The effects of forest management intensity on carbon storage and revenue in Western Washington: A model and Monte Carlo-based case study of tradeoffs at Pack Forest

Paul W. Fischer

A thesis submitted in partial fulfillment of the
requirements for the degree of

Masters of Science, Forest Resources

Masters of Public Administration, Environmental Policy

University of Washington

2013

Committee:

Gregory J. Ettl

Alison Cullen

Gordon Smith

Programs Authorized to Offer Degrees:

School of Environmental and Forest Sciences

Evans School of Public Affairs

University of Washington

Abstract

The effects of forest management intensity on carbon storage and revenue in Western Washington: A model and Monte Carlo-based case study of tradeoffs at Pack Forest

Paul Fischer

Chair of Supervisory Committee:
Gregory J. Ettl

School of Forest Environmental and Forest Sciences

Evans School of Public Affairs

Forest C offsets allow payments to forest owners who improve carbon (C) uptake and storage. I quantified the amount and value of C under different intensities of management practices at Pack Forest in the western Cascade Mountains, Washington using forest inventory data and results from the Forest Vegetation Simulator (FVS) forest growth simulation model. First, differences in C storage were analyzed among eight forest management scenarios over 30-years using multi-objective optimization. Management scenarios included clearcutting in 45-year intervals, Forest Stewardship Council Pacific Coast Standards with 65- and 105-year interpretations of culmination of mean annual increment (cMAI), a thinning regime, and no management. Greater harvest intensity resulted in less C storage, and C in wood products did not make up for harvest losses. At the whole-forest scale, no significant differences in C storage occurred among the five most intensive scenarios, ranging from FSC 105-year cMAI to clearcutting in 45-year rotations. FSC scenarios stored more C than clearcut scenarios within conifer stands in the first 0-30 years following harvest. Differences diminished as stands aged. FSC optimization resulted in a majority of stands harvested before cMAI. Second, net-present-values (NPVs) of clearcutting in 45- and 65-year rotations and no management scenarios were calculated using both timber and C credits for revenue over 40- and 100-years. Carbon mass and harvested board-feet were modeled using average values for age-class-productivity strata derived from forest inventory and FVS model results. Carbon credits were calculated following an American Carbon Registry methodology. Monte Carlo simulations modeled uncertainty in NPV including FVS model error and future prices for timber and carbon credits. Scenarios of increasing C credit price were also conducted. The risk of losing money increased with less intensive management. Forest C projects became more profitable on average as the price of C credits increased, but the probabilities of both large profit and large loss also increased. An average C credit price of $49.87 was required for clearcutting in 65-year rotations and $73.82 per C credit for no management to equal the mean NPV from timber obtained through clearcutting in 45-year rotations. FVS model error contributed more than 70% to variance in NPV results, raising questions on its utility in forest C projects.

Contents

CHAPTER I: Comparing carbon storage in intensive vs. less intensive harvest practices under 30-year management scenarios

1 Managing forests for carbon storage in the Pacific Northwest

Forest management practices can influence uptake and storage of carbon dioxide (CO_2), the leading cause of anthropogenic-induced climate change (IPCC 2007). While the reduction of anthropogenic emissions of CO_2 and other greenhouse gasses (GHGs) is the most important way to prevent climate change (Stern 2006), carbon (C) sequestration provides a way to mitigate climate change as societies transition away from GHG-emitting activities. Forests remove CO_2 from the atmosphere, break down CO_2 molecules, and lock the C into non-volatile molecules such as lignin and cellulose, though CO_2, methane, and other GHGs may be emitted back to the atmosphere through decomposition. Forests are capable of sequestering C in woody biomass, and Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco) -dominated forests in the Pacific Northwest (PNW) are globally important due to large, long-lived trees and a climate that favors slow decomposition (Barker 2008, Luyssaert et al. 2008, Smithwick et al. 2002). In managed forests where trees are grown and harvested for wood products, reducing harvest intensity may result in additional C sequestration (Canadell and Raupach 2008).

Forest management practices can influence C sequestration by increasing or decreasing the amount of C stored in various pools. Carbon pools include live trees, dead snags, downed woody debris, shrubs and forbs, litter and soil organic layers, and deep soil layers (Harmon et al. 1990). Aboveground, root, snag, and log C pools each may respond differently to harvest scenarios. Methods of forest C credit verification measure pools of C that are believed to change significantly following changes in forest management practices, and ignore pools that are believed to remain stable regardless of the relative size of the C pool (Columbia Carbon 2011). Among the pools that may change significantly, C accounting methods only partially account for the change in organic C (C_{org}) according to (1) (Columbia Carbon 2011, Lovett et al. 2006):

$$\mathrm{C}_{\mathrm{org}} = \sum(NPP_p) + C_{dwp} - E_t + C_{whp}; \qquad (1)$$

where $NPP_p = GPP_p - R_p$, and C_{dwp} is the dead wood C pool,

and E_t = C removed through timber harvest,

and C_{whp} = C stored in long-lived harvested wood products.

NPP for trees is typically calculated from tree measurements and biomass allometric equations rather than quantifying *GPP* and *R* independently. A scaling factor is applied to biomass to convert to C mass. Negative C_{org} results in C emissions to the atmosphere as CO_2 or methane, while positive ΔC_{org} is a C sink. Many authors approximate ΔC_{org} with *NEP* (2):

$$NEP = GPP - R_e \; ; \tag{2}$$

where *GPP* is gross primary production,

and R_e is total ecosystem respiration.

Typical forest C accounting methods only partially account for changes in C_{org} and do not fully account for respiration, thus annual or periodic changes in C storage as defined in (1) rather than *NEP* best describes measured C dynamic. In accordance with C offset calculation standards (Columbia Carbon 2011), this paper calculated C storage according to (1).

There is a tradeoff in forest management for C between C stored in long-lived trees on site and the rate of C accumulation which is higher in young forests. Removing biomass through logging decreases in-forest C storage (Harmon et al. 1990, Harmon and Marks 2002), though a portion of that C may be stored in long-lived wood products (Perez-Garcia et al. 2005). Improved growing conditions following harvest typically increases NPP in remaining or newly established vegetation (Janisch and Harmon 2002, Hudiberg et al. 2009). Industrial planting following harvest speeds C sequestration over natural regeneration. However, increased respiration following harvest causes negative *NEP* for up to 30 years in PNW forest systems (Pregitzer and Eskirchen 2004). *NEP* remains positive in stands 30-120 years since disturbance before tree growth rates slow and R_e exceeds *GPP*; though in the absence of disturbance PNW forests may maintain low positive *NEP* over centuries (Janisch and Harmon 2002, Hudiberg et al. 2009). Increasing rotation age and decreasing harvest intensity improves C_{org} storage (Smithwick et al. 2007), as does leaving snags and CWD undisturbed (Jansich and Harmon 2002, Pedlar et al. 2002). Some argue that young forests under industrial management maximize the rate of CO_2 uptake by achieving high rates of *NPP* (Peckman et al. 2012), and C storage projects should emphasize fast growth rather than total storage (Malmsheimer et al. 2008). Carbon stored in shrub, litter, and soil pools is assumed to be stable (Johnson and Curtis 2001), although others have found these pools to change significantly under forest management (Law et al. 2001). When disturbed by equipment during harvest, mechanical site preparation, burning, or erosion following loss of cover vegetation due to herbicide application, soils are known to be C sources to the atmosphere (Jandl et al. 2007), although the C released from operating equipment is negligible (Markewitz 2006).

Improved forest management (IFM) has been proposed as a means to store C in the PNW (Hermann and Lavender 1999; Adams et al. 2005), yet scant research shows how specific forest management practices affect the amount of long-term C storage (e.g., Perez-Garcia 2005). I present a case-study of forest C accounting at the University of Washington's Pack Forest in western Washington. I use Pack Forest's long-term continuous forest inventory (CFI) data, results from the Western Cascade variant (Keyser 2008) of the U.S. Forest Service's Forest Vegetation Simulator (FVS) (revised 2/16/2011) (Stage 1973, Dixon 2002) forest growth and management model, and site- and species-specific biomass allometric equations to examine the effects of eight forest management scenarios on C storage. Using the results of a 30-year multi-objective optimization model, changes in C under management scenarios of varying intensity were quantified and compared.

2 Methods

2.1 Study Site

This study focused on Pack Forest, University of Washington's 1,740 ha experimental forest. Pack Forest is in the Douglas-fir-dominated foothills of Mount Rainier, within the western hemlock (*Tsuga heterophylla (*Raf.) Sarg.) ecological zone (Franklin and Dyrness 1988). The elevation ranges from 270 to 640 m above sea level. Average annual precipitation is 98 cm in a seasonally dry climate; most precipitation falls as rain between October and April (Swanson 2006). The climate is mild, with average July temperature of 18.3°C and January temperature of 3.9°C, with 315 frost-free days (Swanson 2006).

Forest composition and structure has been shaped by infrequent, low-severity natural disturbance and regular harvest since the 1920s.Two fires influenced the forest composition. Many of the oldest stands originated following an 1823 fire. The Eatonville fire of 1926 was of stand-replacing intensity that burned several hundred hectares and was salvage-logged there after (Swanson 2006). Wind and ice damage are infrequent and localized (Swanson 2006). This heterogeneous disturbance history resulted in a range of forest types, from 450 year-old Douglas-fir/western redcedar (*Thuja plicata* Donn)/western hemlock old-growth to second growth hybrid poplar (*Populus trichocarpa* Torr. & Gray x *P. deltoids* W. Bartram ex Marshall) stands. The majority of the forest is second-growth Douglas-fir dominated stands managed for timber production (1,462 hectares or 84% of the land area). Western redcedar and western hemlock are often also dominant components. Red alder (*Alnus rubra* Bong.) often dominates stands occurring on wetter soils. Experimental forestry trials including species trials, and western white pine (*Pinus monticola* Douglas ex D. Don) and ponderosa pine (*Pinus ponderosa* Lawson & C. Lawson) stands are planted in drier sites. Black cottonwood (*Populus balsamifera* L. ssp. *tricocarpa* (Torr. & A. Gray ex Hook.) Brayshaw), bigleaf maple (*Acer macrophyllum* Pursh), Pacific madrone (*Arbutus menziesii* Pursh), Oregon ash (*Fraxinus latifolia* Benth.), and grand fir (*Abies grandis* Douglas ex D. Don) Lindl.) are also found in many stands. Douglas-fir rotation age ranges between 45 and 80 years depending on site productivity and culmination of mean annual increment. Heavy harvesting of timber beginning in the 1970s created a gap in stand ages (following maturation of post-1926 forests); 67% of the land has a dominant cohort less than 50 years old, 23% is between 70 and 100 years, and 9% is older than 100 years. Old-growth and riparian forests under permanent ecological reserve make up 231 hectares (13% of the land area).

A permanent plot network of approximately 450, (0.04-ha) plots in 187 stands was established in 1974 at Pack Forest (McKinley and Turnblom 2002). Measurements include tree species, height, diameter at breast height (DBH), snags, and coarse woody debris. Data from 443 plots were used to initiate virtual forest stands using FVS. Some plots were first modeled to 2010 to advance all plot data into a common year for analysis. FVS was then used to model growth for 30 years, from the base year of 2010. Stands were projected into the future in 5-year steps, and tree list output for each plot were projected under eight different management scenarios.

2.2 Optimization

My analysis built on a multi-objective optimization of forest management that was used to determine spatially-explicit management scenarios that are Pareto-optimal with respect to maximizing timber revenues, C sequestration and contiguous mature forest habitat (Tóth et al. 2010, Tóth et al. in press). Revenue is in net-present-value (NPV) terms. Eight management scenarios were selected for this analysis and are described below.

2.3 Forest Management Scenarios

Long-term ecological reserves and experimental stands were excluded from harvest for all eight management scenarios (Table 1). Other stands along highway corridors and adjacent to conference facilities were restricted to thinning treatments only. All stands were simulated with replanting after harvest, and then grown forward for the remainder of the 30-year planning horizon in FVS.

Table 1. Categories of stands in the management plan and permanent inventory plots categories for Pack Forest stands used in management plans. The reserves were set prior to optimization modeling to meet habitat and research needs of the University of Washington.

Harvest Status	Hectares	Percent	# Stands	# Plots
Harvestable	1,462	84.0	155	381
Ecological/experimental - reserve	231	13.3	21	52
Campus/road buffers - thin	33	1.9	6	10
Non-forest	14	0.8	5	0
Total	1,740	100	187	443

2.3.1 Clearcut 45 year rotation: maximize revenue (abbreviated Clearcut 45)

This scenario simulated the regional industrial standard practice of clearcutting stands with a 45-year rotation. A clearcut treatment was simulated for plots 45-years-old and older. The five largest conifer trees by diameter and seven additional trees between 20 and 51 cm in DBH per hectare were retained with clearcut harvest[1]. All hardwood trees and trees less than 20 cm were removed. Planting was simulated as: 741 Douglas-fir, 62 western red cedar, 124 red alder, 12 big leaf maple, and 12 grand fir seedlings per hectare. The model was constrained to result in an increasing amount of biomass by the end of the modeled time-frame to ensure one measure of sustainable forestry, increasing wood production would be met (Ettl 2010). This treatment complies with Washington State forest practices regulations and is comparable to management under the Sustainable Forestry Initiative (SFI) certification.

2.3.2 Clearcut 45 year rotation with a 41-hectare reserve (abbreviated Clearcut 45 + Reserve)

This management regime is identical to Clearcut 45 with the one difference being the creation of an additional habitat reserve of 41 contiguous hectares of mature forest (age 85+ since stand-initiation). The optimization mode indicates the most efficient stands for this reserve are "Logging Camp" and "Elma Ply" stands.

2.3.3 Clearcut 45 year rotation while increasing average age of production stands by 10 years (abbreviated Clearcut 45 + Increasing Age)

Using the parameters of the Clearcut 45 scenario, this scenario was constrained to increase the average age of production stands (i.e., excluding reserves) by 10 years at the end of the 30-year timeframe. This approach does not require an additional habitat reserve.

2.3.4 FSC 65-year rotation (abbreviated FSC 65) and

2.3.5 FSC 105-year rotation (abbreviated FSC 105)

Following the Pacific Coast Standard (v9) of Forest Stewardship Council (FSC) certification (Brown 2005), stands are eligible for 10% basal area (BA) retention harvest upon culmination of mean annual increment (cMAI). Stands that have not reached culmination MAI are eligible for 30% BA retention harvest. Green-up achieving 3m of height (or canopy closure) is required before adjacent stands are eligible for harvest, maximum harvest size is limited to 24 hectares, with the forest-wide average harvest size no greater than 16 hectares (Brown 2005). Two interpretations of cMAI were analyzed here to bracket the range of likely implementation, simplified as 65- and 105-year rotations.

<u>10% Basal Area Retention</u>

Plots that were optimally selected for harvest at or above the 65- or 105-year-old interpretation of cMAI were simulated with a 10% basal area retention treatment. The treatment was implemented from below by diameter without a species preference in trees 20 cm DBH and

---

[1] This level of tree retention slightly exceeds Washington Forest Practices requirements but aligns with Pack Forest's management objectives. We leave the largest trees; state law requires leaving trees of a minimum diameter. Trees per hectare meet, but do not exceed, Forest Practices requirements.

larger. For trees less than 20 cm DBH, 10% BA was proportionally retained to simulate some trees surviving the harvest operation. Planting was simulated with 494 Douglas-fir, 124 western red cedar, 25 western hemlock, 124 red alder, 25 grand fir, and 25 big leaf maple seedlings per hectare.

30% Basal Area Retention

Plots that were optimally selected for harvest when younger than the 65- or 105- interpretation of cMAI were thinned to 30% basal area retention. The thinning was implemented from below by diameter without species preference in trees 20 cm DBH and larger. For trees less than 20 cm DBH, 30% BA was proportionally retained to simulate some trees surviving the harvest operation. Planting was simulated with 62 Douglas-fir, 247 western redcedar, 62 western hemlock, 12 grand fir, and 12 big leaf maple per hectare. The greater proportion of shade tolerant western redcedar and western hemlock planted than with 10% BA retention simulates natural regeneration, a management preference for restoring western redcedar through planting, and the ability of these species to grow in the shade of the residual overstory.

2.3.6 Thin with 20 year reentry (abbreviated Thin 20)

A thinning regime was modeled with a 20-year reentry period. Thinning was implemented from below by diameter with a species preference favoring dominant species of respective canopy layers. Over a series of thinnings, this preference resulted in the removal of suppressed, intermediate, and then co dominant overstory trees to release growing space for understory individuals while retaining very large trees important for structure. Stands were thinned successively to a stand density index of 210. Eighty-five percent of BA for trees < 20 cm DBH was proportionally retained after each thinning to represent understory individuals surviving the harvest operation. Natural regeneration, underplanting and advanced regeneration were simulated with 50 western red cedar and 25 western hemlock per hectare after each entry.

2.3.7 Clearcut that removes the minimal amount of timber (abbreviated Break-Even)

The model harvested the minimum amount of timber needed to provide revenue sufficient to cover basic forest operations, including land holding costs and minimal staff costs. Stands selected for harvest were clearcut following Clearcut 45 parameters. Stands were eligible for harvest in 45-year rotations.

2.3.8 No active management (abbreviated No Management)

All plots were modeled 30 years into the future to simulate future stand conditions without management.

2.4 Carbon biomass allometric equations

Biomass was calculated from the FVS tree diameter and height output. Aboveground and root biomass allometric equations were selected for six primary trees species in the Pack Forest inventory – Douglas-fir, western hemlock, western redcedar, red alder, bigleaf maple, and western white pine. I conducted a literature review of existing biomass equation libraries such as BIOPAK (Means et al. 1995), Jenkins et al. 2004, and primary literature to identify species-specific allometric biomass equations originating from data samples most similar to Pack Forest's geographic region. Equations were selected to match stand age, whether the stand was naturally regenerated or planted, and the species composition (Appendix 2, summarized in Table 2). Biomass was converted to mass of C for further analysis by assuming 50% C content of biomass; this conversion is used in Harmon et al. (1990) and Perez-Garcia et al. (2005) and is more conservative than Birdsey (1992). Therefore matching of C biomass equations to forest stands was a fundamental step in obtaining as precise C estimates as possible for each plot, stand, and for the entire forest.

Where possible, equations were species-specific and were developed from a dataset in the western Cascades, or, secondarily, the Pacific coast. The equations represented forests of similar developmental state (i.e., plantation forests or unmanaged as appropriate), included height for mature trees, and had comparable diameter ranges to Pack Forest trees. Less specific equations were applied only where no other equations closely met these criteria.

Three sets of aboveground biomass equations were selected for comparison. First, “Simple” equations involved one equation modeling total aboveground biomass using both diameter and height. Second, “Component” equations included different equations for specific diameter ranges and biomass components, typically including height for larger diameter ranges. Third, Jenkins et al. (2003) provided generalized biomass equations using only diameter. Species of low commercial importance had few equations, requiring the use of substitute species or equations from other regions (Appendix 2); fortunately these species represent minor components of the forest.

Equations for each species for belowground root biomass were also included (Table 2). Additional calculations accounted for C in dead roots remaining on-site after harvest. This dead root C was decayed at 15% annually for all species. Fine roots less than 2 mm in diameter were excluded in the original literature. No distinction was made for other root diameter ranges. Root diameter does affect rate of decay, with larger diameter roots decaying more slowly than small diameter roots. Research is limited on root decay rates in Pacific Northwest forests; a rate of 15% is conservative relative to exiting literature. Harmon et al. (2004) found fine root decay rates of 19.1% annually in western Cascade conifer forests while Yavitt and Fahey (1982) observed decay rates of 4.15% annually in coarse roots of lodgepole pine (*Pinus contorta* ssp. *Latifolia* Douglas ex Loudon) in Wyoming. Roots decay more slowly than comparable size branches on the surface of the soil (Gosz et al. 1973).

Table 2. Biomass allometric equations selected for four Pack Forest species. Equations were selected for calculations on a species and stand-by-stand basis; where possible, western Cascade-derived equations were used. Stand age, stocking and species composition (plantation vs. natural) stands was also a criteria for selection where appropriate equations were possible. Simple equations calculate total biomass from height and diameter data, while component and root equations estimate mass in the stem, branches, foliage, and crown. Jenkins equations using national data for each species are used for comparison.

Simple

Species	DBH Range	Component	Equation (x = biomass in g)	Region[1]	Seral[2]	Source[3]
PSME	0-19cm	Total aboveground	X = 37300 + 0.1393 * DBH^2 * HT	C	Y	1
	19cm+	Total aboveground	X = 1054 + 0.2057 * (DBH^2*HT)	WC	G	2
THPL	0-23cm	Total aboveground	X = 40400 + 0.0969 * (DBH)^2 * HT	G	G	1
	23cm+	Total aboveground	X = 1270 + 0.1501 * (DBH^2*HT)	WC	G	2
TSHE	All	Total aboveground	X = 497 + 0.2113 * (DBH^2*HT)	WC	G	2
ALRU	All	Total aboveground	X = 4800 + 0.2065 * (DBH)^2 * HT	G	Y	1

Component

Species	DBH Range	Component	Equation (x = biomass in g)	Region[1]	Seral[2]	Source[3]
PSME	0-12cm	Total aboveground	X = 37300 + 0.1393 * DBH^2 * HT	C	Y	1
	12-30cm	Total stem	X = Exp(4.660412 + 2.4247 * ln(DBH))	WC	M	3
		Branches	X = Exp(3.2137 + 2.1382 * ln(DBH))	WC	G	4
		Foliage	X = Exp(4.0616 + 1.7009 * ln(DBH))	WC	G	4
	30cm+	Total stem	X = -115 + 0.1896 * (DBH^2*HT)	WC	G	2
		Crown	X = Exp(10.914555 + 0.0206 * DBH)	WC	O	5
THPL	0-16cm	Total stem	X = 773 + 0.0755 * (DBH^2*HT)	WC	G	2

		Branches	X = 12000 + 0.0128 * (DBH)^2 * HT	G	G	1
		Foliage	X = 7600. + 0.0067 * (DBH)^2 * HT	G	G	1
	16cm+	Total aboveground	X = 1270 + 0.1501 * (DBH^2*HT)	WC	G	2
TSHE	0-50cm	Total aboveground	X = 497 + 0.2113 * (DBH^2*HT)	WC	G	2
	50+cm	Total stem	X = 337 + 0.1279 * (DBH^2*HT)	WC	G	2
		Crown	X = Exp(10.796355 + 0.0338 * DBH)	WC	O	5
ALRU	All	Total stem	X = Exp(3.97 + 2.56 * ln(DBH))	C	M	6
	All	Crown	X = Exp(2.3429553 + 2.6232 * ln(DBH))	WC	G	7

Roots

Species	DBH Range	Component	Equation (x = biomass in g)	Region[1]	Seral[2]	Source[3]
PSME	All	Below ground	X = Exp(2.2117 + 2.6929 * ln(DBH))	WC	G	4
ALRU	All	Below ground	X = 100 + 480*DBH^2*HT -0.5*(DBH^2*HT)^2	C	Y	4
THPL	All	Below ground	X = Exp (-4.159 + 0 * DBH + 2.519 * (ln(DBH^1)) * 1000	C	G	8
TSHE* (PSME)	All	Below ground	X = Exp(2.2117 + 2.6929 * ln(DBH))	WC	G	4

Jenkins et al. 2003

Species	DBH Range	Component	Equation (x = biomass in g)	Region[1]	Seral[2]	Source[3]
PSME	All	Total aboveground	X = Exp(-2.2304+2.4435*ln(DBH) * 1000	G	G	9
Cedar	All	Total aboveground	X = Exp(-2.0336+2.2592 ln DBH) * 1000	G	G	9

Hemlock	All	Total aboveground	X = Exp(-2.5384+2.4814 ln DBH) *1000	G	G	9
Alder	All	Total aboveground	X = Exp(-2.2094+2.3867 ln DBH) * 1000	G	G	9

*Equation from substitute species was used

[1] C, coastal PNW; WC, western Cascades; G, general; EH, eastern hardwood; RM, rocky mountain

[2] Y, young; M, mature; O, old; G, general

[3] 1, Standish et al. 1985; 2, Shaw 1979; 3, Harmon 1994 in Means et al. 1995; 4, Gholz et al. 1979; 5, Snell and Max 1985; 6, Binkley 1983; 7, Snell and Little 1983; 8, Feller 1992; 9, Jenkins et al. 2003

Appendix 2 shows the equations selected for each diameter range of each of the six common species at Pack Forest, the source of the equations, the regions and age class for which the equations were developed, and the coefficient of determination. Descriptions of equations for each species follow in the appendix. Default equations from the Western Cascade variant of FVS (Keyser 2008) and Jenkins et al. (2003) were used for all other species.

2.5 Dead wood carbon pools

Tóth et al. (in press) calculated C stored in log and snag dead wood pools using a modification of FVS Fire and Fuels Extension Model that transferred snags to a coarse woody debris C pool. Dead wood biomass was calculated using volume equations and decay factors. Results were used in this analysis.

2.6 Carbon stored in harvested wood products

Carbon stored in long-lived wood products and landfills was calculated using the Department of Energy (U.S. DOE) 1605(b) Technical Guidelines (2007). Forest C offset verification protocols including the American Carbon Registry (ACR) (Columbia Carbon 2011) require this method, and the Carbon Action Reserve (CAR 2010) uses an adapted version. Region- and log grade-specific mill efficiency rates account for initial loss of C from wood waste in lumber and paper milling. A time-dependent decay factor was applied, accounting for release of C to the atmosphere as wood products break down. Emissions due to harvest and transportation are partially accounted for here. The hypothetical C benefits of substituting wood products for other materials are not considered legitimate additions of C. Carbon in harvested wood products was calculated at a whole-forest scale thus was not able to be included in plot-level statistical analysis.

2.7 Stratification

All FVS simulations were based on 443 forest plots as part of Pack Forest's long-term CFI. Plots rather than stands were chosen for data analysis because the larger number of plots increases sample size and plots capture the small-scale variation in a stand better than averaging at the stand level. Pregitzer and Eskirchen (2004) found significant differences in C storage in managed stands when placed into groups based on time since stand initiation. Thus, plots were grouped into 12 strata based on stand initiation age, similar site characteristics and similar management histories (Table 3). Stratification was based on forest development stage after Oliver (1981) where stand age represents years since stand initiation. For conifers, large sample size allowed further stratification by low or high site productivity.

Table 3. Stratification categories and number of continuous forest inventory plots for each category used in analysis. Stratification took place by dominant tree type, age in years since stand initiation, and for conifers high- and low- productivity sites. Strata correspond to seral development stages.

Stratum Abbreviation	Description	Justification	Sample Size 2010
A0-30	Alder-dominated stands age 0- 30 years since stand replacing event	Pre-harvest state, model timeframe	15
A31+	Alder-dominated stands age 31+years since stand replacing event	Harvestable status	35
C0-19Hi	Conifer-dominated stands age 0-19 years since stand replacing event, High productivity (Site index >105)	Stand Initiation within model timeframe	24
C0-19Lo	Conifer-dominated stands age 0-19 years since stand replacing event, Low productivity (Site index <105)	Stand Initiation within model timeframe	63
C20-30Hi	Conifer-dominated stands age 20- 30 years since stand replacing event, High productivity (Site index >105)	Stem exclusion within model timeframe	19
C20-30Lo	Conifer-dominated stands age 20- 30 years since stand replacing event, Low productivity (Site index <105)	Stem exclusion within model timeframe	100
C31-44Hi	Conifer-dominated stands age 31-44 years since stand replacing event, High productivity (Site index >105)	Stem exclusion, maturation stage	13
C31-44Lo	Conifer-dominated stands age 31-44 years since stand replacing event, Low productivity (Site index <=105)	Stem exclusion, maturation stage	31
C45-84High	Conifer-dominated stands age 45-84 years since stand replacing event, High productivity (Site index >105)	Harvestable age range	37
C45-84Low	Conifer-dominated stands age 45-84 years since stand replacing event, Low productivity (Site index <=105)	Harvestable age range	48
C85+	Conifer-dominated mature and old stands age 85+ years since stand replacing event. All productivity indices.	Mature and old stands	46
O	Other - mixed stands of various composition, commonly riparian zones	Age-productivity classes did not apply.	12

Conifer strata were dominated by Douglas-fir, western redcedar, and/or western hemlock, though plots frequently included other species. Conifer strata were split into the following age classes: 0-19 years, 20-30 years, 31-44 years, 45-84 years, and 85+ years. Stratum 0-19 represented stand initiation. Stratum 20-30 represented stem exclusion stage for stands harvested within the model time frame. Stratum 31-44 represented stem exclusion stage for stands not harvested during the model timeframe. Stratum 45-84 represented stem exclusion and also suitable for commercial harvest. Stratum 85+ represented stands at the understory re-initiation stage, and also captured stands that were in reserve status. Conifer strata were further divided by site index to capture the range of productivity on Pack Forest soils. A site index of 105 was selected to divide low (≤105) and high (>105) productivity. Plots in stratum 85+ were not divided by site index because sample size was small.

Alder strata included all plots dominated by red alder, including pure and mixed stands. Red alder strata were divided into 2 age categories of 0-30 and 31+. The 0-30 stratum represented stand initiation and stem exclusion, and captured plots harvested within the model timeframe. The 31+ stratum represented plots that were eligible for harvest; these plots were typically in stem exclusion. Small sample size prevented further division of red alder strata.

The “Other” stratum included plots in mixed hardwood-conifer stands, frequently riparian areas. Sample size was too small to permit further division of this stratum, as these stands occupy a small proportion of the landscape.

2.8 Statistical Analysis

Analysis of variance (ANOVA) compared means of per-hectare C at the plot level among strata and forest management scenarios. Tukey’s post-hoc test was used to determine differences among treatments, strata, and pools. Significant differences in means were reported where $p < 0.05$. IBM SPSS Statistics for Windows, v19.0 (2010) was used for statistical analysis.

3 Results

3.1 Aboveground biomass equation comparison

Carbon calculations differed with allometric biomass equations. In model year 2010, both Simple and Component plot-average per-hectare C are significantly larger than Jenkins (both $p<0.001$), while Simple and Component were not significantly different from each other ($p=0.07$). This trend continued throughout the 30-year simulation and across all treatments (Figure 1). Jenkins described significantly lower biomass than Simple ($p<0.005$) and Component ($p<0.027$) calculations across all eight management scenarios, by model year 2040. Simple and Component were not significantly different under any management scenario. Figure 1 shows aboveground C in all of Pack Forest under the three equation sets. No Management and Clearcut 45 scenarios are shown for contrast; other treatments were intermediate between the two.

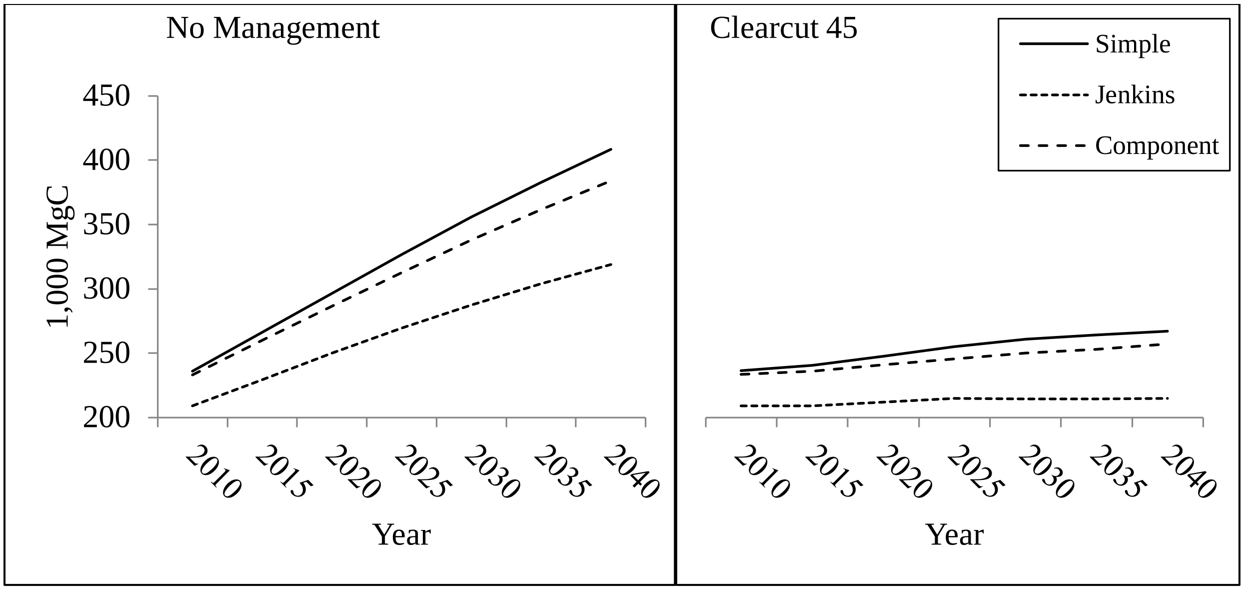


Figure 1. Comparison of aboveground C (Mg) allometric equation sets for all of Pack Forest for the 30-year planning period (2010-2040). No Management and Clearcut 45 scenarios are shown for contrast. Simple and Component include site- and seral stage- specific equations while Jenkins includes national-scale equations. Simple and Jenkins used only one equation to estimate whole-tree biomass, while Component uses several equations for tree components such as stem wood, stem bark, branches, and foliage.

Jenkins et al. (2003) equations were the most conservative equations, yet they were also the least specific to Pack Forest. The Jenkins equations are generalized compilations from different stand ages, forest management practices, and regions of North America. Conversely, the Component equation set was selected from research in west-side Cascade forests whenever possible, applying specific allometric equations to specific diameter ranges for different age-classes. Simple equations were also site-specific, but the whole-tree calculation appeared to be an upper estimate of forest C. Thus, the Component equation set was selected for all aboveground C calculations as it provided the greatest site-specific accuracy in aboveground C calculations for Pack Forest.

3.2 Total C

Total C storage increased as harvest intensity decreased (Figure 2). Mean total C was different among the eight management scenarios in 2040 for all active management scenarios compared to No Management and Thin 20 ($p < 0.01$), with the exception that Thin 20 was not different from Break Even ($p=0.31$) (Figure 3). The No Management and Thin 20 were also not significantly different from each other ($p=0.191$). The Break Even scenario uses the same prescription as Clearcut 45 (but cuts less area), and thus stored more C than Clearcut 45 and Clearcut 45 + Reserve ($p=0.001$, $p=0.009$ respectively, Table 4). No significant differences in mean total MgC per hectare were observed among management scenarios that involved harvest intensity greater than the Break Even scenario (Figure 4).

