IMPLICATIONS OF FOREST PLANNING REQUIREMENTS AND INITIAL RESOURCE SITUATION FOR FOREST SERVICE PRODUCTION LEVEL RISK

James B. Pickens and Peter G. Ashton[1]

ABSTRACT. —This article evaluates the impact of Forest Service planning requirements on the degree of variability associated with periodic harvest targets. It is concluded that the temporal and spatial dispersion harvest requirements provide a degree of portfolio diversification that tends to reduce the variability associated with cutting period harvests. The reduction in variance depends on the "green-up" period, which determines how many cutting periods the harvest of an analysis area must be spread over, and the correlation between harvests across analysis areas. Longer green-up periods tend to spread harvests within an analysis area over more time and reduce harvest level variability, while positive correlations between analysis area yields would increase variability.

INTRODUCTION

The Forest Service (FS) of the United States Department of Agriculture manages forest and rangeland across the United States. It is very important that future timber harvest levels from these lands be predictable because many communities and industries in rural areas are highly dependent on the fiber harvested from FS lands. Unfortunately, there are several factors that dramatically reduce the accuracy of future harvest predictions.

Much uncertainty results from the inherently political environment in which the FS conducts management. This uncertainty is extremely difficult to foresee and respond to because of the relatively short-term nature of the political process, which can be measured by the period between elections, and the long-term nature of forest planning and management. Within the political system, we know well neither the possible future issues nor the probability that those issues will adversely impact planned timber harvest targets.

The prospects for adaptive management approaches in response to another major source of risk, the inherently random fiber production response of the managed forest ecosystem, are much more promising. The growth and development of forests are relatively well understood. Statistically derived growth and yield models providing both the expected production and the anticipated variability for most important forest communities in the US, and more precise information becomes available both through research and observed results of management actions over time. Furthermore, techniques for using single-stand production information to evaluate production level risk associated with implementing a specific harvest schedule at the forest level are available (Hof et al. 1995).

Another related issue is the implications for harvest level risk (variability) resulting from regulations and existing conditions when forest plans are developed. While the results presented by Hof et al. (1995) are only applicable to a single forest with the specified harvest schedule, estimation of the implications from planning characteristics have much broader applicability. This paper presents the results of a study to evaluate the impact of certain forest plan requirements and initial land base age structure on timber harvest risk (variability).

BACKGROUND

Many critical information needs, where the data is currently not known precisely, are encountered during the process of

[1]James B. Pickens, Professor of Forest Management, School of Forestry and Wood Products, Michigan Technological University, Houghton, MI 49931 (906-487-2218; jpickens@mtu.edu) and Peter G. Ashton, Resource Economist, Policy Analysis, U.S. Department of Agriculture, Forest Service, Washington, DC 20250 (202-205-0846).

strategic planning by the FS. This missing information can be divided into two categories, **risk** and **uncertainty**, depending on our degree of understanding of the process generating the unknown information (Davis and Johnson 1987, p.197). Decision making under risk occurs when we do not know precise data values, but we have a relatively good understanding of what might happen; we know the possible future conditions and the probability that each condition will occur. An example of a situation where risk occurs is the future growth and development of a forest. Statistical models predict not only growth, but also allow calculation of the probability distribution around the expected growth. Furthermore, we can estimate the chance of catastrophic events, such as insect or disease outbreaks and fire, based on historical records. Although some of the estimates are not very precise, we at least understand the process generating these data.

Alternatively, decision making under uncertainty involves the worst-case scenario where we do not even know the possible outcomes, much less have any ability to estimate the probabilities of the outcomes. This situation makes planning difficult, and is particularly common where policy decisions occur within a political process. The Forest Service never knows what species will create the next crisis, and even conservative practices, such as old-growth retention, may leave the organization in an untenable situation if the species of interest requires early or intermediate successional stages.

A modeling anomaly first identified by McQuillian (1986) and termed the declining even flow effect (DEFE) was addressed in an earlier study (Pickens et al. 1990). The DEFE is the paradoxical result that subsequent planning iterations using a harvest scheduling model and nondeclining yield constraints can and frequently will select first cutting period harvests lower than the level selected in the first cutting period of the previous planning iteration. The conclusion of the Pickens et al. (1990) study was that the DEFE would be dramatically reduced by requirements of the FS to assure spatial and temporal separation of harvesting activities and the existence of previous regeneration harvests on some of the land base.

