Integrating Variation in Tree Growth into Forest Planning

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Pasanen, K. 1998. Integrating variation in tree growth into forest planning. Silva Fennica 32(1): 11–25.

Forest planning is always influenced by uncertain factors. Variations in growth, outcome of regeneration, timber prices, costs and mortality cannot be avoided, whereas the quality of inventory data and the models used for estimation of the state and development of forests can be improved. Methods have been developed for incorporating risk and attitude toward risk in decision analysis, but there has been a lack of good models for dealing with the various sources of risk. The aim of this study was to estimate stochastic models for the variation in growth of Scots pine (*Pinus sylvestris*), Norway spruce (*Picea abies*) and birch (*Betula pendula* and *Betula pubescens*). The said models had to be capable of generating growth scenarios, and thus correlations between series had to be taken into account. ARMA models were estimated for mean growth index series from Pohjois-Karjala, eastern Finland. Several ARMA models, some of which had seasonal parameters, were found to be adequate for each series. Non-seasonal AR(1) and seasonal AR(1,1) models were used to produce growth scenarios in the case study, in which variation in growth was integrated into forest planning.

Keywords risk, growth index, ARMA models, scenario approach
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Received 14 November 1995 **Accepted** 3 February 1998

1 Introduction

Forest planning always involves risk even though the methods used traditionally have been deterministic. Several methods have been developed for stochastic decision analysis (e.g. Kaya and Buongiorno 1987, Hoganson and Rose 1987, Brazee and Mendelsohn 1988, Caulfield 1988, Marshall 1988, Mendoza and Sprouse 1989) and a good framework has been presented by Brumelle et al. (1990). The approach used in some recent studies (Valsta 1992, Pukkala and Kangas 1996), has been the scenario approach incorporating the various sources of risk and attitude toward risk into the optimization problem. However, the models used for generating growth scenarios, which are needed in these methods, have been inadequate. It has been suggested that autocorrelation should be taken into account when developing better methods (Pukkala and Kangas 1996).

Many growth index series have been published in Finland for different purposes (e.g. Mikola 1950, Tiihonen 1984, Mielikäinen 1991). Many researchers have found autocorrelation in growth index series (Henttonen 1984, Monserud 1986, Visser and Molenaar 1990). Autoregressive moving-average ARMA models have been used assuming growth index series to be stationary. Variation in growth is a complex process, and it has been explained to be the result of climatic conditions. Pukkala (1983) found that the diameter growth of conifers in Finland is influenced by the process of seed production, which in turn is determined by climatic factors. Henttonen (1984), in contrast, concluded that large-area growth variations are not caused by climate. Several spans of periodicities of growth have been reported especially for pine (see Boman 1927 and Mikola 1950). Mikola (ibid.) also mentioned the idea of predicting future growth utilizing the joint effect of different cycles.

The aim of this study was to estimate stochastic models for the variation in the growth of Scots pine, Norway spruce and birch. The said models were required to be capable of generating growth scenarios used in forest planning. Thus, correlations between the stochastic growth indices of different tree species should also be realistic. A secondary goal of this study was to demonstrate the effect of variation in growth (separately and with variation in timber prices) on optimal forest plans under different attitudes toward risk.

Firstly, the measured tree-ring series were standardised by polynomial trend functions. Box-Jenkins ARIMA modelling procedure was then used to find adequate models. The planning procedure developed by Pukkala and Kangas (1996) was used in a case study for estimating the stochastic growth-index models applied.

2 Material and Methods

This study involved using tree-ring indices (cores extracted at breast height) as growth indices,

Table 1. Numbers of tree-ring series measured (age = number of annual rings at breast height).

	Age 71–100	Age 101–130	Age 131–160	Age 160–	Total	Number of stands
Pine	14	10	17	11	52	18
Spruce	11	12	8	1	32	13
Birch	9	11	12	1	33	16
Total	34	33	37	13	117	

although radial growth determined at the centre of gravity of the height of each tree would have provided a more reliable measure of variation in growth (see Vuokila 1960). The tree-ring series (formed after measuring the cores of 117 trees growing in Pohjois-Karjala, eastern Finland) for this study were measured in 1994 (Table 1). Most of the study material was obtained from virgin forests (National Parks or similar conservation areas) and only *Vaccinium* (VT) or *Myrtillus* (MT) site types (Cajander 1926) underlain by mineral soils were included.

