production and simple decay approaches. Findings from this study can provide information to policy makers in considering the HWP in decision making in regard to climate mitigation and adaptation strategies.

Chapter III quantified uncertainty in the estimates of carbon in HWP obtained under four accounting approaches from 1990 to 2014 using Monte Carlo simulation. In addition, sensitivity analysis was also conducted to determine the parameters that were responsible for uncertainty in the carbon estimates in HWP for 2014. The results indicated that there were uncertainties in the estimates of carbon in HWP. The result determined that for 1990, the uncertainty was highest for carbon estimates under the atmospheric flow approach and lowest for estimates under the production and simple decay approaches. In contrast, in 2014, the uncertainty in carbon estimates in HWP was highest for the production and simple decay approaches and lowest for the atmospheric flow approach. The results of sensitivity analysis indicated that under all four accounting approaches, parameter which has the greatest influence in the carbon estimates in HWP was carbon conversion factor for roundwood, sawnwood, chip and particles, other industrial roundwood, and wood residues. In contrast, under all the accounting approaches, parameter decay rate for industrial waste had no contribution to uncertainty in the carbon estimates in HWP. The findings from this can help to identify the parameters that need to be improved to increase the quality of carbon estimates in HWP.

Chapter IV used multi-regional input-output model to estimate domestic carbon emissions and carbon emissions in the international trade of HWP for 2011. The U.S. was the focus country, with taking into account its major trading partners Brazil, Canada, China, Japan, Mexico, and Russia. The production-based carbon responsibility was compared with the consumption-based responsibility. In addition, per-capita emissions were compared against per-capita GDP for the U.S. and its trading partners. Results showed that the U.S. was a net importer of carbon emissions in HWP, meaning that carbon imported from its trading partners was higher that the exported carbon to its trading partners. China was the major contributor of imported carbon emissions. Canada was the biggest recipient of the U.S. exported emissions. The U.S. had emission surplus with Brazil and Mexico. Carbon emissions estimates of the U.S. and its trading partners varied under the production-based and consumption-based accounting method. For the U.S., net importing country for HWP, carbon emissions was higher when the consumption-based method was used instead of the production-based method. The results also showed that per-capita carbon emissions in HWP increased with increase in per-capita GDP. In addition, both the wood and paper products sectors were a net importer of embodied carbon emissions, and the net imported emissions of paper products sector was higher than that of wood products sector. This study can provide insight into the importance of carbon emissions embodied in the international trade of HWP and help policy makers in determining fair allocation method of carbon responsibility.

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APPENDIX A

R CODE FOR CHAPTER II

A.1 R code for estimating carbon stored in the U.S. harvested wood products

```
# -----------------------------------------------------------------------------------------------------------------
# Brief contents
# 0. Libraries and global setting
# 1. Data import and table2.1 (parameters)
# 2. Time series and summary statistics for table2.2
# 3. Data for figure2.1 – Products discarded in SWDS
# 4. Output and figure 2.2 – Annual harvest
# 5. Export results – table2.1, table2.2, table2.3, table2.4

# 0. Libraries and global setting
library(xlsx); library(XLConnect); library(grid); library(ggplot2)
setwd("C:/Users/pshrestha/Dropbox/0. Calculation"); getwd()
source("carbon.R"); source("write.listx.r")
options(stringsAsFactors = FALSE, width = 72, scipen = 999)

# -----------------------------------------------------------------------------------------------------------------
# 1. Data import and table2.1 (parameters)
para   <- read.xlsx(file = "HWP data.xlsx", sheetName = "parameter")
data1 <- read.xlsx(file = "HWP data.xlsx", sheetName = "data")
data2 <- read.xlsx(file = "HWP data.xlsx", sheetName = "swds")

table2.1 <- para

# -----------------------------------------------------------------------------------------------------------------
# 2. Time series and summary statistics for table2.2
dat1    <- data1[1:116, c("RP", "RI", "RE", "LP", "LI", "LE", "BP", "BI", "BE", "JP", "JI", "JE",
          "GI", "GE", "NP", "NI", "NE", "OP", "OI", "OE", "TI", "TE", "UI", "UE", "VI", "VE")]
tsdat1 <- ts(dat1, start = 1900, end = 2015, frequency = 1)
dat2    <- data2[1:116, c("Zd", "Zl", "Wpap", "Ww", "Win")]
tsdat2 <- ts(dat2, start = 1900, end = 2015, frequency = 1)

table2.2 <- bsStat(tsdat1[-116,  ] / 1000)$fstat

