

AN ABSTRACT OF THE DISSERTATION OF

Stephen Richard Mitchell for the degree of Doctor of Philosophy in Forest Science presented on March 5, 2009.

Title: The Effects of Forest Fuel Reduction on Fire Severity and Long-term Carbon Storage

ABSTRACT APPROVED:

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Two forest management objectives being debated in the context of federally managed landscapes in the US Pacific Northwest involve a perceived trade-off between fire restoration and C sequestration. The former strategy would reduce fuel (and therefore C) that has accumulated through a century of fire suppression and exclusion that has led to extreme fire risk in some areas. The latter strategy would manage forests for enhanced C sequestration as a method of reducing atmospheric CO₂ and associated threats from global climate change. We explored the tradeoff between these strategies by modeling their effects at both the stand and landscape-scale. We began with an assessment of the extent to which uncertainties in model parameter values, model structure, and field measurements can influence model performance. We adapted the generalized likelihood uncertainty estimation (GLUE) methodology for Biome-BGC, a widely used terrestrial ecosystem model. We found

that the phenomenon of parameter equifinality exerted significant control on model performance, but that issues with model structure in the Biome-BGC model may present an even greater obstacle to model accuracy. We then examined the effects of fuel reduction on fire severity and the resulting long-term stand-level C storage by utilizing the STANDCARB model for three Pacific Northwest ecosystems: the east Cascades Ponderosa Pine forests, the west Cascades Western hemlock–Douglas fir forests, and the Coast Range Western hemlock– Sitka spruce forests. Finally, we then tested the extent to which various landscape-level fuel reduction treatments, when applied at various annual treatment areas, altered pyrogenic C emissions and long-term C storage in the east Cascades Ponderosa pine ecosystems. For this we employed the LANDCARB model, which models forests throughout a landscape on a stand-by-stand basis. Results from both the stand and landscape-level modeling indicate that, for fuel reduction treatments to be effective in reducing wildfire severity, they must be applied at higher frequencies and over larger areas than they are currently. Furthermore, fuel reduction treatments almost always reduce stand and landscape-level C storage, since reducing the fraction by which C is lost in a wildfire requires the removal of a much greater amount of C, since most of the C stored in forest biomass (stem wood, branches, coarse woody debris) remains unconsumed even by high-severity wildfires.

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The Effects of Forest Fuel Reduction on Fire Severity and Long-term Carbon Storage

by

Stephen Richard Mitchell

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March 5, 2009

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I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Stephen Richard Mitchell, Author

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I also owe a debt to the information technology staff here at Oregon State, specifically Jerry Mohr and Terralyn Vandetta. A project such as this requires a vast amount of computing resources, and both Jerry and Terralyn made it possible for me to utilize these resources. I also owe a debt to Ron Neilson, who was surpassingly generous in letting me use his Linux cluster. Bev Law's generosity in letting me use her data and willingness to engage in discussions about model-data synthesis of data collected at the Metolius sites was also quite helpful. I am also thankful to Norman Christensen at Duke University, for his flexibility in letting me start a postdoctoral

position nine months before defending my dissertation.

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CONTRIBUTION OF AUTHORS

Drs. Mark Harmon and Kari O'Connell were involved in the editing and proofreading of each manuscript. Drs. Keith Beven and Jim Freer were involved in the editing and proofreading of Chapter 2. Recent programming of STANDCARB was done by Adam Moreno and Frank Schneckenberger. Frank Schneckenberger was the primary programmer involved in updating the LANDCARB model, and much of the suggestions for updating and improving LANDCARB were from Dr. Mark Harmon.

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**THE EFFECTS OF FOREST FUEL REDUCTION ON FIRE SEVERITY AND
LONG-TERM CARBON STORAGE**

CHAPTER 1

INTRODUCTION

Stephen R. Mitchell

Introduction

Increases in atmospheric CO₂ concentrations via fossil fuel combustion have long been observed (Revelle and Suess 1957, Revelle 1982) and are widely thought to be causing significant changes in earth's climate (IPCC 2007). Approximately half of all annual fossil fuel emissions remain in the atmosphere, leaving the rest to be absorbed by oceanic and terrestrial ecosystems (Schimel et al. 2001). The potential for terrestrial ecosystems to mitigate current and future atmospheric CO₂ concentrations is a matter of ongoing inquiry and has prompted many studies attempting to estimate carbon sequestration capacities throughout a wide variety of biomes (Harmon et al. 1990, Turner et al. 1995, Harmon et al. 1996, Harmon 2001, Pacala et al. 2001, Hurtt et al. 2002, Smithwick et al. 2002, Pacala et al. 2004).

Wildfires are a significant source of C loss from terrestrial ecosystems and thus exert considerable influence on the global C cycle (Schultz et al. 2000; Bond and Keeley 2005). While carbon accumulation by forests is thought to make up much of the carbon sink currently thought to exist in the continental US (Pacala et al. 2001), there is growing recognition that much of the current sink may be unsustainable. A century-long policy of fire suppression is widely credited with the buildup of uncharacteristic levels of understory fuel biomass in some forest ecosystems and is thought to have contributed to increased levels of wildfire severity (Noss et al. 2006; Donovan and Brown 2007). Simulations suggest that if fire suppression were to fail in the coming years, the current C sink in the coterminous US would rapidly become a C source as a result of extensive burning of large scale wildfires (Hurtt et al. 2002).

High amounts of wildfire-caused C loss often reflect high amounts of forest fuel availability prior to the onset of fire. Given the magnitude of such losses, it is clear that an understanding of the effects of wildfire on long-term C dynamics is essential to a full understanding of the global C cycle. What is not clear is the extent to which repeated fuel removals that are intended to reduce wildfire severity will likewise reduce (or increase) long-term total ecosystem C storage. Reducing fuel loads among the stands with uncharacteristic levels of fuel build up has been proposed as a method of reducing fire severity. Many studies have demonstrated the effectiveness of fuel reduction treatments at the stand level (Stephens 1998, Fulé et al. 2001; Pollet and Omi 2002, Stephens and Moghaddas 2005). While a properly executed reduction in fuels could be successful in reducing forest fire severity and extent, such a treatment may be counterproductive to attempts at utilizing forests for the purpose of long-term C sequestration.

Fuel reduction treatments require the removal of woody and detrital materials to reduce future wildfire severity. Such treatments can be effective in reducing future wildfire severity, but they likewise involve a reduction in stand-level C storage. If repeated fuel reduction treatments decrease the mean total ecosystem C storage by a quantity that is greater than the difference between the wildfire-caused C loss in a treated stand and the wildfire-caused C loss in an untreated stand, the ecosystem will not have been effectively managed for maximal long-term C storage. Further complications arise when dealing with the effects of fuel reduction treatments on fire severity, fire extent, and C storage at the landscape scale, as management constraints

could preclude any attempt to fully utilize Pacific Northwest forests for their full carbon sequestration or biofuels production potential. Currently in the Pacific Northwest there are approximately 3.6×10^6 ha of forests in need of fuel reduction treatments (Stephens and Ruth 2005) and in 2004 the annual treatment goal for this area was 52000 ha (1.44%). Unless a significantly larger fuel reduction treatment workforce is employed, it would take 69 years to treat this area once, a period that approximates the effective duration of fire suppression.

In this dissertation, I begin by ascertaining the parameter and measurement uncertainties inherent in a widely-used terrestrial ecosystem simulation model, Biome-BGC by applying the Generalized Likelihood Uncertainty Estimation (GLUE) framework (Chapter 2). Applying the GLUE framework to a model with low computational requirements allows a quantification of model uncertainty and serves as a starting point for calibrating models with greater computational demand. I then used the STANDCARB model to ascertain the effects of a wide array of fuel reduction treatments on fire severity and long-term ecosystem C storage for stands in the east and west Cascades and the Coast Range (Chapter 3). The stand-level analysis examines not only C storage but also the time required to offset reductions in stand-level C storage with biofuels production. Finally, I used the LANDCARB model to quantify the changes in fire severity and landscape-level C storage that result from a range of annual landscape treatment percentages that are treated with a combination of salvage logging, prescribed fire, a harvest of 50% of all live biomass followed by a

prescribed fire, and a clear-cut followed by a prescribed fire (Chapter 4). I conclude with recommendations for future research directions (Chapter 5).

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CHAPTER 2

MULTIPLE SOURCES OF PREDICTIVE UNCERTAINTY IN MODELED ESTIMATES OF NET ECOSYSTEM CO₂ EXCHANGE.

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Abstract

Net ecosystem CO₂ exchange (NEE) is typically measured directly by eddy covariance towers or is estimated by ecosystem process models, yet comparisons between the data obtained by these two methods can show poor correspondence. There are three potential explanations for this discrepancy. First, estimates of NEE as measured by the eddy-covariance technique are laden with uncertainty and can potentially provide a poor baseline for models to be tested against. Second, there could be fundamental problems in model structure that prevent an accurate simulation of NEE. Third, ecosystem process models are dependent on ecophysiological parameter sets derived from field measurements in which a single parameter for a given species can vary considerably. The latter problem suggests that with such broad variation among multiple inputs, any ecosystem modeling scheme must account for the possibility that many combinations of apparently feasible parameter values might not allow the model to emulate the observed NEE dynamics of a terrestrial ecosystem, as well as the possibility that there may be many parameter sets within a particular model structure that can successfully reproduce the observed data. We examined the extent to which these three issues influence estimates of NEE in a widely used ecosystem process model, Biome-BGC, by adapting the generalized likelihood uncertainty estimation (GLUE) methodology. This procedure involved 400,000 model runs, each with randomly generated parameter values from a uniform distribution based on

published parameter ranges, resulting in estimates of NEE that were compared to daily NEE data from young and mature Ponderosa pine stands at Metolius, Oregon. Of the 400,000 simulations run with different parameter sets for each age class (800,000 total), over 99% of the simulations underestimated the magnitude of net ecosystem CO₂ exchange, with only 4.07% and 0.045% of all simulations providing satisfactory simulations of the field data for the young and mature stands, even when uncertainties in eddy-covariance measurements are accounted for. Results indicate fundamental shortcomings in the ability of this model to produce realistic carbon flux data over the course of forest development, and we suspect that much of the mismatch derives from an inability to realistically model soil respiration. However, difficulties in estimating historic climate data are also a cause for model-data mismatch, particularly in a highly ecotonal region such as central Oregon. This latter difficulty may be less prevalent in other ecosystems, but it nonetheless highlights a challenge in trying to develop a dynamic representation of the terrestrial biosphere.

Keywords: Net ecosystem exchange, Biome-BGC, Ecosystem Model, uncertainty, GLUE, *Pinus ponderosa*, model-data synthesis

Introduction

Increases in atmospheric CO₂ concentrations via fossil fuel combustion have long been observed (Revelle and Suess 1957, Revelle 1982) and are widely thought to be causing significant changes in earth's climate (IPCC 2007). Approximately half of all annual fossil fuel emissions remain in the atmosphere, leaving the rest to be absorbed by oceanic and terrestrial ecosystems (Schimel et al. 2001). The potential for terrestrial ecosystems to mitigate current and future atmospheric CO₂ concentrations is a matter of ongoing enquiry, necessitating long-term studies of net ecosystem CO₂ exchange throughout a wide variety of biomes (Goulden et al., 1996; Law et al., 2003; Baldocchi 2003).

Net ecosystem CO₂ exchange (NEE) is the net CO₂-C exchange from an ecosystem to the atmosphere, calculated as the difference between gross primary production and ecosystem respiration, excluding losses of respiration-derived dissolved inorganic carbon (Chapin et al. 2006). Continuous field estimates of NEE have been measured from over 100 locations using the eddy covariance method and offer a valuable baseline against which model assumptions, parameters, and performance can be ascertained (Schulz et al., 2001; Wang et al. 2001; Thornton et al., 2002; Braswell et al., 2005; Knorr and Kattge 2005; Sacks 2006).

Biophysical models, even those designed to simulate the same phenomena, can differ widely in their structure, assumptions, and philosophy, leading to substantial

uncertainty in their predictions (Franks et al., 1997; Schulz et al., 2001; Raupach et al., 2005). For many terrestrial ecosystem models, a predominant source of model uncertainty stems from an insufficient capacity to provide reliable estimates of ecosystem respiration (R_e) (Davidson 2006, Trumbore 2006). Total ecosystem respiration (TER), defined as the sum of heterotrophic respiration (R_h) and autotrophic respiration (R_a), poses a difficulty to environmental modelers. A large source of the uncertainty in estimates of TER involves the respiratory processes of roots and soil organisms, collectively referred to as soil respiration. Scientists do know that temperature as well as soil moisture exert significant control over soil respiration, but efforts at modeling such dynamics are difficult because of the intricacies involved in disentangling the interactions between seasonal variations in temperature from accompanying variations in soil moisture (Davidson et al. 1998).

Uncertainties inherent in calculations of TER do not end in the soil. Any modeled estimate of R_e requires knowledge of the precise quantities of each respiring component (Law et al., 1999; Litton et al., 2007) and estimates of the growth and maintenance respiration of constituent woody tissues are often calculated and distributed by way of stationary allometric ratios that determine the patterns of biomass allocation. In reality, allometric ratios are not static. Trees with a high capacity for biomass storage can exhibit substantial variation in such ratios due to variation among site conditions as well as stand age; Law et al. (2004a; 2004b) found that xeric systems exhibited decreased below-ground biomass allocation with age while mesic systems exhibited increased below-ground biomass allocation with age.

Similarly, Comeau and Kimmins (1989) found that patterns of new fine root C: new leaf C in *Pinus contorta* can vary considerably as a function of site water availability. Non-allometric parameters can also vary by site and/or stand age. In *Pinus ponderosa*, leaf and fine root turnover varies by elevation (Whittaker and Niering 1968, Whittaker and Niering 1975), and percentages of leaf nitrogen in the enzyme rubisco vary with irradiance (Poorter and Evans 1998). Significant differences in transpiration per unit leaf area have been observed between young and mature stands when water is readily available (Irvine et al. 2004), which may partially explain why leaf water potentials during conductance reactions can show significant inter-site variation within species (DeLucia et al., 1988; DeLucia and Schlessinger 1990).

Issues such as these have prompted model-data synthesis studies. Model-data synthesis, according to Raupach et al. (2005), operates under the assumption that the inherent uncertainties in any dataset are just as important as the data values and should thereby be included in both parameter estimation and data assimilation. For an ecosystem model (and/or in fact any environmental model), this uncertainty lies not just with the observed data but also with the parameters on which the data is conditioned, affecting both the predictive uncertainty of a model-data synthesis and the predicted best estimate. Analyzing these uncertainties effectively requires an acknowledgment of the potential for equifinality in model predictions. The concept of equifinality implies that, within the current capacity of mechanistic modeling, there may be many model structures and parameter sets within a given model structure that

may be acceptable in reproducing the observed behavior of an environmental system (Beven 2002, 2006).

Acknowledgement of model equifinality is essential to predictions drawn from environmental models in that competing models and parameter sets can be considered as multiple working hypotheses about how the system is functioning. Given the limitations of observational data, approximate model assumptions, and lacking independent estimates of the effective parameter values required by a model, it may not be possible to determine uniquely the most likely hypothesis, even if many models can be rejected as unacceptable or non-behavioral. Our goal was to explore the respective contributions of measurement uncertainty, model structure, and parameter equifinality to modeled estimates of NEE. We used the GLUE framework (Fig. 1) in conjunction with a terrestrial ecosystem model, Biome-BGC, to 1) examine model equifinality for combinations of ecophysiological parameter values with respect to NEE dynamics in a semi-arid forest ecosystem, 2) compare differences in parameter uncertainty between two distinct age classes of this ecosystem and 3) ascertain the cause(s) of any model-data mismatch.

Methods

The GLUE Methodology

The GLUE method (Beven and Binley 1992) was developed from the generalized sensitivity analysis of Spear and Hornberger (1980) to deal with multiple acceptable parameter sets within environmental models. Studies of parameter responses have shown that the assumption of a single well-defined optimal parameter

set rarely holds, resulting in the condition of model equifinality (Freer et al., 1996; Franks et al., 1997; Beven and Freer 2001; Schulz et al., 2001). GLUE provides a means of assessing the predictive uncertainty based on a generalized likelihood measure within a Monte Carlo framework. GLUE has been used for a wide range of environmental modeling problems (see Beven and Freer 2001; Freer et al., 2004; Beven 2006, 2008), including the prediction of CO₂ flux data (Franks et al., 1997; Schulz et al., 2001), tree mortality under drought conditions (Martinez-Vilalta et al., 2002) and forest fires (Piñol et al. 2004, 2007).

Utilization of the GLUE method involves a large number of model runs, each of which is driven by randomly generated input parameter values drawn from uniform prior distributions across the range of each parameter. The performance of each run is thereafter deemed behavioral or non-behavioral based upon the comparison of simulated versus observed data. Model runs that do not meet specified acceptability criteria are rejected as non-behavioral and are thus given zero likelihood, removing them from further analysis. In what follows, parameter sets must satisfy two performance criteria to be considered as behavioral and used in prediction. Within the GLUE methodology, each behavioral simulation can be associated with a likelihood weight that depends on performance during comparisons with available observations.

Evaluation of parameter sensitivities

Many randomly generated parameter sets will result in a simulation that is physiologically unsustainable within the applied modeling framework, thus

simulations that resulted in a NEE of 0.0 were excluded from additional analysis *a priori*. For the remaining simulations we used the Nash-Sutcliffe model efficiency coefficient (Nash and Sutcliffe, 1970) to determine whether or not a given set of parameter values should be retained for further analysis. It is defined as:

$$E_j = 1 - \frac{\sum_{i=1}^I (C_o^i - C_m^{i,j})^2}{\sum_{i=1}^I (C_o^i - \bar{C}_o)^2} \quad (1)$$

where C_o^i is observed NEE for day i , \bar{C}_o is the mean of daily observed NEE, and $C_m^{i,j}$ is modeled NEE of day i for parameter set j . Nash-Sutcliffe efficiencies can range from $-\infty$ to 1. An efficiency of 1 ($E = 1$) indicates a perfect match of modeled data to the observed data. An efficiency of 0 ($E = 0$) indicates that the model predictions are as accurate as the mean of the observed data, while an efficiency less than zero ($E < 0$) occurs when the observed mean is a better predictor than the model. Simulations where ($0 \leq E < 1$) were retained for further analysis. Once these parameter combinations were found, we calculated their likelihood weights using the following equation:

$$L(\underline{\Theta}_j | \underline{Y}) = \frac{E_j}{\sum_{j=1}^J E_j} = \frac{\left(\sum_{i=1}^I (C_o^i - C_m^{i,j})^2 \right)^{-1}}{\sum_{j=1}^J \left(\sum_{i=1}^I (C_o^i - C_m^{i,j})^2 \right)^{-1}} \quad (2)$$

where $L(\Theta_j|Y)$ is the likelihood of simulating data Y given parameter set Θ_j , assuming a uniform prior distribution for all parameter sets where $E < 1$. Our method is similar to the sensitivity analysis of Spear and Hornberger (1980) except that there is an additional step of calculating a likelihood weight for each parameter set. This sampling strategy allows any covariation that is important in providing simulations with $0 \leq E < 1$ to be apparent in the likelihood weights whether or not prior covariation has been specified in sampling the parameter sets.

This first threshold condition for a model to be retained for further analysis ($0 \leq E < 1$) is very relaxed. It might be considered less than the minimal requirement for a model to be useful in prediction, since it indicates that the model predictions are merely as accurate as or better than the mean of the observed data. Here, however, we are using it primarily to reveal information about the sensitivity of the simulations to different parameters and combinations of parameters. We later impose an additional criterion for a model performance to be considered behavioral in relation to errors in the observed data. The second threshold criterion is based on comparing annual estimates of NEE from the model to estimates obtained from field measurements, the latter of which includes a term ε , representing the uncertainty in annual estimates of NEE. The term ε is based on the propagation of uncertainty in annual NEE estimates and includes estimates of errors incurred by the instrumentation used in the eddy covariance technique, data gap-filling, as well as spatial and temporal variability, calculated from the estimates of annual measurements of net ecosystem CO₂ exchange

uncertainty from Oren et al. (2006). This ‘effective observation error’ criterion is an example of the approach to model evaluation proposed by Beven (2006) but the concept of including observational uncertainties to construct model performance criteria has been applied previously (Page et al., 2003; Freer et al., 2004). We included this second step in our evaluation procedure to help decide whether or not our model should be consulted as a reliable simulator of NEE. Thus, only simulated annual estimates of NEE that met the following criteria are considered in the behavioral model set:

$$\sum_{i=1}^N C_o^i - 2\varepsilon < \sum_{i=1}^N C_m^i < \sum_{i=1}^N C_o^i + 2\varepsilon \quad (3)$$

Parameter Estimates

Biome-BGC requires 37 ecophysiological parameter values for the simulation of evergreen needle-leaf forests. Of these 37, 13 were allowed to vary (Table 2.1) assuming independent uniform prior distributions across feasible ranges of the parameters in the absence of any strong information about effective parameter values and their covariation. White et al. (2000) performed a sensitivity analysis of model parameters, showing that LAI, FLNR, and C:N_{leaf} were among the most sensitive parameters, and these were some of the parameters we included. Additional selection of parameters that were allowed to vary was based on the range in variation of parameters in the literature. For instance, parameters with a wide range of variability, such as the ratio of new fine root carbon to new leaf carbon (FRC:LC), were chosen for this reason, and parameters for which literature values exhibited little to no

variability were excluded. Our study site has a canopy comprised primarily of Ponderosa pine (*Pinus ponderosa*), a species with input parameters that are generally provided in the compilation by White et al. (2000), and in cases where published parameter values were unavailable, we substituted them from other *Pinus* species. Each parameter range was subsequently expanded to allow for the possibility of yet-unpublished values that might be observed in the field in the future, the uncertainty that may arise from substituting species types when necessary, and the commensurability error between field-measured values and the effective parameter values required to give good results in this model structure.

Study Sites

Data were collected from two sites with eddy covariance towers at Metolius, Oregon, located approximately 64 kilometers north of Bend, Oregon (Fig. 2). Data from the young stand, aged ~23 years, were collected in 2000, while data from the mature stand, aged ~89 years, were collected in 2002. Both sites are dominated primarily by Ponderosa pine (*Pinus ponderosa*) and both have naturally regenerated from clear-cuts. Soils are well drained at both sites. Descriptions of site-specific data are referred to as they were during the time in which the system was simulated. Additional site characteristics are summarized in Table 2.2.

Modeling

All simulations used version 4.1.2 of the Biome-BGC model (Thornton et al. 2002), a widely used terrestrial ecosystem model. Biome-BGC simulates water, carbon, and nitrogen dynamics in plants, litter, and soil, using a daily time step for all

processes (Running and Coughlin, 1988; Thornton, 1998; White et al., 2000). Biome-BGC allows for the option of a spin-up simulation to serve as a basis for an initial estimate of soil C content. Spin-up time is determined by the amount of time it takes to allow soil C to reach equilibrium (Thornton and Rosenbloom, 2005). We incorporated the same randomly generated parameter values in the spin-up simulations for each of our GLUE analysis simulations. In addition to simulating initial estimates of soil C content for each parameter, we incorporated a representation of each stand's disturbance history into the regular (non-spinup) simulations. Our methodology for this was similar to, but not an exact replicate of, the methodology developed by Law et al. (2001). At both stands, a clear-cut was simulated upon the completion of each spin-up simulation by starting a new simulation that included estimates of post-harvest amounts of coarse woody debris, leaf litter, dead fine roots, and soil C pools taken from the amounts of these materials remaining at the end of the spin-up simulation.

Data Collection

Descriptions of NEE collection protocols are described for the young stand in Anthoni (2002) and mature stand data are described in Vickers et al. (in review). In brief, the eddy covariance method estimates NEE flux from the covariance of high-frequency fluctuations in vertical wind velocity and CO₂ concentrations. NEE is calculated as the sum of this flux term and a canopy CO₂ storage term, the latter of which is calculated from the change in CO₂ concentration in the canopy air space as a function of height (Law et al., 1999; Anthoni et al., 2002):

$$NEE = \overline{\omega'c'} + \int_0^z \frac{dc}{dt} dz \quad (4)$$

where $\overline{\omega'c'}$ is the time-averaged eddy flux for CO₂ [covariance between the turbulent fluctuations for vertical wind speed (ω') and scalar concentration (c')] and dc/dt is a vertical storage term that is a function of canopy height (z), which approximates change in CO₂ storage in the canopy air space. NEE, like other measurements taken from an eddy flux tower, is measured at 20Hz and is thereafter averaged into 30-minute intervals which form the dataset of daily estimates of NEE for each respective stand.

Meteorological Data

The driving meteorological data for Biome-BGC is composed of the following inputs given on a daily time step: maximum temperature (T_{max}), minimum temperature (T_{min}), average temperature (T_{avg}), average vapor pressure deficit (VPD) (MPa), average incoming shortwave radiation (\overline{S}_{rad}) ($W\ m^{-2}$), total precipitation (mm), and day length (s). Meteorological instrumentation did not exist at the Metolius site prior to its establishment as an AmeriFlux site, requiring the generation of such data for the years before the eddy correlation instrumentation was installed at the site. This need was met using the DAYMET climate model, a model which gathers data for a user-specified location by extrapolating meteorological readings from surrounding climate stations and adjusting for any changes in elevation (Thornton and Running, 1999; Thornton et al., 2000). DAYMET generated daily climate data from 1980 through

2003 specific to each site. Such a climate record is of sufficient length to capture inter-annual El Niño-Southern Oscillation dynamics, which exert considerable control over the vegetation dynamics of the US Pacific Northwest (Greenland, 1994).

Meteorological data taken from the AmeriFlux instrumentation then replaced the data generated by the DAYMET model for the time span of our analysis. In addition to incorporating meteorological data, Biome-BGC allows for the user to specify yearly CO₂ concentrations at the site, based on annual CO₂ concentrations recorded since 1901, and we utilized this feature to account for changes in atmospheric CO₂.