Several methods can be used to eliminate growth trends from tree-ring series (Visser and Molenaar 1990). There are, however, many difficulties in choosing the best method for a particular purpose (Henttonen 1990, Monserud 1986). The decision taken in this study was to use a third-order polynomial trend function:

$$Y_t = c + t + t^2 + t^3 + \varepsilon \qquad (1)$$

where
Y_t = tree-ring width
c = constant
t = order number of the tree-ring
ε = random term

The trend function used was flexible enough to eliminate the effects of age and tree size and the unusually long-time variation found in some series (Fig. 1). Thus the remaining variation can be considered to be mainly short-term variation with possible medium-term cycles. The growth index series for each individual tree was then calculated as

$$I_t = \left(\frac{Y_t}{\hat{Y}_t}\right)100 \tag{2}$$

where
I_t = growth index value
Y_t = tree-ring width
$\hat{Y}_t$ = value of fitted model
t = order number of the tree-ring

The average growth-index series for Scots pine, Norway spruce, and birch were then calculated as the arithmetic means obtained from the indices of individual trees for each year.

When constructing stochastic models for practical use, the commonly accepted idea of having adequate, but parsimonious (few parameters) models is essential (Box and Jenkins 1976). The use of complex models which show "best" fit with the observed data (i.e. one possible realization of the process to be modelled) can cause serious errors.

In this study, stochastic modelling was based on the estimated growth-index series from 1890 to 1988. The five last years of the series were omitted because experience has shown that the last few indices are always unreliable. The early parts of the series (years before 1890) were not accepted for modelling due to the small number of measurements from those years. ARIMA (AutoRegressive Integrated Moving Average) modelling could be used because the lengths of the series (99) satisfied the minimum (50) suggested by Box and Jenkins (1976).

The growth-index series were considered to be stationary and ARMA models have been estimated in many studies (e.g. Henttonen 1984, Monserud 1986, Visser and Molenaar 1990).

The observed time series z_t is assumed to be generated by linear filtering of the random innovation process a_t (having zero mean and a certain variance). The weights of the linear filter model determine the effects of the previous observations on the current value. If the process z_t varies about the mean with constant variance, the process is stationary.

In an autoregressive (AR) process of order p, the current value z_t is expressed as a finite, linear aggregate of the previous values and a shock a_t

$$\tilde{z}_t = \varphi_1 \tilde{z}_{t-1} + \varphi_2 \tilde{z}_{t-2} + \cdots + \varphi_p \tilde{z}_{t-p} + a_t \tag{3}$$

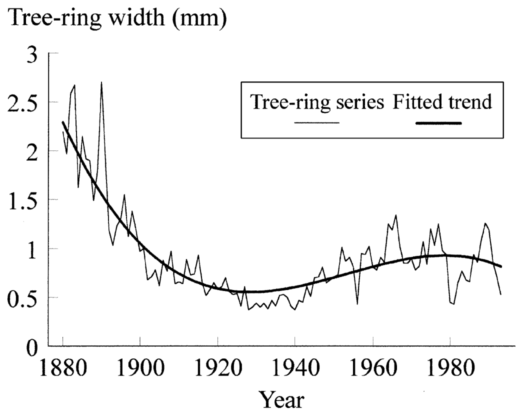

Fig. 1. Polynomial trend function fitted to a tree-ring series.

where
$\tilde{z}_t = z_t - \mu$
$\varphi_1 \cdots \varphi_p$ = autoregressive parameters

Growth index series can also have seasonal properties. An example of seasonal ARMA models, a multiplicative seasonal AR(1,1) model, is defined here by

$$\tilde{z}_t = \varphi_1 \tilde{z}_{t-1} + \phi_1 \tilde{z}_{t-L} - \phi_1 \phi_1 \tilde{z}_{t-L-1} \tag{4}$$

where
$\tilde{z} = z_t - \mu$
φ_1 = first order non-seasonal AR parameter
ϕ_1 = first order seasonal AR parameter
L = length of seasonality

The theory of variation in tree growth is useful background knowledge for the modelling procedure. Modelling various climatic processes (temperature series, etc.) can also support model identification. There was no need to find transfer models because this study was not aimed at explaining variation in growth by other stochastic processes. Instead, it is more useful to get models for the growth variation processes that produce realizations with statistical properties similar to real growth variation.