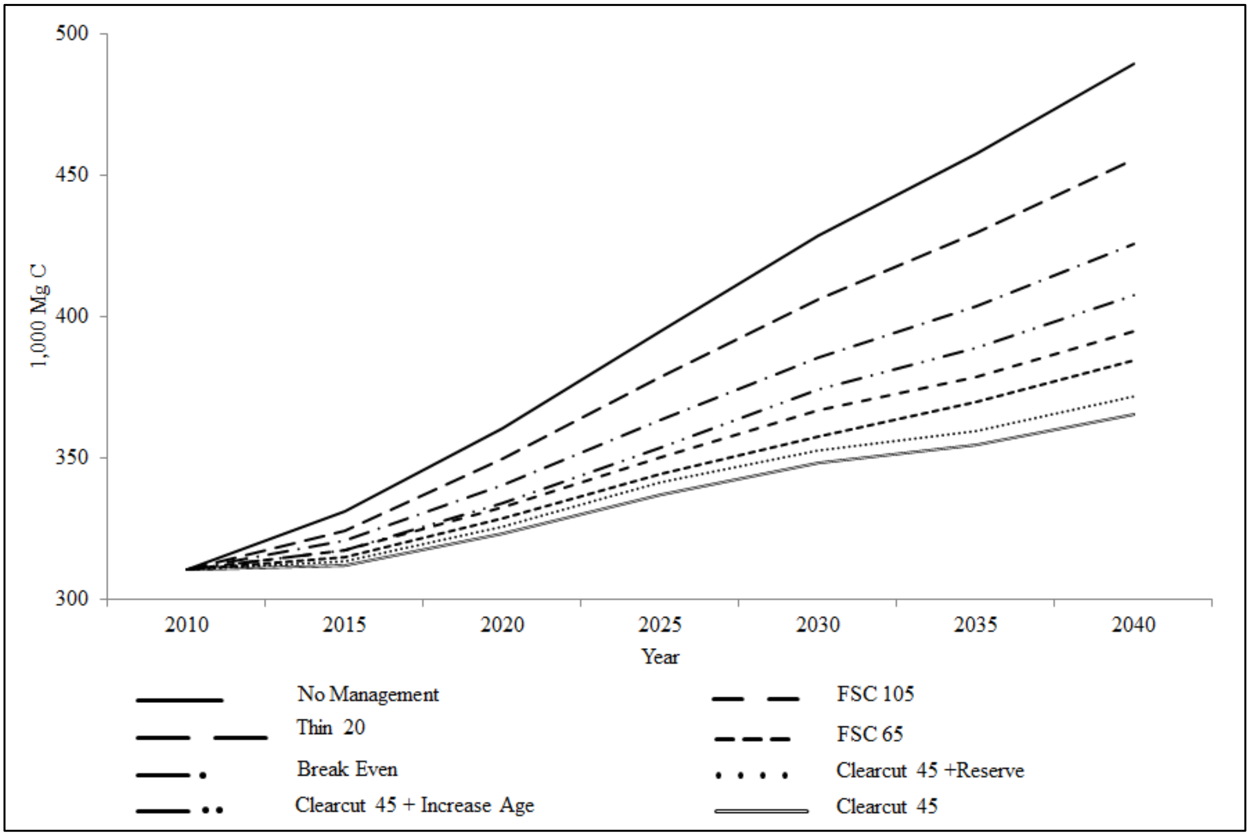


Figure 2: Total C storage under eight management scenarios throughout the 30-year modeled timeframe. Clearcut 45 is the business-as-usual (BAU) management of 45-year clearcut rotations, Clearcut 45 + Reserve is BAU plus a 41-ha mature reserve, FCS 65 follows Forest Stewardship Council requirements assuming cMAI occurs at 65 years, FSC 105 follows FSC requirements assuming cMAI occurs at 105-years, and clearcut 45 + Increasing Age is the BAU with the constraint of increasing the average age of production stands by 10 years over the 20-year modeled timeframe, Break Even is the minimum harvest required to cover land holding and staffing cost, Thin 20 is thinning in 20-year intervals, and No Management is no harvest or other management activities.

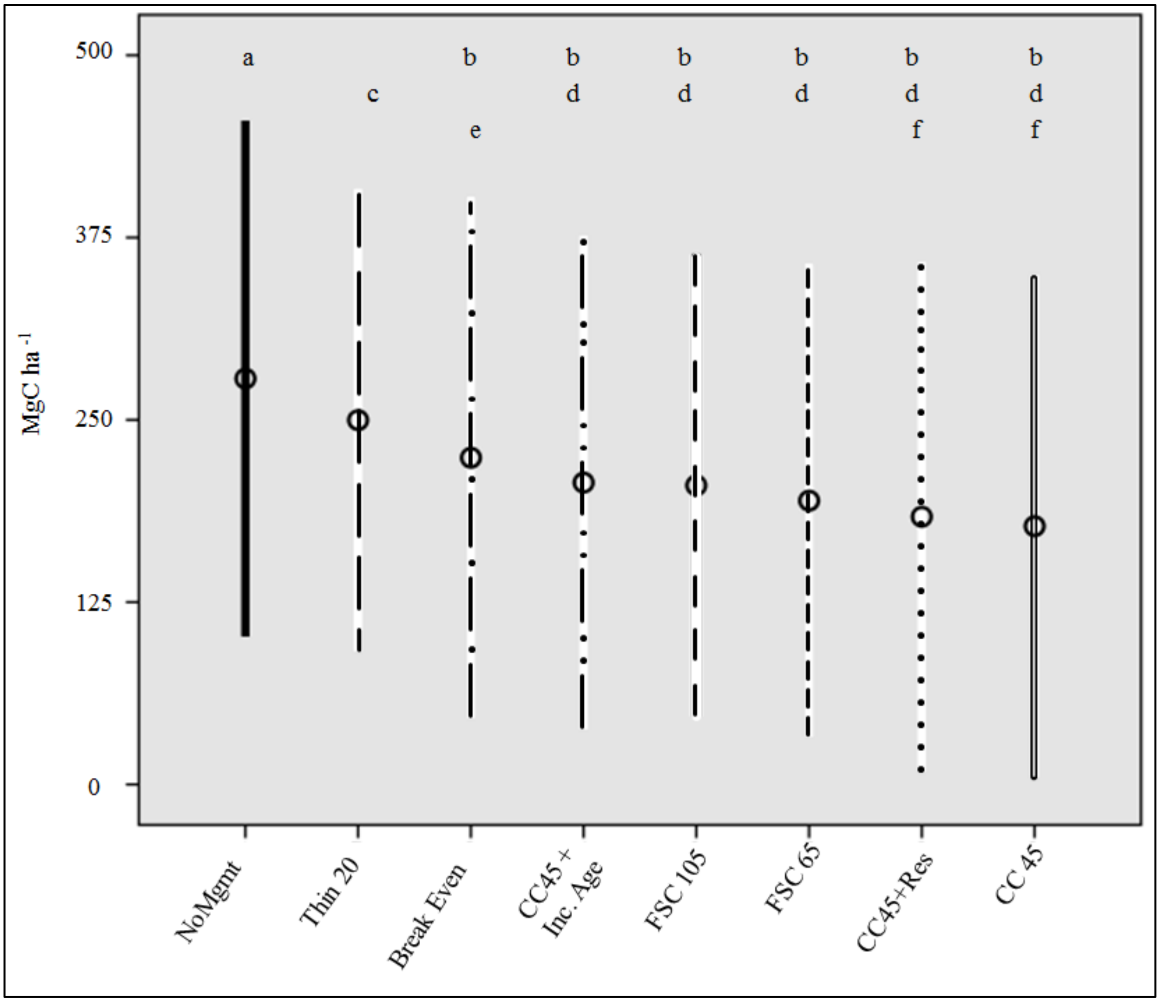


Figure 3: Mean and 1 standard deviation (SD) for per-hectare total MgC under each management scenario in model year 2040. Letters within rows indicate significant differences ($p<0.05$) in means ("a" is different from "b", etc.). NoMgmt is No Management, CC45 + Inc. Age is Clearcut 45 + Increasing Age, CC45+Res is Clearcut 45 + Reserve, and CC45 is Clearcut 45.

3.3 Carbon Pools

Forest management scenarios differed in where C is stored in the forest. Carbon pools were analyzed for statistical significance in the model year 2040 when differences among treatments were greatest. Aboveground C was the largest pool and therefore the primary driver of differences in total C. Root C correlated to aboveground C. The snag and log pools showed little difference among active management scenarios in C stored in dead wood. Notably, C stored in wood products did not approach the amount of C stored on-site under less-intensive management scenarios; wood product pool did not make up for onsite storage (Figure 4, Table 4).

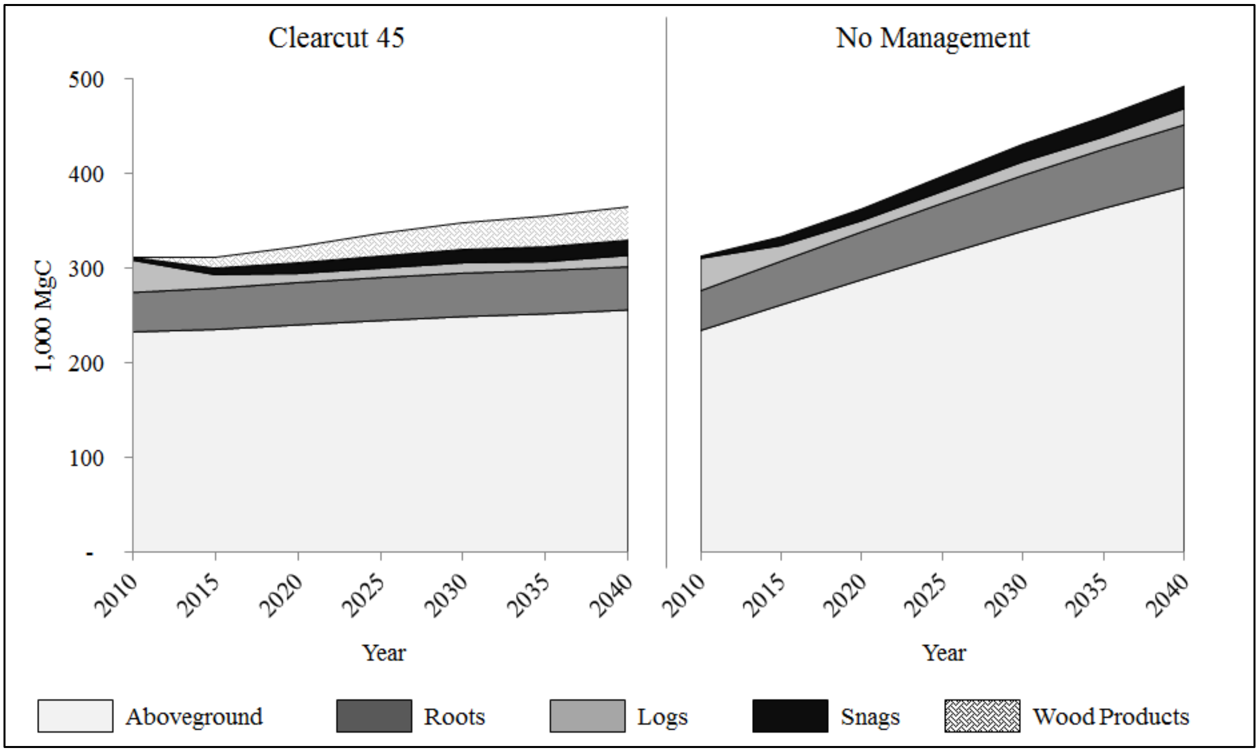


Figure 4: Total C in pools contrasting the most harvest intensive and no management scenarios at Pack Forest.

Aboveground C closely correlated to Total C. In the aboveground pool in 2040, No Management stored significantly more C than all active management scenarios ($p<0.001$) except the Break Even scenario ($p=0.291$). Thin 20 showed no significant difference from FSC 65 and FSC 105 rotations ($p=0.221$, $p=0.799$ respectively), but was larger than Clearcut 45 and Clearcut 45 + Reserve ($p=0.001$, $p=0.012$ respectively). Among the intensive management scenarios of FSC and clearcut harvests, no significant differences were observed.

Table 4. Total C in pools by component parts in modeled year 2040. Within columns of pools, “*”, “†”, and “§” in boxes indicate differences in means at the 0.95 level from “*”, “†”, and “§,” respectively. Wood products pool did not undergo statistical analysis. No Management stored significantly more C than intensive management practices in all pools. No significant differences were revealed among the most intensive management practices.

Management scenario	Total C	Total C/ha	Wood Products[1]	Above ground	Roots[2]	Snags	Logs
Clearcut 45	365,728	210	35,923	256,221 * † §	45,561 * † §	15,948 * †	12,076 *
Clearcut 45 + Reserve	371,825	215	32,429	264,159 * † §	46,656 * † §	16,156 * †	12,425 *
FSC 65	384,483	222	26,649	280,555 * §	49,951 * §	16,202 * †	11,125 *
FSC 105	395,001	227	21,907	292,967 * §	52,177 * §	16,497 * †	11,452 *
Clearcut 45 + Increase Age	407,974	235	26,302	297,898 * §	51,929 * §	18,520 *	13,324
Break Even	426,007	245	19,202	317,361 $\boxed{\S}$	55,074 $\boxed{\S}$	19,621 *	14,748
Thin 20	455,895	262	9,009	352,594 * $\boxed{\dagger}$	61,324 * $\boxed{\dagger}$	20,459 $\boxed{\dagger}$	12,510 *
No Mgmt	489,405	282	-	383,314 $\boxed{*}$ †	65,539 $\boxed{*}$ †	23,544 $\boxed{*}$	17,008 $\boxed{*}$

---

[1] Harvested wood products includes C in long-lived wood products, accounting for mill efficiency and wood product decay following DOE 1605(b) (2007) methods. No statistical analysis was conducted for this pool

[2] Root C pool includes live tree below ground C and below ground C of harvested trees, decayed at 15% annually. Statistical significance is based only on live below ground C.

The root pool mirrored the aboveground pool in statistical significance in 2040. This is likely because like aboveground biomass and root biomass equations were all functions of tree diameter.

In the snag pool in 2040, No Management stored significantly more C than all other scenarios (*p* ranged from 0.01 to <0.001) except Thin 20 (*p*=0.091). Within the active management scenarios, there were no differences among clearcut scenarios and FSC scenarios. Thin 20 stored more C than Clearcut 45 (*p*=0.004), Clearcut 45 + Reserve (*p*=0.008), FSC 65 (*p*=0.01), and FSC 105 (*p*=0.026). Thin 20 was not different from Clearcut 45, Increasing Age (*p*=0.706), nor Break Even (*p*=0.996).

The log pool varied somewhat from the snag pool in 2040. No Management stored more C than all other treatments (*p* ranged from 0.012 to 0.01) except Clearcut 45, Increasing Age (*p*=0.115), and Break Even (*p*=0.646). There were no significant differences in log C among active management scenarios.

Combining the snag and log pools into a deadwood pool, in 2040 No Management held more C than all other scenarios (*p* ranged from 0.043 to <0.001). No differences were found among any other scenarios except FSC 65 stored less C than Break Even (*p*=0.031).

Carbon stored in wood products was calculated at a whole-forest scale rather than the plot level, thus statistical analysis was not possible. Comparing averages without statistical analysis, Clearcut 45 + Increasing Age stored more total C than both FSC scenarios, yet harvested nearly as much or more C in wood products.

Pregitzer and Eskirchen (2004) found generally similar masses of C in aboveground, belowground, and coarse woody debris pools for temperate forests in the Pacific Northwest. My results did not show a “U”-shaped distribution for dead wood; however, managed stands initiated following harvest would have less dead wood than stands initiated following fire. While C pools revealed more detail on the effects of management on C storage, averaging all plots together, regardless of species composition, age or productivity, provided imprecise accounting of the differences in forest management scenarios. Evaluating differences among particular age-class strata more completely describe the effects of different management scenarios.

3.4 Strata

Differentiating plots by age-class-productivity strata resulted in more statistically significant differences in the effects of management scenarios on C storage. Two categories of strata emerged in the data analysis. The first category included plots that were harvested during the 30-year simulation, where the effects of different simulated management scenarios could be observed directly. The second category included plots that were not harvested during the 30-year period. These stands were not harvested and therefore there was no direct harvest effect on these stands. However, C storage among strata for non-harvested stands revealed harvest impacts at a forest-wide scale. The optimization modeling preferentially selected more productive or high wood volume plots for some scenarios; the average C among the remaining plots was lower.

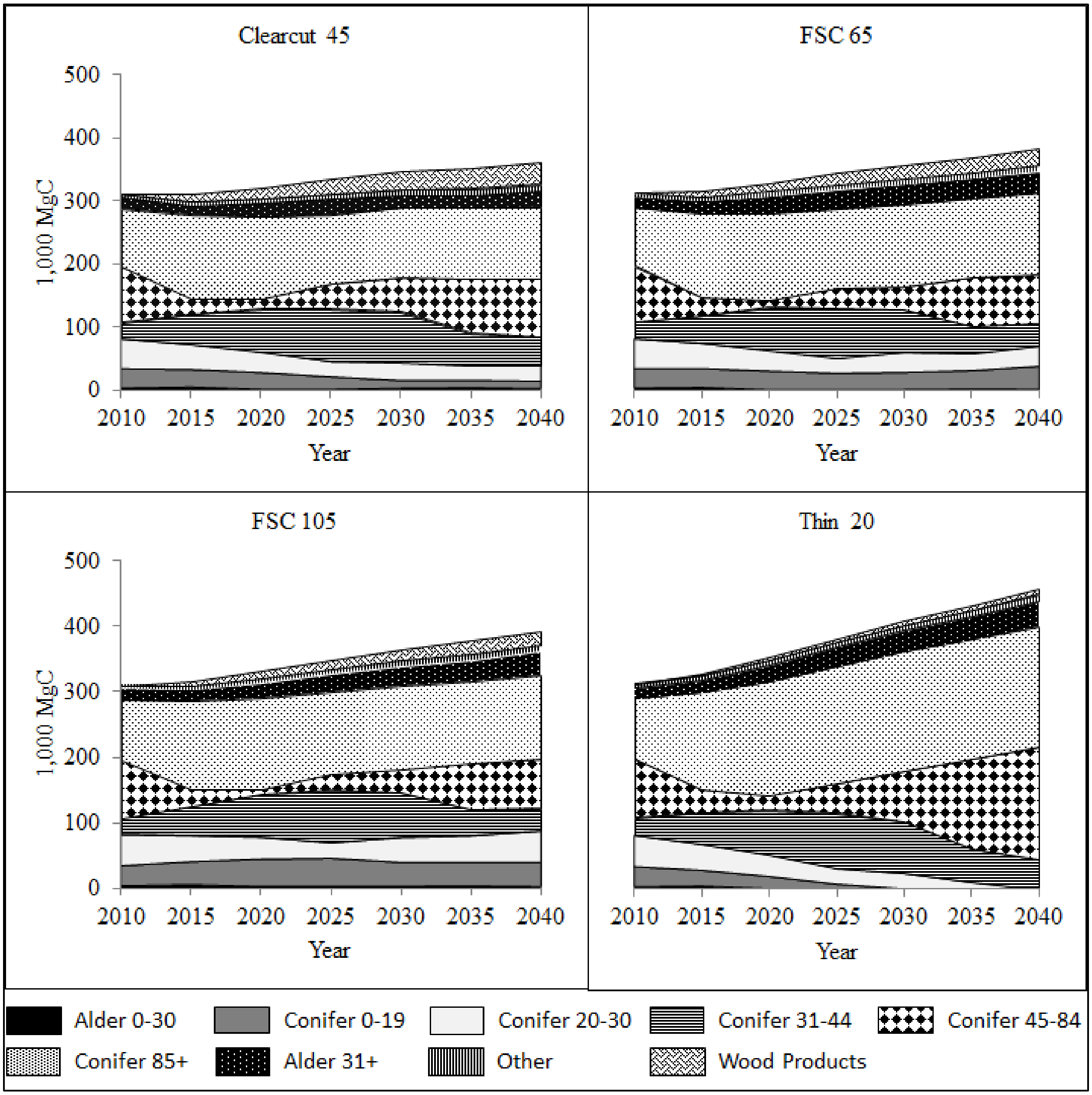


Figure 5: Changes in Total C storage across strata over 30 years of model simulation. The strata are stacked following the legend from left to right with Alder 0-30 on the bottom and wood products on the top. Four scenarios of the eight are shown for contrast. Thin 20 and No Management (not shown) lose the youngest strata as they grow into older age classes by the end of the modeled timeframe.

Changes in strata reveal important consequences of management decisions (Figure 5). Notably, under both Thin 20 and No Management scenarios, the youngest strata of conifers and alders grew into strata older than age 30, effectively losing the youngest cohorts from the forest landscape. Statistically significant results are described in the following sections.

3.4.1 Plots harvested under the 30-year model simulation

Plots comprised of alder age 0-30, and high- and low- productivity conifer plots age 0-19 and 20-30 were tested for differences in average C. ANOVA with Tukey post-hoc was used to assess statistical significance in mean difference within one stratum across all management scenarios at the 0.05 level. Only results from simulation year 2040 were analyzed. Neither No Management nor Thin 20 had any plots in these strata, though a discussion of plots thinned under Thin 20 is included below.

Clearcut 45, Clearcut 45 + Reserve, Clearcut 45 + Increasing Age, and Break Even all have distinct constraints affecting which plots are harvested and the sequence of harvest. However, these management scenarios are identical in that all stands that were selected for harvest were treated the same way – clearcut. Thus, significant differences among these treatments by strata were not anticipated and were not observed.

Table 5. Average total MgC per ha in 2040. Within rows, management scenarios with bolded values and “*” indicate differences in means at the 0.95 level from other management scenarios with non-bold “*”. Similarly, bold values with “§” are significantly different from other values with “§”. FSC scenarios tended to store significantly more C in younger strata, and less C in older strata.

Stratum	CC45	CC45+ Res	CC45+ Inc Age	FSC 65	FSC 105	Break Even	Thin 20	No Mgmt
A0-30	46.5*	60.8*	83.5	60.5*	**124.8***	45.0*	n/a	n/a
A31+	214.2	207.1	214.2	211.5	208.1	207.1	209.8	217.9
C0-19Hi	39.8*§	39.3*§	47.2*§	**109.5**§	**116.4***	40.5*§	n/a	n/a
C0-19Lo	43.2*§	41.3*§	50.2*§	**116.6**§	**118.1***	46.5*§	n/a	n/a
C20-30Hi	92.7*§	95.4*§	105.0*	**117.9***§	**179.4**§*****	101.3*§	n/a	n/a
C20-30Lo	93.9*	96.1*	90.2*	115.9*	**153.5***	80.6*	n/a	n/a
C31-44Hi	192.2	192.2	192.2	169.8	169.8	192.2	192.2	192.2
C31-44Lo	170.3	170.3	170.3	166.1	166.1	170.3	167.0	170.3
C45-84Hi	223.1	224.1	238.0	212.3	209.3	246.4	237.7	258.2
C45-84Lo	187.3*	185.6*	206.6	175.9*§	175.9*§	221.2	**218.7**§	**232.8***
C85+	420.3	400.6	389.9	400.6	400.6	331.4	407.2	404.0
Other	219.9	219.9	242.4	225.1	224.4	242.4	242.4	242.4

Significant differences in total C per hectare among treatments were revealed in alder plots age 0-30 years since stand initiation. FSC 105 stored more C than Clearcut 45, Clearcut 45 + Reserve, and FSC 65, and Break-Even scenarios (*p*<0.001 for all treatments listed). FSC 65, however, was not different from clearcut simulations. Clearcut scenarios were not different from each other.

In young conifer plots age 0-19, both FSC 65 and FSC 105 stored more total C than Clearcut 45, Clearcut 45 + Reserve, Clearcut 45 Increasing Age, and Break-Even scenarios (*p*<0.001 for all treatments listed) for both high- and low- productivity plots. FSC 65 and FSC 105 were not different from each other, and clearcut scenarios were not different from each other. Clearly, in young stands, the 10 to 30% basal area retention required under FSC resulted in significantly more C storage on-site than clearcuts.

In conifer plots age 20-30, FSC 105 stored more total C than all clearcut scenarios (*p*<0.001) for both high- and low- productivity plots. In high-productivity plots, FSC 65 stored more total C than clearcut scenarios with the exception of Clearcut 45 – Increasing Age scenario. In low-productivity plots, FSC 65 did not store more total C than clearcut scenarios. FSC 105 stored more total C than FSC 65 in both high (*p*<0.001) and low (*p*=0.005) productivity plots (Figure 6).

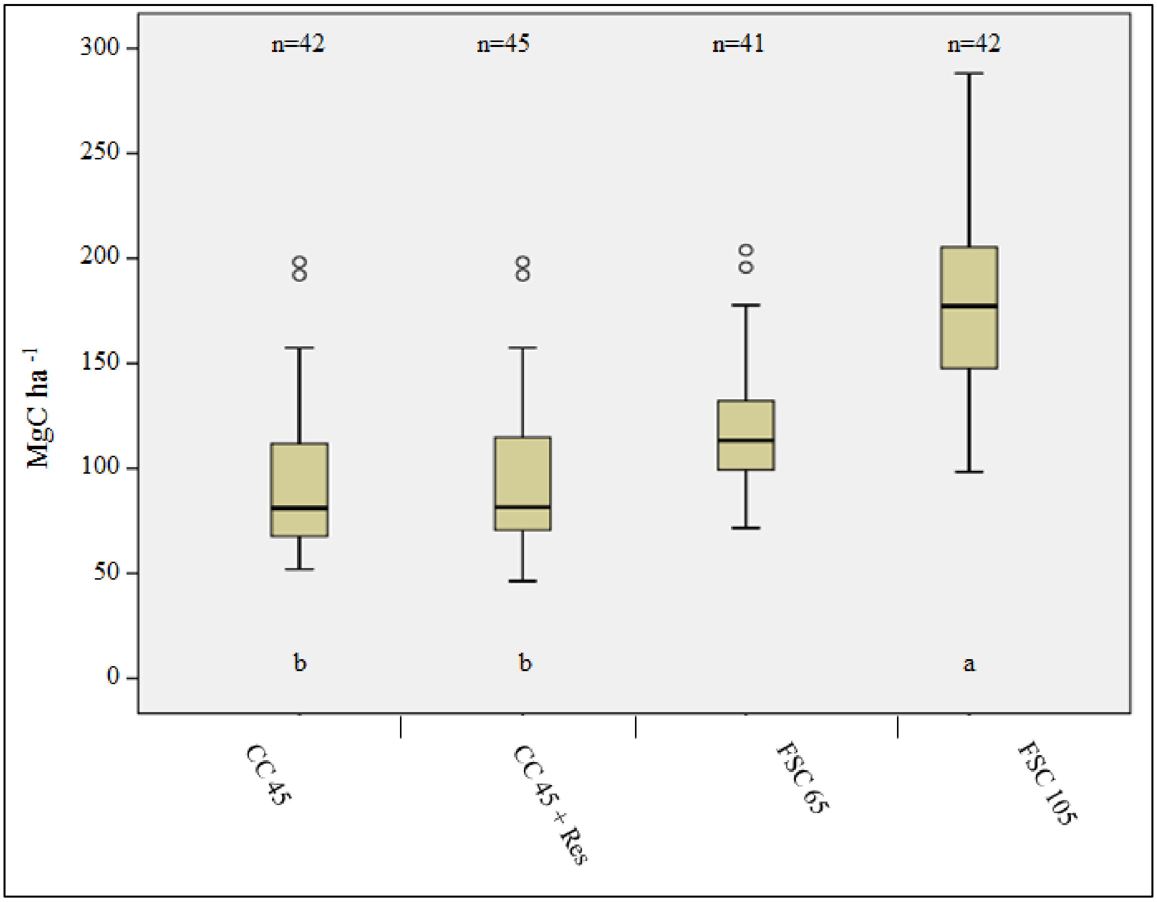


Figure 6: Box-and-whisker plot of high-productivity conifer plots following simulation harvest, age 20-30, total MgC per hectare in 2040. Bar indicates median, box includes 25th to 75th percentiles, and whiskers extend to 5th and 95th percentiles. Circles indicate outliers of 1.5 to 3 interquartile ranges from the mean. Significant differences between FCS and clearcut scenarios diminish as stands age and trees replanted in clearcuts catch-up to BA retentions in FSC scenarios.

Optimization of the FSC scenarios allowed harvesting at 30% BA retention for stands that were younger than the age of cMAI. The optimization resulted in a majority of plots being harvested before cMAI (Table 6), including plots as young as 31 years. FSC 105 harvested all plots at 30% BA retention.

Table 6. Proportion of harvest at 10% and 30% BA retention in FSC scenarios. No plots were allowed to grow to 105-year maturity in the FSC 105 optimization.

	10% BA		30% BA		
	# Plots	ha	# Plots	ha	Age range
FSC 65	70	236	97	384	31 to 56
FSC 105	0	0	165	618	31 to 100

The differences in FSC 65 total C from the 0-19 strata and the low-productivity strata suggests initial gains in C storage diminish as C increases due to more rapid growth modeled in clearcut stands. How C storage under FSC scenarios continues beyond 30 years remains unanswered. One could surmise that as the second cohort develops under the 10% or 30% BA retention, the difference in C storage compared to clearcut scenarios would diminish as clearcut stands catch up. The extent to which the FSC plots' retained trees suppress the second cohort would strongly influence C storage relative to clearcut stands.

3.4.2 Older strata not harvested during 30-year model simulation

In plots where no harvest took place, one might expect no difference among treatments. For example, a plot should store the same amount of C as any other within its stratum under any scenario if the model simulation does not act on that plot. However, significant results were observed in some such strata. These results can be explained by looking at patterns in harvested plots and the effects on remaining unharvested plots. The optimization selected stands for harvest differently under the different management scenarios. If a particular scenario's optimal harvest selects the highest-volume stands from an older strata, the remaining plots within that strata would be lower volume, and thus lower average C.

Alder 31+ showed no differences in total C among treatments. Similarly, both high and low productivity conifer plots age 31-44 showed no differences among treatments.

In high productivity conifer stands age 45-84, no significant differences in total C were observed among treatments. However, in low productivity conifer plots age 45-84, No Management stored more C than Clearcut 45 (*p*=0.036), Clearcut 45 + Reserve (*p*=0.029), FSC 65 (*p*=0.003), and FSC 105 (*p*=0.003). Thin 20 stored more total C than both FSC scenarios (*p*=0.048 for both). No differences were found among clearcut and FSC scenarios. These results suggest high-volume plots were preferentially selected for harvest under the optimization process, such that C storage in the remaining plots in this stratum were lower than the strata average under No Management. The effect was significant in low-productivity plots only, perhaps because the difference in C storage between the lowest- and highest-volume plots of the low-productivity stratum was greater than that in the high productivity stratum. Optimization modeling probably selected highest volume 45-84Lo sites for harvest.

In conifer plots age 85+, and the "Other" stratum, no differences in total C storage were found among treatments.

3.4.3 Thin 20 plots that experiences harvest

The Thin 20 scenario retained the dominant cohort of trees throughout thinning treatments. Thus, stratification based on age of stand since initiation used for all other management scenarios did not capture the effects of thinning on C storage. For Thin 20, strata based on age since thinning treatment were developed instead, allowing analysis of the effects of thinning on C based on a) years since thinning and b) number of thinning entries. While these strata are not directly comparable to strata used for other scenarios, identifying trends in C storage based on time since thinning helps forest managers understand the potential outcomes of thinning treatments. All Thin 20 strata are for plots that experienced thinning under the 30-year model simulation.

Table 7. Average total MgC per ha in 2040 in plots thinned under the Thin 20 scenario. The differences in means among the strata were not significant at the 0.95 level. Thin 20 resulted in more C per ha than all other intensive management practices.

	Conifer		Alder
	High	Low	
1st Thin	277	267	193
2nd Thin	259	237	na

No significant differences were found among strata for total C. Plots that were thinned twice tended to store less C than plots thinned only once (Table 7). However, plots that were thinned twice had fewer years since thinning, on average, compared to plots that were thinned once. Thin 20 tended to store more C following thinning than other management scenarios. For example Clearcut 45 0-19 high productivity conifer stratum stored 39.8 MgC per hectare of C following harvest, and FSC 65 stored 109.4 MgC per hectare in the same stratum, while Thin 20 stored 259 MgC per hectare following the second thinning in high-productivity conifer plots.

3.4.4 Carbon pools within strata

Harvest practices affect C pools within strata. For example, less-intensive harvests may leave more trees to be recruited to snag and log pools. ANOVA with Tukey post-hoc was used to assess statistical significance in mean difference the 0.05 level.

All statistically significant differences in management scenario on the total C pool were also significant in the aboveground pool; no other significant differences were observed in the aboveground pool (Table 8).

Table 8. Average MgC per ha in 2040 in the aboveground C pool. Within rows, management scenarios with bolded values and “*” indicate differences in means at the 0.95 level from other management scenarios with non-bold “*”. Similarly, bold values with “§” are significantly different from other values with “§”. FSC stored more C than more intensive management scenarios in stands regenerating following harvest due to the 10% or 30% BA retention requirement.

	CC45	CC45+ Res	CC45+ Inc Age	FSC 65	FSC 105	Break Even	Thin 20	No Mgmt
A0-30	38.3*	50.4*	64.5	48.2*	**103.8***	37.8*	na	na
A31+	173.5	169.0	175.4	173.0	170.3	169.0	172.0	177.9
C0-19Hi	29.7*§	29.9*§	35.1*§	**84.3§**	**90.4***	30.6*§	na	na
C0-19Lo	29.4*§	28.2*§	33.6*§	**88.2§**	**89.2***	31.9*§	na	na
C20-30Hi	72.4*§	75.6*§	82.3*	**95.1*§**	**142.8***	77.8*	na	na
C20-30Lo	75.1*	76.8*	72.2*	91.9*	**122.1***	64.7*	na	na
C31-44Hi	145.8	145.8	145.8	134.9	134.9	145.8	145.8	145.8
C31-44Lo	129.7	129.7	129.7	125.0	124.8	129.7	127.8	129.7
C45-84Hi	175.7	175.9	186.8	168.3	166.1	192.2	186.6	201.4
C45-84Lo	145.8*	144.1*	160.1	137.1*§	137.1*§	168.5	**170.7§**	**178.4***
C85+	335.8	319	310.9	319.0	319.0	323.7	265.9	319.5
Other	177.2	177.2	194.2	181.6	180.9	194.2	194.2	194.2

Root C pools closely correlated to total C and aboveground C storage. This may be explained by root biomass equations being functions of DBH. Two deviations from significance in aboveground C storage were observed. In low productivity conifer plots age 20-30, FSC 65 stored significantly more root C than most clearcut scenarios including Clearcut 45 (*p*=0.017), Clearcut 45 Increasing Age (*p*=0.011), and Break Even (*p*=0.030). Unlike the aboveground pool, in low productivity conifer plots age 45-84, Thin 20 was not different from any other management scenario (Table 9).

Table 9. Average MgC per ha in 2040 of the root C pool. Within rows, management scenarios with bolded values and “*” indicate differences in means at the 0.95 level from other management scenarios with non-bold “*”. Similarly, values with bold “§” are significantly different from other values with “§”. Root C closely paralleled aboveground C in significant, likely due to both pools depending on tree DBH for biomass estimation.

	CC45	CC45+ Res	CC45 + Inc Age	FSC 65	FSC 105	Break Even	Thin 20	No Mgmt
A0-30	4.0*	5.4*	9.6	6.7*	**14.1***	3.5*	na	na
A31+	24.0	22.7	22.0	22.2	22.0	22.7	22.5	23.0
C0-19Hi	3.5*§	3.5*§	4.4*§	**15.8§**	**17.3***	3.7*§	na	na
C0-19Lo	4.2*§	4.0*§	5.7*§	**18.3§**	**18.8***	5.4*§	na	na
C20-30Hi	10.9*§	11.1*§	12.1*	**14.6*§**	**25.0***	11.9*	na	na
C20-30Lo	10.9*§	11.4*	10.1*§	**16.3*§**	**22.5***	9.1*§	na	na
C31-44Hi	26.9	26.9	26.9	23.5	23.5	26.9	26.9	26.9
C31-44Lo	23.0	23.0	23.0	22.5	22.2	23.0	22.7	23.0
C45-84Hi	29.4	29.7	31.6	27.9	27.7	32.9	33.1	35.3
C45-84Lo	25.0*	24.7*	28.2	24.5*	24.5*	29.9	32.4	**33.4***
C85+	52.6	51.4	50.2	51.4	51.4	52.4	44.7	52.4
Other	23.2	23.2	26.7	24.7	24.7	26.7	26.7	26.7

Snag C pools showed trends distinct from total C or other C pools (Table 10). In high productivity conifer plots age 20-30, FSC 105 stored more snag C than all clearcut scenarios (*p* ranged from <0.001 to 0.031) and FSC 65 (*p*=0.009). In low productivity conifer plots age 20-30, FSC 105 stored more C than Clearcut 45 (*p*=0.041). In low productivity conifer plots age 45-84, both FSC 65 and FSC 105 stored less C than No Management (*p*=0.015 for both).

