PROJECTING CLIMATE CHANGE IMPACTS ON FOREST GROWTH AND YIELD FOR CALIFORNIA'S SIERRAN MIXED CONIFER FORESTS

A Paper From:
California Climate Change Center

Prepared By:

John Battles[1], Timothy Robards[1,2], Adrian Das[3], and William Stewart[1,4]
[1] Department of Environmental Science, Policy, and Management, UC Berkeley
[2] California Department of Forestry and Fire Protection
[3] U.S. Geological Survey Western Ecological Research Center
[4] University of California Cooperative Extension

DRAFT PAPER

DISCLAIMER

Arnold Schwarzenegger, *Governor*

March 2009
CEC-500-2009-047-D

Acknowledgments

We thank the U.S, Department of Agriculture's Forest Service Pacific Southwest Research Station for allowing us to use the Leroy Dolph mixed conifer data; the Northern California Forest Yield Cooperative for allowing us to use their stem analysis and permanent plot data; and Beaty and Associates for providing us with young ponderosa pine plantation data. We gratefully acknowledge the logistical support for field work provided by the Blodgett Forest Research Station. We appreciate the critical reviews (anonymous) of earlier drafts of this work. We thank Aimee Sprague and Jordon Wolfe for their help with all phases of this research. Financial support for this project was provided by California Energy Commission and the California Agricultural Experiment Station.

Preface

The California Energy Commission's Public Interest Energy Research (PIER) Program supports public interest energy research and development that will help improve the quality of life in California by bringing environmentally safe, affordable, and reliable energy services and products to the marketplace.

The PIER Program conducts public interest research, development, and demonstration (RD&D) projects to benefit California's electricity and natural gas ratepayers. The PIER Program strives to conduct the most promising public interest energy research by partnering with RD&D entities, including individuals, businesses, utilities, and public or private research institutions.

PIER funding efforts focus on the following RD&D program areas:

- Buildings End-Use Energy Efficiency
- Energy-Related Environmental Research
- Energy Systems Integration
- Environmentally Preferred Advanced Generation
- Industrial/Agricultural/Water End-Use Energy Efficiency
- Renewable Energy Technologies
- Transportation

In 2003, the California Energy Commission's PIER Program established the **California Climate Change Center** to document climate change research relevant to the states. This center is a virtual organization with core research activities at Scripps Institution of Oceanography and the University of California, Berkeley, complemented by efforts at other research institutions. Priority research areas defined in PIER's five-year Climate Change Research Plan are: monitoring, analysis, and modeling of climate; analysis of options to reduce greenhouse gas emissions; assessment of physical impacts and of adaptation strategies; and analysis of the economic consequences of both climate change impacts and the efforts designed to reduce emissions.

The California Climate Change Center Report Series details ongoing center-sponsored research. As interim project results, the information contained in these reports may change; authors should be contacted for the most recent project results. By providing ready access to this timely research, the center seeks to inform the public and expand dissemination of climate change information, thereby leveraging collaborative efforts and increasing the benefits of this research to California's citizens, environment, and economy.

For more information on the PIER Program, please visit the Energy Commission's website www.energy.ca.gov/pier/ or contract the Energy Commission at (916) 654-5164.

Table of Contents

List of Figures

List of Tables

Abstract

Climate change will have profound effects on the distribution, function, and productivity of California's forests. To provide managers with the means to anticipate likely forest responses to climate change, we initiated the development of a climate-sensitive growth and yield model for the mixed conifer forests of the Sierra Nevada (WS CalClim 1.0). WS CalClim 1.0 was built using the logic and architecture of the WESSIN variant (WS) of the Forest Vegetation Simulator. Our initial focus was on designing and testing a model of ponderosa pine productivity.

In WS CalClim 1.0, ponderosa pine diameter and height growth were positively correlated with annual precipitation and annual air temperature (as measured using degree-day indices). Simulated growth of a commercial pine plantation during a 50-year management cycle (20 to 70 years old) for 18 climate realizations predicted increases in yield as measured in total tree volume. The increased growth was most directly tied to the consistent projections of warmer temperatures during the twenty-first century. Under the different climate scenarios, pine yield increased from 9 percent to 28 percent above baseline by 2100. This result contradicts our previous work, which reported decreases in pine yield by 2100 under similar climate projections. We can not fully explain the discrepancy in the predictions yet we noted that WS CalClim 1.0 skillfully projected ponderosa pine diameter and height growth for a validation data set with little to no bias. Also WS CalClim 1.0 was built using a robust modeling framework and based on richer and more spatially refined tree and climate data sets.

Climate-sensitive growth models are only one element needed for a full accounting of the potential climatic and economic benefits from forestry projects in California. Tracking the net climate benefits of forests will require both an array of field plot data that cover all of California's forests and data sets that can be coordinated with economic information that captures the import and export of forest products and their substitutes. Developing forest management strategies to increase the risk-adjusted level of climate benefits across for California's forests will require integrating these data products into spatially-explicit tools that can analyze the tradeoffs and synergies among competing social goals for forests.

Keywords: Ponderosa pine, Forest Vegetation Simulator, tree mortality, climate-sensitive growth model, WS CalClim 1.0, PRISM, forest management

1.0 Introduction

> With growing concern over potential climate change, the most useful models will be sensitive to key effects of climate change on tree and stand development over long time periods. This will be fundamental to addressing questions of sustainability of forest management.
>
> Monserud 2003

Predictions indicate that climate change will have profound effects on the distribution, function, and productivity of California's forests (Lenihan et al. 2003; Hayhoe et al. 2004; Battles et al. 2008). These changes pose daunting challenges to the widely shared goal of sustainable forest management. The goal is a compelling one—forests should be managed to meet current needs without compromising the ability of future generations to meet their needs. However any plan designed to strike a balance between current and future demands depends on the ability to make reliable projections of forest dynamics. Thus there is a pressing need to provide managers with the means to predict forest responses under a range of expected climate scenarios. Equally important, anticipated changes in productivity over the next century must be considered in policies being designed to promote the use of forestry projects for climate mitigation.

Our earlier research (Battles et al. 2008) suggested that the direction of climate change in California would reduce the productivity of timberlands in the Sierra Nevada. In particular, the growth of ponderosa pine (*Pinus ponderosa*)—a major timber species—declined with drier and warmer weather. We obtained these results by adapting an industry standard planning tool to forecast 30-year tree growth and timber yields for forest stands under a changing climate. Specifically we used CACTOS Version 5.8 (the California Conifer Timber Output Simulator, Wensel et al. 1986) as the base model for projecting future growth. Initially CACTOS was built without reference to climate. Subsequently, differences between observed and predicted growth (Wensel and Turnblom 1998) spurred a basic research effort to quantify the influence of climate on forest growth in the Sierra Nevada (Wensel and Turnblom 1998; Yeh 1997; Yeh et al. 2000; Yeh and Wensel 2000). We used results from this peer-reviewed research to incorporate climate-sensitivity into CACTOS projections ($\text{CACTOS}_{\text{clim}}$). However, we recognized the inherent risk of applying a model, even an adapted one, to situations for which it was not designed (Monserud 2003).

Our current objective is to build from scratch a climate-sensitive forest growth model using the best available data. It must be as inclusive as possible with respect to modeling flexibility and information extent so as to provide results that will accurately depict future climate variability and long-term trends. Our ultimate goal is to produce a tool that will inform forest planning, economic analyses of climate change and the development of adaptation strategies for Sierra Nevada forests.

1.1. Background and Approach

To ensure the generality and accessibility of our work, we built our climate-sensitive model for forests in the Sierra Nevada of California (WS CalClim 1.0) using the logic and architecture of the Forest Vegetation Simulator (FVS, Ritchie 1999). FVS is an individual-tree, nonspatial, stand growth model built around a set of empirically derived equations of diameter growth, height growth, crown ratio, regeneration, and mortality. Growth models are species-specific and are grouped into model variants developed for different forest communities. We modified the growth functions for the variant designed for the forests on the west side of the Sierra Nevada (WESSIN, Dixon 1994). FVS is one of the most widely used forest management growth models with 20 variants representing most forested regions of the United States. It is maintained by the U.S. Forest Service and available for free download to all users (USFS 2008). While we constructed WS CalClim 1.0 to fit within a typical modeling framework, we took the very atypical approach of directly incorporating the influence of climate parameters on tree growth.

One of the most difficult challenges in forest modeling is predicting tree mortality. Typical approaches for modeling individual tree death often focus on immediate measures such as recent growth and/or current stand density. However theory suggests that tree mortality is a cumulative process (Anderson 2000) where the events over the lifetime of an organism influence its likelihood of future survival. Thus consideration of the long-term record of tree growth can improve estimates of tree mortality (Bigler and Bugmann 2003; Bigler et al. 2004; Das et al. 2007). For this analysis, we explored two different approaches to estimate tree mortality. First we simulated mortality following the typical FVS implementation where mortality is divided into two categories: background and density-induced (Dixon 2003). We also built a predictive model of tree mortality that combined measures of average growth, growth trend, and abrupt growth decreases in order to examine the relationship between a tree's growth history and probability of mortality (Das et al. 2007).

For this project, we initially focused on developing and testing WS CalClim 1.0 for ponderosa pine, one of the major timber species in the Sierra Nevada. According to recent estimates, pine growing stock in California exceeds six million cubic feet (FRAP 2003). It is a commercially preferred species that is often grown in single-species plantations. To judge the implications of WS CalClim 1.0 on pine productivity, we obtained inventory data for a young pine plantation and then ran simulations of growth using a realistic management regime and scenarios of climate change. It is only by considering the entire modeling enterprise that we can evaluate the efficacy and feasibility of climate-sensitive growth and yield models.

We recognize that accurate prediction of forest growth is a necessary but not sufficient condition for a full accounting of the potential climatic and economic benefits from forestry projects in California. A more comprehensive approach is needed, one that tracks the conversion of harvested wood products into bioenergy feedstocks as well as status of forest products over their entire life-cycle. For managed forests in temperate regions, a recent paper in *Science* summarized some of the potentials and challenges:

> Joint use of carbon sequestration and the provision of forest-derived products (e.g., timber and biomass for energy) will optimize the contribution of forestry in climate mitigation. Such options are particularly attractive in temperate regions where land availability is limited by high prices and strong competition with other land uses. Although complexities in quantifying the net carbon benefits of some of these activities may limit their role in global carbon markets, they will have a place in national mitigation strategies, particularly when used synergistically with goals and policies other than climate mitigation. For instance, fire reduction policies that require the removal of undergrowth and occasional thinning can contribute to production of bioenergy.

