Abstract. *Qualitative modelling can help us understand and project effects of multiple stresses on trees. It is not practical to collect and correlate empirical data for all combinations of plant/environments and human/climate stresses, especially for mature trees in natural settings. Therefore, a mechanistic model was developed to describe ecophysiological processes. This model is qualitative and incorporates symbolic descriptions of important variables and their relationships. Fuzzy values, such as "zero," "low," "moderate," etc., are used to express quantity and change in the model. A current application of this fuzzy variable model examines the interaction of drought and ozone stresses on a mature ponderosa pine tree. As new empirical results become available, the model can be modified to include realistic baseline values and specific mathematical relationships.*

Simulation of Plant Physiological Processes Using Fuzzy Variables

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Changes in the global environment, such as increases in air pollutants, could profoundly affect the distribution and composition of forests. Anticipated changes include increased levels of air pollutants. Early prediction of forest ecosystem responses to air pollutants is needed to provide lead time for planning (Pathak et al. 1986). If exposure-response relationships are sufficiently understood, major biological, social, and economic impacts (Crocker and Forster 1986) may be avoided by controlling establishment of new pollution sources (e.g., Fox et al. 1989) or by reducing current sources to acceptable levels. The interactions among factors that influence forest health are complex, however, and it will be difficult to predict accurately the combined effects of different stresses without understanding the underlying physical, chemical, and biological processes that operate throughout the atmosphere, plant, and soil.

Ultimately, scientists and managers need to know the regional impacts of climate change and air pollutant impacts on vegetation. Before extrapolating to this level, however, it is necessary to understand how various stresses affect individual plants at specific locations

(Fosberg 1990). We must understand how individual plants respond to environmental influences before we can deal with the aggregations in communities and landscapes.

Numerous authors have recommended modelling in conjunction with laboratory experiments and field studies of forest responses (e.g., Bockheim 1983, Kulp 1987, McClenahen 1983, McLaughlin and Bräker 1985, Reich 1987). There is a continuum of mathematical models ranging from empirical to mechanistic (Isebrands et al. 1990, Olson et al. 1985). The former require large amounts of experimental data and are applicable only to calibration data sets (Dale et al. 1985). Mechanistic models, on the other hand, use descriptive relationships of biological function. Krupa and Kickert (1987) summarize a number of the attempts at mechanistically modelling air pollution effects. Isebrands et al. (1990) comprehensively review mechanistic growth models and describe a process-based model of juvenile *Populus* growth. In our work with ponderosa pine *(Pinus ponderosa* Dougl. ex Laws), I chose a process approach because of its great flexibility in explaining a variety of tree response phenomena (Dahlman 1985).

This paper discusses several topics related to simulation of physiological processes. First, recent efforts to model tree response to stresses are reviewed briefly. Qualitative models are proposed as a way to handle complexity and gaps in knowledge. Second, our modelling approach uses an *influence model* of environmental factors and physiological processes. Third, as a critical aspect of this ecophysiological influence model, fuzzy numbers represent *quantity* and *change* values for each parameter of the model. The mathematics of combining influences and updating parameter values over time is described. Finally, I indicate how this modelling approach is being applied to an individual tree model of ponderosa pine response to stresses.

Physiological Processes

Process-level models for study of environmental impacts on tree growth generally have focused on one of five broad topics (Dixon 1990): 1) vegetative and reproductive growth; 2) photosynthesis, respiration, and carbon allocation; 3) mineral metabolism; 4) growth regulation; or 5) transport of metabolizes. Except for Isebrands et al. (1990) and Chen and Gomez (1990), few have attempted to model most of these five aspects simultaneously. Because each aspect is important for understanding and projecting a tree's combined response to its environment, future modelling efforts should attempt to consolidate these separate components.

Numerous difficulties are associated with creating a large mathematical model of complex physiological processes (Dixon 1990). Experimental results from studies of juveniles must be extrapolated to the function of mature individuals, many assumptions and simplifications must be incorporated to accommodate mathematical specification, and biological accuracy can be lost in complex process models. More pragmatically, all important relationships in an ecosystem model of atmosphere-plant soil (A-P-S) interactions may never be quantified; but there is an urgency to understand and act upon our best intuition now (Bormann 1985). Because the level of detail included in a model is linked to its end use (Wisiol and Hesketh 1987), we may be able to produce greatly simplified yet useful models if we can moderate our expectations for them.

Mathematical model simulations often yield numerical values that have questionable precision with respect to the magnitudes they represent. Often the purpose of these models is to indicate patterns or relationships for interpretation by a scientist or manager. If pattern discovery represents the end use of mathematical simulations, it is reasonable to simulate at a coarse resolution. Our current understanding of mechanistic processes can allow us to develop a less quantitative ecophysiological model with predictive and explanatory capability. Such an approach sacrifices precision for gains in generality and realism (Puccia and Levins 1985).

Qualitative models have properties that are analogous to their quantitative counterparts. Both types propagate values of state variables by way of interrelationships among model variables. The current value of a variable and/or its relationships to other variables determines the variable's value at the next time point during a simulation. Rather than propagating numerical values, however, qualitative models provide more general descriptions of state variables. Therefore, values such as "low," "mod-crate," "increasing," "steady," etc., or -, 0, + often reflect current scientific knowledge better than unrealistic numerical values and poorly understood correlative relationships.

