Using Forest Inventory and Analysis Data To Model Plant-Climate Relationships

Nicholas L. Crookston[1], **Gerald E. Rehfeldt**[2], **and Marcus V. Warwell**[3]

Abstract.—Forest Inventory and Analysis (FIA) data from 11 Western conterminous States were used to (1) estimate and map the climatic profiles of tree species and (2) explore how to include climate variables in individual tree growth equations used in the Forest Vegetation Simulator (FVS). On the first front, we found the FIA data to be useful as training data in Breiman's (2001) Random Forests classification and regression tree algorithm to relate climate variables to the presence and absence of species, thereby defining a species' contemporary climate profile. Predicted bioclimatic maps are presented for Douglas fir (*Pseudotsuga menziesii*) and Engelmann spruce (*Picea engelmannii*). On the second front, a preliminary modification of the basal area increment equation used in the FVS is presented that includes climate drivers. The focus of this work is to start the process of building a new growth equation suitable for use in FVS so that climate can be taken into account when predicting forest dynamics. A framework is introduced that integrates the climate-driven increment equation with genetic response functions that represent the adaptiveness of populations to climate change.

Introduction

Climatic factors play a controlling role in shaping tree distributions (Langlet 1936, Pearson and Dawson 2003, Turesson 1922, Woodward 1987), and it follows that these factors are also important in determining growth and mortality (Rehfeldt *et al.* 2003). These facts, coupled with knowledge that our climate is changing (Houghton *et al.* 2001), suggest that tree distributions will change, and that the growth and mortality rates inherent in forest growth and yield models will be questioned.

How much difference could global warming and associated changes in precipitation make in (1) the distribution of trees, and (2) individual tree growth over the next 60 to 90 years? This time span is well within the expected lifetime of many of the trees currently growing in the West and is therefore quite relevant to those preparing forest management plans. The Forest Vegetation Simulator (FVS) (Crookston and Dixon 2005, Stage 1973, Wykoff *et al.* 1982) is a tool used in preparing those plans. Modification of this model to account for climate change is therefore necessary.

In this article, Forest Inventory and Analysis (FIA) data from 11 Western conterminous States are used to (1) develop bioclimatic models for the occurrence of Douglas fir (DF) (*Pseudotsuga menziesii*) and Engelmann spruce (ES) (*Picea engelmannii*) and (2) calibrate a modified version of the diameter growth model for DF to includes climate variables. The bioclimatic models of species occurrence define the species' contemporary climate profile. For contemporary climate, maps of this profile are predictions of the current species distribution.

Adding climate predictors to the growth model in FVS and recalibrating it using FIA observations of growth, provides a prediction equation that is intuitively appealing but conceptually incomplete. FIA measurements of growth capture the growth response to climate for trees growing in contemporary climates, but not for currently living trees growing in future climates.

[1] Operations Research Analyst, U.S. Department of Agriculture (USDA), Forest Service, Rocky Mountain Research Station, 1221 South Main, Moscow, ID 83843. E-mail: ncrookston@fs.fed.us.

[2] Research Plant Geneticist (retired), USDA Forest Service, Rocky Mountain Research Station, 1221 South Main, Moscow, ID 83843. E-mail: grehfeldt@fs.fed.us.

[3] Plant Geneticist, USDA Forest Service, Rocky Mountain Research Station, 1221 South Main, Moscow, ID 83843. E-mail: mwarwell@fs.fed.us.

Current observations reflect the current states of (1) genetic adaptation and (2) competitive relationships at play at the time of measurement. Therefore, relationships based only on those measurements cannot be used to represent the growth response to climate change. A conceptual framework for further modifying this growth model to represent tree responses to climate change is presented. This conceptual framework recognizes that trees genetically adapt to their climates and that trees from different genotypes will respond differently to climate change.

Methods

Climate Data

The Rehfeldt (2005) climate model consists of thin plate spline surfaces from which a set of climate indicators were predicted. The model is calibrated for all locations within the conterminous Western United States and southwestern Canada, from longitudes between 102 °W and 125 °W and latitudes between 31 °N and 51 °N. The predictions are based on weather observations normalized for 1961 to 1990, the period defined by meteorologists for calculating climatic normals. We believe that these normals suitably overlap the time period of the FIA plot data collected between 1980 and 2004.