# -----------------------------------------------------------------------------------------------------------------
# 3. Data for figure2.1 – Products discarded in SWDS
amtdep <- ts(data = dat2[(91:115), c(3, 4)], start = 1990, end = 2014, frequency = 1)
date      <- as.Date(time(amtdep), format = "%Y"); date
value    <- data.frame(date, amtdep); value

# 3.1 Figure2.1
fig2.1 <- ggplot(value, aes(x = date)) +
      geom_line(aes(y = amtdep[, 1], linetype = 'Paper products discarded')) +
      geom_line(aes(y = amtdep[, 2], linetype = 'Wood products discarded')) +
      scale_linetype_manual(name = "", values = c(1, 3)) +
      scale_x_date(name = "") +
      scale_y_continuous(limits = c(0, 50), name= "Amount discarded in SWDS (Tg per year)") +
      theme(axis.text.x = element_text(size = 9, family = "serif")) +
```

```
     theme(axis.text.y = element_text(size = 9, family = "serif")) +
     theme(legend.text = element_text(size = 9, family = "serif")) +
     theme(legend.position = c(0.8, 0.9)) +
     theme(legend.key = element_rect(fill = "white", color = NA)) +
     theme(legend.background = element_rect(fill = NA, color = NA))

# 3.2 Save figure2.1
ggsave(fig2.1, file = 'Productsdiscardedggplot.png', width = 7, height = 5)

# -----------------------------------------------------------------------------------------------
# 4. Output and figure 2.2 – Annual harvest
output <- carbon(a1 = 0.0000005, a2 = 0.000000295, a3 = 0.00000045, a4 = 0.000000765,
          b = 1.12, k1 = 0.0231, k2 = 0.231, d1 = 0.4, d2 = 0.43, d3 = 0.2, df = 0.5, j1 = 0.05,
          j2 = 0.025, j3 = 0.03, f1 = 0.6, f2 = 1, F = 0.5, ox = 0.1)

# 4.1 Data for figure2.2 - Annual harvest
annhav <- ts(data = output$variables[, 8], start = 1990, end = 2014, frequency = 1)
date     <- as.Date(time(annhav), format = "%Y"); date
value2  <- data.frame(date, annhav)

# 4.2 Figure2.2
fig2.2 <- ggplot(value2, aes(x = date)) +
     geom_line(aes(y = annhav)) +
     scale_linetype_manual(name = "", values = c(1, 3)) +
     scale_x_date(name = "") +
     scale_y_continuous(limits = c(150, 300),
       name = "Timber product output (Tg C)") +
     theme(axis.text.x = element_text(size = 9, family = "serif")) +
     theme(axis.text.y = element_text(size = 9, family = "serif"))

# 4.3 Save figure2.2
ggsave(fig2.2, file = 'Harvesttrend.png', width = 7, height = 5)

# -----------------------------------------------------------------------------------------------
# 5. Export results – table2.1, table2.2, table2.3, table2.4
table2.3 <- output$variables; table2.4 <- output$approaches
tables    <- listn(table2.1, table2.2, table2.3, table2.4)
write.listx(z = tables, file = "HWPPtable.xls")
```

A.2 R code for function of carbon

```
carbon <- function(a1 = 0.0000005, a2 = 0.000000295, a3 = 0.00000045, a4 = 0.000000765,
           b = 1.12, k1 = 0.0231, k2 = 0.231, d1 = 0.4, d2 = 0.43, d3 = 0.2, df = 0.5, j1 = 0.05, j2
           = 0.025, j3 = 0.03, f1 = 0.6, f2 = 1, F = 0.5, ox = 0.1) {

# -----------------------------------------------------------------------------------------------
 # 1. Var1A = carbon stock change in products in Use (IU) from DC
 # 1.1 I.DC.IU.i (inflow) =  ai * (production.i + import.i - export.i)
```

```
I.DC.IU.w <- a1 * ((tsdat1[, 'LP'] + tsdat1[, 'LI'] - tsdat1[, 'LE']) + (tsdat1[, 'OP'] + tsdat1[, 'OI']-
                     tsdat1[, 'OE'])) + a2 * (tsdat1[, 'BP'] + tsdat1[, 'BI']- tsdat1[, 'BE'])
I.DC.IU.p <- a3 * (tsdat1[, 'JP'] + tsdat1[, 'JI'] - tsdat1[, 'JE'])

# 1.2 C.DC.IU (stock) = exp(-ki) * C.DC.IU.t-1 + ((1 - exp(-ki)) / ki) * I.DC.IU.i
C.DC.IU <- ts(data = matrix(data = 0, ncol = 2), start = 1900, end = 2015, frequency = 1)
colnames(C.DC.IU) <- c('C.DC.IU.w', 'C.DC.IU.p')
for(i in 2:length(I.DC.IU.w)) {
  C.DC.IU[1, 'C.DC.IU.w']  <- 0
  C.DC.IU[i, 'C.DC.IU.w']   <- (exp(-k1) * C.DC.IU[i - 1, 1]) +
                                 ((1 - exp(-k1)) / k1) * I.DC.IU.w[i - 1]
  C.DC.IU[1, 'C.DC.IU.p']   <- 0
  C.DC.IU[i, 'C.DC.IU.p']   <- (exp(-k2) * C.DC.IU[i - 1, 2]) +
                                 ((1 - exp(-k2)) / k2) * I.DC.IU.p[i - 1]
}
C.DC.IU <- apply(C.DC.IU, 1, sum)

# 1.3. Var1A (delta.C.DC.IU) = C.DC.IU.t - C.DC.IU.t-1
var1A = ts(data = matrix(data = 0, ncol = 1), start = 1900, end = 2015, frequency = 1)
for(i in 2:length(C.DC.IU)){
    var1A[i] <- C.DC.IU[i] - C.DC.IU[i - 1]
}

# ---------------------------------------------------------------------------------------------------------------
# 2. var1B = carbon stock change in products in SWDS from DC
# 2.1 DD.m.t = W.m.t * dm * df * X (where, X = f1 * Zd + f2 * Zl)
X       <- f1 * tsdat2[, 'Zd'] + f2 * tsdat2[, 'Zl']
DD.p   <- tsdat2[, 'Wpap'] * d1 * df * X
DD.w  <- tsdat2[, 'Ww'] * d2 * df * X
DD.in  <- tsdat2[, 'Win'] * d3 * df * X

# D.a.m.t = DD.m.t + D.a.m.t-1 * exp(- jm)
Da <- ts(data = matrix(data = 0, ncol = 3), start = 1900, end = 2015, frequency = 1)
colnames(Da) <- c('Da.p', 'Da.w', 'Da.in')
for(i in 2:length(DD.p)) {
  Da[i, 'Da.p']   <- DD.p[i] + (Da[i-1, 'Da.p'] * exp(-j1))