In a model of the regulation of the human genes responsible for synthesizing the amino acid tryptophan, Karp and Friedland (1987) organized state variables according to their influences upon each other. Variables assume values such as 0, minimal, maximal, normal, equilibrium, or a value relative to some previous value in the simulation. This model permits several types of influences at varying degrees of resolution. Results of their simulations were consistent with molecular genetic theory (Round 1989).

An Influence Model

An A-P-S model of a mature ponderosa pine tree applies and extends the approach of Karp and Friedland (1987). I call it an "influence model." Others refer to a similar model paradigm as a "systems model" or a "system dynamics model." Quasi-numerical values and relationships propagate values of A-P-S components over time. In addition, specialized relationships are applied to situations in which component responses are not well defined or are dependent on other component processes. Therefore, a range of relationships between A-P-S components can be incorporated.

Both processes and descriptive conditions are considered in this model of plant functioning. For example, photosynthesis is a process and the ratio of new to old needle biomass is a descriptive condition. Processes operate at particular intensity levels in response to certain necessary conditions. Also, processes partially determine the levels of various conditions. For example, photosynthesis contributes to the level of carbohydrate accumulated in plant tissues, and open stomata are necessary for photosynthesis to occur. However, it would be inaccurate to characterize either of those interactions as causation. Therefore, the term "influence" is used because it connotes less direct interactions. Each system component is represented as a *parameter* in our model and can be described by a current value, or "quantity" and a current rate of "change." I refer to system components as parameters because the values of those components completely determine the state of the A-P-S system at any time point. Regardless of the parameter type (process or descriptive condition), one or more additional model parameter(s) may influence the quantity and change of that parameter. In models with a mathematical structure, mathematical functions would represent influences. However, a coarser and less restrictive representation of influences is adopted here. Taken in this sense, our influence model is a generalized form of traditional quantitative mechanistic models.

The partial influence diagram in Figure 1 displays some A-P-S parameters and some influences between parameters. A survey of the available literature on ponderosa pine physiology and consultation with a research scientist produced the model parameters. A preliminary list of parameters and their interactions has been created; a subsequent paper will describe the ponderosa model in greater detail. The primary concern here is with the modelling approach rather than with results.

A parameter description contains three attributes (Fig. 2): 1) a "quantity," which is the current value of the parameter in the simulation; 2) a measure of "change," which tells whether a parameter's value is increasing, decreasing, or steady; and 3) a list of "dependencies" that may have an influence on the parameter. Each dependency includes an indication of the direction (-, +) and strength (e.g., *low, high*) of an influencing parameter. Time of day influences a number of important parameters of interest (such as ozone concentration); that is, these parameters vary in circadian cycles. For example, the ozone concentration varies according to the amount of ultraviolet radiation, which, of course, varies over the course of a day.

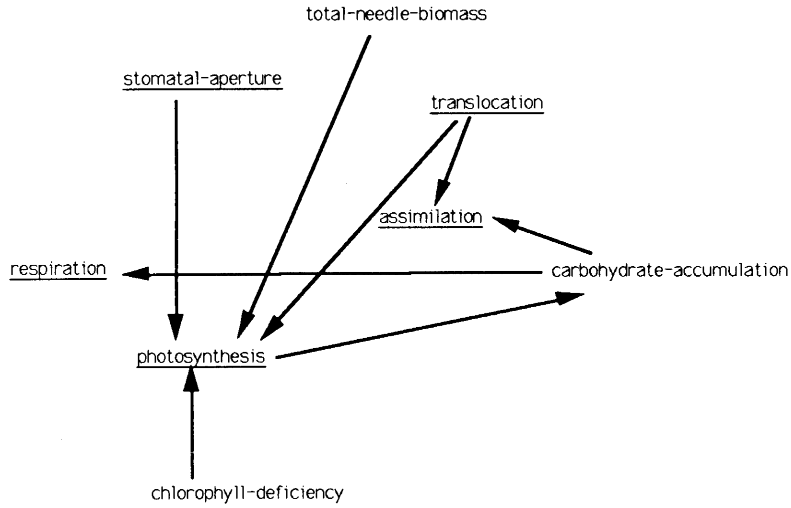

Figure 1. *A subset of a model's parameter set is shown along with arrows indicating influences between parameters. Parameters with an underlined typeface change at hourly intervals.*

Fuzzy Numbers

The attributes "quantity" and "change" of the translocation parameter take on linguistic values in Figure 2, *low* and *slightly-increasing*. These linguistic values can be used as *fuzzy numbers* for the variable attributes "quantity" and "change," and these attributes are then referred to as *fuzzy variables.* Fuzzy numbers are taken from Zadeh's theory of possibility (an extension of probability theory) and his idea of fuzzy sets (Zadeh 1965).

