SECTION II: PROBABILITY AND QUANTITY OF ACORN PRODUCTION: PARAMETERS FOR THE LANDIS ADD-ON MODULE

II.1 INTRODUCTION

This section is devoted to developing methods and formulating routines for utilizing output from the landscape-change model, LANDIS, to spatially predict potential acorn production at a landscape level. The primary tasks are:

i) Describe LANDIS and its relationship to the masting algorithm.

ii) Describe the LANDIS output files utilized in the masting model.

iii) Describe the software used to complete the post-LANDIS modeling

iv) Present a step-by-step description of the model, justifying the parameters and relationships in the model for inferring mast production.

II.1.1 The landscape model: Landis

LANDIS is a spatially explicit and stochastic landscape model capable of simulating large-scale landscape processes as well as fine-scale species-level vegetation dynamics (Mladenoff *et al.* 1996; Mladenoff and He 1999). The model can incorporate landscape-level data from multiple sources including satellite imagery, soils maps, climate maps, digital elevation models, or any other data that can be expressed in a digital GIS-raster format. In addition, LANDIS utilizes object-oriented programming and object-oriented design to efficiently model forest aging; to describe variation in vegetation characteristics; and to incorporate the sources, extent and intensity of disturbances such as fire, wind-throw, and harvest. The landscape is represented as a matrix or grid of land area units of equal size with a spatial resolution ranging from 10 to 500 meters per pixel. These land-area units that I will hereafter refer to as "cells." Each cell in the landscape has a unique identity within the matrix and is defined by its coordinate location (or *x ,y*) in the matrix. The design of LANDIS allows simulations of forest dynamics for large landscapes (>10,000 ha) over long periods of time. Typically, the model operates on a 10-year time-step. LANDIS is specifically designed to simulate change over long periods of time across large landscapes; therefore, analysis of predictions about the behavior of any specific cell or even individual stand representing multiple cells are inappropriate applications of the model.

LANDIS is a stochastic model, that is, it is capable of incorporating parameters under uncertainty. LANDIS simulations are specified to meet a set of objectives, *e.g.* the interaction between harvesting regimes and forest succession (Gustafson *et al*. 2000). Uncertainty is factored into these simulations through the use of probability distributions that model stochastic landscape processes such as the timing and location of natural or anthropogenic disturbance. Therefore, LANDIS results reflect these stochastic elements. At the scale, time-step, and spatial resolution of at which LANDIS operates, masting behavior would have little influence on the outcome of simulation runs. Therefore the masting behavior does not need to be incorporated interactively with the LANDIS simulations. Rather, the LANDIS output files are themselves a set of spatially explicit maps of forest tree composition and age structure at future points in time. These maps, when combined with ecological land types, and other LANDIS input files, can be used to describe the masting potential of the landscape in future decades (Figure II.1). This

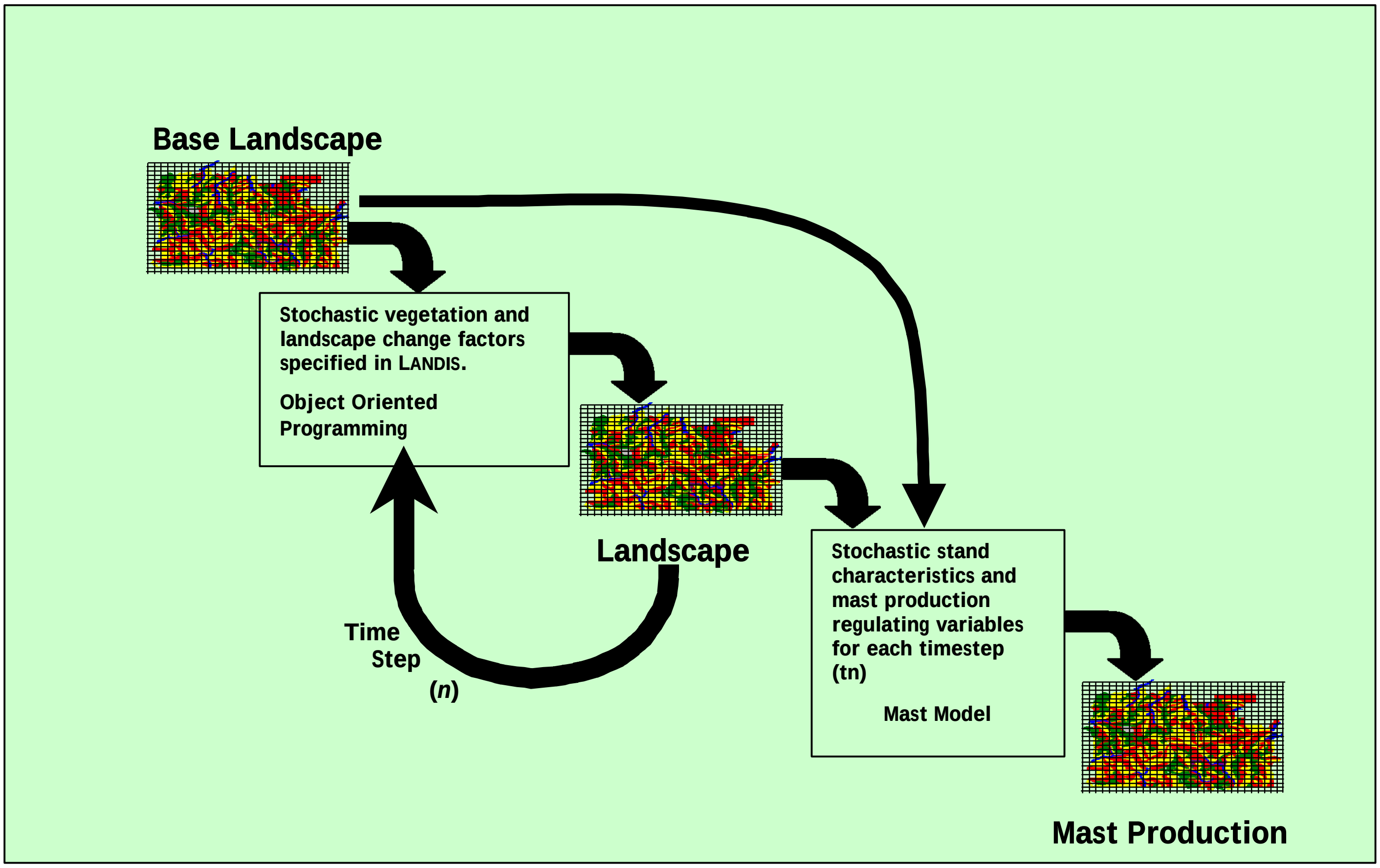


Figure II.1 Schematic of the connection between LANDIS and the spatial masting model.

masting potential can further be adjusted by incorporating variables that are known or are thought to contribute to mast production behavior (*e.g.* weather).

The area that the masting module was specifically designed for and applied to is a 3,216 ha landscape of the Mark Twain National Forest in northern Oregon County in southeast Missouri (Figure II.2). LANDIS has been used previously on this landscape to compare the effects of several management regimes on patterns of forest distribution (Shifley *et al.* 2000). Input files and output files are specific to this test-case. While LANDIS is capable of incorporating many species (*e.g.* Hong and Mladenoff 1999; Hong, *et al*. 1999), the test-cases examined for Missouri have factored only five vegetation groups: white oak, red oak, maple, pine, and empty (Gustafson *et al.* 2000; Shifley *et al.* 2000). The module and algorithm can be adjusted for different landscapes with varying degrees of difficulty. If the major changes relate to stand descriptors such as land types or relate to landscape size and resolution, then the modifications are relatively simple. If the change involves increased number of species or additional data layers (*e.g.* digital elevation models, soils, site index), then the modifications are more complicated.

LANDIS operates on landscape cells (i.e. square pixels or raster units) can range from 10 to 500 m per side. The resolution used for the Missouri landscapes, 30 m per side, has advantages and disadvantages for the development of the masting module. A 30 m cell or 0.09 ha is small enough so that when multiple cells can be combined to define a stand, variation in stand structure and dynamics can be described. This provides greater detail about stand structure and composition than larger cell sizes. For each cell, LANDIS descriptions of age and species structure is limited to a single age for the dominant trees

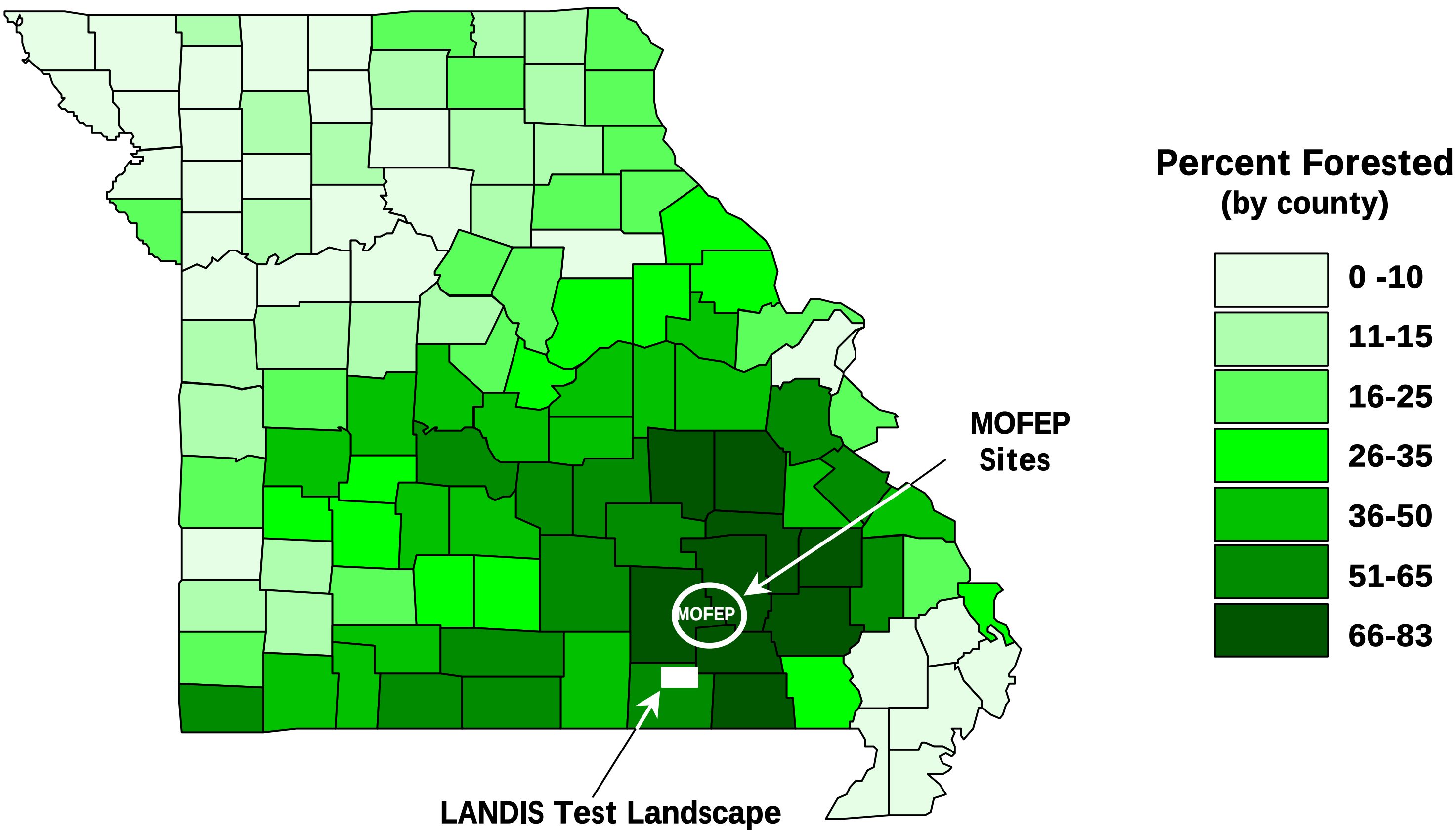


Figure II.2. Location of test-case landscape in Missouri and relationship to MOFEP sites.

and the presence or absence of each of the four species groups without information on the density of trees on the cell. A wide range of un-described variation may still occur in a 30 by 30 m plot in tree species and age structure. Thus, a method for describing the range of vegetation parameters within the 30 m cell under a particular set of conditions is required. For example, two dominant oak trees will produce more acorns than one dominant oak tree and there are conditions that either would favor or disfavor the presence and density of oaks trees in an area.

II.1.1.1. LANDIS base and output files: Oregon County Site

A LANDIS run begins with a set of base maps in the form of GIS raster grids and species lists that describe the initial (t_0) conditions of land form, stand identity, and species group and cohort presence. The algorithms internal to LANDIS operate on these maps to produce a predicted condition at time t_1. The resulting landscape is further manipulated to predict the landscape at the next time step (t_2) (Figure II.1). At each time-step (10 years), including the initial condition (t_0), a set of files is generated that include: i) one age class that describes the age of the dominant species group, ii) presence or absence of all species groups, iii) the identity of the dominant species group, and iv) fire and wind disturbance history (Table II.1) for each cell. The file names indicate the time-step from which they were generated. These files are the base upon which the masting model operates. The number of files generated is a function of the time-span of the simulation and the number of species groups.

Table II.1 Listing and description of LANDIS output files utilized in the masting module. All files except land type and stand identity are produced at each 10-year step of the simulation

Description	Filename	Coding			
[1] Land Type -	LU.txt	0	empty	4	Savanna-Glade
		1	SW Slope	5	Updrain
		2	NE Slope	6	Lime - Glade
		3	Flat	7	Mesic
[1] Stand Identity	STAND.txt	0, n	Unique stand identity code		
Age Class (30 year)	AGE(t).txt	3 = 0 to 29	7 = 120 to 149		
		4 = 30 to 59	8 = 150 to 179 etc		
[1] Age Class (10 year)	AGEP(t).txt	1 = 0 to 9,	2 = 10 to 19 years	etc.	
[1] Red Oak Presence	ROAK.txt	0,3,4	empty, present, absent		
[1] White Oak Presence	WOAK.txt	0,3,4	empty, present, absent		
[1] Pine Presence	PINE.txt	0,3,4	empty, present, absent		
[1] Maple Presence	MAPLE.txt	0,3,4	empty, present, absent		
[1] Dominant Species Group	DOMNT.txt	0,3,4,5,6,	empty, maple, pine white oak, red oak		
Fire Disturbance	FIRE.txt	gradient	Grid components indicate intensity of fire at time *t*.		
Wind Disturbance	WIND.txt	gradient	Grid components indicate intensity of disturbance at time *t*.		

[1] utilized in masting module

II.1.2 Masting module implementation: STATA

A statistics and data management software package, STATA v. 6 (StataCorp 1999), was used to manipulate the output files for the prediction of potential and realized mast production. An automated initial processing procedure (Appendix II.1) accomplishes three tasks.

1. Reads the Land Type file and Stand Identity LANDIS input files as single variable streams and saves the data as separate files in STATA format (LU.dta and Stand.dta).
2. Reads an ASCII file (created by the DOS executable program xy.exe; Appendix II.2) to assign the x and y coordinates for landscape cells (xy.dta).
3. Reads each of the output grids for species group, age, and dominance classes for each time-step, converts the group LANDIS coding to 1/0, *i.e.* presence or absence and saves the files in STATA file format (*e.g.* roak70.dta).
4. Merges land type, coordinate, stand, age, dominance, and species group presence or absence into a single STATA file.
5. Generates species combination presence variables (*e.g.* spc100) for each time-step where combinations of four 0's and 1's indicate the presence or absence of each of the four species groups in a cell (e.g. 1010 indicates the presence of white oak and pine and the absence of red oak and maple).

The STATA variables resulting from the LANDIS model are listed in Table II.2. Although there are 82 variables listed for the 100 year simulation of the test-case, there are really only 11 variables (shaded) that apply to each LANDIS iteration (time-step):

Table II.2 The STATA variables generated from LANDIS output and landscape description files for the 100 year test-case simulation. Shaded variables indicate an example of a set of variables relevant to a single Landis iteration (*t*=30).

	Variable	Label(Description)		Variable	Label(Description)
1	landunit	Land Unit	42	ro60	Red Oak Yr 60
2	stand	Stand ID	43	p60	Pine Yr 60
3	x	Column (long)	44	m60	Maple Yr 60
4	y	Row (lat)	45	agep60	Age Class Yr 60
5	wo0	White Oak Yr 0	46	dom60	Dominant Type Yr 60
6	ro0	Red Oak Yr 0	47	wo70	White Oak Yr 70
7	p0	Pine Yr 0	48	ro70	Red Oak Yr 70
8	m0	Maple Yr 0	49	p70	Pine Yr 70
9	agep0	Age Class Yr 0	50	m70	Maple Yr 70
10	dom0	Dominant Type Yr 0	51	agep70	Age Class Yr 70
11	wo10	White Oak Yr 10	52	dom70	Dominant Type Yr 70
12	ro10	Red Oak Yr 10	53	wo80	White Oak Yr 80
13	p10	Pine Yr 10	54	ro80	Red Oak Yr 80
14	m10	Maple Yr 10	55	p80	Pine Yr 80
15	agep10	Age Class Yr 10	56	m80	Maple Yr 80
16	dom10	Dominant Type Yr 10	57	agep80	Age Class Yr 80
17	wo20	White Oak Yr 20	58	dom80	Dominant Type Yr 80
18	ro20	Red Oak Yr 20	59	wo90	White Oak Yr 90
19	p20	Pine Yr 20	60	ro90	Red Oak Yr 90
20	m20	Maple Yr 20	61	p90	Pine Yr 90
21	agep20	Age Class Yr 20	62	m90	Maple Yr 90
22	dom20	Dominant Type Yr 20	63	agep90	Age Class Yr 90
23	wo30	White Oak Yr 30	64	dom90	Dominant Type Yr 90
24	ro30	Red Oak Yr 30	65	wo100	White Oak Yr 100
25	p30	Pine Yr 30	66	ro100	Red Oak Yr 100
26	m30	Maple Yr 30	67	p100	Pine Yr 100
27	agep30	Age Class Yr 30	68	m100	Maple Yr 100
28	dom30	Dominant Type Yr 30	69	agep100	Age Class Yr 100
29	wo40	White Oak Yr 40	70	dom100	Dominant Type Yr 100
30	ro40	Red Oak Yr 40	71	spc0	Species Code Yr 0
31	p40	Pine Yr 40	72	spc10	Species Code Yr 10
32	m40	Maple Yr 40	73	spc20	Species Code Yr 20
33	agep40	Age Class Yr 40	74	spc30	Species Code Yr 30
34	dom40	Dominant Type Yr 40	75	spc40	Species Code Yr 40
35	wo50	White Oak Yr 50	76	spc50	Species Code Yr 50
36	ro50	Red Oak Yr 50	77	spc60	Species Code Yr 60
37	p50	Pine Yr 50	78	spc70	Species Code Yr 70
38	m50	Maple Yr 50	79	spc80	Species Code Yr 80
39	agep50	Age Class Yr 50	80	spc90	Species Code Yr 90
40	dom50	Dominant Type Yr 50	81	spc100	Species Code Yr 100
41	wo60	White Oak Yr 60	82	symb	Graph Symbol

landunit, stand identity, two coordinate values, four species groups, the dominant species group, the age class of the dominant species group, and the combined species presence variable.   The major advantages to post-LANDIS modeling include reduced memory requirements. LANDIS generates up to 20 Mb of data in 149 text files for the relatively small 36,235 cell, 100 year simulation for the Oregon County test-case, whereas the same base-data manipulated in the mast module is only about 3 Mb when merged into one file in STATA format. Since all the data are loaded into computer memory as one file, calculations are significantly faster. Generating a map of species group distributions takes only a few seconds of computer processing-time. Other advantages of using STATA are: i) most programming tasks are written in plain text thus commands are readily translated into other programming languages, and ii) any generated values are easily exported for use by other software applications.

II.1.3 Summary of approach

For each 10-year time step LANDIS provides a description of each cell that includes the age and identity of the dominant species group, the presence of any other species groups, and the ecological land type. In addition, cells are organized into stands. These attributes can be used to stochastically compute the potential acorn production per stand:

Potential Acorn Production [PAP] = *f* (species, stand structure, land type)

Annual sources of variation such as climate and recent acorn production can be stochastically factored to further adjust and predict realized acorn production:

$$\boxed{\textbf{Realized Acorn Production [RAP]}} = f\ \textbf{(PAP, climate, and recent acorn production)}$$

Thus, the relationships among LANDIS landtype, species density, diameter and tree age need to be examined to estimate the potential acorn production and the relationships among species, flower survival, and climate need to be examined to estimate the realized acorn production.

A difficulty arises when utilizing information from previously published studies of mast production. Studies that test for differences among stands often represent mast production as an average across numerous years. Annual variation is averaged-out of the results. The annual influences are usually not described quantitatively and it is not known if any of the study years represent maximal production. The influence of any one factor cannot be known independently of all other factors. For short-term studies (1 to 4 years), maximum mast production potential may not be expressed due to the inherent year-to-year variability of masting. For long-term studies, average values are presented that summarize mast production across stands, diameter classes, and years. Thus, the relative difference in mast production among species can be seen in some studies but the maximum potential production of a species cannot. For these reasons, the influence of tree- and stand- level factors on the mast production index for the mast model is based on the best available data, but includes some subjective and qualitative estimates for values where adequate information is not available.

II.1.4 Spatial vs.Temporal variability

The spatial model of mast production generates an estimate of the potential mast production. Landis results reflect temporal change over the long term (in 10-year time steps). Mast production varies greatly from year to year, a much shorter span of time. In the next section, variables that affect mast production that are subject to annual variation are developed. These factors include climate and previous acorn production. Adjustments must be employed to compensate for the interactions and confounded relationships between spatial and temporal variability. For example, categories of the LANDIS land type variable, a spatial descriptor, convey topographic position and topographic position has been associated with varying mast production. Temporally variable factors, like relative humidity levels and freezing temperature events during flowering periods have also been found to be related to mast production, but there is a relationship between these factors and topographic position. That is, relative humidity may be lower on ridges providing a higher probability of successful pollination. So, predicting that acorn production is higher on ridges and higher where relative humidity is low may be two approaches to predicting the same effect and may not simply be additive. This again relates to the problem of interpreting previously published studies and incorporating the factors identified since no one study can track all the variables that possibly affect mast production. The model description and implementation accounting for annual variability is presented in Section IV.

II.2 Synthesis and the Spatial Model

The remainder of this section is related to formulating procedures to utilize the LANDIS output in STATA format to predict acorn production based on spatial variability. Ultimately, the mast model (MAST) incorporates two major components of masting behavior: the factors within a stand that describe mast-production (spatial variability) and those external to the stand and subject to annual variability (temporal variability).

II.2.1 Spatial variability

The spatial variability component uses the ten-year age-class distributions for each landscape cell along with the ecological land type values to predict potential acorn production. The synthesis is organized in the order factors are incorporated in the model. The ultimate objective of this synthesis is to provide parameters and methods to utilize LANDIS predictions of landscape change. The synthesis begins with the pertinent LANDIS input and output features. Previous research, FIA, and MOFEP information and data are used to infer effects on mast production. For example, LANDIS provides information on age and, typically, mast production is expressed as a function of tree size, therefore a method of converting from age structure to size structure for each time-step in a general manner is needed.

II.2.3 Synthesis: Spatial Variability

II.2.3.1 Sources of spatial data: FIA Database

The primary source of quantitative data for the species descriptions is the Internet Web Based U.S. Forest Service Forest Inventory and Analysis Data Base Retrieval System (Hansen *et al*. 1992). The inventory protocol and database has been standardized for the eastern states (East Wide Database). Basing the model algorithms and parameters on this source of data will facilitate application of the methods beyond the borders of Missouri. In the most recently completed Missouri inventory (1989), there were 17,270 plots of which 5,077 were classified as forestland. About 178,000 trees (dbh > 1 inch), were measured. Plot descriptors relevant to this study include, location (latitude and longitude), forest type, aspect, "physiographic" class (a rough description of soil moisture characteristics), and slope. Relevant tree traits include species and diameter.

II.2.3.2 Sources of spatial data: MOFEP Pre-Treatment Vegetation inventory

Pre-treatment data for the Missouri Ozark Forest Ecosystem Project (MOFEP) were utilized in parameterization. Measurements were made on about 96,000 trees distributed among 645 plots (Brookshire and Shifley 1997; Shifley and Brookshire 2000). The disparities between the FIA and MOFEP inventories are related to the sampling design, *i.e.* point- *versus* fixed area-sampling and the intensity of the sampling. For each set of data, the values for the observations are expanded differently and for the FIA data, values provided by the table generator were used unless specified otherwise, and simply weighted by sample area for MOFEP data.

II.2.3.3 Sources of spatial data: MOFEP Hard Mast Plots

As part of the MOFEP project, 130 plots were established on MOFEP sites to study mast production (Vangilder 1997). Measurements were made on vegetation following the overall MOFEP protocol (Shifley and Brookshire 2000; Brookshire and Shifley 1997). Twenty traps in a 4 X 5 grid were used to estimate acorn production starting in 1993.