These inputs were the basis of all 400,000 simulations we performed for each of the two stands. We recognize that there will be an interaction between errors in the inputs and any parameter sets that are identified as behavioral within the GLUE methodology (see discussion in Beven, 2006) but, as in very many environmental modeling studies, there is little information available with which to assess the potential input errors. Each *Pinus ponderosa* simulation had 24 fixed ecophysiological parameter values and 13 that were allowed to vary by way of the Fortran90 “rand” random number generator that sampled from a uniform range in potential model parameter values. Ranges for these parameters are given in Table 2.2. The 800,000 total simulations of Biome-BGC and the GLUE analysis were performed on a Linux cluster at the USDA Forest Service Pacific Northwest Research Station in Corvallis, Oregon.

Results

Of the simulations that were run, 73.15% and 77.06% of simulations resulted in a “non-living” and thus rejected simulation for the young and mature stands respectively; 12.40% and 21.81% resulted in live but rejected ($\infty \leq E < 0$) simulations. Of all simulations for the young and mature stands, respectively, 14.45% and 1.13% resulted in live simulations that could be retained for further analysis ($0 \leq E < 1$), shown in Figure 2.3. Of the retained simulations, 98.63% and 99.71% underestimated the magnitude of the NEE estimated by observation for the young and mature stands, respectively.

Figure 2.4 shows plots of the randomly sampled parameter values against posterior likelihood projections. Parameter values for combinations with $E \geq 0$ are shown in grey and behavioral combinations that satisfied both performance criteria are shown in black. Each of these plots represents points on the posterior multi-dimensional surface, projected onto single parameter axes. In all, 5 of the 13 varying parameters show no sensitivities within their range (C:N_{litter}, C:N_{dead wood}, CRC:SC, Ψ_c , Ψ_s), 2 of the 13 parameters show slight preference (C:N_{leaf} and C:N_{fine roots}), and 6 of the 13 parameters (FLNR, FM, FRC:LC, SC:LC, LAI, and g_s max) show strong preference for a certain parameter value (Fig. 4). Exhibition of preferences for these 6 parameter values appears more pronounced in the mature stand, particularly in the likelihood projections of behavioral (annual NEE $\pm 2\varepsilon$) parameter value combinations. The difference between the sets of parameter combinations is less obvious in the young stand since a much higher proportion of parameter combinations were

behavioral. In the mature stand, clustering of these behavioral likelihood projections within a certain parameter value range is pronounced, and this clustering tends to occur in the parameter value ranges that produce the highest likelihood estimates.

$C:N_{\text{leaf}}$ exhibits a slight preference for low values in the young stand and a slight preference for high values in the mature stand. $C:N_{\text{litter}}$ and $C:N_{\text{dead wood}}$ showed no slope across the sampled range in their posterior likelihood projections. $C:N_{\text{fine root}}$ in the young stand also lacked any strong conditioning in the posterior likelihood projections, though lower parameter values in the mature stand showed a tendency to have higher likelihood values. The likelihood projections for the parameter controlling FLNR show a slight absence of lower values for low parameter values in the young stand. A similar absence of low FLNR values is seen for the mature stand, which also show slightly increasing likelihood values for higher parameter values.

FM shows similarity among age classes in the projection of likelihood estimates, with both showing a slight downward sloping pattern for high likelihood values and an absence of low likelihood values for high parameter values. $FRC:LC$ shows high values for low parameter values and an absence of lower likelihood values for high parameter values. $SC:LC$ shows a slight preference for high values in the young stand and a downward sloping likelihood projection in the mature stand. In contrast, likelihood estimates of $CRC:NSC$ do not show any curvature in the posterior likelihood projections across the full range sampled.

Likelihood projections for LAI have a slight downward slope for the young stand and a rapidly increasing slope with an absence of low likelihood values in the

mature stand. LAI estimates taken at these sites, however, were measured to be 0.89 and 2.96 for the young and mature stands, respectively. Maximum stomatal conductance ($g_{s,max}$) however, exhibits a slightly upward-sloping pattern with an absence of low likelihood values for low parameter values in the young stand, while the mature stand shows a rapidly increasing slope to values of $\sim 3.0 \times 10^{-3}$ that thereafter tapers off into a gradually decreasing slope across the upper bounds of high likelihood values, also with a lack of low likelihood values for low parameter values. Plant water stress (Ψ_1) is a cause of stomatal closure and is related to leaf water potentials at the initial and final reductions to stomatal conductance (Ψ_s, Ψ_c) in Biome-BGC. Both of these values are assumed to be negative, since plants are rarely at full hydration. Likelihood projections for both of these values do not show any shaping across the values range.

Parameters that have relatively uniform posterior likelihood projections are those that have less to do with the dynamics of primary production and affected non-photosynthetic biomass, dealing with either stoichiometry or allocation ratios. CRC:SC, a parameter that deals exclusively with non-photosynthetic biomass, controls patterns of biomass allocation in coarse roots and stems, thus has little impact on primary production and respiration. $C:N_{fine\ root}$ had only a very slight shaping in its posterior likelihood projections, and $C:N_{dead\ wood}$ and $C:N_{litter}$ show no discernable influence on NEE, probably due to the comparatively long time scale at which decomposition operates. On a multi-year time scale, a low C:N ratio of dead biomass would, holding climate constant, result in an increased decomposition rate k for these

components, increasing the respiration of CO₂ to the atmosphere. However, it is clear that this effect is difficult to detect due to the influence of climatic constraints. Sun et al. (2004) found that measurements of coarse woody debris respiration in this ecosystem were negligible unless the wood was moist but not waterlogged and under warm climatic conditions, thus coarse woody debris decomposition only occurs during a small part of the year and contributes a marginal amount to TER in this semi-arid forest.

Prediction Uncertainties

As noted earlier, the range of models included in the sensitivity analysis includes many models that have limited predictive power. It is clear, however, that for many parameters the ‘best’ models for the chosen performance measures are distributed throughout the ranges of parameter values tried. The GLUE methodology allows for such equifinality of models in estimating prediction uncertainties by keeping a set of behavioral models thought to be useful in prediction. Beven (2006) has suggested an approach to model rejection based on setting prior limits of acceptability. Here this approach has been implemented by defining such limits on the basis of the effect of error in the field measurements on estimates of annual NEE as in condition (3) above. Behavioral models are then consistent with annual NEE allowing for the estimated errors in the measurements and might therefore be considered as providing reliable simulations of net ecosystem CO₂ exchange.

There are several potential sources of error in NEE estimates that form the basis of our uncertainty estimate ε that we use in our equation (3) to determine model

acceptability. First, the fluxes that are computed over half-hour intervals with the intention of describing ecosystem activities in the sampling footprint are known to include sampling errors, including micrometeorological sampling errors (Baldocchi, 2003) as well as statistical sampling errors from gap-filling methodologies (Falge et al., 2001). These errors are distinct from uncertainties in the spatial and temporal variability in ecosystem activity. Uncertainties in the spatial and temporal variability should not be significantly changed through an increase in averaging time, while micrometeorological sampling errors can be potentially reduced by sampling a greater proportion of eddies and averaging them over a longer time scale (Katul et al., 2001). Oren et al. (2006) separated the contribution of these two factors through temporal averaging of NEE data from towers with overlapping ecosystem activity footprints to ascertain the magnitude of each source of measurement uncertainty, which thereby allowed a calculation of total measurement uncertainty. We calculated ε from averaging the uncertainty propagation estimates of Oren et al. (2006) for the years 1998-2004, calculated to be $100.86 \text{ g C m}^{-2} \text{ yr}^{-1}$.

After application of this term ε into condition (3), a mere 4.07% and 0.0045% (16,276 and 179 out of 400,000) of the simulations resulted in behavioral ($\pm 2\varepsilon$ of annual NEE) estimates for the young and mature stands, respectively (Fig. 5). We note that some may consider this acceptability criterion still to be too generous, and we add that the percent of stands with NEE estimates that were $\pm 50 \text{ g C m}^{-2}$ of annual NEE were 0.31% and 0.000023% (1,256 and 9 out of 400,000) for the young and

mature stands, respectively. Thus, an overwhelming majority of parameter combinations resulted in an inadequate reproduction of observed data and could be rejected.

Discussion

Can Biome-BGC be considered a satisfactory model of these stands?

In using the Generalized Likelihood Uncertainty Estimation (GLUE) technique to analyze the uncertainty that arises when simulating a forest ecosystem at two different age classes with the terrestrial ecosystem model, Biome-BGC, only a very small number of model parameter sets have survived the chosen, rather relaxed, criteria for acceptability. On the basis of the wide range of simulations tried, we do not think that this model provides an adequate reproduction of observed data at these sites. We note that the failure of the many simulations to produce a live stand does not necessarily reflect poorly on the Biome-BGC model, as our range of potential parameter values was large and inevitably leads to many parameter combinations that are physiologically unsustainable. However, it was clear from our posterior likelihood estimates that many of the parameters, despite a broad range in their uniform prior distributions, exhibited little or no sensitivity to variation in their values and thus bear little or no responsibility for model failures.

In the young and mature stands, Biome-BGC does not reliably simulate the magnitude of NEE during the summer months; simulations in the young and mature stands, whether behavioral or non-behavioral, underestimated the magnitude of annual NEE 99.77% and 99.90% of the time. Biome-BGC's tendency to underestimate the

magnitude of NEE is apparent in other studies as well. In an earlier study, Law et al. (2001) performed a model-data comparison of NEE data from an old-growth *Pinus ponderosa* stand at Metolius, OR and found that Biome-BGC underestimated the magnitude of NEE flux by $240 \text{ g C m}^{-2} \text{ yr}^{-1}$.

Substantial differences were observed in the shaping of both the $E \geq 0$ and behavioral likelihood projections between the young and mature stands, indicating the difficulties involved in finding a parameter set that can simulate estimates of NEE over the course of forest development. Differences in the posterior likelihood projections are due to a variety of factors, the most significant of which appears to be Biome-BGC's low capacity for simulating the magnitude of summertime NEE. We found this tendency for NEE magnitude underestimation when we tested Biome-BGC's default model parameter values for an evergreen needle-leaf forest in both the young and mature stands. The young stand produced a NEE estimate of $-168 \text{ g C m}^{-2} \text{ yr}^{-1}$ compared to $-273 \text{ g C m}^{-2} \text{ yr}^{-1}$, while the mature stand produced a NEE estimate of $-286 \text{ g C m}^{-2} \text{ yr}^{-1}$, compared to a measured estimate of $-413 \text{ g C m}^{-2} \text{ yr}^{-1}$. Such results are quite superior to the estimates of most parameter combinations, but it is striking how much default model parameter values differed from the values taken directly from the site itself.

Using site specific estimates for 11 of the 13 varying parameter values for the young stand (see Table 2.2), along with every other substitutable parameter value measured at the site, the simulation produced a non-living simulation. (Parameter values from the mature stand were not available to allow a similar test). This suggests

that, at very least, there is a commensurability issue between measured values of parameters and the effective values required to produce a successful simulation; at worst that there is a significant structural deficiency in the model.

Investigating model failure: simulation of soil hydrology

We initially suspected that difficulties in modeling soil hydraulics in the Metolius ecosystem accounted for the bulk of model-data mismatch. Irvine et al. (2004) showed that while there are substantial inter-stand differences in transpiration that occur when water is readily available at the Metolius sites, cumulative tree transpiration does not differ greatly among differently aged-stands during the growing season, suggesting that water limitations ultimately inhibit GPP. We investigated the possibility of a failure to sufficiently reproduce soil hydrology and evapotranspiration by running 5,000 additional simulations. We evaluated model performance by comparing simulated estimates of soil water potential and evapotranspiration (ET) to measured data in both stands. Results were divergent: the ratio of the modeled estimates of soil water potential to ET were *higher* than the ratio of the measured values for the young stand and *lower* than the ratio of the measured values for the mature stand (Figure 2.6). Such a result clearly shows an inability to model soil water storage and uptake by not only getting the ratios wrong, but by getting them wrong in different ways for differently-aged stands. However, this is not necessarily the dominant factor in the model's inability to reproduce NEE. Plots of annual ET plotted against annual GPP show that measured data can be well within the range of the modeled data plotted for both stands (Figure 2.6), so it is clear that the model can

accurately reproduce estimates of the water use efficiency of photosynthesis (WUE_{Ph}), even if soil hydrology is misrepresented.

Investigating model failure: simulation of Total Ecosystem Respiration (TER)

A further possible cause of the limited success of the Biome-BGC in predicting the observed NEE data is an inability to model TER successfully. On average, ~80% of GPP is respired back to the atmosphere, and soil respiration, which incorporates elements of both R_a and R_h , accounts for more than two-thirds of this flux (Law et al., 1999; Janssens et al., 2001; Xu et al., 2001). Contemporary frameworks for modeling soil respiration, such as the Lloyd and Taylor (1994) function used in our version of Biome-BGC, base calculations on temperature and moisture data, ignoring some of the contributions of canopy processes to soil CO_2 efflux that may be crucial to modeled estimates of NEE. Recent research indicates that failure to incorporate a more direct link between canopy and soil processes in ecosystem simulation models may be problematic. Ekblad and Högberg (2001) and Bowling et al. (2002) used an isotopic technique to show that photosynthate takes only days to become available for root respiration, indicating a relatively tight coupling of above and below-ground processes. Irvine et al. (2005) observed that daily soil CO_2 efflux was linearly related to GPP as measured by the eddy covariance technique ($r^2 = 0.55$, $p < 0.01$), furthering the evidence that GPP makes significant short-term contributions to soil respiration. Our results are an additional indication that the connection between canopy processes and soil respiration is not being made. Even though GPP can be reasonably reproduced, there is still a significant mismatch between modeled and measured

respiration data. This is especially visible when GPP is plotted against TER (Figure 2.6), as the ratio between GPP and TER is too large; almost all of GPP is respired back to the atmosphere, thus yielding the low estimates of the magnitude of NEE.

Difficulties in modeling soil respiration are present in other model-data syntheses as well. Braswell et al. (2005) applied nonlinear inversion to the eddy covariance flux measurements from Harvard Forest using a simplified model of photosynthesis and evapotranspiration and concluded that multi-year eddy flux measurements allow for a tight constraining of photosynthesis, but poor constraints on parameters relating to soil decomposition, which varies at considerably longer time scales than photosynthesis and evapotranspiration. Similarly, Veerbeck et al. (2006) found that the parameter responsible for the greatest amount of uncertainty in the FORUG model was related to soil respiration, and Williams et al. (2005) concluded that long-term measurements of carbon pool sizes are needed to estimate parameters relating to soil decomposition.

As a result, the simulations were best with parameter values that were often on the extreme ends of their specified ranges producing an increase in GPP that compensated for an overestimation of the magnitude of TER. Parameters that have a more direct control over potential GPP, such as those that control leaf production and leaf nitrogen concentration, are clearly among the most sensitive model parameters in Biome-BGC (White et al. 2000) and may be even more so under conditions of chronic water limitation. For instance, low values of FRC:LC imply increased allocation to leaves and thus had high likelihoods in both stands. Like FRC:LC, g_s max showed inter-stand similarities among the posterior likelihood projections, and

high-likelihood values associated with low values for $g_{s,max}$ were consistent with the workings of a water-limited system, since a lower maximal stomatal conductance will result in decreased water loss. Furthermore, low values of FM imply low leaf (and fine root) turnover and had the highest likelihood weights, probably due to reduced construction respiration costs for the leaves that could be used in constructing other biomass components, thereby increasing the magnitude of NEE. Field values of leaf turnover were similar to the high likelihood values in the model, indicating a mean residence times of 3.6 years (FM = 0.28) (Law et al., 2001). Field values of fine root mean residence time were different from leaf values and were estimated at 1.6 years (FM = 0.63) (Law et al., 2001), though estimates of fine root turnover are often problematic (Strand et al., 2008).

Projections for these and other parameters exhibit not only a shaping of maximal values that can be attributed to certain parameter values generating high likelihood estimates, but also strong interaction effects with other parameter values. Both FRC:LC and FM showed high and low likelihoods for low values while showing an absence of low likelihood values for high parameter values while $g_{s,max}$ showed a lack of low likelihood values for low parameter values due to the interaction effects between other parameters. The shaping of the behavioral likelihood projection (shown in black) for $g_{s,max}$ in the mature stand is an exceptional example of the strong interactions that take place with other parameter values. Similarly, while high likelihood values were found for $C:N_{leaf}$ in the young stand, there was a slight tendency for higher likelihood values to be found among high parameter values of

C:N_{leaf} in the mature stand, a phenomenon which we suspect is due to a sensitivity in the interaction with FLNR.

Investigating model failure: Stand history data

We also recognize that one perceived source of model-data mismatch in our analysis may be related to the incorporation of clear-cutting disturbance and its potential effects on legacies of remaining coarse woody debris and their contribution to TER. Even though we incorporated Biome-BGC's pre-disturbance estimates of dead fine roots, leaf litter, soil C, and coarse woody debris into our simulation, our estimates of coarse woody debris did not include the potential contribution of tree stump biomass that would remain following a clear-cut. We know of no appropriate method for estimating the stump biomass that would remain following a clear-cut in a single-life form model such as Biome-BGC since estimates of stem biomass and allometry vary substantially when generated by multiple sets of ecophysiological parameter combinations. However, we do not think that this alters our general conclusions for two reasons. First, as stated above, Sun et al. (2004) found that coarse wood decomposition contributes only a marginal amount to TER in this semi-arid forest, and our modeled results likewise demonstrated the model's insensitivity to parameters such as CRC:SC and C:N_{dead wood}. Second, even if estimates of NEE in this ecosystem were sensitive to the release of CO₂ by coarse woody debris, the incorporation of additional amounts of CO₂ release by decomposing stump materials would merely serve to further decrease the magnitude of NEE and result in even greater model-data mismatch, thereby strengthening our current conclusion.

Investigating model failure: modeled past climate inputs

There is additional uncertainty in the generation of climatic data via the DAYMET model (Thornton and Running 1999). The DAYMET model estimates meteorological data from taking measurements from surrounding weather stations and subsequently uses this data to estimate the meteorological data at a point near those weather stations. This method is most reliable when there are many weather stations close to the point of interest and when the area over which the meteorological data are extrapolated is homogeneous in its climatic patterns. Neither of these conditions is met in an estimation of meteorological data at the Metolius sites. The Metolius sites occur in the eastern Cascade mountain range, where rainfall patterns are tightly coupled to the rain-shadow effect that characterizes Pacific Northwest climate gradients (Waring and Franklin 1979), making reliable generations of site-specific meteorological data difficult, particularly in a region with a relatively sparse population and [presumably] few weather stations.

We ran an informal test of the extent to which an exclusion of DAYMET data resulted in a different number of retained runs by running the model 5,000 times with continuous data taken solely from the Ameriflux instrumentation. Of the simulations for the young stand, 4.56% were retained and 3.94% were behavioral, compared to 14.45% that were retained and 4.07% that were behavioral in the simulations run with climate data generated with the DAYMET model. The mature stand had 7.22% retained and 3.68% were behavioral simulations, compared to 1.13% that were retained and 0.0045% that were behavioral in the simulations run with climate data

generated with the DAYMET model. In other words, using one year's worth of site climate data resulted in a significant reduction of retained runs and a slight reduction in the number of behavioral runs for the young stand. However, this same substitution for the mature stand significantly increased the number of both the retained and behavioral simulations. Furthermore, 67% and 49% of these retained simulations underestimated the magnitude of NEE for the young and mature stands, respectively, which is a much more even error distribution compared to the simulations run with the more complete, though distantly estimated, historical climate data. Such a result partly vindicates the performance of the model if only to raise new questions about the future difficulties of predicting meteorological data throughout the terrestrial biosphere, though we acknowledge that the difficulties involved in predicting climate at our particular points could, in fact, be indicative of a scenario in which such a task is uncharacteristically difficult. Nevertheless, one of the goals of ecological modeling is to simulate an ecosystem, including future changes in response to climate forcing, without any eddy covariance data to aid in model calibration, and we think that our initial modeling exercise that included the DAYMET data is more indicative of the common practices of ecosystem modeling and thus does not represent an extreme case in terms of procedure.

Investigating model failure: lack of temporal parameter variation

Wang et al. (2007) has noted that the CSIRO Biosphere model (CBM) can have very strong performance when photosynthetic parameters (maximum potential carboxylation rate and maximal electron transport rate) are allowed to vary seasonally

(i.e. have different values for the growing season and the dormant season). Such an innovation in the photosynthetic parameters of Biome-BGC may come at the expense of introducing more parameters to be identified, but may nevertheless result in improved model performance. Our version of Biome-BGC might also benefit from having allometric parameters (SC:LC, FRC:LC, CRC:SC) that vary with age, as such parameters are known to vary significantly in the field. As stated previously, Law et al. (2004a; 2004b) found that xeric *Pinus ponderosa* systems exhibited decreased below-ground biomass allocation with age while mesic systems exhibited increased below-ground biomass allocation with age, and Comeau and Kimmons (1989) found that patterns of FRC:LC in *Pinus contorta* can greatly vary as a function of site water availability. Likewise, the likelihood projections for FRC:LC and SC:LC are shaped differently for the two stands, making it clear that accounting for temporal changes in parameter values may be necessary to improve model performance.

Conclusions

We have incorporated the uncertainty that arises from both multidimensional parameter variability and eddy flux measurement uncertainty by simulating 400,000 combinations of 13 parameter values and testing to see if estimates of NEE from those simulations can fall within the bounds of measurement uncertainty inherent in estimates of NEE based on eddy flux measurements. Studies that provide an account of uncertainty to this extent are rare, and our results suggest that Biome-BGC should not be considered to be a reliable simulator of net ecosystem CO₂ exchange in these semi-arid forests and possibly additional ecosystems as well. It is clear that

substantial uncertainties remain in this terrestrial ecosystem modeling scheme and its representation of forest stand development. While recognizing the real need for predictions regarding the dynamics of global change, scientists are often attempting to make predictions under conditions of incomplete knowledge for the ecosystems of concern. It would seem that, in the case of Biome-BGC, there is not only a problem of multidimensional parameter variability that is shared with other models, but also a fundamental deficiency in model structure. We think that the model does not provide a realistic representation of ecosystem respiration, particularly soil respiration, at the study sites, and the only parameter sets that can emulate NEE dynamics are those that manage to compensate for this shortcoming by allocating resources that maximize GPP, no doubt skewing the simulation of other metrics of ecosystem process and function. We think that a rethinking of model structure and parameterization schemes, especially with regard to soil respiration, may be required to adapt Biome-BGC to meet the need of accurate estimates of net ecosystem CO₂ exchange, and we suspect that this is true for other models as well. An incorporation of both measurement uncertainty and parameter variability can play a valuable role in detecting specific problems in model structure and we encourage such a procedure in future ecosystem process model assessments.

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Tables and Figures

Symbol	Variable	Parameter Value Range	Values from Young Sta
FM	annual leaf and fine root turnover fraction (1/yr)	0.1-0.9	0.25
FRC:LC	new fine root C : new leaf C (ratio)	0.1-6.0	6.00
SC:LC	new stem C : new leaf C (ratio)	0.2-2.0	1.48
CRC:NSC	new croot C : new stem C (ratio)	0.2-0.5	N/A
C:N _{leaf}	C:N of leaves (kgC/kgN)	20-90	50.50
C:N _{litter}	C:N of leaf litter, after retranslocation (kgC/kgN)	90-150	95.60
C:N _{fine root}	C:N of fine roots (kgC/kgN)	20-90	46.00
C:N _{dead wood}	C:N of dead wood (kgC/kgN)	200-1800	287.00
LAI	canopy average specific leaf area, projected area basis (m ² /kgC)	0.5-4.0	0.89
FLNR	fraction of leaf N in Rubisco (unitless)	0.01-0.15	0.075
g_{smax}	maximum stomatal conductance, projected area basis (m/s)	0.002-0.012	0.007
Ψ_s	leaf water potential: start of conductance reduction (MPa)	-0.85 - -0.20	N/A
Ψ_c	leaf water potential: complete conductance reduction (Mpa)	-2.3 - -0.9	-1.14

Table 2.1. Biome-BGC Parameters allowed to vary. Site values from Law (personal communication).

	Young	Mature
Latitude	44.44	44.45
Longitude	-121.57	-121.56
Elevation	1165 m	1232 m
Mean DBH (cm)	11.3	29.0
Analysis Period	2000	2002
Stand Age (90 th %tile)	23	89
Overstory LAI	0.89 m ² m ⁻²	2.96 m ² m ⁻²
Species Composition	Pipo	Pipo, Cade
Soil Porosity	Sandy Loam	Sandy Loam

Table 2.2. Site characteristics from Law *et al.* (2003). Species codes: Pipo, *Pinus ponderosa*; Cade, *Calocedrus decurrens*.