Suppose we have a set of diameter measurements from a population of ponderosa pine trees. We might describe a particular measurement as "large" and another one as "small." However, these are vague terms. There is no clear, non-arbitrary boundary between "large" and "small." Obviously, some measurements are going to be much greater than most others and we could say that these are "large." However, other measurements maybe both somewhat "small" and somewhat "large." To account for this vagueness, Zadeh's theory of possibility uses a membership function, μ_{large}, to assign a probability to each measurement reflecting its degree of membership in the fuzzy subset "large." This combination of membership function and measurement values is referred to as a *possibility* distribution. Similarly, a membership function μ_{small} could be defined for "small." For example, Table 1 contains a description of "large" and "small" diameters. Because each fuzzy subset is an independent categorization (such as large diameters or small diameters) of the measurement values, the membership degrees

```
Translocation

Quantity: LOW

Change:   SLIGHTLY-INCREASING

Dependencies: macronutrient-
              deficiency - LOW,
              respiration + HIGH
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Figure 2. *Each parameter contains certain minimal information that describes the state of the parameter and how it relates to other parameters.*

need not sum to unity as in traditional probability theory. A fuzzy representation allows us to talk about vague and uncertain quantities in an intuitive way and does not require that we know specific values in order to do so.

All fuzzy numbers for a fuzzy variable must be defined over some common base of numbers. If no natural basis exists, an arbitrary integer base can be used. For example, the fuzzy variable, “quantity,” in Figure 2 could be defined over the integers O, ...9. Then each fuzzy number that “quantity” might assume, e.g., *low,* is represented as a possibility distribution over those integers, as in the definition of *low* in Table 2. Figure 3 illustrates these ideas graphically; all fuzzy values used in the ponderosa pine model are portrayed. It is important to understand that fuzzy numbers are not exact values, but are descriptions of some vague entity, e.g., low, that we define using a measurement basis and a membership function.

Table 1. *Possibility distributions for the fuzzy sets “large diameters” and “small diameters” consist of diameter measurements and their associated membership values* $0\ \mu\ 1$.

diameter	μ_{large}	μ_{small}
5 cm	0.0	1.0
10 cm	0.2	0.8
15 cm	0.4	0.5
25 cm	0.7	0.1
35 cm	0.9	0.0
45 cm	1.0	0.0

Table 2. *The fuzzy numbers “low” and “slightly-increasing” are defined over the base of integers 0, ...,9 and -5, ... +5, respectively. For both fuzzy numbers, values greater than 3 and less than 0 have membership 0.0, and therefore are not listed.*

basis value	μ_{low}	$\mu_{slightly\text{-}increasing}$
0	0.6	0.6
1	1.0	1.0
2	0.6	0.4
3	0.2	0.0

The fuzzy numbers *zero* (a special fuzzy number to represent a negligible quantity of something), *low, moderate, moderately-high, high,* and *very-high* are defined as the range of “quantity” values that parameters may assume in this qualitative model.

Zadeh also included an extension principle that allows the calculation of mathematical functions of fuzzy numbers. In particular, the traditional arithmetic operations: +, -, *, /, and exponentiation are important. This extension principle becomes important when we combine influences and when we resolve the effect of influences to update parameter Quantities (Figure 2). As fuzzy numbers combine to produce changes in parameter “quantity” values overtime, it will be necessary to allow “quantity” values to both decrease and increase based on “change” values. Because the fuzzy variable, “change,” can be either increasing or decreasing, it will be necessary to use integers with some negative values in the basis. Therefore, the fuzzy variable, “change,” is defined over the basis -5, ... +5. So, *slightly-increasing* might be defined something like in Table 2. Nine linguistic values for “change” have been defined: *strongly-decreasing, decreasing, moderately-decreasing, slightly-decreasing, steady, slightly-increasing, moderately-increasing, increasing,* and *strongly-increasing.*

Calculations with Fuzzy Numbers

For describing arithmetic calculations with fuzzy numbers, I adopt the notation of Schmucker (1984). Thus, the fuzzy number *low* in Table 2 is equivalent to the set {0.6/0, 1.0/1,0.6/2,0.2/3}. More generally, we can define any fuzzy number A as:

$$A=\{a(i)/i \mid 0 \leq i \leq 9\} \quad (1)$$

where a(i) is a membership value and *i* is a basis value. Using this notation, we can define addition,

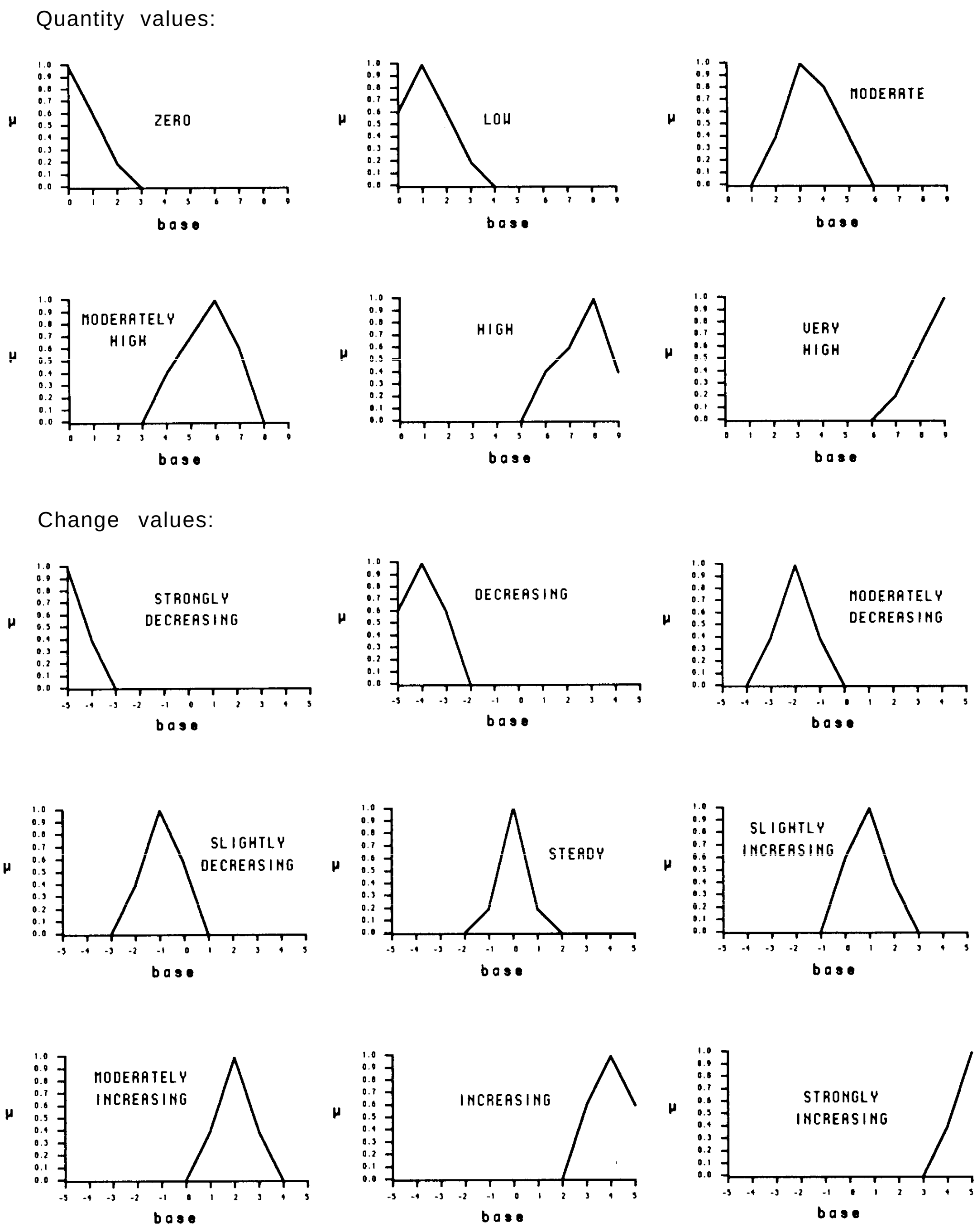