Table 10. Average MgC per ha in 2040 of the snag C pool. Within rows, management scenarios with bolded values and “*” indicate differences in means at the 0.95 level from other management scenarios with non-bold “*”. Similarly, values with bold “§” are significantly different from other values with “§”. Older strata tended to store more C than younger strata, while FSC stored significantly more C than some intensive management practices.

	CC45	CC45+ Res	CC45+ Inc Age	FSC 65	FSC 105	Break Even	Thin 20	No Mgmt
A0-30	2.0	1.5	6.7	3.5	2.7	1.5	na	na
A31+	10.4	9.4	9.6	9.6	9.4	9.4	9.4	10.1
C0-19Hi	4.0	3.2	4.0	5.7	5.4	3.7	na	na
C0-19Lo	5.7	5.4	7.7	6.2	6.2	6.2	na	na
C20-30Hi	3.2*	3.0*	3.7*	3.5*	**5.4***	3.5*	na	na
C20-30Lo	3.0§*	3.0	3.2	**3.7**§	**4.9***	2.5	na	na
C31-44Hi	7.9	7.9	7.9	7.9	7.9	7.9	7.9	7.9
C31-44Lo	7.4	7.4	7.4	7.2	7.4	7.4	7.2	7.4
C45-84Hi	11.6	12.1	12.6	10.1	9.6	13.8	11.9	13.6
C45-84Lo	9.1	9.1	10.6	8.2*	8.2*	11.6	11.1	**12.6***
C85+	19.8	18.3	17.5	18.3	18.3	18.0	13.6	18.0
Other	11.4	11.4	11.9	10.4	10.6	11.9	11.9	11.9

No statistically significant differences in log C were observed under any management scenario (Table 11).

Table 11. Average MgC per ha in 2040 of the log C pool. No significant differences were observed. Older strata tended to store more C regardless of management practice.

	CC45	CC45+ Res	CC45+ Inc Age	FSC 65	FSC 105	Break Even	Thin 20	No Mgmt
A0-30	2.5	3.5	3.0	2.2	4.2	2.5	na	na
A31+	6.2	5.9	7.2	6.4	6.2	5.9	5.9	6.9
C0-19Hi	2.7	2.7	3.7	3.5	3.2	2.5	na	na
C0-19Lo	4.0	3.7	3.2	3.7	4.0	3.0	na	na
C20-30Hi	6.2	5.7	7.2	4.4	6.4	8.2	na	na
C20-30Lo	4.9	5.2	4.7	4.2	4.0	4.2	na	na
C31-44Hi	12.1	12.1	12.1	3.2	3.2	12.1	12.1	12.1
C31-44Lo	10.1	10.1	10.1	11.6	11.9	10.1	9.4	10.1
C45-84Hi	6.7	6.7	6.7	5.9	5.7	7.7	5.9	7.9
C45-84Lo	7.4	7.7	7.9	5.9	5.9	8.6	6.9	8.6
C85+	11.9	11.9	11.4	11.9	11.9	13.3	7.4	14.3
Other	8.2	8.2	9.4	8.6	8.2	9.4	9.4	9.4

Combining the snag and log pools into a deadwood pool reveals one significant difference in average C. In conifer stands age 85 and older, Thin 20 stored less C than No Management (p=0.017), where all other scenarios were not different from No Management. Because plots thinned under Thin 20 were not recorded as re-setting age to zero, old stands that have experienced thinning are compared to old stands that have not experienced thinning under No Management.

4 Discussion

These results concur with other research showing that increased harvest intensity tended to reduce C storage (Harmon and Marks 2002, Harmon et al. 1990). Carbon stored in harvested wood products, even when accounting for C stored in landfilled products, did not compensate for C stored in-forest in scenarios with less intense harvests. Given that substitution effects are not real additional C storage according to C offset methods (Law and Harmon 2011, CAR 2010, ACR 2010), this study's results were comparable to other research on the effects of forest management on C storage (Perez-Garcia et al. 2005 ignoring displacement and substitution effects, Harmon et al. 2009).

At the whole-forest scale, the least intensive management practices–No Management, Thin 20, and Break-Even–stored more C than the more intensive management practices. More surprising is that no statistical differences were observed among management scenarios that included substantial harvest for both total C and individual C pools. At this coarse scale, C storage is not significantly different regardless of harvest intensity among any management practice that involves substantial timber harvest.

Mill efficiency and decay results in only a fraction of C stored in wood products compared to continually accumulating C in-forest under low-intensity activities. Under active forest management scenarios, prominent sources of dead wood – density-dependant mortality and old trees succumbing to disease or mechanical damage – are circumvented through forest management practices. Even Thin 20, which stored significantly more total C than most other management practices, did not store significantly more C in snags or logs. Thin 20 had less C in deadwood most likely because thinning increased the vigor of the plot, reducing mortality and recruitment to the snag and log pools.

Within strata, however, significant differences were detected among treatments. In the subset of plots that were harvested during the 30-year modeled timeframe, the 10% or 30% basal area retention required under FSC scenarios resulted in significant additional C storage compared to clearcut scenarios. Much of the C gain was due to a majority (FSC 65) or entirety (FSC 105) of stands harvested at 30% BA retention. FSC scenarios' initial C gains may diminish over time as clearcut plots grow vigorously and catch up to C storage in FSC plots. Further study is needed to determine if differences in C storage between FSC and clearcut management practices among young stands persist as stands age, or if differences becomes indistinguishable at rotation age.

In this study the optimization model (Tóth et al. in press) maximizes revenue, C storage, and old forest habitat, and there was a preference for harvesting stands that maximized revenue without reducing C. Profit maximization thus leads to trade-offs in management regardless of the harvest system employed. The FSC prescriptions were presumably designed to guide landowners toward more ecological forest management, but these results suggest an unintended consequence of cutting stands before they reach the cMAI may be applied to make up revenue. In fact, FSC may force profit maximizing landowners toward shorter rotations.

For forest owners considering management choices to increase C storage, only the lowest-intensity practices of No Management, Thin 20, and Break Even conclusively stored more C than the regional standard practice of Clearcut 45 over the 30-year model timeframe at the whole-forest scale. FSC scenarios were the only management practices that included both substantial wood product harvest and significantly increased C storage in the first few decades following harvest, though long-term differences in C were not addressed in this study. While not statistically significant, the Clearcut 45 + Increasing Age scenario resulted in a moderate tradeoff between C stored in-forest and C stored in wood products, as others have found when increasing stand age (Harmon et al. 1990, Dewar 1990, Cooper 1983). No Management, Thin 20, and Break-Even resulted in significantly more C storage at the expense of C in harvested wood products, and correlated loss in timber revenue. Tóth et al. (in press) found these management practices to be unprofitable based on timber revenue alone. The feasibility of low-intensive management practices remains questionable.

5 Conclusion

This study found several important conclusions. Biomass equations can significantly affect the estimated or apparent amount of C storage, and choosing site- and age-class specific equations can improve the accuracy of biomass calculations above generalized equations. The effects of management showed two important conclusions. First, among management practices that removed more timber than the Break-Even scenario, no significant differences in C storage occurred at the whole forest level. Only less intensive harvest scenarios that harvest fewer stands (e.g. break even) or that increase stand ages store more C over the modeled timeframe. Specifically, long-rotation FSC management scenarios did not store significantly more C than short-rotation clearcut scenarios. FSC prescriptions do have more C post-harvest than clearcut scenarios because of the structure left behind. Thirty percent BA retention harvest would lead to interesting uneven age systems that could provide greater utility for wildlife (Lindenmayer et al. 2006). FSC scenarios also resulted in greater amounts of C in snags, possibly correlating to better wildlife habitat and more closely emulating natural stand development (Franklin et al. 2002).

FSC prescriptions mandate 30% retention if not at cMAI. The intention of this retention is to motivate more ecological forestry, but if profit motive is included, landowners (as shown by optimization results) should favor cutting before cMAI. Furthermore, optimal harvest when using an interpretation of cMAI for even longer rotations resulted in cutting all the stands early, a perverse unanticipated consequence. It is not clear then if the imposed restriction is meeting its function. Whether forest owners who choose FSC certification would make the same management decisions as did the optimization is questionable.

Forest owners face difficult tradeoffs when considering changing management practices to increase C storage. While low-intensity practices are likely to store more C, achieving an optimal balance between C storage and volume of harvested wood remains a decision fraught with uncertainty. This study showed the subtlety in differences in C storage among forest management practices. The next step is addressing sources of revenue, including timber and C as marketable products, and assessing the profitability of these management practices in balance with the C storage capacity reported here.

CHAPTER II: Uncertainty and decision making in forest C projects

1 Introduction

Forest owners must decide how to best manage a forest for wood volume, quality, price upon harvest, and non-market values like wildlife habitat or recreation. They deal with uncertainty in the long-term consequences of how management choices change forest productivity and the unpredictable ability to realize financial gain due to changes in future trends in price and demand. Payments for forest C offsets has added a layer of complexity to management decisions. Carbon markets are relatively new, and their future price is uncertain (Conte and Kotchen 2010). This study evaluates uncertainty in timber volume, timber prices, C mass, and C credit price to help forest owners understand the role of uncertainty and to describe the possible consequences of entering into agreements to manage for C credits. This study uses a Monte Carlo-based uncertainty analysis to forecast possible revenue from timber and C credits, and provides decision analysis tools to interpret results.

People or organizations who wish to mitigate their greenhouse gas emission can purchase offset credits from C markets. Carbon offset markets were established to provide least-cost greenhouse gas (GHG) mitigation (Falk and Mendelsohn 1993, Sohngen and Mendelsohn 2003), and credits from forestry projects compete with credits from other types of C offset projects such as renewable energy and methane capture. Forest C projects include afforestation, forest preservation, and improved management of wood product-producing forests through improved forest management (IFM) (ACR 2010, CAR 2010). This study focuses on IFM.

In the United States, carbon offsets are typically developed and sold on voluntary markets, although regional regulated mandatory markets exist in the Northeast (RGGI 2005) and California (AB 32 2006). Forest owners who change management practices to increase the amount of C stored in a forest may register their management plan as a C offset project with one of several verifying organizations. Three organizations have authorized IFM methodologies for use in the United States: America Carbon Registry (ACR 2011), Climate Action Reserve (CAR 2010), and Verified Carbon Standard (VCS 2010). Forests verified following methodologies developed under these standards are eligible to enroll in projects whose credits can be bought and sold on voluntary offset markets. Credits may be sold on the California cap-and-trade compliance market if verified under CAR methodology (CARB 2011). Once verified, the C project can receive credits for the additional C stored as a result of the project; typically, 1 credit represents the equivalent of 1 metric tonne (Mg) of CO_2 removed from the atmosphere after deductions for leakage, risk, and uncertainty (ACR 2010, CAR 2010, VCS 2012). The forest owner can then sell the credits to people or organizations who wish to mitigate their GHG emissions.

Changing forest management practices to increase C storage can reduce the concentration of CO_2 in the atmosphere, but forest C projects must also be beneficial to the forest owner. The leading cause of forest loss in the United States is permanent conversion to agriculture or development

(Alig et al. 2009). In western Washington, between 1988 and 2004, 17% of private forest land was converted to agricultural, mixed-rural, and urban development (Bradley et al. 2007). Working forests, where trees are grown, harvested, and replanted for future generations, depend on timber revenue to cover land holding costs and provide income to the forest owner. Increasing C storage typically depends on decreasing timber harvest and forgoing the associated timber revenue. If payments for C are insufficient to compensate foregone timber revenue, the forest owner could be faced with selling the land for a more profitable use – conversion to non-forest. While working (i.e., timber producing) forests offer lower ecological benefits than forest preserves, working forests are far more ecologically beneficial than developed land. Carbon markets for IFM must provide sufficient revenue to help offset the cost of foregone timber revenue.

Many forest owners, particularly industrial forest owners, seek to maximize profit. A profit maximizing landowner would require prices for C credits sufficiently high to equal or exceed the revenue they could get from standard timber harvest. Currently, the value of one unit of harvested timber far exceeds its C storage value. Although verifying organizations and IFM methods have been available for forest owners in western Washington for many years, to date there have been no verified forest C projects in Washington or Oregon (Forest Carbon Portal 2012). This lack of action indicates forest C projects do not make financial sense for forest owners. However, lack of action could also be a result of perceived risk in C projects, including uncertainty over future C prices, or uncertainty of the effects of management practices on timber and C revenue.

Monte Carlo (MC) simulations and probability distributions are common and relatively simple methods used to assess uncertainty in complex systems (Kremer 1983, Smith and Heath 2001). MC probabilistic simulation involves thousands of random samples (“trials”) selected from predefined probability distributions. The result is a probability frequency distribution showing the likelihood of outcomes. This becomes very useful in defining the uncertainty in a payoff function that includes many uncertain variables. Sensitivity analysis of MC results can identify variables that contribute to variance, isolating the important sources of uncertainty in a payout or decision.

MC simulations have been used to assess C dynamics in natural systems (Larocque et al. 2008) and in the forestry sector (Kallio 2010), but never to assess the risk of payment for IFM for a forest C project. This study is the first to use MC simulations and probability distributions to evaluate the effects of forest management and C credit prices on net-present-value (NPV) of revenue in the Pacific Northwest.

This study addresses the risks in forest C projects by accounting for costs and benefits of clearcut harvesting on 45- and 65-year rotations with a no management scenario; each management approach includes revenues from timber, C or both. Using MC simulations to account for uncertainty in data and future prices, revenue distributions show the range of possible outcomes and the likelihood of profit. This study concludes by framing the uncertainty analysis in a forest management decision context, offering methods to account for revenue and non-revenue goals in forest management.

2 Methods

This study uses a probabilistic approach to account for uncertainties in long-term revenue forecasts for forest management scenarios that include sale of both timber and C credits. Net present values (NPVs) were forecasted for three forest management scenarios over 40- and 100-year timeframes. Probability distributions were assigned to 25 variables that contribute to the NPV payout function. Monte Carlo simulation allowed the simultaneous variation of input values in the payout function, resulting in probability density functions (PDFs) that were used to identify likelihoods across a range of revenue outcomes. Scenarios assuming several different discrete prices for C credits were run in order to identify the price at which forest managers would change behavior from timber to C management based on maximizing NPV. PDFs were also used to describe the risk of financial loss or gain. Finally, a decision analytic framework was used to incorporate wildlife habitat scores associated with each management scenario into the payoff function. Because it relies on data from only one forest, this study should be considered a case study, and should be applied cautiously to forestry more broadly, especially outside western Washington.

In this article, C generically refers to molecules that lock C in a non-volatile form; in forests, C is usually stored in cellulose and lignin. CO_2 is the GHG forests are able to remove from the atmosphere, though CO_2, methane, and other GHGs may be emitted back to the atmosphere through decomposition in forests. CO_2e refers to the CO_2 equivalence of the radiative forcing effect of a particular GHG gas and is the common unit for comparing the GHG mitigation capacity of emissions offset projects (IPCC 2007).

Carbon credits are the saleable units that result from C offset projects that are verified under authorized methodologies. Foresters receive payments for C upon verification of IFM projects designed specifically to increase the amount of C above a baseline condition. Increasing C above a baseline is referred to as “additional” C; additionality is a critical component in all three organizations’ methodologies (ACR 2010, CAR 2010, VCS 2007).

Carbon credits are awarded to projects that have demonstrated additional C storage under third-party verification. The number of C credits awarded is not equal to C mass. Credits are awarded as the difference between “with-project” C mass and baseline C mass, adjusted for eligibility and discounts such as leakage and risk buffers and uncertainty in forest measurement data sources. One credit is awarded per additional metric tonne of CO_2e storage as a result of the project after deductions are taken.

2.1 Forest management scenarios

Three forest management scenarios were modeled using Pack Forest inventory.

Clearcut in 45-year rotations (CC45): Stands age 45 years and older are eligible for clearcut harvests in compliance with Washington State Forest Practice regulations and Sustainable Forestry Initiative (SFI) requirements. This scenario is the business-as-usual (BAU) profit maximization scenario that represents industrial standard practices. Carbon credits are not available under this scenario, but this scenario serves as the baseline for C credit calculations.

Clearcut in 65-year rotations (CC65): Stands age 65 years and older are eligible for clearcut harvests in compliance with Washington State Forest Practices regulations and SFI requirements. Increasing length of rotation has been shown to increase C storage (Harmon et al. 2009). This scenario includes revenue from timber and C.

No active management (NoMgmt): No harvest takes place. The scenario represents C maximization. Revenue is entirely from C.

Stand age is defined as the number of years since a stand-initiating event occurred (i.e., harvest or stand-replacing fire) and represents the approximate age of the dominant cohort of trees. Harvest rotations were designed using an even-flow model. The number of hectares harvested per year equals approximately 1740 ha times 1/(rotation age). Thus, stands harvested in year 1 are assumed to have sufficiently regenerated after the end of the rotation cycle, and the cycle reinitiates. Approximately 242 hectares of Pack Forest’s 1,740 hectares were excluded from consideration for harvest due to long-term ecological or research goals. Harvest schedules are specific to Pack Forest’s current timber inventory; comparisons to other forests depend on species and age composition.

2.2 Payout function

A payout function was defined for the purpose of estimating the NPV for each forest management scenario. Future value net benefits were also estimated in 5-year periods. All dollar values were adjusted to 2010 using consumer price index (U.S. Bureau of Labor Statistics 2012).

$$\text{NPV} = \sum_{t=0}^{N} \frac{\mathbf{Costs}_t + [\mathbf{Timber\ volume}_t * \text{Exp}(\text{Ln}(\mathbf{Timber\ price}_t))] + [\#\ \mathbf{C\ credits}_t * \mathbf{C\ credit\ price}_t]}{(1+i)^t} \tag{3}$$

where:

- *t* = model period (0 to 100 in 5-year increments);
- *i* = discount rate;
- **Bold type** = factors that include variables represented by probability distributions in MC simulation;
- Costs include: fixed C verification costs, fixed forest sustainability certification costs, and forest operational costs. Only two cost variables were simulated in MC: weeding and precommerical thin;

- Timber volume is the average thousand-board-feet harvested per period in each of nine log-grades. The following probability distributions are multiplied by this term and simulated in MC:
    - (1 - Sample plot uncertainty)
    - (1 - Growth model uncertainty in board feet)
    - (1 - Conversion calculation of board-feet (Scribner) from tree measurements);
- Timber price is the lognormal probability distribution of average prices of each of nine log-grades. Three time periods are used in MC simulations: a 5-year price, a 10-year price, and a long-term price;
- # C credits is the number of C credits issued following ACR Columbia Carbon (2011) methodology. Carbon credits are calculated from C mass and adjusted for eligibility and deductions for risk, permanence, and leakage. FVS model uncertainty in C mass is simulated in MC by treating the number of C credits as the mean, and using an average SD derived from the variability in percent error from FVS model uncertainty to define the probability distribution.

  Furthermore, the following probability distributions are multiplied by number of C credits:
    - (1 - Sample plot uncertainty)
    - (1 - Biomass allometric equation uncertainty), and;
- C credit price is the normal probability distribution of the 10-year historical average price of forest C credits sold on voluntary over-the-counter markets, or normal probability distributions of C price scenarios.

The following sections describe each term in the payout function in detail.

2.2.1 Forest sustainability certification cost

Forest certification costs were calculated for SFI certification based on the actual cost to Pack Forest when obtaining SFI certification in 2004 (Pack Forest 2005). SFI is the regional industrial standard certification. Initial certification cost of $40,371 was applied in year zero; annual cost of $5,953 was applied in 5-year intervals thereafter. Probabilistic distributions were not developed to represent forest certification costs.

2.2.2 Carbon certification cost

C project and credit fees were determined from the ACR fee structure website (ACR 2012). Fees totaled $1,500 and were applied in year zero, or the year credits were awarded, as appropriate. Initial validation ($27,500), annual verification ($5,500), and decadal validation ($27,500) cost estimates were provided by forest C industry professionals (Smith, personal communication 2011). Costs were assumed to be part of an aggregated C project where multiple land owners pool land and share costs. The cost of independently pursuing C project would have been prohibitively high for a forest of Pack's size. Probabilistic distributions were not developed for C project certification inputs.

2.2.3 Management and land holding costs

All management scenarios included a fixed annual land holding and operations costs, including tax obligations, management, and operation costs of $169.66 per hectare. This is considerably higher than most forests because Pack Forest maintains buildings, roads, and staff to support its research, education, and outreach mission absent in most working forest. Separately, harvest costs were calculated in each period based on acres harvested, planted, weeded, and other timber-related operations. Cost information is from Pack Forest records (Ettl, personal communication 2011) or from a survey of small-scale forest owners (Briggs 2012). Harvests costs for the No Mgmt scenario were zero, while land holding and operations costs were maintained at $169.66 per hectare. This may overestimate land holding and operations costs as fewer resources may be needed if harvest is not part of operations, and is considered conservative.

Harvest costs were applied per thousand-board-feet (MBF) of harvested wood. Harvests costs are higher on steep terrain ($180/MBF rather than $130/MBF), thus a weight-adjusted average harvest cost of $147/MBF was used based on the proportion of slopes greater than 30% in Pack Forest (USDA WSS 2011). Uncertainty parameters were not developed for land holding, management, or harvest costs.

2.2.4 Timber volume

FVS projections created for Tóth et al. (in press) produced per-hectare harvested merchantable timber volume (Scribner board-feet [BF]) for 443 CFI plots. Harvested volumes were categorized by nine log grades including saw logs and pulp. I stratified plot harvest volumes by species composition, stand age, and soil productivity strata. Average harvest volumes for log grade categories within each stratum were summarized in tables by forest type and age (Appendix 3). Hectares of each stratum harvested in each period under this study's three management scenarios were calculated. Harvest volumes were then calculated by multiplying hectares of a stratum harvested by the average volume of wood products, and by log grade, from the table.

2.2.5 Timber price

Average stumpage price (value of tree fiber at a processing plant or sawmill minus the cost of harvesting, transportation to the mill and conversion to an end product such as lumber) per MBF has been recorded for saw logs biannually by Washington State Department of Revenue for tax purposes since 1972 (WDOR 2012), yielding 77 data points for each log grade. Stumpage prices, rather than mill prices, conservatively estimate revenue. Stumpage prices for five grades of saw timber (Douglas-fir #2, Douglas-fir #4/utility, western hemlock/true fir/pine #2, western red cedar #1/camprun, and red alder #1) were used in this analysis—high value grades from recent Pack Forest log sales (Ettl, personal communication). Average Washington pulp prices were obtained from Lindberg (2012) for three species (Douglas-fir, western hemlock, and red alder). A fourth category was calculated for all other species using the average pulp price. This data source was more limited, providing average annual pulp prices since 2006. Prices were converted from per-tonne to per-MBF using Washington Department of Natural Resources conversion factor of 9 short tons pulp per 1 MBF.

2.2.6 C credits

C credits were calculated through a multi-step process following an ACR IFM methodology (Columbia Carbon 2011). First, C mass was derived from the CFI-plot level data created for Tóth et al. (in press). Next, C in harvested wood products and landfills was calculated following the U.S. Department of Energy 1605(b) (2007) method. Greenhouse gas emissions due to harvest and processing are considered deminimus, though processing emissions are partially accounted for in mill efficiency rates in harvested wood product C calculations. Finally, the number of C credits was calculated following the Columbia Carbon (2011) methodology and VCS 2012 Agriculture, Forestry, and Other Land Uuses (AFOLU) non-permanence risk tool (VCS 2012).

Columbia Carbon (2011) determines C credits starting by comparing mass of C storage in with-project scenarios to that of the business-as-usual scenario based on current management practices. The CC45 scenario served as the baseline in C credit calculations. The difference in mass of C storage between the CC45 long-term average baseline and CC65 and NoMgmt scenarios provided the basis for C credit allocation.

Initial steps in C credit calculation are similar to BF calculations in Section 2.2.4. I used per-hectare C mass (Mg) for 443 CFI plots, and stratified each plot by species composition, stand age, and soil productivity. Average C mass for each stratum was summarized in Appendix 3. Hectares of each stratum in each period under the three management scenarios were calculated. In-forest C mass was then calculated by multiplying hectares of a stratum by the average C mass from Appendix 3, a similar approach was used for timber volume calculations.

C stored after 100 years in harvested wood products and landfills was calculated using the U.S. Department of Energy 1605(b) (2007) method as required by Columbia Carbon (2011). Data for wood product and landfill C originated from cubic feet (ft^3) of harvested wood by age-class-productivity strata (Appendix 3). Volume in ft^3 was converted to biomass using species specific gravity. Biomass was converted to mass of C by assuming 50% C content of biomass; this conversion is used in Harmon et al. (1990) and Perez-Garcia et al. (2005) and is more conservative than Birdsey (1992). Section 2.6 in Chapter 1 describes the method in detail.

VCS Agriculture, Forestry, and Other Land Use (AFLOU) Requirements v3.0 (VCS 2012) was used to calculate deductions for financial viability, permanence, and risk of natural disturbance, among other risk factors. Deductions relevant to this analysis increase for unprofitable projects, shorter time commitments, and high frequency and severity of natural disturbance. Further deductions for uncertainty in forest measurements and sample error, and leakage, were calculated following Columbia Carbon (2011). The remaining mass of C is converted to CO_2-equivelants (CO_2e) and translated to C credits, where 1 CO_2e equals 1 C credit. Under ACR, C credits are called Emission Reduction Tonnes (ERTs). ERTs are the product bought and sold on tradable markets.

Two scenarios were used for C credit calculations: a 40- and a 100-year commitment timeframe. A 40-year timeframe is the minimum period allowed to become an ACR-verified C project. A 100-year timeframe was also used; 100 years is the minimum timeframe for CAR forest C projects.

Baseline and deductions were calculated using the Base-Case historic price of C credits of $7.89 for the first 20-year validation period and not re-calculated thereafter. Thus, C projects that become economically feasible at high C price scenarios still used deductions based on the historic price of C. This conservatively underestimates the number of C credits available under C price scenarios. Similarly, additional deductions that may accrue in later validation periods when long-term C losses take place were not accounted. Sensitivity results showed the effect of C credits to be small enough that these methodology omissions are inconsequential in NPV calculations.

2.2.7 Carbon credit price

C price was estimated from surveys of C offset project developers (Diaz et al. 2011, Hamilton et al. 2010, Peters-Stanley et al. 2012). Prices used in this study are for voluntary market over-the-counter credits specifically from forest C projects. Carbon credits sold pre-2002 were condensed into one value in the data source, and annual averages were used for 2003-2012 data. Revenue from C sales is assumed to go entirely to the forest owner, other than per-credit transaction fees. Prices reported in the data sources include credits certified under a variety of organizations, not only ACR credits.

2.2.8 Discount rate

A real discount rate of 5% was used. Five percent is Pack Forest’s standard discount rate (Ettl, personal communication 2011) and is the rate recommended under the American C Registry C accounting methodology used in this analysis (Columbia Carbon 2011). Forest industry companies often apply 6 to 9% discount rate (Vicary 2006), while ecologically-based projects may use a lower discount rate (Weitzman 1999). Water resource projects, for example, are exempt from the U.S. Office of Management and Budget discount rates in favor of lower discount rates for projects with long-term ecological implications (U.S. OMB 1994).

2.3 Uncertainty

Model uncertainty is an important challenge of the forest management decision process and I represented uncertainty in the payout function using probabilistic simulation. Figure 7 shows the influence of sources of uncertainty on NPV. Probability distributions were determined for four terms in the payout function: volume of merchantable timber, mass of C (translated into C credits), timber price, and C credit price. Sources of uncertainty that were excluded from this analysis are also described. MC simulations were run using the Microsoft® Excel spreadsheet add-in Oracle© Crystal Ball version 11.1.2.2.000 (Oracle 2012). Because C mass and volume of harvested timber were obtained from another study, uncertainty associated with data and data modeling that precede C mass and harvested timber volume had to be applied post-hoc. This was accomplished by developing probability distributions in terms of % error of mean values, and then multiplying MC simulations of % error of mean values by C mass and harvested timber volumes (Equation 3).

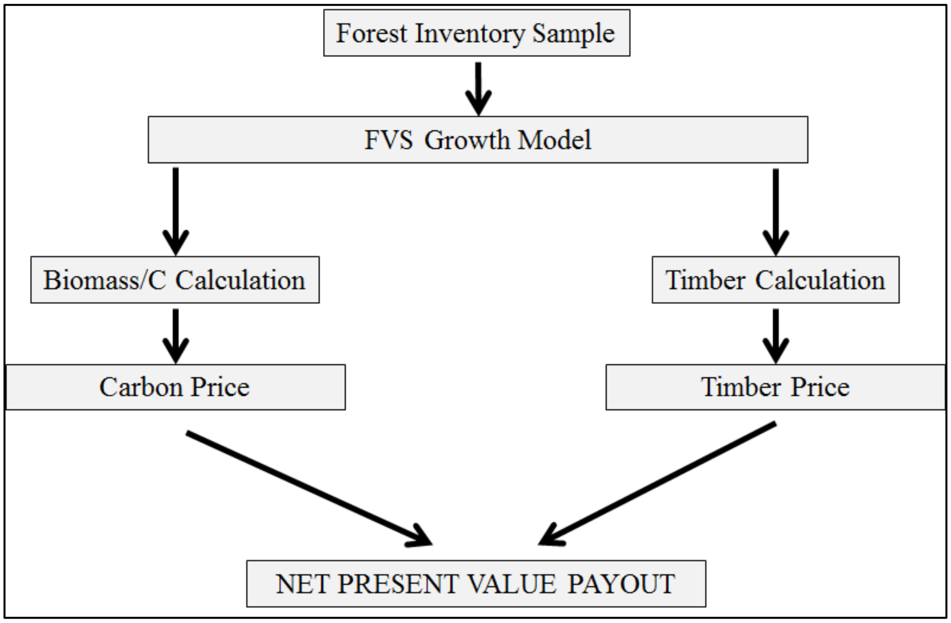


Figure 7: Flow chart of sources of uncertainty in NPV data. Uncertainty in all steps of the analysis carry through to the final payoff.

2.3.1 Forest Sampling Uncertainty

CFI data provided the raw information to FVS growth modeling. FVS calculated both volume of merchantable timber and mass of C. Uncertainty in CFI sampling was expressed as the % difference from average quadratic mean diameter (QMD) for 12 age-class-productivity strata. Diameter at breast height (DBH) and tree height are the raw data from CFI measurements. To account for variability among plots, a single parameter of each plot had to be calculated. QMD (rather than arithmetic mean diameter) is commonly used in forestry. QMD represents the diameter of the statistical tree of average basal area, and correlates to tree volume (Avery and Burkhart 1994). Plots were stratified into 12 age-class strata, and then strata average QMDs were calculated. Finally, % differences between plot QMD and strata average QMD were calculated. The distribution of % difference in QMD from strata average was used as the probability distribution for plot variability, assumed to be a normal distribution (Appendix 5) with average percent of mean equal to -/+0.02 and SD equal to 0.46. This distribution was simulated in MC and applied to both number of C credits and volume of harvested timber (Equation 3).

Pack Forest’s 443 CFI plots are geographically stratified throughout the 187 management units (stands), providing a level of representation of 1 plot per 3.9 hectares. Many factors may affect QMD; environmental conditions, genetic variability, and competition are probably the most significant. Each plot represents a large area. Thus, the plot-level data cannot capture all variability in forest types at Pack Forest. This uncertainty was not included in the probability distribution; thus sample error due to sample size and error due to the stochastic nature of ecological systems are not fully accounted. This initial uncertainty impacts all further growth, volume, and C calculations. Measurement error in tree diameter and height is assumed to be negligible.

Systematic error due to bias in the sampling procedure may occur but is intrinsically difficult to identify (Regen 2002). In the absence of any information source to determine probability distributions, bias in sampling procedure was ignored.

2.3.2 Forest Growth Modeling

FVS is a stand-level forest growth simulation model that informed both volume of merchantable timber and mass of C. FVS model uncertainty (including model error, bias, and variability due to FVS’ randomization of some outputs) was estimated by comparing FVS growth model outputs to measured growth in Pack Forest’s continuous forest inventories (CFI) of stands, and from a study of FVS error at Pack Forest (McKinley and Turnblom 2002). The % error between the 10-year change in FVS and true CFI measurements in timber harvest volume was used as a probability distribution for FVS model uncertainty. McKinley and Turnblom (2002) found an average bias of -16.6% between FVS and measured tree growth, meaning that FVS underestimates forest growth on average by that amount; probability distributions of uncertainty are still required to model uncertainty in this bias . To correct for this bias in C, the mass of C was multiplied by 1.166 before C credits were calculated and before uncertainty was modeled using Monte Carlo simulations. For volume of merchantable timber, bias was corrected in the probability distribution used for Monte Carlo simulations by setting the mean value to -0.16 and then using the parameter of variability as described in the following paragraphs.

While McKinley and Turnblom (2002) reported average error, they did not report parameters of variability or probability distribution sufficient for Monte Carlo simulations. To determine the magnitude and distribution of uncertainty around reported bias in McKinley and Turnblom (2002), I calculated these parameters from 10-year differences in CFI modeled vs. measured trees (Appendix 5). Records of 131 trees that were measured for height and diameter in Pack Forest in 2000 were entered into FVS and growth was modeled over 10 years. The same trees were re-measured in the field in 2010. Both merchantable volume (Scribner BF) and C mass were calculated per hectare from tree records using year 2000 tree measurements, year 2010 tree measurements, and FVS model results for year 2010. The SD of the % error between FVS and true CFI measurements in 10-year change BF was used to define the probability distributions for FVS uncertainty in harvested timber volume. Because of differences in how C credits and BF are calculated, FVS uncertainty in C mass was defined using an average standard deviation applied to the number of C credits generated in each modeled period, as described in the following paragraphs.

Uncertainty in FVS BF was calculated as percent error around the McKinley and Turnblom (2002) mean of -16.6%. Crystal Ball was used to determine a logistic distribution with scale of 0.46 (Appendix 5). Logistic distribution is similar to a normal distribution but with greater probability of values close to the mean as well as greater probability of values in the tails, giving the probability density function a peaked look.

Uncertainty in FVS C was calculated differently. Carbon credits are calculated by subtracting one year's C mass from the previous year's C mass. In years where there is a loss of C, the C credit methodology assigns zero credits. Multiplying a probability distribution times zero credits in years when no credits were issued would result in zero uncertainty, saying I am certain of zero credits in that year. In fact, even zero or negative credits are uncertain. Thus, a standard deviation (SD) had to be developed that could define the distribution of any number of C credits including zero and negative credits. CFI-derived C mass of the 131 trees was multiplied by the McKinley and Turnblom (2002) mean of -16.6% to find the average FVS-derived C mass. The differences between CFI- and average FVS-derived C mass was taken, and the SD of these differences was calculated to be 81,566 $MgCO_2e$ and used for all values of carbon credits. This is essentially an average SD. The number of C credits issued in a year was used as the mean, and this SD defined the variability about the mean. In the absence of better information, a normal distribution was assumed.