In this report, we briefly describe how such an approach could be applied to the forests of California.

2.0 Methods and Results

2.1. Climate Sensitive Forest Growth Model (WS CalClim 1.0)

2.1.1. Data Sources

Three primary data sources provided the tree growth and stand condition information (Table 1) needed to build the climate-sensitive FVS variant for the Sierra Nevada (i.e., WS CalClim 1.0). Data from more than 1,000 plots and 65,000 trees were available from locations throughout the Sierra Nevada biogeographic province (Figure 1). The extent and distribution of these plots helped ensure that a wide range of climatic and biological conditions were included in the growth model development.

Table 1. Data used for model fitting of individual tree growth equations. NCStem: Stem analysis data from the Northern California Forest Yield Cooperative (Biging 1983). NCPlot: Permanent plot and increment core data from the Northern California Forest Yield Cooperative (Wensel 1987). DolphMC: Mixed conifer increment core and permanent plot data from the USDA Forest Service Pacific Southwest Research Station (Dolph 1988).

Data Source	Years Covered (approx.)	No. of Plots	No. of Trees	No. of Diameter Increments	No. of Diameter Remeas.	No. of Height Increments	No. of Height Remeas.
NCStem	1965-1980	105	5,465	4,639	0	2,436	0
NCPlot	1961-1998	622	31,807	3,725	39,741	2,991	44,025
DolphMC	1958-1988	397	31,807	4,436	284	1,417	150

We built a custom data-parsing program to derive diameter and height increments from the available increment and stem analysis data. We also calculated competition indices, site index (based on protocols established by Krumland and Eng 2004), and tree age.

The climate data was obtained from the Parameter-elevation Regression on Independent Slopes Model (PRISM) climate mapping system (PRISM Group 2007). PRISM incorporates point data, a digital elevation model, and expert knowledge of climatic extremes to produce estimates of mean monthly minimum and maximum air temperatures, dewpoint temperature, and precipitation on a 4-kilometer (km) by 4-km grid. PRISM data sets are recognized as the highest quality climate data sets currently available and serve as the United States Department of Agriculture's (USDA's) official climate record (PRISM Group 2007). Raw PRISM data files were processed to produce plot-specific climate parameters and the output was matched to the appropriate tree records.

Validation data were used to provide an independent evaluation of the growth models. Data sources included: Blodgett Forest Research Station (University of California Berkeley Center for

Forestry), Boggs Mountain Demonstration State Forest, LaTour Demonstration State Forest, and Mountain Home Demonstration State Forest (California Department of Forestry and Fire Protection). These research and demonstration forests span a wide geographic range (Figure 1), and thus provided an appropriate test of climate influence on tree growth.

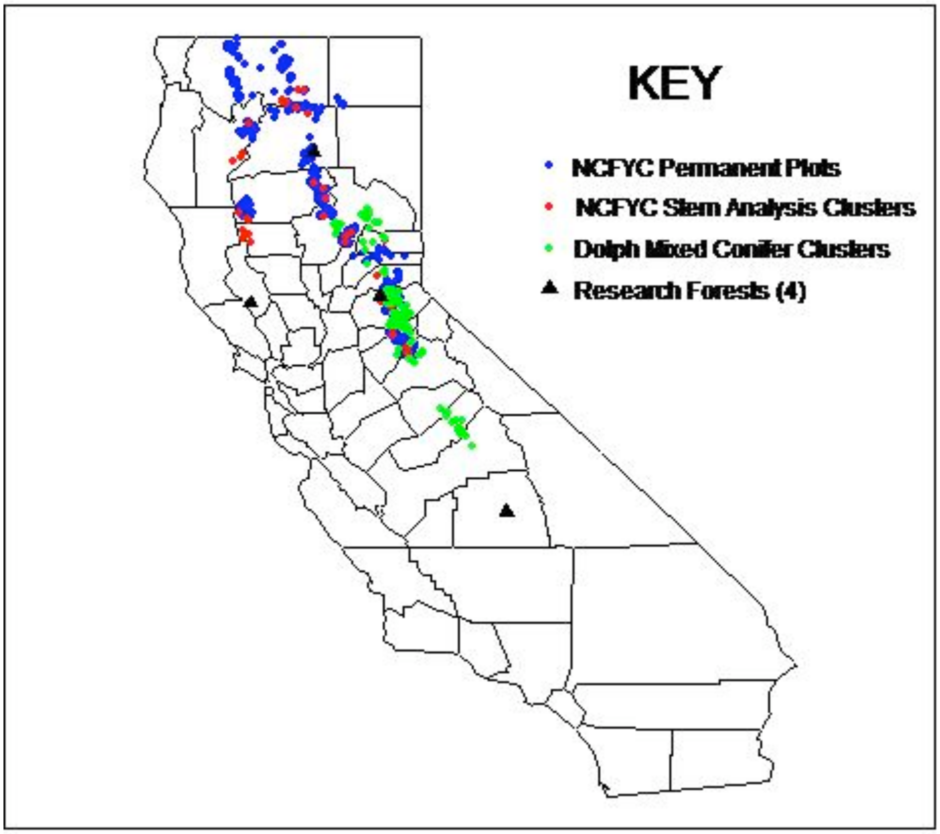

Figure 1. Map of data sources for model fitting and validation

2.1.2. WS CalClim 1.0 Development

A western United States regional height growth model for ponderosa pine was developed by Uzoh and Oliver (2006). They employed a linear mixed-effects approach on an individual-tree distance-independent model using experimental remeasured levels of growing stock data from five studies. Their complete model construction is shown below (Eq. 1):

$$E[\ln(\text{PAIH})] = b_0 + b_1\ln(\text{dbh}) + b_2(\text{dbh})^2 + b_3\text{SIM} + b_4\text{SL}[\cos(\text{ASP})] + b_5\text{ELEVA} + b_6\text{SDI} + b_7\text{BAL} + \hat{h}_l + e_{j(l)} + e_{ik(jl)} \quad \text{(Eq.1)}$$

The predictor is the expectation of the natural log of periodic height increment. The independent variables are diameter at breast height (dbh), site index (SIM), slope and aspect factors (SL, ASP), elevation (ELEVA), stand density index (SDI), and basal area larger than the target tree (BAL). The random effects are trees (i), plots (j) and the five study site locations (*l*). The error term $e_{ik(jl)}$ is a random error term for the i^{th} tree and the k^{th} measurement, assuming that the expectation of location *l* and plot *j* is zero with variance □. The covariance between the observation on the same tree at time *k* and *k*□ separated by *d* years is an autoregressive process given by:

$$\operatorname{Cov}(e_{ik(jl)}, e_{i'k'(j'l')}) = \begin{cases} \sigma^2 \rho^{|d|} & \text{if } i \neq i', k = k', j = j', l = l' \\ \sigma^2 & \text{if } i = i', k = k', j = j', l = l' \\ 0 & \text{otherwise,} \end{cases} \qquad \text{(Eq. 2)}$$

where ρ is the serial correlation coefficient between the measurements on the same tree over time. Using cross validation techniques, Uzoh and Oliver (2006) demonstrated that the mixed-effects model more accurately predicted growth than a function developed using a more traditional linear regression approach.

Stage and Salas (2007) presented growth functions that permit the integration of the topographic components (i.e., slope, aspect, and elevation) into a diameter growth model, but recommended that the model must be considered in its entirety even though in a statistical sense certain parameters may appear non-significant. The incorporation of topography is logical from an ecological consideration of species occurrence and vigor in the Sierra (Royce and Barbour 2001b). When integrated into a tree growth model that has the objective of being sensitive to climate change, however, care must be taken to not force relationships based on past climate. The functional form for plot mean annual increment presented by Stage and Salas (2007) is:

$$\begin{aligned} \ln(MAI) = b_0 &+ s\left[b_1 + b_2\cos(\alpha) + b_3(\sin(\alpha))\right] \\ &+ \ln(el+1) \times s\left[b_4 + b_5\cos(\alpha) + b_6\sin(\alpha)\right] \\ &+ el^2 \times s\left[b_7 + b_8\cos(\alpha) + b_9\sin(\alpha)\right] \\ &+ b_{10}el + b_{11}el^2 + b_{12}\text{Albrx} + b_{13}\text{Albry} \end{aligned} \qquad \text{(Eq. 3)}$$

where *MAI* is the mean annual increment, *b*'s are coefficients, □ is the azimuth of the aspect in degrees, *el* is the elevation (formulated to be invariant to the units used), and Albrx and Albry are the latitude and longitude in Universal Transverse Mercator (UTM) coordinates.

Thus in fitting our ponderosa pine diameter and height growth models, we followed Uzoh and Oliver (2006) recommendations and used a linear mixed effects model with a similar covariance structure. We tested for spatial autocorrelation by recognizing each plot as a random factor, but there was no autocorrelation present. We also incorporated topographic components (following Stage and Salas 2007) and evaluated the performance of a host of climate parameters. There is no analytical method available for calculating p-values or confidence intervals for the regression parameters. Therefore a Markov Chain Monte Carlo method using 1,000 observations was used to estimate unbiased 95% confidence intervals (alpha = 0.05) of the parameters. All statistical analyses were run using the R statistical programming language (R 2008).