Actual plot latitude, longitude, and elevation data were used, rather than the publicly available fuzzed and swapped locations, as input into the climate model. Table 1 lists the variables that were computed for each location; these variables, plus 20 interaction terms, form the list of climate predictors that were used in the analysis.

Table 1.—*Climate variables and their acronyms used as independent variables in regression analyses.*

Name	Definition
mat	mean annual temperature
mtcm	mean temperature in the coldest month
mmin	minimum temperature in the coldest month
mtwm	mean temperature in the warmest month
mmax	maximum temperature in the warmest month
map	mean annual precipitation
gsp	growing season precipitation, April through September
tdiff	summer-winter temperature differential, *mtwm-mtcm*
dd5	degree-days > 5 °C
dd0	degree-days < 0 °C
mindd0	minimum degree-days < 0 °C
sday	Julian date of the last freezing date of spring
fday	Julian date of the first freezing date of autumn
ffp	length of the frost-free period
gsdd5	degree-days > 5 °C accumulating within the frost-free period
d100	Julian date the sum of degree-days > 5 °C reaches 100
ami	annual moisture index, *dd5/map*
smi	summer moisture index, *gsdd5/gsp*
pratio	ratio of summer precipitation to total precipitation, *gsp/map*

Tree Data

Tree data were compiled primarily from three FIA sources. For Idaho, Montana, Wyoming, Nevada, Utah, Colorado, New Mexico, and Arizona, the data were retrieved from the FIA Web site (retrieved March 2005 from http://ncrs2.fs.fed.us/4801/fiadb) and merged into a single database. A key feature of these data is that every FIA plot location is represented in the data, not just those in forested zones. For Washington, Oregon, and California, version 1.4-1 of the Integrated Database (IDB) (Waddell and Hiserote 2004) was combined with newer National Information Management System (NIMS) data provided directly by the Pacific Northwest FIA unit. Combining the data was necessary because the IDB contains plots only from forested zones while the NIMS data has plot records for both forested and non-forested zones. The FIA plot design is generally a cluster of four subplots with a total size of about 0.07 ha for most tree measurements (Bechtold and Patterson 2005). Note that the IDB contains data collected by Federal agencies other than FIA and the sampling designs are not the same. The data in the IDB normalizes the data structure of these disparate inventories, providing a convenient source for analysis.

Presence and Absence Modeling

Breiman's (2001) Random Forests classification and regression tree algorithm was used to model the presence and absence of an individual species. Details of these methods are presented by Rehfeldt *et al*. (2006).

Briefly, Random Forests built a set of 150 to 200 independent classification and regression trees. For each tree, a bootstrap

sample of the observations was drawn. Each case was defined by the presence/absence data and the climate variables. The bootstrap sample was used to build the tree and observations left out of the sample were used to compute the classification error. A prediction was made by running a case down each regression tree resulting in one classification for the case. The class that receives the plurality of votes—a vote is a regression tree predicting a specific class—is the predicted class for a case.

Generally, we ran Random Forests twice. In the first run, all the climate variables were included, and in the second run, the 10 or so most important variables (variable importance is scored by Random Forests) from the first run were used to make runs with larger numbers of regression trees. The latter analysis was then used to predict the presence or absence of the species at each 1-km grid cell in the study area.

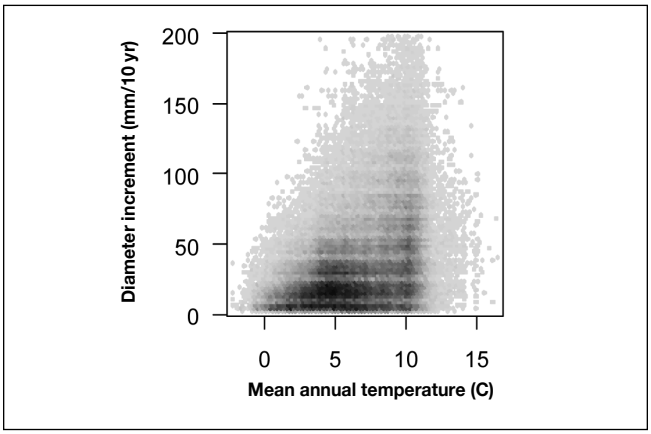
Several versions of Random Forests are available. The one we used is in R (R Development Core Team 2004) and is based on the original program written by Leo Breiman and Adele Cutler (Liaw and Wiener 2005).