II.2.3.4 LANDIS values referenced

Only two of the output values for each of 10-year LANDIS iterations are utilized for mast production: the age of dominants and the land-type (A and B in Figure II.3). For the Missouri landscapes, species presence and absence are an artificial designation. LANDIS output files indicate the presence and absence of the red and white oak groups. On forestland in Missouri, trees of the two groups are usually found occupying the same sites. Both red and white oaks were tallied on 82 percent of the FIA inventory plots that were occupied by oaks (all trees > 12.7 cm DBH) (Table II.4). Red oaks and white oak groups were found individually on about 9 percent each of the remaining plots. A random sample of MOFEP data to simulate the LANDIS cell size of 900 m^2 produced similar results. Of the 645 plots, only one (0.2 %) was occupied by white oak alone and only 2.6% were occupied by only red oak group species. LANDIS simulations in Missouri have typically started with a single species group presence per cell. As “time” passes the cells begin to display the presence of multiple species. For the 100 year test-case simulation, after 50 simulation years only about 30 percent of the cells contain

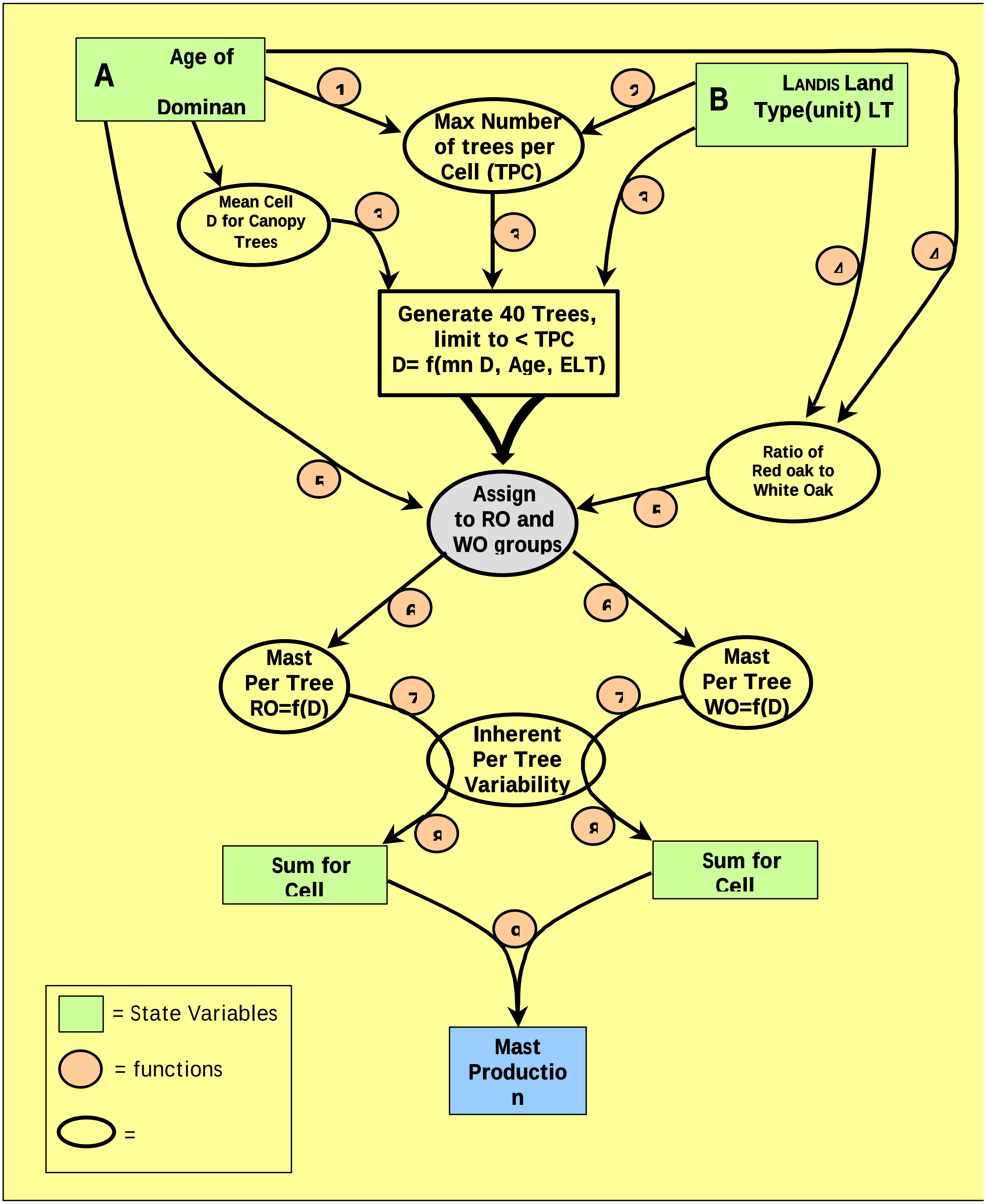


Figure II.3. Flow Chart of mast production model for sites in southern combinations of red and white oak (and pine) and after 100 years only about 60 percent (Figure II.4). Therefore, assigning mast production on a particular cell to either red or white oak based on LANDIS designations would be highly unrealistic.

II.3 SPATIAL RELATIONSHIPS IN THE MAST MODEL

II.3.1 Organization of description

Figure II.3 is a schematic of the general organization of the model. Arrows indicate modeled relationships. The circled number associated with each arrow is used below to reference the relationship. In some cases, where more than one relationship affects a state variable, the actual program code factors the relationships in one function (Table II.3). For clarity of explanation and justification, I have described each relationship separately and labeled these as separate steps.

Inherent to any modeling project is the need to determine parameters. In this case, while I wanted to construct a general method, I could not easily set aside the knowledge that the test-case scenario was in Missouri and more specifically in central-south-east Missouri. As such, the descriptions below are a representation of the method of choosing parameters for a particular landscape. I begin by describing conditions at the state level and narrow the focus when possible using available local data. Likewise, some characteristics are difficult to describe using statewide FIA data and more easily described using local data. Thus the third task is to present the method of factoring these relationship in the LANDIS-STATA-MASTING module for the test case. The programming add-on module formulated in this project is one of many possible approaches to utilizing

Table II.3 A partial listing of programming code for the masting model. The complete code is approximately 8000 lines. Commands enclosed in dased boxes are typically"house-keeping" routines. This program is written in the syntax of the statistical and data management software (Stata (crc-Stata 1999)

```
/* STATA Do file Mast Module */
/* Last edited:   7 Dec 00 - NHS  */

      drop _all                        /*  drop  active data base */
      set memory 132m                  /* assign 132MB   RAM to STATA   */
      use ash_uneven, replace          /*  Open file  */
      keep if stand<50                 /* subsample for model vevelopment */

      set more 1                       /* continuous scroll  */

*
* Est. number of dominant + codominant oak trees per cell by ageclass

      local tpc_sl = -0.099                       /* slope of age tpc relationship*/
      local tpc_con = 24.1                        /* intercept of age tpc relationship*/
      local tpcsdsl = -0.08                       /* slope of age tpc-sd relationship*/
      local tpcsdco = 16                          /* intercept of age tpc-sd relationship*/

      * number of cell canopy oak trees (ccotpc): random selection from normal distribution by age of dominants

      gen ccotpc10 = (`tpc_sl' * agep10 + `tpc_con') + (`tpcsdsl' * agep10 + `tpcsdco') * invnorm(uniform())

* Influence of Landtype on the number of canopy oak trees >12.7 D   MOFEP Based
                                                                                                  */
      /* no affect on types 1,2       Mean =        0.703                                         */
      /*                                                                                          */
      /*            1         0.739      1.052                                                    */
      /*            2         0.747      1.063                                                    */
      /*            3         0.785      1.117                                                    */
      /*            4         0.619      0.881                                                    */
      /*            5         0.569      0.810                                                    */
      /*            6         0.757      1.077                                                    */
      /*            7         0.703      1.000                                                    */

      replace  ccotpc10   =ccotpc10*    1.052   if landunit==1
      replace  ccotpc10   =ccotpc10*    1.063   if landunit==2
      replace  ccotpc10   =ccotpc10*    1.117   if landunit==3
      replace  ccotpc10   =ccotpc10*    0.881   if landunit==4
      replace  ccotpc10   =ccotpc10*    0.810   if landunit==5
      replace  ccotpc10   =ccotpc10*    1.077   if landunit==6

               gen int ccotp10 =      round(ccotpc10,0)   /* number of canopy trees rounded to whole number */
               drop ccotpc*
```

1

2

```
* Estimate of cell-stand mean diameter and distribution by age of dominants
* from FIA data, mean diameter per ageclass

*               Assign a random diameter to 40 trees for each cell for each iteration

      for new t10t1-t10t40: gen X = 0.14* agep10 + 21.5
    1 for new t20t1-t20t40: gen X =0.14* agep20 +21.5
    1 for new t30t1-t30t40: gen X = 0.14* agep30 + 21.5                     /* Mean stand Diameter    0.04    */
    1 for new t40t1-t40t40: gen X = 0.14 * agep40 +21.5                     /* Diameter - Std dev      9      */
    1 for new t50t1-t50t40: gen X = 0.14 * agep50 + 21.5                             /*                      */
    1 for new t60t1-t60t40: gen X = 0.14 * agep60 + 21.5                             /*    age    SD-HAT     */
    1 for new t70t1-t70t40: gen X = 0.14 * agep70 + 21.5                             /*     10        9.4    */
    1 for new t80t1-t80t40: gen X = 0.14 * agep80 + 21.5                             /*     20        9.8    */
    1 for new t90t1-t90t40: gen X = 0.14 * agep90 + 21.5                             /*     30        8.8    */
    1 for new t100t1-t100t40: gen X =  .13 * agep100 + 21.5                          /*     40        9.4    */
    2 for var t20t1-t20t40: replace X =X + (0 + (0.04* agep20 +9.0) * invnorm(u      /*     50       10.0    */
    2 for var t30t1-t30t40: replace X = X + (0 + (0.04* agep30 +9.0) * invnorm(      /*     60       10.6    */
    2 for var t40t1-t40t40: replace X = X + (0 + (0.04* agep40 +9.0) * invnorm(      /*     70       11.2    */
    2 for var t50t1-t50t40: replace X =X + (0 + (0.04* agep50 +9.0) * invnorm(u      /*     80       12.2    */
    2 for var t60t1-t60t40: replace X =X + (0 + (0.04* agep60 +9.0) * invnorm(u      /*     90       12.6    */
    2 for var t70t1-t70t40: replace X =X + (0 + (0.04* agep100 +9.0) * invnorm(      /*    100       13.0    */
    2 for var t80t1-t80t40: replace X =X + (0 + (0.04* agep80 +9.0) * invnorm(u      /*    110       13.4    */
    2 for var t90t1-t90t40: replace X =X + (0 + (0.04* agep90 +9.0) * invnorm(u      /*    120       13.8    */
    2 for var t100t1-t100t40: replace X =X + (0 + (0.04* agep100 +9.0) * invnor      /*    130       14.2    */
                                                                                     /*    140       14.6    */
                                                                                     /*    150       15.0    */
                                                                                     /*    160       16.6    */

      /*       Apply variability   */

      for var t10t1-t10t40: replace X = X + (0 + (0.04* agep10 +9.0) * invnorm(uniform()))


      for var t10t1-t10t40: replace X = 0 if X <0.1       /* replace diameter with 0 if very small */
```

3a

```
/*     Variation in Oak component (prop.)    Stand Structure  (D)                             */
/*     LANDIS              Affect on                      */
/*      Type       ELT      Diameter                      */
/*        1         17         1.04                       */
/*        2         18         0.96                       */
/*        3         11         1.05                       */
/*        4         19         0.95                       */
/*        5         5,7        0.95                       */
/*        6        20,21       0.96                       */
/*        7        other       0.96                       */


      for var  t10t1-t10t40: replace X =  X  * 1.04 if landunit==1
      for var  t10t1-t10t40: replace X =  X  * 0.96 if landunit==2
      for var  t10t1-t10t40: replace X =  X  * 1.05 if landunit==3
      for var  t10t1-t10t40: replace X =  X  * 0.95 if landunit==4
      for var  t10t1-t10t40: replace X =  X  * 0.95 if landunit==5
      for var  t10t1-t10t40: replace X =  X  * 0.96 if landunit==6
      for var  t10t1-t10t40: replace X =  X  * 0.96 if landunit==7
```

3b

```
* Make diameter 0 if tree-N > canopy trees per cell

      replace  t10t1      = 0 if      ccotp10    < 1
```

3c

```
* Regional variation in ratio of red oak and white oak groups

      * by ageclass:    fraction of oaks that are red oak = -0.0027066*(ageclass) + .6286, R2 =.86 for FIA
      * adjustment for Oregon County:  -0.0000179 * ageclass^2 + .644


      gen cfro10 =         -0.0000179*(agep10) + 0.644
      gen cfro20 =         -0.0000179*(agep20) + 0.644
```

4a

```
* Adjust ratio of RO and WO groups for landis land type (unit)

     /*        Land type   MOFEP AVG     Adj.    Var. (SD)*/
     /*                                                    */
     /*            1         0.647      0.88               */
     /*            2         0.609      0.83               */
     /*            3         0.733      1.00               */
     /*            4         0.372      0.51          0.05 */
     /*            5         0.419      0.57               */
     /*            6         0.538      0.73               */
     /*            7         0.553      0.75               */

     gen mncfro10 =          0.75    * cfro10
     replace mncfro10 =      0.88    * cfro10            if landunit==1
     replace mncfro10 =      0.83    * cfro10            if landunit==2
     replace mncfro10 =      1.00    * cfro10            if landunit==3
     replace mncfro10 =      0.51    * cfro10            if landunit==4
     replace mncfro10 =      0.57    * cfro10            if landunit==5
     replace mncfro10 =      0.73    * cfro10            if landunit==6

     *  Add random variability to Fraction red oak group

              replace mncfro10 = mncfro10 + 0.05 * invnorm(uniform())

* Randomly assign trees to ro and wo species groups

     for new t10sp1 - t10sp40:       gen str2 X = "WO"   /* create species for each tree on each cell */
     for new temp1-temp40: gen X = (uniform())

     replace  t10sp1      ="RO" if    temp1      < mncfro1/* randomly assign tree to sp group */
     drop temp1-temp40
```

4b

5b

```
* Adjust diameter for different growth rates for subgenus's
*
*     model of multiplier to get WO
*
*              adjust =     -0.0010492 (age) +    1.010843
*

      replace t10t1  = (agep10 * -0.0010492 + 1.011)       * t10t1 if t10sp1 =="WO"
      replace t10t2 = (agep10* -0.0010492 + 1.011)         * t10t2 if t10sp2 =="WO"
```

5c

```
* Set  diameter to 0 if very small

         for var t10t1-t10t40: replace X = 0 if X <0.1
```

```
*  Tree diameter and mast production (index) relationship----generates a 0-1 index of relative mast production
                                             /*                                                      */
                                             /*                            Coeff. (0-1)    DBH      */
                                             /*                                                      */
         local rod =            -3.361032    /*                             -0.22407      D       */
         local rod2 =            0.1279035   /*          Scaler              0.00853      D2      */
         local rod3 =           -0.0017115   /*        for desired          -1.14E-04     D3      */
         local rod4 =            7.515E-06   /*           range              5.01E-07     D4      */
         local rodc =              28.65     /*        Maximum =    15       1.91000   interc.   */
                                             /*  Similar to range of kg per tree                    */
         local wod =            -1.4629095   /*                             -0.09753      D       */
         local wod2 =            0.0567975   /*                              0.00379      D2      */
         local wod3 =           -0.000705    /*                             -4.70E-05     D3      */
         local wod4 =            2.835E-06   /*                              1.89E-07     D4      */
         local wodc =              11.85     /*                              0.79000   interc.   */

      gen t10rms1          =t10t1*`rod'+(t10t1^2)*`rod2'+(t10t1^3)*`rod3'+ (t10t1^4)*`rod4'+`rodc' if t10sp1=="RO"

      gen t10wms1          =t10t1*`wod'+(t10t1^2)*`wod2'+(t10t1^3)*`wod3'+ (t10t1^4)*`wod4'+`wodc' if t10sp1=="WO"

      replace t10rms1       = 5 If  t10t1 >  91   =="RO"              /*    correct for artifact of*/
```

6ab

```
* Factor per tree inherent variability in acorn production  (randomly assigned)

*              Fraction of population                                /* proportion of population   */
*     Non-producers           0.15                                   /*              0.10            */
*     Low Prod                0.30                                   /*              0.30            */
*     Mod Prod                0.40                                   /*              0.45            */
*     High Prod               0.15                                   /*              0.15            */
*
*     /* macros assigning class thresholds */
*
*     No prod   (  gt )               relative  productior      0.00
*     Low Prod (  gt )        0.15                              0.30
*     Mod Prod (  gt )        0.45                              0.75
*     High Prod(  gt )        0.85                              1.00

      for new t10pr1-t10pr40: gen X = 0
      for new temp1-temp40: gen X = (uniform())
      replace t10pr1 =    0.3    if temp1   >  0.15
      replace t10pr1 =    0.7    if temp1    >  0.45
      replace t10pr1 =    1    if  temp1     >  0.85
      drop temp*
      *  Scale per tree mast production for red oak group by randomly assigned but subjectve  productivity classes

               replace t10rms1          = t10pr1  *  t10rms1

      *  Re-calculate for assignment of inherent productivity  to white oak group

               for new temp1-temp40: gen X = (uniform())

               replace t10pr1 =   0.30  if temp1  >  0.15

*  Scale per tree mast production for white oak group by randomly assigned but subjectve  productivity classes

      replace t10wms1        = t10pr1   *  t10wms1
```

7ab

```
* Set mast production at 0 if trees less that 20 cm in diameter

        replace t10rms1 = 0 if t10t1< 20  & t10sp1 =="RO"

        replace t10wms1 = 0 if t10t1 < 20 & t10sp 1=="WO"

* drop per tree diameter information  for trees 2-40 , tree 1 retained for model evaluation

        drop t10t2-t10t40

* drop per tree inherent productivity information for trees 2-40 , tree 1 retained for model evaluation

        drop    t10pr2-t10pr40
```

```
*  Generate Cell totals for red oak subgenus


     gen  rmst10 =t10rms1 if t10sp1=="RO"
     replace rmst10 =rmst10 +t10rms2 if t10sp2=="RO"

*  Generate Cell totals for white oak subgenus

     gen  wmst10 =t10wms1 if t10sp1 =="WO"
```

8ab

```
* drop per tree mast production  trees 2-40 , tree 1 retained for model evaluation
```

```
        drop    t10sp2-t10sp40

        drop    t10rms2-t10rms40

        drop    t10wms2-t10wms40

* Set cell subgenus mast production to zero if missing

        replace  rmst10 =0 if rmst10 ==.

        replace  wmst10 =0 if wmst10 ==.
```

```
* Generate overall cell mast production  value

        gen mst10 = rmst10+wmst10
```

9

Table II.4. Presence and co-presence of the oak subgenera on sample plots for the statewide FIA inventory and a random sample to simulate a 900m2 plot for the Ozark MOFEP inventory.

	FIA		MOFEP	
Subgenus	**Number of Plots**	**Percent**	**Number of Plots**	**Percent**
White Oak	389	9.0	1	0.2
Red Oak & White Oak	3583	82.5	625	96.9
Red Oak	370	8.5	19	2.6
Total	4342		645	

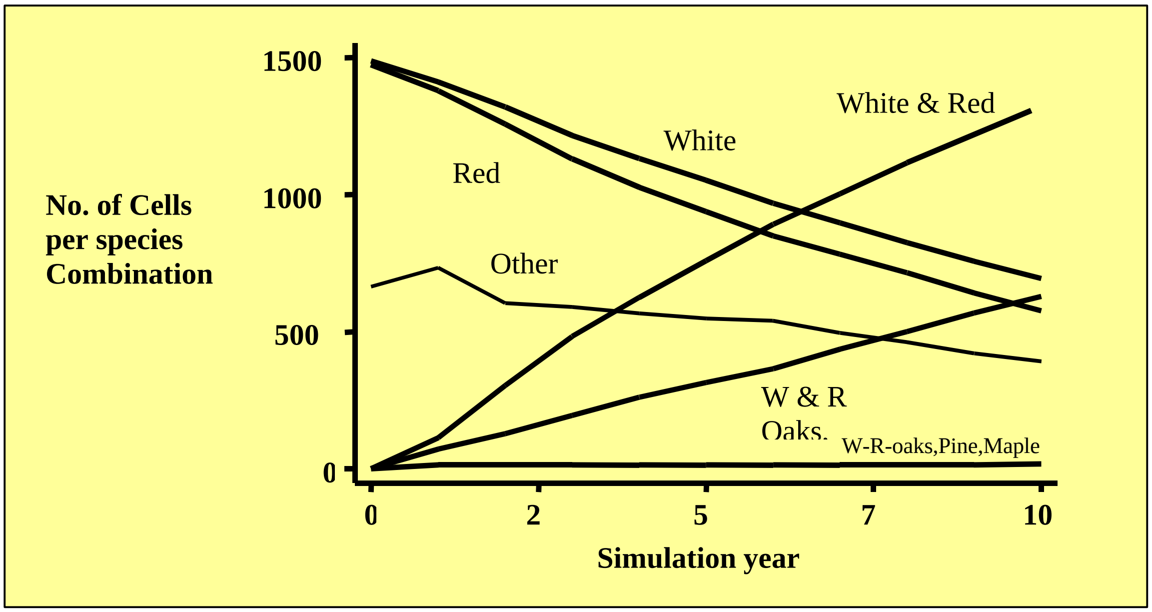


Figure II.4. An example of species combinations from LANDIS output for the simulation test-case. Mixed species sites increase with time.

LANDIS output. It is meant to be an approach that can be customized easily to differing landscapes and differing research questions.

Parameters and justification of modeled relationships will be explained in the order in which the factors enter the model. Reference is made to Figure II.3**,** a flow chart of the model, and Table II.3**,** a partial list of programming code-lines. Since the model predicts mast production at the tree level, many repetitive operations are carried out on individual "trees". The full, unedited model-program consists of about 8,000 lines of code.

II.3.2 Model Step1: Number of trees per cell = f(age class), random selection

An examination of a modified stocking diagram for all trees on a simulated cell-sized area (900m^2), shows that with an average of 56 trees (>2 in. dbh) per cell and an average diameter of 18 cm, the MOFEP sites are stocked at a relatively low level (Figure II.5). This level of productivity is not unexpected for the conditions occurring in southern Missouri. Since dominant and co-dominant trees produce most of the acorns, analysis of FIA and MOFEP data was limited to trees in dominant and co-dominant canopy positions of at least 12.7 cm in diameter (5 in.). Eliminating small trees and trees that are not in a canopy positions favorable to mast production improved my ability to estimate the relationships relevant to mast production.