Figures

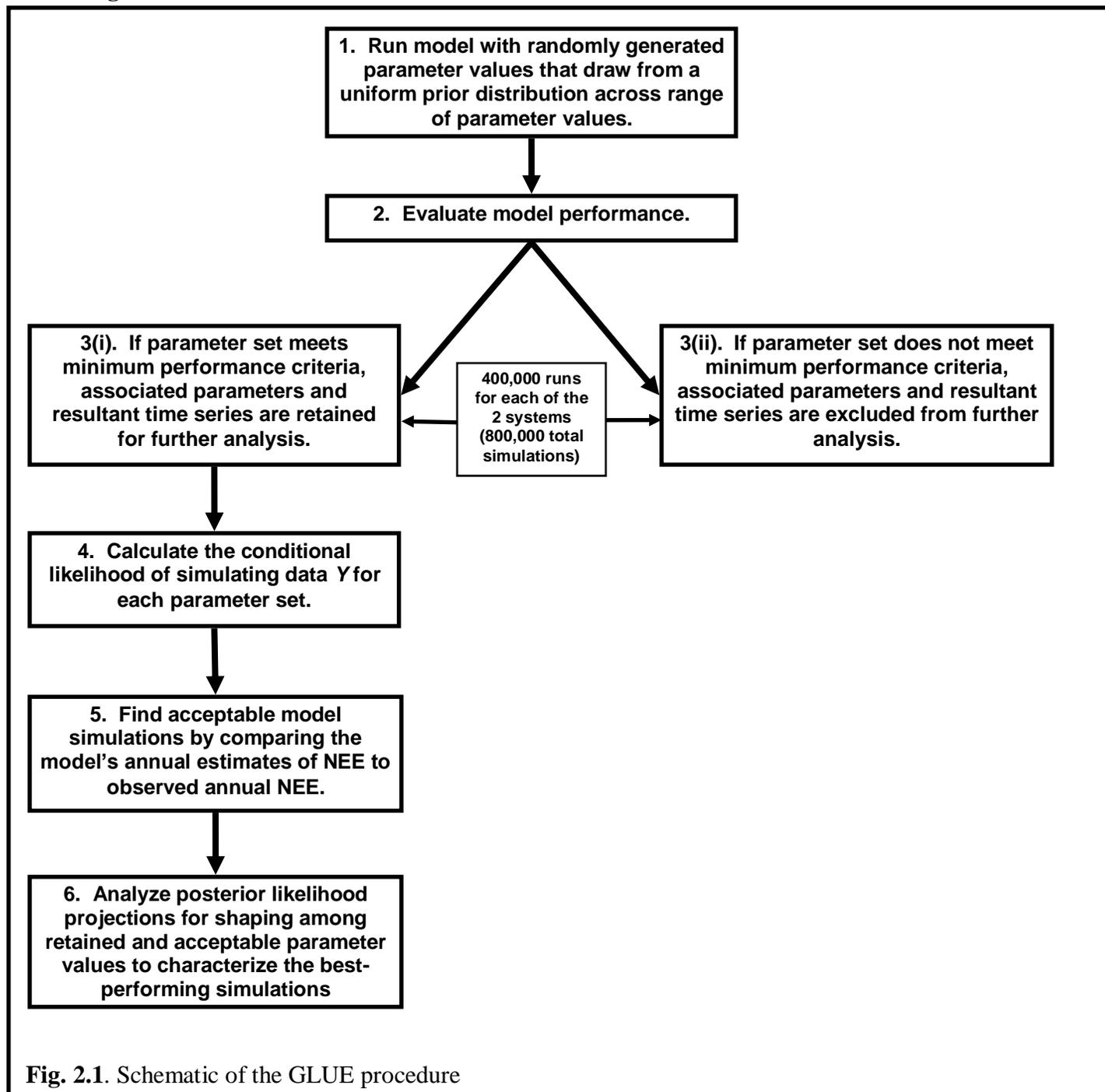


Fig. 2.1. Schematic of the GLUE procedure

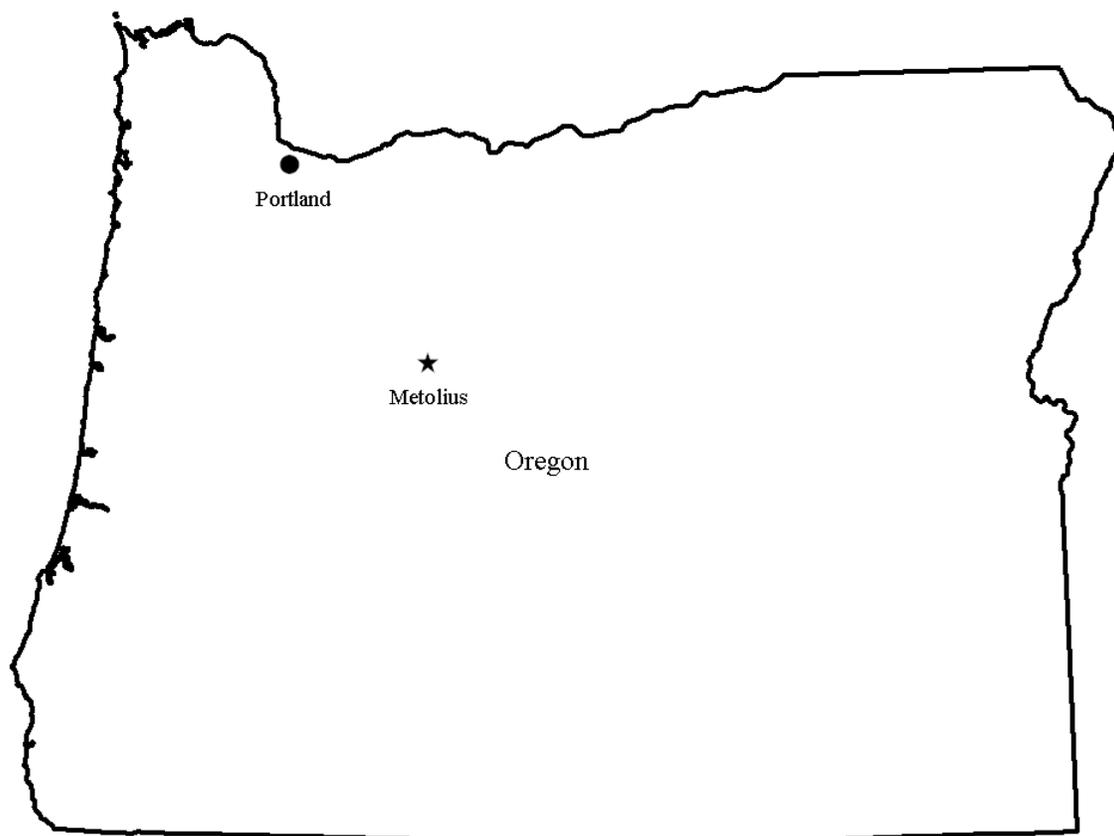


Fig. 2.2. Location of Metolius, Oregon.

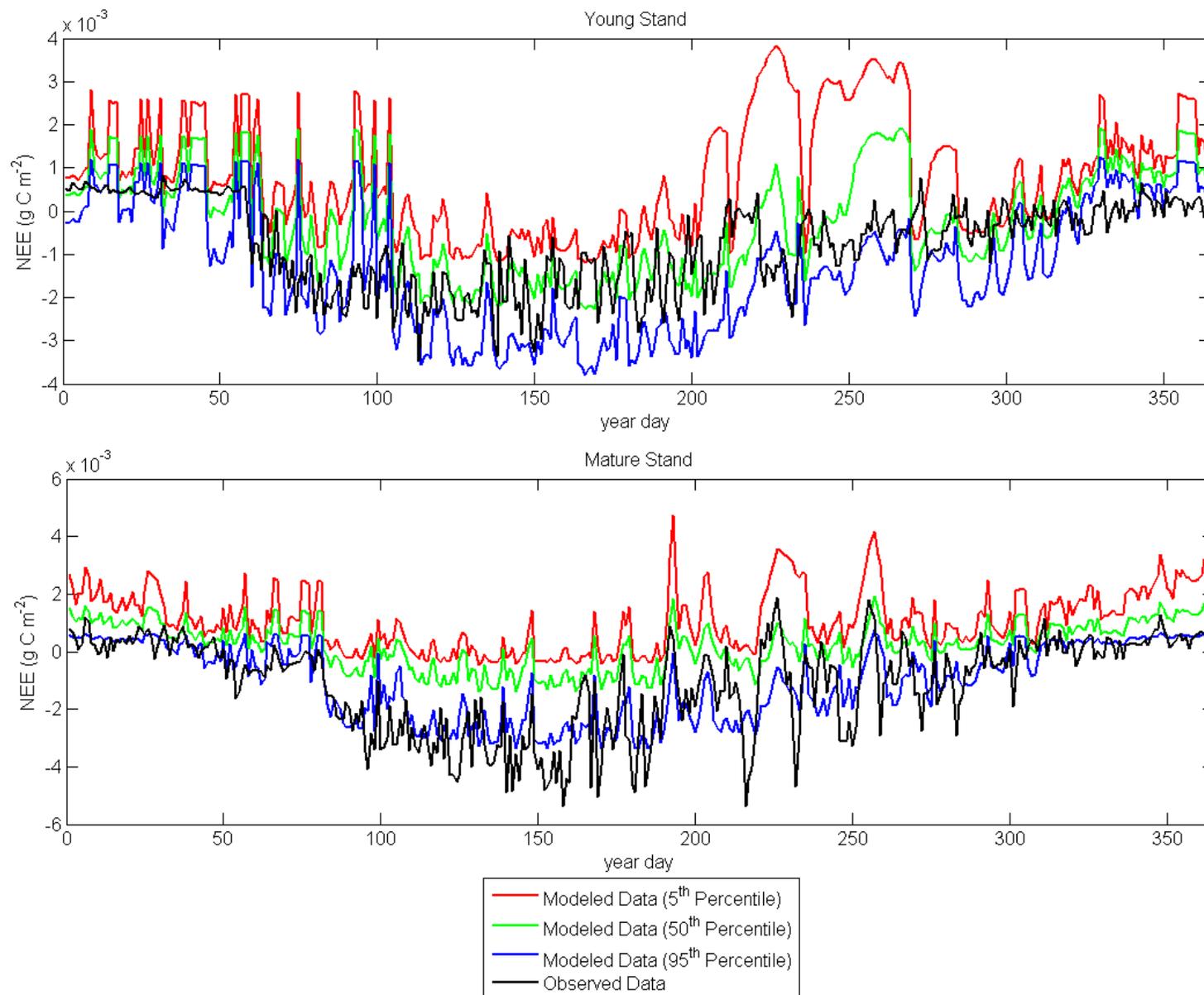


Fig. 2.3. Time series of cumulative distribution percentiles for daily NEE estimates of retained model runs in comparison with observed data.

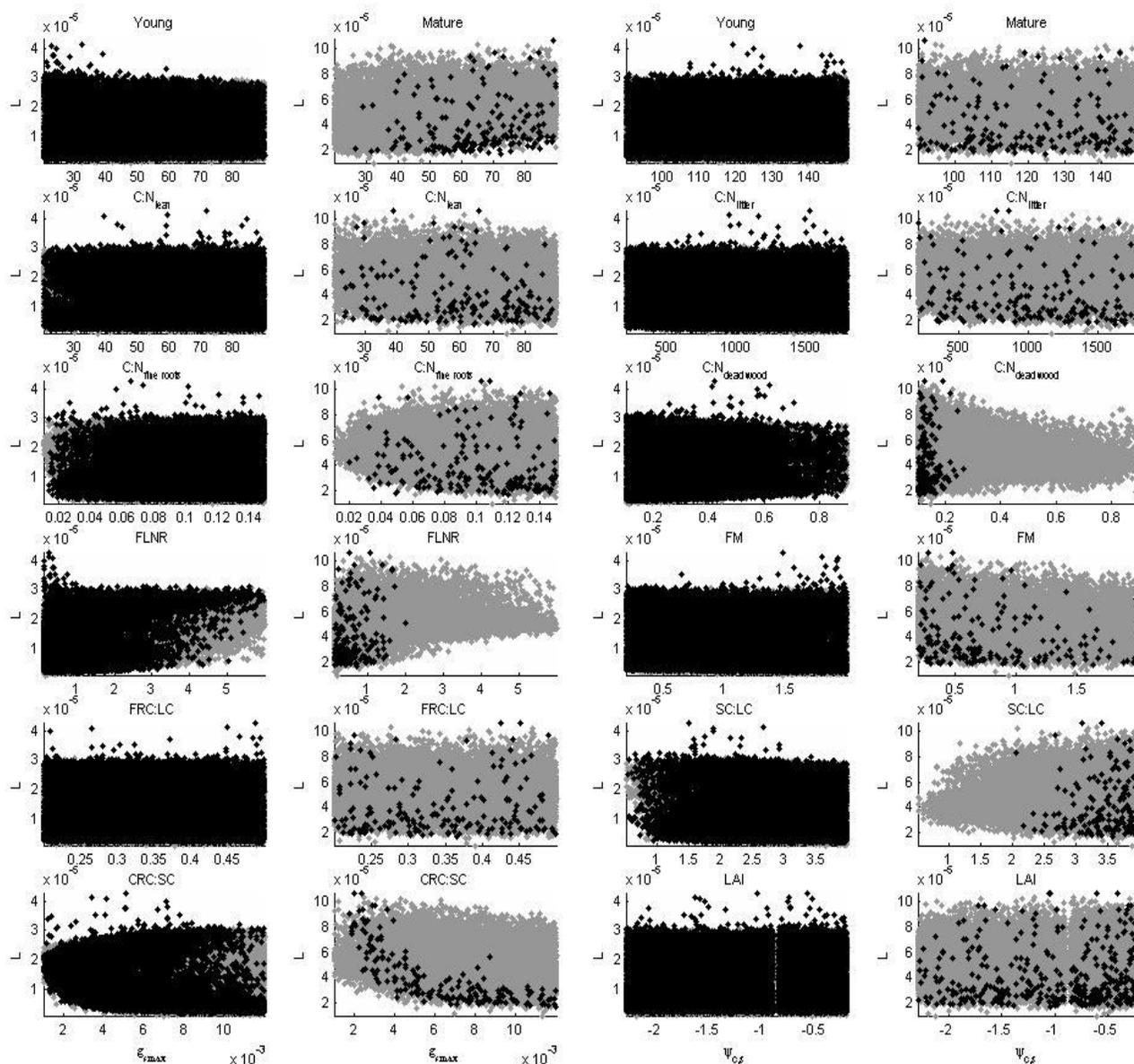


Fig. 2.4. Posterior likelihood (L) projections (from top left) of leaf C:N ratio ($C:N_{\text{leaf}}$), litter C:N ratio ($C:N_{\text{litter}}$), fine root C:N ratio ($C:N_{\text{fine root}}$), and dead wood C:N ratio ($C:N_{\text{dead wood}}$), fraction of leaf nitrogen in Rubisco (FLNR), foliage mortality (FM), new fine root C/new leaf C (FRC:LC), new stem C/new leaf C (SC:LC), and new coarse root C/new stem C (CSC:SC). Leaf area index-projected area basis (LAI), stomatal conductance (g_{smax}), and leaf water potential at the completion (Ψ_c) and start (Ψ_s) of a conductance reaction. Grey points represent retained parameter combinations and black points represent behavioral parameter combinations. All points represent the likelihood projection for a specific parameter in multidimensional parameter space.

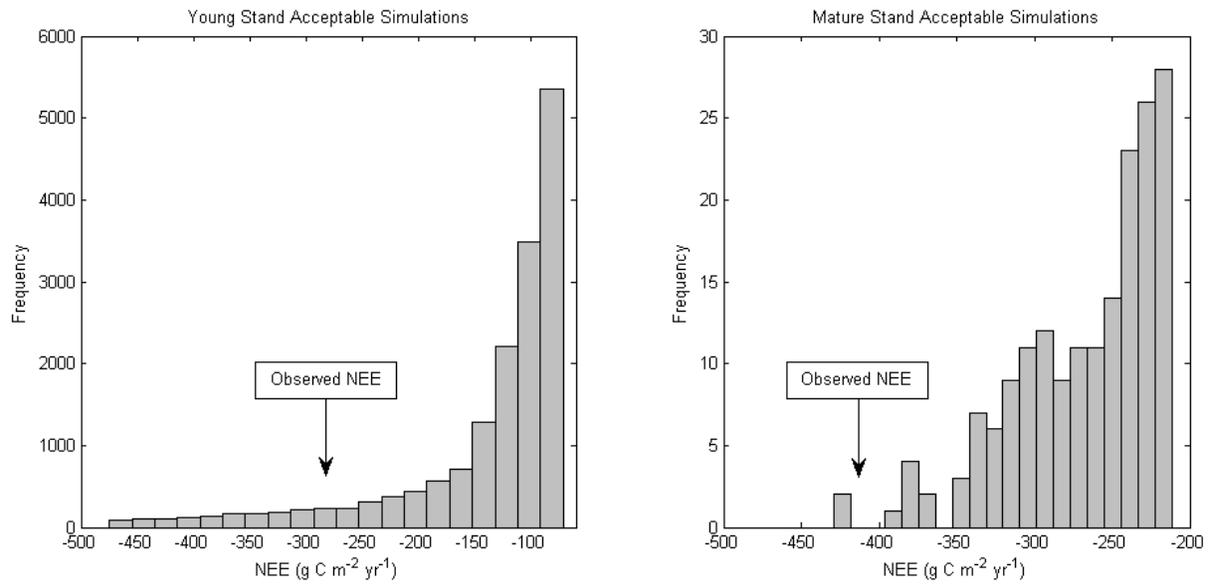


Fig. 2.5. Histograms of NEE estimates resulting from acceptable ($\pm 2\epsilon$) parameter values.

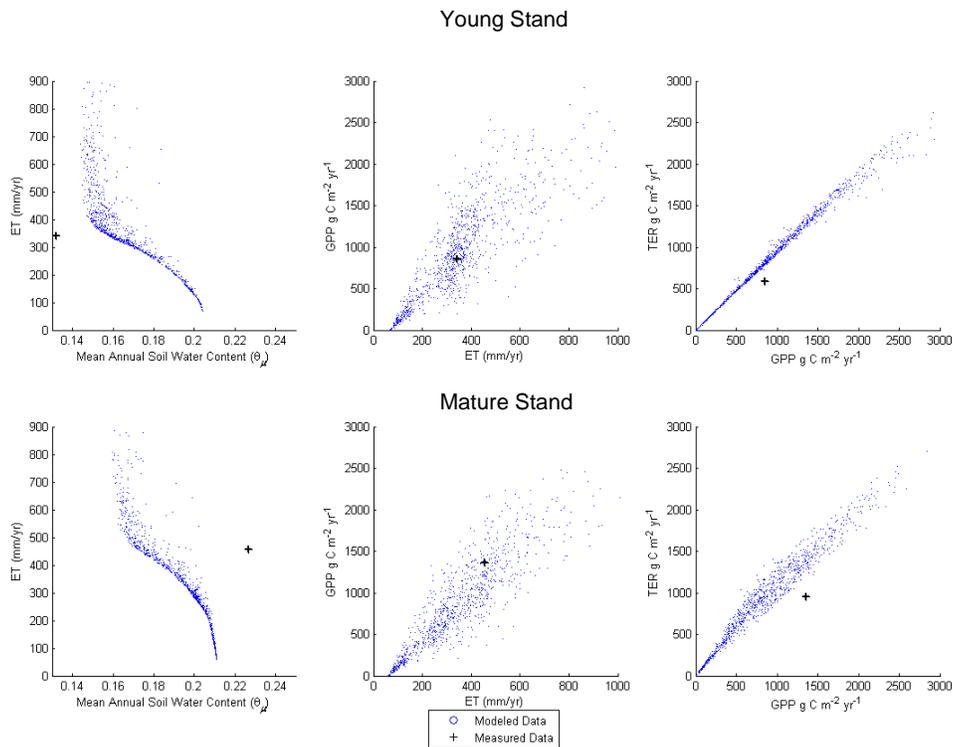


Figure 2.6. Scatterplots of the relationship between annual values for mean soil water content (θ_{μ}) and evapotranspiration (ET), evapotranspiration (ET) and gross primary production (GPP), and gross primary production (GPP) and ecosystem respiration (TER). A total of 5000 retained simulations are plotted. The negative relationship between mean annual soil water content and annual evapotranspiration indicates that higher evapotranspiration results in lower soil water content and vice versa.

CHAPTER 3

**FOREST FUEL REDUCTION ALTERS FIRE SEVERITY AND LONG-TERM
CARBON STORAGE IN THREE PACIFIC NORTHWEST ECOSYSTEMS**

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Abstract

Two forest management objectives being debated in the context of federally managed landscapes in the US Pacific Northwest involve a perceived trade-off between fire restoration and C sequestration. The former strategy would reduce fuel (and therefore C) that has accumulated through a century of fire suppression and exclusion that has led to extreme fire risk in some areas. The latter strategy would manage forests for enhanced C sequestration as a method of reducing atmospheric CO₂ and associated threats from global climate change. We explored the trade-off between these two strategies by employing a forest ecosystem simulation model, STANDCARB, to examine the effects of fuel reduction on fire severity and the resulting long-term C dynamics among three Pacific Northwest ecosystems: the east Cascades Ponderosa pine forests, the west Cascades Western hemlock–Douglas fir forests, and the Coast Range Western hemlock–Sitka spruce forests. Our simulations indicate that fuel reduction treatments in these ecosystems consistently reduced fire severity. However, reducing the fraction by which C is lost in a wildfire requires the removal of a much greater amount of C, since most of the C stored in forest biomass (stem wood, branches, coarse woody debris) remains unconsumed even by high-severity wildfires. For this reason, all of the fuel reduction treatments simulated for the west Cascades and Coast Range ecosystems as well as most of the treatments simulated for the east Cascades resulted in a reduced mean stand C storage. One suggested method of compensating for such losses in C storage is to utilize C harvested in fuel reduction treatments as biofuels. Our analysis indicates that this will not be an effective strategy in the west Cascades and Coast Range over the next 100 years. We suggest that forest management plans aimed solely at ameliorating increases

in atmospheric CO₂ should forego fuel reduction treatments in these ecosystems, with the possible exception of some east Cascades Ponderosa pine stands with uncharacteristic levels of understory fuel accumulation. Balancing a demand for maximal landscape C storage with the demand for reduced wildfire severity will likely require treatments to be applied strategically throughout the landscape rather than indiscriminately treating all stands.

Introduction

Forests of the US Pacific Northwest capture and store large amounts of atmospheric CO₂ and thus help mitigate the continuing climatic changes that result from extensive combustion of fossil fuels. However, wildfire is an integral component to these ecosystems and releases a substantial amount of CO₂ back to the atmosphere via biomass combustion. Some ecosystems have experienced an increase in the amount of CO₂ released due to a century-long policy of fire suppression that has led to increased levels of fuel build up, resulting in wildfires of uncharacteristic severity. Fuel reduction treatments have been proposed to reduce wildfire severity, but like wildfire, these treatments also reduce the C stored in forests. Our work examines the effects of fuel reduction on wildfire severity and long-term C storage to gauge the strength of the potential trade-off between managing forests for increased C storage and reduced wildfire severity.

Forests have long been referenced as a potential sink for atmospheric CO₂ (Vitousek 1991, Turner et al. 1995, Harmon et al. 1996, Harmon 2001, Smithwick et al. 2002, Pacala et al. 2004) and are credited with contributing to much of the current C sink in the coterminous United States (Pacala et al. 2001, Hurtt et al. 2002). This U.S. carbon

sink has been estimated to be between $0.30 - 0.58 \text{ Pg C y}^{-1}$ for the 1980's, of which between $0.17 \times 10^8 - 0.37 \text{ Pg C y}^{-1}$ has been attributed to accumulation by forest ecosystems (Pacala et al. 2001). While the presence of such a large sink has been valuable in mitigating global climate change, a substantial portion of it is due to the development of understory vegetation as result of a national policy of fire suppression (Pacala et al. 2001, Donovan and Brown 2007). Fire suppression, while capable of incurring short-term climate change mitigation benefits by promoting the capture and storage of atmospheric CO_2 by understory vegetation and dead fuels (Houghton et al. 2000, Tilman et al. 2000), has, in part, led to increased and often extreme fire risk in some forests, notably *Pinus ponderosa* forests (Moeur 2005, Donovan and Brown 2007).

Increased C storage usually results in an increased amount of C lost in a wildfire (Fahnestock and Agee 1983, Agee 1993). Many ecosystems show the effects of fire suppression (Schimel et al. 2001, Goodale et al. 2002, Taylor and Skinner 2003), and the potential effects of additional C storage on the severity of future wildfires is substantial. In the *Pinus ponderosa* forests of the east Cascades, for example, understory fuel development is thought to have propagated crown fires that have killed old-growth stands that are not normally subject to fires of high intensity (Moeur et al. 2005). Various fuel reduction treatments have been recommended for risk-prone forests, particularly a reduction in understory vegetation density, which can reduce the ladder fuels that promote such severe fires (Agee 2002, Brown et al. 2004, Agee and Skinner 2005). While a properly executed reduction in fuels could be successful in reducing forest fire severity and extent, such a treatment may be counterproductive to attempts at utilizing forests for the purpose of long-term C sequestration.

Pacific Northwest forests, particularly those that are on the west side of the Cascade mountain range, are adept at storing large amounts of C. Native long-lived conifers are able to maintain production during the rainy fall and winter months, thereby out-competing shorter-lived deciduous angiosperms with a lower biomass storage capacity (Waring and Franklin 1979). Total C storage potential, or upper bounds, of these ecosystems is estimated to be as high as 829.4 Mg C ha⁻¹ and 1127.0 Mg C ha⁻¹ for the western Cascades and Coast Range of Oregon, respectively (Smithwick et al. 2002). Of this high storage capacity for west Cascades and Coast Range forests, 432.8 Mg C ha⁻¹ and 466.3 Mg C ha⁻¹ are stored in aboveground biomass (Smithwick et al. 2002), a substantial amount of fuel for wildfires.

High amounts of wildfire-caused C loss often reflect high amounts of forest fuel availability prior to the onset of fire. Given the magnitude of such losses, it is clear that the effect of wildfire severity on long-term C storage is central to our understanding of the global C cycle. What is not clear is the extent to which repeated fuel removals that are intended to reduce wildfire severity will likewise reduce long-term total ecosystem C storage (TEC_{μ}). Fuel reduction treatments require the removal of woody and detrital materials to reduce future wildfire severity. Such treatments can be effective in reducing future wildfire severity, but they likewise involve a reduction in stand-level C storage. If repeated fuel reduction treatments decrease the mean total ecosystem C storage by a quantity that is greater than the difference between the wildfire-caused C loss in an untreated stand and the wildfire-caused C loss in a treated stand, the ecosystem will not have been effectively managed for maximal long-term C storage.