The same spatial and temporal dispersion constraints have frequently been attacked by forest industry and academicians because of their high opportunity cost, which results because harvest costs are higher per unit on small areas and because highly profitable stands are retained longer, rather than being harvested and replaced with young, vigorous stands soon. Sensitivity analysis conducted as part of the Kootenai National Forest plan showed a 45 percent reduction in present net value (PNV) between an unconstrained profit maximization and the model including the various planning requirements (Pickens et al. 1990)

These planning requirements are included for a variety of reasons such as endangered species, community dependence, soil and water protection, and multiple-use concerns. However, arguably the most important rationale for the planning requirements is their tendency to reduce the risk associated with management of forested ecosystems. The risk-reducing nature of the requirements can be divided into two categories:

1. Reduction in the physical and biological risk associated with a diverse landscape.
2. Reduction in production level risk, and therefore enhanced predictability of output levels, because of portfolio diversification.

Risk reduction associated with heading 1 is well understood. Forests with age and species diversity, even when each stand is an even-aged monoculture, tend to not allow insects, disease, or fire to spread as widely as homogeneous forests. However, the risk reduction associated with heading 2 has not previously been identified or evaluated, and is the primary focus of this paper.

The State-of-the-Art for Incorporating Risk into Harvest Scheduling Models

Decision making under risk is relatively well understood, although the analytic tools employed are frequently conceptually complex and difficult to apply. Forestry land allocation models are quite unique because of their large size and the fact that nearly all of the technical information is not known with certainty (Pickens et al. 1991). Many recent publications within the forestry literature have addressed special cases, particularly the situation where the production information (e.g., - timber yield) is not known with certainty. Early efforts focused on characteristics of solutions where yield information is uncertain (Hof et al. 1988; Pickens and Dress 1988; Pickens and Hof 1988), while later efforts

emphasize using chance constraints, which assure that a constraint or group of constraints will be satisfied some specified proportion of the time (Pickens et al. 1991; Hof et al. 1992). Most recent efforts have addressed improved nonlinear programming algorithms (Weintraub and Vera 1991), pragmatic approaches to address practical problems (Hof et al. 1995), and spatial covariance relationships (Hof et al. 1996). The pragmatic approaches advances are particularly important because they allow calculation of variability around expected production levels and develop formulations which reduce variability without requiring nonlinear or integer programming, or cumbersome iterative approaches, all of which are technically not possible or are operationally very difficult for characteristic large harvest scheduling models.

The Value of Diversification in Reducing Risk

It has long been recognized in the classic finance literature that spreading investments across a range of options can dramatically reduce investment risk so long as covariances between components are small relative to variances (Markowitz 1959).

The risk reduction from diversification occurs because a diversified portfolio can compensate for large losses in one investment by lower losses or gains in other components of the portfolio. The variance associated with any portfolio is:

$$s^2 = \sum_{j=1}^{N} \sum_{k=1}^{N} x_j x_k s^2_{jk} \qquad (1)$$

where s^2 is the variance of return on the portfolio, x_j and x_k are the level of investment in the jth and kth options, and s^2_{jk} is the covariance between the jth and kth investments. If j equals k, then s^2_{jk} is simply the variance of that investment.

The following example demonstrates some of the implications of risk reduction using portfolio diversification. Consider an investor who has $4000 to invest and four possible investments, each of which has an expected annual return of 10 percent and a standard deviation of .1 for each dollar invested. Further, assume that the return is statistically normally distributed. Initially, we will assume that the returns on the various investments are statistically independent.

If the investor chooses to put all $4000 into investment one, the resulting variance can be calculated by Equation 1. Since all of the x_i are zero except x_1, which is $4000, this simplifies to:

$$s^2 = x_1^2 s^2_{11} = 4000^2 x .1^2 = 160{,}000$$

and

$$s = 400$$

If our investor decided to diversity his portfolio equally by putting $1000 into each of the four investments, the variance of his investment would be:

$$s^2 = 4x\,1000^2 x .1^2 = 40{,}000$$

and

$$s = 200$$

Our investor has been able to reduce his risk from a standard deviation of 400 to a standard deviation of 200 by

diversifying his portfolio. Furthermore, the expected return remains unchanged at 10 percent, or $400 over a 1-year period. In fact, the expected return is identical for all of the investment situations discussed in this section.

Another way to view the level of risk associated with a management option is to calculate the probability that some critical threshold is not reached. The first step in this process is to calculate the number of standard deviations that the threshold is from the mean. Because we have assumed return is normally distributed, this value is also a "Z-score" from introductory statistics.