To examine FIA data, trees on FIA plots were selected at random to simulate the cell-sized area (900 m^2). That is, a uniformly distributed random number (0-1) was assigned to each potential mast tree expansion value for "trees per acre" and only those with a random number of less than 0.2223 were used in the analysis. This threshold

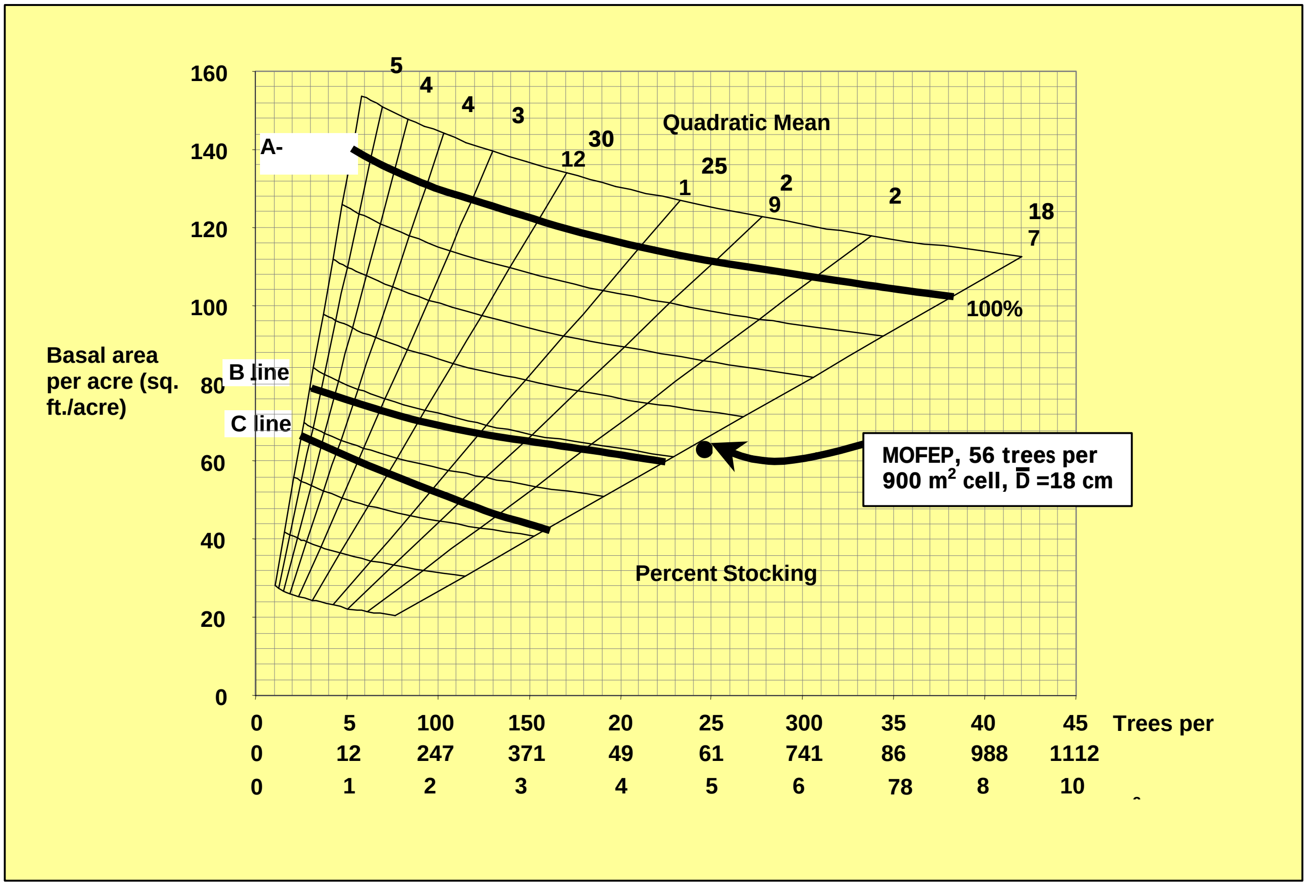


Figure II.5. Gingrich diagram of stand stocking for estimating the number of trees (>2” DBH) per landscape cell (Larsen 2000).

converts the acre-based tree density to the density per 900 m^2. The average number of dominant and co-dominant oak trees per simulated cell (TPC) was calculated (for each FIA plot). Each plot has a representative stand age associated with it, in the case of Missouri, these values range from 0 to 160 years. The simulated FIA cells were categorized into 10-year age classes. This classification corresponds to the 10-year iterations of the LANDIS model. For each age class, the average TPC was calculated for each "cell" as well as the standard deviation (Table II.5). A regression model for predicting the statewide TPC values shows a clear relationship between the mean representative stand age (class) and TPC ($P<0.0005$; $R^2 = 0.76$). In addition the standard deviation associated with each age class is predictable ($R^2 = 0.75$, Figure II.6).

MOFEP vegetation plot data were also examined to estimate the number of trees per cell. Similar to the FIA analysis, the MOFEP trees were randomly selected to simulate a cell-sized area. On average, the 645 simulated 900 m^2 cells had about 4.2 dominant oak trees and 10.3 co-dominant oak trees (Table II.6). The distributions for dominants and co-dominant oak trees follow a nearly normal pattern (Figure II.7) but variation among the co-dominants is much higher than the dominants. The slight disagreement between the means and standard deviations represented in the table and figure is due to the vagaries of random sampling.

Since the FIA based TPC-age class relationship is based on statewide data that might not represent the conditions in southern Missouri and the MOFEP data set has limited information available regarding plot age, the results from the two data sets were considered subjectively to formulate the parameters that estimate TPC for the mast model. Basically, neither data set provides an adequate description of the relationship

Table II.5. Average number of oak trees (>12.7 cm DBH) per estimated 30 X 30 m cell sized plot for dominants and codominants combined by representative stand age class for FIA plots.

Canopy Position	Age Class	Trees per Cell	SD	N
Dominants and	10	13.9	12.6	143
Codominants	20	17.7	15.8	430
Combined	30	23.2	21.5	164
	40	26.6	26.3	388
	50	21.6	18.1	598
	60	19.3	15.7	420
	70	17.9	13.9	407
	80	15.4	11.4	341
	90	14.5	10.3	263
	100	14.8	12.1	209
	110	14.2	11. 5	121
	120	15.5	11.4	56
	130	15.3	11.4	31
	140	10.7	8.7	12
	150	15.1	8.3	8
	160	9.2	6.2	4

Approximate
stand Age range
for MOFEP plots

Table II.6. Average number of trees per estimated 30 X 30 m cell sized plot by canopy position for MOFEP vegetation plots. A uniformly distributed random number was assigned to each tree to reduce the sample size to approximate the Landis cell size.

Crown Position	Code		Non Oaks	Oaks	Total
Dominant	1	Mean	2.11	4.27	6.4
		SD	1.66	2.45	
		N	334	612	
Co-Dominant	2	Mean	3.82	10.26	14.1
		SD	3.18	5.41	
		N	530	642	
Intermediate	3	Mean	3.77	6.58	10.3
		SD	2.79	3.99	
		N	542	631	
Over-topped	4	Mean	2.19	2.41	4.6
		SD	1.59	1.81	
		N	368	427	
Total		Mean	11.9	23.5	35.4
Canopy Trees (Dom & Co-Dom)		Mean	4.89	14.31	
		SD	4.20	6.04	

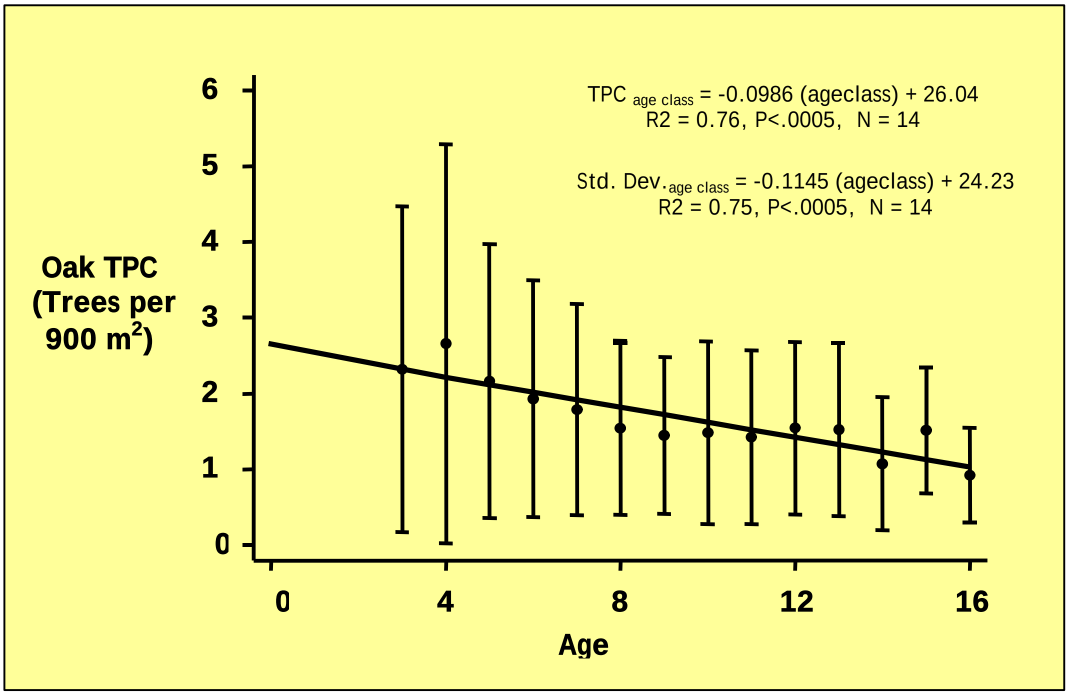


Figure II.6. Estimated dominant and co-dominant oak trees per simulated cell sized area [TPC] (900m$^{2)}$ $\pm$ 1 SD from throughout Missouri. Randomly selected oak trees > 12.7 cm DBH and classified by representative stand age.

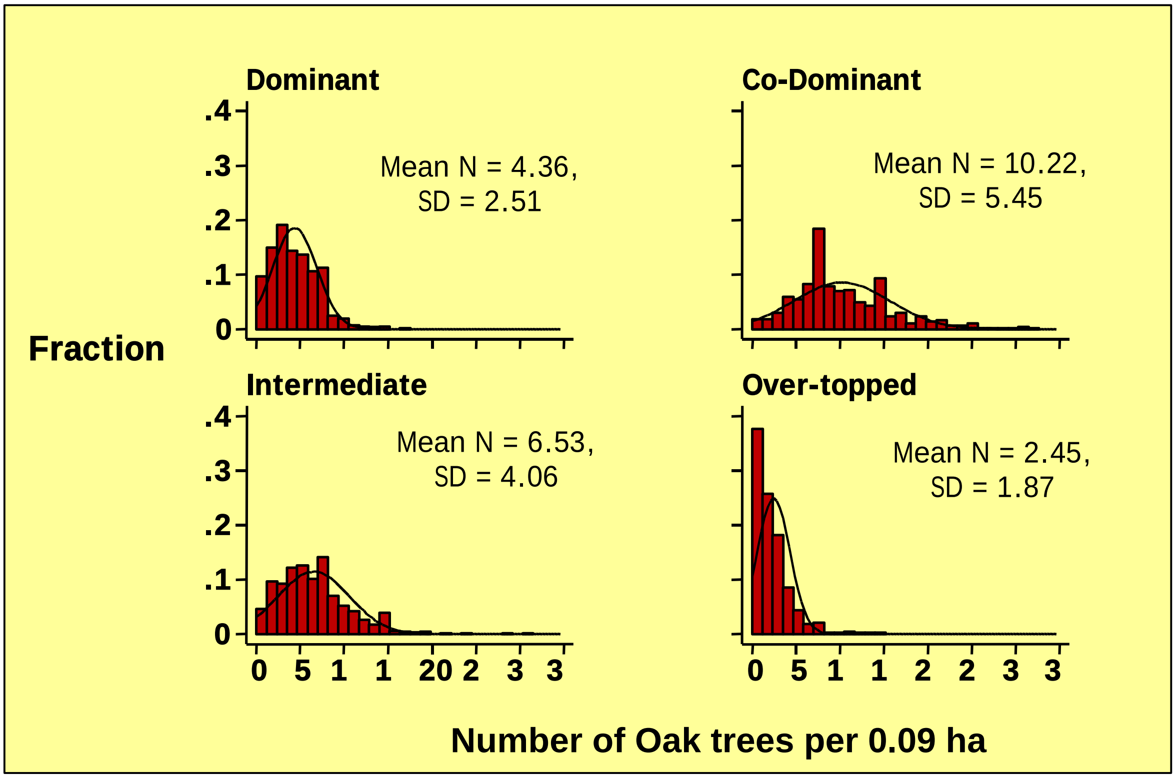


Figure II.7 Distribution of the number of oak trees (>12.7 cm D) per simulated 900 m^2 cell from between age and TPC. The slope of the age TPC age-class relationship was maintained at about –0.10 and the intercept was set at about 24.0 (Table 11.7). The model for predicting the standard deviation for each age class using FIA data was altered to resemble the MOFEP results. The slope of the line was increased to –0.08 and the intercept reduced to 16. Since the normal distribution number at each age class may include TPC<0, this alteration results in a distribution at each age class that is effectively skewed toward fewer numbers of cells with high TPC. It also results in the number of cells assigned to having no oaks (*i.e.* a TPC value of 0 or less) similar to that seen on MOFEP sites.

In summary, the number of trees per cell is calculated by estimating the mean number of trees per cell at each age class using a linear function. Variability in the number of trees per cell is factored by selecting a TPC from a normal distribution at each age class that is defined by a standard deviation that is also estimated using a linear function that reflects increasing variability with increasing age.

II.3.3 Model Step2: Number of trees per cell (TPC) = f(land type)

LANDIS as applied in the Missouri Ozarks factors seven land types. The eleven Ecological Land Types (ELT's) utilized in the MOFEP data can be re-classed to fit into the seven-types used in the southeast Missouri application of LANDIS (Table II.8). Most ELT's and Landis Land Type categories correspond well; the one exception is that MOFEP ELT 11 (Ridge) has no equivalent LANDIS type. This is important for mast production because ridge sites are often among the most productive. An analysis of the MOFEP hard mast plot data indicates that ridge sites (ELT 11) produce mast at a rate that

Table II.7. Age-TPC relationship from statewide FIA summary subjectively adjusted in consideration of MOFEP location and stand characteristics. Predicted estimations are for the number of dominant plus codominant oak trees greater than 12.7 cm DBH.

Age Class	**Predicted TPC**	**Predicted Std. Dev.**	**Subjective Adjustment per MOFEP TPC**	**Subjective Adjustment per MOFEP *SD***	
10	.	.	.	.	
20	.	.	.	.	
30	23.09	20.75	21.09	13.6	
40	22.10	19.60	20.10	12.8	
50	21.12	18.45	19.12	12.0	
60	20.13	17.30	18.13	11.2	
70	19.14	16.15	17.14	10.4	
80	18.15	15.00	16.15	9.6	Approximate
90	17.17	13.85	15.17	8.8	stand Age range
100	16.18	12.70	14.18	8.0	for MOFEP plots
110	15.19	11.55	13.19	7.2	
120	14.21	10.40	12.21	6.4	
130	13.22	9.25	11.22	5.6	
140	12.23	8.10	10.23	4.8	
150	11.25	6.95	9.25	4.0	
160	10.26	5.80	8.26	3.2	

Adjusted $TPC_{\text{canopy oaks}} = -0.099(\text{ageclass}) + 24.1$

Adjusted $SD = -0.08(\text{ageclass}) + 16$

Table II.8 Conversions between LANDIS land type desginations and MOFEP Ecological Land Type (ELT) classifications used in the mast model. ELT 11 was classified with ELT 17 since both have similar mast production potential (per MOFEP hard mast plot analysis). The number (N) refers to the number of plots (MOFEP) and cells (LANDIS test-case) per type

LANDIS Landunits				MOFEP Plot ELT Distributions			
Type	***Description***	**Oregon County Test Case N**	**percent**	***ELT***	***Description***	**N**	**percent**
1	SW Slope	13367	37	17	Side Slope, South and West Aspects, 8-99% slope, Dry Chert Forest	260	40.3
				11	Ridge, Neutral Aspects, 0-8 % slope, Dry Chert Forest	91	14.1
2	NE Slope	12720	35	18	Side Slope, North and East, 8-99% slope, Dry Mesic Chert, Dry-Mesic sand forest	213	33.0
3	Flat	8335	23	15	Flat, Neutral Aspects, 0-8 % slope, Dry Chert forest	5	0.8
4	Savanna/Glade	133	0.4	19	Side slope, South and West, 8-99% slope, Glade Savanna	18	2.8
5	Upland Drainage	1507	4	5	Upl Waterway, neutral Aspects, 0-4 % slope, Dry Bottomland Forest Veg comm.	29	4.5
				7	Toe Slope, All Aspects, 0-14% slope, Mesic Forest	6	0.9
6	Limestone	38	0.1	21	Side slope, all Aspects, 5-99% slope, Dolomite glade, Limestone glade	4	0.6
				22	Side slope, all Aspects, 5-99% slope, xeric limestone forest	3	0.5
				23	Side slope, all Aspects, 5-99% slope, dry limestone forest	9	1.4
7	Mesic	135	0.4	20	Side Slope, North and East, 8-99% slope, Dry Mesic limestone forest	7	1.1

most closely resembles that of South and West sites (ELT 17) (Table II.9; Figure II.8). For this reason, ELT 11 was grouped with ELT 17 in the LANDIS land type 1.

Based on the TPC per ELT data for the MOFEP sites, the TPC is adjusted using a scaling multiplier where the highest TPC on MOFEP sites by the LANDIS Type assignment (Type 3: Flat), is set at 1 and all others scaled accordingly (Table II.10).

II.3.4 Model Step3a: Generation of trees: tree diameter = f(age class)

The previous steps estimate the number of trees per cell. The next group of steps (Figures II.3:a,b,c) generates a set of trees for each cell (40 per cell numbered 1 through 40), assigns a randomly selected diameter, adjusts the diameter for age and land type for each of these cells, and then discards trees to match the previously estimated TPC, *i.e.* tree number id's that exceed the TPC.

LANDIS vegetation information is based on age. Predictions of acorn production potential are most reliable when based on tree size (diameter)(Figure II.9) and canopy position (Downs 1944). Therefore, the relationship between tree age and tree size must be characterized. In general, tree size at any age is highly variable and the relationship is drastically heteroscedastic (Loewenstein et al. 2000). There is a lower variation in diameter at younger ages than at older. However, there is a biological requirement for trees to become larger by the radial growth of conductive tissue each year if they are to survive over the long-term.

The ability to predict the age-diameter relationship is improved for this study due to the nature of masting. Nearly all trees that are mast producing occupy dominant and co-dominant canopy positions and as FIA and MOFEP data record canopy position for

Table II.9. Average acorn production (kg ha^{-1} air-dried) among MOFEP ecological land types (ELT) for three years of pre-treatment collection.

ELT	DESCRIPTION		Year 1993	1994	1995	Mean
			---------- kg ha^{-1} ----------			
5	**Upland Drainage**	**Mean**	5.5	8.9	29.9	15.0
		SD	4.5	9.0	20.8	17.1
		N	10	9	10	
11	**Ridge**	**Mean**	14.6	65.0	44.4	41.3
		SD	12.9	32.9	28.0	33.0
		N	21	21	21	
15	**Flat**	**Mean**	10.3	17.3	15.9	14.5
		SD	1.5	14.7	0.8	7.4
		N	2	2	2	
17	**S & W**	**Mean**	11.7	47.8	25.9	28.3
		SD	10.5	45.4	20.2	32.5
		N	50	49	51	
18	**N & E**	**Mean**	13.1	47.1	32.6	31.0
		SD	12.1	38.8	27.7	31.4
		N	46	46	46	

Table II.10. Number of dominant and co-dominant oaks trees per cell on MOFEP plots by Landis equivalent Land Type

LANDIS Land Type		Trees per Cell	SD	No. of plots	Multiplier
1	**S & W**	15.0	5.8	351	0.987
2	**N & E**	13.9	5.8	213	0.911
3	**Flat**	15.2	9.0	5	1.000
4	**Savanna**	11.6	4.2	18	0.761
5	**Upland Drainage**	12.9	6.8	35	0.846
6	**Limestone**	14.3	6.0	16	0.941
7	**Mesic**	11.6	3.2	7	0.761

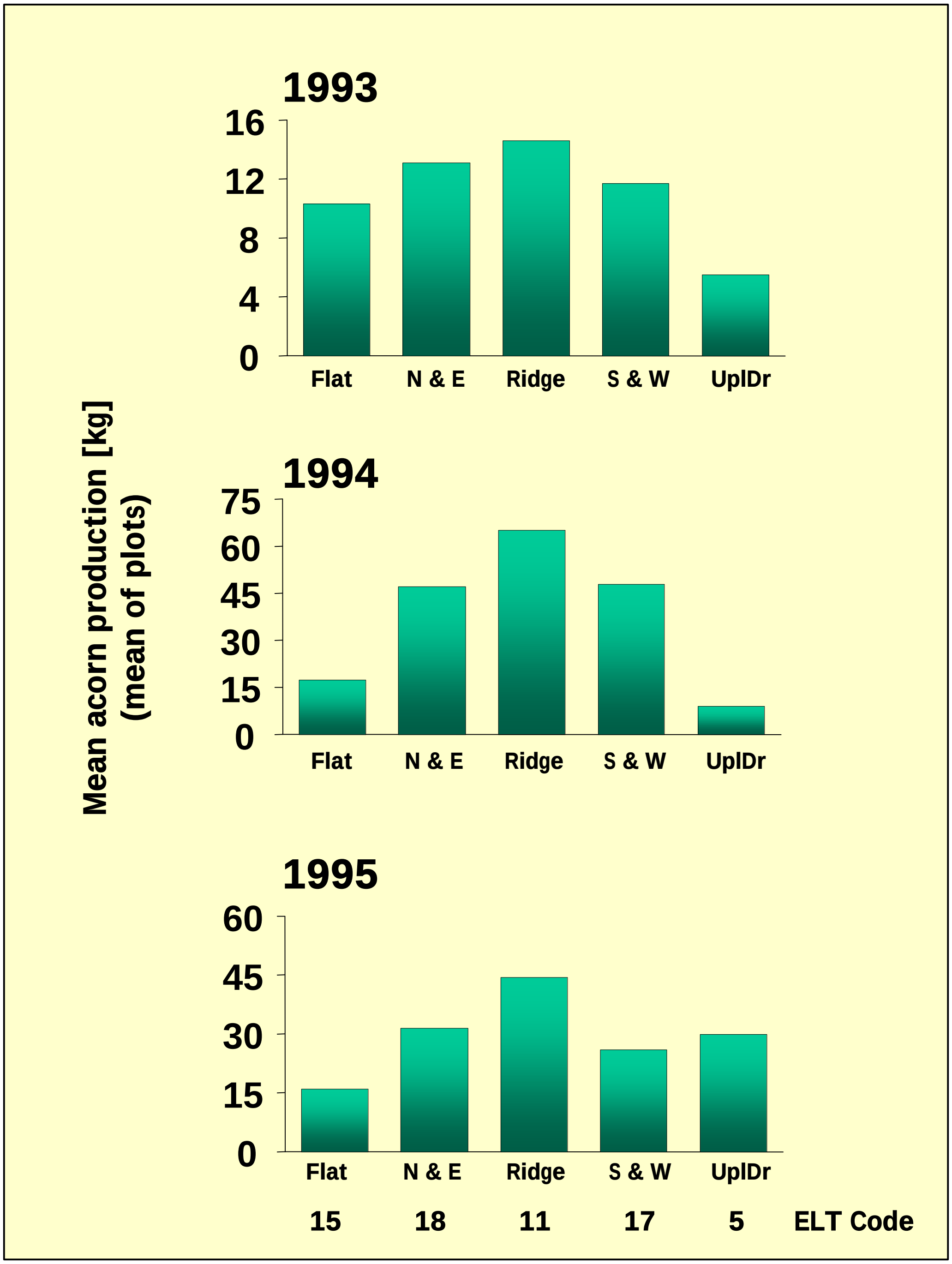


Figure II.8 . Mean acorn production (kg na^{-1}) by year and ELT for the MOFEP hard mast study. Note the differences in the ranges of Y axes.

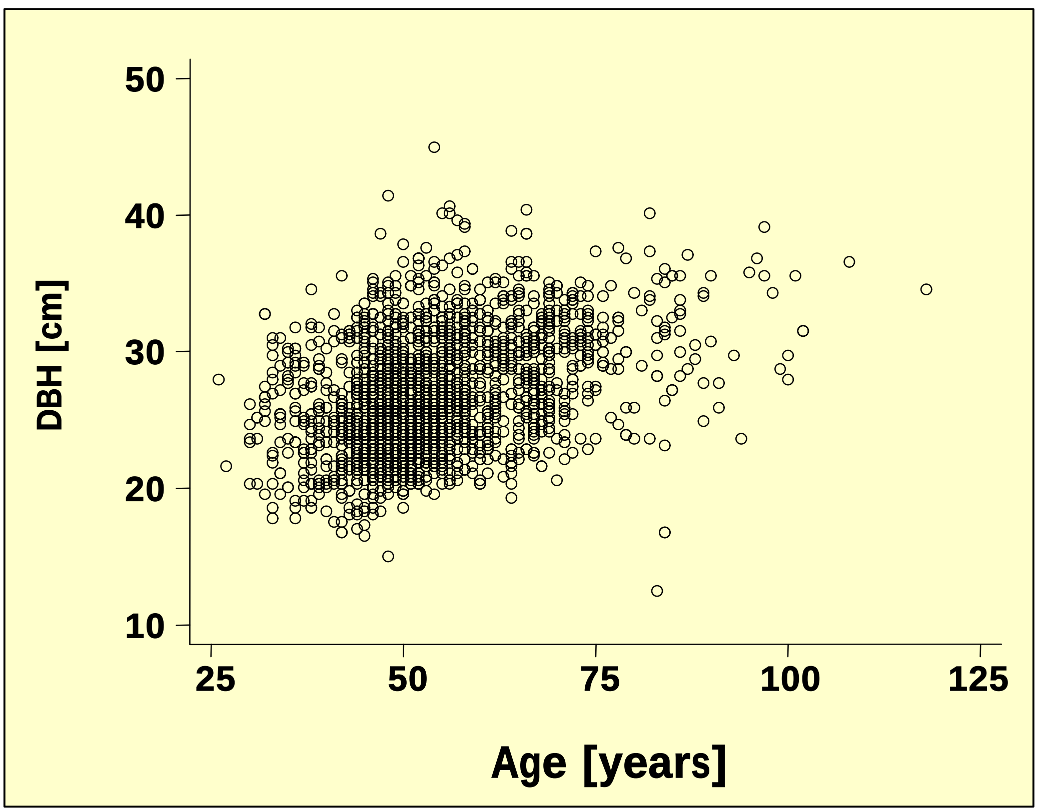
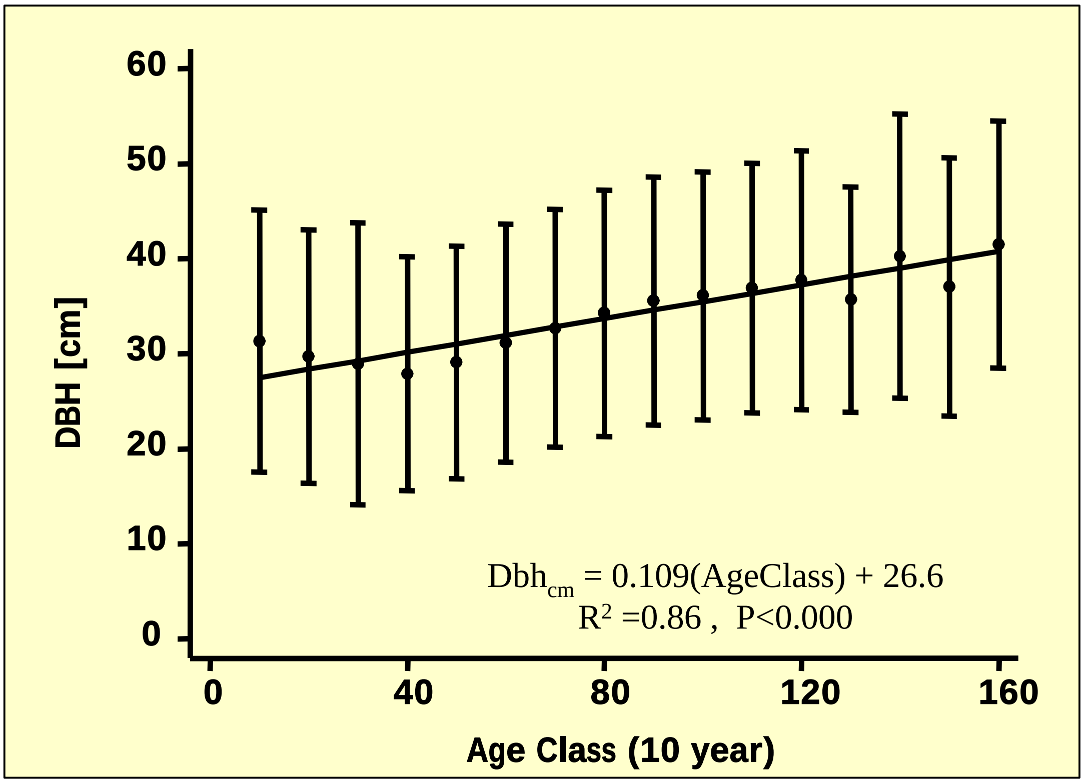


Figure II.9. Diamete-age relationship for MOFEP site index trees.