  Da[i, 'Da.w']  <- DD.w[i] + (Da[i-1, 'Da.w'] * exp(-j2))
  Da[i, 'Da.in']  <- DD.in[i] + (Da[i-1, 'Da.in'] * exp(-j3))
}

# D.d.m.t = D.a.m.t-1 * (1 - exp(-jm)
Dd <- ts(data = matrix(data = 0, ncol = 3), start = 1900, end = 2015, frequency = 1)
colnames(Dd) <- c('Dd.p', 'Dd.w', 'Dd.in')
for(i in 2:length(DD.p)) {
  Dd[i, 'Dd.p']  <- Da[i-1, 'Da.p'] * (1 - exp(-j1))
  Dd[i, 'Dd.w']  <- Da[i-1, 'Da.w']  * (1 - exp(-j2))
  Dd[i, 'Dd.in'] <- Da[i-1, 'Da.in']  * (1 - exp(-j3))
}

# M.g.t = sum(m = 1 to 3) [D.d.m.t * F * 16 / 12] and M.e.t = M.g.t * (1 - ox) * 21(= GWP CH4)
```

```
M.g <- (Dd[, 'Dd.p'] + Dd[, 'Dd.w'] + Dd[, 'Dd.in']) * F * 16 / 12
M.e <- M.g * (1 - ox) * 21

# 2.2 CO2 emission (C.t) = M.g.t * (((1 - F) / F) + ox) * (44 / 16)
C.t <- M.g * ((1 - F) / F + ox) * (44 / 16)

# 2.3 stock (C.DC.SW.t) = [sum(1990 - 2015) (Wm * dm * (1 - df) * X)] - [M.e + C.t] * (12 / 44)
C.a.t <- ts(data = matrix(data = 0, ncol = 1), start = 1900, end = 2015, frequency = 1)
for(i in 2:length(C.t)) {
     C.a.t[i]  <- ((tsdat2[, 'Wpap'] * d1 + tsdat2[, 'Ww'] * d2 +
                   tsdat2[, 'Win'] * d3) * (1 - df) * X)[i] + C.a.t[i-1]
}

C.DC.SW <- ts(data = matrix(data = 0, ncol = 1), start = 1900, end = 2015, frequency = 1)
for(i in 2:length(C.a.t)) {
      C.DC.SW[i]  <- C.a.t[i] - (M.e + C.t)[i] * (12 / 44)
}

# 2.4.  Var1B (delta.C.DC.SW) = C.DC.SW.t - C.DC.SW.t-1
var1B <- ts(data = matrix(data = 0,  ncol = 1), start = 1900, end = 2015, frequency = 1)
for(i in 2:length(C.DC.SW)){
       var1B[i] <- C.DC.SW[i] - C.DC.SW[i - 1]
}

# ----------------------------------------------------------------------------------------------------------------
# 3. V2A = carbon stock change in HWP in use (IU) from domestic harvest (DH)
# 3.1 I.DH.IU.i.t = (NP / (NP + NI - NE + TI - TE + VI - VE) * (a * Production)
K <- (tsdat1[, 'NP'] / (tsdat1[, 'NP'] + tsdat1[, 'NI'] - tsdat1[, 'NE']
       + tsdat1[, 'TI'] - tsdat1[, 'TE'] + tsdat1[, 'VI'] - tsdat1[, 'VE']))
I.DH.IU.w <- K * (a1 * (tsdat1[, 'LP'] + tsdat1[, 'OP']) + a2 * tsdat1[, 'BP'])
I.DH.IU.p  <- K * (a3 * tsdat1[, 'JP'])

# 3.2 C.DH.IU (stock) = exp(-ki) * C.DH.IU.t-1 + ((1 - exp(-ki)) / ki) * I.DH.IU.i.t-1
C.DH.IU <- ts(data = matrix(data = 0, ncol = 2), start = 1900, end = 2015, frequency = 1)
colnames(C.DH.IU) <- c('C.DH.IU.w', 'C.DH.IU.p')
for(i in 2:length(I.DH.IU.w)) {
  C.DH.IU [1, 'C.DH.IU.w'] <- 0
  C.DH.IU [i, 'C.DH.IU.w'] <- (exp(-k1) * C.DH.IU [i - 1, 'C.DH.IU.w']) +
                              ((1 - exp(-k1)) / k1) * I.DH.IU.w[i - 1]
  C.DH.IU [1, 'C.DH.IU.p'] <- 0
  C.DH.IU [i, 'C.DH.IU.p'] <- (exp(-k2) * C.DH.IU [i - 1, 'C.DH.IU.p']) +
                              ((1 - exp(-k2)) / k2) * I.DH.IU.p[i -1]
}
C.DH.IU <- apply(C.DH.IU, 1, sum)

# 3.3 Var2A (delta.C.DH.IU.t) = C.DH.IU.t - C.DH.IU.t-1
var2A = ts(data = matrix(data = 0,  ncol = 1), start = 1900, end = 2015, frequency = 1)
for(i in 2:length(C.DH.IU)){
   var2A[i] <- C.DH.IU[i] - C.DH.IU[i - 1]
}
```

```
 # -----------------------------------------------------------------------------------------------------------
 # 4. Var2B (delta.C.DH.SW) = var1B * [ 1 - (IW / (IW + NP))]
IW  <- tsdat1[, 'LI'] + tsdat1[, 'BI'] + tsdat1[, 'JI']+ tsdat1[, 'GI'] + tsdat1[, 'NI'] + tsdat1[, 'TI']
            + tsdat1[, 'VI']
 var2B <- var1B * (1 - (IW / (IW + tsdat1[, 'NP'])))

# -----------------------------------------------------------------------------------------------------------
 # 5. Var3 (P.IM) = a1 * (TI + VI + LI) + a2 * (JI + GI) + a4 * UI + a1 * b * RI
 var3 <- a1 * (tsdat1[, 'TI']  + tsdat1[, 'VI'] + tsdat1[, 'LI']) + a2 * tsdat1[, 'BI'] + a3 * (tsdat1[, 'JI']
            + tsdat1[, 'GI']) + a4 * tsdat1[, 'UI'] + a1 * b * tsdat1[, 'RI']

 # -----------------------------------------------------------------------------------------------------------
 # 6. Var4 (P.EX) = a1 * (TE + VE + LE) + a2 * (JE + GE) + a4 * UI + a1 * b * RI
 var4 <- a1 * (tsdat1[, 'TE']  + tsdat1[, 'VE'] + tsdat1[, 'LE']) + a2 * tsdat1[, 'BE'] +
            a3 * (tsdat1[, 'JE'] + tsdat1[, 'GE']) + a4 * tsdat1[, 'UE'] + a1 * b * tsdat1[, 'RE']

# -----------------------------------------------------------------------------------------------------------
 # 7. Var5 (H.t) = a1 * b * RP  & var7 (rC.DH.t) = H.t - delta.C.DH.IU - delta.C.DH.SW
 var5 <- a1 * b * tsdat1[, 'RP']
 var7 <- var5 - var2A - var2B

# -----------------------------------------------------------------------------------------------------------
# 8. Combining all variables
 variables <- round(data.frame (year = 1990:2014, cbind(var1A, var1B, var2A, var2B, var3, var4,
                    var5, var7)[-c(1:90, 116), ]), digits = 1)

# -----------------------------------------------------------------------------------------------------------
# 9. Stock change (SC) = (var1A + var1B) * (-44/12), production approach (P) = (var2A + var2B)
#* (-#44/12), atmospheric-flow (AF) = (var1A + var1B + var4 - var3)  * (-44/12), simple decay
#(USDA) = (var5 - #var7)  * (-44/12)
 SC <- (var1A + var1B) * (-44/12)
 P   <- (var2A + var2B) * (-44/12)
 AF <- (var1A + var1B + var4 - var3) * (-44/12)