These distributions represent uncertainty in a limited sample of 10-year periods that does not represent all 10-year periods. Over the decades-long lifetime of a tree, environmental and climatic factors will introduce a much broader range of variability than could have taken place in this sample 10-year periods. Furthermore, C mass tables include data from FVS growth projections of up to 30 years. Assuming the effects of model error compound over time, a 10-year sample will underestimate model error accrued under longer simulations. However, the average period of simulation for data in volume and mass tables, and corresponding uncertainty, are closer to the 10-year sample.

2.3.3 Biomass Allometric Equations

Uncertainty parameters for allometric biomass equations were derived from reported standard errors of the mean in original literature (Appendix 2). While standard errors apply to the sample in the literature, there is more uncertainty about how well the original sample represents Pack Forest trees. Percent errors reported in original literature ranged from <1% to 70% for various biomass components. The average % error in stem biomass for Douglas-fir, the most common species at Pack Forest, was less than 6%. Thus, the average % error from mean values was assumed to have a normal distribution of mean equal to 1.0 and SD of 10%. Probability distributions were applied to the number of C credits in the payout function (Equation 3).

2.3.4 Price of Timber

Distributions of average price for saw logs were determined using tests of normality in SPSS (IBM 2012). Saw log distribution was lognormal. Sample size for pulp wood was too small to determine a unique representative distribution; however it was assumed to be lognormal as well. Prices were truncated at the maximum value from the data plus 1 SD (Appendix 5). Truncation prevented unrealistically high wood prices from distorting the probability distribution.

We applied more recent log prices to the near future, and applied the long-term price range to projections further into the future. Prices for the first 5-year modeled period were constrained to the distribution of prices from the most recent 5 years of recorded prices (WDOR 2012). Prices for the second 5-year modeled period were constrained to the distribution of prices from the most recent 10 years of recorded prices. Prices in all periods thereafter used the full long-term price distribution. This study assumed historic average prices and variability will be the same in the future.

Pearson correlations among wood product prices were calculated from long-term average price data using SPSS (IBM 2012). Correlations were pegged to Douglas-fir #2 saw log prices or Douglas-fir pulp prices and entered into Crystal Ball. Generally, price for softwood saw log grades positively correlated to price of Douglas-fir #2 logs, while pulp prices correlated to price of Douglas-fir pulp. Red alder pulp logs correlated to Douglas-fir saw logs, although red alder saw logs did not significantly correlate to any other log grade.

Table 12. Correlation among wood products were high, particularly among conifer species. Red alder did not correlate to any other log grade.

Price variable	Correlation to DF#2	p(<x)
Douglas-fir #4/Utility	0.82	<0.001
Red Alder pulp	0.56	0.031
Hemlock-Fir-Pine #2	0.92	<0.001
Cedar #1/camprun	0.73	<0.001
Price variable	**Correlation to DF Pulp**	**p(<x)**
Hemlock-Fir-Pine Pulp	0.95	<0.001
Other Pulp	0.97	<0.001

2.3.5 Price of C Credits

Too few data points were available to determine distribution of C credit price, thus a normal distribution was assumed, truncated at \$2 and \$200 per credit. Two dollars represents a price floor; \$200 a price ceiling. Price for C credits is highly variable but only annual averages were used - neither variability nor data sufficient to calculate variability were available (Diaz et al. 2011, Hamilton et al. 2010, Peters-Stanley et al. 2012). However, using average prices despite large variability is appropriate because tens or hundreds of thousands of credits are generated and sellers have the opportunity to sell many times over the course of a forest C project. One would expect that over many transactions the average price of C credits would approach the mean.

This study assumes historic average prices and variability are appropriate for long-term forecasts for the Base-Case scenario. However, C credit price is highly uncertain in the future as interest in voluntary markets and potential regulatory frameworks will dictate prices. Thus, C price scenarios were developed to investigate the effects of C price on forest management decisions. Coefficient of variation was calculated from this historical C price distribution and used to calculate variation in the C credit price scenarios. This method scales variation proportionally as C credit price changes. Thus, it is assumed that future mean C credit price has the same variability as historic mean C credit price.

2.4 Analysis

This study modeled NPV over 40- and 100- year timeframes in 5-year intervals using MC simulations and the NPV payout equation (Equation 3). MC simulations were run simultaneously for 10,000 iterations.

In addition to NPV, annualized future values were calculated as flow of revenue, which is an important consideration in forest management decisions. Forecasts were assigned to NPV equations for each period and for the total sum of NPV. Sensitivity analysis identified key factors by % contribution to the variance of result variables. Sensitivity analysis was calculated using Crystal Ball.

2.4.1 C Price Scenarios

Future price of C is highly variable. Markets for C are relatively new and participating C markets are constantly changing. Furthermore, C price is subject to market-based demand and an uncertain regulatory future. Thus, using historic C price distribution may not represent future C price. Scenarios were developed to investigate possible futures of C price and the corresponding impact on forest management decisions. However, historic variability in average price was assumed to be proportional to the price of C. As C price increases, so does absolute variability. This may overestimate uncertainty in C price; however, regulated markets in Europe that sell for higher values per credit show similar proportional variability (Diaz et al. 2011, Hamilton et al. 2010, Peters-Stanley et al. 2012). In the absence of better information, variability in average C credit price that is proportional to current variability was assumed to be appropriate.

2.4.1.1 Base-Case

NPVs for the three management scenarios were calculated using historic parameters for C price to establish a Base-Case. Frequency distributions were used to find NPV at the 50th percentile and the probability that NPV is equal to or greater than zero. Periodic future value benefits were calculated to find the probability of financial loss in any 5-year period. I ran two scenarios: 1)

Cap-and-Trade prices assumed, and 2) business as usual to bracket the range of anticipated outcomes.

2.4.1.2 Scenario 1: Cap-and-Trade prices

The C price distribution was determined for voluntary over-the-counter C market transactions. However, advocates for C cap-and-trade policies argue that providing government subsidies to create high C prices will incentivize forest C projects. Carbon price probability distributions were set up to represent probable C prices under a subsidized regional or national cap-and-trade policy. Using normal distributions, median price was set to 1) $20 per C credit and 2) $40 per C credit and truncated at $10 to represent a price floor and $200 to prevent unrealistically high prices.

2.4.1.3 Scenario 2: Business As Usual equivalence

The development of functioning ecosystem markets may require C prices that lead to equal incentives for C projects and timber extraction. Changing the price of C can alter the NPV of CC65 and No Mgmt. The C price at which the NPVs of each the CC65 and No Mgmt scenarios equal that of CC45 were calculated.

1) Set CC65 NPV in year 100 = CC45 NPV in year 100
2) Set No Mgmt NPV in year 100 = CC45 NPV in year 100

The output from this approach should help inform policy makers and forest owners of the C price necessary for the expected value of forest C projects to equal the status quo management scenario. The probability distribution informs the financial risk of C projects relative to the status quo.

2.4.2 Value of Information: C Prices

Value of perfect information (VOI) was also calculated for C price. Given policy action could establish a price for C, VOI determines the financial benefit of knowing C price to an individual landowner.

2.4.3 Decision Analysis Framework and Non-Timber Resources

While revenue is a principal consideration in working forests, wildlife, aesthetics, water quality, recreation, and many other values bear on forest management decisions as well. Wildlife habitat values were calculated for three comparable management scenarios over a 30-year period (Ettl, unpublished data). Wildlife habitat values were based on elements of forest characteristics. Wildlife values increased with large trees, standing dead wood and logs, multiple canopy layers, and diversity of tree species. Increases in these characteristics correlate to aesthetic preferences (Kearney and Bradley 2011) and improved water quality. Thus, wildlife values may be used as a proxy for these non-timber resources.

Wildlife values for each management scenario described by Ettl (unpublished data) were translated to a relative score on a 100-point scale. Median 100-year NPVs from each management scenario were also translated to a 100-point scale. Expected value of combined revenue and wildlife scores were calculated and compared. Weights were applied to test how much a forest owner must value wildlife relative to revenue to change the preference for various forest management strategies.

This analysis assumes the proportion of hectares of habitat would remain stable among management scenarios and across longer timeframes. Wildlife scores were converted to a 100-point score using Equation 4, and then combined by averaging the two scores for each management scenario. Bat and squirrel habitat bore equal weight in 100-point conversion.

$$\text{100-point habitat score} = (X - \text{Max}) / (\text{Max} - \text{Min}) * 100 * \text{Weight}; \qquad (4)$$

where:

- Max = maximum value for all values in question;
- Min = minimum value for all values in question; and
- Weight = percent weight applied to variables; weights must add to 100%.

These combined 100-point scores were used to supplement NPV calculations. Median NPVs from the three management scenarios and five C credit price scenarios were converted to a 100-point score for revenue (Appendix 6). With both revenue and wildlife in a common 100-point scale, combinations of the two variables can be compared directly to assess decisions for forest owners who value both revenue and wildlife.

The relative weights may be applied to revenue and wildlife scores to reflect a forest owner's valuation of these resources. Weights are fractions that must add to 1. If a forest owner finds no value in wildlife habitat, revenue receives 100% of the weight and CC45 results in the largest score. If the forest owner exclusively values wildlife habitat without regard to timber value, NoMgmt maximizes his objectives. Two scenarios were run: first, weight wildlife at 10% and revenue at 90%. Second, to find the weight of wildlife a forest owner would need to assign in order to change the preferred management strategy from CC45 to another management practice. Calculations are shown in Appendix 6.

A value-of-information (VOI) analysis was conducted on the three management scenarios and the five C price scenarios. The VOI compared the EV of management decisions in the absence of C price information to the EV of management decision if future C price were known (Appendix 6). This analysis assumed the same probabilities for C prices as in the decision tree described in Section 3.8: a 0.6 probability of Base-Case C prices, 0.25 probability of the $20 credit cap-and-trade scenario, a 0.1 probability of the $40 credit cap-and-trade scenario, a 0.035 probability of the CC65=CC45 scenario, and a 0.015 probability of the NoMgmt=CC45 scenario.

3 Results

Probabilistic modeling allows forest owners to understand the risks of running a profit or loss due to IFM. MC simulations rely on random numbers to simulate the probability of ranges of value within a given distribution. Thus, variability in reported median values for scenarios that are run multiple times, such as CC45, is inherent in the approach. Base-Case parameters were used to run the CC45 simulation 20 separate times, each time using 10,000 trials per run, to test the variability of the results. Mean values for each run consistently fell within +/- 6% of the combined 20-run mean. This uncertainty band is small relative to overall uncertainty in this study as discussed below, and this level of accuracy is assumed to hold for all simulations.

3.1 Forest Management and C Credit Verification

Carbon storage decreased with increasing harvest intensity (Figure 8, Table 13), and C stored in wood products did not account for a loss of in-forest C. I used average values from tables, rather than values simulated in MC to calculate C credits. The CC45 had a negative trend for in-forest C, losing 44,813 Mg CO_2e after 100 years compared to the 20-year average baseline used under ACR Verification (Figure 8). However, CC45 stored 457,347 Mg CO_2e after 100 years in harvested wood products, for a net gain of 412,534 Mg CO_2e.

Clearcutting on a 65 year rotation gained 216,137 Mg CO_2e in-forest until model year 2035, and then decreased, for net in-forest C storage of 121,026 Mg CO_2e. The increase took place under a more lenient harvest sequence as the stands increased in average age from a 45-year rotation to a 65-year rotation, and then leveled. CC65 also stored 420,150 Mg CO_2e in long-lived wood products, 8% less than for CC45. Total C storage for CC65 was 541,176 Mg CO_2e over 100 years. NoMgmt increased C storage steadily in nearly all model periods, increasing 1,645,318 Mg CO_2e over 100 years.

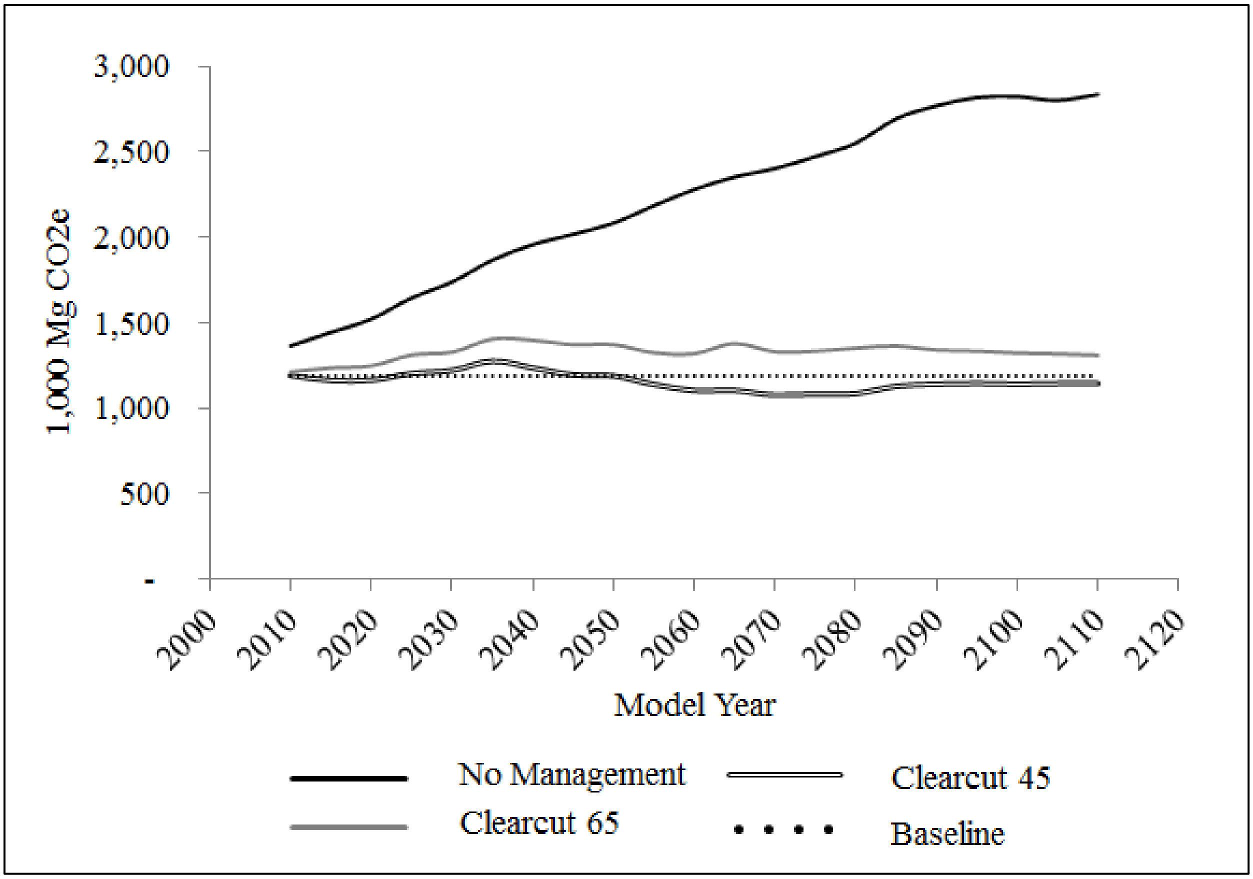


Figure 8: Carbon table results for in-forest C storage over time. Graph includes C stored in harvested wood products. NoMgmt stores far more C than CC45 or CC65. Baseline refers to the long-term average amount of C for CC45, the business-as-usual scenario.

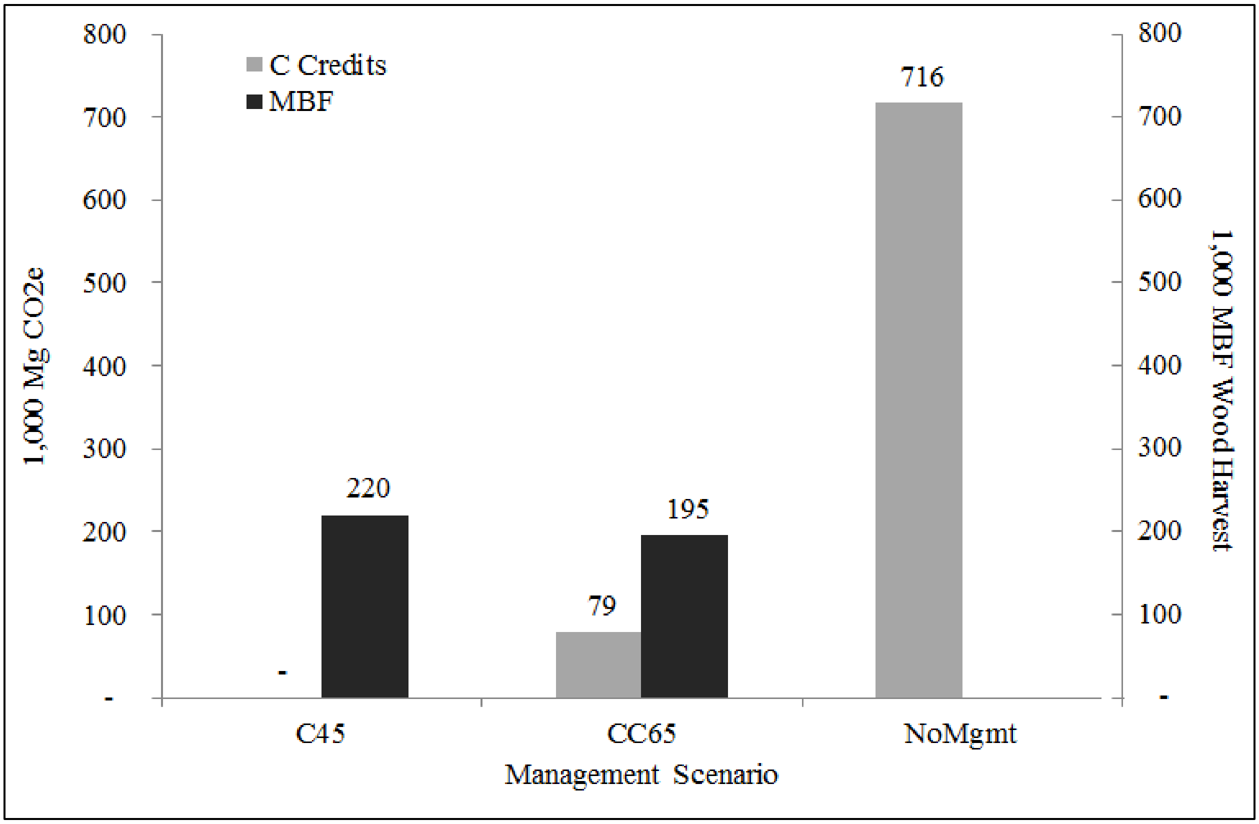


Figure 9: Saleable units of C credits and MBF wood product harvested accrued after 100 years. The C credits represent the additional C which can be attributed to improved forest management after deductions for uncertainty, leakage, and risk buffers calculated according to worksheets quantifying these factors.

VCS (2012) risk calculations create deductions in C credits for sample uncertainty, leakage, and risk. Calculations for deductions and C credits are shown in Appendix 4). Deductions in this case reduced the number of C credits awarded from the mass of CO_2e stored by 22.5% for CC65 and 59.5% for NoMgmt for the 100-year timeframe. NoMgmt was deducted more heavily because of financial insolubility and high opportunity costs – it is a money-losing scenario and suffers large opportunity costs relative to CC45. CC65 had deductions for lack of permanence and moderate opportunity costs. CC45 scenario served as the baseline, thus was not eligible for C credits (Table 13). CC45 produced 219,840 MBF of wood products, and CC65 produced 194,780 MBF in total harvest over the 100-year timeframe (Figure 9). No harvest took place under NoMgmt. After verification deductions, ACR methods awarded CC65 with 78,886 ERTs and No Mgmt with 716,240 ERTs (Figure 9); these C credits would be available for sale on the open market following certification.

Table 13. Carbon accounting of changes in C for the CC65 scenario and the NoMgmt scenario beyond the baseline provided by CC45. The total harvest timber in thousand board feet (MBF), and CO_2e are described; ERT C Credits are the credits that are available for sale from a C project.

	Year 40			Year 100		
Result	C45	CC65	NoMgmt	C45	CC65	NoMgmt
Total MBF harvested	86,072	63,756	-	219,840	194,780	-
Δ CO_2e in-forest	102	216,137	893,281	(44,813)	121,026	1,645,318
Total CO_2e wood prods	214,929	176,730	-	457,347	420,150	-
Total CO_2e storage	215,031	392,867	893,281	412,534	541,176	1,645,318
Total Additional CO_2e	-	177,836	678,250	-	128,642	1,232,784
ERT C Credits	-	109,179	300,649	-	78,886	716,240

3.2 Base-Case Scenario Probability Distributions: Historic C and Timber Prices

Using historic timber and C prices, the “Base-Case” simulated probability distributions for NPV are wide and positively skewed for both CC45 and CC65, and narrow and negative for NoMgmt (Figure 9). CC45 had a mean of \$5,026,923 and a 95% confidence interval (CI) of -\$17,596,434 and \$35,835,741. CC65 was slightly more concise, with a mean of \$2,334,789 and 95% CI of -\$15,168,428 and \$26,745,389. NoMgmt had a high probability of negative NPV, with mean of -\$5,742,373 and 95% CI of -\$10,754,722 and \$344,642.

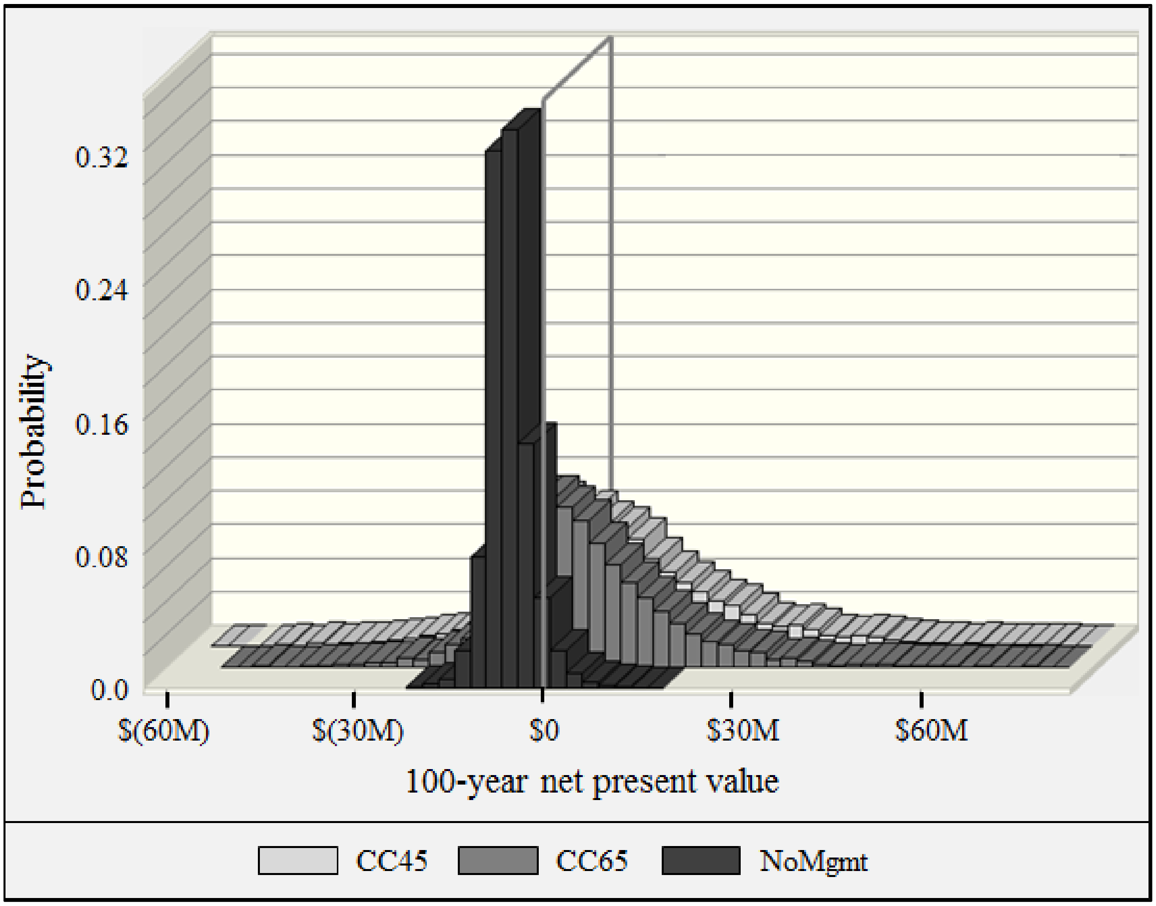


Figure 10: Probability distributions for the Base-Case MC simulations. Vertical line is NPV of 0. The CC45 scenario has the highest mean NPV but the greatest risk of low, and high, NPV as indicated by its relatively broad and low shape. NoMgmt, by comparison, is very likely to have negative NPV, as indicated by the location along the x-axis of its steeple shaped distribution.

Both CC45 and CC65 were more likely than not to generate positive NPV (Table 14). CC45 had a 57.4% chance of positive 100-year NPV. CC65 was riskier with a 51.0% chance of positive NPV, and a 34.1% chance that NPV would be equal to or greater than that for CC45. NoMgmt had a 5.6% chance of positive NPV; value of C credits was not a sufficient source of revenue for no active management to meet the costs of basic operation under the Base-Case C price distribution. Switching from a rotation of 45 to 65 increased the risk of going bankrupt by almost 8% in 40 years. The difference in chance of profit risk narrows somewhat at 100 years, mostly likely due to the diminishing effect of future payments due to discounting.

Disparity between mean and median NPVs for all management scenarios is a result of the shape of the distribution of NPVs. Low median values and higher mean values indicates that while high-payout NPVs are infrequent relative to low-value payouts, high-value payouts are relatively larger, skewing mean NPVs larger and median NPVs smaller.

Table 14. MC simulation results for Base-Case scenario. At the historical distribution of C credit price, C projects are less valuable than timber-based forest management. C projects also have smaller 95% CIs, corresponding to lower risk of loss, as well as lower chance of high payouts. Risk increases as the modeled timeframe increases, as evident by larger 95% CIs.

Scenario	Forecast Year	Mean NPV	Median NPV	95% confidence interval		%(x≥0)
CC45	40	$4,339,708	2,132,147	$(15,510,368)	$31,354,196	57.0
	100	$5,026,923	$2,504,889	$(17,596,434)	$35,835,741	57.4
CC65	40	$1,573,593	$(164,257)	$(13,161,744)	$22,225,830	49.3
	100	$2,334,789	$259,268	$(15,168,428)	$26,745,389	51.0
NoMgmt	40	$(5,304,249)	$(5,616,468)	$(9,827,907)	$64,220	5.1
	100	$(5,742,373)	$(6,145,180)	$(10,754,722)	$344,642	5.6

Sensitivity analysis revealed FVS model uncertainty contributing 70% or more of the overall variance in 100 year NPV. Uncertainty in BF calculated from FVS contributed 76.5% of the overall variance in CC45, while uncertainty in C from FVS calculations contributed 96.0% of variance in NoMgmt (Figure 11). Both BF and C contributed to variance in the CC65 NPV payout function; notably, BF uncertainty contributed 70.8% while C uncertainty contributed only 5.6%. Variation in the forest inventory data also substantially contributed to overall variance in the harvest scenarios: CC45, 14.0%; CC65, 14.0%; but less in NoMgmt: 2.6%. The price of saw log products applied to the first model period (Douglas-fir #2 logs, Hem-fir-pine logs, Douglas-fir #4 logs, and red cedar logs) contributed the majority of the remaining variance for CC45 (8.1%) and CC65 (8.0%). Notably, C price only contributed 0.1% of variance in CC65. Comparatively, C price contributed 1.1% of the remaining variance in NoMgmt. All other variables combined contributed less than 1.5% to overall variance in results for each management scenario.

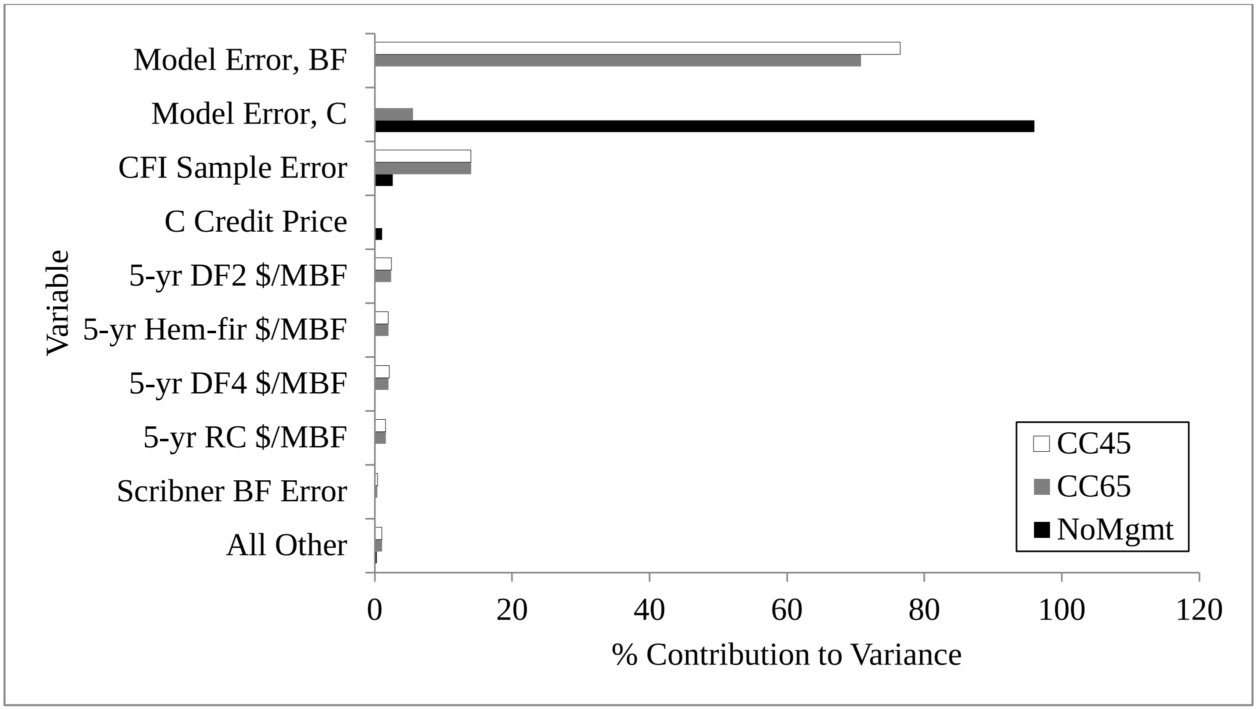


Figure 11: Sensitivity analysis showing percent contribution to variance for Base-Case 100-year NPV consequences. FVS model uncertainty represents by far the largest contribution to variance in NPVs. In other words, FVS model error is what causes the fatter tails in the frequency distribution graphs, which corresponds to increasing risk of gains and losses in NPV.

Variables that did not contribute significantly to overall variance included price of saw logs after the first period, indicating that near-term price of saw logs carries relatively more significance to uncertainty in NPV for CC45 and CC65 management scenarios. The price of pulp logs, uncertainty in biomass equations, red alder price, uncertainty in conversion of tree measurements to Scribner BF, and management costs (e.g., weeding and precommercial thinning) had little or no substantial contribution to variance in 100-year NPV revenue. Results for the 40-year timeframe were comparable. The low sensitivity of the models to C price was somewhat unexpected, and I used two additional scenarios to assess how increasing the price of C might alter model output.

3.3 Cap-and-Trade Scenario

I investigated the effects of a potential cap-and-trade of prices for C credits on NPVs of the management scenarios (Figure 12 and Figure 13). Two cap-and-trade C prices were compared: $20 and $40 mean price per C credit. Under the $20/mean C credit price scenario, C credit price has a price floor of $10. CC65 mean NPV was $2,932,810 with a 52.6% chance of being profitable (Table 15). Under the $40 scenario, CC65 mean NPV was $4,144,136 with a 53.4% chance of profit. NoMgmt mean NPV was negative in both the $20 and $40 scenarios (-3,771,421 and -756,971, respectively). However, NoMgmt had 26.6% and 41.8% chances of profit, respectively. Increasing chances of profit reflected the effect of higher C credit prices on NPV. No variables in the CC45 payout were changed in the C credit scenarios, thus no differences in NPV results were expected or observed. Increasing the price of C with a cap-and-trade approach increases the chance of profit from IFM.

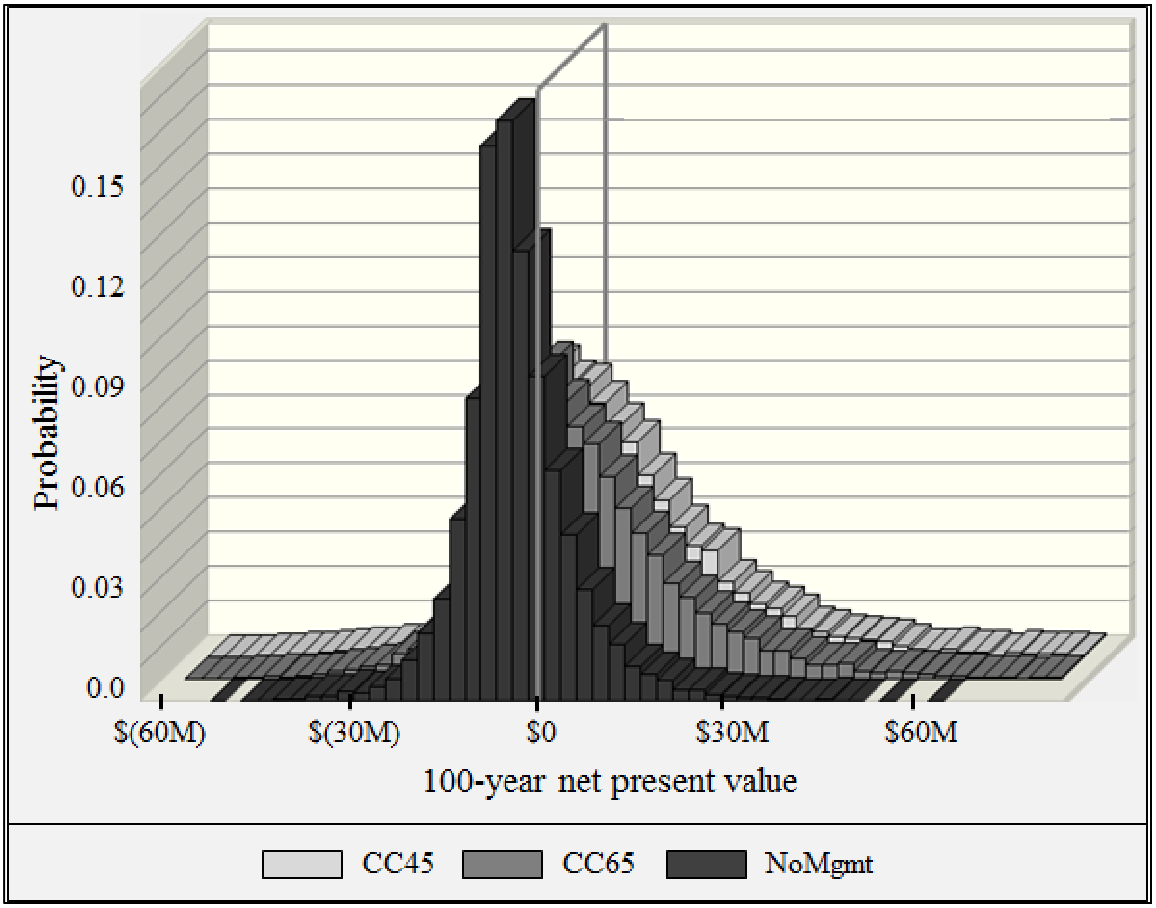


Figure 12: 100-year NPV probability distributions with C credit price of $20 with SD of $6.13. Carbon price was truncated at $10. Vertical line indicates NPV=0. Uncertainty in NPV for both NoMgmt and CC65 increase substantially in this scenario, as shown by the increasingly wide range of possible NPVs.