Quercus alba: $_{cm}$ = 0.080( ) + 29 R

Dbh AgeClass ^{2} =0.52 , $P<0.000$

Q coccinnea: Dbh_{cm} = 0.151(AgeClass) + 23 R^2 =0.85 , $P<0.000$

Dbh_{cm} = 0.100(AgeClass) + 28 R^2 =0.73 , $P<0.000$

Figure II.10 Diameter-age class relationship for FIA data. Fit values are the mean diameter $\pm$ 1SD of codominant and dominant oaks greater than 12.7 cm DBH on forestland per 10-year stand age class.

tallied trees; thus, for this application only dominant and co-dominant oaks are relevant and all other species and canopy classes were eliminated. Moreover, most studies indicate that small trees do not contribute substantially to overall mast production (Downs 1944; Section I: Figure I.1), therefore trees less than 13 cm were eliminated from consideration (5 in.). Consequently, the modeled relationship is the diameter for oak trees greater than 13 cm in diameter occupying dominant and co-dominant positions as a function of 10-year age class. This is compatible with LANDIS output.

The relationship between tree size and age that has been used in the model is based on FIA data and MOFEP site index tree data. Actually, it is a subjectively estimated compromise of the relationships displayed in the two data sets. Analysis of the FIA data is limited by the manner of sampling and reporting. For each FIA plot location, a “representative stand age” is reported. Therefore no individual tree age-tree diameter data are analyzed. Analysis of the MOFEP data is restricted by the small number of trees for which age information is available (2,132) as well as the more narrow ranges of age and diameter.

Regression output statistics for the age-diameter relationship are shown in Appendix II.3. Regression models were fit in two ways. The first (un-summarized) method regressed the diameter for all trees in the age class as a function of age. The second (summarized) fit the mean diameter at each age class to the age class. The standard deviation of mean stand diameters for each age class was also fit and was not found to be significantly different across age classes. The model and a representation of the relationship is shown in Figure II.10. The model for the MOFEP data resulted in a

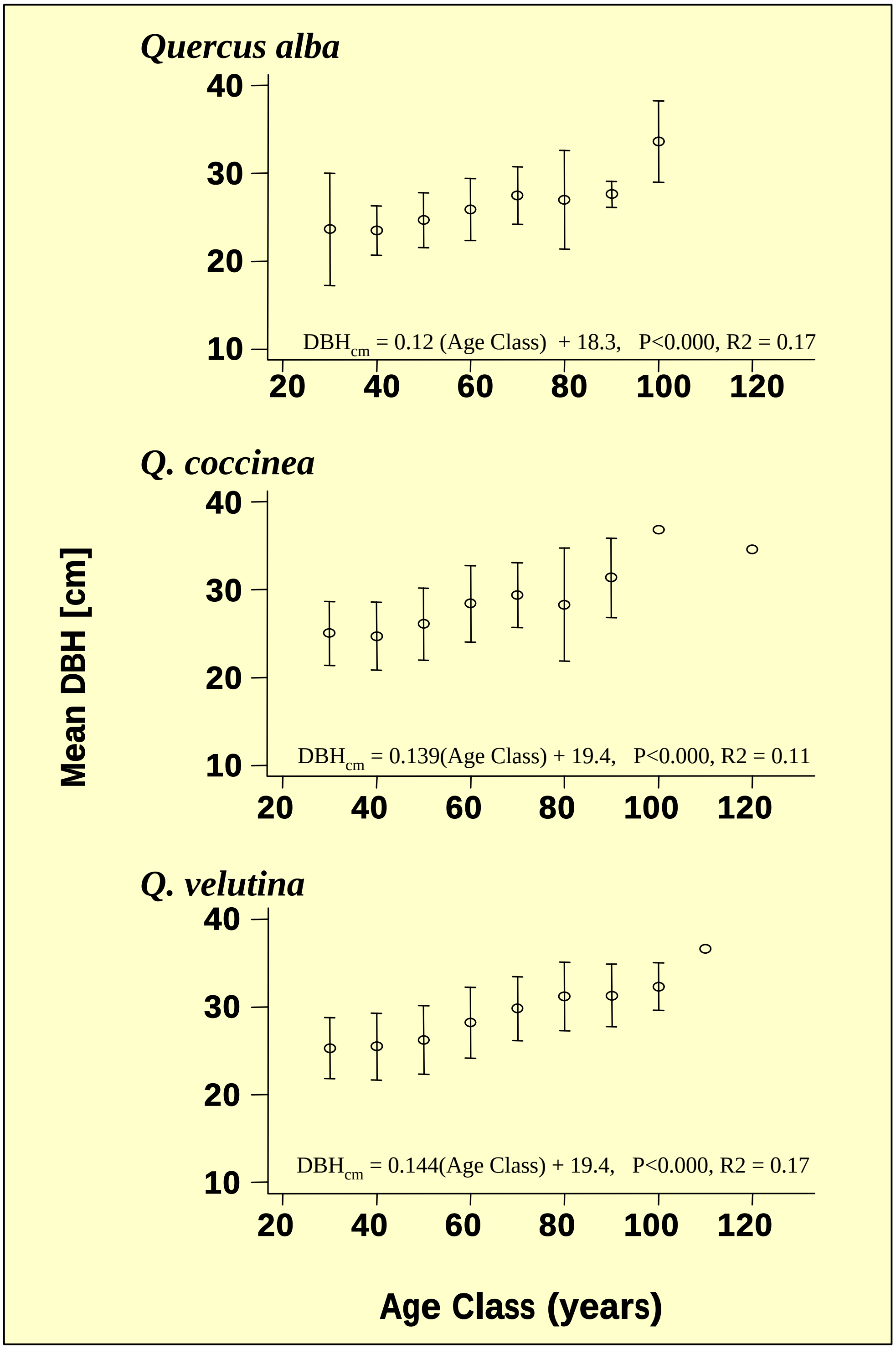


Figure II.11. Age-Diameter relationship for MOFEP Site index trees ranging in diameter from 12 to 45 cm in diameter.

slope that was somewhat higher than that generated from the FIA data and an intercept that was lower (Figure II.11).

As stated earlier, the age-diameter relationship implemented in the mast model is subjective. The data used were often intended for characterizing site productivity indices (Site Index) and not for determining an age-diameter relationship. I believe it is reasonable to assume the range of diameters for young trees is less than that for old trees. For example, at an age of 10 years, there are practical limits regarding the maximum diameter a tree might reach, whereas some older trees can, and often are, slow growing, suppressed in the under-story and relatively small in diameter. I chose to apply increasing variation in diameter with increasing age although the data I had did not support that relationship. I also chose to impose a relationship that more closely resembled that of the MOFEP plots. The FIA data were from plots throughout Missouri and as such covered a wide range of environmental conditions. Although I did not ascribe as much importance to the FIA data, the relationships in the FIA data set in general support the model that was implemented.

The model for the masting module produces predicted mean diameter ranging from 23 cm for 10-year stands to 44 cm for 160-year stands (Table II.11) with predicted standard deviations ranging from 9.4 at 10 years to 15.4 at 160 years. While the mean diameter does not seem to increase as greatly as one might expect from young stands to old stands, this is what typically occurs due to slow-growing trees in the under story. For this model the most important source for increasing diameter over time is the increase in the standard deviation with time. A random sample of 1000 points in a distribution as implemented at the 10-year age class results in a maximum diameter of about 50 cm (20

Table II.11. The predicted relationship between age and diameter and examples of the range of predictions from distributions of 1000 randomly selected observations for each age class.

	For Diameter	For Standard Deviation
Slope Coef.	0.14	0.04
Constant	21.5	9.0

			Example results from 1000 random samples per class		
Age Class	**Predicted Diameter**	**Predicted Standard Deviation**	**Mean**	**Minimum**	**Maximum**
	---------------------------- cm	------------------------			
10	22.9	9.4	22.9	-7.1	50.0
20	24.3	9.8	24.5	-6.9	55.3
30	25.7	10.2	26.1	-1.4	59.0
40	27.1	10.6	26.7	-9.4	59.9
50	28.5	11.0	28.7	-13.5	68.6
60	29.9	11.4	29.6	-14.8	64.4
70	31.3	11.8	31.3	-12.3	66.8
80	32.7	12.2	32.7	-6.0	70.4
90	34.1	12.6	34.0	-10.5	74.3
100	35.5	13.0	35.4	-0.7	74.4
110	36.9	13.4	36.7	-8.1	91.5
120	38.3	13.8	38.2	-6.3	77.1
130	39.7	14.2	40.8	-0.6	87.9
140	41.1	14.6	40.7	0.5	87.0
150	42.5	15.0	42.3	-0.1	80.7
160	43.9	15.4	43.9	-3.1	108.1

slope that was somewhat higher than that generated from the FIA data and an intercept that was lower (Figure II.11).

As stated earlier, the age-diameter relationship implemented in the mast model is subjective. The data used were often intended for characterizing site productivity indices (Site Index) and not for determining an age-diameter relationship. I believe it is reasonable to assume the range of diameters for young trees is less than that for old trees. For example, at an age of 10 years, there are practical limits regarding the maximum diameter a tree might reach, whereas some older trees can, and often are, slow growing, suppressed in the under-story and relatively small in diameter. I chose to apply increasing variation in diameter with increasing age although the data I had did not support that relationship. I also chose to impose a relationship that more closely resembled that of the MOFEP plots. The FIA data were from plots throughout Missouri and as such covered a wide range of environmental conditions. Although I did not ascribe as much importance to the FIA data, the relationships in the FIA data set in general support the model that was implemented.

The model for the masting module produces predicted mean diameter ranging from 23 cm for 10-year stands to 44 cm for 160-year stands (Table II.11) with predicted standard deviations ranging from 9.4 at 10 years to 15.4 at 160 years. While the mean diameter does not seem to increase as greatly as one might expect from young stands to old stands, this is what typically occurs due to slow-growing trees in the under story. For this model the most important source for increasing diameter over time is the increase in the standard deviation with time. A random sample of 1000 points in a distribution as implemented at the 10-year age class results in a maximum diameter of about 50 cm (20

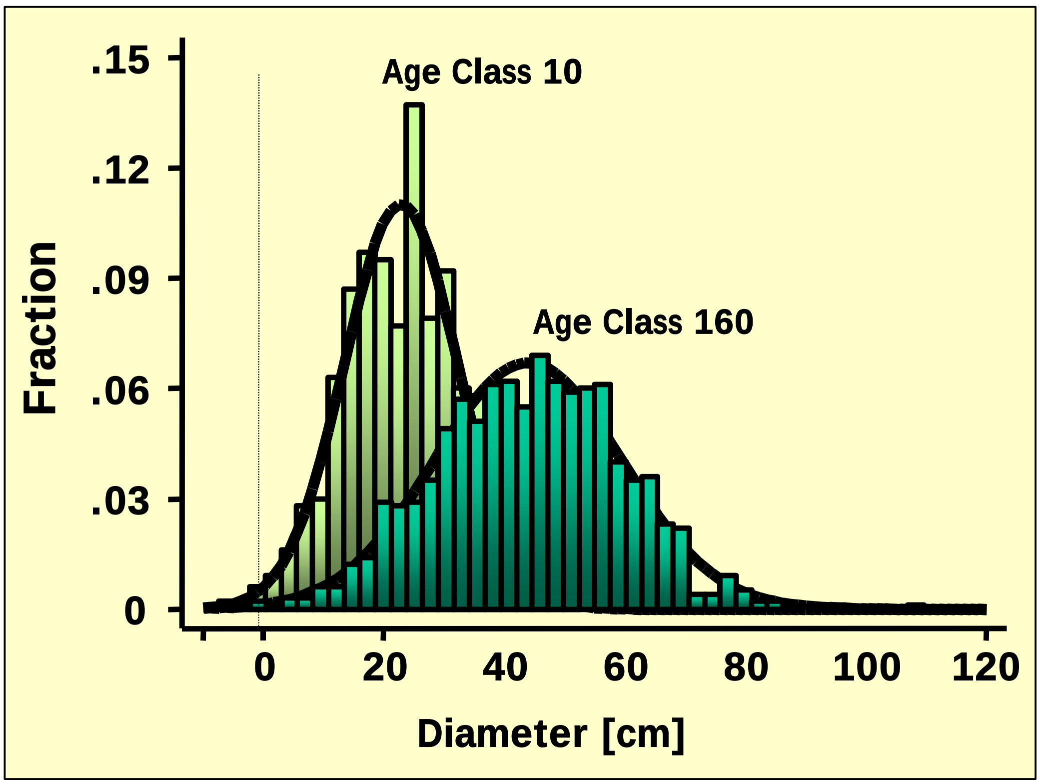


Figure II.12. Example predicted diameter distributions for two age classes based on the relationships factored in the mast model (Table II.12)

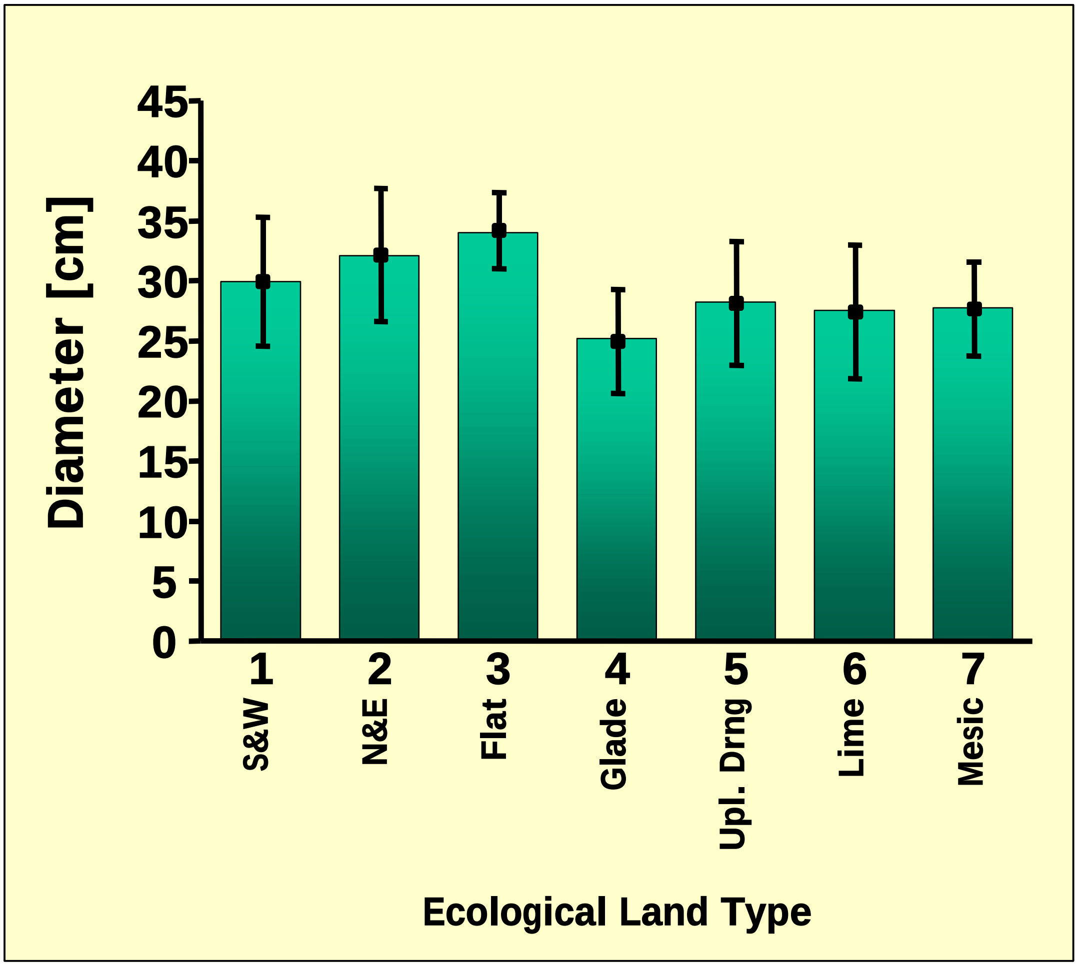


Figure II.13 Differences in mean plot diameter $\pm$ 1SD for grouped MOFEP ecological land types.

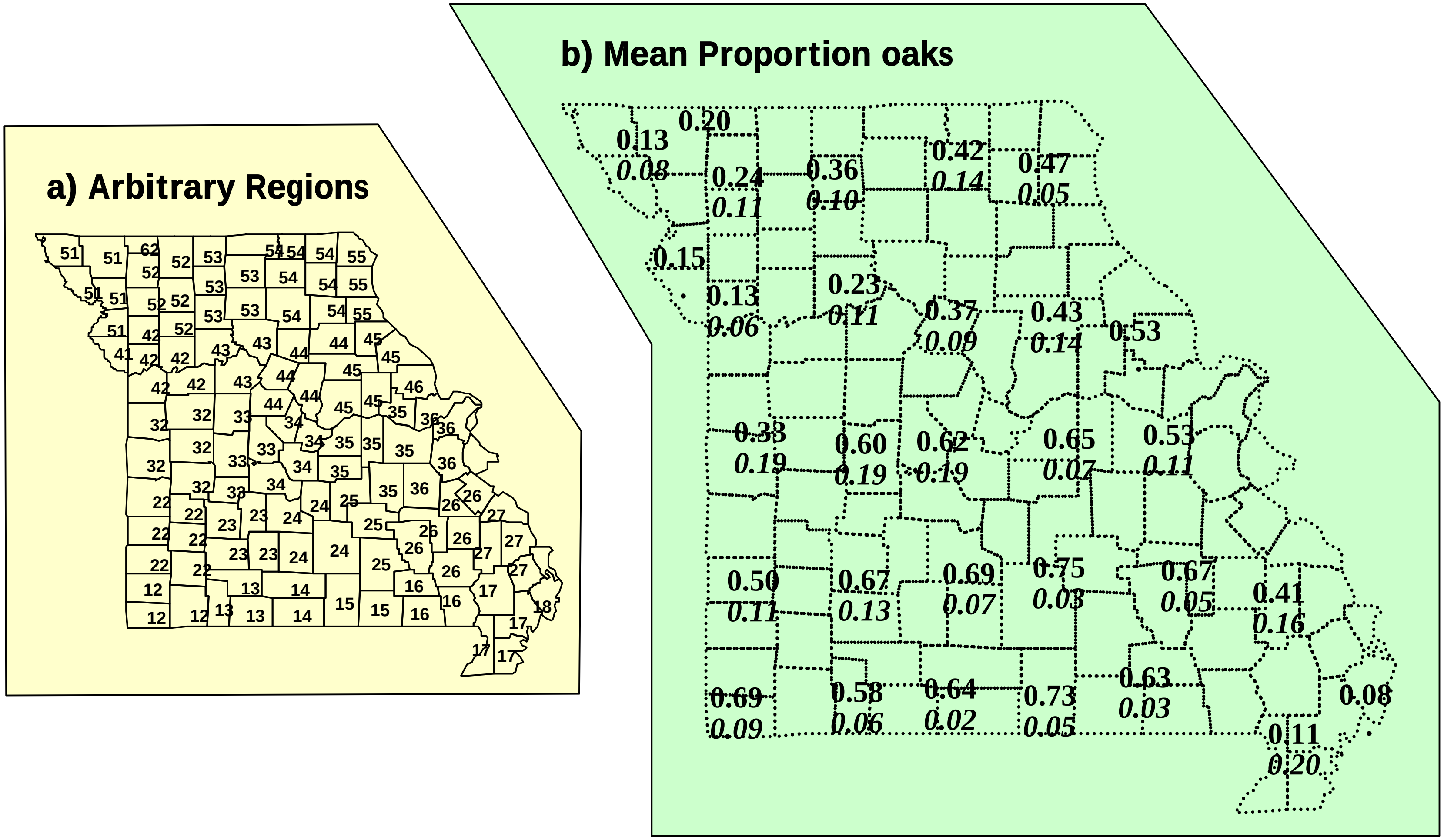


Figure II.14 Proportion of trees on plots that are oaks greater than 12.7 cm DBH (FIA 1989). Missouri was arbitrarily divided into regions (a) and means of county means were calculated (b). Italicized values are the standard deviation.

Table II.12. The relationship among seven ELT's and mean diameter to generate a scaling multiplier for adjusting for differences in topographic position. The multiplier was determined by dividing by the overall mean .

LANDIS Land Type		Mean Diameter [cm]	SD	N	Scaling Multiplier
1	**S & W**	28.7	10.41	11905	1.005
2	**N & E**	30.9	10.77	6524	1.081
3	**Flat**	33.2	7.52	163	1.163
4	**Glade**	24.9	10.26	441	0.869
5	**Upland Drainage**	27.3	9.05	971	0.955
6	**Limestone**	27.5	8.94	527	0.963
7	**Mesic**	27.6	11.34	193	0.964
	mean	28.59			

II.3.6 Model Step3c: Generation of trees: Limit trees to number of TPC

In this step, as stated above, the previously estimated TPC is utilized to remove trees from the cell. Each tree is numbered (1-40), the diameter assigned to those trees with an identity number greater than the TPC are reset as 0. Thus, they do not contribute to mast production.