Basal Area Increment Modeling

To incorporate climate predictors into FVS, there must be a relationship between increment and climate variables. Figure 1 is a scatter diagram of hexagons in which the intensity of black is proportional to the number of observations in each hexagon. This plot shows (1) the maximum growth for DF occurs at a mean annual temperature (*mat*) of about 10 °C, (2) high growth observations are essentially absent at low temperature sites, (3) that upper range of observations essentially stops at about 13 °C, and (4) that the data contains a huge amount of variability. Similar plots were studied for other climate variables. Studying plots like these suggested that a relationship in the data exists between growth and climate, and that relationship should be modeled in a way that provides for a maximum growth to occur below the maximum value of climate predictors.

Wykoff's (1990) basal area increment model is used in FVS. The dependent variable, delta-diameter-squared (*dds*), is directly proportional to basal area increment. The model was fit to the natural log of *dds* to address the statistical properties

Figure 1.—*Observed Douglas fir diameter increment plotted over mat. The intensity of gray is proportional to the number of observations inside a hexagon. The maximum growth for this species occurs at about 10 °C and there are only incidental observations above 13 °C.*



of errors and because the log transformation linearized the essential relationship between the key variables. In the resulting model, *dds* is a product of tree size, site, and competition. Tree *dbh* is the tree size measure. Competition is measured by crown ratio (*CR*), crown competition factor (*CCF*) (Krajicek *et al*. 1961), and the amount of basal area in trees larger than the subject tree (*BAL*). Variables that measure site include slope, aspect, elevation, geographic location, and habitat type (Daubenmire and Daubenmire 1968).

To incorporate climate predictors, we modified Wykoff's model by replacing habitat type and geographic location with *mat* and mean annual precipitation (*map*). In addition to replacing these two site terms, *CCF* was replaced by total plot basal area (*BA*) as done by Stage and Wykoff (1998) to simplify calculations, and $Elev^2$ was removed because it did not improve the model. A squared term *mat* and *map* would have provided for a maximum growth increment (as the scatter plots indicated would be warranted), but those terms also did not statistically improve the model. The resulting equation is

$$\ln(dds) = b_0 + b_1\ln(dbh) + b_2 dbh^2 + b_3 BAL / \ln(dbh+1) + b_4 Slope[\cos(Aspect)] + b_5 Slope[\sin(Aspect)] + b_6 Slope + b_7 Slope^2 + b_8 Elev + b_9 CR + b_{10} BA + b_{11}\ln(mat+10) + b_{12}\ln(map). \quad (1)$$

The nonclimate predictors were derived from the FIA data. Plot *BA* and *BAL* were computed at the FIA subplot level. *Slope* and *Aspect* were taken for the *condition* in which the tree was growing. A condition is a mapped subdivision of the plot that describes homogeneous area. *BA* was backdated to the beginning of the growth measurement period by adding recent mortality. No attempt was made to back date plot density for recent growth. Tree *dbh* was backdated by subtracting measured increment. Past 10-year increment data was measured using increment cores and not based on measures based on successive observations of diameter. When more than one measurement for a given location was found in the data, only the first measurement was used.

Note that predictors *BAL*, *BA*, *CR*, and *dbh* are influenced by climate, but for this preliminary analysis we did not address this issue. Nor did we address two additional statistical issues that should be addressed in a final study: (1) the log transformation introduces bias when *dds* is back transformed and (2) the sample trees are clustered on plots and therefore the errors are partially correlated. Neither of these issues influence the main points made below.

Results

Species Distributions

The classification error for DF is 9.4 percent and for ES it is 9.9 percent. At just under 10 percent, the classification error falls into the category of excellent for comparisons of this type (Landis and Koch 1977). The most important variables (table 1) for DF predictions are *ami, map, tdiff·map*. For ES they are *map·mtc, dd5/gsp,* and *ami* (in the order specified). These variables measure major elements of temperature, precipitation, and seasonal interactions. Grid locations of 1 km predicted to be within the climatic profiles of DF and ES (fig. 2) are presented along with Little's (1971) species distribution maps.

Predicting Diameter Increment

Table 2 contains values for parameters of equation (1) for DF. All are highly significant ($P<.001$, 61,761 observations), and have signs and magnitudes that are generally consistent with previous work (Stage and Wykoff 1998, Wykoff 1990). The model accounts for about 66 percent of the variance in log (*dds*). Attempts to use climate variables other than *mat* and *map* did not materially improve the model. Note that *Elev* is a likely surrogate for climate but attempts to fit the model without it resulted in a poorer model. The modeled response to *mat* and *map* is illustrated in figure 3.

