A recursive multiple regression model for predicting yields of grade lumber from lodgepole pine sawlogs

Andrew F. Howard
Robert Gasson

Abstract

A study was conducted to determine the efficacy of an alternative to least squares methods for fitting regression models to lumber grade yield data. A method based on a simultaneous system of equations was used to specify the regression model. The system of equations was fitted using techniques suitable for models with limited dependent variables. The regression model was used in a study of value loss from beetle-killed timber for four sawmills with unique product lines. The method was shown to give accurate predictions of the yields of individual grades. The rate of decline in recoverable lumber value from dead lodgepole pine trees (with years-since-death) is faster for board mills compared to dimension and stud mills.

Models for predicting the yields of individual grades of lumber from sawlogs are useful to sawmill personnel for a variety of planning activities. In particular, log pricing, production scheduling, and lumber marketing benefit from accurate estimates of lumber grade yields from logs. Historically, a wide range of techniques have been used in the analysis of lumber grade yield data. Most often, yields are simply tabulated as percentages of total green or dry lumber yield, although regression analysis has been tried. Recently, regression techniques have increased in popularity (5,14-16). In these studies, data from many mills were pooled so the results reflect an industry average and should not be used to model the performance of individual mills.

Least squares (LS) regression procedures are most commonly employed for fitting models to predict lumber grade yield from logs. Lumber grade yield data have characteristics that violate various assumptions underlying LS methods. Models fit to these data with LS techniques result in predictions that contradict physical fact, and demonstrate bias and other statistical aberrations. The need exists for exploratory research to identify alternative statistical procedures that address the unique problems associated with fitting regression models to lumber grade yield data.

The objective of the study reported here was to investigate the use of an alternative statistical method for use on lumber grade yield data, and to develop regression models for predicting yields of grade lumber from lodgepole pine sawlogs (*Pinus contorta* var. unspecified) for individual mills. A method based on a simultaneous system of equations was used to specify the regression model. The system of equations was fit using techniques suitable for models with limited dependent variables. The regression model was demonstrated in an analysis of potential value loss from beetle-killed timber for four sawmills with unique product lines.

Lumber yield data

The data used in the study were provided by the USDA Forest Service, Pacific Northwest Research Station. These data were collected in conjunction with its timber quality research program during studies designed to examine the effect of the passage of time on lumber grade recovery in beetle-killed lodgepole pine (2). Two random-length dimension mills, a board mill, and a stud mill participated in the study. The mills were located in three states: Wyoming, Montana, and Oregon. The stud mill had a four-saw scragg headrig and a combination edger. One of the random-length dimension mills had a chipping headrig; the other a circular saw with a battery edger. The board mill was a conventional band mill with a linebar resaw. Summary data on the sample of logs processed at each mill are shown in Table 1. The logs were manufactured into the products normally produced from lodgepole pine at the mills (2).

The authors are, respectively, Assistant Professor and Research Technician, Harvesting and Wood Sci., Univ. of British Columbia, Faculty of Forestry, 2357 Main Mall, Vancouver, BC, Canada V6T 1W5. This paper was received for publication in November 1987.

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TABLE 1. — *Summary data for the sample of logs, by origin.*

	Mill			
	Montana board	Montana dimension	Wyoming dimension	Oregon stud
	Scaling diameter (in.)			
Maximum	15.2	10.3	15.0	12.0
Minimum	6.7	3.6	2.7	3.0
	Length (ft.)			
Maximum	16.8	20.8	18.0	58.0
Minimum	8.3	6.2	8.0	7.0
	No. of logs			
Years-since-death class[a]				
0	174	349	329	77
1	3	17	366	71
2	10	60	4	72
3	39	70	13	82
4		34	7	84

[a] Years-since-death class 0 contains live trees only.

TABLE 2. — *Distribution of lumber yield (BF) by grade and origin.*

	Mill			
Lumber grade	Montana board	Montana dimension	Wyoming dimension	Oregon stud
	(BF)			
C and Better	851	3	0	0
D select	237	5	0	0
Moulding	0	0	44	0
No.1 Common	1,586	55	117	0
No.2 Common	5,348	332	393	0
No.3 Common	4,921	423	1,889	0
No.4 Common	1,198	180	1,450	0
No.5 Common	42	83	1,204	0
Select structural	0	2,823	2,535	0
No. 1	0	1,992	1,973	0
No. 2	0	3,800	3,651	0
No. 3	0	2,686	6,915	0
Economy	0	1,671	2,664	0
8-ft. stud	0	0	976	15,623
P.E.T. stud	0	0	0	6,090
Finger-joint	0	0	0	3,354
Economy stud	0	0	0	3,744