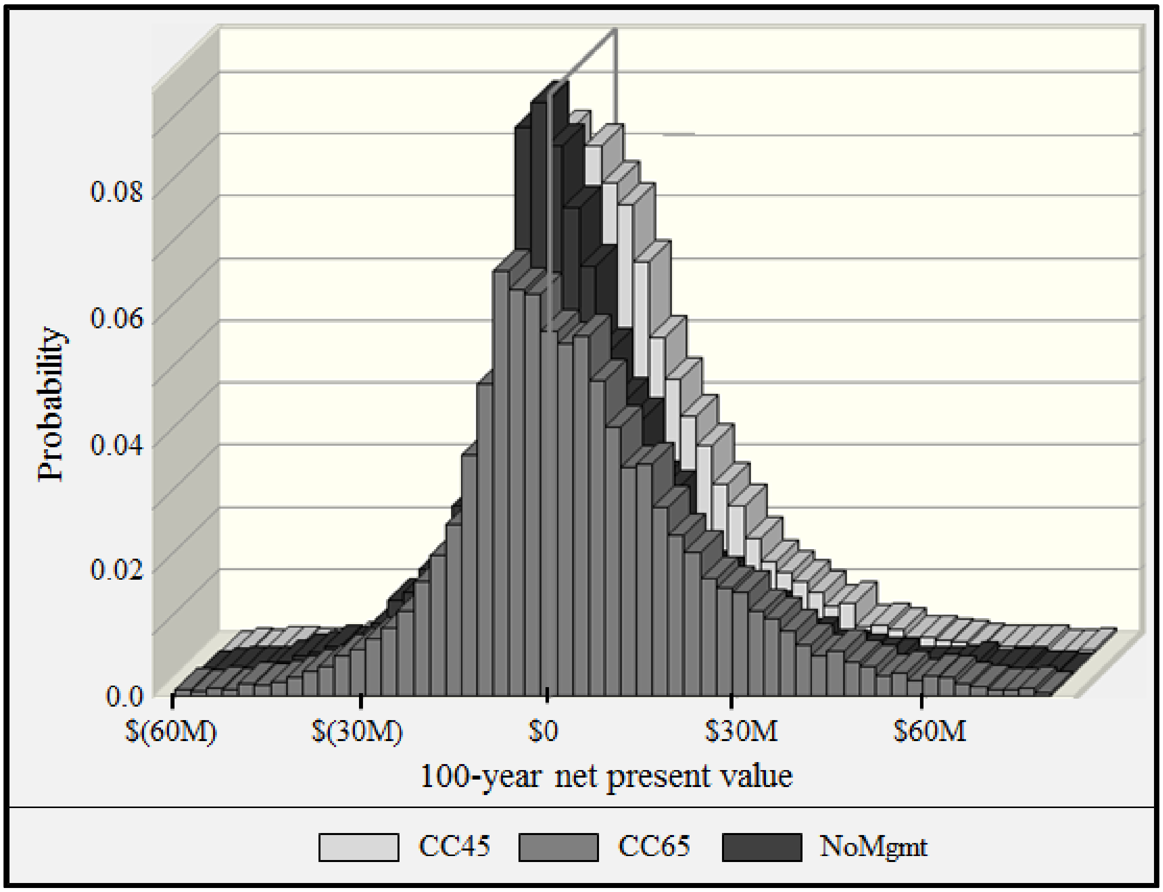


Figure 13: 100-year probability distributions with C credit price of $40 with SD of $12.27. Carbon price was truncated at $10. Vertical line indicates NPV=0. Although the mean NPVs still differ among management scenarios, the shapes of NPV distribution are similar. With-C scenarios have slightly larger tails in the negative zone, resulting in lower mean NPVs.

The 95% CI for the cap-and-trade scenarios increased from the Base-Case simulation, revealing a wider range than for CC45; 95% CI increased as C credit price increased for both CC65 and NoMgmt (Table 15). Under the $40 average price scenario, CC65 100-year NPV 95% CI was -$25,814,255 to $41,087,491. NoMgmt's range shifted comparably, with the 95% CI from -$25,312,646 to $28,340,521.

Table 15. Results for cap-and-trade scenarios. Mean NPV increase as C price increases. 95% CIs also increase as C price increases.

Cap-and-trade C credit mean price =$20, SD=$6.13

Scenario	Forecast Year	Mean NPV	Median NPV	95% Confidence Interval		%(x≥0)
CC65	40	$2,114,298	$270,066	$(16,217,363)	$26,202,443	51.12
	100	$2,932,810	$772,158	$(18,356,172)	$31,060,163	52.58
No Mgmt	40	$(3,811,913)	$(4,585,549)	$(15,493,160)	$9,673,936	24.64
	100	$(3,771,421)	$(4,746,838)	$(16,659,266)	$11,596,296	26.64

Cap-and-trade C credit mean price =$40, SD=$12.27

Scenario	Year	Mean NPV	Median NPV	95% Confidence Interval		%(x≥0)
CC65	40	$3,188,218	$819,728	$(23,162,127)	$35,511,295	52.23
	100	$4,144,136	$1,437,892	$(25,814,255)	$41,087,491	53.42
No Mgmt	40	$(1,532,496)	$(3,041,996)	$(23,712,511)	$24,135,050	39.18
	100	$(756,971)	$(2,704,971)	$(25,312,646)	$28,340,521	41.76

The sensitivity analysis revealed a new trend in contribution to variance. For CC65, FVS model uncertainty in C increased in contribution to variance compared to the Base-Case. Accordingly, BF uncertainty diminished. Carbon credit price also increased in contribution to variance. With mean C credit price of $20, the changes were not large enough to change the order of contribution to variance compared to the Base-Case for CC65. However, at mean C credit price of $40, FVS model error in C contributed more to variance than FVS model error in BF (60.1% and 29.8%, respectively). Changes in C price did not substantially affect the sensitivity results for NoMgmt. Results were similar in the 40-year timeframe.

3.4 Business as Usual Scenario: Finding the C Equivalence Price

A second approach was used to describe the effect of C price and IFM for C, in this scenario the mean price of C credits was determined that is needed so that the mean NPV of CC65 and NoMgmt to equal that of CC45 (Figure 14 and Figure 15). Changing the price of C credits to bring the mean NPV of CC65 into alignment with CC45, resulted in C credits priced at $49.87 with SD of $15.30. This price is approximately six times larger than the average for historic forest C credit used in the Base-Case calculations. Changing the C credit price to force NPV of NoMgmt to equal that of CC45 resulted in a credit price of $73.82 with SD of $22.64. These prices do not reflect the lower deductions that would result with C projects becoming economically competitive. Thus, this scenario under-values C projects if credits were to reach these prices because more credits would be awarded. Simply put, there would be a great incentive to bring C projects to market, and this would change the economics of timber and C markets.

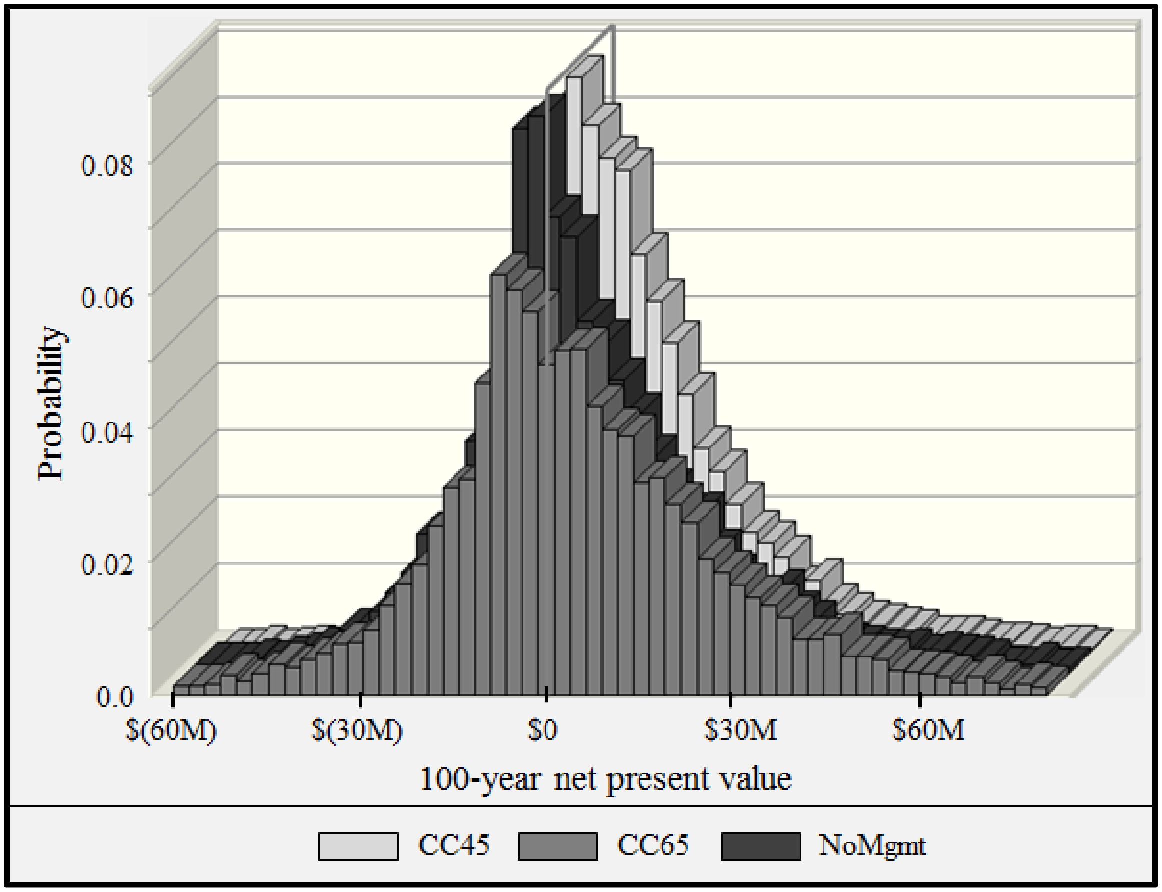


Figure 14: 100-year NPV probability distributions with C credit price of $49.87 with SD of $15.30. Vertical line indicates NPV=0. The tails of these frequency distributions are nearly equal between all management scenarios.

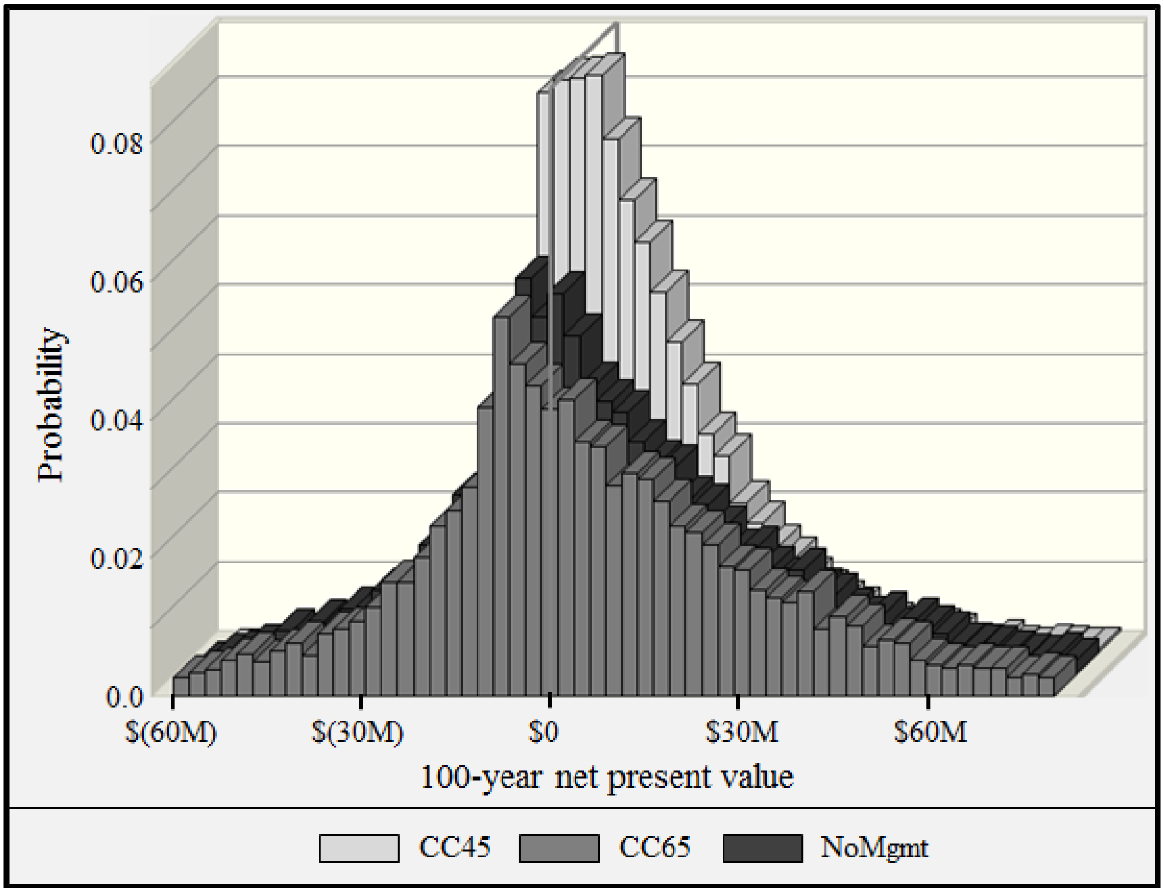


Figure 15: 100-year NPV probability distributions with C credit price of $73.82 with SD of $22.64. Vertical gray line indicates NPV=0. With-C projects now have wide distributions – the probability of very high and very low NPVs are larger than the business-as-usual CC45 scenario.

Increasing the price of C credits increased the range of NPV distributions for both CC65 and NoMgmt. Upper boundary of the 95% CIs for CC65 and NoMgmt were higher than that of CC45 in both equivalence scenarios, indicating there is a chance of payouts that are better than business-as-usual, however the probability of more negative extremes also increased. The 95% CI for CC65 was -$31,251,118 to $48,093,091 with a 53.7% chance of positive NPV for the 100-year CC65=CC45 scenario. Similarly, the 95% CI for NoMgmt was -$41,990,425 and $60,617,789 with a 51.3% chance of positive NPV for the 100-year NoMgmt=CC45 scenario. Results were similar in the 40-year timeframe. Increasing CIs as C price increases is likely due to the proportional increase in SD. No variables in the CC45 payout were changed in the C credit scenarios, thus no differences in NPV results were expected or observed.

Table 16. NPV results for business-as-usual equivalence scenarios. As C price increase, mean NPV as well as risk increase. Results for Clearcut 45 are not shown as they are equal to the results reported in Table 17.

CC65=CC45 (C=$49.87, SD=$15.30)

Scenario	Forecast Year	Mean NPV	Median NPV	95% Confidence Interval		%(x≥0)
CC65	40	$3,758,358	$1,204,906	$(28,063,025)	$41,742,173	52.8
	100	$4,796,755	$1,800,606	$(31,251,118)	$48,093,091	53.7
No Mgmt	40	$(500,519)	$(2,518,735)	$(28,668,011)	$32,253,062	42.7
	100	$628,323	$(1,892,245)	$(30,480,833)	$37,825,136	45.0

NoMgmt=CC45 (C=$73.82, SD=$22.64)

Scenario	Forecast Year	Mean NPV	Median NPV	95% Confidence Interval		%(x≥0)
CC65	40	$4,993,690	$2,058,893	$(39,561,513)	$56,906,136	53.7
	100	$6,176,863	$2,810,483	$(43,724,430)	$64,836,419	54.7
No Mgmt	40	$2,382,900	$(609,321)	$(39,456,651)	$51,925,645	48.9
	100	$4,422,256	$625,917	$(41,990,425)	$60,617,789	51.3

Sensitivity analysis of CC65 in the CC65=CC45 scenario showed that FVS model error in C contributed more to variance than FVS model error in BF, (68.0% and 21.2%, respectively) compared to the Base Case scenario. Contribution to variance for other variables did not substantially change. Notably, the effect of variance in the price of C credits did not increase in contribution to variance for either CC65 or NoMgmt in either equivalence scenario. Sensitivity analysis results did not substantially change for NoMgmt. Results were similar in the 40-year timeframe. It is interesting to note the relative contribution of C or BF calculated in FVS vary based on the relative contribution of each factor to NPV; in this case there is high FVS model error contribution for C.

3.5 Effects of C Verification Cost Assumptions

High C project certification costs may be a barrier to enrolling in forest C projects. The Base-Case scenario (mean C price equal to $7.89) was run with all C certification costs set to zero to investigate the influence on NPV. Carbon certification costs had a negligible effect on CC65 and NoMgmt NPVs. Average NPV increased by less than one percent in the CC65 management scenario for both the 40- and 100-year timeframes. The 100-year NPV was slightly less negative for NoMgmt scenarios improving by approximately 2.2%. The probability of positive NPV was effectively unchanged for both CC65 and NoMgmt. This indicates that C verification cost negligibly impact NPV for projects the size of Pack Forest. These results include the assumption that Pack Forest is part of a pooled group project.

High up-front costs accrue in model year zero when a forest owner must pay for initial C project validation. While mean revenue in the first period was positive for CC65 at Pack Forest, the initial outlay of tens of thousands of dollars may not be feasible for many forest owners. NoMgmt had negative median revenue in all periods of the Base-Case scenario; the effect of verification cost was negligible.

3.6 Effects of Land Holding Cost Assumptions

Land holding costs for Pack Forest are much higher than for typical private forests of industrial or non-industrial management. While fixed costs affect all management scenarios proportionally, forecasting using lower land holding costs brought C projects into profitability at lower C credit prices. CC65 and NoMgmt were still less profitable than the BAU CC45 by the same proportion, but the less-intensive management scenarios generated positive revenue rather than negative revenue at much lower C price when land holding costs are lowered to a regional average. At annual land holding costs of \$49 per hectare (rather than \$170 per hectare in all other scenarios), the NoMgmt scenario broke even (mean 100-yr NPV ≥ 0) at a mean C credit price of \$14.17 (SD=\$4.35). Under the original land holding cost and all other parameters equal, NoMgmt broke even at \$45.28 per C credit. Note that this is the C price at which NoMgmt no longer loses money, not the price at which NoMgmt NPV equals that of CC45.

With lower land holding costs, all management scenarios are more profitable. Although NoMgmt broke even at a relatively low C credit price, the opportunity cost was the same as under the original land holding cost. CC45 median 100-year NPV was \$9.3 million and CC65 median 100-year NPV was \$6.7 million at \$49 per hectare land holding cost and Base-Case C credit price of \$7.89. This information could appeal to small-scale forest owners who do not seek to maximize NPV, and who would be content to operate profitable (but not maximum profit) low-intensity management practices.

3.7 Periodic Revenue Flow

The maximization of NPV is an important calculation for industrial forestry operations. However, forest owners cannot operate over periods of sustained financial loss, regardless of overall NPV, and therefore the even flow of revenue is also important. Undiscounted future value assessed in each period indicated the flow of revenue a forest owner may expect. CC45 maintained positive median periodic future value across all 20 periods of the 100-year timeframe except two periods of low harvest in 2030 and 2035 (Figure 16), with greater than 50% chance of positive revenue flow in most model periods. The time period of 2030 to 2035 stands out as a point in time where Pack Forest will have a greater than 50% chance of losing money—perhaps for as long as 10 years.

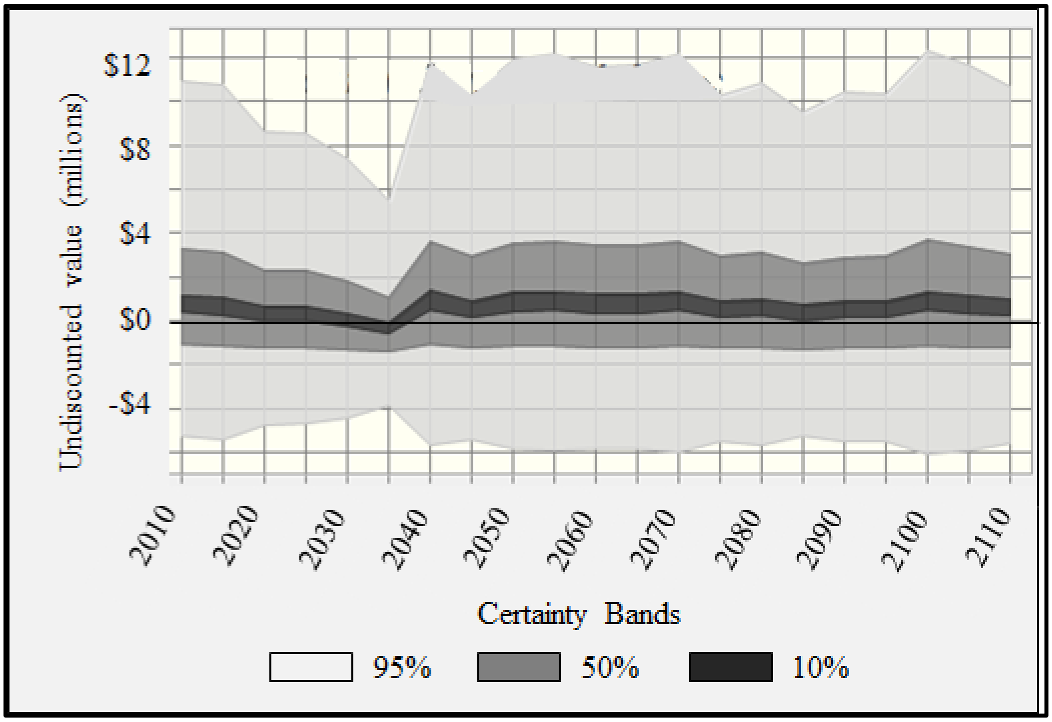


Figure 16: Certainty bands for 100-year NPV for CC45 Base-Case undiscounted periodic future value. Even forest management practices that depend entirely on timber revenue bear a substantial risk of negative revenue flows in modeled periods. The narrow bands around modeled years 2030 and 2035 are the result of less harvest – fewer units of wood products resulted in lower NPV and less absolute uncertatinty.

The CC65 and NoMgmt scenarios are sensitive to C prices (Figure 17). CC65 median periodic future value remained at or just above zero for the first 20 years of the model timeframe in the Base-Case scenario with nearly equal probability of revenue gain or loss. Revenue fluctuated thereafter, with most years generating positive value despite negative median values in model years 35 and 100. Therefore, any decrease in harvest intensity at Pack Forest, results in an increased probability of negative cash flow. Scenarios with increased C price boosted future value for model years five through 25, when CC65 generated C credits. NPV for NoMgmt was well below zero in all years for the Base-Case. NoMgmt NPV’s proportional distribution was unaffected; the median value was dependent on the price of C credits. CC45 was unaffected by scenarios that changed C price.

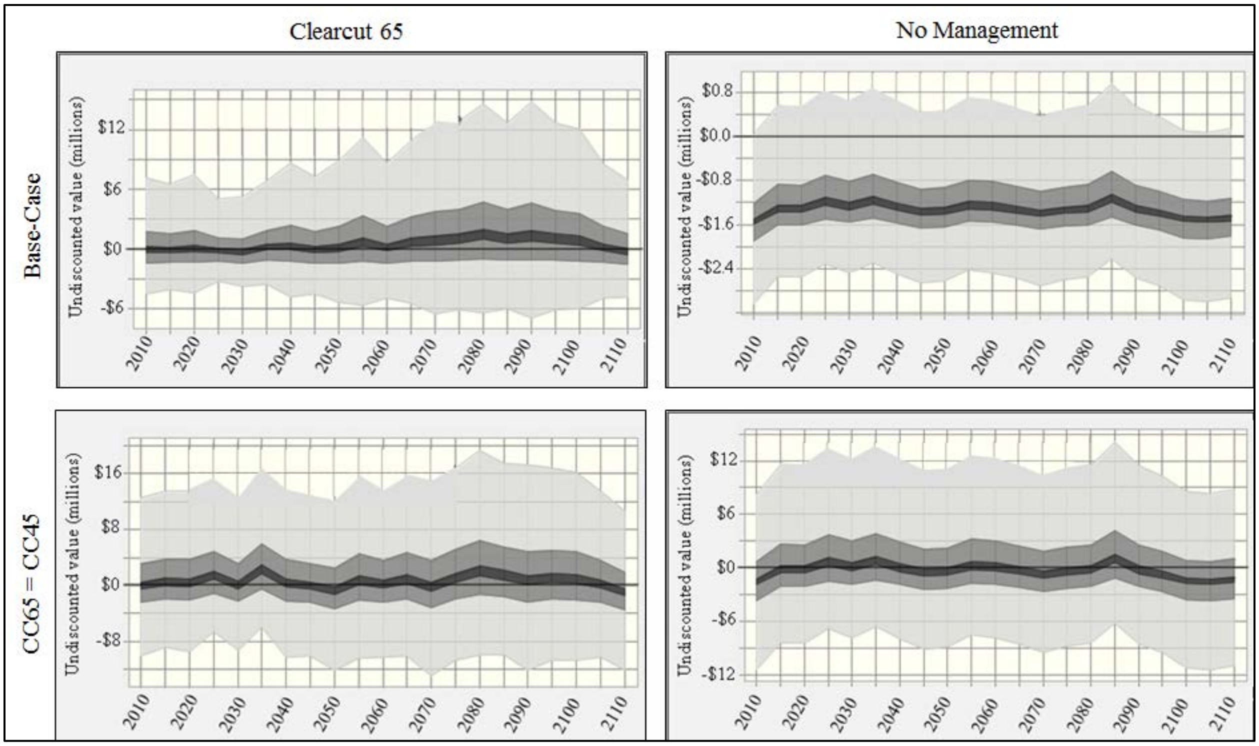


Figure 17: Undiscounted periodic future value probability bands for two C credit price scenarios for CC65 and NoMgmt. Even at high C credit prices, forest C projects risk negative flows of revenue in many modeled periods.

3.8 Decision Framework

While probability models are an effective method of communicating risk and understanding a range of possible outcomes, decision analysis tools can help forest owners quantify tradeoffs in management decisions. I apply a decision framework to forest management scenarios and C price scenarios to provide decision options.

3.8.1 Revenue

A significant uncertainty not addressed in the MC simulations is the relative likelihood of any given C price scenario occurring. A forest owner will earn the largest NPV for CC65 compared to all other management options when the average C credit price is approximately $50 or more, but how likely is a C credit price of $50 or more? For a forest owner, knowing the likelihood of certain C credit prices is a critical piece of information when deciding forest management practices.

This study assumed low C credit prices would be more likely than high C credit prices, by assigning a 0.6 probability to Base-Case C prices, 0.25 probability to the $20 per credit cap-and-trade scenario, a 0.1 probability to the $40 per credit cap-and-trade scenario, a 0.035 probability to the $49.87 per credit CC65=CC45 scenario, and finally, a 0.015 probability to the $73.82

NoMgmt=CC45 scenario. These probabilities were developed to conservatively weight lower-value C credits.

Decision trees were created to guide management decisions. Decision trees present two useful calculations: median payouts (referred to here as "consequences" – some are negative) and expected values (EVs). Using median values from the MC simulation results and the assumed probability of C credit prices stated above, a decision tree was constructed to outline the three discrete management scenarios, the expected consequences under each of the five C price scenarios, and the overall expected value (EV) of the three management scenarios (Appendix 6 and summarized in Table 17). EV represents an average 100-year NPV consequence from all C price scenarios. EV is most appropriate for large-scale forest owners who manage many tracts of land and have the opportunity to sell timber and C many times over the 100-year time frame, so that average values will be applicable. Small-scale forest owners who may only sell timber or C credits a few times over a 100-year span cannot assume they will receive average prices; rather, they will receive a particular price a few times. Assessing median consequences rather than EVs allows a forest owner to decide what possible consequences are within her risk threshold. They can decide their management practice based on risk thresholds such as minimum necessary revenue, aversion to loss, or risk-taking behavior of seeking the greatest possible consequence.

Table 18
Summary of decision tree consequences and expected value. Expected value is an average of payouts weighted by the assumed probability of a particular C price scenario.

Mgmt Scenario	C Price Scenario	Payout	Expected Value
CC45	All	$ 5,026,923	$ 5,026,923
CC65	Base Case	$ 2,334,789	
	C&T20	$ 2,932,810	
	C&T40	$ 4,144,136	
	CC65=CC45	$ 4,796,755	
	NoMgmt=CC45	$ 6,176,863	$ 2,809,029
NoMgmt	Base Case	$ (5,742,373)	
	C&T20	$ (3,771,421)	
	C&T40	$ (756,971)	
	CC65=CC45	$ 628,323	
	NoMgmt=CC45	$ 4,422,256	$ (4,375,651)

In EV terms, CC45 provides the largest 100-year NPV ($5.0 million), followed by CC65 ($2.8 million). NoMgmt returns a negative EV of -$4.4 million. The highest possible consequence is achieved under CC65 when C credit prices are very high (more than $50 per credit), but the probability of high C credit prices is assumed to be very low (5% chance). A risk-taking forest owner, or one who believed C credit prices would surely rise to more than $50, might adopt CC65, understanding that she risks a low NPV at a probability of 0.95. For decisions based entirely on revenue, under no circumstance does NoMgmt appear to be a desirable management scenario – negative EV, negative consequences for the three C price scenarios that add up to 0.95 probability, and consequences that are lower than CC65 for very high prices of C credits.

3.8.2 Wildlife

NPV is one of several factors forest owners take into consideration when deciding on a management scenario. After revenue, wildlife habitat is a prominent management goal. Ettl et al. unpublished data) used Bayesian belief network models to estimate the probability of hectares of select wildlife (Table 18). Two categories of wildlife were chosen to represent unique, though not mutually exclusive, forest habitat requirements: forest bats and Douglas squirrels. Forest bats require large snags for roosting structures, vertical tree canopy cover, and prefer upland roosts within 100m of a stream. Douglas' squirrels require abundant conifer cones for their food source, are dependent on large conifers, and a diversity of species including hardwoods (Ettl et al. unpublished data).

Table 19
Ettl et al. (unpublished data) wildlife hectares occupied were converted to habitat scores on a 100-point scale. The combined score on the right shows the bat and squirrel habitat scores when weighted equally at 0.5 and then combined.

Mgmt Scenario	Bat Habitat (ha)	Squirrel Habitat (ha)	Bat Habitat (100pt score)	Squirrel Habitat (100pt score)	Combined
Initial	25	233	na	na	na
CC45	347	144	0	0	0
CC65	432	184	29	16	23
NoMgmt	637	396	100	100	100

Conversion of variables to a 100-point scale allows comparison of variables that would not otherwise have the same units. Wildlife habitat hectares are converted to 100-point scales according to Table 18. Appendix 6 shows conversion not mean NPV payouts from C price scenarios into 100-point scale. Wildlife and revenue can then be combined to determine the expected utility of wildlife and revenue for forest owners who value wildlife as well as revenue in forest management outcomes. Weights may be multiplied by the 100-point scores to reflect a landowner's relative value for the scores. Weighting wildlife at 10% utility and revenue at 90% utility in Scenario 1, CC45 score was 81.3 points, CC65 was 66.8 points, and NoMgmt was 20.3 points. Thus, a landowner who values wildlife as 10% of the utility he derives from his forest would still opt for CC45 management. Scenario 2 revealed that an owner must value wildlife at 44.2% of the utility he derives from his forest or greater in order to change from CC45 (50.4 points) to NoMgmt (50.6 points).

3.9 Value of Information

Uncertainty in future C credit prices affect management decision today. Regulated C prices could provide certainty in C prices. Knowing C prices before committing to a forest C project would inform forest owners of what distributions of revenue one could expect under various management scenarios. Policymakers could use this information to guide budgets in developing and implementing policies that ensure a predictable C price.

To determine VOI, the same assumptions for the probabilities of C price scenarios were used: 0.6 for Base-Case C prices, 0.25 for the $20 credit cap-and-trade scenario, 0.1 for the $40 credit cap-and-trade scenario, 0.035 for the CC65=CC45 scenario, and 0.015 for the NoMgmt=CC45 scenario. These assumptions resulted in a VOI equal to $17,249 at Pack Forest, or $9.91 per hectare. In other words, NPV of $17,249 is the amount the Pack Forest manager would be willing to pay to know exactly what C price scenario would take effect over the 100-year timeframe. This relatively low VOI indicates the next-best options to CC45 are improbable and offer little additional value. In four out of five C price scenarios, perfect information would not change the forest owner's decision away from CC45. In the instance where CC65 would return higher NPV, the gain in NPV is substantial - approximately 22% more than CC45 NPV. However, the chance of the very high C price scenarios is assumed to be very low (1.5%). Thus, unless a regulated price were very high (approximately $73 per credit), regulated prices would have no effect on a forest owner's management decisions, assuming they manages to maximize profit and is an expected value decision maker.

4 Discussion

This analysis revealed several key findings. Primarily, FVS model uncertainty is important in revenue forecasts, contributing more than 60 percent of the variance in 100-year NPV in this case study. Furthermore, C credit price must be $50 or higher to overcome the opportunity cost of foregone timber revenue. Finally, risk of revenue loss (and gain) increases as dependency on revenue from C increases – there is more money at stake.

Model uncertainty is not just significant in a statistical sense; the uncertainty could substantially change forest management decisions and C policy guidelines. While the uncertainty measured in this study may vary from other forests, the magnitude of the uncertainty warrants skepticism over the role of FVS in long-term forest growth and revenue forecasts. Forest owners relying on forest growth models when assessing management options must carefully interpret results. The FVS forest growth model is sensitive to site-specific factors, and the sample used to calculate model uncertainty was limited. Thus, other locations and different time period comparisons could have uncertainty of different magnitude or distribution.

Sample variability among forest measurement plots was the second-largest contributor to variance in total NPV. This variability can be reduced with better and more thorough sample design. This study relied on long-term, fixed-area plots that provide detailed data for long-term experiments, but faster timber cruise methods such as variable area plots would allow many more plots that provide sufficient information for C and timber volume calculations. Larger sample size coupled with stratification of similar plots would reduce variability.

After model and sample uncertainty, price of wood products drive NPV of CC45 and CC65, while price of C drives NoMgmt NPV. If wood prices remain within the range of 40-year historic variability, the price of C must increase by an order of magnitude to become an economically viable alternative for NPV profit maximization. Management scenarios of intermediate harvest intensity are still profitable, but with large opportunity costs compared to CC45 business-as-usual. CC65, while earning profit under all C credit price scenarios, loses as much as $5 million compared to CC45 at current C prices. For forest owners who make management decisions to maximize NPV, forest C projects are unlikely to compete with CC45. Forest owners who make management decision based on other factors in addition to NPV may be willing to accept the opportunity cost of forgone timber revenue.