Figure 2.—*The white areas are the predicted distribution FIA-style plots that have one or more Douglas fir trees (left), or Englemann spruce (right), mapped at a 1-km grid on a shaded relief map. The black lines are Little's (1971) mapped distributions. The inset on the left is a small area showing the relative resolution of the predictive model versus Little's map. The inset on the right is Sweetgrass Hills, MT, an area that was omitted from Little's range map but correctly predicted to have Englemann spruce.*

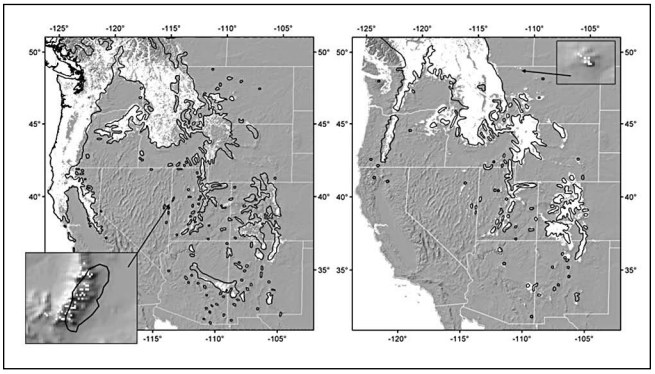
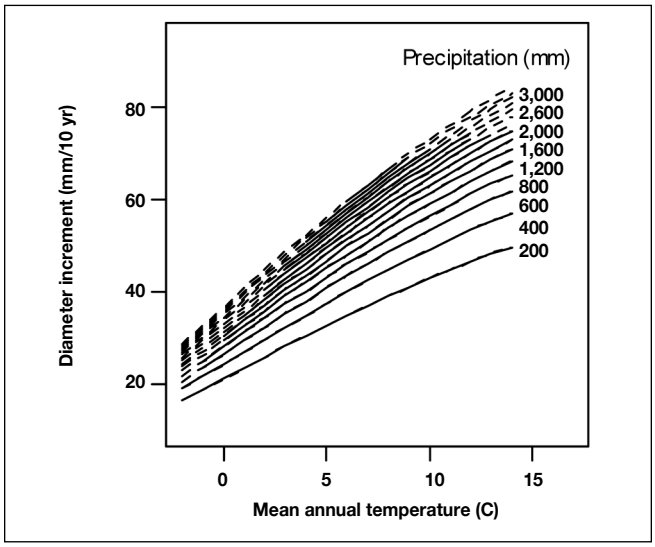


Table 2.—*Regression estimates for equation (1) fit to the Douglas fir data.*

Parameter	Corresponding predictor	Unit	Value
b_0	Intercept	*dds* is in^2	– 4.088
b_1	ln(*dbh*)	*dbh* is in	1.051
b_2	*dbh*^{2}	*dbh* is in	– 0.0003178
b_3	*BAL*/log(*dbh*+1)	*BAL* in ft^2/acre	– 0.008130
b_4	*Slope*[cos(*Aspect*)]	% and radians	0.01973
b_5	*Slope*[sin(*Aspect*)]	% and radians	– 0.07356
b_6	*Slope*	%	– 0.0845
b_7	*Slope*^{2}	%^{2}	– 0.4575
b_8	*Elev*	ft	– 0.00008782
b_9	*CR*	%	0.01468
b_{10}	*BA*	ft^2/acre	0.0003967
b_{11}	ln(*mat*+10)	°C	0.9160
b_{12}	ln(*map*)	mm	0.2260

Figure 3.—*The effects of temperature and precipitation on diameter increment as portrayed by equation (1). The dark lines indicate the approximant range of the temperature and precipitation measurements coincident with observations of Douglas fir growth.*



Discussion

Species Distributions

Rehfeldt *et al*. (2006) explore the results of these analyses in detail. They also present results for seven additional species, provide predictions for the biotic communities of Brown *et al*. (1998), and make predictions on how predicted global warming will cause major shifts in the spatial distribution of contemporary climate profiles.