Our goal was to test the extent to which a reduction in forest fuels will affect fire severity and long-term C dynamics by employing a test of such dynamics at multi-century time scales. Our questions were as follows: 1) To what degree will reductions in fuel load result in decreases in C-stores at the stand level? 2) How much C must be removed to make a significant reduction in the amount of C lost in a wildfire? 3) Can forests be managed for both a reduction in fire severity and increased C sequestration, or are these goals mutually exclusive?

Methods

Model description

We conducted our study using an ecosystem simulation model, STANDCARB, that allows for the integration of many forest management practices as well as the ensuing gap dynamics that may result from such practices. STANDCARB is a forest ecosystem simulation model that acts as a hybrid between traditional single-life form ecosystem models and multi-life form gap models (Harmon and Marks 2002). The model integrates climate-driven growth and decomposition processes with species-specific rates of senescence and stochastic mortality while incorporating for the dynamics of inter- and intra-specific competition that characterize forest gap dynamics. Inter- and intra-specific competition dynamics are accounted for by modeling species-specific responses to solar radiation as a function of each species' light compensation point as well as the amount of solar radiation delineated through the forest canopy to each individual. By incorporating these processes the model can simulate successional changes in population structure and community composition without neglecting the

associated changes in ecosystem processes that result from species-specific rates of growth, senescence, mortality, and decomposition.

STANDCARB performs calculations on a monthly time step and can operate at a range of spatial scales by allowing a multi-cell grid to capture multiple spatial extents, as both the size of an individual cell and the number of cells in a given grid can be designated by the user. We used a 20 x 20 cell matrix for all simulations (400 cells total), with 15m x 15m cells for forests of the west Cascades and Coast Range and 12m x 12m cells for forests of the east Cascades. Each cell allows for interactions of 4 distinct vegetation layers, represented as upper canopy trees, lower canopy trees, a species-nonspecific shrub layer, and a species-nonspecific herb layer. Each respective vegetation layer can have up to 7 live pools, 8 detrital pools, and 3 stable C pools. For example, the upper and lower tree layers are comprised of 7 live pools: foliage, fine-roots, branches, sapwood, heartwood, coarse-roots, and heart-rot, all of which are transferred to a detrital pool following mortality. Dead wood is separated into snags and logs to capture the effects of spatial position on microclimate. After detrital materials have undergone significant decomposition they can contribute material to three increasingly decay-resistant, stable C pools: stable foliage, stable wood, and stable soil. Charcoal is created in both prescribed fires and wildfires and is thereafter placed in a separate pool with high decay resistance. Additional details on the STANDCARB model can be found in Appendix A.

Fire processes

We generated exponential random variables to assign the years of fire occurrence (*sensu* Van Wagner 1978) based on the literature estimates (see experimental design for

citations) of mean fire return intervals (MFRI) for different regions in the US Pacific Northwest. The cumulative distribution for our negative exponential function is given in equation (1) where X is a continuous random variable defined for all possible numbers x in the probability function P and λ represents the inverse of the expected time for a fire return interval given in equation (2).

$$P\{X \leq x\} = \int_0^x \lambda e^{-\lambda x} dx \quad (1)$$

where

$$E[X] = \frac{1}{\lambda} \quad (2)$$

Fire severities in each year generated by this function are cell-specific, as each cell is assigned a weighted fuel index calculated from fuel accumulation within that cell and the respective flammability of each fuel component, the latter of which is derived from estimates of wildfire-caused biomass consumption (see Fahnestock and Agee 1983, Agee 1993, Covington and Sackett 1984). Fires can increase (or decrease) in severity depending on how much the weighted fuel index a given cell exceeds (or falls short of) the fuel level thresholds for each fire severity class (T_{light} , T_{medium} , T_{high} , and T_{max}) and the probability values for the increase or decrease in fire severity (P_i and P_d). For example, while the natural fire severity of many stands of the west Cascades can be described as high severity, other stands of the west Cascades have a natural fire severity that can be best described as being of medium-severity (~60-80% overstory tree mortality) (Cissel et al. 1998). For these stands, medium-severity fires are scheduled to occur throughout the simulated stand and can increase to a high-severity fire depending on the extent to which the weighted fuel index in a cell exceeds the threshold for a high-severity fire, as greater

differences between the fuel index and the fire severity threshold will increase the chance of a change in fire severity. Conversely, medium-severity fires may decrease to a low-severity fire if the fuel index is sufficiently below the threshold for a medium-severity fire. High-severity fires are likely to become medium-severity fires if the weighted fuel index within a given cell falls sufficiently short of the threshold for a high-severity fire, and low-severity fires are likely to become medium-severity if the weighted fuel index in a given cell is sufficiently greater than the threshold for a medium-severity fire. Fuel level thresholds were set by monitoring fuel levels in a large series of simulation runs where fires were set at very short intervals to see how low fuel levels needed to be to create a significant decrease in expected fire severity. We note that, like fuel accumulation, the role of regional climate exerts significant influence on fire frequency and severity and that our model does not attempt to directly model these effects. We suspect that an attempt to model the highly complex role of regional climate data on fine scale fuel moisture, lightning-based fuel ignition, and wind-driven fire spread adds uncertainties into our model that might undermine the precision and applicability of our modeling exercise, and it was for that reason that we incorporated data from extensive fire history studies to approximate the dynamics of fire frequency and severity.

Final calculations for the expected stand fire severity $E[F_s]$ at each fire are performed as follows:

$$E[F_s] = \frac{100}{C} \sum_{i=1}^n c_i^{(l)} m_i^{(l)} + c_i^{(m)} m_i^{(m)} + c_i^{(h)} m_i^{(h)} \quad (3)$$

where C is the number of cells in the stand matrix and $c_i^{(l)}$, $c_i^{(m)}$, and $c_i^{(h)}$ are the number of cells with light, medium, and high-severity fires, and $m_i^{(l)}$, $m_i^{(m)}$, and

$m_i^{(h)}$ represent fixed mortality percentages for canopy tree species for light, medium, and high-severity fires, respectively. This calculation provides an approximation of the number of upper canopy trees killed in the fire. The resulting expected fire severity calculation $E[F_s]$ is represented on a scale from {0-100}, where a severity index of 100 indicates that all trees in the simulated stand were killed.

Our approach at modeling the effectiveness of fuel reduction treatments underscores an important trade-off between fuel reduction and long-term ecosystem C storage by incorporating the dynamics of snag creation and decomposition. Repeated fuel reduction treatments may result in a reduction in long-term C storage, but it is possible that if such treatments are effective in reducing tree mortality they may also offset some of the C losses that would be incurred from the decomposition of snags that would be created in a wildfire of higher severity. STANDCARB accounts for these dynamics by directly linking expected fire severity with a fuel accumulation index that can be altered by fuel reduction treatments while also incorporating the decomposition of snags as well as the time required for each snag to fall following mortality.

Total ecosystem C storage (TEC) is calculated by summing all components of C (live, dead, and stable) storage at each time step j for each replicate i . For each replicate ($i=1,2,\dots,5$) and for each period between fires ($x=1,2,\dots,P_i$), the mean total ecosystem C storage (TEC_{μ}) is calculated by averaging the yearly TEC values ($k=1,2,\dots,R_x$).

$$TEC_{\mu(i,x)} = \frac{1}{R} \sum_{k=1}^R TEC_{(i,x,k)}$$

By aggregating TEC_{μ} values in this manner permits the number of TEC_{μ} values to be the

same as the number of $E[F_s]$ values, permitting a PerMANOVA analysis to be performed on $E[F_s]$ and TEC_{μ} .

Fuel Reduction Processes

STANDCARB's fire module allows for scheduled prescribed fires of a given severity (light, medium, high) to be simulated in addition to the non-scheduled wildfires generated from the aforementioned exponential random variable function. In addition to simulating the prescribed fire method of fuel reduction, STANDCARB has a harvest module that permits cell-by-cell harvest of trees in either the upper or lower canopy. This module allows the user to simulate understory removal or overstory thinning treatments on a cell-by-cell basis. Harvested materials can be left in the cell as detritus following cutting or can be removed from the forest, allowing the user to incorporate the residual biomass that results from harvesting practices. STANDCARB can also simulate the harvest of dead salvageable materials such as logs or snags that have not decomposed beyond the point of being salvageable.

Site Descriptions

We chose the *Pinus ponderosa* stands of the Pringle Falls Experimental Forest as our representative for east Cascades forests (Youngblood et al. 2004). Topography in the east Cascades consists of gentle slopes, with soils derived from aurally deposited dacite pumice. The *Tsuga heterophylla-Pseudotsuga menziesii* stands of the HJ Andrews Experimental Forest were chosen as our representative of west Cascades forests (Greenland 1994). Topography in the west Cascades consists of slope gradients that range from 20 to 60% with soils that are deep, well-drained dystrochrepts. The *Tsuga heterophylla-Picea sitchensis* stands of the Cascade Head Experimental Forest were

chosen as our representative of Coast Range forests. We note that most of the Oregon Coast Range is actually comprised of *Tsuga heterophylla*-*Pseudotsuga menziesii* community types, similar to much of the west Cascades. *Tsuga heterophylla*-*Picea sitchensis* communities occupy a narrow strip near the coast, due to their higher tolerance for salt spray, higher soil-moisture optimum, and lower tolerance for drought compared to forests dominated by *Pseudotsuga menziesii* (Minore 1979), and we incorporate this region in order to gain insight into this highly productive ecosystem. Topography in the Cascade Head Experimental Forest consists of slope gradients of ~10% with soils that are silt loams to silt clay loams derived from marine silt stones. Site locations are shown in Figure 3.1 and are located within three of the physiographic regions of Oregon and Washington as designated by Franklin and Dyrness (1988). Additional site data are shown in Table 3.1.

Experimental Design

The effectiveness of forest fuel reduction treatments is often, if not always, inversely related to the time since their implementation. For this reason, our experiment incorporated a factorial blocking design where each ecosystem was subjected to four different frequencies of each fuel reduction treatment. We also recognize the fact that fire return intervals can exhibit substantial variation within a single watershed, particularly those with a high degree of topographic complexity (Agee 1993, Cissel et al. 1999), so we examined two likely fire regimes for each ecosystem. Historic fire return intervals may become unreliable predictors of future fire intervals (Westerling et al. 2006), thus ascertaining the differences in TEC_{μ} that result from two fire regimes might be a useful

metric in gauging C dynamics resulting from fire regimes that may be further altered as a result of continued global climate change.

We based the expected fire return time in equations (1,2) on historical fire data for our forests on the following studies: Bork (1985) estimated a mean fire return interval of 16 years for the east Cascades *Pinus ponderosa* forests, and we also considered a mean fire return interval of 8 years for this system. Cissel et al. (1999) reported mean fire return intervals of 143 and 231 for forests of medium- and high-severity (stand-replacing) fire regimes, respectively, among the *Tsuga heterophylla-Pseudotsuga menziesii* forests of the west Cascades. Less is known about the fire history of the Coast Range, which consists of *Tsuga heterophylla-Pseudotsuga menziesii* communities in the interior and *Tsuga heterophylla-Picea sitchensis* communities occupying a narrow edge of land along the Oregon Coast. Work by Impara (1997) in the interior region of the Coast Range suggested a natural fire return (expected fire return time) interval of 271 years in the *Tsuga heterophylla-Pseudotsuga menziesii* zone and Long et al. (1998) reported lake-derived charcoal-sediment based estimates of mean fire return interval for the Coast Range forests to be fairly similar, at 230 years. However, the *Tsuga heterophylla-Picea sitchensis* community type dominant in our study area of the Cascade Head Experimental Forest has little resistance to fire and thus rarely provides a dendrochronological record. We estimated a mean fire return interval of 250 years as one fire return interval for a high-severity fire, derived from interior Coast Range natural fire return interval estimates, and also included another high-severity fire regime with a 500 year mean fire return interval in our analysis.

It is important to note that while the forests of the east Cascades exhibit a significant and visible legacy of effects from a policy of fire suppression, many of the mean fire return intervals for the forests of the west Cascades and Coast Range exceed the period of fire suppression (approximately 100 years), and these forests in the west Cascades and Coast Range will not necessarily exhibit uncharacteristic levels of fuel accumulation (Brown et al. 2004). However, the potential lack of an uncharacteristic amount of fuel accumulation does not necessarily preclude these forests from future fuel reduction treatments or harvesting, thus we have included these possibilities in our analysis. The frequencies at which fuel reduction treatments are applied were designed to be reflective of literature-derived estimates of each ecosystem's mean fire return intervals, since forest management agencies are urged to perform fuel reduction treatments at a frequency reflective of the fire regimes and ecosystem-specific fuel levels (Franklin and Agee 2003, Dellasala et al. 2004). Treatment frequencies for the Coast Range and west Cascades were 100, 50, 25 years, plus an untreated control group, while treatment frequencies in the east Cascades were 25, 10, and 5 years, and an untreated control group.

We incorporated six different types of fuel reduction treatments largely based on those outlined in Agee (2002), Hessburg and Agee (2003), and Agee and Skinner (2005). Treatments 2-5 were taken directly from the authors' recommendations in these publications, treatment 1 was derived from the same principles used to formulate those recommendations, and treatment 6, clear-cutting, was not recommended in these publications but was incorporated into our analysis because it is a common practice in many Pacific Northwest forests. Treatments 1-4 were applied to all ecosystems, while

treatments 5 and 6 were applied only to the west Cascades and Coast Range forests, as such treatments would be unrealistic at the treatment intervals necessary to reduce fire severity in the high-frequency fire regimes of the east Cascades *Pinus ponderosa* forests. Note that these treatments and combinations thereof are not necessarily utilized in each and every ecosystem. Managers of forests on the Oregon Coast, for example, would be unlikely to use prescribed fire as a fuel reduction technique. Our experimental design simply represents the range of all possible treatments that can be utilized for fuel reduction and is applied to all ecosystems purely for the sake of consistency.

1) Salvage Logging (SL) - The removal of large woody surface fuels limits the flame length of a wildfire that might enter the stand. Our method of ground fuel reduction entailed a removal of 75% of salvageable large woody materials in the stand. Our definition of salvage logging includes both standing and downed salvageable materials (*sensu* Lindenmayer and Noss, 2006).

2) Understory Removal (UR) - Increasing the distance from surface fuels to flammable crown fuels will reduce the probability of canopy ignition. This objective can be accomplished through pruning, prescribed fire, or the removal of small trees. We simulated this treatment in STANDCARB by removing lower canopy trees in all cells.

3) Prescribed Fire (PF) - The reduction of surface fuels limits the flame length of a wildfire that might enter the stand. In the field, this is done by removing fuel through prescribed fire or pile burning, both of which reduce the potential magnitude of a wildfire by making it more difficult for a surface fire to ignite the canopy (Scott and Reinhardt 2001). We implemented this treatment in STANDCARB by simulating a prescribed fire at low-severity for all cells.

4) *Understory Removal and Prescribed Fire* (UR+PF) -This treatment is a combination of treatments two and three, where lower canopy trees were removed (treatment two) before a prescribed fire (treatment three) the following year for all cells.

5) *Understory Removal, Overstory Thinning, and Prescribed Fire* (UR+OT+PF) - A reduction in crown density by thinning overstory trees can make crown fire spread less probable (Agee 2005) and can reduce potential fuels by decreasing the amount of biomass available for accumulation on the forest floor. Some have suggested that such a treatment will be effective only if used on conjunction with UR and PF (Perry et al. 2004). We simulated this treatment in STANDCARB by removing all lower canopy trees (treatment two), removing upper canopy trees in 50% of the cells, and then setting a prescribed fire (treatment three) the following year. This treatment was excluded from the east Cascades forests because it would be unrealistic to apply it at intervals commensurate with the high-frequency fires endemic to that ecosystem.

6) *Understory Removal, Overstory Removal, and Prescribed Fire (Clear-Cutting)* (UR+OR+PF) - Clear-cutting is a common silvicultural practice in the forests of the Pacific Northwest, notably on private lands in the Oregon Coast Range (Hobbs et al. 2002), and we included it in our analysis for two ecosystems (west Cascades and Coast Range) simply to gain insight into the effects of this practice on long-term C storage and wildfire severity. We simulated clear-cutting in STANDCARB by removing all upper and lower canopy trees, followed by a prescribed burn the following year. This treatment was excluded from the east Cascades forests because it would be unrealistic to apply it at intervals commensurate with the high-frequency fires endemic to that ecosystem.

7) *Control group* – Control groups had no treatments performed on them. The only disturbances in these simulations were the same wildfires that occurred in every other simulation with the same MFRI.

In sum, our east Cascades analysis tested the effects of four fuel reduction treatment types, four treatment frequencies, including one control group, and two site mean fire return intervals (MFRI = 8, MFRI =16). Our analysis of west Cascades and Coast Range forests tested the effects of six fuel reduction treatment types, four treatment frequencies, including one control group, and two site mean fire return intervals (MFRI = 143, MFRI = 230 for the west Cascades, MFRI = 250, MFRI = 500 for the Coast Range) on expected fire severity and long-term C dynamics. This design resulted in 32 combinations of treatment types for the east Cascades and 48 combinations of treatment types and frequencies for each fire regime in the west Cascades and Coast Range with each treatment combination in each ecosystem replicated 5 times.

Biofuel Considerations

Future increases in the efficiency of producing biofuels from woody materials may reduce potential trade-offs between managing forests for increased C storage and reduced wildfire severity. Much research is currently underway in the area of lignocellulase-based (as opposed to sugar or corn-based) biofuels (Schubert 2006). If this area of research yields efficient methods of utilizing woody materials directly as an energy source or indirectly by converting them into biofuels such as ethanol, fuels removed from the forest could be utilized as an energy source and thus act as a substitute for fossil fuels by adding only atmosphere-derived CO₂ back to the atmosphere. However, the conversion of removed forest biomass into biofuels will only be a useful

method of offsetting fossil fuel emissions if the amount of C stored in an unmanaged forest is less than the sum of managed stand TEC_{μ} and the amount of fossil fuel emissions averted by converting removed forest biomass from a stand of identical size into biofuels over the time period considered. We performed an analysis on the extent to which fossil fuel CO_2 emissions can be avoided if we were to use harvested biomass directly for fuel or indirectly for ethanol production. We recognize that many variables need to be considered when calculating the conversion efficiencies of biomass to biofuels, such as the amount of energy required to harvest the materials, inefficiencies in the industrial conversion process, and the differences in efficiencies of various energy sources that exist even after differences in potential energy are accounted for. Rather than attempt to predict the energy expended to harvest the materials, the future of the efficiency of the industrial conversion process, and differences in energy efficiencies, we simply estimated the maximum possible conversion efficiency that can be achieved, given the energy content of these materials. The following procedure was used to estimate the extent to which fossil fuel CO_2 emissions can be avoided by substituting harvested biofuels as an energy source:

- 1) Estimate the mean annual biomass removal that results from intensive fuel reduction treatments.
- 2) Calculate the ratio of the amount of potential energy per unit C emissions for biofuels (both woody and ethanol) to the amount of energy per unit C emissions for fossil fuels.

- 3) Multiply the potential energy ratios by the mean annual quantity of biomass harvested to calculate the mean annual C offset by each biofuel type for each forest.
- 4) Calculate the number of years necessary for biofuels production to result in an offset of fossil fuel C emissions. This procedure was performed for two land-use histories: managed second-growth forests and old-growth forests converted to managed second-growth forests.

Calculations for each ecosystem are shown in Appendix B.

Simulation Spin Up

STANDCARB was calibrated to standardized silvicultural volume tables for Pacific Northwest stands. We then calibrated it to permanent study plot data from three experimental forests in the region (Figure 3.1) to incorporate fuel legacies, which were taken from a 600 year spin-up simulation with fire occurrences generated from the exponential distribution in equation (1) where λ was based on each ecosystem's mean fire return interval. Spin-up simulations were run prior to the initiation of each series of fuel reduction treatments, and simulations were run for a total of 800 years for forests of the east Cascades and a total of 1500 years for simulations of the west Cascades and Coast Range.

Data Analysis

We employed a nonparametric multivariate analysis of variance, PerMANOVA (Anderson 2001), to test group-level differences in the effects of fuel reduction frequency and type on mean total ecosystem C storage and expected fire severity. PerMANOVA employs a test statistic for the F ratio that is similar to that of an ANOVA calculated

using sum of squares, but unlike an ANOVA, PerMANOVA calculates sums of squares from distances among data points rather than from differences from the mean.

PerMANOVA was used instead of a standard MANOVA because it was highly unlikely that our data would meet the assumptions of a parametric MANOVA. PerMANOVA analysis treated fuel reduction treatment type and treatment frequency as fixed factors within each respective fire regime for each ecosystem simulated. The null hypothesis of no treatment effect for different combinations of these factors on TEC_{μ} and $E[F_s]$ was tested by permuting the data into randomly assigned sample units for each combination of factors so that the number of replicates within each factor combination were fixed. Each of our twelve PerMANOVA tests incorporated 10,000 permutations using a Euclidian distance metric, and multiple pairwise comparison testing for differences among treatment types and treatment frequencies was performed when significant differences were detected (i.e., $P < 0.05$).

Results

Results of the PerMANOVA tests indicate that mean expected fire severity ($E[F_s]$) and mean total ecosystem C storage (TEC_{μ}) were significantly affected by fuel reduction type ($P < 0.0001$), frequency ($P < 0.0001$), and interactions between type and frequency ($P < 0.0001$) in all three ecosystems. These results were significant for type, frequency, and interaction effects even when clear-cutting was excluded from the analysis for the west Cascades and Coast Range simulations, just as it was *a priori* for simulations of the east Cascades. When the PerMANOVA was performed on only one of our response variables ($E[F_s]$ or TEC_{μ}), groupwise comparisons of effects of treatment type showed that the most significant effects of treatment and frequency were related to

TEC_{μ} . TEC_{μ} was strongly affected by treatment frequency for each fire regime in each ecosystem ($P < 0.0001$) and consistently showed an inverse relationship to the quantity of C removed in a given fuel reduction treatment and was thus highly related to treatment type. $E[F_s]$, similar to TEC_{μ} , showed significant relationships with treatment frequency for all three ecosystems ($P < 0.0001$), with statistically significant differences among most treatment types. Boxplots of TEC_{μ} and $E[F_s]$ for each treatment type in each fire regime for each ecosystem are shown in Appendix C.

Fuel reduction treatments in east Cascades simulations reduced TEC_{μ} with the exception of one treatment type: UR treatments (see Table 3.2. for acronym descriptions) in these systems occasionally resulted in additional C storage compared to the control group. These differences were very small (0.6-1.2% increase in TEC_{μ}) but statistically significant (Student's Paired T-Test, $P < 0.05$) for the treatment return interval of 10 years in the light fire severity regime #1 (MFRI = 8 years) and for all treatment return intervals in light fire severity regime #2 (MFRI = 16 years). The fuel reduction treatment that reduced TEC_{μ} the least was SL, which, depending on treatment frequency and fire regime, stored between 93-98% of the control group, indicating that there was little salvageable material. UR+PF, depending on treatment frequency and fire regime, resulted in the largest reduction of TEC_{μ} in east Cascades forests, storing between 69-93% of the control group.

Simulations of west Cascades and Coast Range forests showed a decrease in C storage for all treatment types and frequencies. Fuel reduction treatments with the smallest effect on TEC_{μ} were either SL or UR, which were nearly the same in effect. The treatment that most reduced TEC_{μ} was UR+OT+PF. Depending on treatment frequency

and fire regime, this treatment resulted in C storage of between 50-82% of the control group for the west Cascades, and between 65-88% of the control group for the Coast Range. Simulations with clear-cutting (UR+OR+PF), depending on application frequency and fire regime, resulted in C storage that was between 22-58% of the control group for the west Cascades and between 44-87% of the control group for the Coast Range.

Similar to TEC_{μ} , $E[F_s]$ was significantly affected by fuel reduction treatments. Fuel reduction treatments were effective in reducing $E[F_s]$ for all simulations. UR treatments had the smallest effect on $E[F_s]$ in the east Cascades simulations and $E[F_s]$ in the east Cascades simulations was most affected by combined UR+PF treatments applied every 5 years, which reduced $E[F_s]$ by an average of 6.01 units (units range from 0-100, see equation 3) for stands with an MFRI=8 and by 11.08 units for stands with an MFRI=16. In the west Cascades and Coast Range, $E[F_s]$ was least affected by UR treatments, similar to the east Cascades simulations. The most substantial reductions in $E[F_s]$ were exhibited by treatments that removed overstory as well as understory trees, as in treatments UR+OT+PF and UR+OR+PF. In the west Cascades simulations, depending on treatment frequency, $E[F_s]$ was reduced by an average of 11.72-15.68 units where the MFRI=143 and by an average of 3.92-26.42 units where the MFRI=230 when UR+OT+PF was applied. When UR+OT+PF was applied to the Coast Range, $E[F_s]$ was reduced by an average of 7.06-23.72 units where the MFRI=250 and by an average of 1.95-20.62 units where the MFRI=500, depending on treatment frequency. Some UR+OR+PF treatments, when applied at a frequency of 25 years, resulted in $E[F_s]$ that was higher than that seen in UR+OT+PF in spite of lower TEC_{μ} in UR+OT+PF. A result

such as this is most likely due to an increased presence of lower canopy tree fuels as a consequence of the increased lower stratum light availability that follows a clear-cut, as lower canopy tree fuels are among the highest weighted fuels in our simulated stands.