 SD <- (var5 - var7) * (-44/12)

 approaches <- round(data.frame(year = 1990:2014, cbind(SC, P, AF, SD) [-c(1:90, 116), ]),
                       digits = 1)
 colnames(approaches) <- c('year', "Stock-change", "Production", "Atmospheric-flow",
                                      "Simple decay")

  # -----------------------------------------------------------------------------------------------------------
  # 10. Output
  result <- list(variables = variables, approaches = approaches)
  return(result)
}
```

APPENDIX B

R CODE FOR CHAPTER III

B.1 R code for uncertainty analysis in the U.S. HWP carbon estimates

```
# ----------------------------------------------------------------------------------------------------------------
# Brief contents
# 0. Sources and parameters
# 1. Simulation and distribution of uncertain parameters
# 2. Saving results
# 3. Values - degree of freedom (df) and confidence interval (cf)
# 4. Mean and confidence interval for HWP variables
# 5. Mean and confidence interval for approaches
# 6. Export results

# ----------------------------------------------------------------------------------------------------------------
# 0. Sources and parameters
source("carbon.R"); source("HWP.R")

parms <- list(a1 = 0.0000005, a2 = 0.000000295, a3 = 0.00000045, a4 = 0.000000765, b = 1.12,
          k1 = 0.0231, k2 = 0.231, d1 = 0.4, d2 = 0.43, d3 = 0.2, df = 0.5, j1 = 0.05, j2 = 0.025,
          j3 = 0.03, f1 = 0.6, f2 = 1, F = 0.5, ox = 0.1)

# ----------------------------------------------------------------------------------------------------------------
# 1. Simulation and distribution of uncertain parameters
set.seed(123); n <- 50000

a11 <- rnorm(n, mean = 0.0000005, sd = 0.00000078)
a22 <- rnorm(n, mean = 0.000000295, sd = 0.00000018)
a33 <- rnorm(n, mean = 0.00000045, sd = 0.00000027)
a44 <- rnorm(n, mean = 0.000000765, sd = 0.00000046)
k11 <- rtriang(n, min = 0.01155, mode = 0.0231, max = 0.0365)
k22 <- rtriang(n, min = 0.1155, mode = 0.231, max = 0.365)
j11 <- rtriang(n, min = 0.025, mode = 0.05, max = 0.075)
j22 <- rtriang(n, min = 0.0125, mode = 0.025, max = 0.0375)
j33 <- rtriang(n, min = 0.015, mode = 0.03, max = 0.045)
f11 <- rtriang(n, min = 0.03, mode = 0.06, max = 0.09)
f22 <- rtriang(n, min = 0.05, mode = 1, max = 1.5)

# ----------------------------------------------------------------------------------------------------------------
# 2. Saving results
res <- list()
for(i in 1:n){
 res[[i]] <- carbon(a1 = a11[i], a2 = a22[i], a3 = a33[i], a4 = a44[i], b = 1.12, k1 = k11[i],
              k2 = k22[i], d1 = 0.4, d2 = 0.43, d3 = 0.2, df = 0.5, j1 = j11[i], j2 = j22[i],
              j3 = j33[i], f1 = f11[i], f2 = f22[i], F = 0.5, ox = 0.5)
}

# 2.1 Saving results for variables - variables extraction
out <- NULL
for(i in 1:n){
```

```
    one <- res[[i]]$variable
    out <- rbind(out, one)
}
out2 <- out[order(out$year), ]

# 2.2 Saving results for approaches - approaches extraction
out3 <- NULL
for(i in 1:n){
    two <- res[[i]]$approaches
    out3 <- rbind(out3, two)
}
out4 <- out3[order(out3$year), ]

# ---------------------------------------------------------------------------------------------------------------
# 3. Values - degree of freedom (df) and confidence interval (cf)
df <- n - 1; cf <- 0.95

# ---------------------------------------------------------------------------------------------------------------
# 4. Mean and confidence interval for variables
mv <- aggregate(out2[, 2:9], list(out2$year), mean)
colnames(mv) <- c('year', 'var1A', 'var1B', 'var2A', 'var2B', 'var3', 'var4',  'var5', 'var7')

sdv <- aggregate(out2[, 2:9], list(out2$year), sd)
colnames(sdv) <- c('year', 'var1A', 'var1B', 'var2A', 'var2B', 'var3', 'var4',  'var5', 'var7')

lv <- mv[, 2:9] - qt((1 + cf) / 2, df) * sdv[, 2:9] / sqrt(n)
uv <- mv[, 2:9] + qt((1 + cf) / 2, df) * sdv[, 2:9] / sqrt(n)
cv <- cbind(lv$var1A, uv$var1A, lv$var1B, uv$var1B, lv$var2A, uv$var2A, lv$var2B,
        uv$var2B, lv$var3, uv$var3, lv$var4, uv$var4, lv$var5, uv$var5, lv$var7,
        uv$var7)
colnames(cv) <- c('lvar1A', 'uvar1A', 'lvar1B', 'uvar1B', 'lvar2A', 'uvar2A', 'lvar2B',
                'uvar2B', 'lvar3', 'uvar3', 'lvar4', 'uvar4', 'lvar5', 'uvar5',  'lvar7',  'uvar7')

# ---------------------------------------------------------------------------------------------------------------
# 5. Mean and confidence interval for approaches
ma <- aggregate(out4[, 2:5], list(out4$year), mean)
colnames(ma) <- c('Year', 'SC', 'P', 'AF', 'SD')

sda <- aggregate(out4[, 2:5], list(out4$year), sd)
colnames(USDA) <- c('Year', 'SC', 'P', 'AF', 'SD')

la <- ma[, 2:5] - qt((1 + cf) / 2, df) * sda[, 2:5] / sqrt(n)
ua <- ma[, 2:5] + qt((1 + cf) / 2, df) * sda[, 2:5] / sqrt(n)
ca <- cbind(la$SC, ua$SC, la$P, ua$P, la$AF, ua$AF, la$SD, ua$SD)
colnames(ca) <- c('lSC', 'uSC', 'lP', 'uP', 'lAF', 'uAF', 'lSD', 'uSD')

# ---------------------------------------------------------------------------------------------------------------
```

```
# 6. Export results
table3.1 <- mv; table3.2 <- cv; table3.3 <- ma; table3.4 <- ca