The lumber produced during the study was graded in the surfaced dried condition according to the standard grading rules published by the Western Wood Products Association. The distribution of lumber grades by mill is shown in Table 2. In addition to variations in the major product line, each mill employed a different manufacturing strategy depending on the market for chips. Mills with no market for chips attempted to convert larger portions of each log into lumber and so lumber recovery at these mills was higher (2). Mills with good markets for chips had lower lumber recovery. Differences in available markets led to variation in manufacturing practices, which in turn caused between-mill variation in product yields (grades of lumber and volumes of residue). Derivation of mill-specific lumber grade yield models provides the means for simulating the performance of individual mills.

Model development

Past research (11) showed that a logical and workable model for estimating lumber recovery (expressed in a variety of ways) was:

$$Y = b_1L + b_2DL + b_3D^2L + u \qquad [1]$$

where:

Y = variable of interest
D = log scaling diameter (in.)
L = log length (ft.)
b_1, b_2, b_3 = theoretical coefficients
u = error from regression

These researchers fitted the model to sawmill yield data using ordinary least squares (OLS) procedures after correcting for the effects of heteroscedasticity. This was done according to requirements for best linear unbiased estimation (BLUE), which for sawmill yield data was shown to necessitate division of the equation by D^2L.

This specification and method of estimation formed the basis for most of the work on regression models for lumber recovery. However, the approach must be modified in order to predict yields of individual grades of lumber. In particular, three attributes of lumber grade yield data must be considered when fitting these models:

1. Yields of individual grades are highly correlated;
2. Yields of individual grades have a truncated normal distribution with a lower bound of zero;
3. The sum of predicted yields of individual grades must equal the total lumber yield from the log.

Specification of the model as a recursive system of equations incorporates the high degree of correlation between lumber grades explicitly. A recursive system is defined as a simultaneous set of regression equations fitted one at a time in a logical sequence (1). Amateis et al. (1) used this approach for predicting multiple-product yields from weight-scaling data. They fitted the product with the most stringent requirements first, followed by individual products with decreasing restrictions (lower value). This approach can be applied to lumber grade yields by fitting a regression model to the highest grade first, followed by the lower grades in sequence. The model specification used in the study reported here is:

$$\begin{aligned} Y_1 &= b_1D^2L + b_2DL + b_3L + u \\ Y_2 &= b_4D^2L + b_5DL + b_6L + b_7Y_1 + u \qquad [2] \\ Y_3 &= b_8D^2L + b_9DL + b_{10}L + b_{11}(Y_1+Y_2) + u \\ &\vdots \\ Y_n &= b_{m-3}D^2L + b_{m-2}DL + b_{m-1}L + b_m(Y_1+Y_2 \ldots + Y_{n-1}) + u \end{aligned}$$

where:

Y_i = lumber yield grade "i"

A characteristic of sawmill yield data is that yields of individual grades from single logs are often zero, especially for the higher grades (Fig. 1). When regression analysis is applied to these data, the dependent variable is limited, consequently the error terms display a truncated normal or censored distribution (6). Use of LS methods on such data results in models that are biased (7), and can lead to distortion of the regression surface (12). For the case of a single lumber grade and one explanatory variable, the regression model is:

$$Y_i = \beta X_i + u_i \qquad [3]$$

where:

$u_i = N(0,\sigma^2)$

Only values for $Y_i > 0$ are observed, which suggests that:

$$\beta X_i + u_i > 0 \quad [4]$$

or,

$$u_i > 0 - \beta X_i \quad [5]$$

The expected value of u_i in Equation [5] is not zero and is clearly correlated with the explanatory variable. This violates the LS assumption that the error is an independent random variable distributed $N(0,\sigma^2)$. Furthermore, use of LS on such data leads to inconsistent estimates of the parameters.