Modeled estimates of $E[F_s]$ were reflective of the mean amounts of C lost in a wildfire (\bar{C}_{WF}). \bar{C}_{WF} was lower in the stands simulated with fuel reduction treatments compared to the control groups, with the exception of the east Cascades stands subjected to understory removal. Reductions in the amount of C lost in a wildfire, depending on treatment type and frequency, were as much as 50% in the east Cascades, 57% in the west Cascades, and 50% in the Coast Range. In the east Cascades simulations, amounts lost in wildfires were inversely related to the amounts of C removed in an average fire return interval for each ecosystem (Figure 3.2), except for the Light Fire Regime #1 (MFRI=8 years). Simulations in this fire regime revealed a slightly increasing amount of C lost in wildfires with increasing amounts removed, though amounts removed were nonetheless larger than the amounts lost in a typical wildfire.

Biofuels

Biofuels cannot offset the reductions in TEC_μ resulting from fuel reduction, at least not over the next 100 years. For example, our simulation results suggest that an undisturbed Coast Range *Tsuga heterophylla*-*Picea sitchensis* stand (where MFRI=500 years) has a TEC_μ of 1089 Mg C ha⁻¹. By contrast, a Coast Range stand that is subjected to UR+OT+PF every 25 years has a TEC_μ of 757.30 Mg C ha⁻¹. Over a typical fire return interval of 450 years (estimated MFRI was 500 years, MFRI generated from the model was 450 years) this stand has 1107 Mg C ha⁻¹ removed, a forest fuel/biomass production of 2.46 Mg C ha⁻¹ year⁻¹, which amounts to emissions of 1.92 Mg C ha⁻¹ year⁻¹ and 0.96

Mg C ha⁻¹ year⁻¹ that can be avoided by substituting biomass and ethanol, respectively, for fossil fuels (see calculations in Appendix B). This means that it would take 169 years for C offsets via solid woody biofuels and 339 years for C offsets via ethanol production before ecosystem processes result in net C storage offsets (see Figure 3.3). Converting Coast Range old-growth forest to second-growth forest reduces the amount of time required for atmospheric C offsets to 34 years for biomass and 201 years for ethanol, and like all other biofuel calculations in our analysis, these are assuming a perfect conversion of potential energies. West Cascades *Tsuga heterophylla*-*Pseudotsuga menziesii* ecosystems (where MFRI=230 years) that are subjected to UR+OT+PF every 25 years would require 228 years for C offsets using biomass as an offset of fossil fuel derived C and 459 years using ethanol. Converting west Cascades old-growth forest to second-growth forest reduces the amount of time required for atmospheric C offsets to 107 years for biomass fuels and 338 years for ethanol. Simulations of east Cascades *Pinus ponderosa* ecosystems had cases where stands treated with UR stored more C than control stands, implying that there is little or no trade-off in managing stands of the east Cascades for both fuel reduction and long-term C storage.

Discussion

We employed an ecosystem simulation model, STANDCARB, to examine the effects of fuel reduction on expected fire severity and long term C dynamics in three Pacific Northwest ecosystems: the *Pinus ponderosa* forests of the east Cascades, the *Tsuga heterophylla*-*Pseudotsuga menziesii* forests of the west Cascades, and the *Tsuga heterophylla*-*Picea sitchensis* forests of the Coast Range. Our fuel reduction treatments for east Cascades forests included salvage logging, understory removal, prescribed fire,

and a combination of understory removal and prescribed fire. West Cascades and Coast Range simulations included these treatments as well as a combination of understory removal, overstory thinning, and prescribed fire. We also examined the effects of clear-cutting followed by prescribed fire on expected fire severity and long-term C storage in the west Cascades and Coast Range.

Our results suggest that fuel reduction treatments can be effective in reducing fire severity, a conclusion that is shared by some field (Stephens 1998, Pollet and Omi 2002, Stephens and Moghaddas 2005) and modeling studies (Fulé et al. 2001). However, fuel removal almost always reduces C storage more than the additional C that a stand is able to store when made more resistant to wildfire. Leaves and leaf litter can and do have the majority of their biomass consumed in a high-severity wildfire, but most of the C stored in forest biomass (stem wood, branches, coarse woody debris) remains unconsumed even by high-severity wildfires. For this reason, it is inefficient to remove large amounts of biomass to reduce the fraction by which other biomass components are consumed via combustion. Fuel reduction treatments that involve a removal of overstory biomass are, perhaps unsurprisingly, the most inefficient methods of reducing wildfire-related C losses because they remove large amounts of C for only a marginal reduction in expected fire severity. For example, total biomass removal from fuel reduction treatments over the course of a high-severity fire return interval (MFRI=230) in the west Cascades could exceed 500 Mg C ha⁻¹ while reducing wildfire-related forest biomass losses by only ~70 Mg C ha⁻¹ in a given fire (Figure 3.2). Coast Range forests could have as much as 2000 Mg C ha⁻¹ removed over the course of an average fire return interval (MFRI = 500), only to reduce wildfire-related biomass combustion by ~80 Mg C ha⁻¹ (Figure 3.2).

East Cascades simulations also showed a trend of decreasing $E[F_s]$ with increasing biomass removal, though a higher TEC_μ was seen in some understory removal treatments compared to control groups. We believe that the removal of highly flammable understory vegetation led to a reduction in overall fire severity that consequently lowered overall biomass combustion, thereby allowing increased overall C storage. Such a result may be indicative of actual behavior under field conditions, but the very low magnitude of the differences between the treated groups and the control group (0.6%-1.2%) suggests caution in assuming that understory removal in this or any ecosystem can be effective in actually increasing long term C storage. Furthermore, we recognize that the statistically significant differences between the treated and control groups are likely to overestimate the significance of the differences between groups that would occur in the field, as the differences we are detecting are modeled differences rather than differences in field-based estimates. Field-based estimates are more likely to exhibit higher inter- and intra-site variation than modeled estimates, even when modeled estimates incorporate stochastic processes, such as those in STANDCARB. Our general findings, however, are nonetheless consistent with many of the trends revealed by prior field-based research on the effects of fuel reduction on C storage (Tilman et al. 2000), though differences between modeled and field-based estimates are also undoubtedly apparent throughout other comparisons of treated and control stands in our study.

We note an additional difference that may exist between our modeled data and field conditions. Our study was meant to ascertain the long term average C storage (TEC_μ) and expected fire severities ($E[F_s]$) for different fuel reduction treatment types and application frequencies, a goal not to be confused with an assessment of exactly what

treatments should be applied at the landscape level in the near future. Such a goal would require site-specific data on the patterns of fuel accumulation that have occurred in lieu of the policies and patterns of fire suppression that have been enacted in the forests of the Coast Range, west Cascades, and east Cascades for over a century. We did not incorporate the highly variable effects of a century-long policy of fire suppression on these ecosystems, as we know of no way to account for such effects in a way that can be usefully extrapolated for all stands in the landscape. *Pinus ponderosa* forests may exhibit the greatest amount of variability in this respect, as they are among the ecosystems that have been most significantly altered as a result of fire suppression (Veblen et al. 2000, Schoennagel et al. 2004, Moeur et al. 2005). Furthermore, additional differences may be present in our estimates of soil C storage for the east Cascades. Our estimates of soil C storage match up very closely with current estimates from the Pringle Falls Experimental Forest, but it is unclear how much our estimates would differ under different fuel reduction treatment types and frequencies. Many understory community types exist in east Cascades *Pinus ponderosa* forests (i.e. *Festuca idahoensis*, *Purshia tridentata*, *Agropyron spicatum*, *Stipa comata*, *Physocarpus malvaceus*, and *Symphoricarpos albus* communities) (Franklin and Dyrness 1988) and an alteration of these communities may result from fuel reduction treatments such as understory removal or prescribed fire, leading to a change in the amount and composition of decomposing materials, which can influence long-term belowground C storage (Wardle 2002). Furthermore, there may be an increase in soil C storage resulting from the addition of charcoal to the soil C pool, whether from prescribed fire or wildfire (DeLuca and Aplet 2008).

By contrast, ecosystems with lengthy fire return intervals such as those of the west Cascades and Coast Range may not be strongly altered by such a policy, as many stands would not have accumulated uncharacteristic levels of fuel during a time of fire suppression that is substantially less than the mean fire return intervals for these systems. Forests such as these may actually have little or no need for fuel reduction due to their lengthy fire return intervals. Furthermore, fire severity in many forests may be more a function of severe weather events rather than fuel accumulation (Bessie and Johnson 1995, Schoennagel et al. 2004, Brown et al. 2004). Thus, the application of fuel reduction treatments such as understory removal is thought to be unnecessary in such forests and may provide only limited effectiveness (Agee and Huff 1986, Brown et al. 2004). Our results provide additional support for this notion, as they show a minimal effect of understory removal on expected fire severity in these forests, and if in fact climate has far stronger control over fire severity in these forests than fuel abundance, then the small reductions in expected fire severity that we have modeled for these fuel reduction treatments may be even smaller in reality.

We also note that the extent to which fuel reductions in these forests can result in a reduction in fire severity during the extreme climate conditions that lead to broad scale catastrophic wildfires may be different from the effects shown by our modeling results and are likely to be an area of significant uncertainty. Fuel reductions, especially overstory thinning treatments, can increase air temperatures near the ground and wind speeds throughout the forest canopy (van Wagendonk 1996, Agee and Skinner 2005), potentially leading to an increase in fire severity that cannot be accounted for within our particular fire model. In addition to the microclimatic changes that may follow an

overstory thinning, logging residues may be present on site following such a procedure and may potentially nullify the effects of the fuel reduction treatment or may even lead to an increase in fire severity (Stephens 1998). Field-based increases in fire severity that occur in stands subjected to overstory thinning may in fact be an interaction between the fine fuels created by the thinning treatment and the accompanying changes in forest microclimate that may lead to drier fuels and allow higher wind speeds throughout the stand (Raymond and Peterson 2005). While our model does incorporate the creation of logging residue that follows silvicultural thinning, increases in fire spread and intensity due to interactions between fine fuels and increased wind speed wind are neglected. However, we note that even if our model is failing to capture these dynamics, our general conclusion that fuel reduction results in a decrease in long-term C storage would then have even stronger support, since the fuel reduction would have caused C loss from the removal of biomass while also *increasing* the amount that is lost in a wildfire.

The amounts of C lost in fuel reduction treatments, whether nearly equal to or greater than our estimates, can be utilized in the production of biofuels. It is clear, however, that an attempt to substitute forest biomass for fossil fuels is not likely to be an effective forest management strategy for the next 100 years. Coast Range *Tsuga heterophylla*-*Picea sitchensis* ecosystems have some of the highest known amounts of biomass production and storage capacity, yet under the UR+OT+PF treatment a 169 year period is necessary to reach the point at which biomass production will offset C emitted from fossil fuels and 338 years for ethanol production. Likewise, managed forests in the west Cascades require time scales that are too vast for biofuel alternatives to make a difference over the next 100 years. Even converting old-growth forests in these

ecosystems would require at least 33 and 107 years for woody biomass utilization in the Coast Range and west Cascades, respectively, and these figures assume that all possible energy in these fuels can be utilized. Likewise, our ethanol calculations assumed that the maximum theoretical ethanol yield of biomass is realized, which is yet to be done (Schubert 2006); a 70% realization of our maximum yield is a more realistic approximation of contemporary capacities (Galbe and Zacchi 2002).

In addition to these lags, management constraints could preclude any attempt to fully utilize Pacific Northwest forests for their full biofuels production potential. Currently in the Pacific Northwest there are approximately 3.6×10^6 ha of forests in need of fuel reduction treatments (Stephens and Ruth 2005) and in 2004 the annual treatment goal for this area was 52000 ha (1.44%). Unless a significantly larger fuel reduction treatment workforce is employed, it would take 69 years to treat this area once, a period that approximates the effective duration of fire suppression (Stephens and Ruth 2005). The use of SPLATs (strategically placed area treatments) may be necessary to reduce the extent and effects of landscape-level fire (Finney 2001). SPLATs are a system of overlapping area fuel treatments designed to minimize the area burned by high-intensity head fires in diverse terrain. These treatments are costly, and estimates of such treatment costs may be underestimating the expense of fuel reduction in areas with high-density understory tree cohorts that are time-consuming to extract and have little monetary value to aid in offsetting removal expenses (Stephens and Ruth 2005). Nevertheless, it is clear that not all of the Pacific Northwest forests that are in need of fuel reduction treatments can be reached, and the use of strategically placed fuel reduction treatments such as SPLATs may represent the best option for a cost-effective reduction in wildfire severity,

particularly in areas near the wildland-urban interface. However, the application of strategically-placed fuel reduction treatments is unlikely to be a sufficient means in itself toward ecosystem restoration in the forests of the east Cascades. Stand-level ecosystem restoration efforts such as understory removal and prescribed fire may need to be commenced once landscape-level reductions in fire spread risk have been implemented.

Conclusions

Managing forests for the future is a complex issue that necessitates the consideration of multiple spatial and temporal scales and multiple management goals. We explored the tradeoffs for managing forests for fuel reduction vs. C storage using an ecosystem simulation model capable of simulating many types of forest management practices. With the possible exception of some xeric ecosystems in the east Cascades, our work suggests that fuel reduction treatments should be foregone if forest ecosystems are to provide maximal amelioration of atmospheric CO₂ over the next 100 years. Much remains to be learned about the effects of forest fuel reduction treatments on fire severity, but our results demonstrate that if fuel reduction treatments are effective in reducing fire severities in the Western hemlock–Douglas fir forests of the west Cascades and the Western hemlock–Sitka spruce forests of the Coast Range it will come at the cost of long-term C storage, even if harvested materials are utilized as biofuels. We agree with the policy recommendations of Stephens and Ruth (2005) that the application of fuel reduction treatments may be essential for ecosystem restoration in forests with uncharacteristic levels of fuel buildup, as is often the case in the xeric forest ecosystems of the east Cascades. However, this is often impractical and may even be counterproductive in ecosystems that do not exhibit uncharacteristic or undesirable levels

of fuel accumulation. Ecosystems such as the Western hemlock–Douglas fir forests in the west Cascades and the Western hemlock–Sitka spruce forests of the Coast Range may in fact have little sensitivity to forest fuel reduction treatments and may be best utilized for their high C sequestration capacities.

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Tables

	Pringle Falls	HJ Andrews	Cascade Head
Vegetation	PIPO	TSHE-PSME	TSHE-PISI
Elevation	1359	785	287
Mean Annual Temperature (°C)	5.5	8.4	8.6
Mean Annual Precipitation (mm)	544	2001	2536
Soil Porosity	Sandy Loam	Loam	Loam
Mean C Storage Potential	183 Mg C ha ⁻¹	829 Mg C ha ⁻¹	1127 Mg C ha ⁻¹

Table 3.1. Site characteristics from Smithwick et al. (2002). Species codes: PIPO, *Pinus ponderosa*; TSHE, *Tsuga heterophylla*; PSME, *Pseudotsuga menziesii*; PISI, *Picea sitchensis*.

Treatment Abbreviation	Treatment
SL	Salvage Logging
UR	Understory Tree Removal
PF	Prescribed Fire
UR+PF	Understory Tree Removal + Prescribed Fire
UR+PF+OT	Understory Removal + Prescribed Fire + Overstory Thinning
UR+PF+OR	Understory Removal + Prescribed Fire + Overstory Removal

Table 3.2. Treatment Abbreviations

Figure Legends



Figure 3.1 legend.

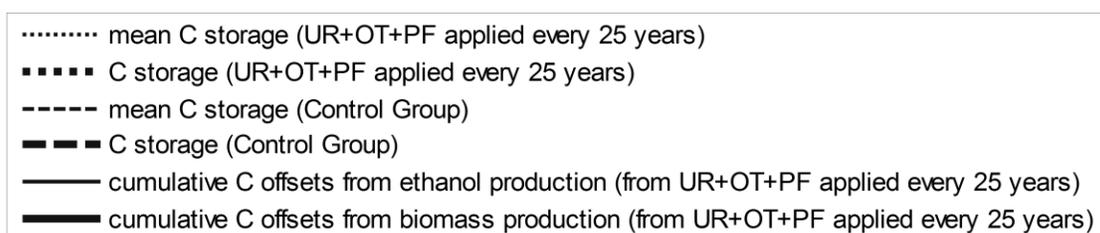


Figure 3.3 legend.

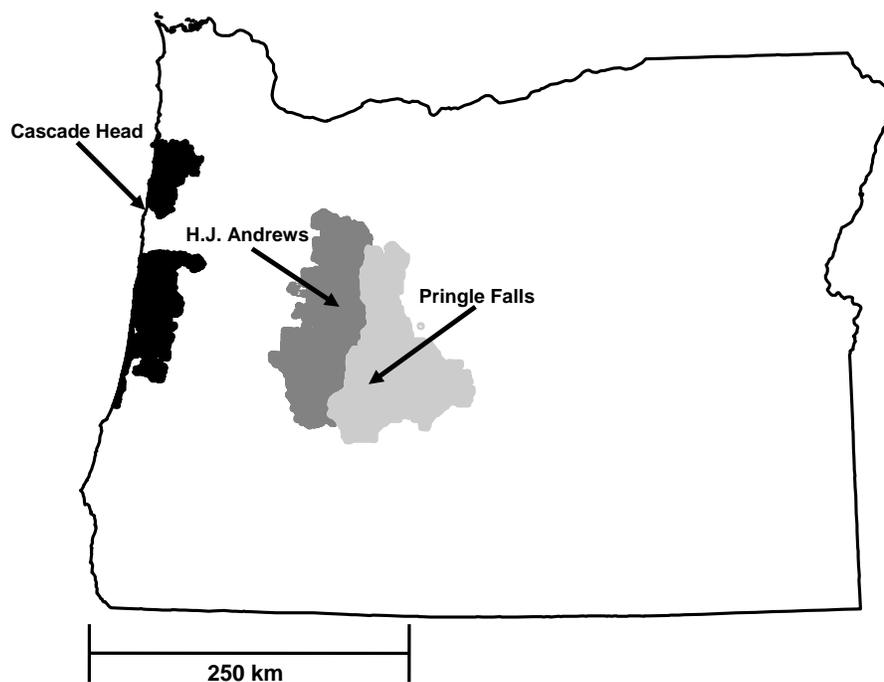
Figures

Figure 3.1. Site locations in Oregon. Pringle Falls is our representative site for the east Cascades, HJ Andrews is our representative site for the west Cascades, and Cascade Head is our representative site for the Coast Range.

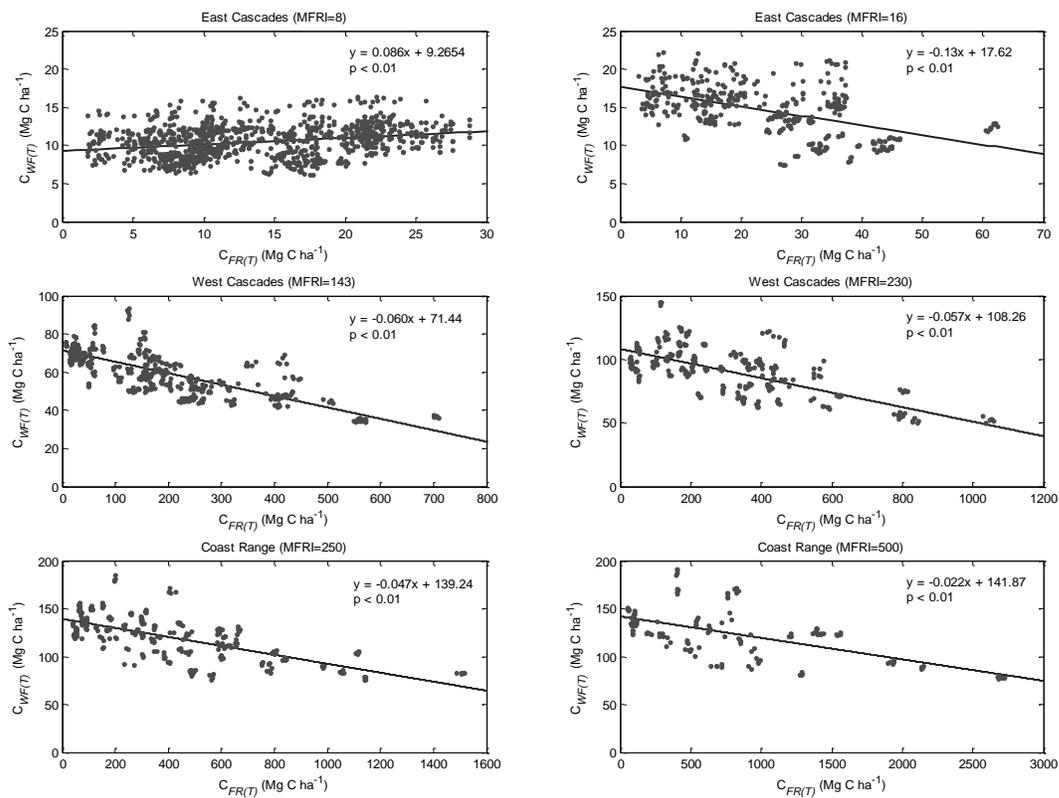


Figure 3.2. Scatterplots of C removed in fuel reduction treatments between wildfires $C_{FR(T)}$ and C lost in wildfires $C_{WF(T)}$ for the east Cascades, west Cascades and Coast Range. Notice the differences in the axes values. Also note the downward sloping trend for all ecosystems except for the east Cascades where MFRI=8 years.

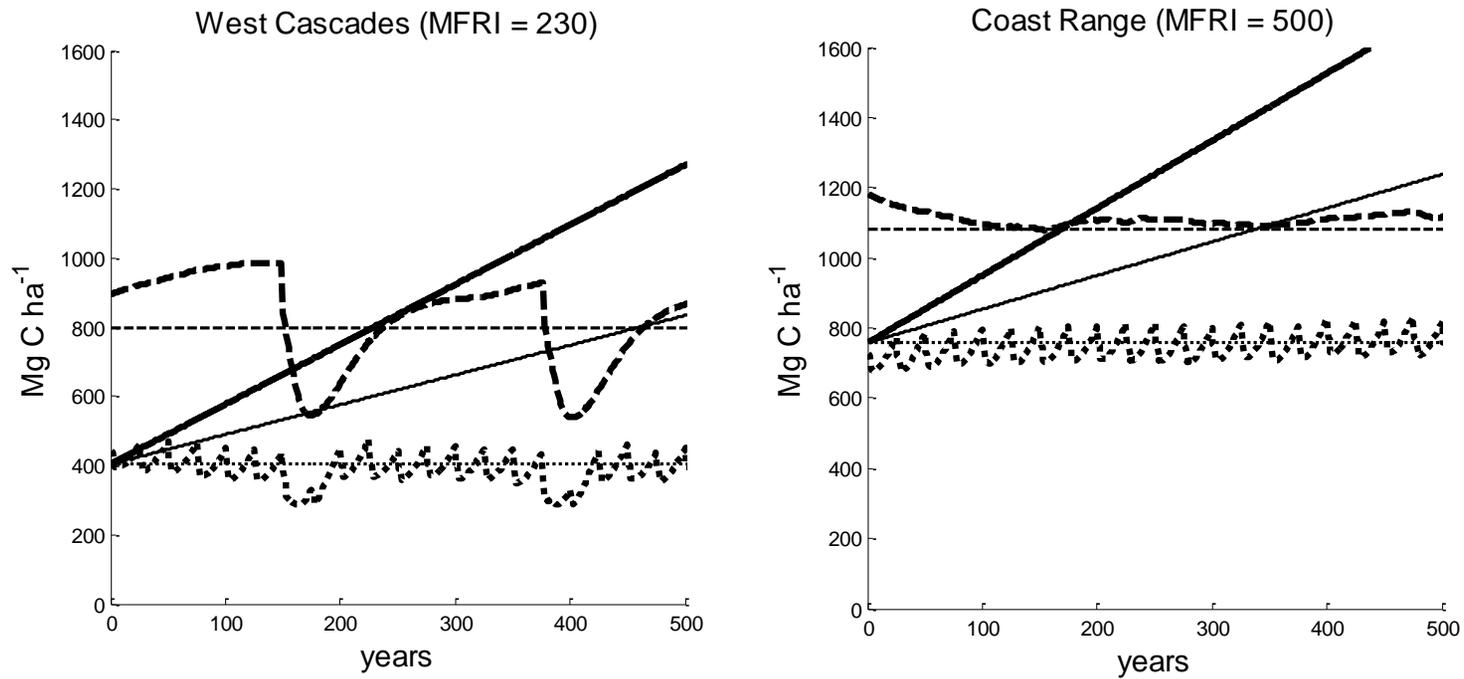


Figure 3.3. Time series plots of C storage, mean C storage, and biofuels offsets for control groups and fuel reduction treatment UR+OT+PF applied to a second-growth forest every 25 years for the west Cascades and Coast Range. East Cascades simulations were excluded from this plot because there was little or no trade-off incurred in managing these forests for both fuel reduction and C sequestration.

CHAPTER 4

**LANDSCAPE-LEVEL FUEL TREATMENTS ALTER PYROGENIC C
EMISSIONS AND REDUCE LONG-TERM CARBON STORAGE IN
PONDEROSA PINE FORESTS**

Stephen R. Mitchell, Mark E. Harmon, Kari E. B. O'Connell, and Frank
Schneckenburger

Abstract

A century of fire suppression in US forests has led to a significant accumulation of understory fuels, particularly in semi-arid ponderosa pine ecosystems throughout the west. Such an extensive development of understory fuels has resulted in wildfires of uncharacteristic severity and areal extent. Efforts have thus been made to reduce understory fuels throughout much of the affected landscapes, including the ponderosa pine ecosystems of central Oregon. However, current annual rates of fuel reduction treatment within these landscapes range from 1-2% of the affected area, meaning that treatment implementation times are in excess of the natural fire return intervals. Such treatments and treatment rates could ultimately prove to be ineffective. Furthermore, since fuel reduction treatments reduce long-term C storage within stands, there are implications for reducing increasing atmospheric CO₂ concentrations. We tested the extent to which various fuel reduction treatments, when applied at various annual treatment rates, altered fire behavior, pyrogenic C emissions, and long-term C storage throughout a landscape. We used LANDCARB, which models forests on a stand-by-stand basis and can simulate both full and partial disturbances including salvage logging, partial harvests, and prescribed fires. Our results indicated that, for fuel reduction treatments to be effective in reducing pyrogenic C emissions, they must be applied at far greater rates (4-6% of the treatment-needing landscape). Furthermore, the reduction in total landscape C storage is substantially larger than the amount of pyrogenic C emissions that are avoided by said treatments. We suggest that strategies aimed at reducing all fuel accumulation throughout the disturbance-prone Ponderosa pine ecosystems, such as those

found in the central Oregon Cascades, are not only unrealistic but may ultimately prove to undermine the role of these forests as a C storage site. Instead, treatments can be placed strategically throughout this and similar landscapes. Future research should investigate the effects of various spatial arrangements of fuel reduction treatments across the landscape.