2.1.3. WS CalClim 1.0 Results

Diameter Growth

Results for the diameter growth equation are given in a mix of U.S. and metric units, as these are the units of measure for the respective parameters. There were 11,334 observations in the regression data set. While some of the topographical variables were not significant as expected (Eq. 4), the full formulation was retained in the final growth equation as recommended by Stage and Salas (2007).

$$
\begin{aligned}
E[\ln(\mathrm{DG})] = b_0 &+ b_1\ln(\mathrm{dbh}) + b_2\mathrm{dbh} + b_3\mathrm{CR} + b_4\left(\frac{\mathrm{BAL}}{\ln(\mathrm{dbh}+1)}\right) + b_5\mathrm{SL} + \\
&b_6\mathrm{PREC} + b_7\mathrm{MAXT5DAYS} + \\
&b_9\mathrm{TRANGE} + b_{10}\mathrm{SL}[\cos(\mathrm{ASP})] + b_{11}\mathrm{SL}[\sin(\mathrm{ASP})] + \\
&b_{12}\mathrm{SL}\left[\ln(\mathrm{ELEV}+1)\right] + b_{13}\mathrm{SL}\left[\ln(\mathrm{ELEV}+1)\right]\cos(\mathrm{ASP}) + \qquad \text{(Eq. 4)} \\
&b_{14}\mathrm{SL}\left[\ln(\mathrm{ELEV}+1)\right]\sin(\mathrm{ASP}) + b_{15}\mathrm{SL}\left[\mathrm{ELEV}\right]^2 + \\
&b_{16}\mathrm{SL}\left[\mathrm{ELEV}\right]^2\cos(\mathrm{ASP}) + b_{17}\mathrm{SL}\left[\mathrm{ELEV}\right]^2\sin(\mathrm{ASP}) + \\
&b_{18}\mathrm{ELEV} + b_{19}\mathrm{ELEV}^2 + b_{20}\mathrm{Albrx} + b_{21}\mathrm{Albry} + e_{ik} + e
\end{aligned}
$$

where DG = annual diameter growth,

dbh = diameter at breast height (in.)

CR = crown ratio

BAL = basal area in trees larger than the subject tree (square feet /acre)

SL = average slope of the plot (%)

PREC = annual precipitation (millimeters, mm)

MAXT5DAYS = number of days in year that temperature at or above 5°C

TRANGE = average temperature range over the year (°C)

ASP = average aspect of the stand (radians)

ELEV = average elevation of the plot (feet)

Albrx = longitude in UTM coordinates

Albry = latitude in UTM coordinates

b_i = regression coefficients

e_{ik} = error of k^{th} measurement on the i^{th} tree

e = unexplained error.

The coefficients and the 95% confidence intervals for these variables are listed in Table 2. As expected, trees with a higher crown ratio (CR) grew faster and trees with higher competition index (index based on BAL, b_4) grew slower. Clearly local topography influenced tree growth with no less than 11 associated variables included to capture the environmental variation associated with topographic differences (Table 2). Growth also increased as a function of increasing latitude and decreasing longitude. The geographical arrangement of the plots around the northern end of the Central Valley made the longitude variable somewhat illogical. While the longitude parameter was statistically significant, it was highly correlated with latitude at 0.918. Dropping longitude from in the model was considered, but a substantial penalty in variance was observed, so it was decided to leave longitude in the model with the caveat that the user must apply the model in logical locations. The model was corrected for log transformation bias (Snowdon 1991) with a resulting factor of 0.168.

The most informative climate variables retained in the model were precipitation (PREC) and two measures of temperature, the total number of days each year where the maximum daily air temperature was ≥ 5°C (MAXT5DAYS) and the average annual range in mean monthly maximum and mean monthly minimum temperatures (TRANGE).

Ponderosa pine diameter growth increased with more precipitation and warmer days as measured by MAXT5DAYS. In contrast, diameter growth decreased as range of temperatures increased. All attempts to refine the models to use seasonal precipitation and temperature did not produce improved models relative to annual values.

Table 2. Coefficients and statistics for ponderosa pine annual diameter growth model used in WS CalClim 1.0. See text for definition of variables.

Parameter	**Coefficient**	**Std. Error**	**t-value**	**Lower 95% CI**	**Upper 95% CI**
Intercept (b_0)	-1.866e+01	1.294e+00	-14.418	-2.153370e+01	-1.618429e+01
log(DBH) (b_1)	8.367e-01	7.135e-02	11.726	4.843457e-01	1.018637e+00
DBH (b_2)	-3.819e-02	4.707e-03	-8.113	-5.139110e-02	-2.424123e-02
Crown Ratio (b_3)	1.593e+00	5.990e-02	26.596	1.390180e+00	1.634660e+00
BAL Index (b_4)	-2.996e-03	1.347e-04	-22.241	-3.186054e-03	-2.629585e-03
Slope (b_5)	-6.598e-03	1.331e-01	-0.050	-2.153327e-01	3.099591e-01
Precipitation (b_6)	3.291e-05	1.606e-06	20.493	2.473077e-05	3.870047e-05
MAXT5DAYS (b_7)	5.931e-03	6.131e-04	9.674	5.021313e-03	8.375859e-03
Temperature Range (b_9)	-1.881e-04	6.053e-05	-3.107	-2.741266e-04	-2.662238e-05
Cos(Aspect) * Slope (b_{10})	-1.785e-01	1.275e-01	-1.400	-4.623452e-01	1.926228e-02
Sin(Aspect) * Slope (b_{11})	1.672e-01	1.041e-01	1.606	4.180390e-02	4.658846e-01
Slope * log(Elev+1) (b_{12})	1.130e-04	1.701e-02	0.007	-3.950711e-02	2.711979e-02
Slope * log(Elev+1) * Cos(Aspect) (b_{13})	2.329e-02	1.623e-02	1.435	-2.138031e-03	5.919769e-02
Slope * log(Elev+1) * Sin(Aspect) (b_{14})	-2.123e-02	1.329e-02	-1.597	-5.917937e-02	-4.750561e-03
Slope * Elev^2 (b_{15})	3.139e-10	4.774e-10	0.658	-5.049413e-10	1.348490e-09
Slope * Elev^2 * Cos(Aspect) (b_{16})	-8.757e-10	4.337e-10	-2.019	-1.767739e-09	-1.736110e-10
Slope * Elev^2 * Sin(Aspect) (b_{17})	4.911e-10	3.614e-10	1.359	9.170710e-11	1.560215e-09
Elevation (b_{18})	-2.051e-04	1.994e-04	-1.028	-5.164087e-04	2.928792e-04
Elev^2 (b_{19})	1.653e-08	2.377e-08	0.695	-4.091342e-08	5.534349e-08
UTM-X (b_{20})	3.917e-03	3.065e-04	12.779	3.351550e-03	4.610263e-03
UTM-Y (b_{21})	2.298e-03	2.009e-04	11.439	1.835708e-03	2.660122e-03

Height Growth

The model formulation was the same as the diameter growth model (Eq. 4) except that the temperature variable MAXT5DAYS was replaced by MINT10DAYS, which was the number of days a year where the daily minimum temperature was ≥ 10°C. MAXT5DAYS can be thought of an index of the number of cold days per year (larger values = fewer cold days). Whereas MINT10DAYS is an index of the number of warm days per year (larger values = more warm days). Both are related to growing season length. Also, dbh was replaced by total height (THT) except in the BAL variable where dbh was retained. There were 11,921 observations in the regression data set. The coefficients and their 95% confidence intervals are listed in Table 3. The model was corrected for log transformation bias (Snowdon 1991) with a resulting factor of 0.248.

Again, crown ratio (CR) was an excellent predictor of growth, but height growth was less influenced by the competition index (BAL, b_4). Topographic variation also helped explain observed differences in height growth but overall height increment was less sensitive than diameter increment. The height growth-climate relationships were the same as for the diameter growth (i.e., growth increases with precipitation and air temperature) except that height growth was positively correlated with temperature range (TRANGE). In other words, as the difference between daily minimum and daily maximum of temperature increases height growth also increases.

Table 3. Coefficients and statistics for ponderosa pine annual height growth model used in WS CalClim 1.0. See text for definition of variables.

Parameter	**Coefficient**	**Std. Error**	**t-value**	**Lower 95% CI**	**Upper 95% CI**
Intercept (b_0)	-5.957e+00	1.033e+00	-5.767	-8.244508e+00	-3.986881e+00
log(THT) (b_1)	6.091e-01	3.784e-02	16.095	5.823818e-01	7.312689e-01
THT (b_2)	-7.339e-03	7.188e-04	-10.210	-9.435084e-03	-6.404087e-03
Crown Ratio (b_3)	1.229e+00	4.940e-02	24.870	1.146082e+00	1.338070e+00
PBAL Index (b_4)	-2.927e-04	1.236e-04	-2.368	-7.782488e-04	-2.635979e-04
Precipitation (b_5)	1.783e-05	1.909e-06	9.342	1.292193e-05	2.062822e-05
MINT10DAYS (b_6)	2.874e-03	3.464e-04	8.297	1.991182e-03	3.358933e-03
Temperature Range (b_7)	3.932e-04	6.722e-05	5.850	3.029568e-04	5.603714e-04
Slope (b_8)	-4.900e-01	1.139e-01	-4.301	-6.498952e-01	-1.896886e-01
Cos(Aspect) * Slope (b_9)	-1.211e-01	1.122e-01	-1.080	-4.349767e-01	-8.978438e-03
Sin(Aspect) * Slope (b_{10})	-4.159e-02	9.116e-02	-0.456	-2.321686e-01	1.126805e-01
Slope * log(Elev+1) (b_{11})	6.029e-02	1.455e-02	4.145	2.211986e-02	8.093697e-02
Slope * log(Elev+1) * Cos(Aspect) (b12)	1.507e-02	1.430e-02	1.054	9.937357e-04	5.508373e-02
Slope * log(Elev+1) * Sin(Aspect) (b_{13})	5.877e-03	1.162e-02	0.506	-1.393593e-02	3.035293e-02
Slope * Elev^2 (b_{14})	-7.736e-10	3.996e-10	-1.936	-1.395162e-09	2.072072e-10
Slope * Elev^2 * Cos(Aspect) (b_{15})	-3.478e-10	3.847e-10	-0.904	-1.473844e-09	-1.603383e-11
Slope * Elev^2 * Sin(Aspect) (b_{16})	-2.998e-10	3.110e-10	-0.964	-9.315672e-10	2.886084e-10
Elevation (b_{17})	-6.123e-04	1.669e-04	-3.669	-8.162919e-04	-1.915689e-04
Elev^2 (b_{18})	4.829e-08	1.953e-08	2.473	-6.100775e-10	7.296860e-08
UTM-X (b_{19})	2.170e-03	2.387e-04	9.092	1.740146e-03	2.739877e-03

UTM-Y (b_{20})	5.722e-04	1.629e-04	3.512	1.916015e-04	8.541555e-04

2.1.4. WS CalClim 1.0 Evaluation

Predictions from the diameter and height growth model were compared to tree measurements from the four research forests (Figure 1) by calculating residuals (observed growth – predicted growth). Since these data were not included in the model development, they represent a true test of model performance. Overall, both models performed well. There were no trends in the diameter growth residuals with tree diameter (dbh) or stand basal area (BAL). The mean annual diameter growth residual was 0.037 inches with a 95% confidence range of 0.021 to 0.052. Thus the CalClim diameter growth model did have a slight tendency to underestimate ponderosa pine diameter increment across the four data sets.