tables    <- listn(table3.1, table3.2, table3.3, table3.4)
write.listx(z = tables, file = "UN-50000.xlsx")
```

B.2 R code for sensitivity analysis for the year 2014

```
a14 <- data.frame(matrix(data = NA, nrow = n, ncol = 5))
for (j in 1:n){
        a14[j, ] <- res[[j]]$approaches[25, ]
}
a14

# varying all parameters variances
vs      <- var(a14[, 2]); vp <- var(a14[, 3]); va <- var(a14[, 4]); vd <- var(a14[, 5])
table0 <- cbind(vs, vp, va, vd)

# varying a11
res1 <- list()
for(i in 1:n){
  res1[[i]] <- carb(a1 = a11[i], a2 = 0.000000295, a3 = 0.00000045, a4 = 0.000000765,
                    b = 1.12, k1 = 0.0231, k2 = 0.231, d1 = 0.4, d2 = 0.43, d3 = 0.2, df = 0.5,
                    j1 = 0.05, j2 = 0.025, j3 = 0.03, f1 = 0.6, f2 = 1, F = 0.5, ox = 0.1)
}
a1 <- data.frame(matrix(data = NA, nrow = n, ncol = 5))
for (j in 1:n){
        a1[j, ] <- res1[[j]]$approaches[25, ]
}

vs1     <- var(a1[, 2]); vp1 <- var(a1[, 3]); va1 <- var(a1[, 4]); vd1 <- var(a1[, 5])
table1 <- cbind(vs1 / vs, vp1 / vp, va1 / va, vd1 / vd)

# varying a22
res2 <- list()
for(i in 1:n){
  res2[[i]] <- carb(a1 = 0.0000005, a2 = a22[i], a3 = 0.00000045, a4 = 0.000000765,
                     b = 1.12, k1 = 0.0231, k2 = 0.231, d1 = 0.4, d2 = 0.43, d3 = 0.2, df = 0.5,
                    j1 = 0.05, j2 = 0.025, j3 = 0.03, f1 = 0.6, f2 = 1, F = 0.5, ox = 0.1)
}

a2 <- data.frame(matrix(data = NA, nrow = n, ncol = 5))
for (j in 1:n){
        a2[j, ] <- res2[[j]]$approaches[25, ]
}

vs2     <- var(a2[, 2]); vp2 <- var(a2[, 3]); va2 <- var(a2[, 4]); vd2 <- var(a2[, 5])
```

```
table2 <- cbind(vs2 / vs, vp2 / vp, va2 / va, vd2 / vd)

# varying a33
res3 <- list()
for(i in 1:n){
  res3[[i]] <- carb(a1 = 0.0000005, a2 = 0.000000295, a3 = a33[i], a4 = 0.000000765,
                    b = 1.12, k1 = 0.0231, k2 = 0.231, d1 = 0.4, d2 = 0.43, d3 = 0.2, df = 0.5,
                    j1 = 0.05, j2 = 0.025, j3 = 0.03, f1 = 0.6, f2 = 1, F = 0.5, ox = 0.1)
}

a3 <- data.frame(matrix(data = NA, nrow = n, ncol = 5))
for (j in 1:n){
        a3[j, ] <- res3[[j]]$approaches[25, ]
}

vs3     <- var(a3[, 2]); vp3 <- var(a3[, 3]); va3 <- var(a3[, 4]); vd3 <- var(a3[, 5])
table3 <- cbind(vs3 / vs, vp3 / vp, va3 / va, vd3 / vd)

# varying a44
res4 <- list()
for(i in 1:n){
  res4[[i]] <- carb(a1 = 0.0000005, a2 = 0.000000295, a3 = 0.00000045, a4 = a44[i],
                   b = 1.12, k1 = 0.0231, k2 = 0.231, d1 = 0.4, d2 = 0.43, d3 = 0.2, df = 0.5,
                    j1 = 0.05, j2 = 0.025, j3 = 0.03, f1 = 0.6, f2 = 1, F = 0.5, ox = 0.1)
}

a4 <- data.frame(matrix(data = NA, nrow = n, ncol = 5))
for (j in 1:n){
        a4[j, ] <- res4[[j]]$approaches[25, ]
}

vs4     <- var(a4[, 2]); vp4 <- var(a4[, 3]); va4 <- var(a4[, 4]); vd4 <- var(a4[, 5])
table4 <- cbind(vs4 / vs, vp4 / vp, va4 / va, vd4 / vd)

# varying k11
res5 <- list()
for(i in 1:n){
  res5[[i]] <- carb(a1 = 0.0000005, a2 = 0.000000295, a3 = 0.00000045, a4 =
                   0.000000765, b = 1.12, k1 = k11[i], k2 = 0.231, d1 = 0.4, d2 = 0.43, d3 = 0.2,
                   df = 0.5, j1 = 0.05, j2 = 0.025, j3 = 0.03, f1 = 0.6, f2 = 1, F = 0.5, ox = 0.1)
}

a5 <- data.frame(matrix(data = NA, nrow = n, ncol = 5))
for (j in 1:n){
        a5[j, ] <- res5[[j]]$approaches[25, ]
```

```
}

vs5     <- var(a5[, 2]); vp5 <- var(a5[, 3]); va5 <- var(a5[, 4]); vd5 <- var(a5[, 5])
table5 <- cbind(vs5 / vs, vp5 / vp, va5 / va, vd5 / vd)

# varying k22
res6 <- list()
for(i in 1:n){
  res6[[i]] <- carb(a1 = 0.0000005, a2 = 0.000000295, a3 = 0.00000045, a4 =
              0.000000765, b = 1.12, k1 = 0.0231, k2 = k22[i], d1 = 0.4, d2 = 0.43, d3 = 0.2,
              df = 0.5, j1 = 0.05, j2 = 0.025, j3 = 0.03, f1 = 0.6, f2 = 1, F = 0.5, ox = 0.1)
}

a6 <- data.frame(matrix(data = NA, nrow = n, ncol = 5))
for (j in 1:n){
        a6[j, ] <- res6[[j]]$approaches[25, ]
}

vs6     <- var(a6[, 2]); vp6 <- var(a6[, 3]); va6 <- var(a6[, 4]); vd6 <- var(a6[, 5])
table6 <- cbind(vs6 / vs, vp6 / vp, va6 / va, vd6 / vd)

# varying j11
res7 <- list()
for(i in 1:n){
  res7[[i]] <- carb(a1 = 0.0000005, a2 = 0.000000295, a3 = 0.00000045, a4 =
              0.000000765, b = 1.12, k1 = 0.0231, k2 = 0.231, d1 = 0.4, d2 = 0.43, d3 = 0.2,
              df = 0.5, j1 = j11[i], j2 = 0.025, j3 = 0.03, f1 = 0.6, f2 = 1, F = 0.5, ox = 0.1)
}

a7 <- data.frame(matrix(data = NA, nrow = n, ncol = 5))
for (j in 1:n){
        a7[j, ] <- res7[[j]]$approaches[25, ]
}

vs7     <- var(a7[, 2]); vp7 <- var(a7[, 3]); va7 <- var(a7[, 4]); vd7 <- var(a7[, 5])
table7 <- cbind(vs7 / vs, vp7 / vp, va7 / va, vd7 / vd)

# varying j22
res8 <- list()
for(i in 1:n){
  res8[[i]] <- carb(a1 = 0.0000005, a2 = 0.000000295, a3 = 0.00000045, a4 =
               0.000000765, b = 1.12, k1 = 0.0231, k2 = 0.231, d1 = 0.4, d2 = 0.43, d3 = 0.2,
               df = 0.5, j1 = 0.05, j2 = j22[i], j3 = 0.03, f1 = 0.6, f2 = 1, F = 0.5, ox = 0.1)
}
```

```
a8 <- data.frame(matrix(data = NA, nrow = n, ncol = 5))
for (j in 1:n){
        a8[j, ] <- res8[[j]]$approaches[25, ]
}