Identification was based on the analysis of the original series. The peaks in the periodograms revealed the possible lengths of the cycles in the series. The significance of the periodocities was evaluated by checking the cumulative periodograms. Autocorrelation functions (acf) and partial autocorrelation functions (pacf) were calculated for identifying the model. By careful analysis of the shapes of acf and pacf, an initial guess about possible models can be offered (see Box and Jenkins 1976, Chatfield 1980).

Diagnostic checks (see Box and Jenkins 1976) were based on the residuals of the estimated models. The first step was to check the p-values of the parameters. Due to its ineffectiveness, the Portmonteau Q-test value was not used for any conclusions (see Chatfield 1980). Secondly, acf and pacf of the residuals were analysed visually to obtain more information about the adequacy of the model and about possible seasonality of the process. When all parameters and autocorrelation of the residuals for higher lag were found to be statistically significant ($p < 0.05$), an additional term was needed. If seasonality was indicated by autocorrelation analysis of the residuals, a seasonal parameter (length of the lag where significant acf or pacf of the residuals was found) was added and the modelling procedure was repeated. The cumulative periodogram check on residuals was also applied to reveal possible seasonality.

The aim of this study was to estimate models to be used in the growth-scenario simulator. Thus cross-correlations of series had to be taken into account. This problem was solved by utilizing the covariance structure of the residuals of the estimated models. The Cholesky decomposition matrix (**Q**) of the covariance matrix of the residuals was calculated. New correlated innovators (a_1, a_2, a_3) for three estimated ARMA models were obtained by multiplying normally (N(0,1)) distributed random terms (e_1, e_2, e_3) by matrix **Q** (see Kennedy and Gentle 1980):

$$\begin{bmatrix} a_1 \\ a_2 \\ a_2 \end{bmatrix} = \mathbf{Q} \begin{bmatrix} e_1 \\ e_1 \\ e_3 \end{bmatrix} \tag{5}$$

3 Results

3.1 Growth-Index Series

Stochastic models were based on average growth-index series from 1890 to 1988 (Fig. 2, Appendix 1). Variation in the growth of spruce was smallest and it was uniform in both halves of the series (Table 2). In the pine series, standard deviation was clearly smaller in the second half (1940...1988) than earlier. In the case of birch, variation after year 1939 was higher than in the first half. The correlations between the tree species were all positive and significant at 2 % level of risk, except for the correlation between pine and birch. The series on spruce and birch were the most closely correlated, while the correlation between pine and birch was weak.

Table 2. Standard deviations for different periods in the series and correlations between the series.

Series (n = 99)	Pine	Spruce	Birch
Standard deviation			
1890...1939	16.01	11.04	14.72
1940...1988	11.91	10.23	17.35
1890...1988	14.01	10.65	16.32
Correlations			
Pine	1		
Spruce	0.23 (p = 0.02)	1	
Birch	0.16 (p = 0.11)	0.43 (p = 0.00)	1