II.3.7 Model Step4a: Species Group Distribution: RO:WO ratio = f(age class)

By county, oaks comprise from near 0 to nearly 100 percent of the trees over 13 cm in diameter (Table II.13). The high standard deviations listed in Table II.13 are the result of a low number of plots per county. To improve the prediction, Missouri was divided into geographic regions defined by a 5 by 7 grid of latitude and longitude (approximately 0.8 degree resolution) (Figure II.14a). This provides a much clearer impression of the variability in the oak component of forests within the state ranging from about 70 percent in the Ozarks to about 30 percent at the northern border of Missouri (Figure II.14.b; Table II.14). Based on the MOFEP data the oaks, overall, comprise about 72 percent of the trees greater than 12.7 cm DBH (Figure II.15). There are some differences in the oak component among Ecological Land Types (ELT) for the MOFEP sites. ELT's 17 and 18 do not differ substantially from the overall mean. This is an artifact of the way the over-all mean was calculated, *i.e.* these two ELT's comprise about 73 percent of the plots, therefore the mean is weighted toward these values (see Table II.9 for a listing of number of plots per land type). Notably, ELT 15 (neutral aspects, 0-8 percent slope), has a slightly higher oak component (~83 percent) and the analogous LANDIS land type comprises 23 percent of the cells in the test-case. ELT 5

Table II.13 : Proportion of trees over 12.7 cm DBH that are oaks on forestland by county in Missouri (FIA 1989)

County	Fraction Oak	SD	Lat. (deg. N)	Long. (deg. W)	County	Fraction Oak	SD	Lat. (deg. N)	Long. (deg. W)
Adair	0.64	0.4795	40.19	92.61	Linn	0.23	0.4245	39.85	93.11
Andrew	0.06	0.2354	39.97	94.83	Livingston	0.29	0.4553	39.78	93.59
Atchison	0.08	0.2680	40.44	95.47	Macon	0.43	0.4958	39.79	92.56
Audrain	0.29	0.4536	39.21	91.77	Madison	0.65	0.4775	37.46	90.33
Barry	0.59	0.4924	36.65	93.77	Maries	0.64	0.4808	38.16	91.93
Barton	0.51	0.5009	37.51	94.27	Marion	0.42	0.4943	39.81	91.65
Bates	0.13	0.3372	38.22	94.34	Mc Donald	0.75	0.4353	36.62	94.34
Benton	0.70	0.4594	38.27	93.27	Mercer	0.37	0.4844	40.40	93.59
Bollinger	0.59	0.4927	37.31	90.06	Miller	0.74	0.4390	38.22	92.43
Boone	0.34	0.4756	38.95	92.33	Mississippi	0.08	0.2694	36.75	89.29
Buchanan	0.08	0.2682	39.63	94.85	Moniteau	0.49	0.5007	38.67	92.53
Butler	0.67	0.4720	36.80	90.47	Monroe	0.45	0.4982	39.51	91.95
Caldwell	0.09	0.2929	39.65	93.98	Montgomer	0.57	0.4949	38.89	91.49
Callaway	0.55	0.4973	38.83	91.89	Morgan	0.78	0.4164	38.39	92.89
Camden	0.82	0.3824	38.03	92.78	New Madrid	0.00	0.0000	36.58	89.60
Cape Girar	0.39	0.4875	37.43	89.65	Newton	0.75	0.4353	36.93	94.38
Carroll	0.11	0.3161	39.43	93.49	Nodaway	0.20	0.4046	40.39	94.91
Carter	0.62	0.4863	36.96	90.96	Oregon	0.70	0.4592	36.71	91.41
Cass	0.21	0.4093	38.65	94.30	Osage	0.62	0.4857	38.47	91.88
Cedar	0.66	0.4757	37.71	93.84	Ozark	0.65	0.4778	36.65	92.43
Chariton	0.24	0.4256	39.50	92.95	Pemiscot	0.00	0.0000	36.23	89.75
Christian	0.63	0.4829	36.93	93.10	Perry	0.45	0.4979	37.71	89.88
Clark	0.47	0.4999	40.41	91.71	Pettis	0.34	0.4736	38.74	93.20
Clay	0.12	0.3301	39.32	94.43	Phelps	0.74	0.4367	37.85	91.81
Clinton	0.22	0.4140	39.58	94.40	Pike	0.47	0.4993	39.36	91.27
Cole	0.44	0.4971	38.48	92.27	Platte	0.15	0.3548	39.39	94.77
Cooper	0.28	0.4512	38.87	92.80	Polk	0.59	0.4926	37.61	93.41
Crawford	0.79	0.4098	37.96	91.30	Pulaski	0.63	0.4832	37.80	92.20
Dade	0.47	0.5001	37.45	93.79	Putnam	0.56	0.4976	40.47	92.79
Dallas	0.82	0.3824	37.70	93.00	Rallis	0.28	0.4479	39.55	91.50

Table II.13 (continued) : Proportion of trees over 12.7 cm D. that are oaks on forestland by county in Missouri (FIA 1989)

County	Fraction Oak	SD	Lat. (deg. N)	Long. (deg. W)	County	Fraction Oak	SD	Lat. (deg. N)	Long. (deg. W)
Daviess	0.39	0.4882	39.94	94.03	Randolph	0.48	0.5004	39.40	92.47
De Kalb	0.24	0.4284	39.91	94.33	Ray	0.08	0.2697	39.34	94.03
Dent	0.79	0.4083	37.61	91.49	Reynolds	0.70	0.4564	37.36	90.96
Douglas	0.63	0.4843	36.92	92.46	Ripley	0.61	0.4872	36.67	90.88
Dunkin	0.04	0.2019	36.29	90.09	S Genevieve	0.59	0.4918	37.91	90.20
Franklin	0.62	0.4867	38.38	91.09	Saline	0.34	0.4737	39.10	93.20
Gasconade	0.67	0.4691	38.45	91.52	Schuyler	0.37	0.4847	40.46	92.51
Gentry	0.22	0.4146	40.24	94.41	Scotland	0.30	0.4613	40.44	92.13
Greene	0.54	0.4988	37.30	93.27	Scott	0.20	0.3983	37.13	89.59
Grundy	0.39	0.4887	40.10	93.57	Shannon	0.73	0.4438	37.18	91.40
Harrison	0.25	0.4353	40.35	94.02	Shelby	0.40	0.4896	39.84	91.97
Henry	0.26	0.4409	38.41	93.74	St Charles	0.39	0.4885	38.71	90.75
Hickory	0.57	0.4950	37.94	93.29	St Clair	0.62	0.4862	38.01	93.75
Holt	0.23	0.4239	40.04	95.16	St Francois	0.71	0.4548	37.81	90.48
Howard	0.30	0.4603	39.16	92.64	St Louis	0.48	0.5006	38.61	90.55
Howell	0.77	0.4208	36.78	91.87	Stoddard	0.42	0.4934	36.92	90.00
Iron	0.72	0.4504	37.54	90.77	Stone	0.59	0.4921	36.71	93.45
Jackson	0.15	0.3617	39.03	94.28	Sullivan	0.51	0.5007	40.21	93.12
Jasper	0.47	0.4998	37.18	94.29	Taney	0.52	0.4999	36.65	93.04
Jefferson	0.57	0.4949	38.25	90.54	Texas	0.65	0.4779	37.33	91.94
Johnson	0.43	0.4948	38.75	93.74	Vernon	0.32	0.4684	37.84	94.26
Knox	0.25	0.4324	40.11	92.09	Warren	0.58	0.4936	38.78	91.18
Laclede	0.73	0.4419	37.67	92.56	Washington	0.66	0.4750	37.98	90.88
Lafayette	0.05	0.2271	39.07	93.81	Wayne	0.66	0.4753	37.12	90.47
Lawrence	0.60	0.4913	37.13	93.74	Webster	0.74	0.4404	37.29	92.87
Lewis	0.51	0.5004	40.12	91.69	Worth	0.20	0.4028	40.48	94.42
Lincoln	0.53	0.4995	39.05	90.95	Wright	0.76	0.4250	37.26	92.48

Table II.14 The average proportion of trees that are oaks for each geographic region. Regions determined by dividing the ranges of latitude and longitude into distances of approximately 0.85 degrees resulting in 30 regions. Listed values are the means of the average of all plots per county means in the region.

Arbitrary Region	Mean Proportion Oaks	SD	n
12	0.69	0.09	3
13	0.58	0.06	3
14	0.64	0.02	2
15	0.73	0.05	2
16	0.63	0.03	3
17	0.11	0.20	4
18	0.08	0.00	1
22	0.50	0.11	6
23	0.67	0.13	4
24	0.69	0.07	4
25	0.75	0.03	3
26	0.67	0.05	6
27	0.41	0.16	4
32	0.33	0.19	5
33	0.60	0.19	4
34	0.62	0.19	4
35	0.65	0.07	6
36	0.53	0.11	4
41	0.15	0.00	1
42	0.13	0.06	5
43	0.23	0.11	3
44	0.37	0.09	5
45	0.43	0.14	5
46	0.53	0.00	1
51	0.13	0.08	5
52	0.24	0.11	5
53	0.36	0.10	5
54	0.42	0.14	7
55	0.47	0.05	3
62	0.20	0.00	1
Statewide	0.46	0.22	114

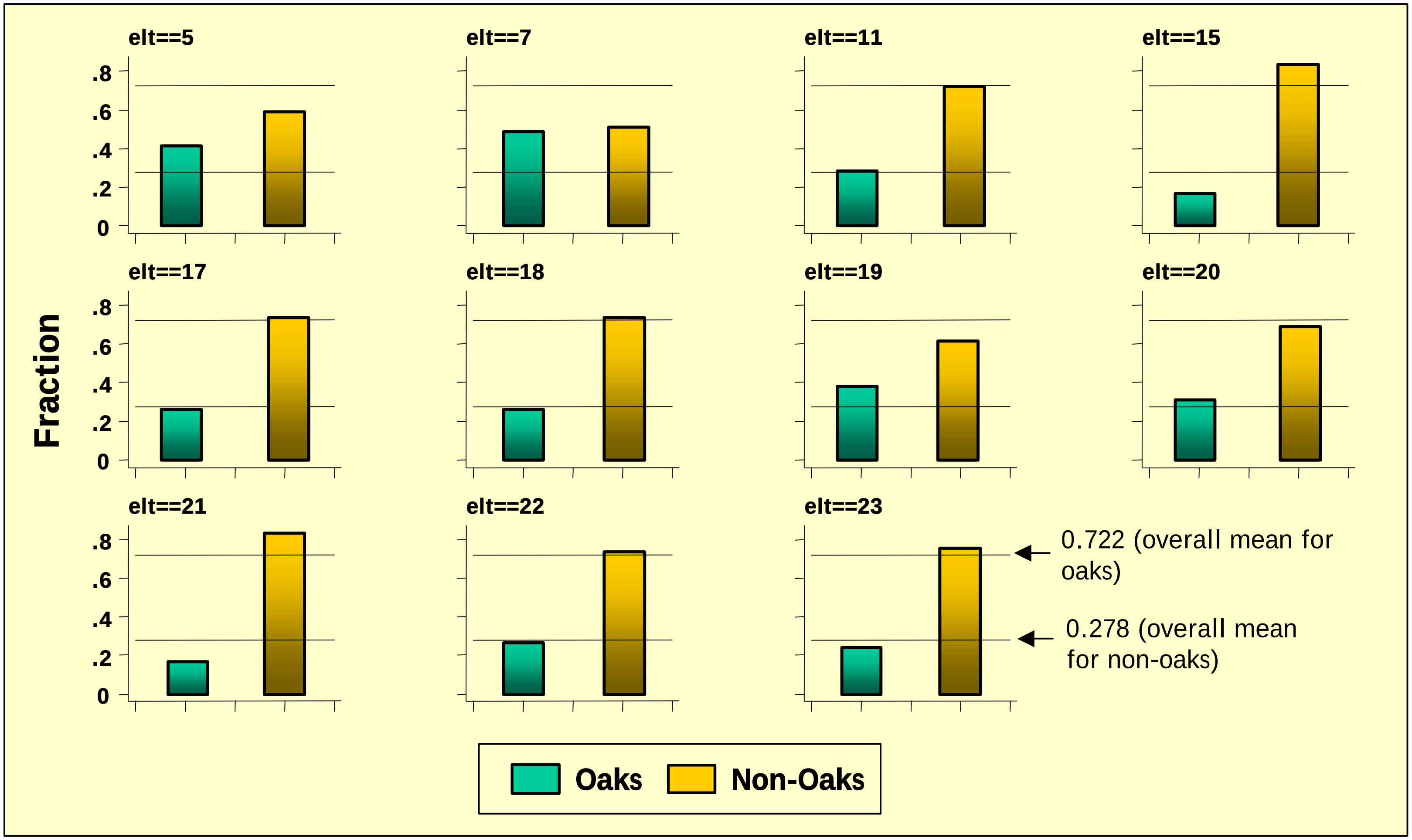
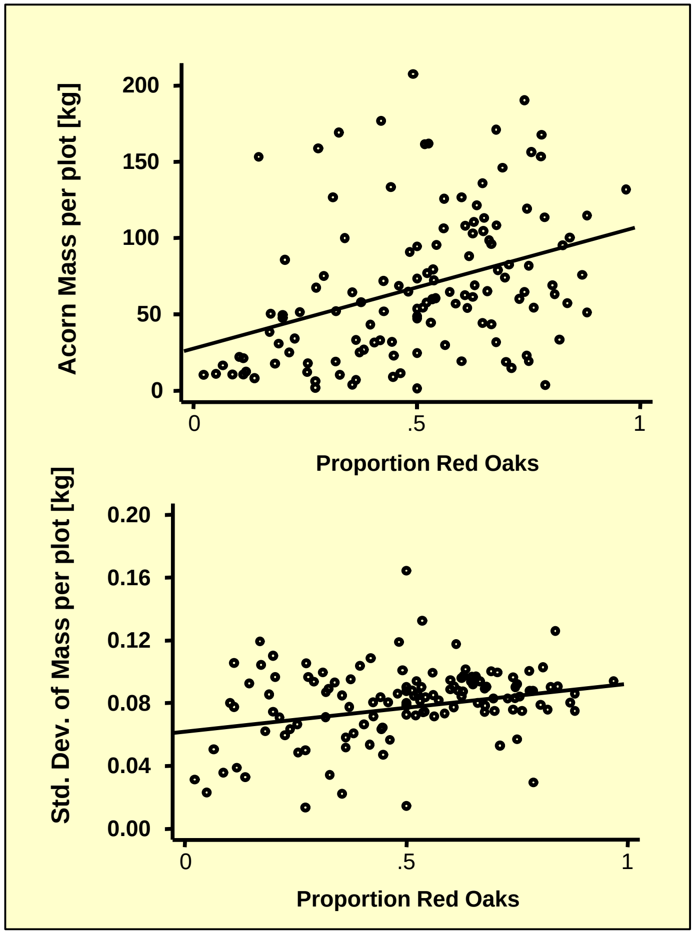


Figure II.15 Distributions of oaks and non-oaks (numbers of trees) per MOFEP plots by Ecological Land Type (ELT) class.



kg per plot = Proportion Red oak (83.3)+25.96

P>|t| = 0.000, R^2_{adj} = 0.14

Variation in Mast Production [kg SD] = Proportion Red oak (0.0319)+0.065

P>|t| = 0.001, R^2_{adj} = 0.08

Figure II.16. The relationship between mast production and the red oak component. Increasing red oak resulted in increased mast collection in sampling traps.

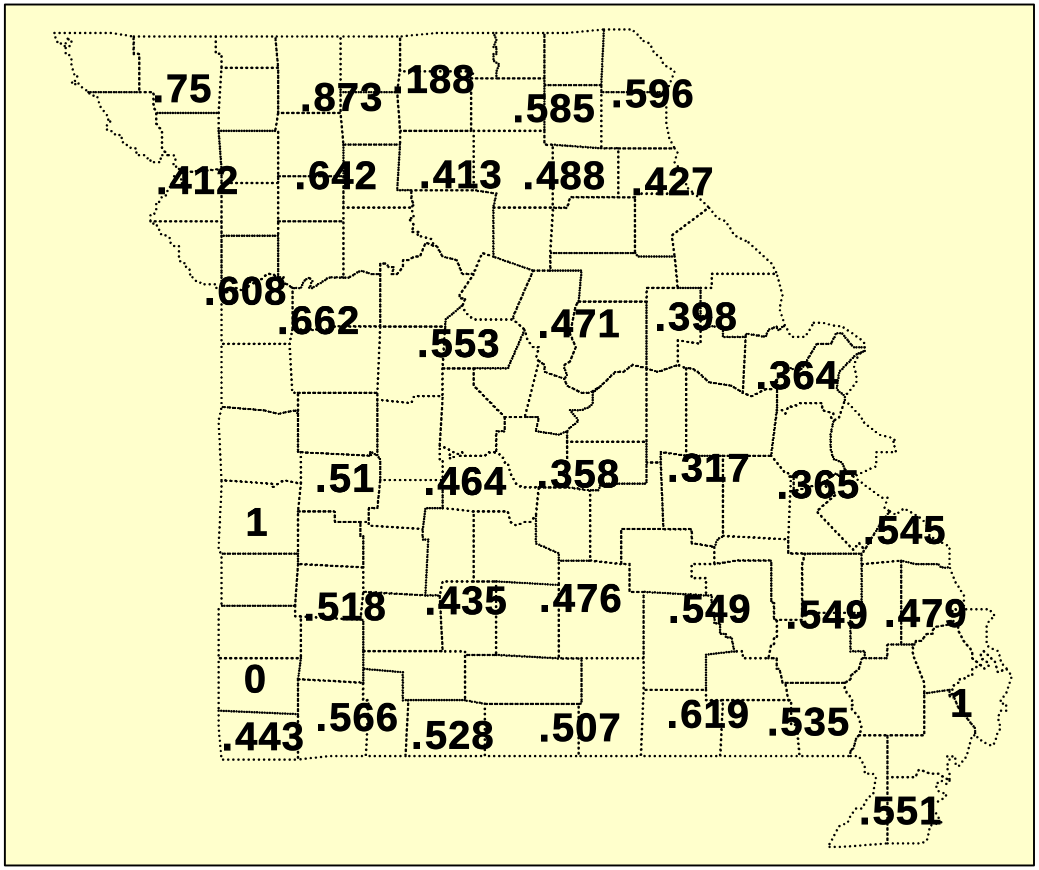


Figure II.17 By region, fraction of oaks that are in the subgenus *Erythrobalanus* (red oaks).

versus about 110 white oak trees per hectare. The MOFEP inventory data show that for the white oak group, *Q. alba* is the most important species (Figure II.18). The next most abundant white oak species, *Q. stellata*, is roughly one-quarter the abundance of *Q. alba* and has a notably lower acorn production rate (Figure II.19). The two most important red oak species, *Q. velutina* and *Q. coccinea*, each are similar in abundance to *Q. alba* alone. They also differ in acorn production rates with *Q. coccinea* being much higher than *Q. velutina*.

The first approximation to account for differences between red oaks and white oaks was accomplished by determining the fraction of oaks from the FIA inventory that were in the red oak group by age class (Table II.15). Since these ratios are for plots throughout Missouri and the test-case landscape is in Oregon county in southern Missouri, the ratios were adjusted upward so that the ratio at about 80 years closely resembles the ratio found in the region surrounding Oregon county (Figure II.14). Fitting the ratio to the square of the age class (Table II.15) provides the relationship used in the mast model (STEP 4a): a variable, Canopy Fraction Red Oak (CFRO), is generated as a function of age for each cell.

II.3.8 Model Step4b: Species Group Distribution: Ratio = f(land type)

Similar to adjustments noted above, an adjustment was made for differences in the red oak component among MOFEP land types (Table I.16). This was implemented using a scaling factor. At this stage, the Canopy Fraction Red Oak (CFRO) is also adjusted by adding normal random variability at a rate based on the ranges found among the regions

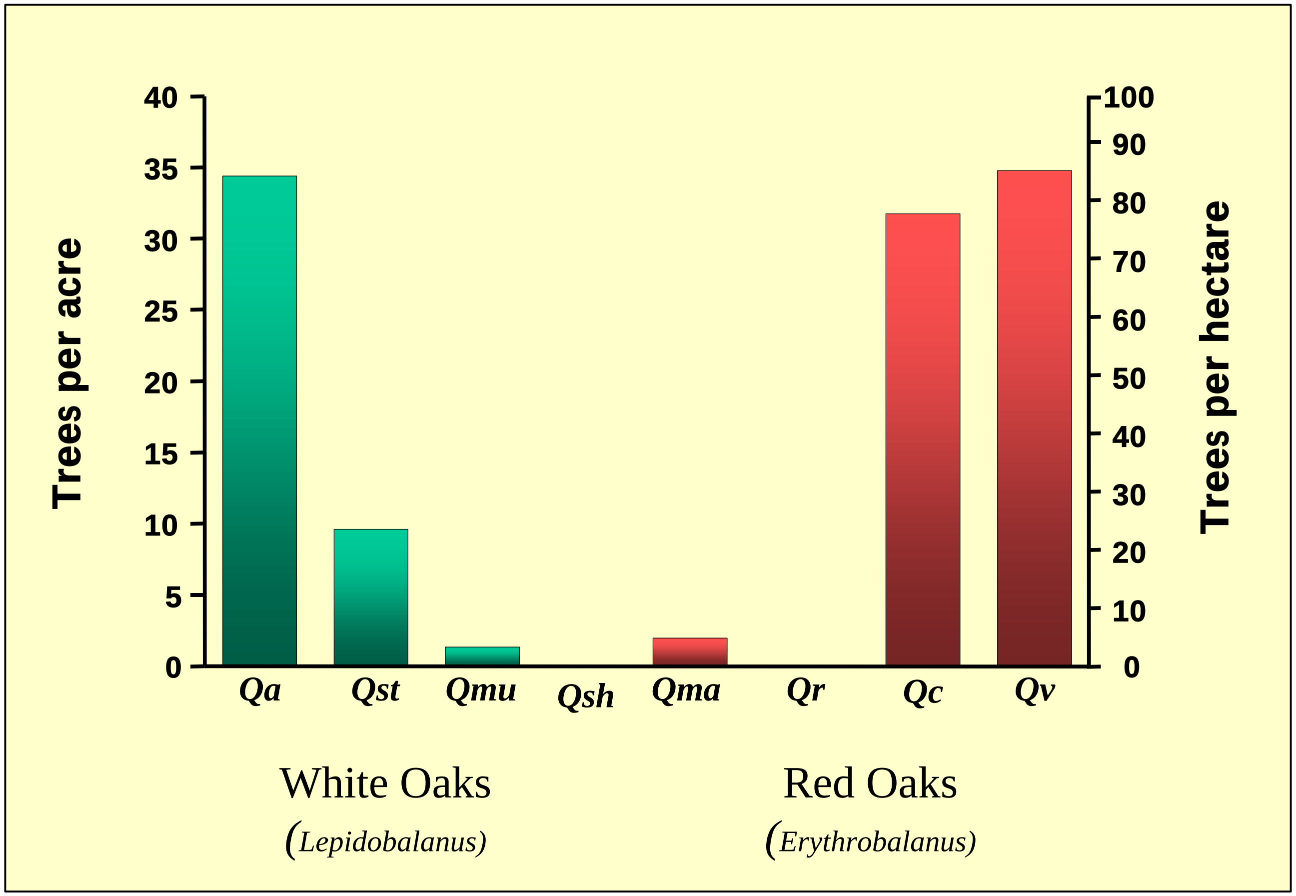


Figure II.18 Distribution of oak species across all MOFEP plots.

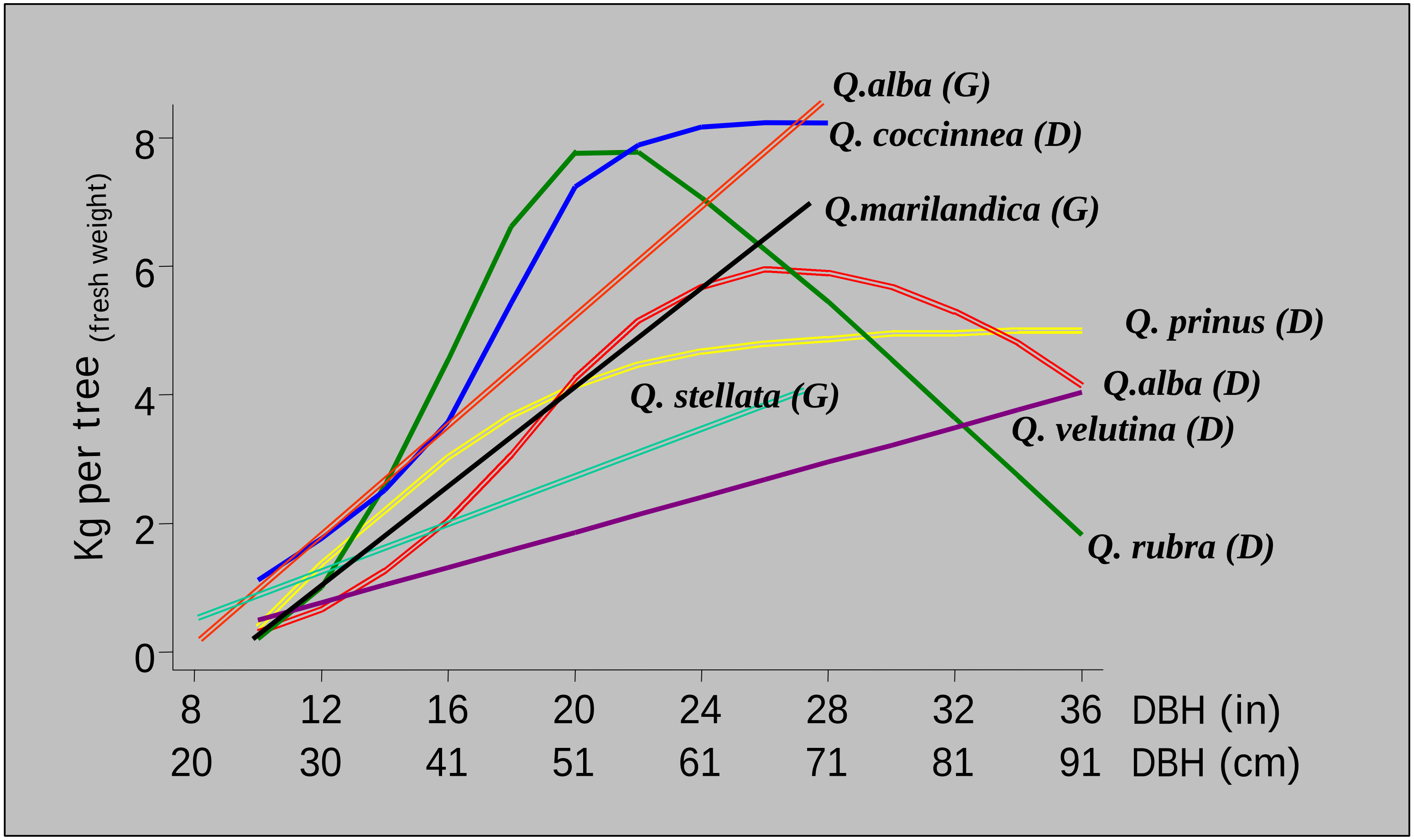


Figure II.19 Comparative acorn production by species and diameter. Species names followed by (G) denote projections from Goodrum (1971) and (D) from Downs (1944). Solid single lines indicate species of the *Erythrobalanus* subgenus (red oaks) and double lines indicate *Lepidobalanus* species (white oaks).

versus about 110 white oak trees per hectare. The MOFEP inventory data show that for the white oak group, *Q. alba* is the most important species (Figure II.18). The next most abundant white oak species, *Q. stellata*, is roughly one-quarter the abundance of *Q. alba* and has a notably lower acorn production rate (Figure II.19). The two most important red oak species, *Q. velutina* and *Q. coccinea*, each are similar in abundance to *Q. alba* alone. They also differ in acorn production rates with *Q. coccinea* being much higher than *Q. velutina*.