Although fewer data were available for validation of the height growth (tree height is measured less often than tree diameter), the available results indicated that the CalClim height growth model performed well. No trends were observed in the residuals. Moreover the mean annual height growth residual was 0.180 feet with a 95% confidence range of -0.086 to 0.446, indicating no significant prediction bias.

2.2. Models of Tree Mortality

2.2.1. Default Mortality Estimator

The default mortality function in WS CalClim 1.0 was modeled in two parts: background and density-induced. Background mortality was estimated as a weighted stochastic process where weights were based on the relative size (dbh) of a tree and its shade tolerance factor. In effect, smaller, less-shade tolerant trees were more likely to be killed by background events. Density dependent mortality was a function of the species' weighted stand density index (SDI, Reineke 1933). Density dependent mortality was induced at 55% of the maximum SDI and stand densities was never permitted to exceed 85% of the maximum (Ritchie 1999). Note that neither part of the default mortality estimator directly accounted for inter-tree competition.

2.2.2. Cumulative-Growth Mortality Estimator

We developed a mortality estimator for ponderosa pine based on an analysis of the long-term growth record. We collected, processed, and measured more than 200 ponderosa pine tree ring samples from the Blodgett Forest Research Station. We crossdated these samples to correct for measurement errors. We then generated an extensive list of candidate mortality functions that included elements from the long-term growth record, including average recent diameter growth, the trend in diameter growth, and the presence of abrupt declines in growth (Das et al. (2007). Survival probability was modeled using the logistic function with the general form given below:

$$\pi(x) = \frac{e^{g(x)}}{1 + e^{g(x)}} \quad \text{(Eq. 5)}$$

where π(x) is survival probability and g(x) is a linear function of growth indices.

We used the growth records from live and dead tree to fit these models. For all models we compared performance using the following statistics:

1. Akaike Information Criteria (AIC): a measure of the likelihood of the model given the data that penalizes the more complex models (i.e., models with more variables).

2. Receiving Operator Characteristics (ROC): a measure of the model's predictive skill. ROC = 0.5 indicates no predictive skill; ROC > 0.7 indicates a reasonable fit.
3. Fit of unweighted sum of squares: a measure of the total amount of prediction error. Values reported as p-values that range from 0 to 1 with larger numbers indicating less error.

Based on these results, we proposed the following specification for ponderosa pine survival probability equation:

$$g(x) = 5.7 + 1324 slope15rba - 0.67 \operatorname{int} 5 \qquad (Eq.6)$$

where $g(x)$ is the linear function of growth indices used to estimate survival probability (Eq. 5), *slope15rba* is the slope of the relative basal area increment for the last 15 years, and *int5* is the number of sharp declines in growth during the last five years. An abrupt decline was defined as a drop in year to year growth increment of 50% or more. The implications of this model are that a positive trend in relative basal area increment during the past 15 years indicates a higher probability of survival while the occurrence(s) of abrupt annual growth declines in the last five years indicates a lower probability of survival. The predictive ability of this model was solid (ROC = 0.72) as was the fit (p = 0.69). The model also outperformed the baseline mortality model, which is determined solely by the last five years of diameter growth (ROC = 0.53 and p = 0.52).

2.3. Forest Simulations under Future Climate Scenarios

2.3.1. Study Site

We initiated our simulations with forest inventory data from a 20 years-old pine plantation near Whitmore in Shasta County, California. Shasta is major timber producing county. In 2007, 191,618 million board feet of timber were harvested (11.8% of total volume in the state) with a value of $43,948,866 (third highest value by county, California State Board of Equalization 2008). The stand was planted with ponderosa pine after a fire and is being managed as a commercial operation. At the start of our simulations (stand age = 20 years-old), there were 295 trees/ac with a basal area of 72 square feet per acre (ft^2/ac) and a total volume of 794 cubic feet per acre (ft^3/ac).

2.3.2. Downscaled Climate Change Scenarios

Two of the climate parameters needed for WS CalClim 1.0 required daily maximum and minimum air temperature. Thus we obtained results from three global climate models (GCMs) where downscaled data was available on a daily basis. The three models included in our analysis were the GFDL model (version CM2.1, NOAA Geophysical Fluid Dynamics Laboratory, Princeton New Jersey, Anderson et al. 2004), the CNRM-CM3 model (Center National Weather Research, Toulouse, France, Salas-Mélia et al. 2005), and the PCM (Parallel Climate Model) (Meehl and Washington group at the National Center for Atmospheric Research [NCAR] in Boulder, Colorado; Meehl et al. 2003). We used the downscaled data from the nearest gridpoint (1/8 degree grid) to our study site. We choose the climate predictions generated by the constructed analogues (CA) downscaling technique because of its greater skill in capturing daily variability in temperature and precipitation (Maurer and Hidalgo 2008). All of our climate data were obtained from the 2008 Scenarios—Simulation Data and Information webpage (Tyree 2008).

Impacts were analyzed for two greenhouse gas (GHG) emissions scenarios: A2 (relatively high emissions) and B1 (low emissions). For the A2 scenario, carbon dioxide (CO_2) emissions continue to climb throughout the century, reaching almost 30 Gt yr^{-1} (gigatonnes per year), so that by the end of the century CO_2 concentration reaches more than triple its pre-industrial level. For the B1 scenario, CO_2 emissions peak just below 10 Gt yr^{-1} in mid-century before dropping below present-day levels by 2100. This corresponds to a doubling of CO_2 concentration relative to its pre-industrial level by the end of the century (Cayan et al. 2008).

Table 4. Summary of annual climate parameters used in the CalClim variant of FVS. Means (standard deviations) are given for each time period. Daily climate data based on downscaled (analog method) for three global climate models under two different emissions scenarios.

	Time Period	PREC (mm)		MAXT5DAYS (days)		MINT10DAYS (days)		TRANGE (°C)	
		A2	B1	A2	B1	A2	B1	A2	B1
GFDL CM2.1	1951–2000	372.0	372.0	310.9	310.9	30.9	30.9	15.2	15.2
		(83.0)	(83.0)	(14.1)	(14.1)	(10.8)	(10.8)	(0.6)	(0.6)
	2011–2060	347.9	388.6	323.3	322.6	52.9	47.4	15.6	15.4
		(74.8)	(88.9)	(11.9)	(12.8)	(11.9)	(11.1)	(0.7)	(0.7)
	2051–2100	344.2	369.9	336.9	327.9	78.1	57.6	16.0	15.6
		(83.9)	(84.2)	(84.2)	(12.9)	(16.1)	(11.4)	(0.6)	(0.7)
CNRM CM3	1951–2000	494.9	494.9	305.0	305.0	29.5	29.5	14.5	14.5
		(125.2)	(125.2)	(13.4)	(13.4)	(10.6)	(10.6)	(0.7)	(0.7)
	2011–2060	539.8	546.5	311.1	312.5	57.4	55.3	14.4	14.5
		(145.5)	(128.5)	(12.6)	(11.6)	(13.3)	(11.7)	(0.6)	(0.6)
	2051–2100	528.2	546.5	327.4	316.9	94.2	71.1	14.2	14.7
		(110.4)	(117.9)	(12.2)	(14.8)	(14.3)	(10.6)	(0.5)	(0.7)
NCAR PCM1	1950–1999	498.6	498.6	315.4	315.4	25.3	25.3	15.3	15.3
		(152.1)	(152.1)	(14.5)	(14.5)	(7.3)	(7.3)	(0.6)	(0.6)
	2011–2060	520.2	549.4	319.8	320.7	41.7	33.7	15.1	15.2
		(128.0)	(143.0)	(13.2)	(11.9)	(11.3)	(7.5)	(0.6)	(0.6)
	2050–2099	490.1	506.0	334.4	328.7	59.4	42.3	15.4	15.4
		(129.0)	(108.4)	(12.6)	(13.5)	(12.8)	(9.6)	(0.6)	(0.7)

2011–2060	136	2270	1612	157	2249	1612
2050–2099	159	2399	1764	148	2338	1692

2.3.4. Simulation Results

All six downscaled climate realizations for the site in Shasta County predicted consistent increases in air temperature during the next century. In contrast, changes in precipitation were more variable among the realizations and of a much smaller magnitude (Table 4). As expected, daily maximum and minimum air temperatures increased more steeply during next century under the more severe (i.e., A2) GHG emissions scenario. While predicted temperature trends were similar among the GCMs, predicted precipitation varied among the models. In most cases (8 out of 12), precipitation increased above the baseline but never more than 10% (Table 4). For example, CNRM forecasted a warmer and wetter climate for our site in the next century, contrasting with the expectations of a warmer and slightly drier climate from the GFDL model.

Despite the changes in projected climates, it is important to note that the range of values in these future scenarios did not exceed the range included in model development. Our models were based on field data across a large latitudinal gradient (Figure 1) collected over a 40-year period (Table 1). This spatial breadth and temporal depth ensured the inclusion of extreme climate conditions on tree growth in CalClim 1.0. Thus for the scenarios explored in this research, we are not attempting to predict forest growth for entirely novel conditions.

In terms of climate parameters that influence growth in WS CalClim 1.0, MINT10DAYS increased the most both in relative and absolute terms during the century. In some cases, the mean number of MINT10DAYS doubled and even tripled by the end of the century (Table 4, Figure 2). While overall mean air temperatures rose under all realizations, the range in temperature (i.e., the average difference between daily minimum and maximum temperature) changed very little (Table 4).