Figure 3. *Each fuzzy number, for both "quantity and" "change" variables, appears as a relationship between basis values, either 0, ...,9 or -5, ..., +5, and degrees of membership μ.*

subtraction, multiplication, division, and exponentiation as:

$$A + B = \{\min(a(i), b(i))/[i + j] \mid 0 \leq i,j \leq 9\}$$

$$A - B = \{\min(a(i), b(i))/[i - j] \mid 0 \leq i,j \leq 9\}$$

$$A * B = \{\min(a(i), b(i))/[i * j] \mid 0 \leq i,j \leq 9\} \qquad (2)$$

$$A / B = \{\min(a(i), b(i))/[i / j] \mid 0 \leq i,j \leq 9\}$$

$$\exp(A) = \{a(i)/\exp(i) \mid 0 \leq i \leq 9\}$$

For each of the binary operators f, the *min* operation in the above definitions computes one of the degrees of membership for $k=f(i, j)$ in the set f (A, B). Because this set is the union of all degrees of membership for all k, we can take the maximum membership value for each k (Schmucker 1984). These arithmetic operations produce fuzzy numbers that are defined over bases containing values not in the original basis. For example, A + B, where A and B are "quantity" values, is defined over the set of integers (0, ... 18}. Also, a, a non-fuzzy number, is equivalent to the set {1.0/a}. Therefore, when either A or B is a non-fuzzy number, the calculations still work properly to produce a fuzzy number. The *max* operation dissolves, however, because there is only one argument in each case.

Each of the last two fuzzy arithmetic operations in (2) produces basis values that are real numbers, rather than integers. In practice, integer approximations are often used to keep calculations manageable. However, this approximation can cause serious calculation errors, especially when a fuzzy number with basis values between 0 and 1 is used as a percentage for another fuzzy number. This is the case in our parameter update equations (7) and (8), below. Despite the additional computation required, it is essential for our application to maintain real number basis values during intermediate calculations.

Clements (1977) and others suggest that convexity and normalization operations be performed after fuzzy arithmetic calculations. Convexity ensures that there is only one basis value with greatest membership degree. In Figure 3, convexity corresponds to a graph with only a single maximum or peak. Normalization produces a fuzzy number where at least one basis value has a membership degree of 1.0; each of the graphs in Figure 3 is normal as well as convex. Schmucker (1984) presents a risk analysis application of fuzzy sets in which convexity and normalization are performed after each intermediate calculation. Our implementation of fuzzy numbers and arithmetic only performs those operations when translating a fuzzy number back to a linguistic term, e.g., *low, moderate,* etc. Applying convexity and normalization operations after each arithmetic calculation rather than after final calculations does not seem to alter the results in equation (8). It is therefore done only after the final calculations.

Fuzzy numbers, as presented in (1), do not convey much meaning to users of a qualitative model. Meaning is provided for users by translating calculated fuzzy numbers back into the set of linguistic terms defined initially. A three-step process is used to interpret any fuzzy number A. First, we truncate the set describing A to exclude any basis values outside the range specified for that type of fuzzy number. For the "quantity" value of a parameter, we would remove all values less than O or greater than 9. We round non-integer basis values to the nearest integer. Next, we apply the convexity and normalization operations to produce a fuzzy number *A';* this step permits us to compare *A'* to each fuzzy number, Z, in our range, i.e., *zero, low, moderate,* etc., which are also convex and normal. Finally, we use a procedure (Schmucker 1984) to map *A'* to our range of fuzzy numbers using Euclidean distance measure as in (3). Then, the linguistic term, Z, with the smallest Euclidean distance to *A'*, is our fuzzy number interpretation for *A'*.

$$\text{distance}(Z, A') = \left[\sum_{i=0}^{9} (z(i) - a'(i))^2\right]^{1/2} \qquad (3)$$

Combining Influences

Most parameters are influenced by more than one parameter. Consequently, our fuzzy variable model must contain some mechanism to aggregate those influences into the combined effect on a parameter of interest. The combined influences determine the "quantity" and "change" values of the parameter for the next time interval. The level of influence assigned to each influencing parameter, as in Figure 2 *(low, high),* allows the model to recognize multiple influences acting differentially on a single parameter. Each influence that is active for a particular parameter at a particular time point operates on that parameter independently. Precondition specifications for each influence may accommodate any need for dependencies between influences.