The TOBIT procedure (12) represents an alternative to LS appropriate for models with limited dependent variables. For illustration, consider the TOBIT model for a single explanatory variable and lumber grade:

$$\begin{aligned} Y_i &= \beta X_i + u_i \text{ if } Y_i > \text{bound, and} \\ Y_i &= \text{bound otherwise} \end{aligned} \quad [6]$$

The bound is the point of truncation (zero for lumber grade yield data) and u_i is $N(0,\sigma^2)$. The TOBIT model is based on the assumption that the same parameters determine both the value of the dependent variable when it is greater than the bound, and the probability that it is at the bound (8). Expected values for the TOBIT model are computed as:

$$E[Y_i] = X_i B_i F(Z) + \sigma f(Z) \quad [7]$$

where:

F = normal cumulative distribution function, $N(0,\sigma^2)$
f = the corresponding normal density function
X_i = vector of explanatory variables
B_i = vector of parameter estimates from TOBIT
$E[Y_i]$ = expected value of the yield of lumber grade i
Z = $X_i B_i/\sigma$

Another problem with models derived using LS, which is related to the distribution of the dependent variable, is that predictions include negative volumes for some grades. This is problematic for two reasons. First, potential users may be skeptical of formulas that yield meaningless results (contradict physical fact). Secondly, if LS coefficients are used, it is not clear how to treat the negative values; they could either be set equal to zero or added to the total yield for the grade. Use of TOBIT models avoids this problem because predictions based on Equation [7] must be positive.

The necessity of the sum of the yields of individual grades equaling the total yield observed from the log was addressed in the manner employed in earlier studies (1, 3). These researchers predicted the yields of the more valuable products directly, and obtained the yield of the final product by subtraction. In the study reported here, all but the lowest lumber grade (or aggregate class) were fitted. An equation to predict the total board foot (BF) yield from logs was also fitted for each mill using OLS. Dummy variables were included in the total yield models for each mortality class to show volume loss through time from deterioration. The yield of the final grade was determined by subtracting the sum of the yields for all higher classes from the prediction of the total yield from the log.

Regression analysis

The model specification shown in Equation [2] was expanded to include dummy variables for each mortality class. Interaction terms were specified for each of the explanatory variables in the basic model, including the cumulative yield variable starting with the equation for the second lumber grade. Regression models were fitted separately for each mill.

Parameters were estimated with the TOBIT procedure in the SHAZAM econometric statistical package (13). A modified, backwards elimination technique was used to determine the final model specification. At each step, the t-ratios of the coefficients were examined,

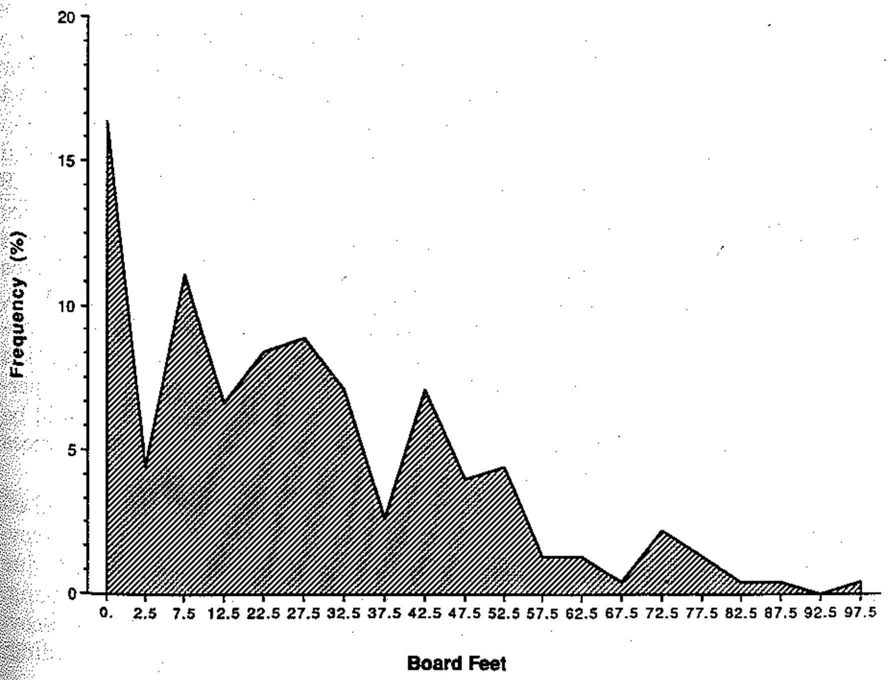

Figure 1. — Plot of percent of No. 2 Common lumber produced from single logs in a Montana board mill.