Industrial forests (>400 hectares, WFPA 2005) typically manage to maximize NPV. Industrial forests compose a majority of the private forest land in western Washington, about 59% or 1.5 million hectares out of 2.17 million hectares (WFPA 2005 in Erickson and Rinehart 2005). Wide-spread changes in forest management can only occur if profit-maximizing forest owners implement changes. This is unlikely without a dramatic increase in C prices, and ease of achieving C credits in a fluid C market. However, small-scale forest owners compose a substantial portion forest land. This group of owners may be more willing to adopt forest C projects. Of course, small landowners are also least like to be able to benefit from a change in management; they cannot get credits for improved forest management if they are already low-intensity harvesters. This has important implications for the likelihood of forest C projects to be implemented in the Pacific Northwest. Industrial landowners could be eligible for a change in management but require incentives to implement IFM. One way to encourage C projects might be to provide incentives for small landowners to continue to manage for C, and by correlation wildlife habitat of mature-forest species, rather than trying to change industrial management.

The implications of these results should be framed as what efforts will substantially change behavior. Forest C credits are not viable at an industrial scale at probable C prices. Regulating C credit price to compensate for the opportunity cost of foregone timber revenue could come with a high social cost. Carbon credits offset CO_2 emissions, and if emissions are worth $50/credit CO_2e, the corresponding economic cost of GHG mitigation will be very large – fossil fuel-based energy generation would bear the added cost of GHG emissions commensurate with $50/credit offsets, with repercussions throughout the economy.

Probable C credit prices could be sufficient to incentivize changes in forest management decisions for small-scale forest owners who include other factors in addition to NPV. These forest owners must be prepared to forego some revenue for values of wildlife, recreation, or a personal standard of stewardship. Timing of payments could also be a motivation factor for small-scale forest owners. Given fewer hectares of forest, harvests and corresponding timber payments take place infrequently on small-scale forests. Annual payments from C credits may be more appealing than maximizing NPV from a few harvests over a lifetime. For these owners, payments for C credits could partially offset foregone timber revenue. While small-scale forest owners may substantially value non-revenue aspects of their forests, an owner would need to gain nearly half of their utility from their forest from non-revenue sources such as wildlife before justifying a switch to a less-intensive forest C project.

Forest C projects also carry greater risk of both high payouts and large losses. Further research is needed to determine small-scale forest owners' risk profiles – perhaps some would embrace the chance at higher revenue while others would avoid the risk of severe financial loss. If small-scale forest owners are the target of a C policy or incentive program, keeping costs of verification low could allow more forest owners to participate. While verification costs were not substantial in changing Pack Forest's NPV, smaller-scale forests generate less revenue, so the fixed cost of verification becomes proportionally larger and may be a formidable barrier to C projects.

In a survey of forest owner's interests in Washington, respondents criticized the "hassle factor" in non-timber management incentive programs (RTI 2009). Verified C projects require extensive inventory analysis and record-keeping, burdening forest owners who do not have administrative capacity. Reducing project complexity could incentivize forest owners to adopt C projects. However, reducing costs and complexity run the risk of reducing quality and rigor of C offsets.

Policies that stabilize the price for C credits also reduce the risk associated with relying on C credits for revenue. Forest owners could assess profitability with greater confidence, knowing that regulated prices with price floors and ceilings reduce the risk of low C credit prices. Maintaining substantial timber harvest as part of a forest C project such as CC65 protects forest owners from losses if C markets are weak. Similarly, should wood products decline in value as global competition for wood products increases, C credits could diversity a forest owner's revenue portfolio, protecting against long-term decline in timber markets. Incentive programs that lower land holding costs, for example lowering taxes, would increase the likelihood of positive revenue. Reducing property tax rates for forest owners committed to forest C projects could be an efficient mechanism for incentivizing C projects.

Forest C credits are popular because buyers perceive ecological or social co-benefits. Tropical forest C projects that offer significant ecological or social benefits in addition to C (example: Plan Vivo 2008) are currently in operation. Comparable value-added C credits could be developed for regional applications, increasing price. Alternatively, multiple revenue sources for non-timber products, such as payments for conservation easements in addition to C credits, could reduce the opportunity cost of non-intensive forest management practices.

This research is a case-study; some results may only be applicable to Pack Forest, while other results may be useful to many forest owners in western Washington. The CFI sample error and FVS model uncertainty calculated in this study should not be applied blindly to other forests. However, knowing that model uncertainty is such an important source of error is widely applicable. Parameters for wood prices and C prices are universal, but they may be less important relative to model uncertainty.

This study simplifies a forest owner's ability to change management practices in response to changing prices of timber or C. Owners have the flexibility to decide when to harvest – typically, harvest intensifies when timber prices are high. Conversely, during periods of low timber prices, some owners are forced to harvest more than planned in order to meet minimum revenue thresholds. Forest owners motivated to harvest under both situations rapidly exploit their timber capital. Carbon projects require long-term commitments, but forest owners have the opportunity to sell credits at their discretion, meaning they can wait until prices are high. Therefore management plans that use IFM to accumulate C credits may provide an opportunity to diversify revenue streams.

The assumptions of this study appear to overestimate the probability of financial loss for timber revenue. While a harvest of negative BF of timber is impossible, the method of applying uncertainty in timber volume essentially allows just that. The payout function treats negative BF as if the owner were paying the price for those units of timber. A forest owner would typically not harvest in years where profitable timber harvest would not occur, thus limiting losses to land holding and management costs. However, if a land owner did not harvest in any year and paid land holding costs every year, loss would be limited to -$30 million based on 100 years of paying $170 per acre. The 95% CI for CC45 was within that range, indicating overestimation of negative revenue did not cause unreasonable results.

This study only evaluates C credits verified and sold on voluntary markets. California's GHG emission cap-and-trade policy went into action in November 2012, with expectations of strong demand for C credits sold at higher prices on the compliance market. Verification for the California compliance market requires a 100-year commitment for forest C projects and has more strict review processes. This market is still too new to conclude that clear differences will emerge between it and the voluntary C market on which ACR credits are sold.

5 Conclusion

Accounting for uncertainty in data and assumptions provides a more complete profile of potential consequences of forest management decisions when considering uncertain risks of C projects. Carbon projects compete with business-as-usual forest management only at very high C credit prices. Carbon projects can be profitable, but suffer opportunity costs. Small-scale forest owners who value other forest qualities in addition to NPV may be interested in C projects. Ultimately, profitable forest management choices are in the best interest of forest owners and the provision of ecological services; working forests are sustainable forests. Forest owners should consider C projects but be aware of the weak influence of C credit prices on revenue; until C prices increase due to popular voluntary demand, incentive programs, or regulation, maintaining substantial timber harvest as part of a forest C project increases the chances of profitability.

Future research could model small-scale forest owner's utility from forest C projects using utility maximization outcomes rather than revenue, including such variables such as timing of payment, and administrative capacity for C projects. Further research into uncertainty in FVS is also warranted. Specifically, studies should strive to understand whether uncertainty is a product of variability in tree growth, stochastic events that affect true tree growth, or other factors.

6 Acknowledgements

I thank my thesis committee Greg Ettl, Alison Cullen, and Gordon Smith for their persistence and guidance; Jeff Comnick and Kevin Cedar for their help working with the Pack Forest inventory database and C calculations; my lab mates Kate McBurney, Rhiannon Fox, Hyunju Lee, Julie Baroody, Kendal Becker, and Kiwoong Lee for their honest critiques; my fiancé Marie Quasius for her love and tolerance; David Layton for advice on comparing revenue and wildlife outcomes; Patrick Green for his help with ecological discounting; and Dan Stonington for advice on FSC management and certification.

7 References

Adams A.B., R.B. Harrison, R.S. Sletten, B.D. Strahm, E.C. Turnblom, and C.M. Jensen, 2005. Nitrogen-fertilization impacts on carbon sequestration in managed coastal Douglas-fir stands of the Pacific Northwest. Forest Ecology and Management 220, 313-325.

Alig, R.J., A.J. Plantinga, D. Haim, M. Todd, 2009. Changes in U.S. land use including forests, 1982 to 2002, with projections to 2062. Gen. Tech. Rep. PNW-GTR-PNW-GTR-815, Portland, OR: USDA Forest Service, Pacific Northwest Research Station.

American Carbon Registry (ACR), 2012. ACR Fee Schedule – Published May 1, 2012. http://americanCregistry.org/membership/fee-schedule-may-2012. Accessed September 2012.

American Carbon Registry (ACR), 2010. American Carbon Registry Forest Carbon Project Standard, Version 2.1. Winrock International, Little Rock, Arkansas.

Assembly Bill (AB) 32, 2006. California Global Warming Solutions Act. Section 38500.

Avery, T.E. and H. Burkhart, 2002. Forest Measurements 5th Edition. McGraw-Hill, Boston, MA. 456 p.

Barker, J.S., 2008. Decomposition of Douglas-fir coarse woody debris in response to differing moisture content and initial heterotrophic colonization. Forest Ecology and Management 255, 598–604.

Binkley, D., 1983. Ecosystem production in Douglas-fir plantations: interaction of red alder and site fertility. Forest Ecology and Management 5, 215-227.

Birdsey, R.A., 1992. Carbon storage and accumulation in United States forest ecosystems. Gen. Tech. Rep. WO-59. Washington D.C.: U.S. Department of Agriculture, Forest Service, Washington Office. 51p.

Bradley, G., A. Erickson, A. Robbins, G. Smith, L. Malone, L. Rogers, M. Connor, 2007. Future of Washington's Forest and Forest Industries Study. Study 4: Land Conversion. Rural Technology Initiative. http://www.ruraltech.org/projects/fwaf/final_report/index.asp. Accessed October 2012.

Briggs, D., 2012. Management practices on Pacific Northwest west-side industrial forest lands, 1991-2005: with projections to 2010, Draft. University of Washington Stand Management Cooperative.

Brown, J. K., 1978. Weight and density of crowns of Rocky Mountain conifers. United States Department of Agriculture, Forest Service, Research Paper INT-197, Intermountain Forest and Range Experiment Station, Odgen, UT.

Brown, N., 2005. Revised Final Pacific Coast Regional FSC Standard Version 9.0. Forest Stewardship Council, U.S. Board.

California Air Resources Board (CARB), 2011. Compliance Offset Protocol, U.S. Forest Projects. California Environmental Protection Agency. http://www.arb.ca.gov/regact/2010/capandtrade10/copusforest.pdf. Accessed November 2012.

Canadell, J.G. and M.R. Raupach, 2008. Managing Forests for Climate Change Mitigation. Science 320, 1456–7.

Climate Action Reserve (CAR), 2010. Forest Project Protocol Version 3.2. http://www.climateactionreserve.org/how/protocols/adopted/forest/current/. Accessed February 2011.

Columbia Carbon LLC, 2011. Improved Forest Management Methodology for Quantifying

GHG Removals and Emission Reductions through Increased Forest Carbon Sequestration on Non-Federal U.S. Forestlands. American Carbon Registry (ACR). 39 pp.

Conte, M.N. and M.J. Kotchen, 2010. Explaining the price of voluntary carbon offsets. Climate Change Economics 1:2, 93-111.

Cooper, C.F., 1983. Carbon storage in managed forests. Canadian Journal of Forest Research 13(1), 155-166.

Dewar, R.C., 1990. A model of carbon storage in forests and forest products. Tree Physiology 6 (4), 417-428.

Diaz, D., K. Hamilton, and E. Johnson, 2011. State of the forest carbon markets 2011: from canopy to currency. Ecosystem Marketplace Annual Report.

Dixon, G.E., comp. 2002. Essential FVS: A user's guide to the Forest Vegetation Simulator. Internal Rep. Fort Collins, CO: U. S. Department of Agriculture, Forest Service, Forest Management Service Center. 209p. (Last Revised: April 2007).

Erickson, A. and J. Rinehart, 2005. Private forest landownership in Washington State. Rural Technology Initiative, University of Washington, Seattle, WA. http://www.nwenvironmentalforum.org/documents/SciencePapers/tp1.pdf. Accessed October 2012.

Ettl, G.J., 2012. Personal communication. University of Washington, Seattle, WA.

Ettl, G.J., 2010. The Deniable Truth of Sustainable Forestry. Northwest Science 8, 307-309.

Falk, I. and R. Mendelsohn, 1993. The Economics of Controlling Stock Pollutants: An Efficient Strategy for Greenhouse Gases. Journal of Environmental Economics and Management 25(1), 76-88.

Feller, M., 1992. Generalized versus site-specific biomass regression equations for Pseudotsuga menziesii var. menziesii and Thuja plicata in coastal British Columbia. Bioresource Technology 39, 9-16.

Forest Carbon Portal, 2012. Project Inventory. http://www.forestcarbonportal.com/. Accessed September 2012. Ecosystem Marketplace, Washington, D.C.

Franklin, J.F. and C. T. Dyrness, 1988. Natural vegetation of Oregon and Washington. Corvalis, OR; Oregon State University Press.

Franklin, J.F. T.A. Spies, R. Van Pelt, A.B. Carey, D.A. Thornburgh, D. Rae Berg, D.B. Lindenmayer, M.E. Harmon, W.S. Keeton, D.C. Shaw, K. Bible, and J. Chen 2002. Disturbances and structural development of natural forest ecosystems with silvicultural implications, using Douglas-fir forests as an example. Forest Ecology and Management 155, 399–423.

Gholz, H.L.; C.C. Grier, A.G. Campbell, A.T. Brown, 1979. Equations for estimating biomass and leaf area of plants in the Pacific Northwest. Res. Pap. 41. Corvallis, OR: Oregon State University, School of Forestry.

Gosz, J.R., G.E. Likens, and F.H. Bormann, 1973. Nutrient release from decomposing leaf and litter in the Hubbard Brook Forest, New Hampshire. Ecological Monographs. 43:173-191.

Hamilton, K., U. Chaokkalingam, and M. Bendana, 2010. State of the forest carbon markets 2009: taking root and branching out. Ecosystem Marketplace Annual Report.

Harmon, M E, W.K. Ferrell, and J.F. Franklin, 1990. Effects on carbon storage of conversion of old-growth forests to young forests. Science 247 (4943), 699–702.

Harmon, M. 1994. Unpublished equations. Corvallis, OR: Oregon State University, Forest

Science Department. In Software for computing plant biomass – BIOPAK Users' Guide, U.S. Forest Service General Technical Report PNW-GTR-340. Means, J.E., H.A. Hansen, G.J. Koerper, P.B. Alaback, and M.W. Klopsch, 1994.

Harmon, M.E and B. Marks, 2002. Effects of Silvicultural Practices on Carbon Stores in Douglas-fir – Western Hemlock Forests in the Pacific Northwest , U.S.A.: Results from a Simulation Model. Canadian Journal of Forest Research 32, 863–877.

Harmon, M.E., A. Moreno, and J.B. Domingo, 2009. Effects of partial harvest on the C stores of Douglas-fir/western hemlock forest: a simulation study. Ecosystems 12, 777-791.

Harmon, M.E., K. Bible, M.G. Ryan, D.C. Shaw, H. Chen, J. Klopatek, and X. Li, 2004. Production, respiration, and overall C balance in an old-growth *Pseudotsuga-Tsuga* forest ecosystem. Ecosystems 7, 498-512.

Hermann, R.K. and D.P. Lavender, 1999. Douglas-fir planted forests. New Forestry.17/18, 53-70.

Hudiburg, T., B. Law, D.P. Turner, J. Campbell, D. Donato, and M. Duane, 2009. Carbon Dynamics of Oregon and Northern California Forests and Potential Land-based Carbon Storage. Ecological Applications 19 (1), 163–180.

IBM Corp, 2010. IBM SPSS Statistics for Windows, Version 19.0. Armonk, NY: IBM Corp.

Intergovernmental Panel on Climate Change (IPCC), 2007. Climate Change 2007: The Physical Science Basis. Summary for Policy Makers. (13 November 2007; www.ipcc.ch/).

Jandl, R., M. Lindner, L. Vesterdal, B. Bauwens, R. Baritz, F. Hagedorn, D.W. Johnson, K. Minkkinen, and K.A. Byrne, 2007. How Strongly Can Forest Management Influence Soil Carbon Sequestration? Geoderma 137 (3-4), 253–268.

Janisch, J.E. and M.E. Harmon, 2002. Successional Changes in Live and Dead Wood Carbon Stores: Implications for Net Ecosystem Productivity. Tree Physiology 22 (2-3), 77–89.

Jenkins, J., D. Chojinacky, L. Heath, and R. Birdsey, 2003. National-scale biomass estimators for United States tree species. Forest Science 49(1), 12-35.

Jenkins, J., D. Chojinacky, L. Heath, and R. Birdsey, 2004. Comprehensive database of diameter-based biomass regressions for North American tree species. U.S. Forest Service General Technical Report NE-31.

Johnson, D.W. and P.S. Curtis, 2001. Effects of Forest Management on Soil C and N Storage: Meta Analysis. Forest Ecology and Management 140 (2-3), 227–238.

Kallio, A.M., 2010. Accounting for uncertainty in a forest sector model using Monte Carlo simulation. Forest Policy and Economics 12, 9-16.

Kearney, A.R. and G.A. Bradley, 2011. The effect of viewer attributes on preference for forest scenes: Contributions of attitudes, knowledge, demographic factors, and stakeholder group membership. Environment and Behavior 43(2): 147-181.

Keyser, C.E., comp. 2008 (revised September 6, 2012).Westside Cascades (WC) Variant Overview – Forest Vegetation Simulator. Internal Rep. Fort Collins, CO: U. S. Department of Agriculture, Forest Service, Forest Management Service Center. 93p.

Kremer, J.N., 1983. Ecological implications of parameter uncertainty in stochasitc simulation. Ecological Modeling 18(3-4), 187-207.

Larocque, G.R., J.S. Bhatti, R. Boutin, and O. Chertov, 2008. Uncertainty analysis in carbon cycle models of forest ecosystems: research needs and development of a theoretical framework to estimate error propagation. Ecological Modeling 219, 400-412.

Law, B.E., P.E. Thornton, J. Irvine, P.M. Anthoni, and S. Van Tuyl, 2001. Carbon storage and fluxes in ponderosa pine forests at different developmental stages. Global Change

Biology 7, 755-777.

Law, B.E. and M.E Harmon, 2011. Forest Sector Carbon Management, Measurement and Verification, and Discussion of Policy Related to Climate Change. Carbon Management 2 (1): 73–84.

Lindberg, J., 2012. The Washington Log Market Report. Vancouver, WA. Photocopy of electronic mail messages. Seattle, Wash. : University of Washington Libraries.

Lindenmayer, D.B., J.F. Franklin, and J. Fischer, 2006. General management principles and a checklist of strategies to guide forest biodiversity conservation. Biological Conservation 131, 433-445.

Lovett, G.M., J.J. Cole, and M.L. Pace, 2006. Is net ecosystem production equal to ecosystem carbon accumulation? Ecosystems 9, 152:155.

Luyssaert, S., E.D. Schulze, A. Börner, A. Knohl, D. Hessenmöller, B.E. Law, P. Ciais, and J. Grace, 2008. Old-growth Forests as Global Carbon Sinks. Nature 455 (7210), 213–5.

Malmsheimer, R.W., P. Heffernan, S. Brink, D. Crandall, F. Deneke, C. Galik, E. Gee, 2008. Forest Management Solutions for Mitigating Climate Change in the United States. Journal of Forestry April/May, 1–59.

Markewitz, D., 2006. Fossil fuel carbon emissions from silviculture: impacts on net carbon sequestration in forests. Forest Ecology and Management 236, 153–161.

McKinley, M. and E. Turnblom, 2002. Pack Forest Growth Model Calibration Using CFI. University of Washington College of Forest Resources. http://www.packforest.org/plan/Sensitivity_files/PackSensitivity_files/CFIFinalWriteUp.htm. Accessed November 2012.

Means, J.E., H.A. Hansen, G.J. Koerper, P.B. Alaback, and M.W. Klopsch, 1994. Software for computing plant biomass – BIOPAK Users' Guide, U.S. Forest Service General Technical Report PNW-GTR-340.

Oliver, C.D., 1981. Forest Development in North America Following Major Disturbances. Forest Ecology and Management 3, 153–168.

Oracle, 2012. Crystal Ball version 11.1.2.2.000, Fusion Edition, Release 11.1.2.2.000. Http://www.oracle.com/crystalball

Pack Forest, 2005. Fact Sheet: Pack Forest Green Certification. Center for Sustainable Forestry at Pack Forest. University of Washington. http://www.packforest.org/research/certfactsheet.pdf. Accessed March 2011.

Pedlar, J.H., J.L. Pearce, L.A. Venier, and D.W. McKenney, 2002. Coarse Woody Debris in Relation to Disturbance and Forest Type in Boreal Canada. Forest Ecology and Management 158, 189–194.

Perez-Garcia, J., B. Lippke, J. Comnick, and C. Manriquez, 2005. An Assessment of Carbon Pools, Storage, and Wood Products Market Substitution Using Life-cycle Analysis Results. Wood and Fiber Science 37, 140–148.

Peters-Stanley, M., K. Hamilton, and D. Yin, 2012. Leveraging the landscape: State of the forest carbon markets 2012.Ecossytem Marketplace annual report.

Plan Vivo, 2008. The Plan Vivo Standards. http://www.planvivo.org/wp-content/uploads/Plan-Vivo-Standards-20081.pdf. Accessed November 2012.

Pregitzer, K.S. and E.S. Euskirchen, 2004. Carbon Cycling and Storage in World Forests: Biome Patterns Related to Forest Age. Global Change Biology 10, 2052–2077.

Regen, H.M., M. Colyvan, and M.A. Burgman, 2002. A taxonomy and treatment of uncertainty for ecology and conservation biology. Ecological Applications 12(2), 618-628.

Regional Greenhouse Gas Initiative (RGGI), 2005. Memorandum of Understanding. RGGI.org.

RTI, 2009. Retention of high-valued forest lands at risk of conversion to non-forest uses in Washington State. Final report. College of Forest Resources, University of Washington. http://www.ruraltech.org/projects/wrl/sfr/report/index.asp. Accessed October 2012.

Shaw, DL, 1979. Biomass equations for Douglas-fir, western hemlock, and red cedar in Washington and Oregon. In Forest Resource Inventories. Edited by Frayer I. Fort Collins: Colorado State University pp 763-781.

Smith, Gordon, 2011. Personal communication.

Smith, J.E. and L.S. Heath, 2001. Identifying influences on model uncertainty: an application using a forest carbon budget model. Environmental Management. 27(2), 253-267.

Smithwick, E.A.H., M.E. Harmon, and J.B. Domingo, 2007. Changing Temporal Patterns of Forest Carbon Stores and Net Ecosystem Carbon Balance: The Stand to Landscape Transformation. Landscape Ecology 22 (1), 77–94.

Smithwick, E.A.H., M.E. Harmon, S.M. Remillarad, S.A. Acker, and J.F. Franklin, 2002. Potential Upper Bounds of Carbon Stores in Forests of the Pacific Northwest. Ecological Applications 12 (5), 1303–1317.

Snell, J. and S. Little, 1983. Predicting crown weight and bole volume of five western hardwoods. Gen. Tech. Rep. PNW-151. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Forest and Range Experiment Station.

Snell, J. and T. Ma,. 1985. Estimating the weight of crown segments for old-growth Douglas-fir and western hemlock. Res. Pap. PNW-329. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Forest and Range Experiment Station.

Sohngen, B. and R. Mendelsohn, 2003. An optimal control model of forest carbon sequestration. American Journal of Agricultural Economics. 85(2), 448-457.

Stage, A.R., 1973. Prognosis model for stand development. USDA Forest Service Res. Pap. INT-137, 32 p., illus. (Intermountain Forest & Range Experiment Station, Ogden, Utah 84401.)

Standish, J.T., G.H. Manning, and J.P. Demaerschalk, 1985. Development of biomass equations for British Columbia tree species. Inf. rep. BC-X-264. Pacific Forest Research Center. Canadian FS.

Stern, Sr.N., 2006. Stern Review: The Economics of Climate Change. UK Department of Energy and Climate Change. http:// www.hm-treasury.gov.uk/stern_review_report.htm. Accessed June 2012.

Swanson, M., 2006. Special paper: Center for Sustainable Forestry at Pack Forest. 25 pp.

Tóth, S.F., G.J. Ettl , N. Könnyű, S.S. Rabotyagov, and L.W. Rogers, In press. ECOSEL: Multi-Objective Optimization to Sell Forest Ecosystem Services. Forest Policy and Economics.

Tóth, S.F, G.J. Ettl, and S.S. Rabotyagov, 2010. ECOSEL: An Auction Mechanism for Forest Ecosystem Services. Mathematical and Computational Forestry & Natural-Resource Sciences 2, 99-116.

U.S. Bureau of Labor Statistics, 2012. Consumer Price Index, All urban consumers - (CPUI-U), U.S. city average, all items. ftp://ftp.bls.gov/pub/special.requests/cpi/cpiai.txt. Accessed September 2012.

U.S. Department of Agriculture, 2011. Web Soil Survey: Pierce County, Washington. Natural Resource Conservation Service. http://websoilsurvey.nrcs.usda.gov/app/. Accessed September 2012.

U.S. Department of Energy, Office of Policy and International Affairs, 2007. Technical Guidelines: Voluntary Reporting of Greenhouse Gases (1605(b)) Program.

U.S. Office of Management and Budget, 1994. Circular No. A-94 Revised. Memorandum for heads of executive departments and establishments. Subject: Guidelines and Discount Rates for Benefit-Cost Analysis of Federal Programs.

Verified Carbon Standard (VCS), 2010. Approved VCS Methodology VM0003: Methodology for Improved Forest Management Through Extension of Rotation Age Version 1.0. Sectoral Scope 14.

Verified Carbon Standard (VCS), 2012. AFOLU non-permanence risk tool version 3.1. Procedural Document. 18 pp.

Vicary, B.P., 2006. Edited by B.C. Mendell. Timberland Report Vol. 8, No. 3. James W. Sewall Company. http://www.forisk.com/UserFiles/File/Vol8%20No3.pdf. Accessed November 2012.

Washington Department of Revenue (WDOR), 2012. Stumpage value determination tables. http://dor.wa.gov/content/findtaxesandrates/othertaxes/timber/forst_stump.aspx. Accessed September 2012.

Washington Forest Protection Association (WFPA), 2005. Forest Facts and Figures. http://www.forestsandfish.com/PressRoom/pdfs/FFF-2005new.pdf.

Weitzman, M.L., 1999. Discounting and Intergenerational Equity. Chapter Three. Edited by P. Portney and J. Weyant. Washington D.C.: Resources for the Future: 23.

Whittaker, R. H., F.H. Bormann., G.E. Likens, and T.G. Siccama, 1974. The Hubbard Brook Ecosystem Study: forest biomass and production. Ecological Monographs 44, 233-254.

Yavitt, J.B. and T.J. Fahey, 1982. Loss of mass and nutrient changes of decaying woody roots in lodgepole pine forests, southeastern Wyoming. Canadian Journal of Forest Resources 12, 745-752.

8 Appendices

8.1 Appendix 1: Acronyms

ACR	American Carbon Registry
ANOVA	Analysis of variance
BA	Basal area
BAU	Business as usual
BF	Board-feet
C	Carbon
CAR	Climate Action Reserve
CFI	Continuous forest inventory
CI	Confidence interval
cMAI	Culmination of mean annual increment
CO_2	Carbon dioxide
CO_2e	Carbon dioxide equivalent
DBH	Diameter at breast height
EV	Expected value
FSC	Forest Stewardship Council
FVS	Forest Vegetation Simulator
GHG	Greenhouse gas
IFM	Improved Forest Management
MAI	Mean annual increment
MBF	Thousand-board-feet
MC	Monte Carlo
NEP	Net ecosystem productivity
NPP	Net primary productivity
NPV	Net present value
PDF	Probability density function
PNW	Pacific Northwest
QMD	Quadratic mean diameter
SD	Standard deviation
SFI	Sustainable Forestry Initiative
VCS	Verified Carbon Standard
VOI	Value of information

8.2 Appendix 2: Biomass Allometric Equation Selection

8.2.1 Analysis of allometric biomass equations by species

ALL SPECIES

Jenkins et al. 2003:

Total aboveground biomass: This article is commonly used for standard biomass equations. Jenkins et al. 2003 calculated generalized equations from many existing allometric equations in literature for a wide variety of North American species. As a result, the Jenkins equations tend to give average or low biomass predictions as the Pacific Northwest, and Pack forest, tend to be more productive than other forested areas of North America. I used a Jenkins equation for every species as a way to compare the simple and component sets of equations.

DOUGLAS-FIR

Simple:

Small trees of DBH 0-19 cm:

Total aboveground biomass: Standish et al. 1985**.** This equation provides a concise prediction of biomass in smaller trees. These data come from unmanaged second growth Douglas-fir stands in British Columbia using a diameter range from 4.5 to 66 cm, and height to 44 m. Sample size was 49 with an R^2 of 0.99. No similar equation existed for Washington/western Cascades.

Intermediate and mature trees of DBH 19+ cm:

Total aboveground biomass: Shaw 1979. Shaw's data are from western Cascade Douglas-fir forests with a strong sampling of large trees. Diameters ranged from 2.5 to 162 cm with a sample size of 144 trees. R^2 equals 0.69. I tolerate low R^2 because wide variance in large trees, and such a broad sample of trees, is expected. This equation included the greatest range of diameters and uses tree height.

Component:

Small trees of DBH 0-12 cm:

Total aboveground biomass: Standish et al. 1985. See comments for 'Simple: Small trees' above.

Intermediate trees of DBH 12-30 cm:

Stem wood and bark biomass: Harmon 1994. Harmon 1994 developed a Douglas-fir total stem biomass equation most appropriate for mid-range diameters at Pack Forest. While his sample included trees up to 212cm DBH, most of the sample applies to trees in a mature, but not old-growth, stand category. With a very large sample size of 215 trees, the R^2 equals 0.97.

Branches, foliage biomass: Gholz et al. 1979. Douglas-fir diameters ranged from 2.3 to 135 cm with a sample size of 26 and R^2 of 0.96. This diameter range includes a good sample of harvest-size trees. Other authors provide better biomass equations for small and large diameter trees.

Gohlz et al. are the only authors to develop an allometric equation for live root biomass, which I also applied to western hemlock and western white pine as no other equations were available.

Mature trees of DBH 30+ cm:

Stem wood and bark biomass: Shaw 1979. His data are from western Cascade Douglas-fir forests with a strong sampling of large trees. Diameters ranged from 2.5 to 162 cm with a sample size of 144 trees. R^2 equals 0.69. I tolerate low R^2 because wide variance in large trees is expected. This equation includes the most big trees and the largest trees of any equation. The height component is critical in large trees as site index, damage, competition, and other factors affect height, thus biomass, in bigger trees.

Live crown biomass: Snell and Max 1985 developed crown biomass equations for large-diameter Douglas-fir in the western Cascades. Douglas-fir sampled ranged from 60 to 160cm DBH. The larger trees tend to show more variance, thus R^2 was relatively low at 0.73.

Roots: Gholz et al. 1979 are the only authors to develop an allometric equation for live root biomass.

RED ALDER

Simple:

Total above ground biomass: Standish et al. 1985. Using a coastal BC research area, Standish et al. sampled trees ranging from about 6 to 33cm DBH with an R^2 equal to 0.99. While this equation is based on data that do not go larger than 33.3 cm DBH, it is the only equation for total aboveground biomass equation that includes height.

Component:

Stem wood and bark biomass: Binkley 1983. His data are from BC coastal and western Washington second-growth forests. Diameters range from 6 to 20 cm with a sample size of 12 and R^2 equal to 0.98. Diameter range is limited in this sample and does not include the range of diameters found in the Pack Forest inventory. Sample size is relatively small but R^2 is strong. Red alder equations were somewhat limited and this equation showed the best fit geographically and for sample diameter ranges.

Live crown biomass: Snell and Little 1983. While this equation does not include height as a parameter, the relatively large trees included in the sample (alder DBH range 2.5 to 63cm) and western Cascade research site make these equation the most appropriate for Pack Forest. R^2 equals 0.94 for alder.

Roots:

Gholz et al. 1979 are the only authors to develop an equation modeling red alder root biomass.

WESTERN RED CEDAR

Simple:

Small trees of DBH 0-23 cm:

Total aboveground biomass: Standish et al. 1985. Sample size was 70 trees and, R^2 equaled 0.97 in coastal British Columbia forests.

Intermediate and mature trees of DBH 23+ cm:

Total aboveground biomass: Shaw 1979. Because the Shaw data include such large trees, his equations provide valuable predictions for the most important contributors to C storage in Pack Forest. Sample size equals 26, tree diameters range from 2.5 to 119.6 cm DBH, and R^2=0.90. Data were from western Cascade forests in Washington and Oregon. The equation includes height.

Component:

Small trees of DBH 0-16 cm:

Stem wood and bark biomass: Shaw 1979. Using a sample size of 26 and tree diameters ranging from 2.5 to 119.6 cm DBH, Shaw studied western Cascade forests in Washington and Oregon. R^2=0.93. The equation includes height.

Branches, foliage biomass: Standish et al. 1985. While sample size was sufficiently large (70 trees for each biomass component), R^2 values were below 0.65 for branch and foliage biomass.

Intermediate and mature trees of DBH 16+ cm:

Total above ground biomass: Shaw 1979, see ‘Simple’ above.

Roots: Feller 1992 provided the western red cedar root biomass equation. His data are from BC coastal and forests. Diameters ranged from 12 to 47cm with a sample size of 7 and R^2 equal to 0.96. This was the only equation available for western red cedar root biomass.

WESTERN HEMLOCK

Simple:

Total aboveground biomass: Shaw 1979. The equation includes height, and DBH ranges from 2.5 to 92 cm. R^2 = 0.88 from 47 samples in western Cascade forests.

Component:

Small and intermediate trees 0-50 cm:

Total aboveground biomass: Shaw 1979. See ‘Simple’ above.

Mature trees 50+ cm:

Stem wood and bark biomass: Shaw 1979. Sample size equals 47, tree diameters range from 2.5 to 92 cm DBH in western Cascade forests. R^2=0.97. The equation includes height.

Live crown biomass: Snell and Max developed crown biomass equations for large-diameter western hemlocks (50+cm) in the western Cascades. Western hemlocks sampled ranged from 30 to 110cm DBH. The larger trees tend to show more variance, thus R^2 was relatively low at 0.82.

Roots: Gholz et al. 1979 Douglas-fir equation. No equation was found for western hemlock root biomass.

BIGLEAF MAPLE

Simple:

Total aboveground biomass: No equations have been developed for total aboveground biomass for bigleaf maple.

Component:

Stem wood and bark biomass: Gholz et al. 1979 provided equations for bigleaf maple stem wood and stem bark biomass. These data were from a research site in western Cascade forests. Bigleaf maple samples ranged from 7.5 to 38cm in diameter and R^2 of 0.98 and 0.99 for stem bark and wood, respectively.

Live crown biomass: Snell and Little 1983 provide crown biomass equations. While their equations don't include height as a parameter, the relatively large trees included in the sample 5.1 to 45.7cm) and western Cascade research site make these equation the most appropriate for Pack Forest. R^2 equals 0.93.