For simplicity, let us assume that there is only one influence on a particular parameter, *P (e.g.,* respiration in Fig. 1). The influencing parameter, *I* (in this case carbohydrate accumulation), has a particular value for "change," from the preceding time interval. Our description of respiration contains a strength value, *s,* which indicates how strongly carbohydrate accumulation "change," affects respiration "change," *P.* The strength value may be one of the fuzzy numbers: *low, moderate, moderately-high, high, very-high.* Whens is *very-high,* then the "change" value of respiration should be identical to that of carbohydrate accumulation, i.e., they vary coincidentally. For values ofs less than *very-high, P* should be some fraction of The following expression describes this relationship:

$$\Delta P = (s/\textit{very-high}\ )\ \Delta I = w\ \Delta I \tag{4}$$

The weight, w, for any influence on a parameter is represented by the strength value,s, divided by the value *very-high* (the maximum strength value).

To determine a parameter's new "change" value when several influences are acting upon it, we calculate the fuzzy average of all active influences. This calculation can be expressed as:

$$\Delta P = (\sum_j w_j \cdot \Delta I_j\ )\ /\ j \tag{5}$$

The weights, *wj,* incorporate differential influences by parameters. In effect, we are averaging weighted influences. Each strength value modifies its corresponding influence rather than specifying the relative contribution of each influence to the total. This mechanism for combining influences has three obvious consequences: 1) positive (increasing "change") and negative (decreasing "change") influences tend to "cancel" each other out, 2) a small (near *steady)* "change" value for any particular parameter moderates the influence of other parameters, and 3) both the magnitude of "change" for an influencing parameter and the strength value for that influence affect the final "quantity" value of an influenced parameter. Specialized accumulator functions for any parameter or preconditions that determine whether particular influences are active can accommodate exceptions to this method (5) for combining influences.

Updating Parameter Quantities

Once we have calculated the net influence *P)* arising from all active influences, we must apply *P* to calculate a new value for the parameter "quantity," *P*. A nonlinear, sigmoid activation function, such as (6), is often used in situations where asymptotic change is desirable. Figure 4 illustrates this asymptotic property (Wasserman 1990) of equation (6). The "quantity" value changes very gradually at large negative and large positive values of net influence— where *P* is near *strongly-decreasing* or *strongly-increasing.* Also, net influence values near, but not equal to, *steady* result in an abrupt change away from *moderate* "quantity" values, *F P),* because the slope of the function in this neighborhood is relatively steep.

$$F(\Delta P) = 1/(1 + e^{-\Delta P}) \tag{6}$$

To calculate a new "quantity" value Q_{new} of a parameter from a previous "quantity" value, Q_{old}, it becomes necessary to create *F',* a function of both Δ P and Q_{old}. There are several criteria for *F' P,* Q_{old}*).* First, the effect of a *steady* influence should be no change in a parameter's "quantity," i.e., $Q_{new} = Q_{old}$. Second, Q_{new} should be equal to Q_{old} plus a portion of the maximum possible value that Q_{old} can change. And third, the effect of the net influence, *P,* combined with Q_{old} should be asymptotic. In viewing Figure 5, the reader should note that Q_{old} is variable, and therefore moves along the *F P)* axis. The shape of the curve changes, but it remains asymptotic about the inflection point *(steady,* Q_{old}*).* We treat *P* <steady and *P* ≥ *steady* as separate

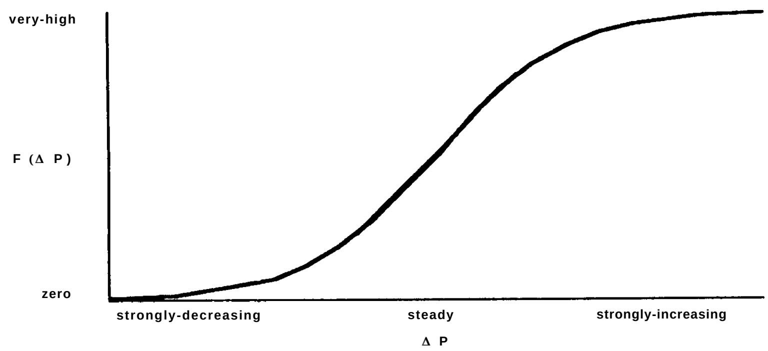

Figure 4. *The asymptotic nature of the logistic function (6) produces high sensitivity to influences near steady and reduced sensitivity near extreme influence values.*

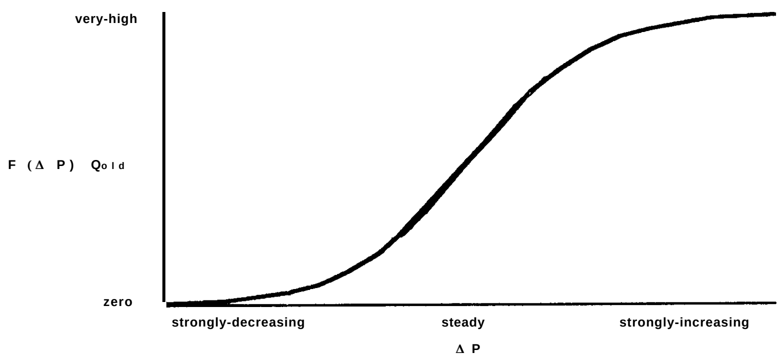

Figure 5. *The relationship between net influence P and the new "quantity" value F P) for the parameter should include the previous "quantity" value of the parameter, Q_{old}. However, Q_{old} is not a fixed quantity, and therefore we must consider F' P, Q_{old}).*

cases, because the maximum possible value that Q_{old} can change is different for each. Using Δ_{max} as the maximum possible value for change and using $(1 - e^{-\Delta P})$ or $(1 - e^{\Delta P})$ as the percentage modifiers (fuzzy numbers between O and 1), we can calculate Q_{new} as in (7).

$$Q_{new} = \begin{cases} Q_{old} + \Delta_{max}(1 - e^{-\Delta P}) & \Delta P \geq \textit{steady} \\ Q_{old} + \Delta_{max}(1 - e^{\Delta P}) & \Delta P \leq \textit{steady} \end{cases} \qquad (7)$$