TABLE 3. — *Lumber grades for which equations were fitted.*[a]

Lumber grade	Mill: Montana board	Montana dimension	Wyoming dimension	Oregon stud
C and Better	×			
D Select	×			
Moulding				
No.1 Common	×		×	
No.2 Common	×	×	×	
No.3 Common	×	×	×	
No.4 Common	×	×	×	
No.5 Common	+	×	×	
Select structural		×	×	
No. 1		×	×	
No. 2		×	×	
No. 3		×	×	
Economy		+	+	
8-ft. stud			×	×
P.E.T. stud				×
Finger-joint				×
Economy stud				+

[a] × = regression fit; + = yield found by difference.

and the variable with lowest t-value was discarded. A regression equation was accepted when all t-values were greater than or equal to 1.2 ($\alpha = .15$). A relatively large significance level was chosen in an attempt to obtain equations with greater precision (minimum standard error from regression).

The estimating sequence for each mill began with the highest grade produced by the mill. In some instances, there was insufficient lumber volume for an individual grade to permit fitting. In these cases, yields of two or more grades were aggregated and the model was fitted to the combined lumber class. Table 3 shows a summary of the lumber grades for each mill for which equations were fitted.

Marketing strategies influenced the relative yields of individual grades at all of the mills. The board mill tried for No. 2 Common and better and the dimension mills No. 2 and better. No deliberate attempt was made to increase the yields of higher grades at any of the mills, so the relative yields are not necessarily indicative of the potential recovery from the sample logs.

Results and discussion

The results of the study are presented in two parts. First, the ability of the regression equations to fit the sample data is demonstrated. Second, the regression models are used to examine the potential effect of mortality class on lumber grade recovery and value. Actual prices were used in an attempt to quantify the decline in value experienced by an individual mill processing a specific tract of timber at a particular point in time. This approach presumably reflects practices of sawmillers engaged in timber appraisal and is not appropriate for assessing long-term trends in loss of value.

Tables 4 and 5 show predicted and observed lumber grade yields and values for the board mill and one of the dimension mills by mortality class. Lumber value was determined by multiplying a representative price for each grade by the corresponding grade yield. Lumber prices were taken from a trade newsletter (10). Prices for adjacent grades were used for grades not reported separately in the newsletter. For the board mill, the total value of predicted yields for all grades and mortality classes was only 3 percent less than the actual value. The regression model shows downward bias for upper grades. For many of the grades, the predicted and actual yields are extremely close. Results for the Montana dimension mill are less impressive. Total predicted value was 11 percent less than the actual. The greatest discrepancy resulted from a 1,007.51 BF shortfall in select structural for live logs. For all other grades in every mortality class, predicted and actual yields were close. This held true even for grades and mortality classes with very small yields. The results for the remaining dimension mill showed a 14.4 percent overprediction of value. For this mill, the model overestimated the yield of select structural for the 1-year-since-death class by more than 1,000 BF (246%). Otherwise, the predicted and actual yields were similar. The Oregon stud mill showed a 2.9 percent underestimation of value. All yields and values were extremely close. The total value of lumber for the actual yields for all mills, grades, and mortality classes was $15,547.34; the predicted value was $15,597.88, which indicates that, on the whole, the prediction system fits the data reasonably well. Further aggregation of the yields of individual grades might improve the performance of the system. In application, this would be desirable to reflect more closely the marketing practices at individual mills.

The models were used to estimate the potential effect of mortality class on lumber yield and value recovery. Lumber degrade can occur following mortality due to bark beetle attack from decay, checking and splitting, and the spread of the blue stain fungus. Lumber recovery may decrease slowly while the tree is still standing,

TABLE 4. — *Predicted and observed yield and value, Montana board mill.*[a]

Mortality class and lumber grade	Yield: Observed	Yield: Predicted	Value: Observed	Value: Predicted
0 years since death	(BF)		(total $)	
C and Better	851.00	661.93	702.08	546.09
D Select	237.00	166.36	195.52	137.25
No. 1 Common	1,571.00	1,031.17	573.41	376.38
No. 2 Common	5,042.00	5,099.03	1,840.33	1,861.14
No. 3 Common	3,154.00	3,901.32	825.79	916.81
No. 4 Common	594.00	536.92	98.01	88.59
No. 5 Common	21.00	447.28	3.46	73.80
Total	11,830.00	11,844.01	4,238.61	4,000.07
1 year since death				
No. 2 Common	11.00	0.00	4.01	0.00
No. 3 Common	86.00	96.60	20.21	22.70
No. 4 Common	6.00	0.00	0.99	0.00
No. 5 Common	0.00	7.69	0.00	1.27
Total	103.00	104.29	25.21	23.97
2 years since death				
No. 1 Common	7.00	0.00	2.56	0.00
No. 2 Common	33.00	57.16	12.05	20.86
No. 3 Common	215.00	186.72	50.53	43.88
No. 4 Common	193.00	193.58	31.84	31.94
No. 5 Common	5.00	28.81	0.82	4.75
Total	453.00	466.27	97.79	101.44
3 years since death				
No. 1 Common	8.00	0.00	2.92	0.00
No. 2 Common	262.00	268.15	95.63	98.87
No. 3 Common	1,106.00	1,113.93	259.91	261.77
No. 4 Common	405.00	427.87	66.82	70.60
No. 5 Common	16.00	533.41	2.64	88.01
Total	1,797.00	2,343.36	427.92	518.26