Roots:

Whittaker et al. 1974. As I could find no equations for bigleaf maple below-ground biomass, I selected Whittaker et al.'s equation for sugar maple roots as a proxy. Notably, sugar maple is a "hard" maple with a higher specific gravity than the "soft" bigleaf maple. I did not adjust Whittaker et al.'s equation to compensate for this difference. The effect on biomass calculations is expected to be negligible.

WESTERN WHITE PINE

Simple: Total aboveground biomass: Standish et al. 1985.

Component:

Stem wood and bark biomass: Standish et al. 1985. These authors developed some of the few biomass equations available for western white pine. I used stem wood and bark biomass equations.

Live crown biomass: Brown 1978. While these data are from northern Idaho and western Montana, the range of diameters is more robust than Standish et al. 1985 British Columbia work. $R^2 = 0.95$.

Roots: Gholz et al. 1979 Douglas-fir equation. No equation was found for western white pine root biomass.

8.2.2 Selected Allometric Biomass Equations

Category	Species	DBH Range	Biomass component	Equation	Source	Region	Seral Stage	R^2
Simple	PSME	0 to 19cm	Total aboveground biomass	37300 + 0.1393 * DBH^2 * HT	Standish et al. 1985	Coast	Young	0.99
		19cm+	Total aboveground biomass	1054 + 0.2057 * (DBH^2*HT)	Shaw 1979	Western Cascades	General	0.69
Component	PSME	0 to 12cm	Total aboveground biomass	37300 + 0.1393 * DBH^2 * HT	Standish et al. 1985	Coast	Young	0.99
		12cm to 30cm	Total stem biomass	Exp(4.660412 + 2.4247 * ln(DBH))	Harmon 1994	Western Cascades	Mature	0.973
			Branches	Exp(3.2137 + 2.1382 * ln(DBH))	Gholz et al. 1979	Western Cascades	General	0.92
			Foliage	Exp(4.0616 + 1.7009 * ln(DBH))	Gholz et al. 1979	Western Cascades	General	0.86
		30cm+	Total stem biomass	-115 + 0.1896 * (DBH^2*HT)	Shaw 1979	Western Cascades	General	0.74
			Total live crown	Exp(10.914555 + 0.0206 * DBH)	Snell and Max 1985	Western Cascades	Old	0.73
Jenkins	Douglas-fir	All	Total aboveground biomass	Exp(-2.2304+2.4435*ln(DBH) * 1000	Jenkins et al. 2003	General	General	NA
Roots	PSME	All	Below ground (live roots)	Exp(2.2117 + 2.6929 * ln(DBH))	Gholz et al. 1979	Western Cascades	General	0.96

Category	Species	DBH Range	Biomass component	Equation	Source	Region	Seral Stage	R^2
Simple	ALRU	All	Total aboveground biomass	4800 + 0.2065 * (DBH)^2 * HT	Standish et al. 1985	General	Young	0.99
Component	ALRU	All	Total stem biomass	Exp(3.97 + 2.56 * ln(DBH))	Binkley 1983	Coast	Mature	0.98
		All	Crown biomass	Exp(2.3429553 + 2.6232 * ln(DBH))	Snell and Little 1983	Western Cascades	General	0.94
Jenkins	Alder	All	Total aboveground biomass	Exp(-2.2094+2.3867 ln DBH) * 1000	Jenkins et al. 2003	General	General	NA
Roots	ALRU	All	Below ground (live roots)	100 + 480*DBH^2*HT - 0.5*(DBH^2*HT)^2	Gholz et al. 1979	C	Young	NA

Category	Species	DBH Range	Biomass component	Equation	Source	Region	Seral Stage	R^2
Simple	ACMA	n/a	n/a	NONE AVAILABLE	n/a			
Component	ACMA	All	Total live crown biomass	Exp(4.0543553 + 2.1505 * ln(DBH))	Snell and Little 1983	Western Cascades	General	0.93
			Stem bark biomass	Exp(2.3338 + 2.574 * ln (DBH))	Gholz et al. 1979.	Western Cascades	Old	0.98
			Stem wood biomass	Exp(3.4148 + 2.723 * ln (DBH))	Gholz et al. 1979.	Western Cascades	Old	0.99
Jenkins	Soft maple	All	Total aboveground biomass	Exp(-1.9123+2.3651 ln DBH) * 1000	Jenkins et al. 2003	General	General	NA
Roots	ACSA	All	Roots*	Loginv(1.7362 + 2.2006 * (log10(DBH^1)))	Whittaker et al. 1974	General	General	NA

Category	Species	DBH Range	Biomass component	Equation	Source	Region	Seral Stage	R^2
Simple	THPL	0-23cm	Total aboveground biomass	40400 + 0.0969 * (DBH)^2 * HT	Standish et al. 1985	General	General	0.97
		23cm+	Total aboveground biomass	1270 + 0.1501 * (DBH^2*HT)	Shaw 1979	Western Cascades	General	0.90
Component	THPL	0-16	Total stem biomass	773 + 0.0755 * (DBH^2*HT)	Shaw 1979	Western Cascades	General	0.93
			Biomass branches live (including top <2.5 cm)	12000 + 0.0128 * (DBH)^2 * HT	Standish et al. 1985	General	General	0.66
			Total foliage biomass	7600. + 0.0067 * (DBH)^2 * HT	Standish et al. 1985	General	General	0.62
		16cm+ DBH	Total aboveground biomass	1270 + 0.1501 * (DBH^2*HT)	Shaw 1979	Western Cascades	General	0.90
Jenkins	Cedar	All	Total aboveground biomass	Exp(-2.0336+2.2592 ln DBH) * 1000	Jenkins et al. 2003	General	General	NA
Roots	THPL	All	Roots	Exp (-4.159 + 0 * DBH + 2.519 * (ln(DBH^1)) * 1000	Feller 1992	Coast	General	0.94

Category	Species	DBH Range	Biomass component	Equation	Source	Region	Seral Stage	R^2
Simple	TSHE	All	Total aboveground biomass	497 + 0.2113 * (DBH^2*HT)	Shaw 1979	Western Cascades	General	0.88
Component	TSHE	0-50cm	Total aboveground biomass	497 + 0.2113 * (DBH^2*HT)	Shaw 1979	Western Cascades	General	0.88
		50cm+	Total stem biomass	337 + 0.1279 * (DBH^2*HT)	Shaw 1979	Western Cascades	General	0.97
		50cm+	Crown Biomass	Exp(10.796355 + 0.0338 * DBH)	Snell and Max 1985	Western Cascades	Old	0.82
Jenkins	Hemlock	All	Total aboveground biomass	Exp(-2.5384+2.4814 ln DBH) *1000	Jenkins et al. 2003	General	General	NA
Roots	PSME	All	Below ground (live roots)	Exp(2.2117 + 2.6929 * ln(DBH))	Gholz et al. 1979	Western Cascades	General	0.96

Category	Species	DBH Range	Biomass component	Equation	Source	Region	Seral Stage	R^2
Simple	PIMO	All	Total aboveground biomass (without dead branches)	20800 + 0.1544 * (DBH)2 * HT	Standish, J.T. et al. 1985.	General	General	0.96
Component	PIMO	All	Live crown biomass	1655.6122 - 1.254999*DBH^3 +0.028441*DBH^2*HT	Brown, J. K. 1978.	Rocky Mountains	General	0.95
			Biomass stem bark (without top < 2.5cm)	1200 + 0.0112 * (DBH)^2 * HT	Standish, J.T. et al. 1985.	General	General	0.96
			Biomass stem wood (without top < 2.5cm)	2300 + 0.1204 * (DBH)^2 * HT	Standish, J.T. et al. 1985.	General	General	0.99
Jenkins	Pine	All	Total aboveground biomass	exp(-2.5356+2.4349*ln(DBH) * 1000	Jenkins et al. 2003	General	General	NA
Roots	PSME	All	Below ground (live roots)	Exp(2.2117 + 2.6929 * ln(DBH))	Gholz et al. 1979.	Western Cascades	General	0.96

8.3 Appendix 3: Volume and Mass Tables

8.3.1 Board-Feet Table

Board feet (BF) were used for harvested wood product calculations. BF were later converted to thousand-board-feet (MBF), equal to BF divided by 1000. Yellow highlights indicate strata that had no data and average values were used. Orange highlights are the average values and values used for plots age 105 and older.

“Alder” refers to plots dominated by alder, “CHi” are high-productivity conifer plots, “CLo” are low-productivity conifer plots, and “Other” refers to all other plots.

Board Feet (BF)		Average per acre (BF)				Standard Deviation			
Year Range	Log Grade	A	CHi	CLo	O	A	CHi	CLo	O
045-54	DF2	1,152	8,452	7,025	1,125	2,027	8,027	11,651	-
	DFUtil	1,152	9,990	8,728	5,534	1,288	5,463	4,175	-
	DFPulp	1,342	8,945	9,689	7,818	1,292	4,330	4,105	-
	RASaw	3,004	-	40	-	2,868	-	173	-
	RAPulp	6,618	259	277	387	4,090	519	916	-
	HemSaw	3,146	1,527	880	16,759	3,667	2,896	3,365	-
	HemPulp	1,030	682	449	4,886	1,103	823	1,163	-
	RC	1,261	-	289	546	2,769	-	1,958	-
	Other Pulp	-	14	718	222	-	39	2,291	-
055-64	DF2	18,209	9,100	7,018	1,125	8,397	5,723	5,092	-
	DFUtil	4,210	8,804	9,871	5,534	2,422	2,470	7,090	-
	DFPulp	3,447	5,036	9,436	7,818	1,660	1,239	5,651	-
	RASaw	615	1,152	-	-	870	2,531	-	-
	RAPulp	1,174	1,597	191	387	442	1,409	288	-
	HemSaw	321	1,769	-	16,759	454	2,248	-	-
	HemPulp	749	386	840	4,886	1,059	246	1,879	-
	RC	-	240	-	546	-	588	-	-
	Other Pulp	-	270	81	222	-	429	182	-

065-74	DF2	2,295	24,360	11,956	1,125	5,131	8,112	12,463	-
	DFUtil	2,209	10,478	10,592	5,534	4,615	5,250	6,791	-
	DFPulp	1,970	5,611	7,647	7,818	3,293	2,579	4,455	-
	RASaw	4,110	292	298	-	7,136	505	1,689	-
	RAPulp	5,149	525	510	387	4,708	547	1,211	-
	HemSaw	83	277	733	16,759	186	479	2,724	-
	HemPulp	107	739	536	4,886	239	1,071	1,105	-
	RC	-	2,010	237	546	-	3,481	1,488	-
	Other Pulp	9,175	-	1,130	222	9,291	-	3,368	-
075-84	DF2	12,032	25,711	19,484	1,125	14,813	12,950	10,875	-
	DFUtil	6,113	15,001	12,901	5,534	7,288	10,408	9,515	-
	DFPulp	1,639	3,790	4,456	7,818	2,770	3,120	2,792	-
	RASaw	1,084	1,073	973	-	1,878	3,191	3,165	-
	RAPulp	5,112	789	1,110	387	4,261	1,479	1,765	-
	HemSaw	-	1,715	861	16,759	-	4,319	2,105	-
	HemPulp	-	682	691	4,886	-	1,071	951	-
	RC	-	-	183	546	-	-	505	-
	Other Pulp	1,689	-	1,214	222	2,925	-	4,273	-
085-94	DF2	4,775	21,500	19,793	1,125	8,375	13,874	10,106	-
	DFUtil	2,466	13,137	14,217	5,534	3,810	9,333	6,945	-
	DFPulp	1,754	4,547	4,698	7,818	2,105	3,515	2,597	-
	RASaw	2,753	709	81	-	4,058	1,653	257	-
	RAPulp	5,480	1,161	362	387	4,147	1,592	625	-
	HemSaw	1,626	1,455	129	16,759	2,971	3,493	345	-
	HemPulp	616	916	428	4,886	931	1,286	745	-
	RC	630	294	242	546	2,013	1,060	765	-
	Other Pulp	2,547	5,711	3,360	222	5,903	13,818	5,167	-

095-104	DF2	4,775	11,336	11,956	1,125	8,375	6,314	12,463	-
	DFUtil	2,466	8,141	10,592	5,534	3,810	4,997	6,791	-
	DFPulp	1,754	3,359	7,647	7,818	2,105	1,709	4,455	-
	RASaw	2,753	463	298	-	4,058	1,024	1,689	-
	RAPulp	5,480	1,534	510	387	4,147	2,723	1,211	-
	HemSaw	1,626	3,750	733	16,759	2,971	7,007	2,724	-
	HemPulp	616	1,953	536	4,886	931	2,952	1,105	-
	RC	630	1,052	237	546	2,013	3,070	1,488	-
	Other Pulp	2,547	2,537	1,130	222	5,903	3,885	3,368	-
105+ Average Totals	DF2	4,775	16,695	11,956	1,125	8,375	12,431	12,463	-
	DFUtil	2,466	11,408	10,592	5,534	3,810	7,761	6,791	-
	DFPulp	1,754	5,207	7,647	7,818	2,105	3,691	4,455	-
	RASaw	2,753	619	298	-	4,058	1,924	1,689	-
	RAPulp	5,480	959	510	387	4,147	1,650	1,211	-
	HemSaw	1,626	1,924	733	16,759	2,971	4,232	2,724	-
	HemPulp	616	939	536	4,886	931	1,582	1,105	-
	RC	630	381	237	546	2,013	1,598	1,488	-
	Other Pulp	2,547	1,733	1,130	222	5,903	6,837	3,368	-

Board Feet (BF)		Plot Count			
Year Range	Log Grade	Alder	CHi	CLo	Other
045-54	DF2	10	13	46	1
	DFUtil	10	13	46	1
	DFPulp	10	13	46	1
	RASaw	10	13	46	1
	RAPulp	10	13	46	1
	HemSaw	10	13	46	1
	HemPulp	10	13	46	1
	RC	10	13	46	1
	OtherPulp	10	13	46	1
055-64	DF2	2	6	5	0
	DFUtil	2	6	5	0
	DFPulp	2	6	5	0
	RASaw	2	6	5	0
	RAPulp	2	6	5	0
	HemSaw	2	6	5	0
	HemPulp	2	6	5	0
	RC	2	6	5	0
	OtherPulp	2	6	5	0
065-74	DF2	5	3	0	0
	DFUtil	5	3	0	0
	DFPulp	5	3	0	0
	RASaw	5	3	0	0
	RAPulp	5	3	0	0
	HemSaw	5	3	0	0
	HemPulp	5	3	0	0

	RC	5	3	0	0
	OtherPulp	5	3	0	0
075-84	DF2	3	14	23	0
	DFUtil	3	14	23	0
	DFPulp	3	14	23	0
	RASaw	3	14	23	0
	RAPulp	3	14	23	0
	HemSaw	3	14	23	0
	HemPulp	3	14	23	0
	RC	3	14	23	0
	OtherPulp	3	14	23	0
085-94	DF2	0	13	10	0
	DFUtil	0	13	10	0
	DFPulp	0	13	10	0
	RASaw	0	13	10	0
	RAPulp	0	13	10	0
	HemSaw	0	13	10	0
	HemPulp	0	13	10	0
	RC	0	13	10	0
	OtherPulp	0	13	10	0
095-104	DF2	0	11	0	0
	DFUtil	0	11	0	0
	DFPulp	0	11	0	0
	RASaw	0	11	0	0
	RAPulp	0	11	0	0
	HemSaw	0	11	0	0
	HemPulp	0	11	0	0
	RC	0	11	0	0
	OtherPulp	0	11	0	0

105+ Average Totals	DF2	20	60	84	1
	DFUtil	20	60	84	1
	DFPulp	20	60	84	1
	RASaw	20	60	84	1
	RAPulp	20	60	84	1
	HemSaw	20	60	84	1
	HemPulp	20	60	84	1
	RC	20	60	84	1
	OtherPulp	20	60	84	1

8.3.2 Carbon Tables

Carbon mass (metric tons (Mg) of C) was used for C credit calculations.

“Alder” refers to plots dominated by alder, “CHi” are high-productivity conifer plots, “CLo” are low-productivity conifer plots, “C85+” are conifer plots age 85 and older, and “Other” refers to all other plots.

Carbon	Average Total C per Acre (MgC)				
Year Range	Alder	CHi	CLo	C85+	Other
0-14	13.4	20.3	25.5	-	21.2
015-24	23.1	30.4	35.2	-	40.2
025-34	41.8	50.0	49.3	-	51.7
035-44	53.4	73.1	64.4	-	73.2
045-54	66.3	81.4	75.8	-	92.7
055-64	68.5	86.6	76.9	-	110.6
065-74	71.0	113.6	72.1	-	-
075-84	75.7	119.6	119.6	-	59.8
085-94	94.0	-	-	110.3	64.5
095-104	113.0	-	-	113.1	72.8
105-114	138.6	-	-	130.3	79.3
115-124	-	-	-	132.6	-
125-134	-	-	-	104.0	-
135-144	-	-	-	113.0	-
145-155	-	-	-	118.1	-
155+	-	-	-	201.7	-

Standard Deviation of Total C per Acre					
Age Range	A	CHi	CLo	C85+	Other
0-14	5.5	12.5	35.0	-	-

015-24	11.9	15.9	42.6	-	5.2
025-34	19.7	21.7	42.4	-	16.2
035-44	22.8	31.5	43.4	-	22.6
045-54	28.5	35.8	43.3	-	30.3
055-64	25.8	29.0	34.7	-	41.8
065-74	30.9	50.6	18.3	-	-
075-84	40.8	61.4	58.3	-	31.7
085-94	32.9	-	-	58.5	39.3
095-104	29.5	-	-	64.0	46.1
105-114	32.3	-	-	70.6	57.0
115-124	-	-	-	52.9	-
125-134	-	-	-	20.3	-
135-144	-	-	-	21.9	-
145-155	-	-	-	27.0	-
155+	-	-	-	148.5	-

Plot Count of Total C per Acre

Age range	A	CHi	CLo	C85+	Other	Row Total
0-14	49	132	241	-	1	423
015-24	45	143	274	-	3	465
025-34	40	114	381	-	11	546
035-44	60	104	346	-	14	524
045-54	63	62	244	-	13	382
055-64	30	22	59	-	7	118
065-74	13	11	5	-	-	29
075-84	14	44	58	-	6	122

085-94	14	-	-	104	10	128
095-104	14	-	-	68	10	92
105-114	8	-	-	54	9	71
115-124	-	-	-	16	-	16
125-134	-	-	-	4	-	4
135-144	-	-	-	4	-	4
145-155	-	-	-	2	-	2
155+	-	-	-	175	-	175
Column Total	350	632	1,608	427	84	3,101

8.3.3 Cubic Feet Table

Cubic feet were used for long-lived wood product C calculations. Yellow highlights indicate strata that had no data and average values were used. Orange highlights are the average values and values used for plots age 105 and older.

"Alder" refers to plots dominated by alder, "CHi" are high-productivity conifer plots, "CLo" are low-productivity conifer plots, and "Other" refers to all other plots.

Cubic Feet (CuFt)		CuFt - Per-Acre averages				Count			
Year Range	Log Grade	A	CHi	CLo	O	A	CHi	CLo	O
045-54	DF2	407	1,984	2,011	8,173	10	13	46	1
	DFUtil	885	1,889	2,201	2,092	10	13	46	1
	DFPulp	1,224	1,908	2,366	613	10	13	46	1
	RASaw	717	216	22	-	10	13	46	1
	RAPulp	1,469	582	128	281	10	13	46	1
	HemSaw	395	664	285	-	10	13	46	1
	HemPulp	223	286	187	-	10	13	46	1
	RC	233	13	22	-	10	13	46	1
	OtherPulp	-	9	154	-	10	13	46	1
055-64	DF2	4,250	1,363	1,089	8,173	2	6	5	0

	DFUtil	1,838	1,778	2,149	2,092	2	6	5	0
	DFPulp	2,823	1,699	2,962	613	2	6	5	0
	RASaw	-	273	-	-	2	6	5	0
	RAPulp	20	476	317	281	2	6	5	0
	HemSaw	-	320	-	-	2	6	5	0
	HemPulp	328	97	251	-	2	6	5	0
	RC	-	72	-	-	2	6	5	0
	OtherPulp	37	73	31	-	2	6	5	0
065-74	DF2	3,884	4,771	2,559	8,173	5	3	0	0
	DFUtil	3,908	2,622	2,343	2,092	5	3	0	0
	DFPulp	1,683	1,007	2,047	613	5	3	0	0
	RASaw	282	1,025	91	-	5	3	0	0
	RAPulp	218	643	208	281	5	3	0	0
	HemSaw	75	453	244	-	5	3	0	0
	HemPulp	82	177	233	-	5	3	0	0
	RC	115	-	55	-	5	3	0	0
	OtherPulp	1,924	-	274	-	5	3	0	0
075-84	DF2	2,816	3,010	2,926	8,173	3	14	23	0
	DFUtil	1,423	2,880	2,353	2,092	3	14	23	0
	DFPulp	692	1,866	1,323	613	3	14	23	0
	RASaw	1,000	124	100	-	3	14	23	0
	RAPulp	1,317	303	259	281	3	14	23	0
	HemSaw	453	35	317	-	3	14	23	0
	HemPulp	340	168	373	-	3	14	23	0
	RC	78	-	155	-	3	14	23	0
	OtherPulp	736	673	445	-	3	14	23	0
085-94	DF2	2,307	2,819	4,916	8,173	0	13	10	0
	DFUtil	1,981	2,219	3,054	2,092	0	13	10	0
	DFPulp	1,453	1,831	1,822	613	0	13	10	0

	RASaw	555	102	421	-	0	13	10	0
	RAPulp	904	580	398	281	0	13	10	0
	HemSaw	265	386	17	-	0	13	10	0
	HemPulp	214	160	109	-	0	13	10	0
	RC	144	227	-	-	0	13	10	0
	OtherPulp	700	475	541	-	0	13	10	0
095-104	DF2	2,307	2,438	2,559	8,173	0	11	0	0
	DFUtil	1,981	1,769	2,343	2,092	0	11	0	0
	DFPulp	1,453	1,377	2,047	613	0	11	0	0
	RASaw	555	21	91	-	0	11	0	0
	RAPulp	904	161	208	281	0	11	0	0
	HemSaw	265	488	244	-	0	11	0	0
	HemPulp	214	292	233	-	0	11	0	0
	RC	144	244	55	-	0	11	0	0
	OtherPulp	700	486	274	-	0	11	0	0
105+	DF2	2,307	2,565	2,559	8,173	20	60	84	1
Average	DFUtil	1,981	2,195	2,343	2,092	20	60	84	1
Totals	DFPulp	1,453	1,718	2,047	613	20	60	84	1
	RASaw	555	180	91	-	20	60	84	1
	RAPulp	904	432	208	281	20	60	84	1
	HemSaw	265	380	244	-	20	60	84	1
	HemPulp	214	208	233	-	20	60	84	1
	RC	144	104	55	-	20	60	84	1
	OtherPulp	700	358	274	-	20	60	84	1

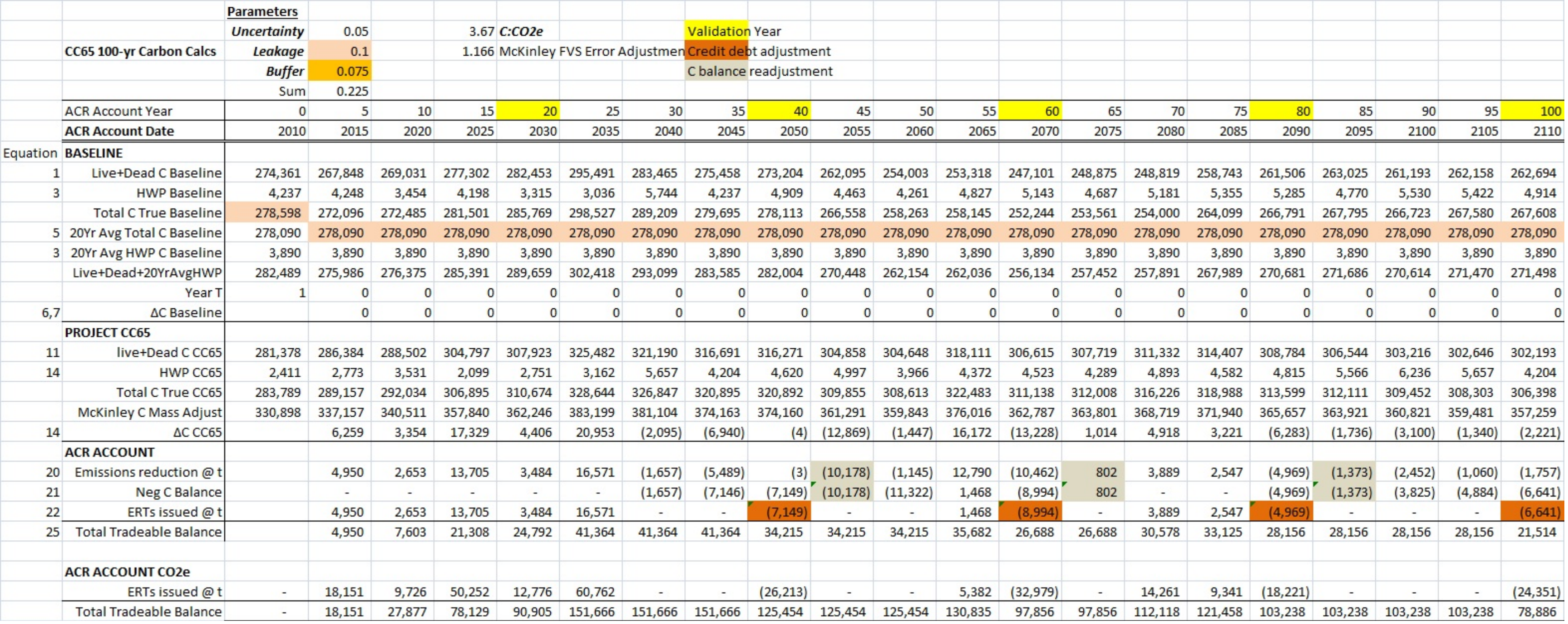
8.4 Appendix 4: Carbon credit calculation spreadsheets.

CC65 40-yr C Credits	Deductions								
	Uncertainty	0.05		3.67	*C:CO2e*			Validation	Year
	Leakage	0.1		1.166	McKinley FVS Bias			Debt	Adjust
	Buffer	0.195							
	Sum	0.345							
ACR Account Year	0	5	10	15	20	25	30	35	40
ACR Account Date	2010	2015	2020	2025	2030	2035	2040	2045	2050
BASELINE									
Live+Dead C Baseline	274,361	267,848	269,031	277,302	282,453	295,491	283,465	275,458	273,204
HWP Baseline	4,237	4,248	3,454	4,198	3,315	3,036	5,744	4,237	4,909
Total C True Baseline	278,598	272,096	272,485	281,501	285,769	298,527	289,209	279,695	278,113
20Yr Avg Total C Baseline	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090
20Yr Avg HWP C Baseline	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890
Live+Dead+20YrAvgHWP	282,489	275,986	276,375	285,391	289,659	302,418	293,099	283,585	282,004
Year T	1	0	0	0	0	0	0	0	0
ΔC Baseline		0	0	0	0	0	0	0	0
PROJECT CC65									
live+Dead C CC65	281,378	286,384	288,502	304,797	307,923	325,482	321,190	316,691	316,271
HWP CC65	2,411	2,773	3,531	2,099	2,751	3,162	5,657	4,204	4,620
Total C True CC65	283,789	289,157	292,034	306,895	310,674	328,644	326,847	320,895	320,892
McKinley C Mass Adjust	330,898	337,157	340,511	357,840	362,246	383,199	381,104	374,163	374,160
ΔC CC65		6,259	3,354	17,329	4,406	20,953	(2,095)	(6,940)	(4)
ACR ACCOUNT									
Emissions reduction @ t	-	4,308	2,308	11,927	3,032	14,422	(1,442)	(4,777)	(3)
Neg C Balance	-	-	-	-	-	-	(1,442)	(6,219)	(6,222)
ERTs issued @ t	-	4,308	2,308	11,927	3,032	14,422	-	-	(6,222)
Total Tradeable Balance	-	4,308	6,617	18,544	21,576	35,997	35,997	35,997	29,776
ACR ACCOUNT CO2e									

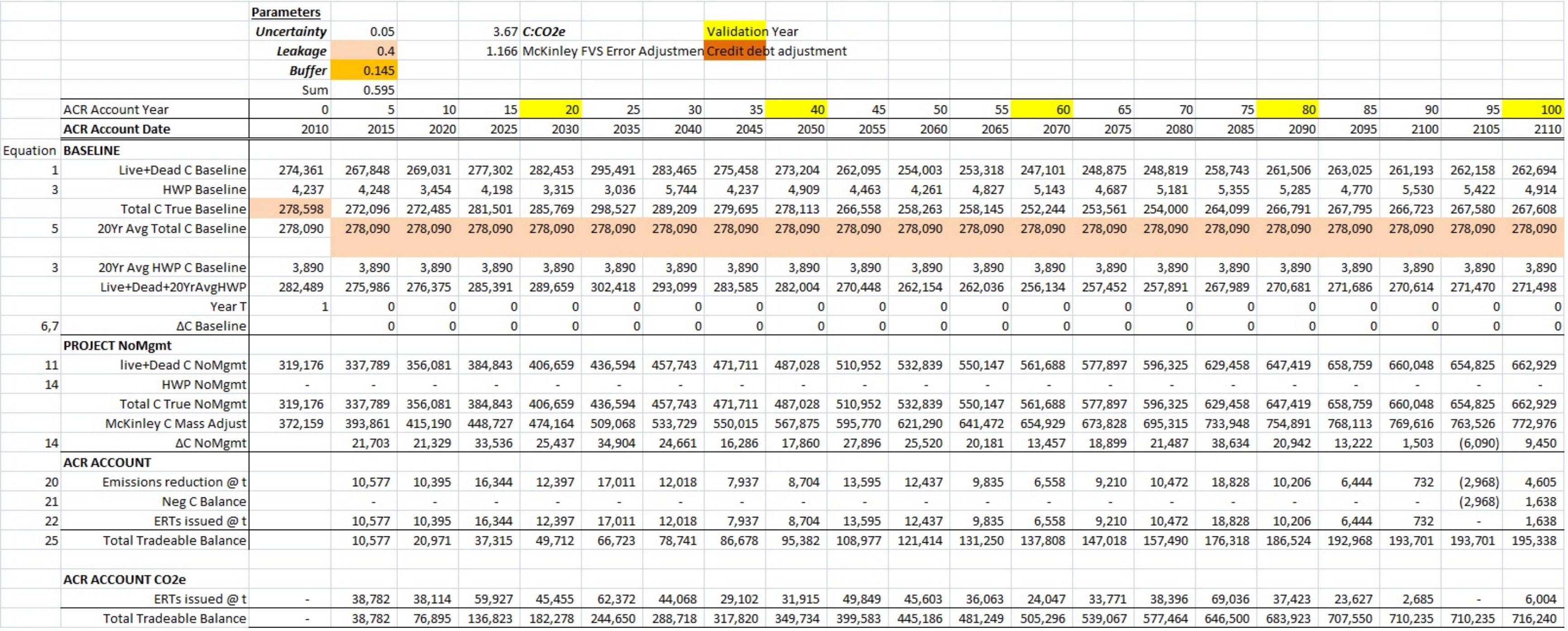
ERTs issued @ t	-	15,796	8,464	43,733	11,118	52,879	-	-	(22,812)
Total Tradeable Balance	-	15,796	24,261	67,993	79,112	131,991	131,991	131,991	109,179

NoMgmt 40-yr C Credits	Deductions								
	Uncertainty	0.05		3.67	C:CO2e			Validation	Year
	Leakage	0.4		1.166	FVS Bias			Debt	Adjust
	Buffer	0.265							
	Sum	0.715							
ACR Account Year	0	5	10	15	20	25	30	35	40
ACR Account Date	2010	2015	2020	2025	2030	2035	2040	2045	2050
BASELINE									
Live+Dead C Baseline	274,361	267,848	269,031	277,302	282,453	295,491	283,465	275,458	273,204
HWP Baseline	4,237	4,248	3,454	4,198	3,315	3,036	5,744	4,237	4,909
Total C True Baseline	278,598	272,096	272,485	281,501	285,769	298,527	289,209	279,695	278,113
20Yr Avg Total C Baseline	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090
20Yr Avg HWP C Baseline	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890
Live+Dead+20YrAvgHWP	282,489	275,986	276,375	285,391	289,659	302,418	293,099	283,585	282,004
Year T	1	0	0	0	0	0	0	0	0
ΔC Baseline	-	0	0	0	0	0	0	0	0
PROJECT NoMgmt									
live+Dead C NoMgmt	319,176	337,789	356,081	384,843	406,659	436,594	457,743	471,711	487,028
HWP NoMgmt	-	-	-	-	-	-	-	-	-
Total C True NoMgmt	319,176	337,789	356,081	384,843	406,659	436,594	457,743	471,711	487,028
McKinley C Mass Adjust	372,159	393,861	415,190	448,727	474,164	509,068	533,729	550,015	567,875
ΔC NoMgmt		21,703	21,329	33,536	25,437	34,904	24,661	16,286	17,860
ACR ACCOUNT									
Emissions reduction @ t	-	9,092	8,936	14,050	10,657	14,623	10,332	6,823	7,482
Neg C Balance	-	-	-	-	-	-	-	-	-
ERTs issued @ t	-	9,092	8,936	14,050	10,657	14,623	10,332	6,823	7,482
Total Tradeable Balance		9,092	18,028	32,078	42,735	57,358	67,690	74,513	81,995
ACR ACCOUNT CO_2e									

ERTs issued @ t	-	33,339	32,765	51,517	39,076	53,618	37,883	25,017	27,435
Total Tradeable Balance	-	33,339	66,103	117,620	156,695	210,313	248,196	273,213	300,649