The following example uses the critical threshold of zero return, which coincides with the investor not losing on the investment. For the undiversified investor, the Z-score for zero return is:

$$Z = \frac{x - u}{s} = \frac{0 - 400}{400} = -1.0$$

From a normal probability distribution table, the chance that $Z \geq -1.0$ is .8413. Therefore, the undiversified investor will make money in about 84 percent of the years, and will loose money during 16 percent of the years. For the diversified investor, the Z-score for zero return is:

$$Z = \frac{x - u}{s} = \frac{0 - 400}{200} = -2.0$$

The chance that $Z \leq -2.0$ is .9772. Therefore, the diversified investor will make money in about 98 percent of the years, and lose money in only 2 percent of the years.

The Importance of Correlation between Investments in Portfolio Management

Recall that we assumed that the return on the various investments were statistically independent. This assumption is not generally true for either financial investments or forest management decisions. Most financial markets are positively correlated with each other, with some correlations quite strong.

Stocks within the same industry generally move as a group. If one oil company has a good year, it is very likely that other oil companies will also prosper. This translates statistically into strong positive correlations. Furthermore, most other investment alternatives are positively correlated. Generally, the entire stock market either gains or looses together, and the stock and bond markets also tend to move in the same direction. However, the degree of correlation across the entire market is much weaker than within a given industry.

The presence of positive correlations between investments tends to reduce the amount of risk reduction possible from portfolio diversification. If we consider the above example with even diversification among the four possible investments, but with a .5 correlation coefficient between each pair of investments, the resulting standard deviation would be 265. This result is between the diversified portfolio value of 200 when independence is assumed and the undiversified portfolio value of 400. If the various investments were all perfectly correlated with each other, then there would be a standard deviation of 400 and a loss of all of the risk reduction potential of diversification.

It is possible that some investments would tend to move in opposite directions. This translates statistically into a situation with negative correlation coefficients. When alternative investments are negatively correlated, it is possible to reduce the variability of return even more than when returns are statistically independent. If the investment was again split evenly between the four investments, and each of the pairs of investments had a correlation coefficient of -.5, the resulting standard deviation of the investment would be 100. This is only one-fourth of the variability of the undiversified investment, and only half the variability of the diversified portfolio with statistically independent investments. Unfortunately, there are very few investment options that are negatively correlated with overall stock market

performance that offer competitive expected returns. Finally, if we could separate the investments into two groups that were perfectly and negatively correlated, then we could eliminate all investment risk and receive an assured 10 percent annual return.

Potential for using Portfolio Diversification to Reduce Harvest Level Risk

The above examples show the potential to reduce risk by portfolio diversification in financial markets, and emphasize the importance of correlations between the yield of the various options. The diversification strategies can also be applied to the management of a forest to reduce various forms of risk. One important source of risk is the variability associated with timber harvest when forest plans are implemented and growth and yield information is random; this issue is addressed below using the general context of Forest Service planning. Specifically, the implications of forest planning regulations and the current age-class structure of the forest are addressed. Information concerning spatial and temporal correlations of timber yields is limited, and will be addressed below.

The pragmatic approaches work of Hof et al. (1995) emphasizes the importance of a portfolio diversification approach to reduce the risk associated with planned timber harvest levels. Their case study demonstrates the value of diversification in the time-dynamic harvest scheduling case when correlations are zero both over time and across the landscape. Furthermore, a significant opportunity to reduce risk has been demonstrated by Hof et al. (1996) when positive spatial correlations are included. Their results reduced production level risk by spreading harvest widely across the landscape for a range of alternative harvest targets and harvest cost scenarios.

The current state-of-the-art does not allow inclusion of temporally correlated yield in optimization models because this case generally involves correlation between rather than within rows (Miller and Wagner 1965; Hof et al. 1992). Unfortunately, the strongest case can be made for yield correlations over time and within a stand rather than across the landscape at a point in time. The yield at a future point in time is clearly strongly correlated with the current stocking in the stand for two reasons; much of the future stocking will be the same volume that currently occupies the stand and the amount of mortality and new growth is strongly related to the current stocking.