vs8 <- var(a8[, 2]); vp8 <- var(a8[, 3]); va8 <- var(a8[, 4]); vd8 <- var(a8[, 5])
table8 <- cbind(vs8 / vs, vp8 / vp, va8 / va, vd8 / vd)

# varying j33
res9 <- list()
for(i in 1:n){
  res9[[i]] <- carb(a1 = 0.0000005, a2 = 0.000000295, a3 = 0.00000045, a4 =
                0.000000765, b = 1.12, k1 = 0.0231, k2 = 0.231, d1 = 0.4, d2 = 0.43, d3 = 0.2,
                df = 0.5, j1 = 0.05, j2 = 0.025, j3 = j33[i], f1 = 0.6, f2 = 1, F = 0.5, ox = 0.1)
}

a9 <- data.frame(matrix(data = NA, nrow = n, ncol = 5))
for (j in 1:n){
        a9[j, ] <- res9[[j]]$approaches[25, ]
}

vs9     <- var(a9[, 2]); vp9 <- var(a9[, 3]); va9 <- var(a9[, 4]); vd9 <- var(a9[, 5])
table9 <- cbind(vs9 / vs, vp9 / vp, va9 / va, vd9 / vd)

# varying f11
res10 <- list()
for(i in 1:n){
  res10[[i]] <- carb(a1 = 0.0000005, a2 = 0.000000295, a3 = 0.00000045, a4 =
                 0.000000765, b = 1.12, k1 = 0.0231, k2 = 0.231, d1 = 0.4, d2 = 0.43, d3 = 0.2,
                 df = 0.5, j1 = 0.05, j2 = 0.025, j3 = 0.03, f1 = f11[i], f2 = 1, F = 0.5, ox = 0.1)
}

a10 <- data.frame(matrix(data = NA, nrow = n, ncol = 5))
for (j in 1:n){
        a10[j, ] <- res10[[j]]$approaches[25, ]
}

vs10 <- var(a10[, 2]); vp10 <- var(a10[, 3]); va10 <- var(a10[, 4]); vd10 <- var(a10[, 5])
table10 <- cbind(vs10 / vs, vp10 / vp, va10 / va, vd10 / vd)

# varying f22
res11 <- list()
for(i in 1:n){
```

```
  res11[[i]] <- carb(a1 = 0.0000005, a2 = 0.000000295, a3 = 0.00000045, a4 =
              0.000000765, b = 1.12, k1 = 0.0231, k2 = 0.231, d1 = 0.4, d2 = 0.43, d3 = 0.2,
              df = 0.5, j1 = 0.05, j2 = 0.025, j3 = 0.03, f1 = 0.6, f2 = f22[i], F = 0.5, ox = 0.1)
}

a11 <- data.frame(matrix(data = NA, nrow = n, ncol = 5))
for (j in 1:n){
        a11[j, ] <- res11[[j]]$approaches[25, ]
}

vs11    <- var(a11[, 2]); vp11 <- var(a11[, 3]); va11 <- var(a11[, 4]); vd11 <- var(a11[, 5])
table11 <- cbind(vs11 / vs, vp11 / vp, va11 / va, vd11 / vd)

# Export results
tab <- rbind(table1, table2, table3, table4, table5, table6, table7, table8, table9, table10,
           table11)
table <- listn(Green et al.)
write.listx(z = table, file = 'sen-final-50000-indices.xlsx')
```

APPENDIX C

R CODE FOR CHAPTER IV

C.1 R program for estimating carbon embodied in trade of the U.S. HWP

```
# -----------------------------------------------------------------------------------------------------------------
# Brief contents
# 0. Libraries and global settings
# 1. Import raw data
# 2. Direct and indirect carbon emissions
# 3. Emissions embodied by each sector in each region
# 4. Emissions embodied in harvested wood products sectors only
# 5. Multilateral trade balance of wood sector and paper sector
# 6. Emissions from production-based and consumption-based method
# 7. Per-capita emissions versus per-capita GDP
# 8. Graphs
# 9. Export results - tables and figures

# -----------------------------------------------------------------------------------------------------------------
# 0. Libraries and global settings
library(xlsx); library(XLConnect); library(erer); library(grid); library(ggplot2)
setwd("C:/Users/Prativa/Dropbox/3/0. R/data.xlsx"); getwd()
source("write.listx.r")
options(stringsAsFactors = FALSE, width = 72, scipen = 999)

# -----------------------------------------------------------------------------------------------------------------
# 1. Import raw data
des    <- read.xlsx(file = "data.xlsx", sheetName = "Description")
data1 <- read.xlsx(file = "data.xlsx", sheetName = "MRIO")
data2 <- read.xlsx(file = "data.xlsx", sheetName = "DCE")
data3 <- read.xlsx(file = "data.xlsx", sheetName = "GDP")

table4.1 <- des[1:15, 4:5]
table4.2 <- data2[1:16, 2:10]  / 1000
allname <- c('US', 'Brazil', 'Canada', 'China', 'Germany', 'Japan', 'Mexico', 'Russia',  'ROW')
colnames(table4.2) <- allname
rownames(table4.2) <- c('20', '21t22', '23', '24t25', '27t28', '36t37', '51t52', '60t62', '64', '70t74',
                                     'AtB', 'C', 'F', 'J', 'LtO', 'Total')

# -----------------------------------------------------------------------------------------------------------------
# 2. Carbon emissions direct and indirect
# 2.1 Coefficient matrix (A) and Leontief Inverse matrix (I)
A <- round(as.matrix(data1[, 2:136]) %*% (data1[, 146] ^ (-1) * diag(135)), digits = 4)
L <- round(solve(diag(135) - A), digits = 4)

# 2.2 Direct emission intensity (e) and diagonalizing it (ed)
f   <- cbind(t(data2[-16, 'US']), t(data2[-16, 'BRA']), t(data2[-16, 'CAN']),  t(data2[-16, 'CHN']),
         t(data2[-16, 'DEU']), t(data2[-16, 'JPN']), t(data2[-16, 'MEX']), t(data2[-16, 'RUS']),
         t(data2[-16, 'ROW']))
e   <- f / t(data1[, 'TO'])
ed <- e[1, ] * diag(135)
```

```
# 2.3 Carbon emissions associated with final demand (E = ed * L)
E <- ed %*% L

# -------------------------------------------------------------------------------------------------------------
# 3. Emissions embodied by each sector in each region
# 3.1 Diagonalizing each region final demand by each sector (yd)
yfd <- round(data1[, c('Usfd', 'BRAfd', 'CANfd', 'CHNfd', 'DEUfd', 'JPNfd', 'MEXfd', 'RUSfd',