Introduction

Wildfires have long been a predominant agent of disturbance in the Pacific Northwest (Heyerdahl et al. 2001; Wright and Agee 2004) and have influenced the structure, composition, and functioning of a broad range of forest ecosystems endemic to the region (Agee and Huff 1987; Cwynar 1987; Morrison and Swanson 1990; Huff 1995). Wildfires exert significant control on a wide array of ecosystem properties, including nitrogen cycling (Smithwick et al. 2005), the density and composition of tree species (Zenner 2005), wildlife habitat (Smith 2000), and landscape pattern (Romme 1982; Turner et al. 1994). Wildfires also exert considerable influence on the global C cycle by acting as a “global herbivore,” transforming large amounts of complex organic molecules into simpler organic and mineral products (Bond and Keeley 2005). For this reason, assessments of the carbon cycle and its role in global climate change require consideration of this fundamental ecosystem process (Schultz et al. 2000).

The amount of C lost from wildfires is generally, but not unconditionally, reflective of the amount of aboveground C available for consumption by wildfires. Like fire frequencies, these amounts show regional dependency, as patterns of aboveground C accumulation, similar to patterns of fire frequency, are influenced by gradients in mean

annual temperature (T_{μ}) and precipitation, leading to substantial differences in regional C dynamics. Potential upper bounds of C storage in Coast Range forests ($T_{\mu} = 8.43$ °C, precip = 2575 mm/yr) is ~1127 Mg C/ha, while west Cascades *Tsuga heterophylla*-*Pseudotsuga menziesii* forests ($T_{\mu} = 8.63$ °C, precip = 2002 mm/yr) can store ~829 Mg C/ha and east Cascades *Pinus ponderosa* forests ($T_{\mu} = 5.50$ °C, precip = 544 mm/yr) store ~195 Mg C/ha (Smithwick et al. 2002). The combination of low potential C storage and persistent conditions of fuel flammability in the east Cascades *Pinus ponderosa* forests results in a high frequency, but low magnitude, of C loss via wildfire. By contrast, west Cascades and Coast Range ecosystems possess high potential C storage and exhibit a low frequency, but high magnitude, of wildfire-related C loss (Fahnestock and Agee 1983; Agee 1993).

The high C storage potential of the Pacific Northwest, particularly among forests on the west side of the Cascade Range, has led many to emphasize the C sequestration capacities of these forests as part of efforts to mitigate continued climatic change (Turner et al. 1995, Harmon et al. 1996, Harmon 2001, Smithwick et al. 2002). These forest ecosystems, along with others, make up much of the carbon sink currently thought to exist in the continental US (Pacala et al. 2001). However, there is growing recognition that much of the current sink may be unsustainable. A century-long policy of fire suppression is widely credited with the buildup of uncharacteristic levels of understory fuel biomass that are thought to have contributed to increased levels of wildfire severity (Noss et al. 2006; Donovan and Brown 2007). Simulations suggest that if fire suppression were to fail in the coming years, the current C sink in the coterminous US

would rapidly become a C source as a result of extensive burning of large scale wildfires (Hurt et al. 2002). The extent to which each fire regime has been altered due to the comparatively recent policy of fire suppression is dependent on each site's fire regime. Stands with MFRI's that exceed the century-long period of fire suppression may not exhibit the consequences of fire suppression policies, while other stands with MFRI's that are a fraction of the period of fire suppression are likely to have levels of understory fuels that are a significant departure from historical conditions and may result in fires of higher severity (Brown et al. 2004).

Reducing fuel loads within and among the stands with uncharacteristic levels of fuel build up has been proposed as a method of reducing fire severity. Fuel reduction treatments include understory removal, prescribed fire, and overstory thinning applied by themselves or in combination with each other (Agee and Skinner 2005). Many studies have demonstrated the effectiveness of fuel reduction treatments at the stand level (Fiedler et al. 1998, Stephens 1998, Fulé et al. 2001, Pollet and Omi 2002, Stephens and Moghaddas 2005). However, the implementation of these treatments can be problematic and potentially ineffective when applied at the landscape scale. Stephens and Ruth (2005) note that there is (or was) 3.6×10^6 ha of Pacific Northwest forests in need of fuel reduction treatments and that the treatment goal for this area in 2004 was 52000 ha, and much of this area lies in the disturbance-prone dry provinces east of the Cascade Crest (Spies et al. 2006). At this rate of treatment, it would take 69 years to treat this entire area once, and if the frequency at which fuel reduction treatments can be applied across the landscape is significantly lower than the frequency at which fires naturally occur, then

the fuel reduction treatments may ultimately be ineffective. In other words, even if pyrogenic C emissions can be reduced by having fuel reduction treatments applied at their current rates, application times may be so extended that available fuel loads may recover to or even exceed their pre-treatment levels. Furthermore, even if the entire landscape could be treated, not all of it will necessarily burn, thus many of the fuel reduction treatments will be applied throughout an area that might not have needed them, resulting in an unnecessary amount of C loss from the treatments. Finally, evidence from a related modeling study we conducted suggests that, even if fuel reduction treatments are effective in reducing fire severity at the stand level, they almost always result in a reduction in mean total ecosystem C storage depending on the amount of C removal needed to reduce wildfire severity exceeds the amount lost in the wildfire (Mitchell et al. 2009). Thus, if landscapes of the Pacific Northwest are to be managed for maximal long-term C storage, fuel reduction treatments may be counterproductive to that goal even when they are successful in reducing both fire severity and pyrogenic C emissions.

Our research is designed to answer the following questions: 1) What are the effects of fuel treatments on landscape-scale C storage in the *Pinus ponderosa* forests of the east Cascades? 2) Can fuel reduction treatments be applied sufficiently fast enough to significantly reduce wildfire risk across this landscape? 3) Given the above, how can these forests be managed for both maximal C storage and reduced wildfire severity?

Methods

Model Description

We conducted our study using a significantly updated version of the ecosystem simulation model LANDCARB discussed in Wallin et al. (1996). LANDCARB is a landscape-level C model that uses many of the same parameter files as the more computationally complex stand-level process model called STANDCARB (Harmon and Marks 2002). Although LANDCARB contains many of the same processes and controls as STANDCARB, they are implemented in a simpler fashion. Both models integrate climate-driven growth and decomposition processes with species-specific rates of senescence and mortality while incorporating for the dynamics of inter- and intra-specific competition that characterize forest gap dynamics. Inter- and intra-specific competition dynamics are accounted for by modeling species-specific responses to solar radiation as a function of each species' light compensation point as well as the amount of solar radiation delineated through the forest canopy. By incorporating these dynamics, these models simulate successional changes without neglecting the associated changes in ecosystem processes that result from species-specific rates of growth, senescence, mortality, and decomposition.

LANDCARB represents stands on a cell-by-cell basis, with the aggregated matrix of stand cells representing an entire landscape. Each cell in LANDCARB simulates a number of cohorts that represent different episodes of disturbance and colonization. Each cohort contains up to four layers of vegetation (upper tree layer, lower tree layer, shrub and herb) that each have up to seven live pools, eight dead pools, and three stable pools. For example, the upper and lower tree layers are comprised of 7 live pools: foliage, fine-roots, branches, sapwood, heartwood, coarse-roots, and heart-rot, all of which are

transferred to a detrital pool following mortality. Detrital pools in a cell can potentially contribute material to three, relatively decay-resistant, stable C pools: stable foliage, stable wood, and stable soil. There are also two pools representing charcoal.

Fire processes

We generated exponential random variables to assign the years of fire occurrence (*sensu* Van Wagner 1978) based on the literature estimates of Bork (1985) for mean fire return intervals (MFRI) for east Cascades *Pinus ponderosa* ecosystems. The cumulative distribution for our negative exponential function is given in equation (1) where X is a continuous random variable defined for all possible numbers x in the probability function P and λ represents the inverse of the expected time for a fire return interval given in equation (2).

$$P\{X \leq x\} = \int_0^x \lambda e^{-\lambda x} dx \quad (1)$$

where

$$E[X] = \frac{1}{\lambda} \quad (2)$$

Fire severities in each year generated by this function are cell-specific, as each cell is assigned a weighted fuel index calculated from fuel accumulation within that cell and the respective flammability of each fuel component, the latter of which is derived from estimates of wildfire-caused biomass consumption (see Fahnestock and Agee 1983, Agee 1993, Covington and Sackett 1984). Fires can increase (or decrease) in severity depending on how much the weighted fuel index a given cell exceeds (or falls short of)

the fuel level thresholds for each fire severity class (T_{light} , T_{medium} , T_{high} , and T_{max}) and the probability values for the increase or decrease in fire severity (P_i and P_d). Low-severity fires, such as those in east Cascades, may increase to a medium-severity fire if the fuel index sufficiently exceeds the threshold for a medium-severity fire. Fuel level thresholds were set by monitoring fuel levels in a large series of simulation runs where fires were set at very short intervals to see how low fuel levels needed to be to create a significant decrease in expected fire severity. We note that, like fuel accumulation, the role of regional climate exerts significant influence on fire frequency and severity and that our model does not attempt to directly model such effects. We suspect that an attempt to model the highly complex role of regional climate data on fine scale fuel moisture, lightning-based fuel ignition, and wind-driven fire spread adds uncertainties into our model that might undermine the precision and applicability of our modeling exercise, and it was for that reason that we incorporated data from extensive fire history studies to approximate the dynamics of fire frequency and severity. Mean total landscape C storage (TLC_μ) is calculated by summing all components of C (live, dead, and stable) storage at each time step and averaging them for all stands and fire regimes throughout the simulated landscape.

Fuel Reduction Processes

LANDCARB's fire module allows for scheduled prescribed fires of a given severity (light, medium, high) to be simulated in addition to wildfires. LANDCARB also has a harvest module that permits cell-by-cell harvest of trees, simulated thinning treatments as well as total harvests in each cell. A new cohort in the cell is established

once some of the materials in a cell are harvested. Harvested materials can be left in the cell as detritus following cutting or can be removed from the forest, allowing the user to incorporate the residual biomass that results from harvesting practices. LANDCARB can also simulate the harvest of dead salvageable materials such as logs or snags that have not undergone significant decomposition.

Study Sites

We chose the *Pinus ponderosa* stands of the Pringle Falls Experimental Forest (Figure 4.1) as our calibration point for east Cascades forest landscapes (Youngblood et al. 2004). *Pinus contorta* was also present, with an understory of antelope bitterbrush (*Purshia tridentata*) snowbrush (*Ceanothus velutinus*), and greenleaf manzanita (*Arctostaphylos patula*). Topography consists of gentle slopes, with sandy loam soils derived from aerially deposited dacite pumice. As many as 16 distinct age cohorts can be found at Pringle Falls, with some individuals reaching ages in excess of 600 years. Older, larger trees appeared to be randomly distributed throughout the stands, and large standing snags were also a common feature. We calibrated the model to this forest not because old-growth *Pinus ponderosa* ecosystems are predominant throughout the region, but because prior experience in model calibration has shown that if the model can be calibrated to both silvicultural yield tables and old-growth biomass estimates, the model can accurately represent the dynamics of growth and decomposition throughout all stages of succession.

Experimental Design

The effectiveness of forest fuel reduction treatments is often, if not always, inversely related to the time since their implementation. For this reason, our experiment incorporated a factorial blocking design where each ecosystem was subjected to four different frequencies of each fuel reduction treatment, including a control group which was not treated. Estimating the percentage of the landscape that can theoretically be treated is a challenge since the potential landscape treatment percentage relies on the size and per-area efficiency of federal fuel reduction workforces, both sources of significant uncertainty. Stephens and Ruth (2005) stated that 3.6×10^6 ha (26.71% of all federal land in the PNW) are (or were) in need of fuel reduction treatments, and that 52000 ha were scheduled for fuel reduction treatments in 2004. A fuel reduction at this rate amounts to an annual treatment of 1.44% of the treatment-needing landscape. Our analysis assumed that the percentage which can be treated each year is variable, so that we can account for many realistic scenarios, particularly the possibility of an increase in size and efficiency of federal fuel reduction workforces. We assumed that 1%, 2%, and 4% of each landscape can be treated each year, and that the entire landscape we are simulating is in need of treatment. To implement this scenario, we simulated a total of 100 stand grid cells for each treatment, frequency, and fire regime and treated 1, 2, or 4 cells for each simulation year.

We based the expected fire return time in equations (1, 2) on historical fire data for our forests from the estimates of Bork (1985), who estimated a mean fire return interval of 16 years for the east Cascades *Pinus ponderosa* forests. We generated three

separate fire histories using the same mean fire return interval to account for the variation in the fire regimes throughout the landscape. The frequencies at which fuel reduction treatments are applied were designed not only to reflect the maximum percentage of the landscape that can be treated each year, but were also indicative of the literature-derived estimates of each ecosystem's mean fire return intervals, since forest management agencies are urged to perform fuel reduction treatments at a frequency reflective of the fire regimes and ecosystem-specific fuel levels (Franklin and Agee 2003, Dellasala et al. 2004). We incorporated four different types of fuel reduction treatments largely based on those outlined in Agee (2002), Hessburg and Agee (2003), and Agee and Skinner (2005). Treatments 2 and 3 were taken directly from the authors' recommendations in these publications, treatment 1 was derived from the same principles used to formulate those recommendations, and treatment 4, clear-cutting, was not recommended in these publications but was incorporated into our analysis because it is a common practice in many Pacific Northwest forests. We ran the model with a 500 year spin-up simulation to account for build up of soil C, coarse woody debris, and other types of successional legacies. Once the 500 year spin-up simulation was completed, we excluded all fires for 100 years to simulate a century of anthropogenic fire suppression.

1) Salvage Logging (SL) - The removal of large woody surface fuels limits the flame length of a wildfire that might enter the stand. Our method of fuel reduction entailed a removal of 75% of salvageable large woody materials in the stand. Our definition of salvage logging includes both standing and downed salvageable materials (*sensu* Lindenmayer and Noss, 2006).

2) **Prescribed Fire (PF)** - The reduction of surface fuels limits the flame length and spread rate of a wildfire that might enter the stand. In the field, this is done by removing fuel through prescribed fire or pile burning, both of which reduce the potential magnitude of a wildfire by making it more difficult for a surface fire to ignite the canopy (Scott and Reinhardt 2001). We implemented this treatment in LANDCARB by simulating a prescribed fire at low-severity in the designated cells. To account for the usual monitoring and control that accompanies a prescribed fire, we modified the prescribed fire parameters so that the fires could not increase to a medium or high severity, even if the fuel load was theoretically high enough to propagate an increase in fire severity. Wildfire parameters, however, were set to allow an increase in fire severity under conditions of excessive fuel accumulation.

3) **50% Harvest plus Prescribed Fire (50%H + PF)** - A reduction in crown density by thinning overstory trees can make crown fire spread less probable (Agee and Skinner 2005) and can reduce potential fuels by decreasing the amount of biomass available for accumulation on the forest floor. Some have suggested that such a treatment will be effective only if used on conjunction with understory removal and PF (Perry et al. 2004). We simulated this treatment in LANDCARB by removing 50% of biomass in both the upper and lower canopy of the treated cells and then setting a prescribed fire (treatment two) the following year.

4) **Understory Removal, Overstory Removal, and Prescribed Fire (Clear-Cutting)** (100%H + PF) - Clear-cutting is a not common silvicultural practice in the dry forests of the east Cascades and we included it in our analysis simply to gain insight into

the effects of this practice on long-term C storage and wildfire severity. We simulated clear-cutting in LANDCARB by removing all trees, followed by a prescribed burn the following year.

5) *Control group* – Control groups had no treatments performed on them. The only disturbances in these simulations were the same wildfires that occurred in every other simulation.

The extent of the annual placement of treatments throughout the forests of our simulated study area will determine which ecosystems have their mean total ecosystem C storage (TLC_{μ}) altered the most by each treatment, allowing us to gauge their different responses to fuel treatments and their effectiveness in reducing the severity of naturally occurring wildfires. We also simulated these treatments and their respective frequencies under a regime of fire suppression. Fire suppression was simulated by simply not having any wildfires in the simulations after the 600 year spinup, even though fuel reduction treatments were performed. We also included a control group for the fire suppression simulations, which had no fuel reduction treatments applied, as well as no wildfires.

In sum, our analysis tested the effects of four fuel reduction treatment types, including clear-cutting, and four treatment frequencies, including one control group, for three separate fire histories in landscapes where fires are allowed to burn naturally. We also simulated the same four fuel reduction types and frequencies, including a control group, for landscapes where fires are actively and successfully suppressed (or simply do not occur) after the 600 year spin-up simulation.

Simulation Spin Up

LANDCARB was compared to the STANDCARB model, which had previously been calibrated to standardized silvicultural volume tables for Pacific Northwest stands to confirm that temporal patterns of C accumulation were similar. We then calibrated LANDCARB to permanent study plot data. Our calibrations were based on permanent study plots in the Pringle Falls Experimental Forest. We incorporated fuel legacies in the LANDCARB model from a 600 year spin-up simulation with fire occurrences generated from the exponential distribution in equation (1) where λ was based on each ecosystem's mean fire return interval. Total simulation time was 800 years, meaning that 200 years of fuel reduction treatments were analyzed.

Data Analysis

LANDCARB models forest stand dynamics in a purely deterministic manner, and the only source of stochasticity in LANDCARB is in the calculation of fire severity based on fuel accumulation. However, the chances of wildfire severity changing from a low-severity to a medium or high severity are very low, and since we are not explicitly simulating the interactive effect of fuel suppression on wildfire severity, making LANDCARB's calculations of fire severity almost entirely deterministic. Without any major source of stochasticity we saw no reason to perform statistical hypothesis testing on model results. Instead, we averaged the results of each treatment type and frequency for all 100 cells that were simulated for each fire history/regime. We then averaged the results of all three fire histories/regimes for each treatment type and frequency to ascertain the landscape-level response to the treatments.

Results

Among the simulations where wildfires were allowed to occur, almost all of the fuel reduction treatments within each respective fire regime resulted in a reduction in landscape-level C storage compared to the untreated control (Figure 4.2). SL resulted in the lowest reduction in TLC_{μ} , storing between 76-99% of the control group, depending on annual treatment extent. PF had a similar magnitude of effect, as such treatments stored between 71-97% of the control group. The 50%H + PF treatment, however, had a much larger impact on TLC_{μ} , storing between 46-86% of TLC_{μ} in the control group, and the 100%H + PF treatment stored between 25-74% of the control group. In every case but one, an increase in annual treatment extent resulted in a reduction in C storage. The one exception occurred in the case of SL, where a 2% annual landscape treatment resulted in a slightly higher TLC_{μ} than a 1% annual landscape treatment.

There was significant overlap in the SL treatments among the control and the other annual treatment areas. PF treatments at 1% and 2% of total treatment area were only 2% and 3% lower than the control group, respectively, while the 4% annual treatment area was 11% lower than the control group. The trend toward a more pronounced reduction in C storage with increasing landscape treatment areas became larger with the intensity of the fuel reduction treatments. The 50%H + CC treatment had a much larger difference between the control group and the 1 and 2% annual landscape treatment area, and a much larger difference between the control group and the 4% annual treatment area simulations. The 100%H + CC treatment was similar with larger differences between the control groups and all annual treatment areas.

The overall effect of the fuel reduction treatments was to lower pyrogenic C emissions (Figure 4.3). However, the reductions were generally minimal for SL and PF, and were only noticeably effective for 50%H+PF and 100%H+PF. Among the latter two treatment types, the overall magnitude of this reduction in C loss was actually quite small when compared to the rather drastic reduction in TLC_{μ} that accompanies these treatment types and frequencies.

Discussion

We ran the LANDCARB model to ascertain the effects of different fuel reduction treatment types and annual treatment areas on landscape-level C storage in the *Pinus ponderosa* ecosystems of the east Cascades. Our fuel reduction treatment types included salvage logging (SL), prescribed fire (PF), a 50% harvest followed by a prescribed fire (50%H + PF) and a 100% harvest followed by a prescribed fire (100%H + PF). Annual treatment areas amounted to 4%, 2%, and 1% of the landscape, equivalent to a stand level treatment return interval of 25, 50, and 100 years. All of the fuel reduction treatment types and annual treatment areas had lower C storage than the control groups, with C storage values between 25-99% of the unmanaged landscape. For fuel reduction treatments to result in *increased* C storage, the model must assume that the absence of one of the fuel components that is removed results in a significantly reduced wildfire severity.

Such an overall reduction in landscape-level C storage following fuel reduction is unsurprising given what is known about the combustion percentages of certain C storage mediums. Even high-severity wildfires in the *Tsuga heterophylla*-*Pseudotsuga menziesii*

forests of the west Cascades, which are significantly more intense than the low-severity wildfires considered in this study, only release ~15% of total stand C storage (Fahnestock and Agee 1983, Campbell et al. 2007). According to our modeled estimates, low-severity wildfires in the *Pinus ponderosa* ecosystems result in a 4% reduction of total stand C storage, yet many fuel reduction treatments, particularly harvests of live standing biomass, are removing a percentage far greater than the amount lost in a low-severity fire. The net effect of these treatments on the magnitude of pyrogenic C emissions is merely a slight reduction in an already low percentage of biomass combustion. In other words, the amount of C lost in the fuel reduction treatment is much higher than the amount that can be lost in a wildfire, making fuel reduction treatments counterproductive to a maximization of long-term C storage.

While there is little doubt that fuel reduction treatments can ultimately reduce fire severity and long-term C storage at the stand level, the emergent effects of different spatial placements throughout the landscape are less certain. Agee et al. (2000) argued that the use of shaded fuelbreaks, when properly executed, can have a significant influence on fire behavior by reducing intensity within specially designated defensible fuel profile zones. Likewise, Finney (2001) employed a simulation of mixed-conifer forests of the Sierra Nevada using the FARSITE model and showed that strategically placed area treatments significantly reduced fire spread and severity when only ~19% of the simulated landscape had been treated. However, unlike the FARSITE model, our version of LANDCARB does not incorporate the spatial effects of strategically placed area treatments or fuel breaks, which can significantly alter the behavior and extent of a

wildfire, and the capacity for studying the effects of spatial arrangements of fuel reduction treatments will be incorporated into future version of the model for testing. Furthermore, unlike the STANDCARB model, LANDCARB cannot simulate the exclusive harvest of understory cohorts due to the high computational demand of simulating this individual-level process at a landscape scale. This shortcoming is significant because the simulation of understory removal treatments for the *Pinus ponderosa* ecosystems of the east Cascades actually resulted in an *increase* in stand C storage, albeit a very slight one (Mitchell et al. 2009). The underlying reason for understory tree removal to result in increased C storage is the fact that understory tree biomass was weighted highly in the model's fuel index to account for the role that it can play as a ladder fuel that can propagate crown fires, thus having no understory tree biomass could significantly reduce wildfire severity. However, caution was urged in interpreting this result for two reasons. First, the difference between the understory removal treatment groups and the control groups was minimal (0.6-1.2%). Second, it is possible that understory trees were given a fuel index weighting that was higher than what would be reflected in the field. We think that our calculations of landscape-level C storage are quite conservative because they assume that there are no spatial interactions of fuel reduction treatments and that there is no possibility of an understory removal that could lead to increased C storage by a decrease in fire severity resulting from a removal of ladder fuels. In other words, our estimates reflect a *minimum* amount of landscape-level C storage in response to fuel reduction treatments from which we can then interpret our results.

Uncertainties aside, it is nevertheless useful to examine the simulations that best emulate those treatment scenarios. The actual extent of the landscape that can be treated annually lies between 1-2%, and since strategically placed treatments typically involve an understory and partial overstory removal, we think that our simulations of a 50% harvest followed by a prescribed fire (50% H + PF) best reproduces those treatments. These treatments reduce mean landscape C storage by 16-22%, depending on the annual percentage of the landscape that is treated. According to modeled estimates of Finney (2001) they can be effective if at least ~19% of the landscape has been treated, meaning that, with our 1-2% annual treatment area, they can be applied in as little as 10-20 years. One unknown, however, is what to do once 19-20% of the landscape has been treated with all the necessary strategically placed area treatments. We do not know whether more C could be stored if management were to implement the same fuel reduction treatments on the same strategically placed areas throughout the landscape that had been treated before, or if it would be better to continue treating the landscape systematically until it is treated in its entirety. We suspect that the latter strategy would be better for an overall reduction in fire severity, but we are unsure as to whether it would result in more or less long-term C storage. However, if fire continues to be suppressed within the untreated parts of the landscape there will likely be additional fuel accumulation which may result in wildfires that burn with greater severity, which could reduce the effectiveness of the strategically placed area treatments.