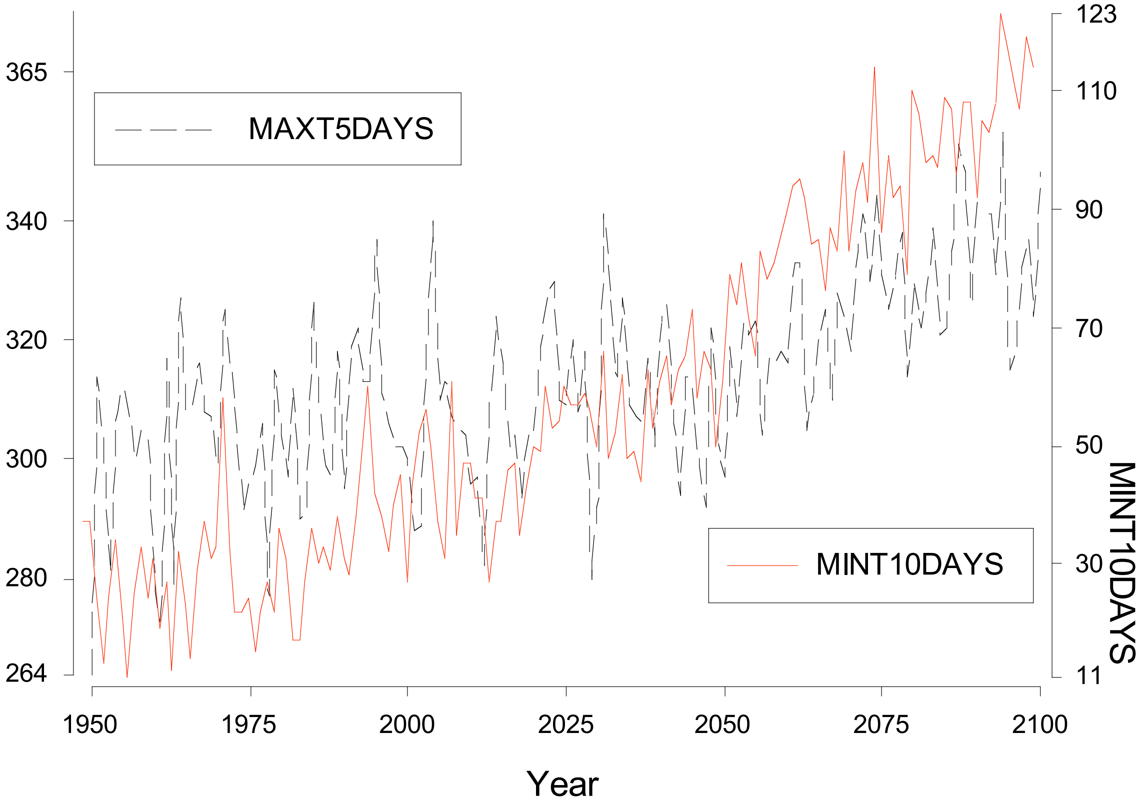

Figure 2. Annual estimates from 1950–2100 for two climate parameters influencing diameter and height growth in WS CalClim 1.0. Projections based on downscaled estimates from the CNRM-CM3 global circulation model using the A2 emissions scenario.

Growth of the ponderosa pine plantation increased under all climate realizations (Table 5). Comparing baseline (1951–2000) to the end of the century (2050–2100), increases in total volume increment (ft^3/ac) ranged from 9.2% (NCAR, B1) to 27.7% (CNRM, A2). Mid-century growth projections (2011–2060) were always greater than baseline time period but less than the end of the century. The major driver of the simulated increase in volume growth was the sharp rise in tree height growth. As noted above, in WS CalClim 1.0 the most informative climate variables related to air temperature were measured in degree-days. For diameter growth, the best predictor of annual growth was the number of days per year where the maximum daily temperature was ≥ 5°C (MAXT5DAYS). For height growth, the best predictor was the number of days per year where the minimum daily air temperature was ≥ 10°C (MINT10DAYS). Since MINT10DAYS increased much more than MAX5DAYS for all climate realizations (Table 4), tree height increased proportionally more than diameter growth. For example, under the CNRM A2 climate realization, the relative increases in tree height (Figure 3B) were much greater than relative increase in basal area (a metric based solely on tree diameter increment, Figure 3A) and the pattern in volume increment (Figure 3C) more closely matched the trends in height growth.

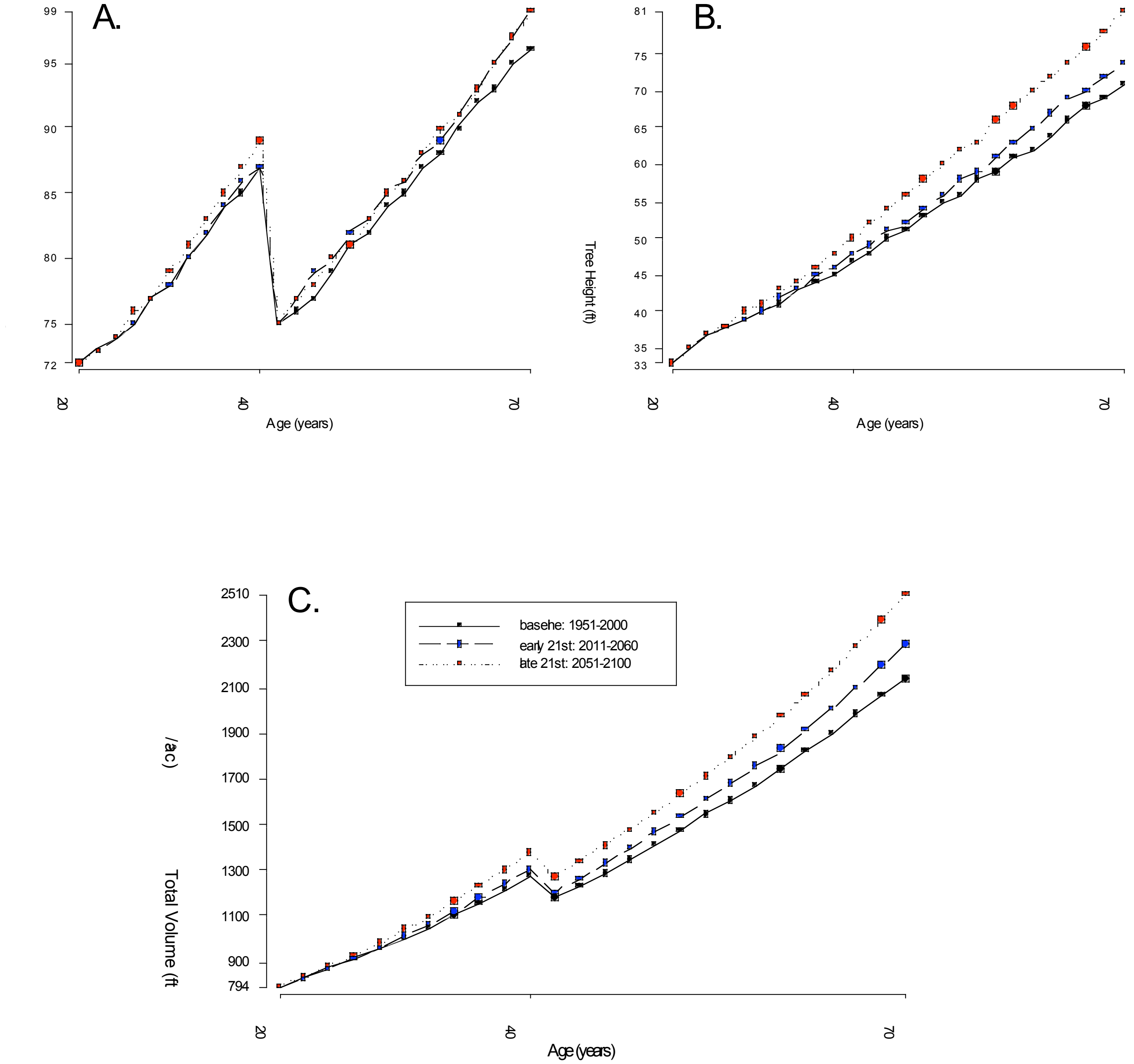

Figure 3. Forest growth projections for a 20 years-old pine plantation under the A2 emissions scenario using WS CalClim 1.0. Climate parameters were derived from downscaled estimates from the CNRM-CM3 global circulation model: (A) Basal area projections; (B) Tree height projections; (C) Total volume projections.

2.3.5. Sensitivity Analysis

The four climate parameters included in the growth models co-varied under the suite of realizations used in this analysis. The degree-day variables that were derived from air temperature (i.e., MAX5DAYS and MINT10DAYS) always changed in the same direction. They increased and therefore the influence on forest growth was always synergistic. On the other hand, changes in precipitation and temperature range sometimes worked in synergy with temperature (increased growth) and sometimes in antagonism (decreased growth). To quantify the independent impact of the climate parameters, we examined the effects of each parameter in isolation.

We used the climate projections from 1951–2000 from the NCAR PCM1 model as a baseline for a sensitivity analysis. For each climate parameter, we calculated the minimum and maximum changes observed among all 36 climate scenarios (Table 4). We then ran growth simulations for our test case where we varied one climate parameter in turn. All the other parameters remained at baseline levels. The results are nine yield projections (baseline + 8 single variable projections, Table 6). Our measure of sensitivity was the proportional difference in the total volume of wood growth over a 50-year period compared to baseline: $(NET_{\text{climate parameter}} – NET_{\text{baseline}}) / NET_{\text{baseline}} *100\%$.

Table 6. Sensitivity analysis of forest yield predictions due to changes in individual climate parameters. Management scenarios begin with 20 years of growth for a stand is 20 years old at the start. After 20 years, there is a commercial harvest to a target basal area = 75 ft^2/ac. The stand then grows for another 30 years without further intervention. The default mortality function for CalClim was used. Reported below is total volume in ft^3/ac. Net is the total volume of wood grown (Final - Initial + Harvest). % Change was calculated with reference to the baseline results.

	Harvest	Final	Net	% Change
Baseline	146	2194	1546	--
PREC +10%	146	2195	1547	0.06
PREC - 7%	146	2192	1544	-0.12
MAXT5DAYS +10%	186	2340	1732	12
MAXT5DAYS +4%	166	2264	1636	5.8
MINT10DAYS +219%	155	2674	2035	31.6
MINT10DAYS +67%	149	2267	1622	4.9
TRANGE +5%	147	2226	1579	2.1

TRANGE - 2%	147	2181	1534	-0.78

As noted above, MINT10DAYS was the climate parameter predicted to experience the greatest proportional increase over the next 100 years. Given the magnitude of change and its influence on tree growth, MINT10DAYS was the single most influential determinant of forest yield (Table 6). In contrast, the relatively small shifts in PREC had a negligible affect on forest growth. For example, a 10% increase in PREC lead to <1% increase in yield (Table 6). Clearly increases in temperature as measured with MINT10DAYS (fewer cold days) and MAXT5DAYS (more warm days) were the major drivers of the observed increases in forest growth.