[a] Predicted values are reported as zero for models found to be nonsignificant.

TABLE 5. — *Predicted and observed yield and value, Montana dimension mill.*[a]

Mortality class and lumber grade	Yield		Value	
	Observed	Predicted	Observed	Predicted
0 years since death	(BF)		(total $)	
No. 2 Common	364.00	234.05	132.86	85.43
No. 3 Common	266.00	250.36	62.51	58.84
No. 4 Common	53.00	41.98	8.74	6.93
No. 5 Common	53.00	63.10	8.74	10.41
Select structural	2,750.00	1,742.49	693.00	439.11
No. 1	1,825.00	1,676.30	346.75	318.50
No. 2	2,781.00	3,047.87	528.39	579.10
No. 3	876.00	740.18	79.72	67.36
Economy	789.00	1,758.81	31.56	70.07
Total	9,757.00	9,548.14	1,898.28	1,635.73
1 year since death				
No. 2 Common	8.00	0.00	2.92	0.00
No. 3 Common	8.00	0.00	1.88	0.00
No. 4 Common	3.00	0.00	0.50	0.00
No. 5 Common	5.00	0.00	0.50	0.00
Select structural	21.00	0.00	5.29	0.00
No. 1	31.00	0.00	5.89	0.00
No. 2	155.00	201.40	29.45	38.27
No. 3	81.00	46.36	7.37	4.22
Economy	27.00	93.23	1.08	3.73
Total	328.00	340.99	55.20	46.21
2 years since death				
No. 2 Common	10.00	0.00	3.65	0.00
No. 3 Common	61.00	74.11	14.34	17.42
No. 4 Common	45.00	34.24	7.43	5.65
No. 5 Common	11.00	0.00	1.82	0.00
Select structural	47.00	0.00	11.84	0.00
No. 1	35.00	0.00	6.65	0.00
No. 2	418.00	421.29	79.42	80.05
No. 3	639.00	628.25	58.15	57.17
Economy	185.00	386.93	7.40	15.48
Total	1,451.00	1,544.82	190.69	175.76
3 years since death				
No. 2 Common	13.00	0.00	4.74	0.00
No. 3 Common	59.00	48.50	13.86	11.40
No. 4 Common	61.00	60.45	10.06	9.97
No. 5 Common	11.00	0.00	1.82	0.00
Select structural	5.00	0.00	1.26	0.00
No. 1	101.00	100.60	19.19	19.11
No. 2	328.00	336.07	62.32	63.85
No. 3	780.00	790.99	70.98	71.98
Economy	406.00	417.28	16.24	16.69
Total	1,764.00	1,645.89	200.48	193.01
4 or more years since death				
No. 3 Common	29.00	0.00	6.82	0.00
No. 4 Common	18.00	0.00	2.97	0.00
No. 5 Common	3.00	0.00	0.50	0.00
Select structural	0.00	0.00	0.00	0.00
No. 1	0.00	245.29	0.00	46.61
No. 2	118.00	161.11	22.42	30.61
No. 3	310.00	173.52	28.21	15.79
Economy	264.00	168.72	10.56	6.75
Total	742.00	748.64	71.47	99.75

[a] Predicted values are reported as zero for models found to be non-significant.

TABLE 6. — *Effect of years since death on lumber value recovery.*

Mortality class	Aggregate lumber value			
	Montana board	Montana dimension	Wyoming dimension	Oregon stud
	($)			
0 years	3,896.95	1,635.73	1,774.51	790.29
1 year	2,187.53	1,260.10	1,675.91	713.80
2 years	2,004.67	1,078.81		714.68
3 years	2,563.68	993.82		599.69
4 years		998.98		

but once the tree has fallen, recoverable yield declines rapidly. Lumber recovery may not be affected even by long periods between death and harvest, provided the trees remain standing (9). Decline in grade recovery, on the other hand, can begin immediately following attack by the beetle. Blue stain may appear within a tree very soon after the start of beetle attack and stain most of the sapwood within 1 year of tree mortality (4). While checks and splits may affect the strength of lumber, blue stain affects only its appearance, although the stain may mask other defects. Since boards are graded on appearance, the value of boards recovered from beetle-attacked trees declines rapidly following tree death. The less rapid decline in the value of dimension lumber, including studs, is related to the development of splits and cracks as the tree dries out following death (2).