One point of contention to our analysis may be that harvested materials could be used as a C storage medium (as lumber) or as a source of bioenergy (as wood energy or

ethanol), and that using harvested biomass these manners may ultimately result in a net offset of atmospheric CO₂, whether through C storage or as a substitute for fossil fuels. While an offset by one means or another is inevitable, the utility of offsetting atmospheric CO₂ is nevertheless a matter of long it will take the C removed from the landscape to offset the reduction in stand C storage, given the current imperative of reducing the rate of increase of CO₂ emissions. We calculated the amount of C stored throughout the landscape for different annual treatment areas, as well as the amount stored if all C harvested from the landscape is utilized as lumber and does not decompose. Both of these assumptions are quite unrealistic but are nevertheless useful as an exercise. Figure 4.4 shows the amounts of landscape level C storage for all harvest treatments (SL, 50%H + PF, 100%H + PF), as well that same amount plus all harvested materials (sapwood and heartwood, excluding heart-rot biomass). Assuming 100% utilization and no decomposition, it takes just over 50 years for harvested materials, utilized as lumber, to result in an increase in net C storage. Such a result may seem counterintuitive, but should nevertheless be expected since much of the forest biomass (stumps, coarse roots, fine roots, and other unsalvageable material) remains on site following harvest and subsequently decomposes, thereby offsetting much of the C stored in harvested materials. The time required for a net C offset is even greater when harvested materials are used as bioenergy. Based on our conversion efficiencies of 0.78 and 0.39 for wood energy and bioethanol as calculated in Appendix 2, using these harvested materials for wood energy or bioethanol rather than lumber would increase the offset time by 28% and 157%, respectively.

Another possible point of contention is that the carbon sequestration costs of fuel reduction are outweighed by the benefits gained by taking steps to restore the disturbance regime to something that is closer to the natural range of variability (Landres et al. 1998). The natural range of disturbance variability, however, may change as climate continues to change; Westerling et al. (2006) showed that contemporary wildfires occupy a greater extent at a greater frequency than they did previously. Fortunately, these ecosystems might be able to adapt to a significant increase in fire frequency; Savage and Swetnam (1990) found that pre-settlement fire return intervals for *Pinus ponderosa* ecosystems in Northern Arizona occurred as frequently as every ~2.8 years. However, tree mortality rates, independent of wildfire-related mortality, have also increased rapidly over the last century, a result that van Mantgem et al. (2009) suggest is due to regional warming and consequent increases in soil water deficits, and it remains to be seen whether drought-related mortality will play a larger role in altering the structure and composition of these forests than changes in fire frequency.

Ultimately, the decision on how to further restore the fuel conditions to which the *Pinus ponderosa* is adapted to will probably be drawn from a continuous assessment of how the fires respond to the treatments in lieu of the future changes in wildfire frequency as well as non-wildfire related mortality. Of greater certainty is the fact that, compared to some of the other regions of the Pacific Northwest, the ecosystems of the east Cascades have significantly lower carbon storage potential, making a managed offset of the losses in C storage that arise from landscape-level fuel reduction treatments more achievable.

For example, the difference between the landscape managed with 50% H + PF applied annually to 1-2% of the landscape and the control group actually amounts to a maximum difference of between 38.56 and 60 Mg C ha⁻¹. Such a difference can easily be made up for in the forests of the Coast Range or the west Cascades, which can store 1127 and 829 Mg C ha⁻¹ if allowed to reach later stages of succession. This difference is between 3-5% of what can be stored in the Coast Range and 5-7% of what can be stored in the west Cascades, a goal that could easily be met by management in the Siuslaw and Willamette National forests. Meeting the goals of ecosystem management, such as C sequestration and/or a return to natural disturbance regimes, may therefore require the collaboration of management agencies from different ecoregions.

Managing the disturbance-prone ecosystems of the Deschutes National Forest for C storage, for example, may be at odds with a return to natural disturbance types and frequencies, and may even be counterproductive to the continued attempt to restore the old-growth habitat required by northern Spotted Owl (*Strix occidentalis*) populations as stipulated by the Northwest Forest Plan (Spies et al. 2006). For these reasons, we suggest that any future public or private carbon management incentives allow for cross-district collaboration so that ecosystem restoration and carbon sequestration can be a collaborative, rather than local, effort. Districts such as the Deschutes National Forest should not have to be penalized for attempting to restore characteristic disturbance regimes at the expense of short-term reductions in C storage. This may prove to be an issue in C offsets and accounting, as our results show that when fire is excluded from these ecosystems, C can accumulate for over 100 years before reaching a near steady

state of C storage, suggesting that even more C storage could be attained if fire suppression were to continue. We suggest that policymakers should be careful not to encourage such short-term gains at the expense of an extensive fuel accumulation that could lead to additional wildfires of uncharacteristic severity, as well as a loss in natural variability.

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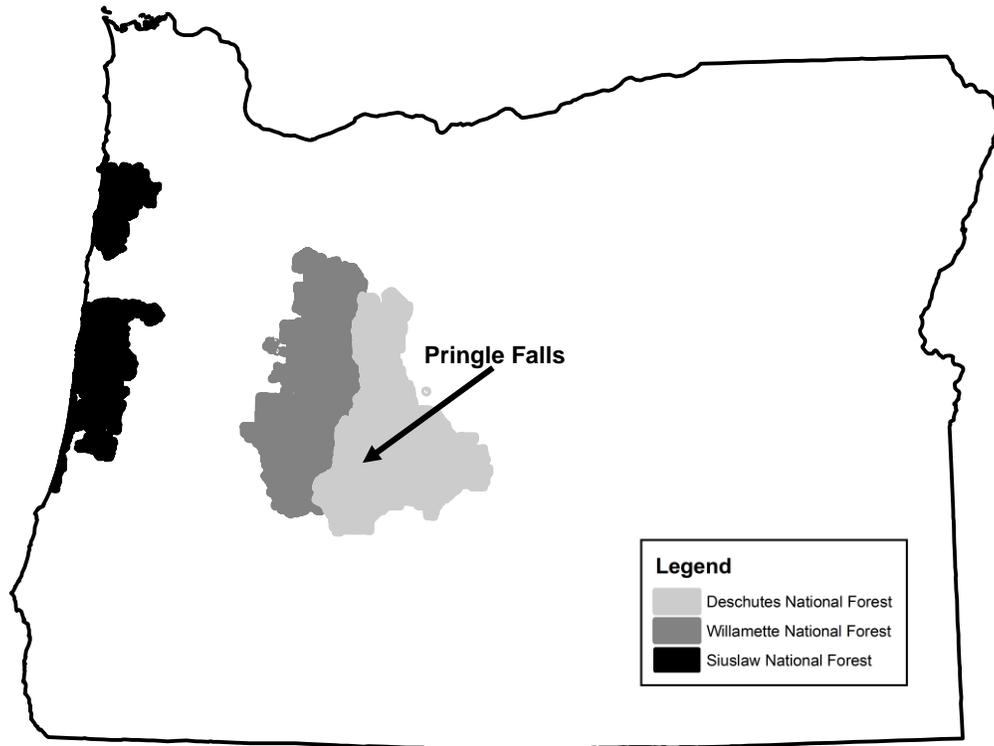
Figures

Figure 4.1. Study site location and surrounding area.

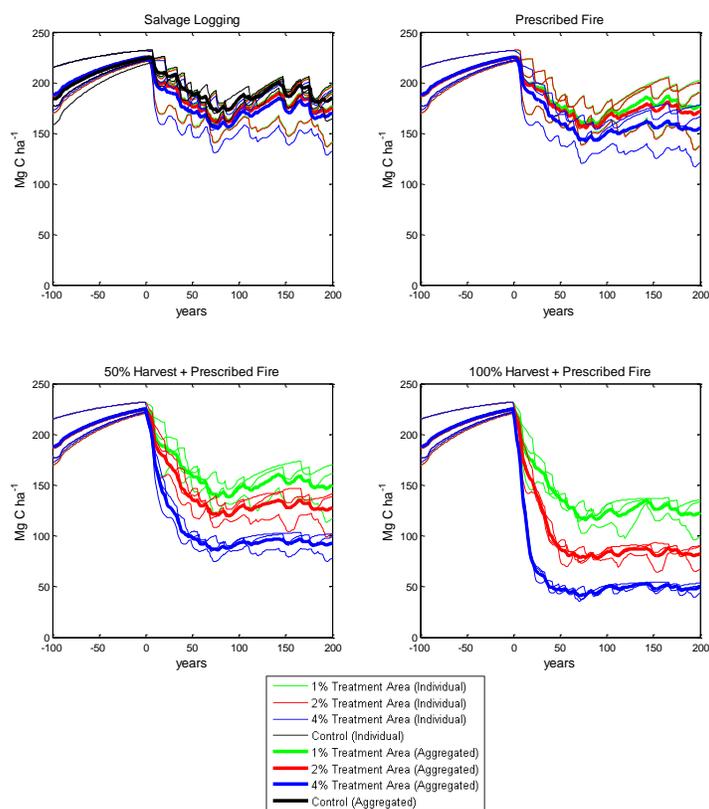


Figure 4.2. Landscape-level simulations of four different fuel reduction treatment types at three different frequencies plus a control group and their effects on C storage for three separate fire regimes. Note that negative years represent time before present, during which fires were suppressed and ecosystem C storage increased.

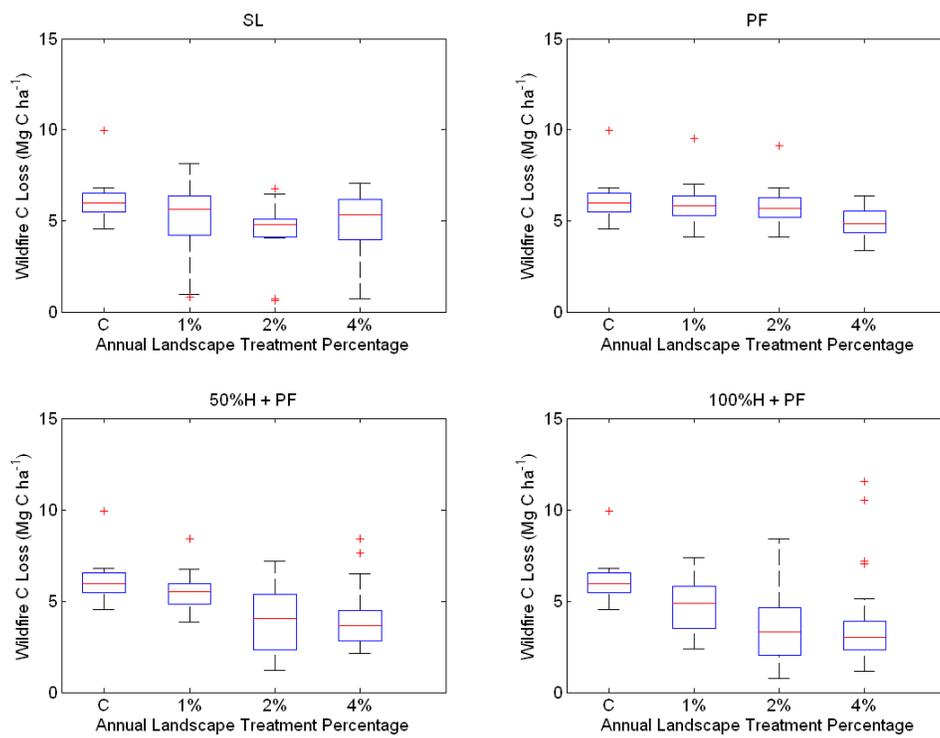


Figure 4.3. Boxplots of C losses from wildfire for all treatment types and annual treatment areas (C=Control Group).

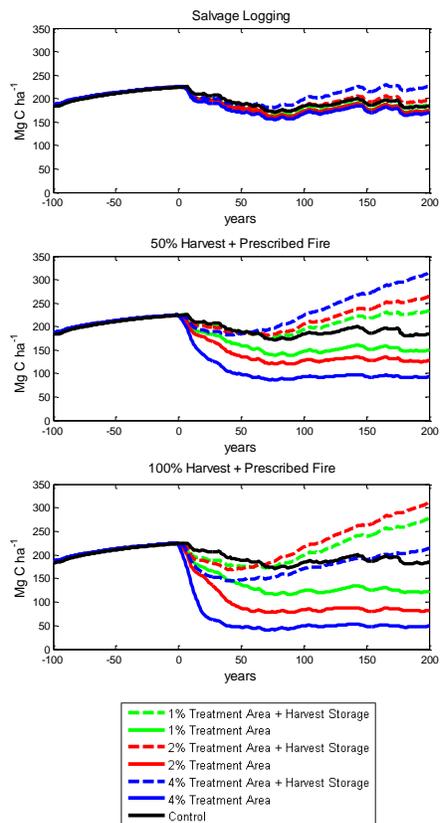


Figure 4.4. Landscape-level simulations of three of the four different fuel reduction treatment types at three different frequencies plus a control group and their effects on C storage for three separate fire regimes. C storage of harvested materials plus landscape-level C storage is shown in the dotted lines.

CHAPTER 5

CONCLUSIONS

Stephen R. Mitchell

Conclusions

Environmental models are laden with uncertainty (Beven 2006) but if properly parameterized and calibrated they can provide useful insights for understanding ecosystem dynamics. While estimates from ecosystem simulation models will almost certainly deviate from the measured values in the ecosystem that is being simulated, they can nevertheless answer key questions about ecosystem processes, even if the answer itself is subject to a degree of imprecision. However, it is imperative that the issue of model uncertainty is explicitly addressed and parameterized before conclusions from the research are drawn. For that reason, this research began with an attempt to quantify all of the uncertainty that can arise from measurement uncertainty, parameter equifinality, and model structure (chapter two). To accomplish this goal, the generalized likelihood uncertainty estimation (GLUE) methodology was used in conjunction with Biome-BGC, a widely used terrestrial ecosystem simulation model. The GLUE methodology involved 400,000 model runs, each with randomly generated parameter values from a uniform distribution based on published parameter ranges, resulting in estimates of NEE that were compared to daily NEE data from young and mature ponderosa pine stands at Metolius, Oregon. Of the 400,000 simulations run with different parameter sets for each age class (800,000 total), over 99% of the simulations underestimated the magnitude of net ecosystem CO₂ exchange, with only 4.07% and 0.045% of all simulations providing satisfactory simulations of the field data for the young and mature stands, even when uncertainties in eddy-covariance measurements are accounted for. Results indicated fundamental shortcomings in the ability of this model to produce realistic carbon flux

data over the course of forest development, and modeled estimates of ecosystem respiration, specifically soil respiration, appeared to play a significant role in model-data mismatch.

What was most useful to the ensuing research was the examination of parameter sensitivity. Once an in-depth understanding of model uncertainty and parameter equifinality was acquired, the STANDCARB model was calibrated to silvicultural yield tables and permanent study plot data. This prepared the model for experimentation with the primary research questions for chapter three. Our questions were as follows: 1) To what degree will reductions in fuel load result in decreases in C-stores at the stand level? 2) How much C must be removed to make a significant reduction in the amount of C lost in a wildfire? and 3) Can forests be managed for both a reduction in fire severity and increased C sequestration, or are these goals mutually exclusive? We focused this research on the western hemlock-sitka spruce forests of the Coast Range, the Western Hemlock-Douglas Fir forests of the west Cascades, and the Ponderosa Pine forests of the east Cascades. We looked at several fuel reduction treatment types: salvage logging, understory removal, prescribed fire, understory removal followed by prescribed fire, understory removal plus a 50% overstory removal followed by prescribed fire, and clear-cutting followed by a prescribed fire. Our simulations indicated that fuel reduction treatments in these ecosystems consistently reduced fire severity. However, reducing the fraction by which C is lost in a wildfire required the removal of a much greater amount of C, since most of the C stored in forest biomass (stem wood, branches, coarse woody debris) remains unconsumed even by high-severity wildfires. For this reason, all of the

fuel reduction treatments simulated for the west Cascades and Coast Range ecosystems as well as most of the treatments simulated for the east Cascades resulted in a reduced mean stand C storage. One suggested method of compensating for such losses in C storage is to utilize C harvested in fuel reduction treatments as biofuels. Our analysis indicated that this will not be an effective strategy in the west Cascades and Coast Range over the next 100 years. We suggested that forest management plans aimed solely at ameliorating increases in atmospheric CO₂ should forego fuel reduction treatments in these ecosystems, with the possible exception of some east Cascades ponderosa pine stands with uncharacteristic levels of understory fuel accumulation.

These results may be indicative of a need for field-based research on the effects of understory removal and salvage logging in Ponderosa Pine ecosystems. The fact that, for some simulations in the east Cascades, *more* C was stored when salvage logging and understory removal treatments were applied, was slightly surprising, though easily explained in the case of understory removal. Our fuel weighting scheme placed proportionally low weights on biomass components that had low percentages of their biomass consumed in field studies, high weights on biomass components that had high percentages of their biomass consumed, and placed an even higher weight on vegetation capable of propagating crown fires (i.e. understory trees). Even though this fuel weighting scheme was logical, the weighting of understory trees was done without a complete knowledge of how much understory tree biomass is necessary to lead to a wildfire of uncharacteristically high severity.

These uncertainties in what should be considered an appropriate fuel weighting scheme may further interact with the lack of a mechanistic micrometeorological fire driver, and may further compound any mismatches between our models and reality. High-severity fires that occur independently of excessive fuel accumulation and are solely the result of extreme drought conditions and lightning-based ignition, for example, are ignored in the current modeling framework unless they are artificially incorporated. However, it may be that STANDCARB and LANDCARB are actually more accurate when not attempting to mechanistically account for these factors, and we note the overall quality of simulations from both models which, once properly calibrated, can yield results that are strongly representative of field conditions reported by Smithwick et al. (2002). In other words, a more parsimonious approach to wildfire modelling, which was based on randomly generated mean fire return interval estimates taken from dendrochronological reconstructions (Bork 1985, Cissel et al. 1998) may be advantageous over more mechanistic and climate-sensitive approaches (see Miller and Urban, 2000).

In chapter four a study of the landscape-level effects of fuel reduction treatments on pyrogenic C emissions and total landscape C storage was conducted. We tested the extent to which various fuel reduction treatments, when applied a various annual treatment areas, altered pyrogenic C emissions and long-term C storage in Ponderosa Pine ecosystems of the Deschutes National Forest. For this analysis we used the LANDCARB model, which models forests on a stand-by-stand basis and can simulate complete stand harvests as well as partial disturbances including salvage logging, partial harvests, and prescribed fires. Our results indicated that, for fuel reduction treatments to

be effective, they must be applied over landscape areas far larger than current extents. Furthermore, the reduction in total landscape C storage was substantially larger than the amount of pyrogenic C emissions that are avoided by the fuel reduction treatments. We suggested that strategies aimed at reducing all fuel accumulation throughout the disturbance prone Ponderosa Pine ecosystems of the Deschutes National Forest may ultimately prove to undermine the role of these forests as a C storage medium, and we recommend that fuel reduction treatments instead be placed strategically throughout this and possibly other landscapes with similar conditions. We also suggested that future research investigate the effects of various spatial arrangements of fuel reduction treatments across the affected landscape.

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Appendix A. STANDCARB Model Description.

STANDCARB contains 11 major modules that perform specific functions. The following describes each module as well as modifications relative to version 1.0 of the model (Harmon and Marks 2002).

PLANT AND DIEOUT Modules.

The PLANT and the DIEOUT modules determine the "birth" and "death", respectively of plant layers and are the most analogous to those found in a typical gap model (Urban and Shugart 1992). The PLANT module determines when herb, shrub, upper tree layer or lower tree layers establish in a cell and determines which tree species will establish in a cell depending upon the local abundance of species as well as the light, temperature, and moisture conditions present as predicted by the NEIGHBOR and CLIMATE modules.

The DIEOUT module determines when the upper tree layer is replaced given that trees have a finite lifespan. Trees are represented by a cohort of multiple individuals until they reach an age when self-thinning would leave a single tree and tree crowns reach their maximum horizontal extent. Tree mortality at this point means that the upper tree layer has to be replaced by the PLANT module. In version 2.0 the time a cell reaches a single upper tree is determined stochastically once the minimum age has been reached.

NEIGHBOR Module.

This module simulates the interaction among the cells arranged on the rectangular grid work regarding light. Diffuse radiation can be blocked in eight directions (every 45

degrees), whereas direct radiation is only blocked on the east, southeast, south, southwest, and west facing directions. The degree of shading is determined by the relative heights of trees in cells and the distance among cells. The height is estimated from the age of the upper tree layer in each cell and a Chapman-Richards equation that specifies the maximum height of a species and the age that maximum was reached. Boundary effects, a problem in all spatially explicit models, are addressed by assuming the surrounding forest height was the same as average of the simulated forest. In version 2.0 the maximum tree height is a function of site index.

GROWTH Module.

This module calculates the mass of the seven live parts or C pools and is divided into nine functions which perform specific calculations including the absorption of light and foliage growth; the allocation of production to fine roots and woody plant parts; respiration from living parts; heartwood and heart-rot formation; losses from mortality, litterfall, and pruning; calculation of live stores; and conversion of bole mass to wood volume. Each of these functions is invoked for each plant layer present in a cell.

Parameters controlling these functions are specific to plant layers and in the case of trees, are specific to species.

The growth of each layer is a function of the amount of foliage present in a layer that is, in turn, dependent on the amount of light absorbed by them. Light is expressed as a percentage of full sunlight and we assume that if taller layers are present they will absorb light before underlying layers. The light coming into a cell can be reduced by shading

from surrounding cells (see NEIGHBOR module); although in version 2.0 a small proportion of direct light is allowed to pass through neighboring cells to account for the sun flecks passing through minor openings. Layers are able to increase their foliage mass until the light compensation point for that layer or species of tree is reached. The amount of light remaining below the foliage of each layer is a function of the mass of foliage of that layer as defined by a Beers-Lambert equation.

The photosynthate produced by foliage is allocated to the sapwood, branches, fine roots and coarse roots by assuming that rates of allocation are fixed. In version 2.0 the production of the trees changes with age, so that as trees reach their maximum height their production declines by an amount set by the user. This was done to account for the fact that production in older forests appears to be limited relative to younger forests (Acker et al 2000, Acker et al 2002). While there is some dispute about the exact cause of this phenomenon, there is little doubt it occurs in many types of forests (Ryan et al. 1997). Allocation rates are set to give the proportions of a typical tree >50 cm diameter at breast height as solved by allometric biomass equations (Means et al. 1994). We used this diameter range because the proportions of tree parts become relatively stable at this size.

Losses to live parts occur as respiration, mortality, and formation of new materials (e.g., sapwood forms heartwood). Respiration losses are deducted from the allocation added to woody plant parts. Respiration of all plant parts except heartwood is estimated from their mass and a respiration rate that is a Q10 function of mean annual temperature (Ryan 1990). The mass transferred from sapwood to heartwood for each tree layer is determined

by the rate of heartwood formation and the mass of sapwood. The rate of heartwood formation is parameterized so that the proportion of boles in sapwood matches the values in mature trees of the various tree species (Lassen and Okkonee 1969). In version 2.0 heart-rot is formed from heartwood after trees reach a minimum age, although the year heart-rot begins to form in a particular cell is stochastic. Losses for parts occur as tree mortality or in the case of non-bole parts via pruning (i.e., branches and coarse roots) or normal turnover (i.e., litterfall or fine root death). Losses can also occur due to timber harvest (see HARVEST module) and fire (see BURNKILL module).

MORTALITY Module.

This module determines the mortality rate of foliage, fine roots, branches, and coarse roots when entire trees die and/or when parts are pruned. Sapwood and heartwood are only transferred to dead pools when entire trees die. Foliage, branches, fine roots, and coarse roots are transferred to dead pools when both entire trees die and when these parts are self pruned. The turnover of foliage and fine roots are constants based on the longevity of these parts. It is assumed that as the amount of light absorbed by the stand increases, pruning of branches and coarse roots as well as the mortality rate for entire trees increases. However, mortality of upper trees also depends upon the time a species has occupied a cell. When a single tree is in the upper tree layer, then mortality is a function of tree longevity and becomes independent of light.

DECOMPOSE Module.

This module simulates the input, decomposition, and storage of C in dead and stable pools. The functions contained in this module calculate the total amount of input from the various layers and parts, the effect of substrate quality on decomposition, the rate of decomposition, change in detritus stores, the transfer to and loss from stable pools. All detritus pools are named after the corresponding live plant parts with the prefix Dead added with the exception that heart-rot contributes to dead heartwood. In version 2.0 dead sapwood and dead heartwood are separated into standing and downed material to account for the different microclimates of these two positions. Another change in version 2.0 was made to account for the fact a period of decomposition is required before stable materials are formed, dead pools are tracked using a cohort structure for each year's input for a cell. Once a lag time modified by climatic conditions has been exceeded a dead pool cohort is stochastically transferred to the appropriate stable pool. Another change in version 2.0 is that there are three "stable" pools. Dead foliage is transferred to stable foliage (i.e., the organic horizon), aboveground dead wood pools to stable wood, and dead fine and coarse roots to stable soil.

The balance for each detritus pool is the inputs minus the losses from decomposition, consumption by fire, salvage harvest of dead wood, and transfers to the stable pools. For any given year, input can come from several sources: 1) litterfall, pruning, and mortality, 2) the dying out of the upper tree layer, 3) thinning and harvesting, and 4) fire killed plants. The decomposition rate of each dead pool cohort is dependent on the weighted average substrate quality of the inputs to that pool. The overall decomposition rate is calculated from the substrate quality effect and the effects of the abiotic factors as

calculated in the Climate module. Losses from harvest and fire are calculated by the HARVEST and SITEPREP modules.

Changes in a stable pool C is determined by the balance of C transferred from the dead pools minus the losses from decomposition as a function of the particular stable pool in question and the effects of temperature and moisture calculated by the CLIMATE module. It is assumed that stable foliage decomposes faster than stable wood, which in turn decomposes faster than stable soil.

SOIL TEXTURE Module.

The maximum amount of water storage in a soil is based upon the soil texture, depth, and fraction of soil free of coarse particles (<2 mm diameter). The fraction of the soil volume that can store water between field capacity and the wilting point is based on soil texture and the fraction of the soil profile with soil particles.