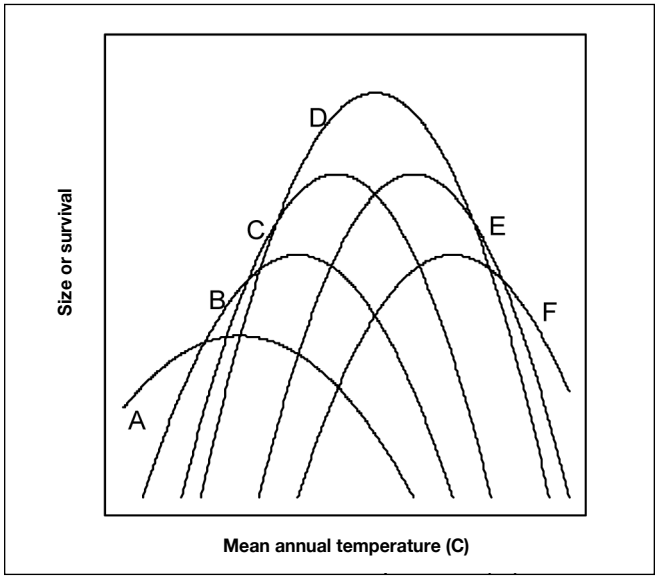
The Random Forests predictions are, in our view, astonishingly good. To the casual observer this raises the question that the procedure is overfitting the data. Note that Breiman (2001) has proven that the method cannot overfit the data, and we found no evidence that the classification error approached zero as parameters were added. To the contrary, as superfluous predictor variables are added, prediction errors increase.

Predicting Diameter Increment

The modified diameter increment model (fig. 3) predicts that an increase or decrease in temperature or precipitation will translate directly into a corresponding increase or decrease in growth. On the surface, therefore, it would appear that we have achieved our goal of modifying the FVS growth equation so that it is sensitive to global warming. The curves, however, illustrate the breadth of physiologic plasticity within the species, not within individual trees. Individual trees are adapted to only a portion of the environmental heterogeneity faced by the species. The equation, therefore, is suitable for predicting a change in growth given a change in climate only to the extent that the individual trees undergoing the climate change are adapted to the new climate. The adaptive response of individual trees, measured by the response for individual genotypes, determines the individual growth response to climate change (Langlet 1936; Rehfeldt *et al*. 1999, 2002, 2003).

Figure 4 illustrates the response of populations of trees to gradients in *mat*. For geneticists, a population is an artificial grouping of trees all of which are adaptively similar and, therefore, grow in similar environments. An implication from

Figure 4.—*Diagrammatic representation of the response of populations to mean annual temperature and competitive pressures from other populations. The realized niches of each population is limited to the locations on the curves that are not overlapped. Population D is growing at its optimum mat, which also happens to be the optimum for the species as a whole, while other populations are growing below their own optimums and their individual optimums are below the population optimum.*



Source: Rehfeldt et al. *1999.*

figure 4 is that if *mat* increases in a forest currently inhabited with trees from population A, a forester will observe an increase in growth up to the optimum for population A and then observe a decrease in growth at *mat* levels that are still much lower than the optimum for the species as a whole. To capture the increase in growth one would expect from a warming climate, the trees from population A must be replaced with members of a more suitable population.

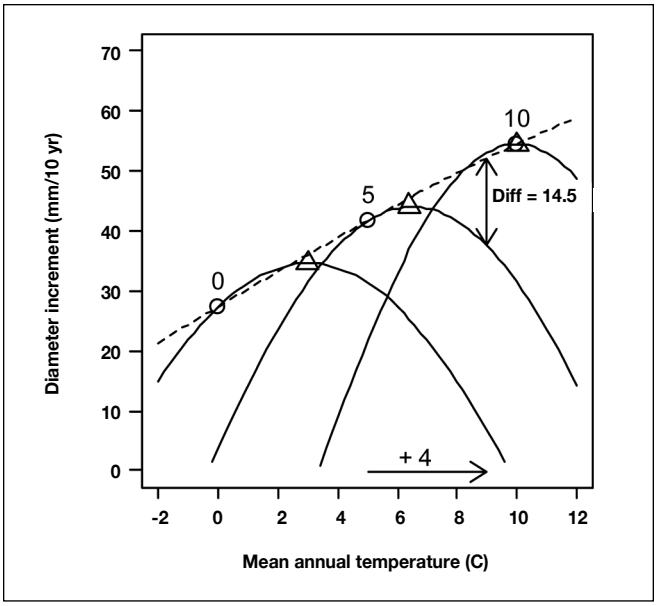
To incorporate climate variables into FVS, two kinds of information must be integrated: (1) thousands of observations from the FIA plots represent observations from the realized niche (figs. 1 and 3) and (2) results from the genetic experiments (as represented by the stylized drawing in figure 4) that represent the fundamental niche.