When the net influence on a parameter is greater than steady, i.e., increasing, the maximum change, Δ_{max} for an influenced parameter would be the difference between its previous value Q_{old} and the maximum possible value *very-high*, i.e., Δ_{max} = *(very-high - Q_{old}).* When the net influence on a parameter is less than *steady, i.e.,* decreasing, the maximum change, Δ_{max}, for an influenced parameter would be $-Q_{old}$. Inserting the appropriate values of Δ_{max} into (7) and including a scale factor, α, into the exponent, P, we obtain the formula.

$$Q_{new} = \begin{cases} Q_{old} + (\textit{very-high} - Q_{old})(1 - e^{-\alpha \Delta P}) & \Delta P \geq \textit{steady} \\ Q_{old}\, e^{\alpha \Delta P} & \Delta P \leq \textit{steady} \end{cases} \qquad (8)$$

The scale factor, a ($0 < \alpha < 1$), flattens out the sigmoid curve to dampen the effect of P values. Without a scale factor, even small values of P (near *steady)* produce large differences between the old and new values of a parameter "quantity." Strength values,s, assigned to each influence, merge the differential influences of several parameters on a particular parameter. The combining function (5) incorporates these strength values. The scale factor, a, only serves to modify our combining function (8). A scale factor of 0.27 in (8) seems to produce intuitively acceptable values for updating parameter "quantity" values.

There are several things to notice about (8) and the values it produces:

1. When P equals *steady,* $Q_{new} = Q_{old}$.
2. When Q_{old} is near *zero,* $P >$ *steady* has a greater influence than a corresponding value of $P <$ *steady*.
3. Similarly, when Q_{old} is near *very-high,* a "change" value that is decreasing $P <$ *steady)* has a greater influence than a corresponding $P >$ *steady*.

Because (8) functions as in 2 and 3, above, "quantity" values tend toward "normal" or *moderate* values and away from extreme values *(zero, very-high).* Consequently, deviations from "normal" that result from parameter influences can be offset rather quickly by subsequent parameter influences. When Q_{old} equals 1/2 of *very-high,* the function $F' P, Q_{old})$ *is* symmetric about the value $P =$ *steady.* This function also meets the two following criteria: (1) as influence becomes very positive, Q_{new} approaches *very-high* and (2) as influence becomes very negative, Q_{new} approaches *zero.*

To provide the reader with a feel for the result of using fuzzy numbers and the mathematics presented above, Table 3 contains an application of these ideas. The fuzzy number definitions from Figure 3 are used in (8) to arrive at a fuzzy number describing the new "quantity" value resulting from a net influence (row) applied to an old "quantity" value (column). The Euclidean distance method of equation (3) produces a linguistic term that most closely approximates the fuzzy number calculated in (8). Each linguistic term so calculated appears as an entry in the table. The reader should bear in mind that the entries of Table 3 are only *approximations* of the actual fuzzy numbers calculated. Some information is lost in this simplification. Actual fuzzy numbers, rather than linguistic approximations, are maintained during simulation calculations.

Model Simulation

I have not presented a model of ponderosa pine in this paper; that effort is currently ongoing. Such a model has been developed, but it has not been completely implemented at this writing. In this report, an attempt has been made, however, to describe and to justify a new modeling methodology that we are applying to the problem of individual tree response to stresses. In this section I provide a glimpse into how we plan to use this methodology to answer environmental and physiological questions.

At each simulated clock tick (hourly), each parameter's "quantity" and "change" values receive new values. We have selected an hourly time frame to enable us to investigate differential plant responses for certain conditions that vary in an hourly fashion, e.g., peak versus chronic ozone exposure, radiation, temperature. Parameters that change over a different time frame (e.g., daily) change at appropriate multiples of hourly time. Throughout any given simulation day, light, soil moisture, and temperature operate as forcing functions (controlling parameters) and implicitly affect certain model parameters: ozone level, transpiration, stomatal aperture, photosynthetic rate, water flow, etc. These secondary parameters, in turn, affect the remaining parameters of the model.

Currently we are calibrating this model of ponderosa pine physiology to obtain "reasonable" simulations over the course of an "average" day. That is, without any damaging stresses active, a ponderosa pine tree should exhibit "normal" patterns of growth and senescence. Model parameter