The first approximation to account for differences between red oaks and white oaks was accomplished by determining the fraction of oaks from the FIA inventory that were in the red oak group by age class (Table II.15). Since these ratios are for plots throughout Missouri and the test-case landscape is in Oregon county in southern Missouri, the ratios were adjusted upward so that the ratio at about 80 years closely resembles the ratio found in the region surrounding Oregon county (Figure II.14). Fitting the ratio to the square of the age class (Table II.15) provides the relationship used in the mast model (STEP 4a): a variable, Canopy Fraction Red Oak (CFRO), is generated as a function of age for each cell.

II.3.8 Model Step4b: Species Group Distribution: Ratio = f(land type)

Similar to adjustments noted above, an adjustment was made for differences in the red oak component among MOFEP land types (Table I.16). This was implemented using a scaling factor. At this stage, the Canopy Fraction Red Oak (CFRO) is also adjusted by adding normal random variability at a rate based on the ranges found among the regions

Table II.15 The relationship of age class to the ratio between the red oak and white oak subgenera for FIA data and adjustment for Oregon county. Decreasing red oak component reflects differences in species longevity.

Age Class	Red Oak Subgenus	White Oak Subgenus	Proportion of All Oak in RO Group	Adjusted Value for Oregon County
	Number of trees			
10	712	663	0.518	0.65
20	2289	2019	0.531	0.64
30	1034	816	0.559	0.62
40	2848	2482	0.534	0.61
50	4516	4545	0.498	0.59
60	3220	3283	0.495	0.58
70	3192	3545	0.474	0.56
80	2786	2813	0.498	0.55
90	1813	2519	0.419	0.51
100	1360	2142	0.388	0.46
110	586	1414	0.293	0.42
120	295	765	0.278	0.38
130	147	411	0.263	0.33
140	66	143	0.316	0.29
150	33	121	0.214	0.24
160	8	73	0.099	0.20

```
CFRO for Oregon county + f(Age squared) - subjective adjustment

Source |       SS       df       MS                    Number of obs =      16
---------+------------------------------               F(  1,    14) = 3669.11
Model |   .33247513      1   .33247513                 Prob > F      =  0.0000
Residual |  .001268607    14  .000090615               R-squared     =  0.9962
---------+------------------------------               Adj R-squared =  0.9959
Total |  .333743737    15  .022249582                  Root MSE      =  .00952

------------------------------------------------------------------------------
cfro         Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
age2  |  -.0000179  2.95e-07     -60.573   0.000       -.0000185  -.0000172
_cons |   .6440737   .0036445    176.724   0.000        .636257    .6518905
```

Table II.16. The relationship among MOFEP ELT's and the mean fraction of the canopy trees greater than 12.7 cm in diameter that are red oaks.

LANDIS Land Type		Mean Fraction Red Oak	Standard Deviation	N	Scale Factor Multiplier
1	**S & W**	0.741	0.151	351	0.891
2	**N & E**	0.743	0.158	213	0.894
3	**Flat**	0.831	0.180	5	1.000
4	**Savanna**	0.647	0.117	18	0.778
5	**Upland Drainage**	0.593	0.164	35	0.713
6	**Limestone**	0.732	0.173	16	0.881
7	**Mesic**	0.700	0.102	7	0.842
	Mean	0.712	0.149		

II.3.9 Model Step5a: Tree species assignment: white oak or red oak group

In the two previous steps a number (between 0 and 1) was generated that is an estimate of the fraction of the oak canopy trees per cell that are in the red oak sub-genus. In step 5a, a temporary variable is generated for each tree that is a randomly selected number uniformly distributed between 1 and 0. The CFRO is compared to the temporary variable and if the CFRO is less than the temporary variable associated with a tree, that tree is assigned to the red oak group. If the temporary number is greater than the CFRO number it is assigned to the white oak group.

II.3.10 Model Step5b: Tree Species assignment: Adjusted for species growth rates

There are differences among oak species in tree size and age among species (Figure II.19). Since tree size is the predictor of mast production, the differences in growth rates need to be addressed. In the previous step, the trees were assigned to either the red oak group or the white oak group. FIA data and MOFEP data were used to characterize the differences in the growth rates. If trees were assigned to the red oak group the diameter assigned to that tree was not adjusted. If the tree was assigned to the white oak group, the diameter was adjusted to show a slower growth rate (Table II.17):

$$DBH_{wo} \text{ adjustment scale factor} = -0.001 * \text{age class} + 1.01$$

II.3.11 Model Step 6a,b: Tree Acorn Production: Mast Index = f(diameter)

To adjust for differences in mast production among species groups, the data of Downs (1944), Goodrum (1971), and Greenberg (2000) were consulted. The data

Table II.17 The relationship between red oaks and white oaks used for adjusting for differences in growth rates. Diameters are originally generated for RO and multiplied by the factor below to get white oak diameter. The modeled diameter age relationships are from FIA and MOFEP generalizations.

```
. regress change in diameter = f(age)


  Source |       SS       df       MS                  Number of obs =      18
---------+------------------------------               F(  1,    16) =  714.08
   Model |  .053337409     1  .053337409               Prob > F      =  0.0000
Residual |  .001195096    16  .000074693               R-squared     =  0.9781
---------+------------------------------               Adj R-squared =  0.9767
   Total |  .054532505    17  .003207794               Root MSE      =  .00864

------------------------------------------------------------------------------
  change |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
     age |  -.0010492   .0000393    -26.722   0.000      -.0011325    -.000966
   _cons |   1.010843   .0042501    237.841   0.000       1.001833    1.019853
------------------------------------------------------------------------------
```

$$\mathbf{DBH_{wo} = DBH(-.0010492(Age) + 1.010843)}$$

suggest that in terms of diameter, red oaks increase in acorn production at a higher rate and peak at a smaller size than white oaks. For Missouri, the relatively high productivity of red oak group is reduced by the large fraction of the population comprised of the low mast producing black oak (*Q. velutina*). Similarly, white oak group mast production is reduced somewhat by the population of post oak (*Q. stellata*) component of the forest. The high density of these two low mast producing species results in a relatively low rate of mast production.

The average mast production per tree was calculated for each size class provided by Downs (1944) and Goodrum (1971) (Figure II.19). The subgenus averages were then calculated for each size class. A relative index was calculated that sets the highest production at 15 and scales all other production rates accordingly. A complex function was determined using diameter taken to the 2nd, 3rd, 4th power that accurately depicts the relationship between size and the mast production index (Figure II.20). This relationship is reasonable, although for diameters greater than 91 cm mast production increases exponentially for the red oak group. An adjustment is made to the few trees that are assigned very large diameters. Likewise at very small diameters both red oak and white oak groups display large mast production. Since small trees do not contribute substantially to the overall acorn crop, mast production for trees less than 20 cm in diameter is set at 0.

A stochastic element is not added to this function. Given the large number of trees on which the model operates (for the test-case, about 1.4 million) and the scale of the model, adding a random factor at this point would only serve to shift the results among cells. That is, if the mast production of one tree is adjusted by reducing the index

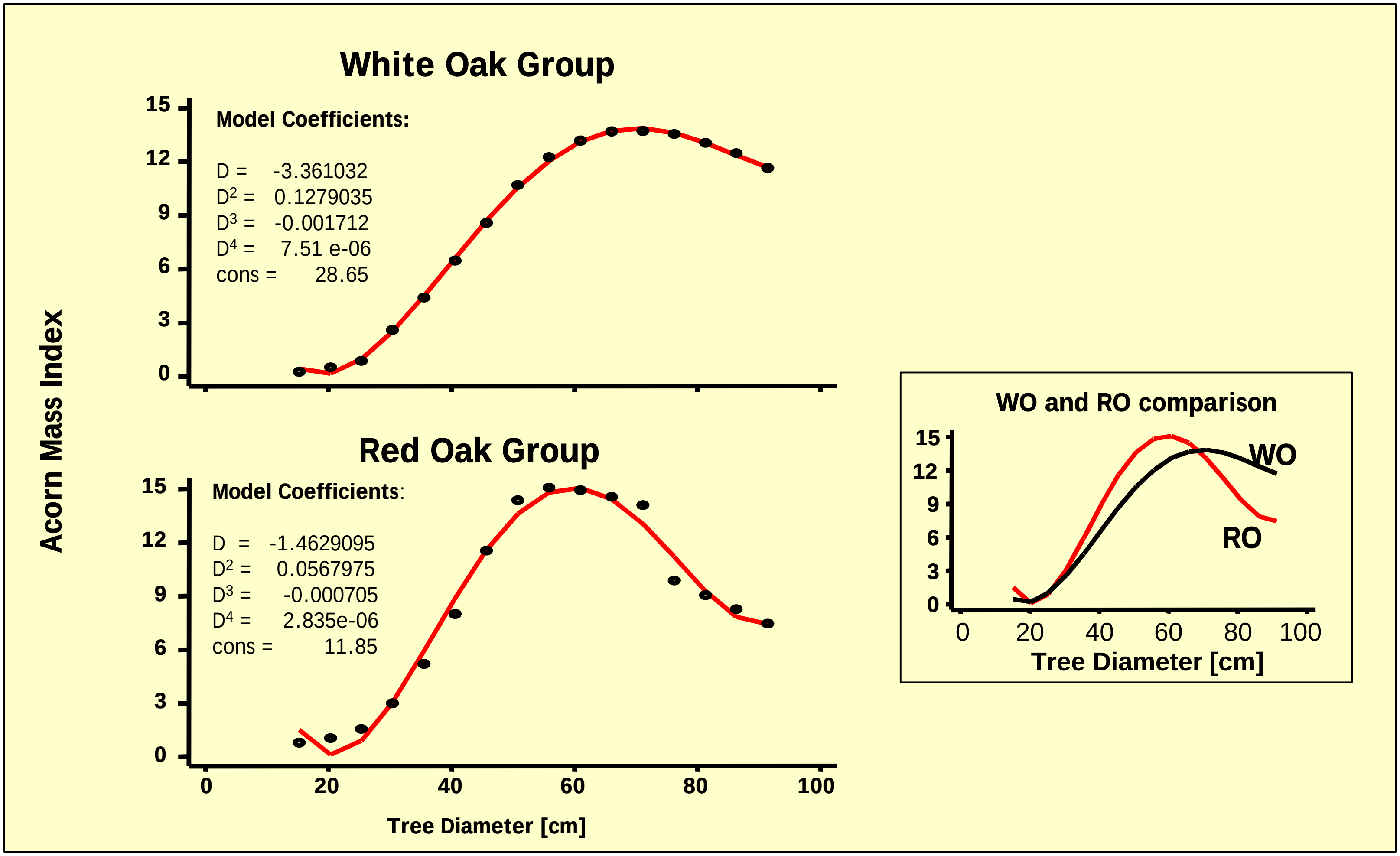


Figure II. 20. Modeled relationship between tree diameter and acorn production (mass) for Missouri. Red oaks decline at higher diameter due to low productivity of *Q. velutina* and low presence of *Q. rubra.*

factor by 2, then it is likely that some other tree under the same site conditions in the landscape will be adjusted upward to the production level of the previous tree. The net results in terms of the model are increased complexity without providing an increase in information.

II.3.12 Model Step 7a,b: Tree Acorn Production: Inherent variability among trees

In previous steps, trees were assigned a diameter and then to a species group. In this step, the substantial variability in acorn production that exists among individual trees is incorporated (see Section I.1.1.6). For example, Post (1998) recorded that 4 of 22 (18 percent) of trees failed to produce acorns. Over 9 years there were consistent differences among trees in acorn production for a study in central Missouri (Cecich and Sullivan 1999). On a scale of 0-1 where 1 is the maximum number of acorns per species recorded on a branch end, the indices for ranged from 0.01 to 0.27 over 10 years for *Q. alba* and from 0.00 to 0.33 over 9 years for *Q. velutina* (Table II.18). The source of most of the reduction in the index by tree is due to annual influences, however some trees clearly display superior acorn production that transcends annual variation (Figure II.21). This variation may be attributable to many sources. Inherited genetic flaws could cause staminate and pistillate flower abortion or ill-timed flower maturity relative to pollination. Trees with inherited low vigor may not have the resources to complete acorn production. In addition, stressful micro-site conditions could lead to low vigor and reduced acorn production. To some extent these conditions are addressed in the model through differences in land type. However, individual trees may be situated adversely whereas neighboring trees on the same cell are not, *e.g.* growing on shallow soil due to a

Table II.18 Among year and among tree variation in the number of acorns produced from 5 branch ends from each of 21 trees expressed as an index from 0 - 100 where 100 is the maximum number of acorns produced by a tree by species across all years (Cecich and Sullivan 1999 and more recently collected data).

Year of Acorn Maturation (Primary C Allocation)

	Tree No.	**90**	**91**	**92**	**93**	**94**	**95**	**96**	**97**	**98**	**99**	***Mean***	***SD***
Quercus alba	**1**	0.10	0.06	0.00	0.00	0.00	0.10	0.06	0.00	0.23	0.00	0.05	0.07
	2	0.08	0.24	0.06	0.13	0.00	0.13	0.15	0.00	0.23	0.06	0.11	0.08
	3	0.06	0.05	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02
	4	0.00	0.00	0.02	0.00	0.00	0.18	0.00	0.00	0.03	0.00	0.02	0.06
	6	0.13	0.05	0.08	0.10	0.05	0.26	0.06	0.00	0.40	0.00	0.11	0.13
	7	0.00	0.02	0.00	0.03	0.00	0.15	0.02	0.00	0.03	0.00	0.02	0.04
	8	0.02	0.02	0.00	0.06	0.00	0.52	0.10	0.00	0.06	0.00	0.08	0.16
	9	0.10	0.00	0.02	0.02	0.00	0.10	0.05	0.00	0.00	0.02	0.03	0.04
	11	1.00	0.00	0.15	0.21	0.00	0.24	0.37	0.00	0.74	0.00	0.27	0.35
	Mean	0.16	0.05	0.04	0.06	0.01	0.18	0.09	0.00	0.19	0.01	0.08	
	SD	0.32	0.08	0.05	0.07	0.02	0.15	0.12	0.00	0.25	0.02		0.10

Table II.18 (Continued) Among year and among tree variation in the number of acorns produced from 21trees in central Missouri.

	Tree No.	90	91	92	93	94	95	96	97	98	99	*Mean*	*SD*
Q. velutina	**1**		0.04	0.00	0.22	0.35	0.08	0.04	0.39	0.00	0.18	0.15	0.15
	2		0.20	0.00	0.43	0.16	0.00	0.06	0.43	0.00	0.00	0.14	0.18
	3		0.00	0.22	0.04	0.29	0.24	0.18	0.06	0.00	0.00	0.12	0.12
	4		0.29	0.00	0.02	0.06	0.00	0.06	0.24	0.00	0.02	0.08	0.11
	5		0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.02	0.00	0.01
	6		0.18	0.00	0.12	0.14	0.00	0.02	0.16	0.00	0.00	0.07	0.08
	7		0.00	0.00	0.00	0.10	0.12	0.00	0.00	0.00	0.22	0.05	0.08
	8		0.02	0.24	0.31	0.04	0.10	0.14	0.37	0.00	0.06	0.14	0.13
	9		0.06	0.00	0.08	0.08	0.00	0.10	0.41	0.00	0.04	0.09	0.13
	10		0.45	0.08	0.49	0.00	0.16	0.18	0.31	0.00	0.02	0.19	0.19
	11		1.00	0.51	0.39	0.37	0.02	0.24	0.39	0.00	0.04	0.33	0.31
	12		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mean		0.19	0.09	0.18	0.13	0.06	0.09	0.23	0.00	0.05	0.11	
	SD		0.29	0.16	0.18	0.13	0.08	0.08	0.18	0.00	0.07		0.12

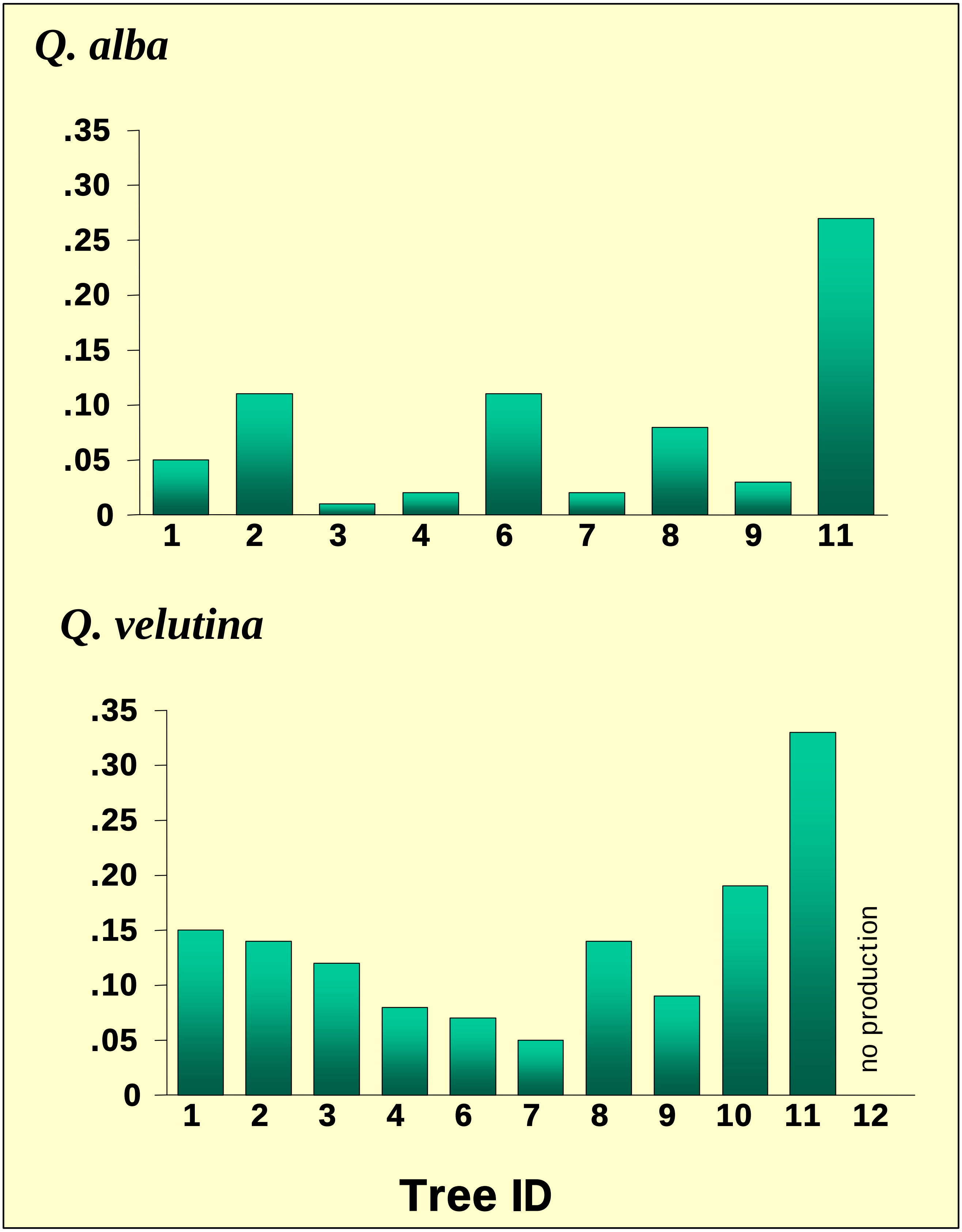


Figure II.21 Variation in an acorn production index (0-1) for 21 trees in central Missouri.

rock outcrop. The 21 trees in the aforementioned central Missouri study are growing on similar sites and influenced by similar climate patterns, yet substantial differences in acorn production were observed (Cecich and Sullivan 1999).

Regardless of the source of variation, this variation must be included in the model. To simulate it, four subjective production levels were imposed on all the trees included in the landscape (Table II.19). As in previous routines, a uniformly distributed random variable was generated for each tree and production levels were assigned according to the population distribution listed in Table II.19. Random variation in these values has not been introduced for reasons stated previously. In addition, since intensive silviculture could reduce the number of non- and low-producers, this routine (7a,b) has been formulated in the simplest manner possible to facilitate alternative management scenarios.

II.3.13 Model Steps 8a,b and 9: Tree Acorn Production: Mast Production per cell

To calculate the cell mast production index, first two new variables for each cell are generated. These variables are the sum of the individual tree indices for each subgenus. The 100-year (10 iteration) test-case database at this point in the model includes over 1800 variables per cell. To reduce memory requirements and enhance performance, at this stage in the model many variables are discarded. The variables that describe the characteristics of the first tree (diameter, species, mast production) are retained and those variables associated with the remaining 39 trees are discarded. This includes diameter, species, productivity level, and mast production information thereby reducing the dataset by about 1600 variables. Information for the first tree is maintained

Table II.19 Subjective production levels and scale factors assigned randomly to each tree in the mast model.

Production Level	**Fraction of Population**	**Scale Factor Multiplier**
No production	0.15	0.00
Low Productoin	0.30	0.30
Moderate Production	0.40	0.75
High Production	0.15	1.00

for evaluating the effect of the various procedures in the model. The cell mast production index is generated by adding the red oak mast index to the white oak mast index.

II.4 ANNUAL VARIABILITY

II.4.1 Temporal variability: Sources of data

With the exception of one observation of the results of freezing of staminate or pistillate oak flowers (Cecich, pers. comm.), the influence of climate on acorn production success is anecdotal and suggestive but not conclusive. For example, since 1959 the Missouri Department of Conservation has conducted annual counts of mast production for the purpose of setting policies regarding limits on wild game harvest. These acorn counts are conducted for most counties where oaks are prevalent; however, climate data for these specific counties are not available. As a consequence, while differences in mast production can be detected among regions in Missouri, differences in climate cannot.

The period during which both acorn production and daily climate data is available does not span a wide enough range to reach statistically conclusive assertions regarding acorn production. For example, the statewide mast index has been conducted for about 40 years. In that forty years, one might expect (speculatively) about 6 incidents of below freezing temperatures during critical phases of flowering that would affect acorn production. In an examination of side-by-side patterns of temperature and acorn production, one might expect to see this influence. However, since factors such as the negative effects of high relative humidity, the positive effect of a cool period following pollination, and the previous year acorn production level are also varying, the effect of freezing or any one factor is obscured.

My intent is for this model to be viewed as a top-down approach. That is, it is to be based on the causative factors of masting behavior rather than just modeling the acorn production across the landscape based on previous area-based studies of acorn production. The three climate factors I modeled are potential for freezing, potential for favorable relative humidity, and the potential for a favorable temperature regime (warm-cool) during flowering, pollination, and fertilization.

Daily climate data are available from the National Climate Data Center (NCDC, 2000) for several metropolitan sites in Missouri dating back to 1918. I examined data from seven widely distributed sites in Missouri. I limited my examination to the critical flowering period between mid-April and mid-May. The importance in acorn production that flowering success entails can be seen by considering that, on average, about 90 percent of flowers fail to produce acorns (Cecich and Sullivan 1999). Therefore, an increase in flowering success by only 10 percent would double the acorn crop.

Temperature data are the most widely available information. An examination of the climate data allows possible freezing events to be identified during this period as well as patterns of warm and cool temperatures. Relative humidity data are much more sparsely available. The longest record dates to 1918 for Springfield. Data are available for Kansas City, St. Louis, and Columbia as far back as the 1940's, but for these sites there are periods during which data are not available.

My method for examining these data was largely observational. I examined the patterns in the climate data and judged whether, i) a particular year may have been negatively impacted by freezing temperatures based on the data, ii) relative humidity during the flowering period seemed to be favorable or unfavorable, and iii) there appeared to be a warm period during flowering followed by a cool period.