Our suggestion for integrating these model components is illustrated in figure 5. At the beginning of simulations, and so long as climate change does not occur, the growth for individual trees follows equation (1). Growth under climate change scenarios is a function of the corresponding solid lines. In a simulation, each tree will be represented by a different solid line. The parameters for the shape and location of the solid line are derived from species-specific relationships developed from common garden experiments. For trees growing in the extremes of a population, the mean realized niche (circles) is much further to the left of the corresponding optimum for the population (triangles).

It is reasonable to question why approaches like those of Wensel and Turnblom (1998) and Yeh and Wensel (2000) were not chosen as the basis for our efforts. These researchers related annual deviations from model-based estimates of growth to contemporary weather. The models used did not contain climate variables. Their work is relevant to the job of accounting for short-term deviations around average trends while our approach concentrates on accounting for shifts in the averages. Despite this difference in temporal resolution, the dearth of data available for understanding climate effects on growth justifies further work toward capitalizing on both fronts.

Another question is why we are not proposing using so-called process-based models to account for these effects. For example, why not use the weather-driven model built by Milner *et al.* (2002)? That group adapted Running and Coughlan's (1988) whole stand physiological model (Forest-BGC) to an individual tree, distance independent model for use with FVS. Forest-BGC contains empirical components that drive the disaggregation of net biomass production to individual trees. The net production is nonspecific, assuming that a suitable photosynthetic engine exists on the site. The species present on the site, and the assumptions that they are appropriately adapted, are exactly the same for Forest-BGC as for the Wykoff-style diameter increment model. That is, they too fail to account for the genetic factor.

Figure 5.—*Diagram shows how the proposed combined model should work. The dotted line is the base increment model (equation [1] with 800 mm of precipitation, dbh = 30 cm, 80 percent crown, no basal area in larger trees, flat ground, and other predictors set at their sample means), and the circles correspond to three example locations along the mat gradient. The two arrows illustrate the difference in predicted growth using dotted lines model and the solid lines for an increase in mat from 5 to 9 °C.*



Conclusions

FIA data proved useful in predicting species distributions, and the Random Forests program proved to be a powerful tool for this purpose. In addition, these data, coupled with climate data, provide a strong basis for building models of diameter increment as a function of contemporary climate. These data alone, however, do not provide a way to predict increment in the face of climate change. Measurements are needed from individual trees growing in places where growth has been followed through periods of climate change that are about equal in magnitude to the magnitude of the future expected change, or where members of genetic populations (provenances) have been planted in a range of climatic conditions and then monitored. In either case, the broad-scale measurements of diameter increment supplied by FIA have a place in this work.

Acknowledgments

The authors thank Sharon Woudenberg and Ron Tymcio of FIA from Ogden, UT; Jeremy Fried, Dale Weyermann, Sally Campbell, and Andy Gray of FIA from Portland, OR; and Dennis Ferguson, Andy Hudak, and Jeff Evans from our research group for help with data, comments, review, and technical support.

Literature Cited

Bechtold, W.A.; Patterson, P.L., eds. 2005. The enhanced Forest Inventory and Analysis program—national sampling design and estimation procedures. Gen. Tech. Rep. SRS-80. Asheville, NC: U.S. Department of Agriculture, Forest Service, Southern Research Station. 85 p.

Breiman, L. 2001. Random forests. Machine Learning. 45: 5-32.

Brown, D.; Reichenbacher, F.; Franson, S. 1998. A classification of North American biotic communities. Salt Lake City: University of Utah Press. 152 p.

Crookston, N.L.; Dixon, G.E. 2005. The Forest Vegetation Simulator: a review of its structure, content, and applications. Computers and Electronics in Agriculture. 49(1): 60-80.

Daubenmire, R.; Daubenmire, J.B. 1968. Forest vegetation of eastern Washington and northern Idaho. Technical Bulletin 60. Pullman, WA: Washington Agricultural Experiment Station. 104 p.