Table 3. *Total fuzzy influence, P, (row) applied to the current "quantity,"* Q_{old}*, (column) produces a new current fuzzy "quantity,"* Q_{new}*, (entries). These entries are the best linguistic fit between the actual calculated value and the vocabulary of possible linguistic terms, and therefore are only approximate. Influence "change" terms are defined over the set of integers [-5, . . . , +5]. "quantity" terms are defined over the set of integers [0, ... 9].*

Total Fuzzy Influence *P*	Current Fuzzy Quantity Q_{old}: Zero	Low	Moderate	Moderately High	High	Very High
Strongly Decreasing	**Zero**	**Zero**	**Low**	**Low**	**Low**	**Low**
Decreasing	**Zero**	**Zero**	**Low**	**Low**	**Moderate**	**Moderate**
Moderately Decreasing	**Zero**	**Low**	**Low**	**Moderate**	**Moderate**	**Moderately High**
Slightly Decreasing	**Zero**	**Low**	**Moderate**	**Moderately High**	**Moderately High**	**High**
Steady	**Zero**	**Low**	**Moderate**	**Moderately High**	**High**	**Very High**
Slightly Increasing	**Low**	**Moderate**	**Moderate**	**Moderately High**	**High**	**Very High**
Moderately Increasing	**Moderate**	**Moderate**	**Moderately High**	**High**	**High**	**Very High**
Increasing	**Moderately High**	**Moderately High**	**High**	**High**	**Very High**	**Very High**
Strongly Increasing	**Moderately High**	**Moderately High**	**High**	**High**	**Very High**	**Very High**

values are considered "normal" when they are neither unusually elevated, such as *very-high* or *high* in the case of senescent characteristics (e.g., chlorosis), nor unusually depressed, such as *zero* or *low* in the case of growth characteristics (e.g., respiration). When this has been accomplished, we can then proceed to daily, weekly, monthly and seasonal simulations under similarly "normal" conditions. The results should be consistent with intuitive expectations of unstressed plant growth. Once "normal" conditions can be modeled with reasonable qualitative accuracy, then divergent diurnal scenarios can be investigated. These will include different background ozone levels, different peak ozone levels, variations in moisture stress, and various combinations of ozone exposure and moisture stress.

Stresses can exert influence over many different time frames. Plant responses to various diurnal schemes alone do not provide answers to exposure-response questions. Responses of greatest interest are those that occur as a result of physiological changes/adaptions over a growing season. These are the result of cumulative and continuous changes in plant processes in response to environmental stresses.

Parameters that change over longer time frames, e.g., total needle biomass, reproductive growth, vegetative growth, etc., should possess "quantity" and "change" values that reflect those long-term phenomena.

In addition to the scientific questions mentioned above, models at the stand and landscape levels may benefit from the results of this model. However, because the outputs of this model are not quantitative, its link to other models will be different. A qualitative model might distinguish differences in growth patterns associated with age or site or species; these different growth patterns might "suggest" adjustments to existing mathematical growth models. In turn, these mathematical models could simulate the growth of different age/site/species combinations. Analysis of long-term growth under these different scenarios may allow scientists to project competitiveness and distributional changes overlarge geographical areas. McBride et al. (1985) performed a similar exercise by comparing Douglas-fir and ponderosa pine in mixed stands. A qualitative model adapted to investigate genetic variations could be part of a similar analysis to project regional effects. While our model is designed to investigate scientific questions about individual tree responses, the modification of existing mathematical growth models (using the results of our qualitative simulations) and then the application of those growth models may provide results that forecast or permit the investigation of effects on a geographic scale.

Discussion

The modelling approach described above is an attempt to organize and explore many of the prevailing ideas that have surfaced in research on ozone effects on ponderosa pine. These ideas, or hypotheses, have resulted from basic research. Each experiment, however, can only investigate a small portion of the larger question of air pollution effects, effects that are often complicated by other environmental factors, such as moisture stress. A qualitative modelling approach synthesizes widely scattered knowledge about the mechanisms of air pollutant impacts to suggest how diverse interactions, both compounding and antagonistic, might alter tree responses to its environment. Developing an analogous, purely quantitative model would likely be impossible given our current state of knowledge in this area.