        'ROWfd')], 2)

yd <- matrix(data = 0, ncol = 135, nrow = 135)
for(m in 1:9){
 for(k in 1:9){
 m2  <- ((m - 1) * 15 + 1) : (m * 15)
 k2  <- ((k - 1) * 15 + 1) : (k * 15)
 yd[m2, k2] <- diag(x = yfd[m2, k])
 }
}

# 3.2 Emissions embodied in final demand by each sector in each region (Ers)
Ers <- E %*% yd

# -------------------------------------------------------------------------------------------------------------
# 4. Emissions embodied in harvested wood products sectors only
Eh <- Ers[, c(1:2, 16:17, 31:32, 46:47, 61:62, 76:77, 91:92, 106:107, 121:122)]
colnames(Timmer et al.) <- c('USc1', 'USc2', 'BRAc1', 'BRAc2', 'CANc1', 'CANc2', 'CHNc1',
                  'CHNc2',  'DEUc1', 'DEUc2', 'JPNc1', 'JPNc2', 'MEXc1', 'MEXc2', 'RUSc1',
                  'RUSc2', 'ROWc1', 'ROWc2')

# 4.1 Trade balance for harvested wood products sector
Ehp <- rbind(colSums(Eh[1:15, ]), colSums(Eh[16:30, ]), colSums(Eh[31:45, ]),
        colSums(Eh[46:60, ]), colSums(Eh[61:75, ]), colSums(Eh[76:90, ]),
        colSums(Eh[91:105, ]), colSums(Eh[106:120, ]), colSums(Eh[121:135, ])) / 1000

# 4.2 Multilateral trade balance of embodied carbon (me)
c1 <- Ehp[, c('USc1', 'BRAc1', 'CANc1', 'CHNc1', 'DEUc1', 'JPNc1', 'MEXc1',  'RUSc1',
       'ROWc1') ]
c2 <- Ehp[, c('USc2', 'BRAc2', 'CANc2', 'CHNc2', 'DEUc2', 'JPNc2', 'MEXc2',  'RUSc2',
       'ROWc2')]
me <- round(c1 + c2, digits = 4)
rownames(me) <- colnames(me) <- allname

# 4.2.1 Emissions embodied in imports (EI)
im <- me
im[row(im) == col(im)] = 0
imp <- im; imp

EI <- colSums(imp)

# 4.2.2 Total emissions under consumption-based and share of embodied emissions
tecons <- colSums(me)
```

```
share   <- (EI / tecons) * 100

# 4.2.3 combining all
table3 <- rbind(me, tecons, EI, share)
rownames(table3) <- c(rownames(me), 'Total emissions (Consumer responsibility)',
                      'Emission in imports', 'Share of embodied emissions (%)')

# 4.3 Net trade balance of embodied carbon (net)
net <- me - t(me); net
tb   <- colSums(net); tb
table4 <- rbind(net, tb); table4
rownames(table4) <- c(rownames(net), 'Trade balance')

# ----------------------------------------------------------------------------------------------------------
# 5. Multilateral trade balance of wood sector (Ewp) and paper sector (Epp)
Ewp <- round(c1, digits = 4)
rownames(Ewp) <- colnames(Ewp) <- allname
table4.5 <- Ewp

Epp <- round(c2, digits = 4)
rownames(Epp) <- colnames(Epp) <- allname
table4.6 <- Epp

# 5.1 Exports to and imports from other countries - wood products sector
name     <- c('Brazil', 'Canada', 'China', 'Germany', 'Japan', 'Mexico', 'Russia', 'ROW')
EEw      <- Ewp[1, name]
EIw      <- Ewp[name, 1]
BEETw <- EEw - EIw

# 5.2 Exports to and imports from other countries - paper products sector
EEp      <- Epp[1, name]
EIp      <- Epp[name, 1]
BEETp <- EEp - EIp

# ----------------------------------------------------------------------------------------------------------
# 6. Emissions from production-based accounting (Ep) and consumption-based (Gemechu et al.)
Ep <- rowSums(me[, 1:9])
Ec <- colSums(me[1:9, ])

# ----------------------------------------------------------------------------------------------------------
# 7. Per-capita emissions versus per-capita gdp
# 7.1 In log forms - gdp (lgdp), direct emissions per capita (lepc), emissions under consumer
#responsibility (lec), emissions from wood sector (lew), emissions from paper sector (lep)
lgdp <- log10(data3[1:8, 'gdp.capita'])
lepc <- log10(data3[1:8, 'dce'] / data3[1:8, 'pop'])
lec   <- log10(as.matrix(Ec[1:8])[, 1] / data3[1:8, 'pop'])
lew  <- log10(as.matrix(colSums(Ewp[, 1:8])[1:8])[, 1] / data3[1:8, 'pop'])
lep  <- log10(as.matrix(colSums(Epp[, 1:8])[1:8])[, 1] / data3[1:8, 'pop'])
```

```
dat <- data.frame(cbind(lgdp, lepc, lec, lew, lep)); dat

# 7.2 Regression and summary statistics for lepc, lec, lew, and lep
rlepc <- lm(lepc ~ lgdp, data = dat)
rlec   <- lm(lec ~ lgdp, data = dat)
rlew  <- lm(lew ~ lgdp, data = dat)
rlep   <- lm(lep ~ lgdp, data = dat)

reg   <- listn(rlepc, rlec, rlew, rlep); reg
els <- NULL
for(i in 1:4){
 res <- reg[[i]]
 els <- cbind(els, c(summary(res)$coefficients[2, c(1, 4)],
          summary(res)$r.squared))
}
elst <- els[c(1, 3, 2), ]
colnames(elst)  <- c('DE', 'EEC', 'EEC-WP', 'EEC-PP')
rownames(elst)  <- c('Elasticity(E)', 'R2', 'pvalue')
table4.7 <- elst

# ------------------------------------------------------------------------------------------------------------
# 8. Graphs
# 8.1 Bar diagram for consumption-based vs. production-based emissions
cp     <- stack(data.frame(cbind(Ec, Ep)))
dats  <- cbind(rep(c('US', 'Brazil', 'Canada', 'China', 'Germany', 'Japan', 'Mexico', 'Russia',
            'ROW')), cp)
colnames(dats) <- c('country', 'values', 'types')

cpe <- ggplot(data = dats, aes(x = country, y = values, fill = types, group = types)) +
          geom_bar(width = 0.7, color = "black", stat = "identity", position = position_dodge()) +
          labs(y = "Mt CO2") +
          scale_fill_manual(values = c("#990000", "blue"),