II.4.2 Temporal variability: Freezing temperatures

Temperatures below about 29 F (-1 C) have been shown to damage oak flowers and affect acorn production. In southeast Missouri, temperatures below 30 F were recorded for about 13 percent of the years from 1918 to 1999 (Table II.21; Figure I.22). These data do not account for the effect of local topography on temperature. A subjective listing was made for each year based on my opinion of whether the oak flowers for a particular year might be subjected to freezing temperatures (Appendix II.5). The patterns of daily temperature were examined and favorable or unfavorable conditions were noted. Figure II.23 shows examples of the patterns of daily minimum temperature for 15 years and two examples of years that were classified as favorable or unfavorable. Note that a comparison of freezing temperatures in Table II.20 corresponds to the examples shown in Figure II.23. Table II.21 is a summary of this examination of the climate patterns. Overall, the number of potential freezing events (about 20 percent) based on my subjective observation exceeds that indicated in the more objective data of Table II.21. The objective data do not always indicate the influences of temperature completely. For example, the data in Table II.20 show that relative to some other years, 1997 was a mild year in terms of freeze-events with only one day of recorded freezing temperatures at two of the sites (Rolla and Salem). Other years have as many as five freezing events during the period of oak flower development (1983). An examination of

Table II.20 Number of days with minimum temperature below 30 F per station by year (between Apr15 and May14)

Year	Rolla	Salem	Poplar Bluff	South-East Missouri
1918	1	1	0	0.667
1919	0	1	0	0.333
1920	0	0	0	0.000
1921	1	2	1	1.333
1922	0	0	0	0.000
1923	1	1	0	0.667
1924	0	0	0	0.000
1925	0	0	0	0.000
1926	1	1	2	1.333
1927	1	1	1	1.000
1928	1	2	2	1.667
1929	0	0	0	0.000
1930	0	1	0	0.333
1931	0	2	0	0.667
1932	0	1	0	0.333
1933	0	0	0	0.000
1934	0	1	0	0.333
1935	1	1	1	1.000
1936	0	4	2	2.000
1937	0	0	0	0.000
1938	0	0	0	0.000
1939	0	0	0	0.000
1940	0	0	0	0.000
1941	0	0	0	0.000
1942	0	0	0	0.000
1943	1	2	1	1.333
1944	0	1	0	0.333
1945	0	0	0	0.000
1946	0	1	0	0.333
1947	0	1	0	0.333
1948	0	0	0	0.000
1949	1	2	0	1.000
1950	1	1	0	0.667
1951	2	3	1	2.000
1952	0	2	0	0.667
1953	4	4	1	3.000
1954	0	0	0	0.000
1955	0	0	0	0.000
1956	1	4	0	1.667
1957	0	0	0	0.000
1958	0	0	0	0.000
1959	0	0	0	0.000
1960	0	2	0	0.667
1961	0	3	0	1.000
1962	1	2	0	1.000
1963	0	2	0	0.667
1964	0	0	0	0.000
1965	0	0	0	0.000
1966	0	1	0	0.333
1967	1	0	0	0.333
1968	0	0	0	0.000
1969	0	0	0	0.000
1970	0	0	0	0.000
1971	0	0	0	0.000
1972	0	0	0	0.000
1973	0	0	0	0.000
1974	0	0	0	0.000
1975	0	0	0	0.000
1976	0	3	0	1.000
1977	0	0	0	0.000
1978	0	0	0	0.000
1979	0	0	0	0.000
1980	0	1	0	0.333
1981	0	0	0	0.000
1982	0	3	0	1.000
1983	2	5	1	2.667
1984	0	0	0	0.000
1985	0	0	0	0.000
1986	0	1	0	0.333
1987	0	0	0	0.000
1988	0	2	0	0.667
1989	0	0	0	0.000
1990	0	0	0	0.000
1991	0	0	0	0.000
1992	0	1	0	0.333
1993	0	1	0	0.333
1994	0	0	0	0.000
1995	0	0	0	0.000
1996	0	0	0	0.000
1997	1	1	0	0.667
1998	0	0	0	0.000
1999	0	0	0	0.000
Total	22	68	13	34
Number of Years T<30	17	37	10	11
# years	82	82	82	82
Fraction of years: T<30	0.207	0.451	0.122	0.134

Table II.21 Subjective rankings of favorable or unfavorable climate conditions for recording stations throughout Missouri. Negative implies a negative impact on potential mast production and positive implies the opposite. Favorable indicates the fraction of years viewed to display markedly positive conditions for that climate variable.

			Number of Years Reviewed	Negative	Neutral	Positive
Relative Humidity	**St. Louis**	**Count**	33	13	16	3
		Fraction		0.39	0.48	0.09
	Columbia Springfield	**Count**	62	30	21	11
		Fraction		0.48	0.34	0.18
Potentially Freezing Temperature	**Throughout Missouri**	**Count**	86	17		
		Fraction		0.20		
Warm/Cool Temperature Sequence	**Throughout Missouri**	**Count**	86		13	
		Fraction			0.15	

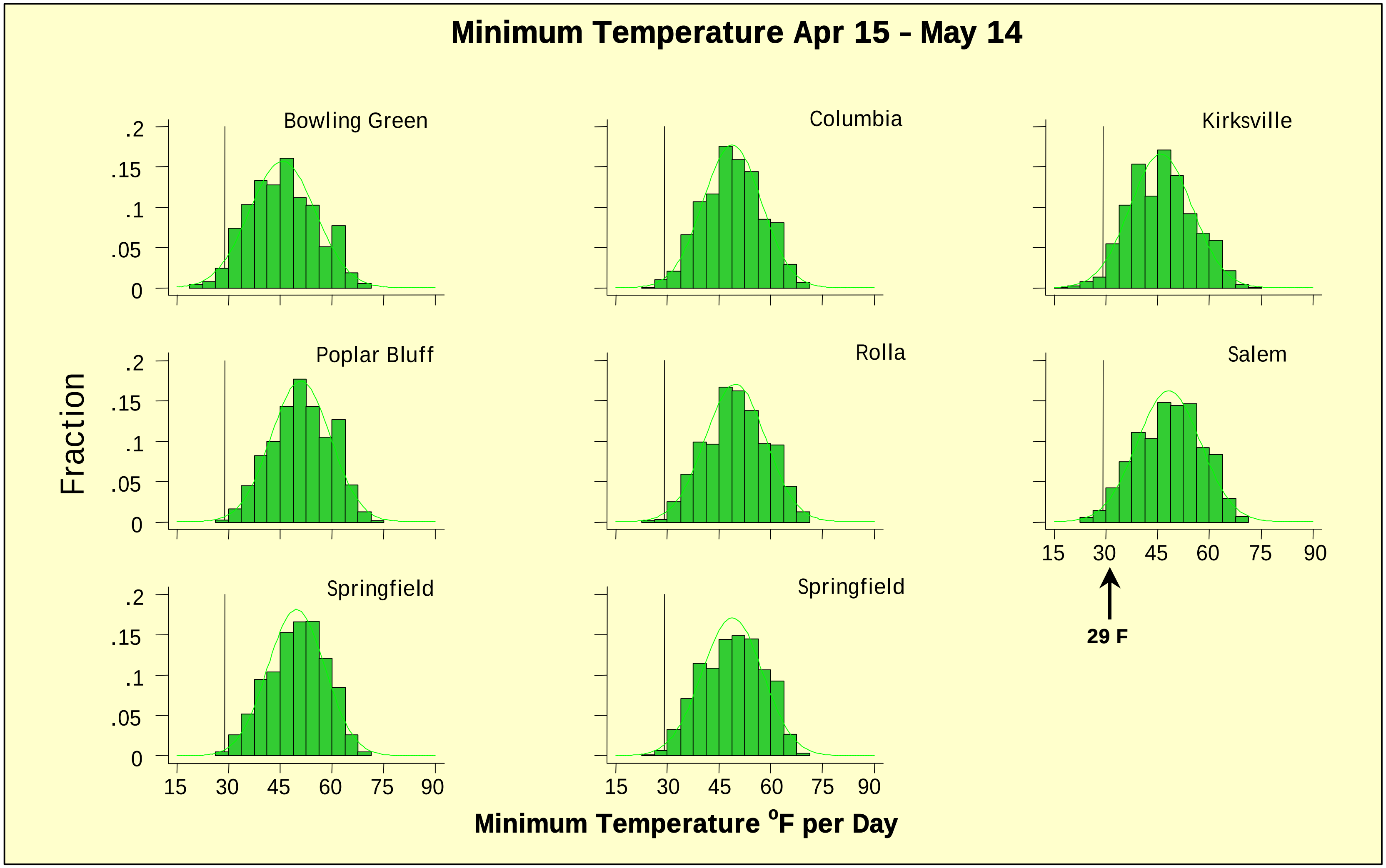


Figure II.22 Distributions of minimum temperature by climate station around Missouri during the period in which pollination occurs. Flowers are temperature sensitive and at or below 29 F, complete acorn crop failure can occur (NCDC, 2000).

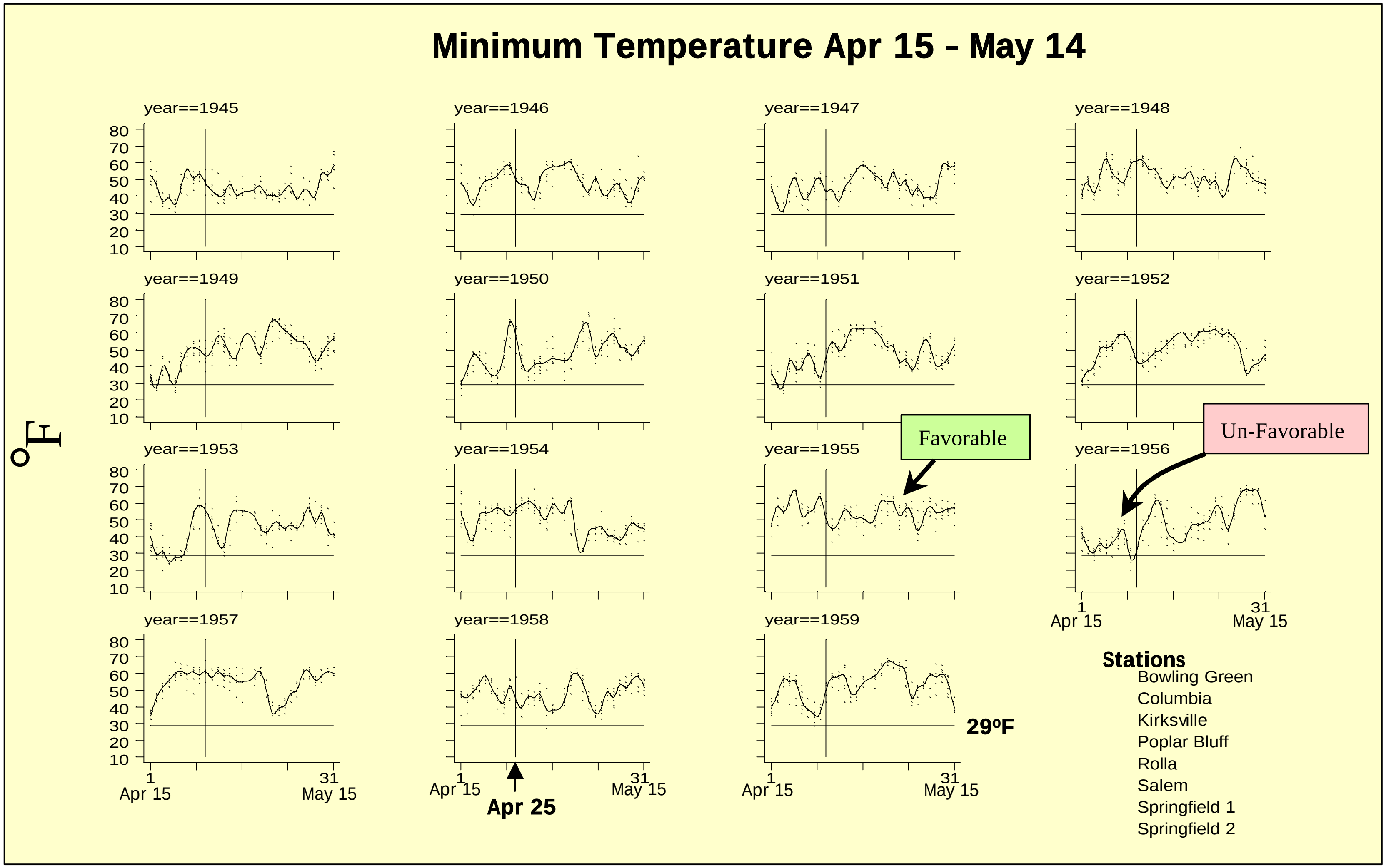


Figure II.23 Smoothed average minimum daily temperatures across Missouri between April 15th and May 14th for 15 years.

the patterns of temperature for 1997 does not conclusively indicate a freeze event (Figure II.24) yet we observed an almost total loss of the acorn crop for that year.

II.4.3 Temporal variability: Warm-cool period during flowering

Several studies have suggested that a warm period during pistillate flower development followed by a cool period increases flowering success by increasing the probability of synchronization between staminate flower pollen dispersal and conditions favorable for pistillate flower maturity. In a procedure similar to that stated above, the patterns of temperature during the flowering period were examined for 86 years and judged to be either favorable for not. I believe about 15 percent of these years showed a favorable temperature regime for acorn production (Table II.21). It is not surprising, but there were no years that I deemed had a favorable temperature regime but freezing temperature events; however, several of the years that I deemed had a good temperature regime also had freezing temperatures according to the objective temperature record (Table II.20).

II.4.4 Temporal variability: Relative humidity

Relative humidity during pollination affects acorn production. Since pollen is wind dispersed, pollen deposition is much more subject to chance, *i.e*. insects are not visiting flowers intentionally. High relative humidity can inhibit pollen release and low relative humidity favors pollen dispersal. Figure II.25 shows the patterns of daily pollen counts and relative humidity in St. Louis during 1999. Beginning on about the 11th day of the series, daily minimum relative humidity drops to below 40 percent and remains

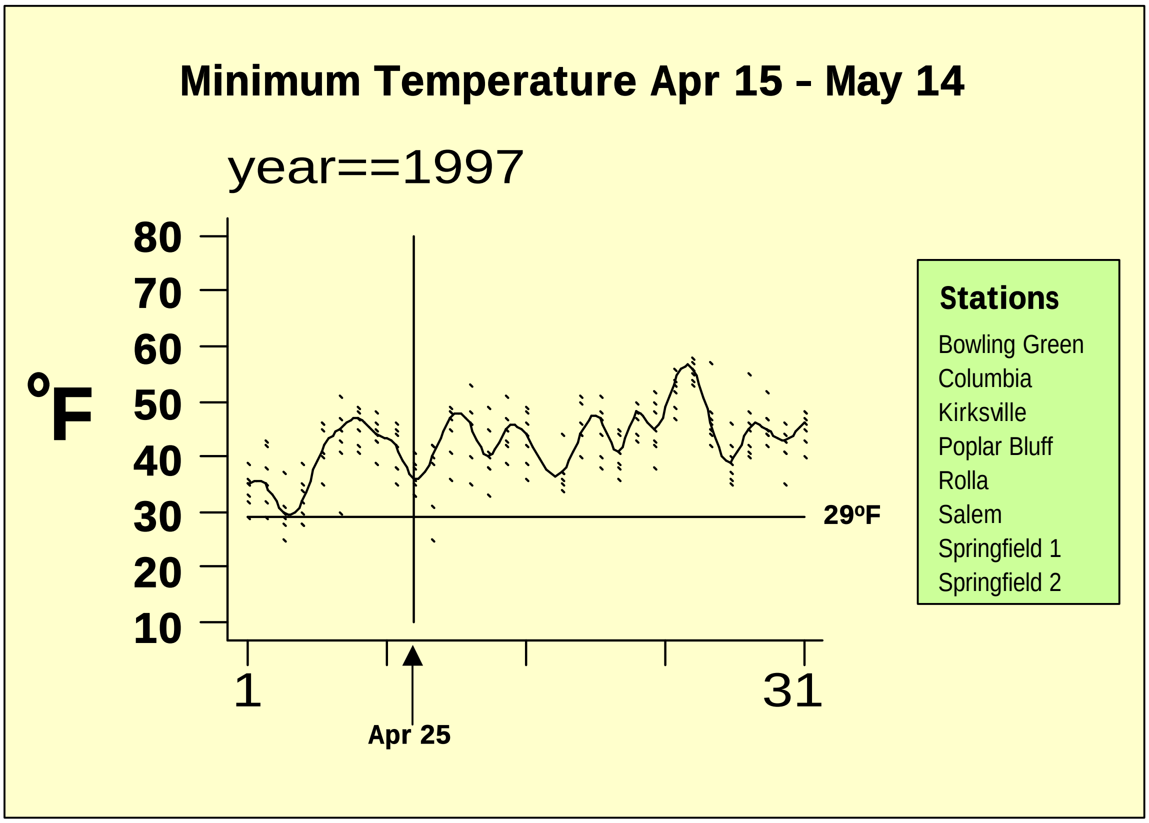


Figure II.24 Smoothed average daily minimum temperatures across Missouri between April 15th a nd May 18th for 1997. (NCDC 2000)

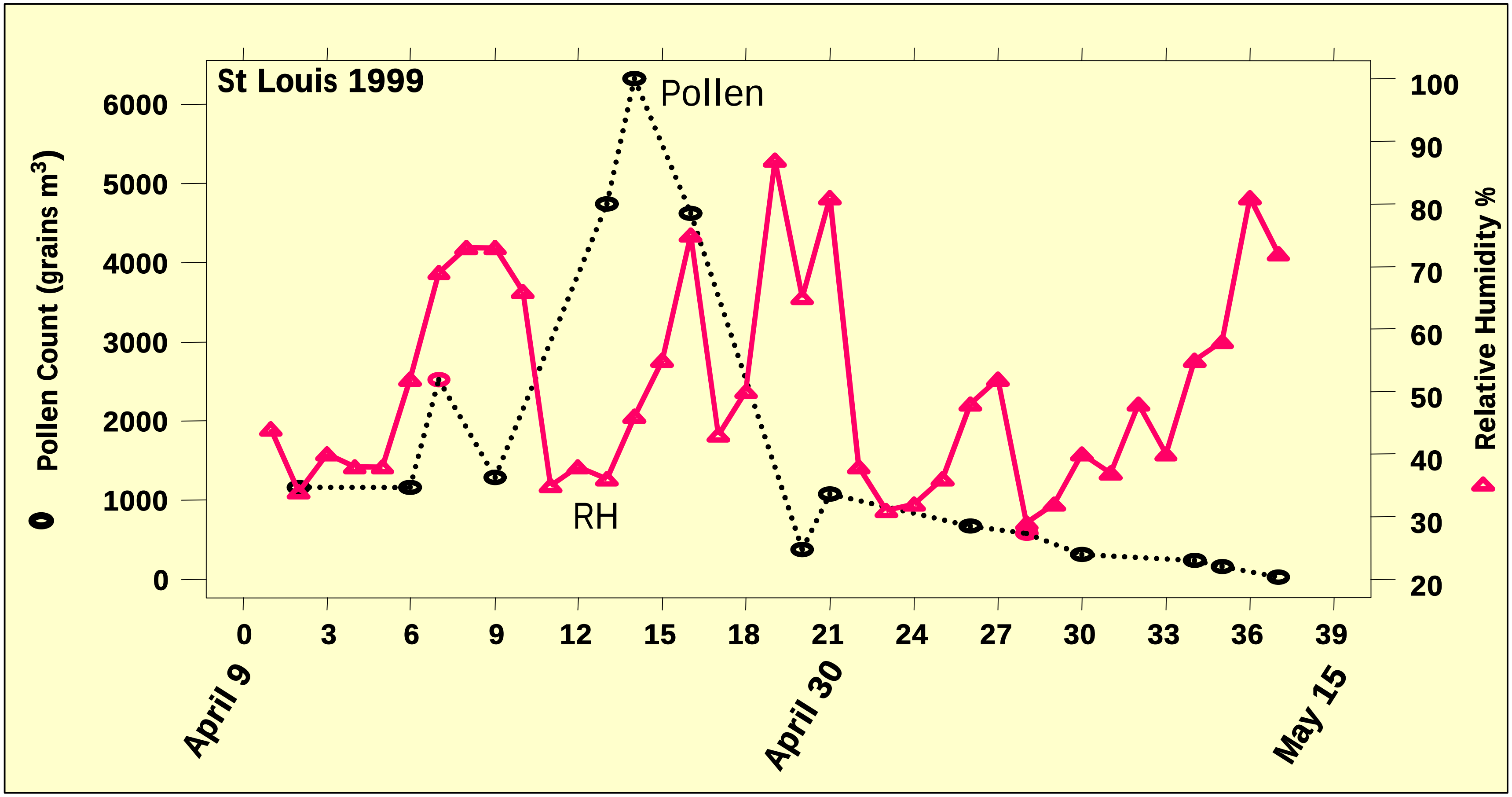


Figure II.25 Airborne pollen (identified as mostly oak) relative to patterns of daily minimum relative humidity for 1999 in St Louis, Missouri (courtesy of Robert Nicolotti, St. Louis county Health Department).

low for 3 days. There is a corresponding increase in airborne pollen beginning at about the same time. When relative humidity increases on about the 16th day of the sequence, the pollen count decreases. Although these are data for only one year, this result supports the concept that low relative humidity favors pollen dispersal. However, even if pollen dispersal is favored, the pistillate flowers may not be in the necessary phase of flower development to accept pollen.

Plots of daily relative humidity (Figure II.26) were examined and conditions each year were classified as negative, neutral, or positive where positive implies fair conditions and favorable implies very-good conditions. About 13 percent of the years examined (33 for St. Louis and 62 for Columbia and Springfield) were classified as positive. The negative and neutral categories each were about 40 percent. If the relative humidity conditions do influence negatively 40 percent of the yearly acorn crops, this is probably one of the most important factors in acorn production.

II.4.5 Temporal variability: Predicting acorn production in the masting model

The LANDIS model generates output files for each 10-year iteration. To examine annual variability a separate model was developed that takes the output from a specified iteration and applies the climate factors listed above in a stochastic manner. This procedure can be repeated to develop an estimate of the range of acorn production for a landscape at the specified time-step. The model is relatively simple and easily allows alteration of the probabilities and variation of negative and positive conditions for acorn production. In addition, once the annual variation model has been run iteratively, previous year acorn production can be estimated. Allocation of resources to acorn

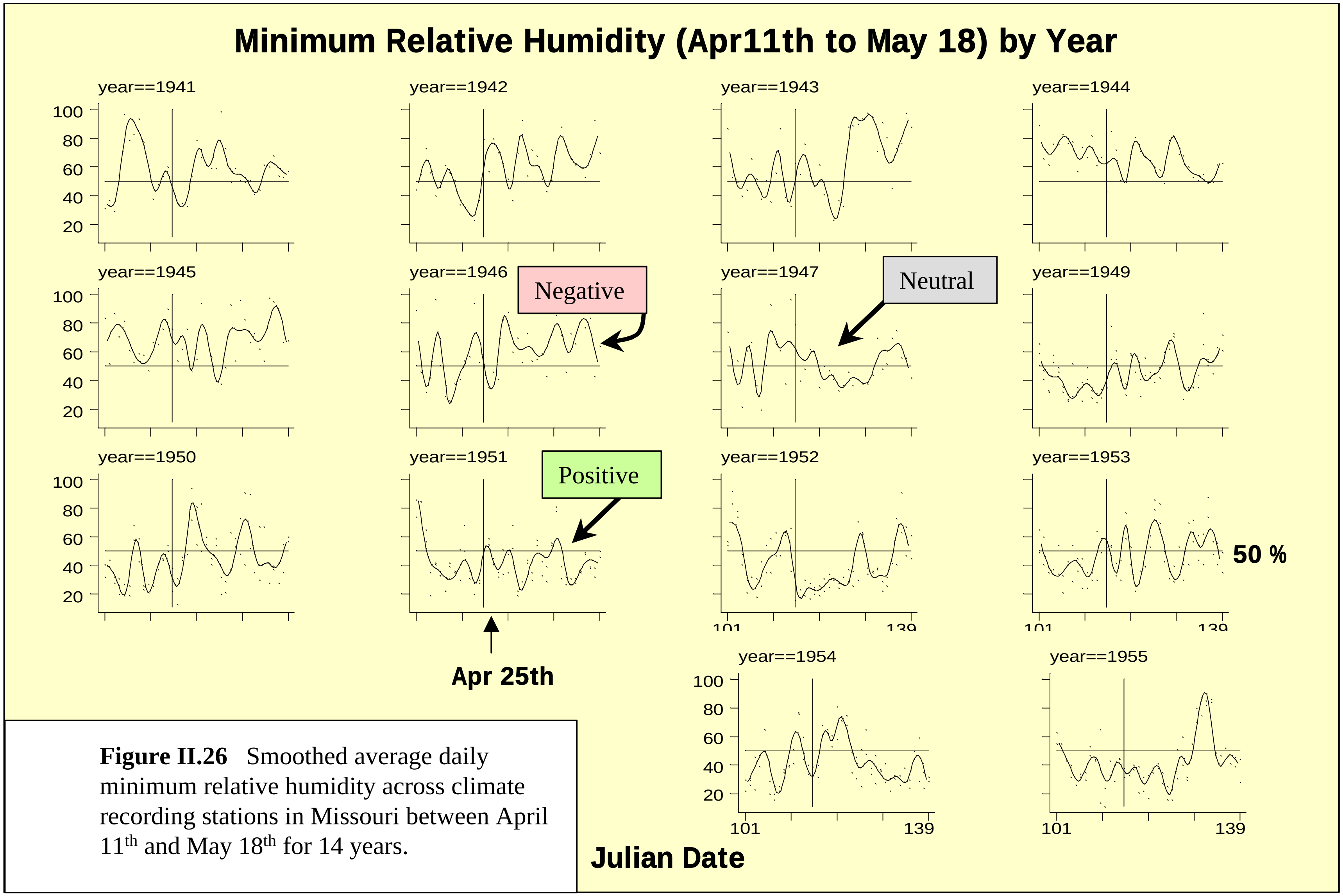


Figure II.26 Smoothed average daily minimum relative humidity across climate recording stations in Missouri between April 11th and May 18th for 14 years.

production in one year affects the ability of a tree to produce acorns the following year. This annual variation model is presented and implemented in Section III: *Implementation and behavior of the masting model*.