The parameter update scheme described in (8) is the default mechanism. In our work to date, however, I have noticed situations in which new parameter values may be calculated more realistically by applying heuristic rules rather than this fuzzy mathematics. Because our program implementation is object oriented, these special cases are easily accommodated. Fuzzy if-then rules can be stored at the appropriate location in an object hierarchy to implement exceptions to our standard update scheme.

Fuzzy numbers may cause some interpretation problems between scientists. Although fuzzy numbers are explicitly defined, as in Figure 3, there is no guarantee that most knowledgeable specialists will agree on those definitions. Every atmospheric deposition scientist understands 60 ppb (7 hr growing season mean) ozone exposure. On the other hand, if you ask each to provide a possibility distribution for low ozone exposure, there will likely be some discrepancies in their descriptions. Most, however, should be similar. Because the numbers used in our modelling methodology are defined by an individual scientist, or by a group of scientists, and not universally accepted as are real numbers, such a model tends toward a "personal" simulation model. This personal model incorporates the objects to be modeled, their interaction mechanisms, and a particular measurement scale.

While mathematical models propagate point values (numbers), our qualitative model propagates distributions. These distributions are labeled with linguistic terms. Output from a qualitative model is a range of values (the possibility y distribution of some linguistic term) and contains some explicit measure of uncertainty. Mathematical models produce a single numerical value without any sense for its precision.

Our use of arbitrary base scales, 0-9 and -5- +5, eliminates the need to devise accurate value ranges for the parameter attributes, "quantity" and "change." In many cases, these values would be difficult to produce for mature plants because they must be extrapolated from studies of juveniles. Instead, fuzzy values represent relative ranges of "quantity" and "change" for the plant/site being modelled. These values are the subjective assessments of a competent scientific specialist. Incorporation of those assessments into a computer-based model, however, allows the scientist to reason at a familiar level of resolution, but beyond the normal, human limits of complexity. By giving the scientist a wide-angle lens with which to view things, perhaps the traditional myopic vision of scientific investigation can be broadened to create a larger, i.e., more inclusive but less detailed, picture of the world.

Model validation will necessarily be very difficult. Quantitative models of mature tree response to stresses are similar in this regard, however, because studies on mature trees are difficult. Our model could be validated with respect to moisture stress through existing databases that contain growth and environmental variables. Also, an influence model that represents juvenile trees could be compared to juvenile-studies data on ozone and moisture stress. Then known differences between juvenile and mature tree physiology might translate into the creation of a mature tree version of the validated juvenile model. Finally, the nature of the influence model and its implementation will allow us to record and explain how various parameters are changing over time in response to other parameters. For this purpose, our model is more transparent than traditional mathematical models. Also, model validation might proceed in an intuitive manner by closely examining intermediate steps of a simulation.

Nothing in this modelling methodology restricts its use to ponderosa pine or to ozone/drought questions only. The conceptual structure can be adapted to other scientific inquiries by defining anew model, i.e., adding new parameters and redefining parameter interactions. Therefore, the methodology adapts to any species and any locality, and addresses any scientific questions for which it has the appropriate knowledge structure.

As noted above, use of a qualitative approach attempts to include aspects of both generality and realism. Generality allows the model to be applied to many different plant/site/genotype situations with only minor modifications. Realism means that it can be used to make real world policy decisions because it addresses interacting stresses at a level of resolution adequate for managers. Prior experiences with managers' needs for decision guidelines (Fox et al. 1989, Schmoldt and Peterson 199 1) indicate that scientists are hesitant to provide arbitrary threshold values for decision making. A qualitative model can help eliminate scientists' reluctance to extrapolate beyond what they can confidently demonstrate with empirical relationships, and can provide managers with what they need to cope with a changing environment.

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