Table 6 shows the predicted effect of the number of years since death on the value of the lumber in the sample for each mill. The board mill showed a 34 percent decline in lumber value after 3 years. The loss is directly attributable to the reduction in yield of No. 2 Common and better lumber. This finding corroborates earlier studies (2) in which blue stain was identified as the principal cause of degrade. Value loss in the dimension and stud mills was less rapid and more evenly distributed over the mortality classes.

Inconsistencies in the trend of value loss with time-since-death are shown for three of the four mills. These apparent abberations indicate that while the regression technique used can fit satisfactory models for small sample sizes (Table 4, 1- and 2-yr. mortality classes), the sample may not be appropriate for predicting overall trends for the population. In other words, these inconsistencies are data-dependent rather than an indication that the estimating technique is unsatisfactory.

Conclusions

Specification of lumber grade yield models as a simultaneous system of equations and fitting the models using techniques suitable for data with limited dependent variables is a promising alternative to traditional LS procedures. This approach resolves both theoretical and practical problems that arise when LS methods are used to fit lumber grade yield equations. Models derived using this new technique can provide accurate estimates of the yields of individual grades for relatively small populations of logs. The method was shown to give satisfactory results for mills with widely different product lines.

The rate of decline in recoverable lumber value from dead lodgepole pine trees with years-since-death depends on the relative values of the different lumber grades. Dimension mills can lose almost half the value of trees within 2 years of mortality. Even stud mills may lose nearly one-fifth of the value within 4 years of mortality. Board mills can lose nearly one-half of the value in the first year. Overall lumber recovery declines slowly while trees are standing, but value drops much more quickly. The findings demonstrate the importance of timely salvage of beetle-killed stands and the need to incorporate estimates of value and volume loss into planning activities.

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Researchers study effects of stress on oak trees

The drought of 1988 could lead to larger than usual populations of gypsy moths in the next few years, Penn State researchers predict.

"Pest outbreaks have been widely associated with times of drought," said Jack Schultz, assistant professor of entomology. "But this long-held view has never been tested in any rigorous way."

He and Marc Abrams, assistant professor of forest ecology and physiology, have received a $300,000 grant from the National Science Foundation for a study on stress-mediated interactions among oaks, the gypsy moth, and a baculovirous. The funding runs through 1991.

The researchers are using two oak species, northern red oak and chestnut oak, at the seedling and sapling stages to study the effects of different amounts of nutrients (fertilizers) and water on the oaks. The stress levels vary according to the amounts of nutrients and water.

"We are examining the effect of moisture and nutrient treatments on the physiology of the trees, including the rate of photosynthesis and the changes in leaf chemistry," Abrams said.

Abrams, a specialist in oak physiology, is concentrating on what drought does to a plant to make it more susceptible to pests. Schultz, a chemical ecologist, is focusing research on what chemical changes a plant may undergo as a result of drought. Schultz is conducting some of his research at his 120-acre Wind Ridge Farm, where he has planted more than 70 oaks that are now 5 feet tall.

Schultz said, "We don't know what causes a pest outbreak, but we think it may be due to the leaves' increased attractiveness to pests. When a tree is stressed, it may be less able to produce protective chemicals to prevent pests from eating its leaves.

"One theory is that if the food quality is good enough, gypsy moths will lay more eggs, causing an outbreak the next spring. In this situation, the mechanisms for eliminating the caterpillars cannot keep pace with the population explosion."

Trees respond to drought by increasing the nutrients and sugars in their cells, a process known as osmotic adjustment. This would increase the food quality of the leaves.

Alternatively, some plants increase their defensive compounds when stressed. The gypsy moths, in turn, would then be eating leaves with higher amounts of defensive compounds in them, such as tannins and other phenolic compounds, and using these defensive compounds to protect themselves against the virus.

The researchers think the increased nutrients, sugars, and defensive compounds found in leaves as a result of drought actually increase the suitability of the trees for the gypsy moth, resulting in a population explosion.