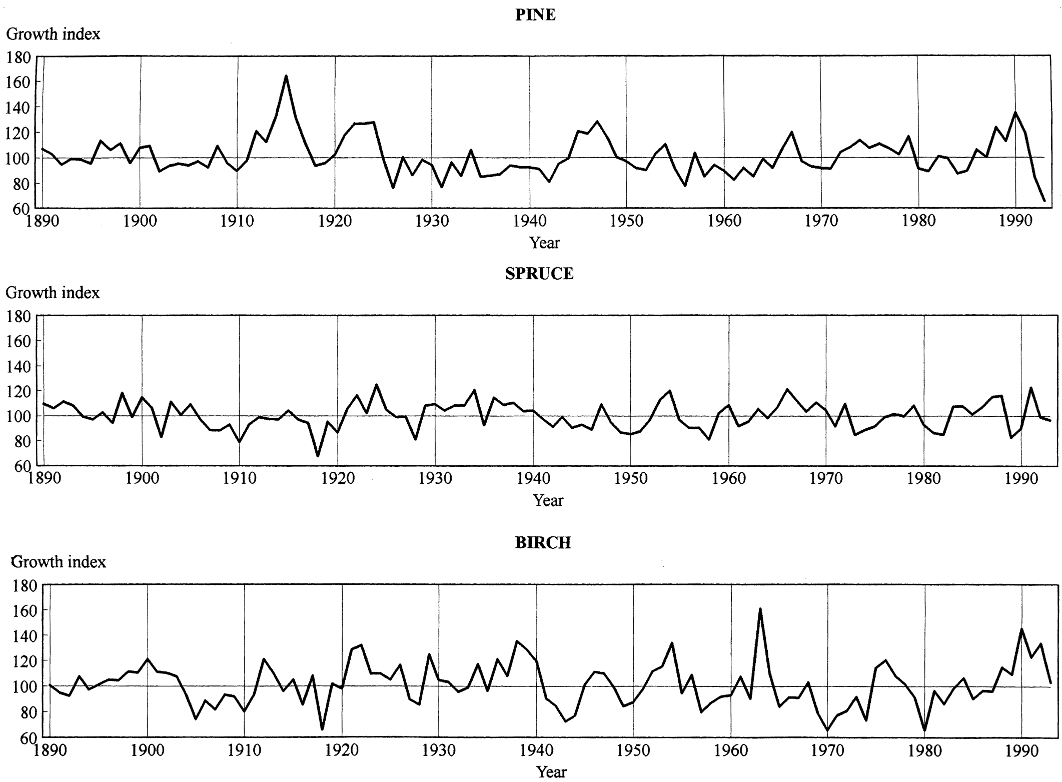

Fig. 2. Calculated growth index series from 1890 to 1993. (The last five indices are shown but they were not used.)

3.2 Stochastic Models for Variation in Growth

Autocorrelations (acf) and partial autocorrelations (pacf) indicated that AR(1) or MA(2) models may be suitable (Fig. 3). This is because of the cut-offs in the pacfs after the first lag and in the acfs after the second lag.

The periodograms for the original series revealed several peaks at different cycle lengths (33, 11, 8 and 7 years for pine; 33, 11, 8 and 6 years for spruce; and 12, 8 and 4 years for birch). The cumulative periodograms indicated clearly significant seasonality (1 % level of risk) for pine and birch, but the periodicity for spruce was statistically significant at the 5 % risk level.

Several models were found to be adequate for each series during the modelling procedure. The non-seasonal AR(1) model was the best choice for each series when a simple model was needed (Table 3).

For pine, the residual autocorrelations and partial autocorrelations (AR(1) and MA(2) models) were not significant at the 5 % risk level except in lag 7. This indicated a 7-year cycle in the series. Some seasonality was also found in the residuals of the models for spruce and birch. The seasonal AR(1,1) models were fitted for each series (Table 3) and statistically clearly significant ($p < 0.02$) seasonal parameters were found for pine and birch. The significance of the seasonal parameter for spruce was weak. The seasonality was greatest for pine and birch. For spruce and birch, parameters were negative, indicating that the cycle lengths were 8 and 12 years, respectively.