2.4. Assessment of Forest Management Activities.

When considering the potential impacts of climate change on forest management in California, it is important to recognize that the range of options available to managers varies greatly. Both ecosystem productivity and land ownership matter. Of the 33% of California that is classified as forest (3 x 10^7 acres), 59% is timberland available for management (Table 7). The remainder is either too unproductive (24% of all California forest land) or is legally reserved (e.g., parks, 17% of total).

Table 7. Forest land ownership in California in 2005. Units = thousand acres.

Owner Class	Unreserved Forest Land		Legally Reserved Forest Land		
	Timberland	Unproductive	Productive	Unproductive	Total
Corporate Private	4,402	338	0	0	4,740
Noncorporate Private	4,593	3,907	0	0	8,500
State and Local	258	211	381	215	1,065
U.S. Forest Service	9,784	2,424	2,626	923	15,757
Other Federal	514	986	993	663	3,156
All owners	19,551	7,866	4,000	1,801	33,218

Source: Christensen et al. 2008.

To quantify the range of management activity on the 1.9 x 10^7 acres of timberland (Table 7), it is necessary to consider different behavioral classes within the various ownership categories and the different types of forest management practices that could be used (Table 8). Corporate private forestlands are overwhelmingly managed to maximize value through the sustainable production of wood products. Noncorporate private forests are mainly family forests and have more diverse management approaches. On an acreage basis, approximately one-quarter of the acres have commercial harvests, one-quarter of the acres have some degree of vegetation management to reduce risk (primarily fire risk reduction), and one-half of the acres are in a "let grow" status (sensu Butler 2008).

The goals of state and local government forest lands in California are primarily to provide open space, recreation, and habitat value with minimal levels of vegetation management for fire risk reduction, forest health, and public safety. More than half of federal forest lands have no roads and are unlikely for regulatory or practical reasons to ever have any vegetation management activities. Of the roaded areas of federal forest lands, environmental restrictions further limit where vegetation management could be undertaken. Thus in total, about 25% of California forests could potentially be managed as even-aged plantations—the scenario we explored in this report.

Table 8. California forest area by owner and probable management actions. Units = thousands of acres.

Owner/Management	Area	Percent of Forest Area (%)	Fire Suppression	Risk Mgt w/ Veg Mgt	Commercial Harvest
Corporate Private + Family Forest /Timber	6,856	21	6,856	6,856	6,856
Noncorporate Private w/o Family Forest/Timber	6,383	20	6,383	2,570	0
Public/ Some Management	7,724	24	7,724	4,505	1,287
Public/ No Management	12,255	36	3,791	266	0
TOTAL	33,217	100	24,754	14,197	8,143
Percent of Forest Area (%)			75	43	25

3.0 Conclusions and Implications

3.1. Prospects for WS CalClim 1.0

Several measures of design and performance recommend further development and testing of WS CalClim 1.0, the initial version of a climate-sensitive growth and yield model of forest growth in the Sierra Nevada. WS CalClim 1.0 was based on the proven model logic of FVS. The specific growth functions used in WS CalClim 1.0 incorporated recent advances in forest biometry (e.g., Uzoh and Oliver 2006; Stage and Salas 2007). An extensive database of tree growth records was assembled (more than 11,000 ponderosa pine records) and then matched with the highest quality climate data available (i.e., PRISM 2008). The parameterization of the final functional forms of the growth equations used a sophisticated and flexible statistical approach that directly tested for confounding effects due to spatial autocorrelation and provided confidence intervals for all coefficients included in the model (Table 2, Table 3). Most importantly, both of the growth submodels in WS CalClim 1.0 were able to predict diameter and height increments in the validation data sets with little (diameter increment) to no bias (height increment). Also the application of WS CalClim 1.0 to the baseline growth projections for a typical 20 years-old ponderosa pine plantation produced 50-year yield estimates that qualitatively matched current expectations. Finally, because it was designed as a variant of FVS, WS CalClim 1.0 shares a common software interface, thus ensuring widespread availability.

On the other hand, WS CalClim 1.0 is a new model incorporating innovative features. More extensive testing is necessary to ensure that this ponderosa pine model adequately captures the range of possible behavior.

3.2. Comparison of WS CalClim 1.0 with CACTOS$_{clim}$

The initial results from WS CalClim 1.0 directly contradict our earlier analysis of the likely impacts of climate change on forest productivity in the Sierra Nevada (Battles et al. 2008). In the previous effort, we reported that pine plantation yields declined from 5% to 25% by the end of the twenty-first century (Battles et al. 2008). Here we reported increases that ranged from 9% to 28% by the end of the century (Table 5). Differences among the climate scenarios account for part of the discrepancy. In particular, there were no significant trends in projected precipitation from the downscaled climate scenarios used in Battles et al. (2008), whereas there were modest increases in precipitation in 8 out of the 12 cases explored here (Table 4). Nevertheless, the two models do incorporate disparate relationships between pine growth and air temperature. Yeh and Wensel (2000) found a strong negative correlation between mean summertime air temperature and pine diameter growth. We used these results to adjust predictions from the CACTOS model to account for changes in climate. (Note: we referred to this climate-adjusted version as $\text{CACTOS}_{\text{clim}}$). In contrast, the growth models in WS CalClim 1.0 had a strong positive relationship between pine growth and air temperature (as measured by degree day variables, MAXT5DAYS, MINT10DAYS). Below we discuss several major differences between the two models:

1. The climate adjustments to CACTOS were based on the premise that all of the non-random differences between the projected growth from a calibrated CACTOS model and the observed growth from stem analysis could be explained by changes in climate (Wensel and Turnblom 1998; Yeh and Wensel 2000). Other factors not accounted for in the original CACTOS that could lead to the overestimates of growth (e.g., growth declines due to air pollution, pest outbreaks, or disease interruptions) were not considered.
2. Advances in the probabilistic and spatial interpolation of climate data provided WS CalClim 1.0 with precisely matched and widely vetted climate inputs. The PRISM climate data used in WS CalClim 1.0 was available on a 4-km by 4-km grid (PRISM Group 2007). Yeh and Wensel (2000) relied on much coarser regional estimates derived from a customized interpolation of records from the 32 weather stations in the vicinity of their tree growth data (Yeh et al. 2000).
3. Data used to develop WS CalClim 1.0 was a super set of the data available to Yeh and Wensel (2000), and thus WS CalClim 1.0 considered tree growth and climate records from a greater temporal and spatial range.
4. The scale of the analyses of climate-growth relationships varied. Yeh and Wensel (2000) used stem analysis to collect 15 years of annual growth increments. In contrast, much of the tree growth information used in WS CalClim 1.0 was based on inventories that periodically (i.e., every two to five years) measure diameter growth. Thus Yeh and Wensel had a much finer temporal scale and could explore intra-annual (i.e., seasonal) and biennial relationships between climate variables (e.g., total winter rainfall, previous summer mean air temperature) and tree annual increment.

Despite these distinctions between the two models, the diametrical opposition of the results was surprising. We cannot determine the precise reasons for the disparity in expectations without deconstructing CACTOS and the peer-reviewed research that provided the climate adjustments. However it seems that the two models keyed into different components of future climate.

Tree growth in Sierran conifer forests is strongly controlled by the onset of warmer spring conditions as well as the timing of the end of moisture availability in late summer (Royce and Barbour 2001a, 2001b). Cactos$_{\text{clim}}$ appeared to respond to increased air temperature by projecting temperature-induced moisture stress, while WS CalClim 1.0 used the increased temperature to extend a temperature-limited growing season. The few studies that have examined the relationship between pine productivity and climate described a trade-off between increased growth due to the extension of the growing seasons afforded by warmer temperatures and reduced growth due to shortages in plant water availability (Matala et al. 2005; Girardin et al. 2008). The importance of these trade-offs to accurate predictions have spurred interest in hybrid modeling approaches (Monserud 2003; Girardin et al. 2008). These systems retain the specificity and empiricism of growth and yield models but also incorporate results from process models that provide updated information on water and nutrient supply.

3.3. The Mortality Models

In this application of WS CalClim 1.0 we did not compare the performance of the two tree mortality models. Throughout our simulations of ponderosa pine plantation growth, we used the default FVS model. In the context of managed stands where density is controlled and predicted growth only increased with a warming climate, changes in the probability of mortality due to slow growth was not a major concern. However our empirical results suggest that the cumulative mortality model will provide more accurate estimates of tree survival probability for ponderosa pine growing in high density, closed canopy forests. Incorporating these alternative mortality models into CalClim and evaluating their impact on stand dynamics is a high priority for future work.

3.4. Implications

3.4.1. Climate-sensitive Forest Growth and Yield Models

Clearly, predictions of increases in productivity of a preferred timber species (pine) in the Sierran timberlands throughout the twenty-first century have ramifications for economic and policy planning. The first priority is to confirm these results before developing climate adaptation strategies or conducting detailed downstream economic analyses. In addition, the inherent limitations of using a growth and yield model along with various climate change projections must be recognized. The goal of WS CalClim is to provide site-specific predictions of future stand dynamics. Although we are building the capacity to respond to climate in the model, we are not incorporating other physiological or ecological processes that may influence growth that operate at a seasonal rather than annual time scale. As noted above, tree growth in the Sierra Nevada is strongly influenced by the trade-off between an extended growing season and moisture limitations. The accuracy of different climate model estimates of seasonal trends in temperature, vapor pressure deficits, and soil moisture availability is not known.

WS CalClim also does not consider changes in tree growth due to the direct effects of higher atmospheric CO_2 concentrations (nor does CACTOS$_{\text{clim}}$). An authoritative review of the best evidence to date suggests that the increased productivity in closed-canopy forests caused by CO_2 fertilization effects is likely to be short-lived (Korner 2006) and other resource limitations (e.g., nutrients, water) constrain growth. A strict statistical model like WS CalClim will never capture theses processes.