CLIMATE Module.

This module estimates the effect of temperature, precipitation, and solar radiation on the establishment of tree species, growth of plants, autotrophic respiration, and decomposition. The processes of water interception, evapotranspiration, and water stores, as well as the effects of climate on decomposition and growth are calculated each month on each cell, whereas for plant respiration effects are calculated annually. The effect of temperature on plant part respiration is modeled as a Q10 relationship. For the dead pools we assumed there is an optimum temperature for decomposition.

To estimate the amount of water available for plant growth and decomposition, the interception by the canopy, woody detritus, and forest floor is calculated. Monthly total potential evapotranspiration of the site is calculated using a modification of the Priestly-Taylor method (Bonan 1989, Jensen 1973, Campbell 1977). Total potential evapotranspiration for a month is assumed to be proportional to the estimated solar irradiance, the monthly mean air temperature, and number of days in a month. The constants used to solve the Priestly-Taylor method are empirically derived after Jensen and Haise (1963) and Jensen (1973) from elevation and the mean minimum and mean maximum daily temperatures for the warmest month of the year. To estimate the potential amount of transpiration by plants, the total potential evapotranspiration is reduced to account for the evaporation portion of the water loss. The actual transpiration losses each month are controlled by the soil water stores and a linear function of foliage mass. The effect of soil moisture on transpiration is calculated from a modification of the relationship developed by Emmingham and Waring (1977). Volumetric moisture content is converted to water potential using a reciprocal function similar to Running and Coughlan (1988).

The moisture content of six detritus pools and the mineral soil is calculated monthly and represents the balance of inputs through precipitation/throughfall and outputs via evapotranspiration. The loss of water from the mineral soil is controlled solely by the transpiration from plants. The rate that water is lost from detritus pools is calculated from the monthly evaporative demand (a function of radiation received and temperature) multiplied by a pool-specific drying constant. Decomposition is limited by moisture when

either it is too low (i.e., a matric effect) or too high water (i.e., a limitation of oxygen diffusion).

HARVEST, BURNKILL, AND SITEPREP Modules.

The HARVEST, BURNKILL, and SITEPREP modules determine if a cell is to be disturbed by silvicultural treatments, timber harvest, or fire and the degree to which these disturbances reallocate the C in the living and dead pools.

If a harvest activity occurs in a given simulation year, then the Harvest module determines which type and spatial pattern of activity is to occur. Activities include cutting and harvesting of trees (cut trees can be left onsite), salvage of dead wood, and site preparation fires. Cutting and removal may be performed on either the upper or lower tree layer or for certain target species on all or a subset of cells.

The BURNKILL module determines the timing and amount of live vegetation killed by natural- or management-caused fire reducing the amount of live C in the GROWTH module and transferring some to the Decompose module as fire-killed detritus inputs. Not all the live vegetation killed by fire is necessarily transferred to detritus; some is consumed by the fire itself. The fraction of plant material killed and consumed by fire also increases with fire severity. Above- and below-ground plant parts are consumed by fire to different degrees, with below-ground parts having less material consumed for a given fire severity.

When a natural- or management-caused fire occurs the SITEPREP module determines the degree that dead pools are reduced. The degree that the dead pools are reduced is determined by the user; we have assumed that as fire severity increases from low to high the fraction of each of the above-ground detritus pools removed by fire increases. It is assumed that the stable soil pool does not decrease when there is a fire.

Appendix B. Energy conversions and time required for biofuel offsets to exceed ecosystem carbon reductions.

A. Energy Conversions

Energy can be obtained through the combustion of woody biomass, ethanol, and automotive fossil fuel, and all of these materials emit C upon combustion. However, the amount of C emitted for each unit of energy derived from their combustion varies due to the differences in potential energy of each material. In the below calculations we estimated ratios of the amount of C emitted per unit energy between biofuels (woody biomass and bioethanol) and automotive fossil fuel. This was done to establish a conversion efficiency among our C based energy sources to ascertain how much biofuels C must be emitted for a certain amount of energy compared to how much fossil fuel C must be emitted for the same amount of energy.

Note that we have assumed maximum energy conversion efficiencies. We did this because biofuels are currently an area of intense research, and it was unlikely that we could provide a conversion efficiency that would not be outdated shortly after publication. We also assumed, only for the sake of simplicity, that no CO₂ would be emitted during the process of harvesting the biomass. Consequently, our calculations give an estimate of the shortest possible time to an offset of ecosystem C reduction.

Biomass Energy Conversion Efficiency

To calculate the conversion efficiency of woody biomass energy C to fossil fuel energy C, we first obtained estimates of the amount of energy in woody biomass and fossil fuel.

Wood biomass energy content[†]: 20 GJ t⁻¹ (t = 1 ton)

Fossil fuel energy content[†]: 43.50 GJ t⁻¹ (Lower Heating Value)

Next, we obtained estimates of the amount of C in woody biomass and fossil fuel.

C ratio in fossil fuel* = 0.85 t C / t fossil fuel

C ratio in biomass** = 0.50 t C / t biomass

Finally, we calculated the ratio between the energy output for each unit of C emitted between biomass and fossil fuel.

Ratio of C emissions per unit energy = (20 GJ t⁻¹ / 0.5 t C emissions) / (43.50 GJ t⁻¹ / 0.85 t C emissions) = **0.7816 Conversion Efficiency for Biomass-Derived C.**

Ethanol Conversions

To calculate the conversion efficiency of ethanol energy C to fossil fuel energy C, we first obtained estimates of the amount of ethanol that can come from 1 Mg C.

Ethanol production from dry biomass[‡] = 455 liters of ethanol from 1 Mg dry biomass

Fraction of C in ethanol[†] = 0.5

Increase in efficiency for ethanol compared to fossil fuels = 15%

455 liters of ethanol from 1 Mg dry biomass / 0.5 = 910 liters of ethanol from 1 Mg C

We then found the ratio in volumetric energy content between ethanol and fossil fuel.

Ratio in volumetric energy content between ethanol and fossil fuel[†] = 75,670 Btu gal⁻¹ / 131,800 Btu gal⁻¹ * 1.15 = 0.6602

We multiplied this ratio by our estimate of the amount of potential ethanol production per Mg C to obtain the amount of ethanol-derived fossil fuel energy per Mg C emissions.

910 liters ethanol per Mg C * 0.6602 = 600.78 liters of ethanol-derived fossil fuel energy per Mg C emissions.

Finally, we found the amount of C emitted per unit fossil fuel energy and used it to calculate the ratio between the energy outputs for each unit of C emitted for ethanol and fossil fuel.

Fossil fuel energy per unit C emitted by combustion[†] = 1547 liters of fossil fuel energy per Mg C emissions.

600.78 liters of ethanol-derived fossil fuel energy per Mg C emissions / 1547 liters of fossil fuel energy per Mg C emissions = **0.3884 Conversion Efficiency for Ethanol-Derived C.**

B. Time for Biofuel Offsets to Exceed Ecosystem C Reductions.

Once conversion efficiencies were established, we took the modeled estimate of the average amount of biomass produced every year under the fuel reduction treatment conditions and multiplied it by the conversion efficiency to establish the amount of fossil fuel C that was being offset each year, assuming that all biomass removed was utilized for biofuels. This is shown in the below calculations for the west Cascades and Coast Range, once for biomass and once for ethanol.

Coast Range Biomass and Ethanol Offsets

Mean Annual C Offset for Biomass

$2.46 \text{ Mg C ha}^{-1} \text{ yr}^{-1} * 0.7816 = 1.92 \text{ Mg C ha}^{-1} \text{ yr}^{-1}$ mean C offset by biomass each year for UR+OT+PF applied every 25 years (MFRI=230) in the Coast Range.

Mean Annual C Offset for Ethanol

$2.46 \text{ Mg C ha}^{-1} \text{ yr}^{-1} * 0.3884 = 0.96 \text{ Mg C ha}^{-1} \text{ yr}^{-1}$ mean C offset by ethanol each year for UR+OT+PF applied every 25 years (MFRI=230) in the Coast Range.

West Cascades Biomass and Ethanol Offsets

Mean Annual C Offset for Biomass

$2.21 \text{ Mg C ha}^{-1} \text{ yr}^{-1} * 0.7816 = 1.73 \text{ Mg C ha}^{-1} \text{ yr}^{-1}$ mean C offset by biomass each year for UR+OT+PF (MFRI=230) in the west Cascades

Mean Annual C Offset for Ethanol

$2.21 \text{ Mg C ha}^{-1} \text{ yr}^{-1} * 0.3884 = 0.86 \text{ Mg C ha}^{-1} \text{ yr}^{-1}$ mean C offset by ethanol each year for UR+OT+PF applied every 25 years (MFRI=230) in the west Cascades.

Time for Biofuel Offsets to Exceed Ecosystem C Reductions.

After the average amount of C offset was calculated, we calculated how long it would take for C offsets from biofuels to result in a net offset of potential atmospheric C emissions. Calculations for the amount of time required to reach equilibrium were performed for two different land-use histories. The first assumed that the stand was currently managed under the fuel reduction treatment scenario described above. We estimated time to equilibrium for this scenario by calculating the difference between the mean C storage of the control group and the mean C storage of the fuel reduction treatment group before dividing that by our estimate of C that was being offset each year by biofuels production.

The second land-use history assumed that the stand was old growth before being converted via clear-cut to a second-growth forest, utilizing C removed in the clear-cut for biofuels. We estimated time to equilibrium for this scenario by multiplying the amount of C removed in a clear-cut by the conversion efficiency factor and subtracting this quantity, along with the mean C storage of the fuel reduction treatment group, from the

mean C storage of the control group before dividing that by our estimate of C that was being offset each year by biofuels production. These calculations are shown in the calculations below for the west Cascades and Coast Range, once for biomass and once for ethanol.

Coast Range Years to Reach Equilibrium for Biomass and Ethanol

Years to Reach Equilibrium for Biomass

$(1082.21 \text{ Mg C ha}^{-1} - 757.30 \text{ Mg C ha}^{-1}) / 1.92 \text{ Mg C ha}^{-1} \text{ yr}^{-1} = 169.22 \text{ yr}$ to reach equilibrium via biomass for UR+OT+PF applied every 25 years (MFRI=230) in the Coast Range.

Years to Reach Equilibrium for Biomass (when converted from old-growth)

$(1082.21 \text{ Mg C ha}^{-1} - 757.30 \text{ Mg C ha}^{-1} - 332.36 \text{ Mg C ha}^{-1} * 0.7816) / 1.92 \text{ Mg C ha}^{-1} \text{ yr}^{-1} = 33.93 \text{ yr}$ to reach equilibrium via biomass for UR+OT+PF applied every 25 years (MFRI=230) in the Coast Range.

Years to Reach Equilibrium for Ethanol

$(1082.21 \text{ Mg C ha}^{-1} - 757.30 \text{ Mg C ha}^{-1}) / 0.96 \text{ Mg C ha}^{-1} \text{ yr}^{-1} = 338.48 \text{ yr}$ to reach equilibrium via ethanol for UR+OT+PF applied every 25 years (MFRI=230) in the Coast Range.

Years to Reach Equilibrium for Ethanol (when converted from old-growth)

$(1082.21 \text{ Mg C ha}^{-1} - 757.30 \text{ Mg C ha}^{-1} - 332.36 \text{ Mg C ha}^{-1} * 0.3884) / 1.11 \text{ Mg C ha}^{-1} \text{ yr}^{-1} = 176.42 \text{ yr}$ to reach equilibrium via ethanol for UR+OT+PF applied every 25 years (MFRI=230) in the Coast Range.

West Cascades Years to Reach Equilibrium for Biomass and Ethanol

Years to Reach Equilibrium for Biomass

$(798.0804 \text{ Mg C ha}^{-1} - 403.67 \text{ Mg C ha}^{-1}) / 1.73 \text{ Mg C ha}^{-1} \text{ yr}^{-1} = 227.98 \text{ yr}$ to reach equilibrium via biomass for UR+OT+PF (MFRI=230) in the west Cascades.

Years to Reach Equilibrium for Biomass (when converted from old-growth)

$(798.0804 \text{ Mg C ha}^{-1} - 403.67 \text{ Mg C ha}^{-1} - 268.01 \text{ Mg C ha}^{-1} * 0.7816) / 1.73 \text{ Mg C yr}^{-1} = 106.89 \text{ yr}$ to reach equilibrium via biomass for UR+OT+PF (MFRI=230) in the west Cascades.

Years to Reach Equilibrium for Ethanol

$(798.08 \text{ Mg C ha}^{-1} - 403.67 \text{ Mg C ha}^{-1}) / 0.86 \text{ Mg C ha}^{-1} \text{ yr}^{-1} = 458.62 \text{ years}$ to reach equilibrium via ethanol for UR+OT+PF applied every 25 years (MFRI=230) in the west Cascades.

Years to Reach Equilibrium for Ethanol (when converted from old-growth)

$(798.0804 \text{ Mg C ha}^{-1} - 403.67 \text{ Mg C ha}^{-1} - 268.01 \text{ Mg C ha}^{-1} * 0.3884) / 0.86 \text{ Mg C ha}^{-1} \text{ yr}^{-1} = 337.57 \text{ years}$ to reach equilibrium via ethanol for UR+OT+PF applied every 25 years (MFRI=230) in the west Cascades.

Sources

† Data taken from Wright et al. (2006)

‡ Data taken from Galbe and Zacchi (2002)

*Data from EIA (1994)

** Data taken from Waring and Schlesinger (1985)

§ Data taken from Bailey (1996)

Appendix C. Total ecosystem C storage (TEC_{μ}) and expected fire severities ($E[F_s]$) for each treatment, fire regime, and ecosystem.

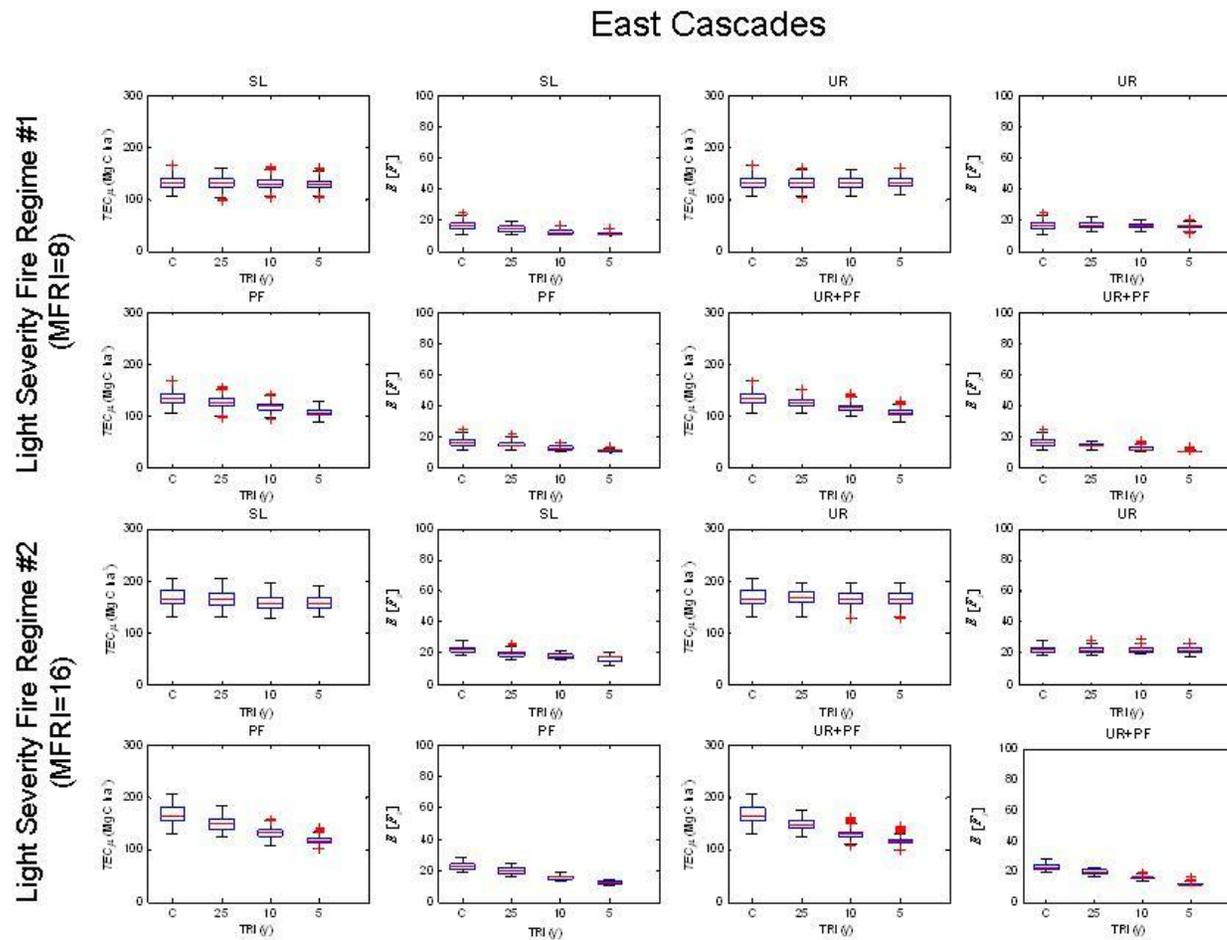


Figure 1. East Cascades mean total ecosystem C storage (TEC_{μ}) and expected fire severity $E[F_s]$ for salvage logging (SL), understory removal (UR), and understory removal and prescribed fire (UR+PF) for each treatment return interval (TRI) and control group (C) for each fire regime.

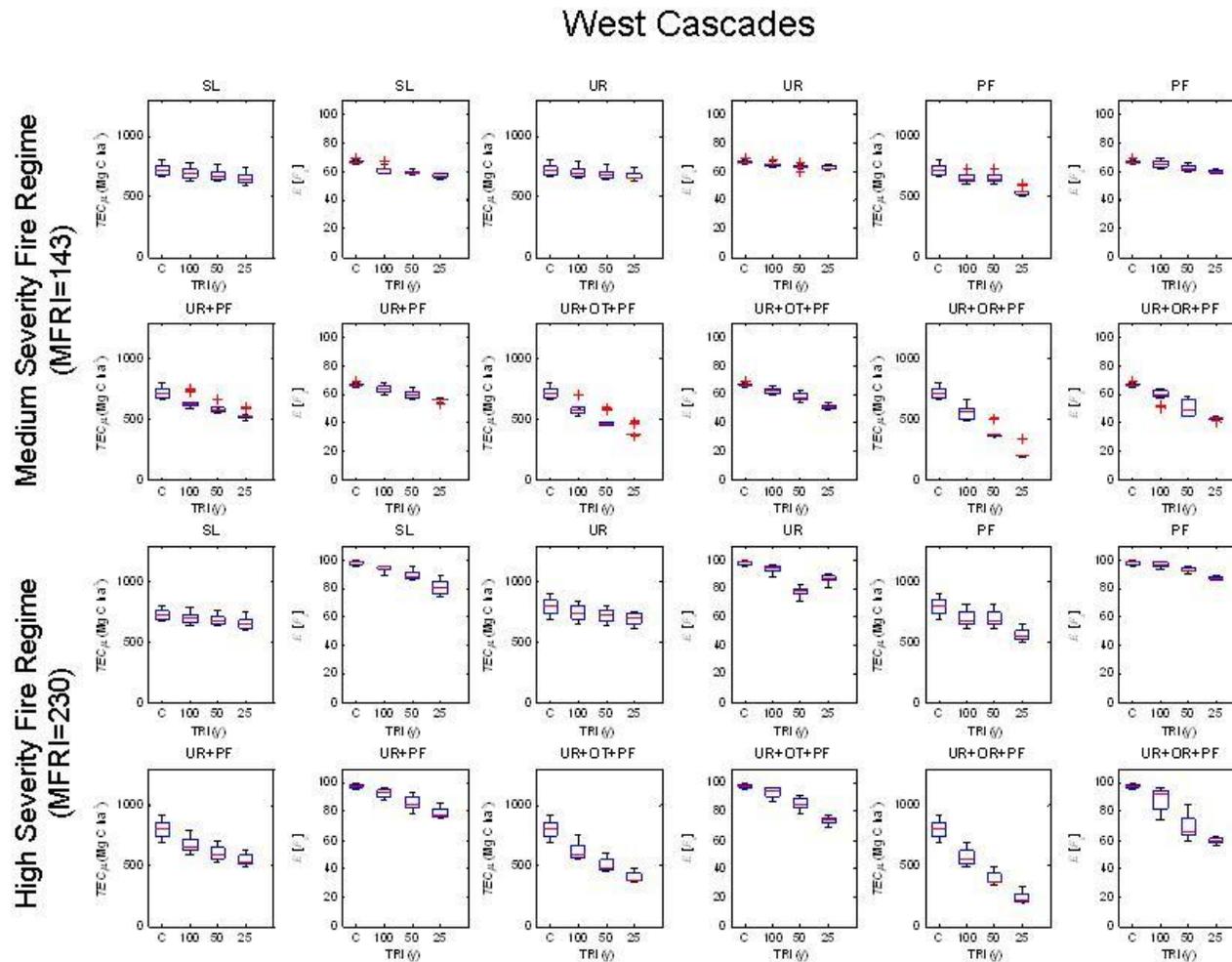


Figure 2. West Cascades mean total ecosystem C storage (TEC_{μ}) and expected fire severity $E[F_s]$ for salvage logging (SL), understory removal (UR), understory removal and prescribed fire (UR+PF), understory removal, overstory thinning, and prescribed fire (UR+OT+PF), and understory removal, overstory removal, and prescribed fire (UR+OR+PF) for each treatment return interval (TRI) and control group (C) for each fire regime.

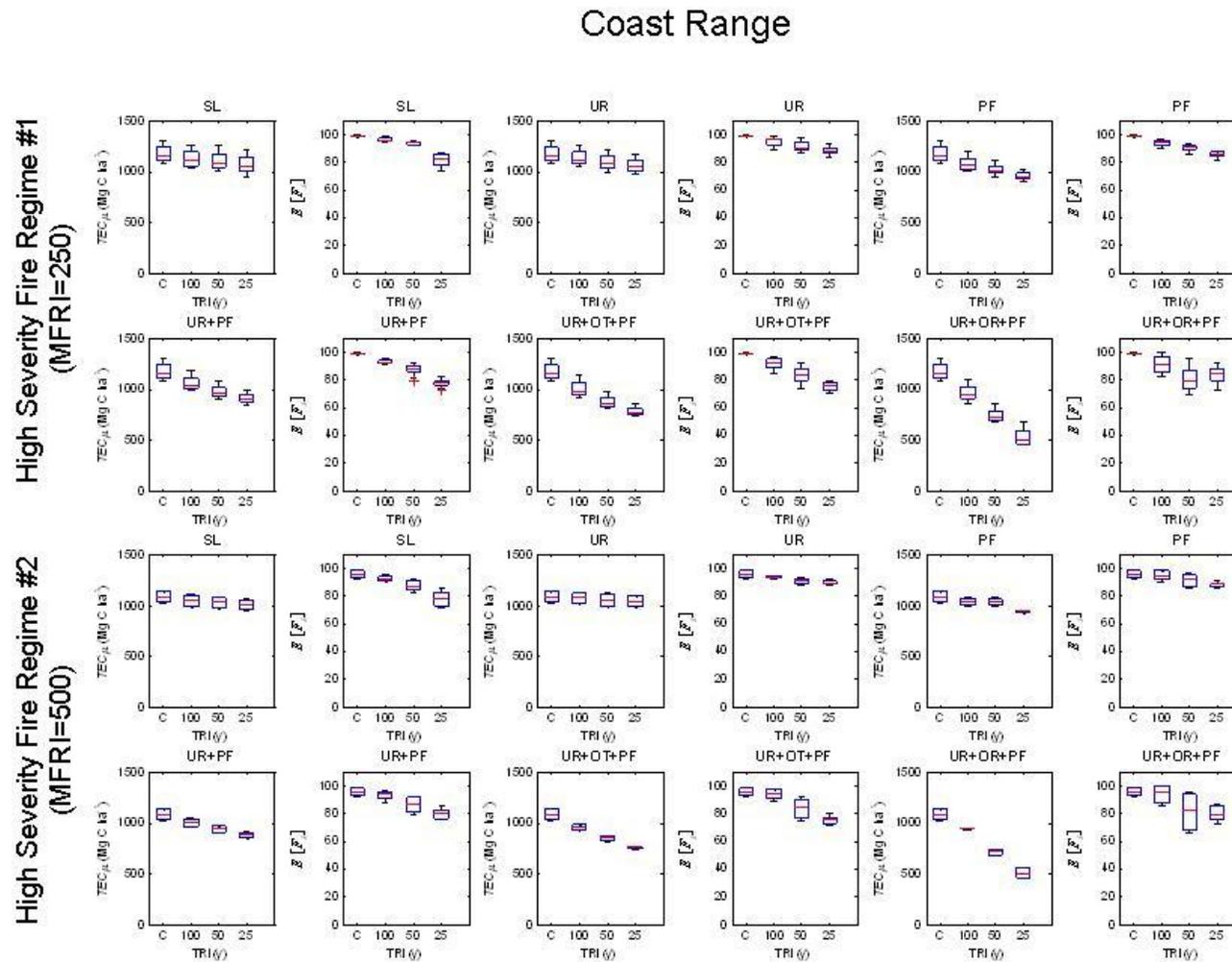


Figure 3. Coast Range mean total ecosystem C storage (TEC_{μ}) and expected fire severity $E[F_s]$ for salvage logging (SL), understory removal (UR), understory removal and prescribed fire (UR+PF), understory removal, overstory thinning, and prescribed fire (UR+OT+PF), and understory removal, overstory removal, and prescribed fire (UR+OR+PF) for each treatment return interval (TRI) and control group (C) for each fire regime.