            labels = c('Consumption-based emissions', 'Production-based emissions')) +
          scale_y_continuous(expand = c(0, 0))
fig4.1 <- cpe + theme_bw() +
          theme(axis.text.y = element_text(size = 12, family = "serif"),
            axis.title.x = element_blank(),
            axis.title.y = element_text(vjust = 1.5),
            legend.position  = "top",
            legend.direction = "vertical",
            legend.title = element_blank(),
            legend.margin = unit(1, "cm"),
            panel.grid.major = element_line(color = "NA"),
            panel.border = element_rect(color = "NA"),
            axis.line.x = element_line(color = "black"),
            axis.line.y = element_line(color = "black"))

# 8.2 Bar diagram for wood products sector
we      <- stack(data.frame(cbind(EEw, EIw, BEETw))); we
```

```
dats1  <- cbind(rep(c('Brazil', 'Canada', 'China', 'Germany', 'Japan', 'Mexico',  'Russia', 'ROW')),
          we)
colnames(dats1) <- c('country', 'values', 'emissions')

ewp <- ggplot(data = dats1, aes(x =country, y = values, fill = emissions)) +
        geom_bar(width = 0.7, color = "black", stat = "identity", position = position_dodge()) +
        labs(y = "Mt CO2") +
        coord_flip()+
        scale_fill_manual(values = c("#990000", "blue", "green"),
          labels = c('Emissions in trade', 'Emissions in exports', 'Emissions balance in imports')) +
        scale_y_continuous(expand = c(0, 0), limits = c(-0.4, 0.4))
fig4.2 <- ewp + theme_bw() +
      theme(axis.text.y = element_text(size = 12, family = "serif"),
         axis.title.x =   element_text(vjust = 0),
         axis.title.y = element_blank(),
         legend.position  = "top",
         legend.direction = "horizontal",
         legend.title = element_blank(),
         legend.margin = unit(1, "cm"),
         panel.grid.major = element_line(color = "NA"),
         panel.border = element_rect(color = "NA"),
         axis.line.x = element_line(color = "black"),
         axis.line.y = element_line(color = "black"))

# 8.3 Bar diagram for paper products sector
pe       <- stack(data.frame(cbind(EEp, EIp, BEETp)))
dats2  <- cbind(rep(c('Brazil', 'Canada', 'China', 'Germany', 'Japan', 'Mexico', 'Russia', 'ROW')),
           pe)
colnames(dats2) <- c('country', 'values', 'emissions')

fig4.3 <- fig4.2 %+% dats2 + scale_y_continuous(expand = c(0, 0), limits = c(-2.0, 3)

# 8.4 Plot for per-capita emissions as a function of per-capita gdp
da1 <- ggplot(dat, aes(x = lgdp, y = lepc)) +
       geom_point(size = 2) +
       geom_smooth(method = "lm", se = FALSE, fullrange = TRUE) +
       geom_text(aes(label = c('US', 'Brazil', 'Canada', 'China', 'Germany', 'Japan', 'Mexico',
            'Russia')), check_overlap = TRUE, vjust = 0.5, hjust = -.18, size = 2.5) +
       scale_x_continuous(limits = c(3.5, 5))
fig4.4 <- da1 + labs(x = 'log(GDP)', y = 'log(CO2)')

# 8.5 Plot for consumption based emissions and gdp
da2 <- ggplot(dat, aes(x = lgdp, y = lec)) +
      geom_point(size = 2.5) +
      geom_smooth(method = "lm", se = FALSE, fullrange = TRUE) +
      geom_text(aes(label = c('US', 'Brazil', 'Canada', 'China', 'Germany',  'Japan', 'Mexico',
         'Russia')), check_overlap = TRUE, vjust = 0.5, hjust = -.2, size = 3) +
      scale_x_continuous(limits = c(3.5, 5))
fig4.5 <- da2 + labs(x = 'log(GDP)', y = 'log(CO2)')
```

```
# 8.6 Plot for carbon embodied in wood products and gdp
da3 <- ggplot(dat, aes(x = lgdp, y = lew)) +
        geom_point(size = 2) +
        geom_smooth(method = "lm", se = FALSE, fullrange = TRUE) +
        geom_text(aes(label = c('US', 'Brazil', 'Canada', 'China', 'Germany', 'J', 'Mexico', 'Russia')),
             check_overlap = TRUE, vjust = 0.1, hjust = -.2, size = 2.5) +
        scale_x_continuous(limits = c(3.5, 5))
fig4.6 <- da3 + labs(x = 'log(GDP)', y = 'log(CO2)')

# 8.7 Plot for carbon embodied in paper products sector and gdp
da4 <- ggplot(dat, aes(x = lgdp, y = lep)) +
         geom_point(size = 2.5) +
         geom_smooth(method = "lm", se = FALSE, fullrange = TRUE) +
         geom_text(aes(label = c('US', 'Brazil', 'Canada', 'China', 'Germany',
           'Japan', 'Mexico', 'Russia')), check_overlap = TRUE, vjust = 0.5,
           hjust = 1.2, size = 2.8) +
         scale_x_continuous(limits = c(3.5, 5))
fig4.7 <- da4 + labs(x = 'log(GDP)', y = 'log(CO2)')

# ---------------------------------------------------------------------------------------------------------------
# 9. Export results - tables and figures
# 9.1 Export tables
tables <- listn(table4.1, table4.2, table4.3, table4.4, table4.5, table4.6, table4.7)
write.listx(z = tables, file = "CembodiedHWP.xls", row.names = TRUE)

# 9.2 Export figures
ggsave(fig4.1, file = '4.1.png', width = 7, height = 5)
ggsave(fig4.2, file = '4.2.png', width = 7, height = 5)
ggsave(fig4.3, file = '4.3.png', width = 7, height = 5)
ggsave(fig4.4, file = '4.4.png', width = 7, height = 5)
ggsave(fig4.5, file = '4.5.png', width = 7, height = 5)
ggsave(fig4.6, file = '4.6.png', width = 7, height = 5)
ggsave(fig4.7, file = '4.7.png', width = 7, height = 5)
```