We suggest the best way to proceed is to build on the prospects of WS CalClim 1.0 while testing critical components of $\text{CACTOS}_{\text{clim}}$. Further sensitivity analysis of pine growth models in WS CalClim 1.0 would help quantify the relative contribution of each of the climate parameters. Given the importance of the timing of the energy and water supply, a detailed analysis of the climate-growth relationship for the subset of records with annual resolution would help specify the nature of the trade-off between an extended growing season and induced moisture stress. Also, evaluating the ability of $\text{CACTOS}_{\text{clim}}$ to predict tree growth in our validation data would be very informative. Ultimately the lessons learned in the development, application, and evaluation of these models define the critical gaps on our understanding and outline the necessary empirical research to fill these gaps.

3.4.2. Forest Policy and Economics

The economic chapter of this report was originally designed to follow up on the oft-stated hypothesis that future climate conditions would be sufficiently different than those of past century and would require major changes in the species and stocking levels per acre if the owners were to maintain the value of their commercial timberlands. The assumption was that a surge of harvest volumes, much of it being of lower value than the high quality timber that constitutes the overwhelming share of taxable revenue for the industry, would present a challenge that could be profitably addressed by an expansion of the wood chip-fired energy infrastructure of California.

However the results from our initial analysis suggest that existing ponderosa pine forests are reasonably well adapted for the climate stresses and will grow slightly faster under future climate scenarios. Continued developments in our modeling efforts indicate that all the major species in the Sierran mixed-conifer forest are likely to grow better under future climate scenarios (T. Robards, personal communication). This conclusion is conditional as it assumes a future where historic tree mortality rates prevail. This assumption is difficult to test. There is also evidence that California forests are already experiencing significant increases in new mortality associated with changes in climate (van Mantgem et al. 2009). Moreover, other novel disturbances whether they are related to climate or not (e.g., increased wildfire risk, pest and pathogen outbreaks) can alter predictions of carbon dynamics in forests. For example, the mass tree mortality associated with insect outbreaks across vast expanses of Canada's conifer forest has shifted projections. Canadian forests are now expected to be near-term sources of CO_2 rather than long-term sinks (Kurz et al. 2008).

Analyses of managed forests cannot rely solely on forest measurements since the full accounting of climate benefits requires tracking the harvested wood products into bioenergy feedstocks, as well as following the long-lived products over a century of use. The purpose of this section is to describe how such an approach could be applied to the forest area of California. The mandate from the state for more renewable energy and the potential to use vegetation management approaches to achieve diverse forest goals not related to the production of timber provides unique opportunities that could meet Canadell and Taupacuh's (2008) goal to "optimize the contribution of forestry in climate mitigation."

3.4.3. Climate Benefits from Forest Management

The key elements in a comprehensive accounting of climate benefits from managed forests are: (1) tracking biomass flows, and (2) assessing risk. The U.S. Department of Energy's Voluntary

Reporting of Greenhouse Gases (1605(b)) Program (USDOE 2008) and California's Greenhouse Gas Emissions Inventory (California Climate Change Portal 2008) both track the direct and indirect climate benefits from the forest sector. The direct benefits are accounted for in the net GHG emissions for forest lands that show a significant sink even when mortality events such as forest wildfires are taken into account. The indirect benefits provided by the substitution of fossil fuels with carbon-neutral energy used in the manufacturing, residential, and electricity sectors are less apparent, as they are small compared to the total emissions of those three sectors. However a growing body of evidence suggests that these benefits are real; they are achievable, and they are on par in terms of magnitude with "in-the-forest" sequestration of carbon (Eriksson et al. 2007; Hennigar et al. 2008; Sathre and Gustavsson 2008; Schlamadinger et al. 2007).

Another major concern for California's forest is the potential effects of climatically driven increases in wildfire area (e.g., Westerling et al. 2006). The impacts of these fires will depend both on weather and the fuel loading within the forest. In a recent analysis, Christensen et al. (2008) used the Forest Vegetation Simulator (FVS) and its Fire and Fuels Extension (FFE) to project wildfire risk from the most recent forest data collected as part of Forest Inventory and Analysis (FIA) program. They concluded that under extreme fire weather conditions, wildfires in California would be limited to surface fires on 72% of the forest (Christensen et al. 2008). Of the remaining 28% of forests at risk of destructive crown fires, they suggested that vegetation management in these stands could reduce this potential loss. Some of the treatments could produce substantial amounts of biomass that need to be taken off site to reduce short-term fire risks and long term GHG emissions as it decomposes. Net treatment costs can be reduced if harvested products are collected and sold for use in bioenergy production. Increases in burned biomass in wildfires will also increase smoke emissions that cause significant negative human health impacts, especially when it covers major residential areas. All of these potential changes to California's forests under climate change scenarios need to be considered within a transparent geographic information system that can also include cost and benefit calculations.

3.4.4. Next Steps

Tracking the net climate benefits of forests and related forest products will require both an array of field plot data that cover all of California's forests as well as data sets that can be coordinated with economic data that captures that import and export of forest products and their substitutes such as cement in construction and fossil fuels for energy generation. Although forests managed by different owners may look similar, the rates of growth, utilization of harvested products, and management of low-probability but high-impact risks such as intense wildfires vary considerably. Ensuring that a quantity of sequestered forest carbon offsets an emission requires that the forest carbon be monitored and guaranteed for 100 years. The only statewide accounting of forest inventories with a statistically valid basis of field plots, assessment of natural threats, and databases that can be linked to the import and export of wood products is the FIA reporting system managed by the U.S. Forest Service. It is based on 7,000 forest plots that are spaced at approximate 3-mile intervals. It has a number of analytical models linked to the plot level data that can be verified in the field when plots are remeasured. For example, the Biosum model (Fried and Christensen 2004; Barbour et al. 2008) can estimate the harvested wood products that could be produced from various vegetation management treatments given different price assumptions. Because it based on a spatial system with field plots, it could be expanded to track GHG emissions as well as changes in the risk factors relevant for wildfires and insect outbreaks that may be exacerbated by climate change. Other spatially defined variables such as the current and potential future extent and population of various plant and animal species are based on spatial models that use maps rather than plot data. In addition the smoke from wildfires will always be a major public health risk that must be considered along with the GHG emissions. All of these overlapping goals and programs will require revenue from interested beneficiaries ranging from local users of open space to state taxpayers to buyers of forest products and services.

For the 25% of forest area in California where sustainable forest management is currently practiced, there is a need to develop and validate climate-sensitive growth models for all the major species grown under managed conditions. Management by informed decision makers can change species mix and management to reduce potential negative impacts of various climate projections. The majority of the new climate benefits from this sector will show up as the sustainably produced forest products replace more GHG emission-intensive alternatives in the energy generation and building sectors. Across an additional 18% of forest area where sustainably produced forest products may be produced but are not an explicit management goal, there is scope for experimenting with vegetation management that could significantly reduce the predicted increases of GHG emissions from climate-induced increases in wildfires, insect and disease outbreaks, and possibly severe storms. There will be tradeoffs with open space values, wildlife habitat values, net water yields, and forest resiliency that will undoubtedly vary with forest type. These situations are well suited to the use of an experimental design approach at a significant enough scale and diversity that will produce management insights within the next 10 years. For the remaining 57% of forest area where the vegetation management is rarely used except for discrete projects to protect public safety or during fire suppression, the interplay between forest growth, forest mortality, and catastrophic wildfire events will determine net GHG emissions.

Developing forest management strategies to increase the risk-adjusted level of climate benefits across all California forests and forest products will require the use of spatial tools to analyze the various tradeoffs and synergies among the different social goals and private value maximizing goals. Forest governed under different state and federal laws have different rules that govern the tradeoffs among various goals. The efficient management of products that are the main product (e.g., sustainably managed private forest plantations) or simply a by-product (e.g., wood chips produced from fire risk reduction activities) of different forest management regimes depends on the economic geography of road networks, location of sawmills and cogeneration facilities, links to the statewide electricity grid, and other factors. The public health impacts of existing and predicted future levels of wildfire smoke emissions depend on the proximity of wildfires to densely populated areas. A next step would be to develop a transparent and comprehensive set of tools that can combine both spatial data and different assumptions on future prices and technologies. Such a set of tools could be used to illustrate the tradeoffs and synergies among different social goals for forests—climate benefits, open space benefits, forest structure goals, and broader biodiversity goals.

4.0 References

Anderson, J. J. 2000. "A vitality-based model relating stressors and environmental properties to organism survival." *Ecological Monographs* 70:445–470.

Anderson, J. L., V. Balaji, A. J. Broccoli, W. F. Cooke, T. L.Delworth, K. W. Dixon, L. J. Donner, K. A. Dunne, S. M. Freidenreich, S. T. Garner, R. G. Gudgel, C. T. Gordon, I. M. Held, R. S. Hemler, L. W. Horowitz, S. A. Klein, T. R. Knutson, P. J. Kushner, A. R. Langenhost, N. C. Lau, Z. Liang, S. L. Malyshev, P. C. D. Milly, M. J. Nath, J. J. Ploshay, V. Ramaswamy, M. D. Schwarzkopf, E. Shevliakova, J. J. Sirutis, B. J. Soden, W. F. Stern, L. A. Thompson, R. J. Wilson, A. T. Wittenberg, and B. L. Wyman. 2004. "The new GFDL global atmosphere and land model AM2-LM2: Evaluation with prescribed SST simulations." *Journal of Climate* 17:4641–4673.

Barbour, R., J. Fried, P. Daugherty, G. Christensen, and R. Fight. 2008. "Potential biomass and logs from fire-hazard-reduction treatments in Southwest Oregon and Northern California." *Forest Policy and Economics* 10: 400–407.

Battles, J. J., T. Robards, A. Das, K. Waring, J. K. Gilless, G. Biging, and F. Schurr. 2008. "Climate change impacts on forest growth and tree mortality: A data-driven modeling study in a mixed-conifer forest of the Sierra Nevada." *Climatic Change* 87:S193–S213.

Biging, G. S. 1983. Stem analysis procedures for use in obtaining time series forest growth data. Northern California Forest Yield Coop Research Note Univ. of Cal. Berkeley. 6:46.

Bigler, C., and H. Bugmann. 2003. "Growth-dependent tree mortality models based on tree rings." *Canadian Journal of Forest Research* 33:210–221.

Bigler, C., J. Gricar, H. Bugmann, and K. Cufar. 2004. "Growth patterns as indicators of impending tree death in silver fir." *Forest Ecology and Management* 199:183–190.