Appendix II.1

The instructions and program for writing a file to generate the coordinate system (x,y) to maintain the spatial relationships of the landscape cells.

```
==================================================
            Instructions for using xy.exe
==================================================
  xy.exe is a C++ program to write an ascii
    file that consists of x y coordinates listed
    in the same order as LANDIS output, i.e.
    left to right, top to bottom  Where the
    beginning y values are the maximum.
  to use and output a standard coordinate file:
    at the dos prompt:

            type:     xy > xy_coor.txt <enter>

            type:     integer # of columns or x <enter>

            type:     integer # of rows or y <enter>

    ***Note that you will not be a prompted to key-in the
    x and y values.  For LANDIS output, these values
    can be found at the top of each output file.
==================================================
```

Program Code:

```
// "Loop Program to write file for  X Y coordinates for LANDIS Analysis"

#include <iostream.h>
int main()
{
        int xmax, ymax, ix, iy;
        cin >> xmax;
        cin >> ymax;
        iy = ymax;
        ix = 1;

        while (iy >= 1)
        {
                while (ix <= xmax)
                {
                        cout << ix << " "<< iy <<"\n";
                        ix = ix++;
                }
                ix = 1;
                iy = iy - 1;
        }
  return 0;
}
```

Appendix II.2

ANALYSIS OF AGE DIAMETER RELATIONSHIP

```
FIA DATA

. use master,replace
(Missouri FIA 1986)

. drop if glucur>45
(15727 observations deleted)

. drop if mast==0
(81379 observations deleted)

. drop if dbh_cm<12.7
(27752 observations deleted)

. drop if crclass<2
(804 observations deleted)

. drop if crclass>3
(6304 observations deleted)

. des

Contains data from master.dta
  obs:        46,073                          Missouri FIA 1986
 vars:            51                          6 Dec 2000 07:07
 size:     6,496,293 (99.4% of memory free)
---------------------------------------------------------------------------
Sorted by:  region  spp
```

UNSUMMARIZED DATA

```
 regress dbh_ age_c

  Source |       SS       df       MS                  Number of obs =   46073
---------+-----------------------------               F(  1, 46071) = 2665.78
   Model |  421832.167     1  421832.167               Prob > F      =  0.0000
Residual |  7290267.08 46071  158.239827               R-squared     =  0.0547
---------+-----------------------------               Adj R-squared =  0.0547
   Total |  7712099.25 46072  167.392326               Root MSE      =  12.579

------------------------------------------------------------------------------
  dbh_cm |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
   age_c |    .106974   .0020719     51.631   0.000        .102913    .1110349
   _cons |   26.58882   .1440829    184.538   0.000       26.30642    26.87123
------------------------------------------------------------------------------
```

Robust Regression

```
. rreg dbh_ age_c

   Huber iteration 1:  maximum difference in weights = .84622814
   Huber iteration 2:  maximum difference in weights = .09046306
   Huber iteration 3:  maximum difference in weights = .0126226
Biweight iteration 4:  maximum difference in weights = .29394816
Biweight iteration 5:  maximum difference in weights = .00750564

Robust regression estimates                            Number of obs =   46073
                                                       F(  1, 46071) = 3839.01
                                                       Prob > F      =  0.0000

------------------------------------------------------------------------------
  dbh_cm |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
   age_c |   .1161158   .0018741     61.960   0.000       .1124426     .119789
   _cons |   24.56794   .1303251    188.513   0.000        24.3125    24.82338
------------------------------------------------------------------------------
```

SUMMARIZED DATA

```
. collapse (mean) dbh_cm (sd) sd=dbh_cm (count) n=dbh_cm, by(age_c)

. regress dbh_cm age_c

  Source |       SS       df       MS              Number of obs =      16
---------+------------------------------          F(  1,    14) =   92.72
   Model |  268.224981     1  268.224981           Prob > F      =  0.0000
Residual |  40.4981424    14  2.89272445           R-squared     =  0.8688
---------+------------------------------          Adj R-squared =  0.8595
   Total |  308.723123    15  20.5815415           Root MSE      =  1.7008

------------------------------------------------------------------------------
  dbh_cm |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
   age_c |   .0888199   .0092239      9.629   0.000       .0690366    .1086031
   _cons |    28.0651   .8919076     31.466   0.000       26.15215    29.97805
------------------------------------------------------------------------------
```

ROBUST REGRESSION

```
. rreg dbh_cm age_c

   Huber iteration 1:  maximum difference in weights = .44927052
   Huber iteration 2:  maximum difference in weights = .28858723
   Huber iteration 3:  maximum difference in weights = .072762
   Huber iteration 4:  maximum difference in weights = .01937513
Biweight iteration 5:  maximum difference in weights = .29455394
Biweight iteration 6:  maximum difference in weights = .25468218
Biweight iteration 7:  maximum difference in weights = .06967336
Biweight iteration 8:  maximum difference in weights = .12271219
Biweight iteration 9:  maximum difference in weights = .0461413
Biweight iteration 10:  maximum difference in weights = .02909695
Biweight iteration 11:  maximum difference in weights = .00620458

Robust regression estimates                            Number of obs =      16
                                                       F(  1,    14) =  235.99
                                                       Prob > F      =  0.0000
------------------------------------------------------------------------------
  dbh_cm |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
   age_c |   .1088868   .0070881     15.362   0.000       .0936843    .1240893
   _cons |    26.5845   .6853894     38.787   0.000       25.11449    28.05452
------------------------------------------------------------------------------

. regr sd  age_c

  Source |       SS       df       MS              Number of obs =      16
---------+------------------------------          F(  1,    14) =    0.06
   Model |   .05675374     1   .05675374           Prob > F      =  0.8039
Residual |  12.4134079    14  .886671996           R-squared     =  0.0046
---------+------------------------------          Adj R-squared = -0.0666
   Total |  12.4701617    15  .831344112           Root MSE      =  .94163

------------------------------------------------------------------------------
      sd |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
   age_c |   -.001292   .0051067     -0.253   0.804      -.0122448    .0096608
   _cons |   12.88841   .4937963     26.101   0.000       11.82932     13.9475
------------------------------------------------------------------------------

. rreg sd  age_c

   Huber iteration 1:  maximum difference in weights = .62331693
   Huber iteration 2:  maximum difference in weights = .04037684
Biweight iteration 3:  maximum difference in weights = .27871753
Biweight iteration 4:  maximum difference in weights = .12775988
Biweight iteration 5:  maximum difference in weights = .02839892
```

```
Biweight iteration 6:  maximum difference in weights = .02016617
Biweight iteration 7:  maximum difference in weights = .00750228

Robust regression estimates                           Number of obs =      16
                                                      F(  1,    14) =    0.12
                                                      Prob > F      =  0.7384

------------------------------------------------------------------------------
      sd |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
   age_c |   .0011926   .0035002      0.341   0.738      -.0063146    .0086997
   _cons |   12.46691   .3384523     36.835   0.000         11.741    13.19282
------------------------------------------------------------------------------
```

Unsummarized data by species

```
. regres dbh_cm age_c if sp_name=="Qa"

  Source |       SS       df       MS                  Number of obs =   12790
---------+------------------------------               F(  1, 12788) =  791.85
   Model |  114137.692     1  114137.692               Prob > F      =  0.0000
Residual |  1843261.85 12788  144.139963               R-squared     =  0.0583
---------+------------------------------               Adj R-squared =  0.0582
   Total |  1957399.54 12789  153.053369               Root MSE      =  12.006

------------------------------------------------------------------------------
  dbh_cm |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
   age_c |   .1004158   .0035684     28.140   0.000       .0934211    .1074104
   _cons |   27.45452   .2733949    100.421   0.000       26.91863    27.99042
------------------------------------------------------------------------------


. regres dbh_cm age_c if sp_name=="Qv"

  Source |       SS       df       MS                  Number of obs =   13214
---------+------------------------------               F(  1, 13212) =  879.86
   Model |  135560.331     1  135560.331               Prob > F      =  0.0000
Residual |  2035572.27 13212  154.069957               R-squared     =  0.0624
---------+------------------------------               Adj R-squared =  0.0624
   Total |  2171132.60 13213  164.317914               Root MSE      =  12.412

------------------------------------------------------------------------------
  dbh_cm |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
   age_c |    .125013   .0042145     29.662   0.000        .116752    .1332741
   _cons |   25.79462   .2739227     94.167   0.000       25.25769    26.33155
------------------------------------------------------------------------------


. regres dbh_cm age_c if sp_name=="Qc"

  Source |       SS       df       MS                  Number of obs =    3203
---------+------------------------------               F(  1,  3201) =  201.69
   Model |  24529.2939     1  24529.2939               Prob > F      =  0.0000
Residual |  389303.023  3201  121.619189               R-squared     =  0.0593
---------+------------------------------               Adj R-squared =  0.0590
   Total |  413832.317  3202  129.241823               Root MSE      =  11.028

------------------------------------------------------------------------------
  dbh_cm |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
   age_c |   .1063874   .0074912     14.202   0.000       .0916994    .1210753
   _cons |   25.45232   .4716323     53.966   0.000       24.52759    26.37705
------------------------------------------------------------------------------
```

```
. regres dbh_cm age_c if sp_name=="Qst"

  Source |       SS       df       MS              Number of obs =    8955
---------+------------------------------           F(  1,  8953) =  251.37
   Model |  30493.7008     1  30493.7008           Prob > F      =  0.0000
Residual |  1086103.26  8953  121.311657           R-squared     =  0.0273
---------+------------------------------           Adj R-squared =  0.0272
   Total |  1116596.96  8954  124.703704           Root MSE      =  11.014

------------------------------------------------------------------------------
  dbh_cm |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
   age_c |   .0646732   .0040792     15.855   0.000       .0566771    .0726693
   _cons |   26.10225   .2773953     94.098   0.000       25.55849    26.64601
------------------------------------------------------------------------------
```

Summarized Data

```
. collapse (mean) dbh_cm (sd) sd=dbh_cm ,by(age_c sp_)

. regres dbh_cm age_c if sp_name=="Qa"

  Source |       SS       df       MS              Number of obs =      16
---------+------------------------------           F(  1,    14) =   36.58
   Model |  217.271329     1  217.271329           Prob > F      =  0.0000
Residual |  83.1436117    14   5.9388294           R-squared     =  0.7232
---------+------------------------------           Adj R-squared =  0.7035
   Total |  300.414941    15  20.0276627           Root MSE      =   2.437

------------------------------------------------------------------------------
  dbh_cm |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
   age_c |   .0799396   .0132163      6.049   0.000       .0515933    .1082858
   _cons |   29.23663   1.277959     22.878   0.000       26.49568    31.97758
------------------------------------------------------------------------------


. regres dbh_cm age_c if sp_name=="Qst"

  Source |       SS       df       MS              Number of obs =      16
---------+------------------------------           F(  1,    14) =   17.24
   Model |  49.9929305     1  49.9929305           Prob > F      =  0.0010
Residual |  40.5950033    14  2.89964309           R-squared     =  0.5519
---------+------------------------------           Adj R-squared =  0.5199
   Total |  90.5879337    15  6.03919558           Root MSE      =  1.7028

------------------------------------------------------------------------------
  dbh_cm |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
   age_c |   .0383455   .0092349      4.152   0.001       .0185386    .0581525
   _cons |    27.9345   .8929736     31.283   0.000       26.01927    29.84974
------------------------------------------------------------------------------


. regres dbh_cm age_c if sp_name=="Qc"

  Source |       SS       df       MS              Number of obs =      15
---------+------------------------------           F(  1,    13) =   81.50
   Model |  704.278144     1  704.278144           Prob > F      =  0.0000
Residual |  112.343324    13  8.64179413           R-squared     =  0.8624
---------+------------------------------           Adj R-squared =  0.8518
   Total |  816.621468    14  58.3301048           Root MSE      =  2.9397

------------------------------------------------------------------------------
  dbh_cm |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
   age_c |   .1512812   .0167577      9.028   0.000       .1150783     .187484
   _cons |   23.41443   1.560058     15.009   0.000       20.04413    26.78473
------------------------------------------------------------------------------
```

```
. regres dbh_cm age_c if sp_name=="Qv"

  Source |       SS       df       MS              Number of obs =      16
---------+------------------------------           F(  1,    14) =   41.65
   Model |  337.878577     1  337.878577           Prob > F      =  0.0000
Residual |   113.56177    14  8.11155498           R-squared     =  0.7484
---------+------------------------------           Adj R-squared =  0.7305
   Total |  451.440347    15  30.0960231           Root MSE      =  2.8481

------------------------------------------------------------------------------
  dbh_cm |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
   age_c |   .0996875   .0154459      6.454   0.000       .0665594    .1328157
   _cons |   27.87646   1.493545     18.665   0.000       24.67312     31.0798
------------------------------------------------------------------------------

. log off
```

MOFEP AGE –Diameter analysis

```
Contains data from siteindex.dta   MOFEP Veg data
  obs:         2,396
 vars:            10                          6 Dec 2000 08:00
 size:       126,988 (100.0% of memory free)
-------------------------------------------------------------------------------
   1. site      byte   %8.0g
   2. plot      byte   %8.0g
   3. tree      byte   %8.0g
   4. spp       int    %8.0g
   5. age       byte   %8.0g
   6. dbh       float  %9.0g
   7. sp_nm     str27  %27s
   8. mast      float  %9.0g
   9. ageclass  float  %9.0g
  10. dbh_cm    float  %9.0g
-------------------------------------------------------------------------------
Sorted by:

. drop if mast==0
(264 observations deleted)

. drop if agecl>200
(75 observations deleted)

. regre dbh_cm agec

  Source |       SS       df       MS                  Number of obs =    2057
---------+------------------------------               F(  1,  2055) =  325.41
   Model |  5187.46764     1  5187.46764               Prob > F      =  0.0000
Residual |  32758.9551  2055  15.9410974               R-squared     =  0.1367
---------+------------------------------               Adj R-squared =  0.1363
   Total |  37946.4228  2056  18.4564313               Root MSE      =  3.9926

------------------------------------------------------------------------------
  dbh_cm |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
ageclass |   .1360355   .0075411     18.039   0.000       .1212466    .1508245
   _cons |   19.38299   .4211485     46.024   0.000       18.55707    20.20892
------------------------------------------------------------------------------

. xi:regre dbh_cm agec i.sp
sp ambiguous abbreviation
r(111);

. xi:regre dbh_cm agec i.sp_nm
i.sp_nm               Isp_nm_1-4   (Isp_nm_1 for sp_nm==Qa omitted)

  Source |       SS       df       MS                  Number of obs =    2057
---------+------------------------------               F(  4,  2052) =   98.14
   Model |  6093.60052     4  1523.40013               Prob > F      =  0.0000
Residual |  31852.8222  2052  15.5228179               R-squared     =  0.1606
---------+------------------------------               Adj R-squared =  0.1589
   Total |  37946.4228  2056  18.4564313               Root MSE      =  3.9399

------------------------------------------------------------------------------
  dbh_cm |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
ageclass |    .139351   .0076423     18.234   0.000       .1243635    .1543385
Isp_nm_2 |   1.710879   .2634959      6.493   0.000       1.194131    2.227626
Isp_nm_3 |   3.659152   2.795233      1.309   0.191      -1.822637    9.140942
Isp_nm_4 |   1.991519   .2671734      7.454   0.000        1.46756    2.515478
   _cons |   17.63254   .4942489     35.675   0.000       16.66326    18.60182
------------------------------------------------------------------------------
```

```
. regre dbh_cm agec if sp_nm=="Qc"

  Source |       SS       df       MS              Number of obs =     970
---------+------------------------------           F(  1,   968) =  119.68
   Model |  2044.77832     1  2044.77832           Prob > F      =  0.0000
Residual |  16538.5947   968  17.0853251           R-squared     =  0.1100
---------+------------------------------           Adj R-squared =  0.1091
   Total |   18583.373   969  19.1778875           Root MSE      =  4.1334

------------------------------------------------------------------------------
  dbh_cm |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
ageclass |   .1390586   .0127112     10.940   0.000       .1141139    .1640032
   _cons |   19.35857   .6717333     28.819   0.000       18.04035    20.67679
------------------------------------------------------------------------------

. regre dbh_cm agec if sp_nm=="Qa"

  Source |       SS       df       MS              Number of obs =     301
---------+------------------------------           F(  1,   299) =   62.37
   Model |  713.351648     1  713.351648           Prob > F      =  0.0000
Residual |   3419.8446   299  11.4376074           R-squared     =  0.1726
---------+------------------------------           Adj R-squared =  0.1698
   Total |  4133.19625   300  13.7773208           Root MSE      =   3.382

------------------------------------------------------------------------------
  dbh_cm |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
ageclass |   .1280137   .0162096      7.897   0.000       .0961143     .159913
   _cons |   18.28378   .9512954     19.220   0.000        16.4117    20.15586
------------------------------------------------------------------------------

. regre dbh_cm agec if sp_nm=="Qv"

  Source |       SS       df       MS              Number of obs =     784
---------+------------------------------           F(  1,   782) =  158.69
   Model |  2411.95304     1  2411.95304           Prob > F      =  0.0000
Residual |  11885.3829   782  15.1986994           R-squared     =  0.1687
---------+------------------------------           Adj R-squared =  0.1676
   Total |  14297.3359   783  18.2596883           Root MSE      =  3.8986

------------------------------------------------------------------------------
  dbh_cm |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
ageclass |   .1439142   .0114241     12.597   0.000       .1214886    .1663397
   _cons |   19.36395   .6659218     29.078   0.000       18.05674    20.67116
------------------------------------------------------------------------------

. collapse (mean) dbh_cm (sd) sd=dbh_cm, by(agecl sp_nm)

. regre dbh_cm agec

  Source |       SS       df       MS              Number of obs =      28
---------+------------------------------           F(  1,    26) =   94.28
   Model |  289.045915     1  289.045915           Prob > F      =  0.0000
Residual |  79.7074254    26  3.06567021           R-squared     =  0.7838
---------+------------------------------           Adj R-squared =  0.7755
   Total |  368.753341    27  13.6575311           Root MSE      =  1.7509

------------------------------------------------------------------------------
  dbh_cm |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
ageclass |   .1278932   .0131712      9.710   0.000       .1008194    .1549671
   _cons |   19.97317   .9530482     20.957   0.000       18.01415    21.93219
------------------------------------------------------------------------------
```

```
. regre sd agec if sp_nm=="Qv"

  Source |       SS       df       MS              Number of obs =       8
---------+------------------------------           F(  1,     6) =    1.84
   Model |   .31101985     1   .31101985           Prob > F      =  0.2234
Residual |  1.01236144     6  .168726906           R-squared     =  0.2350
---------+------------------------------           Adj R-squared =  0.1075
   Total |  1.32338129     7   .18905447           Root MSE      =  .41076

------------------------------------------------------------------------------
      sd |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
ageclass |  -.0086054   .0063382     -1.358   0.223      -.0241144    .0069037
   _cons |   4.193568   .4368319      9.600   0.000       3.124679    5.262457
------------------------------------------------------------------------------

. regre sd agec if sp_nm=="Qc"

  Source |       SS       df       MS              Number of obs =       7
---------+------------------------------           F(  1,     5) =    2.57
   Model |  1.90248657     1  1.90248657           Prob > F      =  0.1696
Residual |  3.69617174     5  .739234348           R-squared     =  0.3398
---------+------------------------------           Adj R-squared =  0.2078
   Total |  5.59865831     6  .933109719           Root MSE      =  .85979

------------------------------------------------------------------------------
      sd |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
ageclass |   .0260664   .0162485      1.604   0.170      -.0157015    .0678344
   _cons |   2.810347   1.027642      2.735   0.041       .1687076    5.451986
------------------------------------------------------------------------------

. regre sd agec if sp_nm=="Qa"

  Source |       SS       df       MS              Number of obs =       8
---------+------------------------------           F(  1,     6) =    0.28
   Model |   .79268416     1   .79268416           Prob > F      =  0.6163
Residual |  17.0437349     6  2.84062249           R-squared     =  0.0444
---------+------------------------------           Adj R-squared = -0.1148
   Total |  17.8364191     7  2.54805987           Root MSE      =  1.6854

------------------------------------------------------------------------------
      sd |      Coef.   Std. Err.       t     P>|t|       [95% Conf. Interval]
---------+--------------------------------------------------------------------
ageclass |  -.0137381   .0260065     -0.528   0.616      -.0773737    .0498976
   _cons |   4.741451   1.792375      2.645   0.038       .3556669    9.127235
------------------------------------------------------------------------------

END MOFEP
```

Appendix II.3

ANALYSIS OF DIAMETER - LAND TYPE RELATIONSHIP

```
. oneway ANOVA dbh_cm  landis_landtype,  bonf


                        Analysis of Variance
    Source              SS         df      MS            F     Prob > F
------------------------------------------------------------------------
Between groups      1580.37131      6   263.395218      9.98     0.0000
 Within groups      16841.6476    638   26.3975667
------------------------------------------------------------------------
    Total           18422.0189    644   28.6056194

Bartlett's test for equal variances:  chi2(6) =   4.2698  Prob>chi2 = 0.640


                Comparison of (mean) dbh_cm by (mean) lnds_elt
                                (Bonferroni)
Row Mean-|
Col Mean |          1          2          3          4          5          6
---------|------------------------------------------------------------------
       2 |    2.13436
         |      0.000
         |
       3 |    4.06816     1.9338
         |      1.000      1.000
         |
       4 |   -4.78107   -6.91543   -8.84923
         |      0.003      0.000      0.015
         |
       5 |   -1.73449   -3.86886   -5.80265    3.04658
         |      1.000      0.001      0.388      0.868
         |
       6 |   -2.42484    -4.5592     -6.493    2.35623   -.690345
         |      1.000      0.014      0.292      1.000      1.000
         |
       7 |   -2.17221   -4.30657   -6.24037    2.60886   -.437719    .252626
         |      1.000      0.619      0.807      1.000      1.000      1.000
```

Appendix II.4 Judgment-based analysis of potential climate conditions for acorn production (na = data not available, 1 = positive influence, -1 negtive, 0 = no opinion)

Year	Freeze (negative)	Warm-Cool (positive)	Percent Relative Humidity (negative or Positive)	Year	Freeze (negative)	Warm-Cool (positive)	Percent Relative Humidity (negative or positive)
1918	-1	0		1964	0	0	1
1919	-1	0		1965	0	0	na
1920	0	0		1966	0	0	na
1921	0	1	-1	1967	0	1	na
1922	0	0	-1	1968	0	0	na
1923	0	0	-1	1969	-1	0	na
1924	0	0	0	1970	-1	0	na
1925	0	1	1	1971	0	0	na
1926	0	0	1	1972	-1	0	na
1927	-1	0	-1	1973	0	0	na
1928	0	0	1	1974	0	0	na
1929	0	0	-1	1975	0	0	na
1930	-1	0	-1	1976	-1	0	na
1931	0	0	-1	1977	0	0	na
1932	0	1	1	1978	0	0	na
1933	0	0	-1	1979	0	1	na
1934	-1	0	1	1980	0	0	na
1935	0	1	-1	1981	0	0	na
1936	-1	0	1	1982	-1	0	na
1937	0	0	-1	1983	-1	0	na
1938	0	0	-1	1984	0	0	-1
1939	0	0	1	1985	0	0	-1
1940	0	0	1	1986	0	0	1
1941	0	0	-1	1987	0	0	1
1942	0	1	-1	1988	0	0	1
1943	0	0	-1	1989	0	1	1
1944	0	0	-1	1990	0	0	-1
1945	0	0	-1	1991	0	0	-1
1946	0	1	-1	1992	0	0	1
1947	0	0	1	1993	-1	0	-1

1948	0	1	0
1949	0	0	1
1950	0	0	1
1951	0	0	1
1952	0	0	1
1953	-1	0	1
1954	0	1	1
1955	0	1	1
1956	-1	0	1
1957	0	0	1
1958	0	0	1
1959	0	0	1
1960	0	0	1
1961	0	1	-1
1962	0	0	1
1963	-1	0	1

1994	0	1	1
1995	0	0	-1
1996	0	0	-1
1997	-1	0	1
1998	0	0	-1
1999	0	0	-1