The support for spatially correlated yields is much less compelling. Reed and Burkhart (1985) present and discuss statistical tests for identifying spatial correlations and test a range of parameters for spatial correlation at the stand level. Although some significant spatial correlations are identified, it seems likely that these correlations take place at a very fine scale because they noted that separate plots within a stand often have very different spatial correlation patterns. Furthermore, differences in product classes (their parameter closest to stand yield) generally occurred because of species composition differences. Species composition differences occur in response to microsite differences within the stand.

Czaplewski et al. (1994) investigated spatial autocorrelation of diameter growth across widely separated areas in the state of Georgia using continuous forest inventory plots. Their results identified several cases of significant spatial autocorrelation. However, their analysis to identify the specific source of the spatial autocorrelation showed that a large share of the effect resulted from a small area with highly correlated observations, rather than a general trend across the landscape.

Taken together, the results of Reed and Burkhart (1985) and Czaplewski et al. (1994) generally support the existence of some degree of spatial autocorrelation in timber yield. However, this relationship is probably not particularly large and the scale where the effect could be expected is uncertain.

CASE STUDY

This study evaluated the change in risk, as measured by the standard deviation, that could be expected as various forest planning requirements were included in the harvest scheduling model. The point of departure for the study is the previous DEFE study (Pickens et al. 1990), which evaluated three characteristics of the forest planning process. Each characteristic is present in all forest planning models, but was absent in McQuillian's (1986) evaluation:

1. Spatial and temporal dispersion constraints to assure the 40 acre clearcut size limitation.
2. Prescriptions which allow intermediate harvests and inclusion of more realistic yield information. [Note: McQuillan assumed constant old-growth yield, with regenerated stand yields of zero until age 70. At age 70, yield jumped to 25 mbf per acre, with no further growth thereafter.]
3. Inclusion of a land base which is not entirely old growth.

Characteristics 1 and 3 were evaluated for their impact on production level risk. The second characteristic was not addressed because the impact of more complex yield functions is ambiguous, and depends on the specific yields. However, it is likely that more realistic yield functions would tend to diversify the harvest in any cutting period across more analysis areas because of the inclusion of partial harvests, which were not allowed in McQuillan (1986).

Models including characteristics 1 and 3 were compared with the base model from Pickens et al. (1990). This formulation used the resource situation described by McQuillan (1986), but is formulated and solved using the FORPLAN (Johnson et al. 1986) harvest scheduling system. The base model includes five analysis areas, each with 1000 acres and having identical site productivity and stocking. The prescriptions allowed are clearcutting and minimum level management. The forest is currently comprised of old-growth stands which have 15 thousand board feet (mbf) per acre, and no net volume change is expected. Regenerated stands are expected to have no volume until age 70, at which time the volume is 25 mbf/ac and does not change as the stands age. Current product price is $300/mbf, but is expected to increase by 1.5 percent per year for the next 50 years, after which it will not change. The only difference between analysis areas is the cost associated with timber harvesting. The harvest costs are $170, $290, $410, $530, and $650 per mbf for analysis areas 1 through 5 respectively. These costs are assumed to be the same for both old-growth and regenerated stands. The discount rate is 4 percent, and all revenues and costs are assumed to occur at the midpoint of the cutting period. Land area, nondeclining flow, and a limit of harvest below the long-run sustained yield level were the only constraints included in the base formulation. The objective was to maximize present net value over a 12 cutting period planning horizon, with each planning period 10 years long.

Chosen Land Allocations

Tables 1 to 3 present the selected land allocations for the base solution, the solution with spatial dispersion constraints, and the solution when the initial land base is not entirely old growth, respectively.

Table 1.—Land allocations for the base model

Cutting Period	Analysis Areas				
	1	2	3	4	5
1	667				
2	333	333			
3		667			
4			667		
5			333	333	
6				667	
7					667
8	667				
9	333	333			
10		667			
11			667		
12			333	333	

Table 2.—Land allocations for the model with spatial and temporal dispersion constraints

Cutting Period	Analysis Areas				
	1	2	3	4	5
1	250	155			
2	250	250			
3	250	250	23		
4	250	173	250		
5		173	250	250	
6			250	250	173
7			227	250	195
8	250	155		250	
9	250	250			91
10	250	250	23		250
11	250	173	250		
12		173	250	250	

Table 3: Land allocations for the modified land base model

Cutting Period	Analysis Areas								
	1	2	3	4	5	R11[a]	R12	R21	R22
1	400								
2	200	200							
3		400							
4			481						
5			519	432					
6				284			200		200
7				284		200		200	
8	400				284				
9	200	200			284				
10		400			284				
11			481		148				
12			591	191					

[a] The analysis areas starting with R are previously harvested areas. The first digit represents the original analysis area number, while the second digit indicates the age in cutting periods at the midpoint of the first cutting period.