		Parameters																				
		Uncertainty	0.05		3.67	*C:CO2e*			Validation Year													
	CC65 100-yr Carbon Calcs	***Leakage***	0.1		1.166	McKinley FVS Error Adjustmen			Credit debt adjustment													
		Buffer	0.075						C balance readjustment													
		Sum	0.225																			
	ACR Account Year	0	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75	80	85	90	95	100
	ACR Account Date	2010	2015	2020	2025	2030	2035	2040	2045	2050	2055	2060	2065	2070	2075	2080	2085	2090	2095	2100	2105	2110
Equation	**BASELINE**																					
1	Live+Dead C Baseline	274,361	267,848	269,031	277,302	282,453	295,491	283,465	275,458	273,204	262,095	254,003	253,318	247,101	248,875	248,819	258,743	261,506	263,025	261,193	262,158	262,694
3	HWP Baseline	4,237	4,248	3,454	4,198	3,315	3,036	5,744	4,237	4,909	4,463	4,261	4,827	5,143	4,687	5,181	5,355	5,285	4,770	5,530	5,422	4,914
	Total C True Baseline	278,598	272,096	272,485	281,501	285,769	298,527	289,209	279,695	278,113	266,558	258,263	258,145	252,244	253,561	254,000	264,099	266,791	267,795	266,723	267,580	267,608
5	20Yr Avg Total C Baseline	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090
3	20Yr Avg HWP C Baseline	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890
	Live+Dead+20YrAvgHWP	282,489	275,986	276,375	285,391	289,659	302,418	293,099	283,585	282,004	270,448	262,154	262,036	256,134	257,452	257,891	267,989	270,681	271,686	270,614	271,470	271,498
	Year T	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6,7	ΔC Baseline		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	PROJECT CC65																					
11	live+Dead C CC65	281,378	286,384	288,502	304,797	307,923	325,482	321,190	316,691	316,271	304,858	304,648	318,111	306,615	307,719	311,332	314,407	308,784	306,544	303,216	302,646	302,193
14	HWP CC65	2,411	2,773	3,531	2,099	2,751	3,162	5,657	4,204	4,620	4,997	3,966	4,372	4,523	4,289	4,893	4,582	4,815	5,566	6,236	5,657	4,204
	Total C True CC65	283,789	289,157	292,034	306,895	310,674	328,644	326,847	320,895	320,892	309,855	308,613	322,483	311,138	312,008	316,226	318,988	313,599	312,111	309,452	308,303	306,398
	McKinley C Mass Adjust	330,898	337,157	340,511	357,840	362,246	383,199	381,104	374,163	374,160	361,291	359,843	376,016	362,787	363,801	368,719	371,940	365,657	363,921	360,821	359,481	357,259
14	ΔC CC65		6,259	3,354	17,329	4,406	20,953	(2,095)	(6,940)	(4)	(12,869)	(1,447)	16,172	(13,228)	1,014	4,918	3,221	(6,283)	(1,736)	(3,100)	(1,340)	(2,221)
	ACR ACCOUNT																					
20	Emissions reduction @ t		4,950	2,653	13,705	3,484	16,571	(1,657)	(5,489)	(3)	(10,178)	(1,145)	12,790	(10,462)	802	3,889	2,547	(4,969)	(1,373)	(2,452)	(1,060)	(1,757)
21	Neg C Balance		-	-	-	-	-	(1,657)	(7,146)	(7,149)	(10,178)	(11,322)	1,468	(8,994)	802	-	-	(4,969)	(1,373)	(3,825)	(4,884)	(6,641)
22	ERTs issued @ t		4,950	2,653	13,705	3,484	16,571	-	-	(7,149)	-	-	1,468	(8,994)	-	3,889	2,547	(4,969)	-	-	-	(6,641)
25	Total Tradeable Balance		4,950	7,603	21,308	24,792	41,364	41,364	41,364	34,215	34,215	34,215	35,682	26,688	26,688	30,578	33,125	28,156	28,156	28,156	28,156	21,514
	ACR ACCOUNT CO2e																					
	ERTs issued @ t	-	18,151	9,726	50,252	12,776	60,762	-	-	(26,213)	-	-	5,382	(32,979)	-	14,261	9,341	(18,221)	-	-	-	(24,351)
	Total Tradeable Balance	-	18,151	27,877	78,129	90,905	151,666	151,666	151,666	125,454	125,454	125,454	130,835	97,856	97,856	112,118	121,458	103,238	103,238	103,238	103,238	78,886



		Parameters																				
		Uncertainty	0.05		3.67	***C:CO2e***			Validation Year													
		Leakage	0.4		1.166	McKinley FVS Error Adjustmen			Credit debt adjustment													
		Buffer	0.145																			
		Sum	0.595																			
	ACR Account Year	0	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75	80	85	90	95	100
	ACR Account Date	2010	2015	2020	2025	2030	2035	2040	2045	2050	2055	2060	2065	2070	2075	2080	2085	2090	2095	2100	2105	2110
Equation	**BASELINE**																					
1	Live+Dead C Baseline	274,361	267,848	269,031	277,302	282,453	295,491	283,465	275,458	273,204	262,095	254,003	253,318	247,101	248,875	248,819	258,743	261,506	263,025	261,193	262,158	262,694
3	HWP Baseline	4,237	4,248	3,454	4,198	3,315	3,036	5,744	4,237	4,909	4,463	4,261	4,827	5,143	4,687	5,181	5,355	5,285	4,770	5,530	5,422	4,914
	Total C True Baseline	278,598	272,096	272,485	281,501	285,769	298,527	289,209	279,695	278,113	266,558	258,263	258,145	252,244	253,561	254,000	264,099	266,791	267,795	266,723	267,580	267,608
5	20Yr Avg Total C Baseline	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090	278,090
3	20Yr Avg HWP C Baseline	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890	3,890
	Live+Dead+20YrAvgHWP	282,489	275,986	276,375	285,391	289,659	302,418	293,099	283,585	282,004	270,448	262,154	262,036	256,134	257,452	257,891	267,989	270,681	271,686	270,614	271,470	271,498
	Year T	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6,7	ΔC Baseline		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	PROJECT NoMgmt																					
11	live+Dead C NoMgmt	319,176	337,789	356,081	384,843	406,659	436,594	457,743	471,711	487,028	510,952	532,839	550,147	561,688	577,897	596,325	629,458	647,419	658,759	660,048	654,825	662,929
14	HWP NoMgmt	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Total C True NoMgmt	319,176	337,789	356,081	384,843	406,659	436,594	457,743	471,711	487,028	510,952	532,839	550,147	561,688	577,897	596,325	629,458	647,419	658,759	660,048	654,825	662,929
	McKinley C Mass Adjust	372,159	393,861	415,190	448,727	474,164	509,068	533,729	550,015	567,875	595,770	621,290	641,472	654,929	673,828	695,315	733,948	754,891	768,113	769,616	763,526	772,976
14	ΔC NoMgmt		21,703	21,329	33,536	25,437	34,904	24,661	16,286	17,860	27,896	25,520	20,181	13,457	18,899	21,487	38,634	20,942	13,222	1,503	(6,090)	9,450
	ACR ACCOUNT																					
20	Emissions reduction @ t		10,577	10,395	16,344	12,397	17,011	12,018	7,937	8,704	13,595	12,437	9,835	6,558	9,210	10,472	18,828	10,206	6,444	732	(2,968)	4,605
21	Neg C Balance		-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	(2,968)	1,638
22	ERTs issued @ t		10,577	10,395	16,344	12,397	17,011	12,018	7,937	8,704	13,595	12,437	9,835	6,558	9,210	10,472	18,828	10,206	6,444	732	-	1,638
25	Total Tradeable Balance		10,577	20,971	37,315	49,712	66,723	78,741	86,678	95,382	108,977	121,414	131,250	137,808	147,018	157,490	176,318	186,524	192,968	193,701	193,701	195,338
	ACR ACCOUNT CO2e																					
	ERTs issued @ t	-	38,782	38,114	59,927	45,455	62,372	44,068	29,102	31,915	49,849	45,603	36,063	24,047	33,771	38,396	69,036	37,423	23,627	2,685	-	6,004
	Total Tradeable Balance	-	38,782	76,895	136,823	182,278	244,650	288,718	317,820	349,734	399,583	445,186	481,249	505,296	539,067	577,464	646,500	683,923	707,550	710,235	710,235	716,240

2.2 INTERNAL RISKS

Table 1	Project Management	Points	40 Yr CC65 Applicable	40 Yr NoMgmt Applicable	100 Yr CC65 Applicable	100 Yr NoMgmt Applicable
a	>25% not native/suitable	2	0	0	0	0
b	Ongoing enforement	2	0	0	0	0
c	Mgmt team w/ out experience	2	0	0	0	0
d	Mgmt team > 1 day away	2	0	0	0	0
e	*Mit: Mgmt team w/ AFOLU experience*	-2	0	0	0	0
f	*Mit: Adaptive mgmt plan*	-2	0	0	0	0
Total			0	0	0	0

Table 2	Financial Viability	Points	40 Yr CC65 Applicable	40 Yr NoMgmt Applicable	100 Yr CC65 Applicable	100 Yr NoMgmt Applicable
a	Breakeven point >10 yrs	3		3		3
b	Breakeven point 7-10 yrs	2				
c	Breakeven point 4-7 yrs	1				
d	Breakeven point <4 yrs	0	0		0	
e	Secured <15% of funding before breakeven	3				
f	Secured 15-40% of funding before breakeven	2				
g	Secured 40-80% of funding before breakeven	1				
h	Secured >80% of funding before breakeven	0	0	0	0	0
i	*Mit: Have 50% of cash out before breakeven*	-2				
Total			0	3	0	3

Table 3	Opportunity Cost	Points	40 Yr CC65 Applicable	40 Yr NoMgmt Applicable	100 Yr CC65 Applicable	100 Yr NoMgmt Applicable
a	NPV of most profitable alt. worth >100%	8		8		8
b	NPV of most profitable alt. worth 50-100%	6				
c	NPV of most profitable alt. worth 20-50%	4	4		4	
d	NPV of most profitable alt. worth +/-20%	0				
e	NPV is 20-50% more than most profitable alt.	-2				
f	NPV is >50% more than most profitable alt.	-4				
g	Mit: Project proponent is a non-profit org	-2				
h	Mit: Legally binding commitment over credit period	-2	-2	-2	-2	-2
i	Mit: Legally binding commitment over 100 yrs	-8				
Total			2	6	2	6

Table 4	Project Longevity	Points	40 Yr CC65 Applicable	40 Yr NoMgmt Applicable	100 Yr CC65 Applicable	100 Yr NoMgmt Applicable
a	W/o legal agreement to continue mgmt	24 - (Yrs/5)	16	16	4	4
b	W legal agreement to continue mgmt	30 - (Yrs/2)				
Total			16	16	4	4
TOTAL INTERNAL RISK			18	25	6	13

2.3 EXTERNAL RISKS

Table 6	Land Tenure	Points	40 Yr CC65 Applicable	40 Yr NoMgmt Applicable	100 Yr CC65 Applicable	100 Yr NoMgmt Applicable
a	Ownership and resource rights held by same entitiy	0	0	0	0	0
b	Ownership and resource rights held by different entitiy	2				
c	Tenure disputes in >5% of project area	10				
d	Tenure disputes exist in project area	5				
e	*Mit: Legally binding commitment over credit period*	-2	-2	-2	-2	-2
f	*Mit: Tenure dispute resolution plan in place*	-2				
Total			0	0	0	0

Table 7	Community Engagement	Points	40 Yr CC65 Applicable	40 Yr NoMgmt Applicable	100 Yr CC65 Applicable	100 Yr NoMgmt Applicable
a	<50% of reliant HH living w/in project area consulted	10				
b	<20% of reliant HH living w/in 20km of project area consulted	5				
c	*Mit:I Progect generated net positive impacts reliant HH*	-5				
Total			0	0	0	0

Table 8	Politcal Risk	Points	40 Yr CC65 Applicable	40 Yr NoMgmt Applicable	100 Yr CC65 Applicable	100 Yr NoMgmt Applicable
a	Governance score of < -0.79	6				
b	Governance score of -0.79 to <-0.32	4				
c	Governance score of -0.32 to < 0.19	2				
d	Governance score of 0.19 to < 0.82	1				
e	Governance score of >0.82	0	0	0	0	0
f	*Mit*: Country has FCS standards body (2.3.3. 2) d)	-2	-2	-2	-2	-2
Total	*Total may not be less than zero*		0	0	0	0

	40 Yr CC65	40 Yr NoMgmt	100 Yr CC65	100 Yr NoMgmt
TOTAL EXTERNAL RISK	0	0	0	0

2.4 NATURAL RISKS

Table 10

Natural Risk	Likelihood					
Significance	< 10yrs	10-25 yrs	25-50 yrs	50-100 yrs	>100 yrs	Applicable
Catastrophic (>70% loss of C stocks)	FAIL	30	20	5	0	
Devastating (50 - 70% loss C stocks)	30	20	5	2	0	
Major (25 - 50% loss of C stocks)	20	5	2	1	0	0
Minor (5 - 25% loss of C stocks)	5	2	1	1	0	1
Insignificant (<5% loss of C stocks) or transient (full recovery in 10 yrs)	2	1	1	0	0	1
No Loss	0	0	0	0	0	
Total						2
Mitigation			Score			Applicable
Prevention measures are implemented			0.5			0.5
Proven history of containing natural risk			0.5			0
Both of above			0.25			0
None of above			1			0
Total						0.5
Score for each natural risk applicable to the project (LS x M)						Score
Fire						0
Pest and disease outbreaks						1
Extreme Weather						0.5
Geological Risk						n/a
Other natural risk						n/a

TOTAL NATURAL RISK	1.5

Table 11	Overall Risk Rating	40 Yr CC65 Applicable	40 Yr NoMgmt Applicable	100 Yr CC65 Applicable	100 Yr NoMgmt Applicable
a	Internal Risk	18	25	6	13
b	External Risk	0	0	0	0
c	Natural Risk	1.5	1.5	1.5	1.5

	40 Yr CC65	40 Yr NoMgmt	100 Yr CC65	100 Yr NoMgmt
TOTAL RISK RATING	19.5	26.5	7.5	14.5
DEDUCTION	0.195	0.265	0.075	0.145

8.5 Appendix 5: Probability Distributions

Assumption	Description	Distribution	Parameters	Values	Range	Correlations	Coefficient
Pulp: DF $/MBF	Long-term price of Douglas-firpulp log-grades. Ln converted.	Lognormal	Location	0.00	-Infinity, 6.61	OtherHDWpulp $/MBF	0.93
			Mean	5.68		HemFirPine pulp $/MBF	0.95
			Std. Dev.	0.17			
Pulp: HemFirPine $/MBF	Long-term price of hemlock, fir, and pine pulp log-grades. Ln converted.	Lognormal	Location	0.00	-Infinity, 6.69	DF pulp $/MBF	0.95
			Mean	5.68			
			Std. Dev.	0.11			
Pulp: RA $/MBF	Long-term price of red alder pulp log-grades. Ln converted.	Lognormal	Location	0.00	-Infinity, 6.40	DF2 $/MBF	0.56
			Mean	5.74			
			Std. Dev.	0.16			
Pulp: OtherHWD $/MBF	Long-term price of all other hardwood pulp log-grades. Ln converted.	Lognormal	Location	0.00	-Infinity, 6.57	DF pulp $/MBF	0.93
			Mean	5.70			
			Std. Dev.	0.15			
Saw: DF2 $/MBF	Long-term price of Douglas-fir #2 saw log-grades. Ln converted.	Lognormal	Location	0.00	-Infinity, 7.85	Cedar camprun $/MBF	0.73
			Mean	6.32		RA pulp $/MBF	0.56
			Std. Dev.	0.37		DFUtility/4 $/MBF	0.82
						HemFirPine2 $/MBF	0.92
Saw: DFUtility/4 $/MBF	Long-term price of Douglas-fir #4 saw log-grades. Ln converted.	Lognormal	Location	0.00	-Infinity, 7.45	DF2 $/MBF	0.82
			Mean	5.95			
			Std. Dev.	0.37			

Saw: HemFirPine2 $/MBF	Long-term price of hemlock, fir, and pine #2 saw log-grades. Ln converted.	Lognormal	Location	0.00	-Infinity, 7.51	DF2 $/MBF	0.92
			Mean	5.96			
			Std. Dev.	0.37			
Saw: Cedar camprun $/MBF	Long-term price of cedar saw log-grades. Ln converted.	Lognormal	Location	0.00	-Infinity, 8.40	5-Yr DF2$/MBF	0.73
			Mean	6.54			
			Std. Dev.	0.48			
Saw: RA1 $/MBF	Long-term price of red alder #1 saw log-grades. Ln converted.	Lognormal	Location	0.00	-Infinity, 7.25	None	-
			Mean	5.29			
			Std. Dev.	0.67			
Saw: DF2 5-Yr $/MBF	5-year price of Douglas-fir #2 saw log-grades. Ln converted.	Lognormal	Location	0.00	-Infinity, 7.85	DF4 5-yr$/MBF	0.82
			Mean	5.97		RC 5-yr $/MBF	0.73
			Std. Dev.	0.24		HemFir 5-yr $/MBF	0.92
Saw: DF4 5-yr $/MBF	5-year price of Douglas-fir #4 saw log-grades. Ln converted.	Lognormal	Location	0.00	-Infinity, 7.45	5-Yr DF2$/MBF	0.82
			Mean	5.86			
			Std. Dev.	0.23			
Saw: HemFir 5-yr $/MBF	5-year price of hemlock, fir, and pine #2 saw log-grades. Ln converted.	Lognormal	Location	0.00	-Infinity, 7.51	5-Yr DF2$/MBF	0.92
			Mean	5.65			
			Std. Dev.	0.25			
Saw: RC 5-yr $/MBF	5-year price of red cedar #2 saw log-grades. Ln converted.	Lognormal	Location	0.00	-Infinity, 8.40	5-Yr DF2$/MBF	0.73
			Mean	6.47			
			Std. Dev.	0.14			

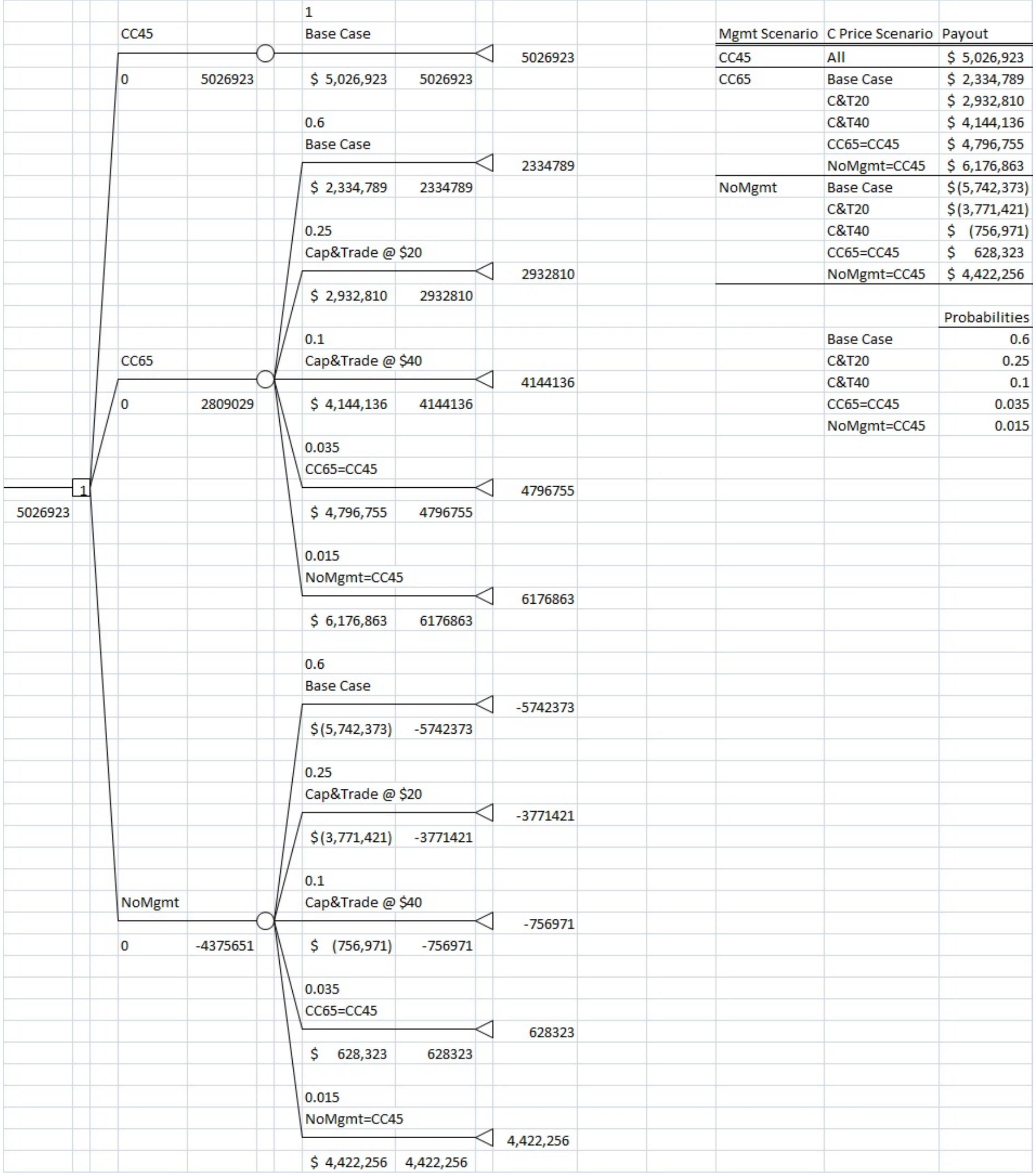
Saw: RA1 5-yr $/MBF	5-year price of red alder #1 saw log-grades. Ln converted.	Lognormal	Location	0.00	-Infinity, 7.25	None	-
			Mean	6.10			
			Std. Dev.	0.33			
Saw: DF2 10-yr $/MBF	10-year price of Douglas-fir #2 saw log-grades. Ln converted.	Lognormal	Location	0.00	-Infinity, 7.85	RC 10-yr $/MBF	0.73
			Mean	6.08		DF4 10-yr $/MBF	0.82
			Std. Dev.	0.22		HemFir2 10-yr $/MBF	0.92
Saw: DF4 10-yr $/MBF	10-year price of Douglas-fir #4 saw log-grades. Ln converted.	Lognormal	Location	0.00	-Infinity, 7.45	DF2 10-yr $/MBF	0.82
			Mean	5.98			
			Std. Dev.	0.22			
Saw: HemFir2 10-yr $/MBF	10-year price of hemlock, fir, and pine #2 saw log-grades. Ln converted.	Lognormal	Location	0.00	-Infinity, 7.51	DF2 10-yr $/MBF	0.92
			Mean	5.67			
			Std. Dev.	0.20			
Saw: RC 10-yr $/MBF	10-year price of red cedar #2 saw log-grades. Ln converted.	Lognormal	Location	0.00	-Infinity, 8.40	DF2 10-yr $/MBF	0.73
			Mean	6.56			
			Std. Dev.	0.18			
Saw: RA1 10-yr $/MBF	10-year price of red alder #1 saw log-grades. Ln converted.	Lognormal	Location	0.00	-Infinity, 7.25	None	-
			Mean	6.05			
			Std. Dev.	0.25			
ACR credit price - Base Case	Uncertainty in price of ACR C credits - historic varibability.	Normal	Mean	7.89	2, 200	None	-
			Std. Dev.	2.42			
ACR credit price - Cap&Trade $20	Uncertainty in price of ACR C	Normal	Mean	20	10, 200	None	-

	credits - average $20/credit scenario		Std. Dev.	6.13			
ACR credit price - Cap&Trade $40	Uncertainty in price of ACR C credits - average $40/credit scenario.	Normal	Mean	40	10, 200	None	-
			Std. Dev.	12.27			
ACR credit price - BAU equivilent CC65	Uncertainty in price of ACR C credits - average $49.87/credit scenario.	Normal	Mean	49.87	2, 200	None	-
			Std. Dev.	15.3			
ACR credit price - BAU equivilent NoMgmt	Uncertainty in price of ACR C credits - average $73.82/credit scenario.	Normal	Mean	73.82	2, 200	None	-
			Std. Dev.	22.64			
Weeding	Uncertainty in cost of weeding.	Lognormal	Location	0.00	-/+ Infinity	None	-
			Mean	4.10			
			90%	4.33			
Precommercial thin	Uncertainty in cost of pre-commercial thin.	Lognormal	Location	0.00	-/+ Infinity	None	-
			Mean	4.70			
			90%	5.07			
CFI_QMDΔStrataMean	Variation in plot QMD in the initial forest sample plots (continuous forest inventory, or CFI)	Normal	Mean	-0.02	-/+ Infinity	None	-
			Std. Dev.	0.44			

FVS vs CFI standard error C (CO2e)	Model uncertainty in difference between FVS growth model and true tree measurements after conversion to C mass (MgC)	Normal	Mean	0.00	-/+ Infinity	None	-
			Std. Dev.	81,566			
FVS vs CFI % error BF	Model uncertainty in difference between FVS growth model and true tree measurements after conversion to board-feet.	Logistic	Mean	-0.17	-/+ Infinity	None	-
			Scale	0.46			
Biomass Eq Uncertainty	Uncertainty in biomass allometric equations. Assumed 10% error.	Normal	Mean	1.00	0.00, Infinity	None	-
			Std. Dev.	0.10			
Scribner MBF conversion	Uncertainty in conversion of tree measurements to board-foot estimates using Scribner method.	Beta	Minimum	-0.01	-	None	-
			Maximum	3.31			
			Alpha	0.67			
			Beta	20.06			

8.6 Appendix 6: Decision Analysis: Decision Tree and VOI Calculations

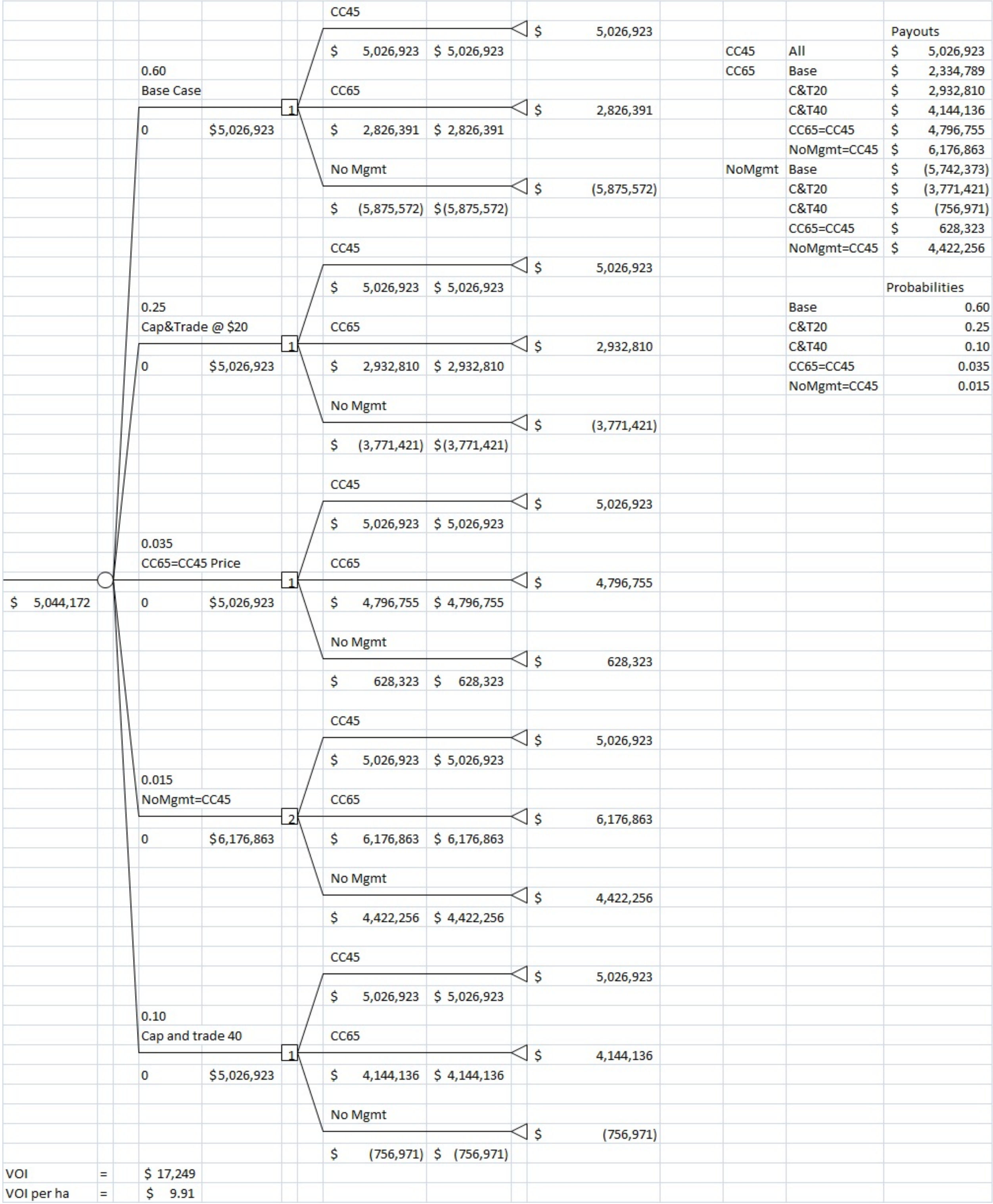
Figure 18: Decision Tree. Expected NPV of CC45 is the highest of the three management scenarios, totaling $5,026,923. Payout values in the column to the right of the triangles represent average NPV for a particular price- and management-scenario combination. Assumptions are listed at the right.



Mgmt Scenario	C Price Scenario	Payout
CC45	All	$ 5,026,923
CC65	Base Case	$ 2,334,789
	C&T20	$ 2,932,810
	C&T40	$ 4,144,136
	CC65=CC45	$ 4,796,755
	NoMgmt=CC45	$ 6,176,863
NoMgmt	Base Case	$(5,742,373)
	C&T20	$(3,771,421)
	C&T40	$ (756,971)
	CC65=CC45	$ 628,323
	NoMgmt=CC45	$ 4,422,256

	Probabilities
Base Case	0.6
C&T20	0.25
C&T40	0.1
CC65=CC45	0.035
NoMgmt=CC45	0.015

Figure 19: Value of Information Tree. The per-hectare dollar value of information shown in the bottom left corner is the value in NPV that a forest owner would be willing to pay for this information. Policy makers could use this to inform incentive programs for forest C projects.



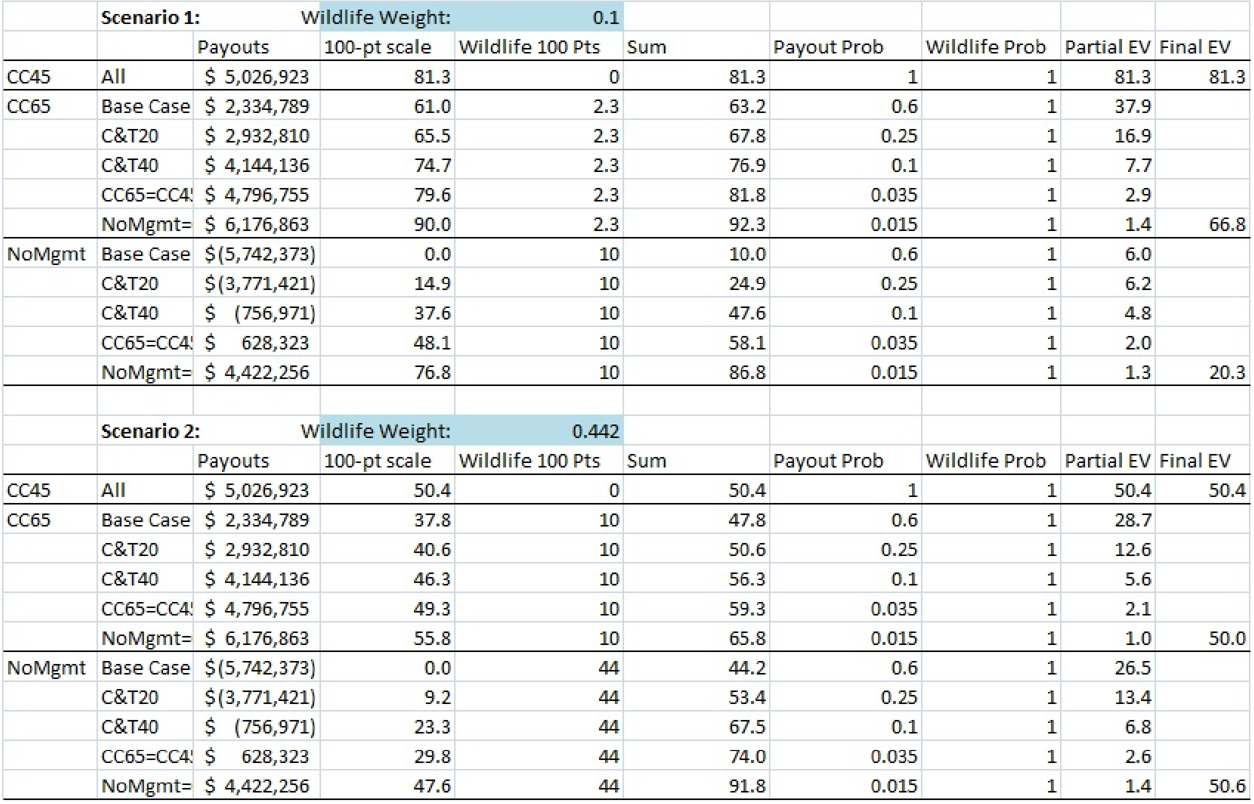
		Payouts
CC45	All	$ 5,026,923
CC65	Base	$ 2,334,789
	C&T20	$ 2,932,810
	C&T40	$ 4,144,136
	CC65=CC45	$ 4,796,755
	NoMgmt=CC45	$ 6,176,863
NoMgmt	Base	$ (5,742,373)
	C&T20	$ (3,771,421)
	C&T40	$ (756,971)
	CC65=CC45	$ 628,323
	NoMgmt=CC45	$ 4,422,256

	Probabilities
Base	0.60
C&T20	0.25
C&T40	0.10
CC65=CC45	0.035
NoMgmt=CC45	0.015

VOI = $ 17,249

VOI per ha = $ 9.91

Figure 20: 100-point score conversions and calculations. A forest owner would need to value wildlife nearly as much as revenue (44.2%) before changing management practices solely to improve wildlife conditions. In this case, NoMgmt would result in the most desirable combination of revenue and wildlife.



	Scenario 1:		Wildlife Weight:	0.1					
		Payouts	100-pt scale	Wildlife 100 Pts	Sum	Payout Prob	Wildlife Prob	Partial EV	Final EV
CC45	All	$ 5,026,923	81.3	0	81.3	1	1	81.3	81.3
CC65	Base Case	$ 2,334,789	61.0	2.3	63.2	0.6	1	37.9	
	C&T20	$ 2,932,810	65.5	2.3	67.8	0.25	1	16.9	
	C&T40	$ 4,144,136	74.7	2.3	76.9	0.1	1	7.7	
	CC65=CC4	$ 4,796,755	79.6	2.3	81.8	0.035	1	2.9	
	NoMgmt=	$ 6,176,863	90.0	2.3	92.3	0.015	1	1.4	66.8
NoMgmt	Base Case	$(5,742,373)	0.0	10	10.0	0.6	1	6.0	
	C&T20	$(3,771,421)	14.9	10	24.9	0.25	1	6.2	
	C&T40	$ (756,971)	37.6	10	47.6	0.1	1	4.8	
	CC65=CC4	$ 628,323	48.1	10	58.1	0.035	1	2.0	
	NoMgmt=	$ 4,422,256	76.8	10	86.8	0.015	1	1.3	20.3
	Scenario 2:		Wildlife Weight:	0.442					
		Payouts	100-pt scale	Wildlife 100 Pts	Sum	Payout Prob	Wildlife Prob	Partial EV	Final EV
CC45	All	$ 5,026,923	50.4	0	50.4	1	1	50.4	50.4
CC65	Base Case	$ 2,334,789	37.8	10	47.8	0.6	1	28.7	
	C&T20	$ 2,932,810	40.6	10	50.6	0.25	1	12.6	
	C&T40	$ 4,144,136	46.3	10	56.3	0.1	1	5.6	
	CC65=CC4	$ 4,796,755	49.3	10	59.3	0.035	1	2.1	
	NoMgmt=	$ 6,176,863	55.8	10	65.8	0.015	1	1.0	50.0
NoMgmt	Base Case	$(5,742,373)	0.0	44	44.2	0.6	1	26.5	
	C&T20	$(3,771,421)	9.2	44	53.4	0.25	1	13.4	
	C&T40	$ (756,971)	23.3	44	67.5	0.1	1	6.8	
	CC65=CC4	$ 628,323	29.8	44	74.0	0.035	1	2.6	
	NoMgmt=	$ 4,422,256	47.6	44	91.8	0.015	1	1.4	50.6