Houghton, J.T.; Ding, Y.; Griggs, D.J.; *et al.*, eds. 2001. Climate change 2001: the scientific basis. Contributions of Working Group 1 to the Second Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, United Kingdom: Cambridge University Press.

Landis, J.R.; Koch, G.G. 1977. The measurement of observer agreement for categorical data. Biometrics. 33: 159-174.

Langlet, O. 1936. Studies on the physiologic variability and their relationship with the climate. Meddelelser Statens Skogsförsöksanstalt. 29: 217-470. In Swedish.

Liaw, A.; Wiener, M. 2005. randomForest: Breiman and Cutler's Random Forests for classification and regression. R package. Ver. 4.5-4. http://cran.r-project.org/src/contrib/Descriptions/randomForest.html.

Little, E.L., Jr. 1971. Atlas of United States trees. Vol. 1. Conifers and important hardwoods. Misc. Pub. 1146. Washington, DC: U.S. Department of Agriculture. 9 p.

Milner, K.S.; Coble, D.W.; Smith, E.L.; McMahan, D.J. 2002. FVSBGC: a dual resolution hybrid model with physiological and biometrical growth engines. In: Crookston, N.L.; Havis, R.N., comps. Proceedings, second forest vegetation simulator conference. Proc. RMRS-P-25. Ogden, UT: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 208 p.

Pearson, R.G.; Dawson, T.P. 2003. Predicting the impacts of climate change on the distribution of species: Are bioclimate envelope models useful? Global Ecology & Biogeography. 12: 361-371.

R Development Core Team. 2004. R: a language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing. http://www.r-project.org.

Rehfeldt, G.E. 2005. A spline model of climate for the western United States. Gen. Tech. Rep. RMRS-GTR-165. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 21 p.

Rehfeldt, G.E.; Crookston, N.L.; Warwell, M.V.; Evans, J.S. 2006. Empirical analyses of plant-climate relationships for the western United States. International Journal of Plant Sciences. 167(6): 1123-1150.

Rehfeldt, G.E.; Tchebakova, N.M.; Milyutin, L.I.; Parfenova, E.I.; Wykoff, W.R.; Kouzmina, N.A. 2003. Assessing population responses to climate in *Pinus sylvestris* and *Larix* spp. of Eurasia with climate-transfer models. Eurasian Journal of Forest Research. 6(2): 83-98.

Rehfeldt, G.E.; Tchebakova, N.M.; Parfenova, Y.I.; Wykoff, W.R.; Kuzmina, N.A.; Milyutin, L.I. 2002. Intraspecific responses to climate in *Pinus sylvestris*. Global Change Biology. 8: 912-929.

Rehfeldt, G.E.; Ying, C.C.; Spittlehouse, D.L.; Hamilton, D.A. 1999. Genetic responses to climate in *Pinus contorta*: niche breadth, climate change, and reforestation. Ecological Monographs. 69(3): 375-407.

Running, S.W.; Coughlan, J.C. 1988. A general model of forest ecosystem processes for regional applications: I. Hydrologic balance, canopy gas exchange and primary production processes. Ecological Modeling. 42: 125-154.

Stage, A.R. 1973. Prognosis model for stand development. Res. Pap. INT-137. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station. 32 p.

Stage, A.R.; Wykoff, W.R. 1998. Adapting distance-independent forest growth models to represent spatial variability: effects of sampling design on model coefficients. Forest Science. 44(2): 224-238.

Turesson, G. 1922. The genotypical response of the plant species to habitat. Hereditas. 3: 211-350.

Waddell, K.L.; Hiserote, B. 2004. The PNW-FIA integrated database [CD-ROM]. Ver. 1.4. Portland, OR: U.S. Department of Agriculture, Forest Service, Forest Inventory and Analysis Program, Pacific Northwest Research Station. http://www.fs.fed.us/pnw/fia/publications/data/data.shtml.

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

Woodward, F.I. 1987. Climate and plant distribution. London: Cambridge University Press. 190 p.

Wykoff, W.R. 1990. A basal area increment model for individual conifers in the northern Rocky Mountains. Forest Science. 36(4): 1077-1104.

Wykoff, W.R.; Crookston, N.L.; Stage, A.R. 1982. User's guide to the Stand Prognosis Model. Gen. Tech. Rep. INT-133. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station. 112 p.

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