Butler, B. J. 2008. "Family forest owners of the United States, 2006." *USDA Forest Service. General Technical Report: GTR NRS 27.*

California Climate Change Portal. 2008. California's Greenhouse Gas Emissions Inventory. Webpage. Accessed 2 February 2008. www.climatechange.ca.gov/inventory/index.html

California State Board of Equalization. 2008. California Timber Harvest by County. Webpage. Accessed 10 October, 2008. www.boe.ca.gov/proptaxes/pdf/ytr362007.pdf.

Cayan, D. R, E. P. Maurer, M. D. Dettinger, M. Tyree, and K. Hayhoe. 2008. "Climate change scenarios for the California region." *Climatic Change* 87:S21–S42.

Christensen, G. A., S. J. Campbell, and J. S. Fried (Editors). 2008. "California's forest resources, 2001–2005: Five-year Forest Inventory and Analysis Report." *USDA Forest Service. General Technical Report: PNW-GTR-783.*

Das, A., J. J. Battles, N. L. Stephenson, and P. J. van Mantgem. 2007. "The relationship between tree growth patterns and likelihood of mortality: A study of two tree species in the Sierra Nevada." *Canadian Journal of Forest Research* 37:580–597.

Dixon, Gary E. 1994. Western Sierra Nevada Prognosis geographic variant of the Forest Vegetation Simulator. Fort Collins, Colorado: Timber Management Service Center.

Dixon G. E. (comp.) 2003. *Essential FVS: A User's Guide to the Forest Vegetation Simulator.* Internal Rep. Fort Collins, Colorado: USDA, Forest Service, Forest Management Service Center. 193p.

Dolph, K. L. 1988. *Predicting height increment of young-growth mixed conifers in the Sierra Nevada.* USDA Forest Service Research Paper PSW-191:7.

Eriksson, E., A. Gillespie, L. Gustavsson, O. Langvall, M. Olsson, R. Sathre, and J. Stendahl. 2007. "Integrated carbon analysis of forest management practices and wood substitution." *Canadian Journal of Forest Research* 37: 671–681.

FRAP. 2003. *The Changing California: Forest and Range Assessment 2003.* Online technical report of the California Fire and Resource Assessment Program. http://frap.cdf.ca.gov/assessment2003/.

Fried, J. and G. Christensen. 2004. "FIA BioSum: a tool to evaluate financial costs, opportunities, and effectiveness of fuel treatments." *Western Forester* 49:12–13.

Girardin, M. P., F. Raulier, P. Y. Bernier, and J. C. Tardif. 2008. "Response of tree growth to a changing climate in boreal central Canada: A comparison of empirical, process-based, and hybrid modelling approaches." *Ecological Modelling* 213:209–228.

Hayhoe, K., D. Cayan, C. B. Field, P. C. Frumhoff, E. P. Maurer, N. L. Miller, S. C. Moser, S. H. Schneider, K. N. Cahill, E. E. Cleland, L. Dale, R. Drapek, R. M. Hanemann, L. S. Kalkstein, J. Lenihan, C. K. Lunch, R. P. Neilson, S. C. Sheridan, and J. H. Verville. 2004. "Emissions pathways, climate change, and impacts on California." *Proceedings of the National Academy of Sciences of the United States of America* 101:12422–12427.

Hennigar, C. R., D. A. MacLean, and L. Amos-Binks. 2008. "A novel approach to optimize management strategies for carbon stored in both forests and wood products." *Forest Ecology and Management* 256:786-797.

Körner, C. 2006. "Plant CO_2 responses: An issue of definition, time and resource supply." *New Phytologist* 172:393–411

Krumland, B., and H. Eng. 2004. Site index systems for major young-growth forest and woodland species in Northern California. California Forestry Report. Cal. Dept. of Forestry & Fire Protection. Sacramento. 4:256.

Kurz, W. A., G. Stinson, G. J. Rampley, C. C. Dymond and E. T. Neilson. 2008. "Risk of natural disturbances makes future contribution of Canada's forests to the global carbon cycle highly uncertain." *Proceedings of the National Academy of Sciences of the United States of America* 105:1551–1555.

Lenihan, J. M., R. Drapek, D. Bachelet, and R. P. Neilson. 2003. "Climate change effects on vegetation distribution, carbon, and fire in California." *Ecological Applications* 13:1667–1681.

Lenihan, J. M., D. Bachelet, R. J. Drapek, and R. P. Neilson. 2008. "The response of vegetation distribution, ecosystem productivity, and fire in California to future climate scenarios simulated by the MC1 dynamic vegetation model." *Climatic Change* 87: S215–S230.

Matala, J, R. Ojansuu, H. Peltola, R. Sievänen, and S. Kellomäki. 2005. "Introducing effects of temperature and CO_2 elevation on tree growth into a statistical growth and yield model." *Ecological Modelling* 181:173–190

Maurer, E. P., and H. G. Hidalgo. 2008. "Utility of daily vs. monthly large-scale climate data: An intercomparison of two statistical downscaling methods." *Hydrology and Earth System Science* 12:551–563.

Meehl, G. A., W. M. Washington, T. M. L. Wigley, J. M. Arblaster, and A. Dai. 2003. "Solar and greenhouse gas forcing and climate response in the twentieth century." *Journal of Climate* 16:426–444.

Monserud, R. A. 2003. "Evaluating forest models in a sustainable forest management context." *Forest Biometry, Modelling and Information Science* 1:35–47.

PRISM Group. 2007. Oregon State University. Data available for download at www.prism.oregonstate.edu/.

R 2008. R Statistical Package. The R foundation for statistical computing. Program available for download at www.r-project.org/.

Rickebusch, S., W. Thuiller, T. Hickler, M. B. Arau´, M. T. Sykes, O. Schweiger, and B. Lafourcade. 2008. "Incorporating the effects of changes in vegetation functioning and CO_2 on water availability in plant habitat models." *Biology Letters* 4:556–559.

Reineke, L. H. 1933. "Perfecting a stand density index for even-aged forests." *Journal of Agricultural Research* 46:627–638.

Ritchie, Martin W. 1999. *A compendium of forest growth and yield simulators for the Pacific Coast states.* General Technical Report: PSW-GTR-174. Albany California. Pacific Southwest Research Station, Forest Service, U.S. Department of Agriculture. 59 p.

Royce, E. B, and M. G. Barbour. 2001a. "Mediterranean climate effects. I. Conifer water use across a Sierra Nevada ecotone**."** *American Journal of Botany* 88:911–918

Royce, E. B., and M. G. Barbour. 2001b. "Mediterranean climate effects. II. Conifer growth phenology across a Sierra Nevada ecotone." *American Journal of Botany* 88:919–932.

Salas-Mélia, D., F. Chauvin, M. Déqué, H. Douville, J. F. Gueremy, P. Marquet, S. Planton, J. F. Royer, and S. Tyteca. 2005. Description and validation of the CNRM-CM3 global coupled model, CNRM working note 103.

Schlamadinger, B., N. Bird, T. Johns, S. Brown, J. Canadell, L. Ciccarese, M. Dutschke, J. Fiedler, A. Fischlin, P. Fearnside, C. Forner, A. Freibauer, P. Frumhoff, N. Hoehne, M. U. F. Kirschbaum, A. Labat, G. Marland, A. Michaelowa, L. Montanarella, P. Moutinho, D. Murdiyarso, N. Pena, K. Pingoud, Z. Rakonczay, E. Rametsteiner, J. Rock, M. J. Sanz, U. A. Schneider, A. Shuidenko, M. Skutsch, P. Smith, Z. Somogyi, E. Trines, M. Ward, and Y. Yamagata. 2007. "A synopsis of land use, land-use change and forestry (LULUCF) under the Kyoto Protocol and Marrakech Accords." *Environmental Science and Policy*: 271–282.

Snowdon, P. 1991. "A ratio estimator for bias correction in logarithmic regressions." *Canadian Journal of Forest Research* 21:720–724.

Stage, A. R., and C. Salas. 2007. "Interactions of elevation, aspect, and slope in models of forest species composition and productivity." *Forest Science* 53:486–492.

Tyree, M. 2008. Scenarios — Simulation Data and Information. Webpage. Last updated September 29, 2008. http://meteora.ucsd.edu/cap/scen08_data.html.

Uzoh, F. C. C., and W. W. Oliver. 2006. "Individual tree height increment model for managed even-aged stands of ponderosa pine throughout the western United States using linear mixed effects models." *Forest Ecology and Management* 221:147–154.

USDOE. 2008. The U.S. Department of Energy's Voluntary Reporting of Greenhouse Gases (1605(b)) Program. Webpage. Accessed 2 February. www.pi.energy.gov/enhancingGHGregistry/.

USFS. 2008. United States Forest Service. Forest Vegetation Simulator. Download at www.fs.fed.us/fmsc/fvs/software/index.shtml.

van Mantgem, P. J., N. L. Stephenson, J. C. Byrne, L. D. Daniels, J. F. Franklin, P. Z. Fule, M. E. Harmon, A. J. Larson, J. M. Smith, A. H. Taylor, and T. T. Veblen. 2009. "Widespread Increase of Tree Mortality Rates in the Western United States." *Science* 323:521–524.

Wensel, L. C., P. J. Daugherty, and W. J. Meerschaer. 1986. CACTOS User's Guide: The California conifer timber output simulator. Division of Agricultural Science, University of California, Berkeley. Bulletin 1920.

Wensel, L. C. 1987. "Tree height and diameter growth models for Northern California conifers." *Hilgardia* 55:21.

Wensel, L. C., and E. C. Turnblom. 1998. "Adjustment of estimated tree growth rates in northern California conifers for changes in precipitation levels." *Canadian Journal of Forest Research* 28:1241–1248.

Westerling, A., H. Hidalgo, D. Cayan, and T. Swetnam. 2006. "Warming and Earlier Spring Increase Western U.S. Forest Wildfire Activity." *Science* 313: 940-94.

Yeh, H-Y. 1997. The relationship between tree diameter growth and climate for coniferous species in northern California. Ph.D. dissertation, University of California, Berkeley.

Yeh, H-Y., and L. C. Wensel. 2000. "The relationship between tree diameter growth and climate for coniferous species in northern California." *Canadian Journal of Forest Research* 30:1463–1471.

Yeh, H-Y., L. C. Wensel, and E. C. Turnblom. 2000. "An objective approach for classifying precipitation patterns to study climatic effects on tree growth." *Forest Ecology and Management* 139:41–50.