Inspection of Table 1 shows that the base model employed an “all or nothing” approach when selecting which analysis areas to harvest in each cutting period. All of the scheduled removals were cut from 667 acres of analysis area 1 in the first cutting period. Second cutting period harvests were achieved by harvesting the remaining 333 acres of analysis area 1 and 333 acres from analysis area 2. This pattern continues, with the scheduled harvests taken entirely from the most profitable analysis area in each cutting period.

The pattern of harvests when spatial dispersion/40 acre clearcut limits was included was very different. These constraints require that not more than one quarter of the analysis area can be harvested in any one cutting period. The logic behind these constraints is that analysis areas generally occupy large contiguous areas, and that they can only be harvested using a checker board pattern. Only one of each block of four 40-acre squares can be cut in any one cutting period (assuming that the "green-up period" is one cutting period). This spreads the harvest of each analysis area over at least four cutting periods. This pattern automatically leads to reduced production level risk because of increased diversification of the areas harvested in any one cutting period.

The pattern of scheduled harvests using the modified land base presented in Table 3 also shows some degree of diversification of periodic harvests. It is worth noting, however, that the diversification seen in this case is primarily a result of the choice of previously harvested areas, which were chosen to conform with the spatial dispersion constraints.

Table 4 presents the expected harvest by cutting period, the standard deviation (SD) associated with the expected harvest, and the coefficient of variation (CV) of the expected harvest for each of the three solutions when no inter-analysis area correlation of harvest estimate errors is assumed and the CV for each analysis area is 0.30. Coefficient of variation is calculated as the standard deviation of yield divided by the expected yield, and is a useful method to compare variability when the estimated parameters (cutting period expected means) are quite different.

Table 4.—Comparison of variability associated with the different model formulations

Cutting Period	Base Model Formulation			Spatial Dispersion Formulation			Modified Land Base Formulation		
	Yield[a]	SD	CV	Yield	SD	CV	Yield	SD	CV
1	10,005	3,002	0.30	6,075	1,324	0.22	6,000	1,800	0.30
2	9,990	2,119	0.21	7,500	1,591	0.21	6,000	1,273	0.21
3	10,005	3,002	0.30	7,845	1,594	0.20	6,000	1,800	0.30
4	10,005	3,002	0.30	10,095	1,771	0.18	7,215	2,165	0.30
5	9,990	2,119	0.21	10,095	1,771	0.18	14,265	3,039	0.21
6	10,005	3,002	0.30	10,095	1,771	0.18	14,260	2,477	0.17
7	10,005	3,002	0.30	10,080	1,755	0.17	14,260	2,477	0.17
8	16,675	5,003	0.30	13,875	2,476	0.18	14,260	3,261	0.23
9	16,650	3,532	0.21	13,865	2,683	0.19	14,260	2,477	0.17
10	16,675	5,003	0.30	16,825	2,886	0.17	14,260	3,261	0.23
11	16,675	5,003	0.30	16,825	2,952	0.18	16,285	3,827	0.24
12	16,650	3,532	0.21	16,825	2,952	0.18	19,970	4,201	0.21

[a] Yields are not strictly nondeclining because reported acreages are rounded to the nearest integer.

The average CVs are 0.27, 0.19, and 0.23 for the base, spatial dispersion, and modified land base formulations, respectively. The spatial dispersion constraints produced solutions which were, on average, only 70 percent as variable as the base case solutions. This demonstrates that the variability of projected harvests will, in general, tend to be reduced significantly by inclusion of spatial dispersion constraints. The modified land base solution produced solutions which were 85 percent as variable as the base case solutions.

DISCUSSION

Forest Service land management plans were developed using FORPLAN models which were very highly constrained. Although each forest, and therefore each model, operates under different conditions and constraints, there are certain constraint sets and initial conditions which all forests share. One limitation which is always included is a set of constraints to assure spatial and temporal separation of regeneration harvests. These constraints are often formulated to

assure that not more than 25 percent of an analysis area is regenerated within the time required for harvests to reach "green-up." These constraints also provide an additional benefit because the degree of variability associated with planned harvests is reduced by spreading harvest among many analysis areas.

This "portfolio diversification" reduced the variability of scheduled cutting period harvests by 30 percent in the case study model presented above. However, because of the small number of analysis areas present in the case study, the expected reduction in variability would be higher for actual forest planning models. If the green-up period is one ten-year cutting period, then the maximum reduction in variability would be 50 percent. If the green-up period was greater than one decade, then the degree of portfolio diversification would be even greater because the harvest of a single analysis area would be spread over more than four cutting periods, and the number of analysis areas cut in any one cutting period would be greater. If the yields were positively correlated across analysis areas, then the degree of variability reduction would be less, while negative correlations would provide for even greater reduction in variability.

All national forests have areas which have previously been regeneration harvested. The existence of these previously harvested areas tends to add spatial and temporal diversity to the forest. Furthermore, it tends to smooth the temporal flow of harvest variability. This occurs because the previously regenerated areas add to the diversity of analysis areas harvested. Table 4 shows this tendency for the modified land base formulation. As long as harvests were limited to the old-growth stands, the CV ranged between 0.21 and 0.30. After the regenerated stands became available for harvest in cutting period 6, the CV tended to be smaller with a range from 0.17 to 0.24. Furthermore, since previous harvests have generally occurred over a long period on most national forests, the variability of harvest levels between periods would be expected to be quite low. This would occur because successive cutting periods would have a strong tendency to harvest from the same analysis areas as previous cutting periods.

LITERATURE CITED

CZAPLEWSKI, RAYMOND L., ROBIN M. REICH, AND WILLIAM A. BECHTOLD. 1994. Spatial autocorrelation in growth of undisturbed natural pine stands across Georgia. *Forest Science* 40(2): 314–28.

DAVIS, L.S., AND K.N. JOHNSON. 1987. *Forest management*. McGraw-Hill.

HOF, JOHN, MICHAEL BEVERS, AND JAMES PICKENS. 1995. Pragmatic approaches to optimization with random yield coefficients. *Forest Science* 41(3): 501–12.

HOF, JOHN, MICHAEL BEVERS, AND JAMES PICKENS. 1996. Chance-constrained optimization with spatially correlated forest yields. *Forest Science* 42(1): 118–23.

HOF, JOHN G., BRIAN M. KENT, AND JAMES B. PICKENS. 1992. Chance constraints and chance maximization with random yield coefficients in renewable resource optimization. *Forest Science* 38(2): 305–23.

HOF, J.G., K.S. ROBINSON, AND D.R. BETTERS. 1988. Optimization with expected values of random yield coefficients in renewable resource linear programming. *Forest Science* 34(3): 634–46.

JOHNSON, K.N., T.W. STUART, AND SARAH A. CRIM. 1986. *FORPLAN Version 2: An overview*. Land Management Planning Systems Section. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Forest and Range Experiment Station.

MARKOWITZ, H. 1959. *Portfolio selection: Efficient diversification of investment*. NY: Wiley.

MILLER, B.L., AND H.M. WAGNER. 1965. Chance constrained programming with joint constraints. Operations Research 13:930–45.

MCQUILLAN, A.G. 1986. The declining even flow effect—Non sequitur of national forest planning. *Forest Science* 32(4): 960–72.

PICKENS, JAMES B., AND PETER E. DRESS. 1988. Use of stochastic production coefficients in linear programming models: Objective function distribution, feasibility and dual activities. *Forest Science* 34(3): 574–91.

PICKENS, JAMES B., AND JOHN G. HOF. 1988. Accounting for stochastic variation in linear programming technical coefficients. In *The 1988 Symposium on Systems Analysis in Forest Resources*, 54-58. Gen. Tech. Rep. RM-161. U.S. Department of Agriculture, Forest Service.

PICKENS, JAMES B., JOHN G. HOF, AND BRIAN M. KENT. 1991. Use of chance-constrained programming to account for stochastic variation in the A-matrix of large scale linear programs: A forestry application. *Annals of Operations Research* 31: 511–26.

PICKENS, JAMES B., BRIAN M. KENT, AND PETER G. ASHTON. 1990. The declining even-flow effect and the process of national forest planning. *Forest Science* 36(3): 665–79.

REED, DAVID D., AND HAROLD E. BURKHART. 1985. Spatial autocorrelation of individual tree characteristics in loblolly pine stands. *Forest Science* 31(3): 575–87.

WEINTRAUB, A., AND J. VERA. 1991. A cutting plane approach for chance constrained linear programs. *Operations Research* 39: 776–85.