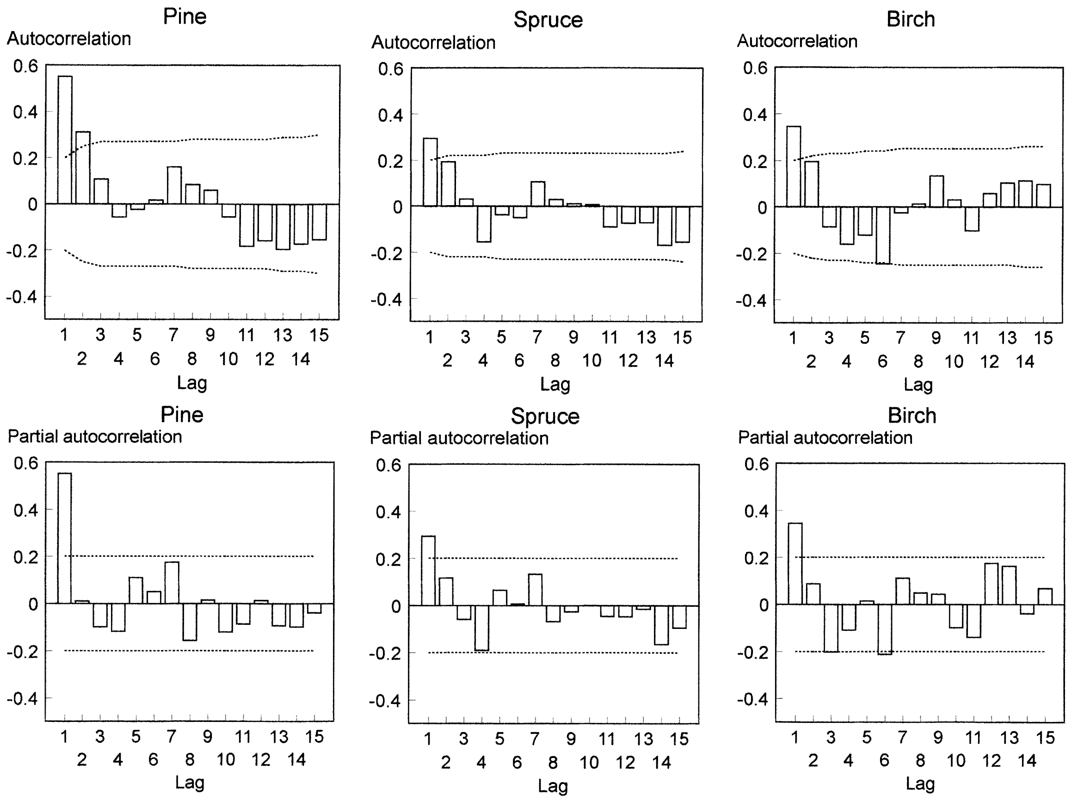

Fig. 3. Estimated autocorrelations and partial autocorrelations for the growth index series of pine, spruce and birch (broken lines = 5 % confidence limits).

Table 3. Non-seasonal and seasonal AR models for growth level variation of pine, spruce and birch.

Series	Model type	Coefficients	p-value	Stand.dev. of residuals
Pine	AR(1)	Lag 1 = 0.561	0.000	11.766
		Mean = 101.382	0.000	
	AR(1,1)	Lag 1 = 0.592	0.000	11.476
		Lag 7 = 0.251	0.017	
		Mean = 101.958	0.000	
Spruce	AR(1)	Lag 1 = 0.299	0.003	10.125
		Mean = 100.561		
	AR(1,1)	Lag 1 = 0.318	0.002	9.995
		Lag 4 = –0.190	0.066	
		Mean = 100.489		
Birch	AR(1)	Lag 1 = 0.346	0.000	15.445
		Mean = 100.238		
	AR(1,1)	Lag 1 = 0.351	0.000	15.013
		Lag 6 = –0.255	0.012	
		Mean = 100.247		

3.3 Generating Stochastic Growth Scenarios

Two groups of models (non-seasonal and seasonal AR models, Table 3) were selected for further use in this study. Thus both non-seasonal and seasonal growth scenarios were produced in the case study. The correlations and covariances of the residuals were slightly smaller for the seasonal models than for the non-seasonal ones (Tables 4 and 5).

The models for the mutually correlated innovators (a) for the three non-seasonal AR(1) models were as follows

$$\begin{aligned} a_{pine} &= 11.706e_1 \\ a_{spruce} &= 4.022e_1 + 9.235e_2 \\ a_{birch} &= 2.534e_1 + 5.747e_2 + 14.024e_3 \end{aligned} \tag{6}$$

where the coefficients were taken from the

Table 4. Correlations (r) and covariances (c) of residuals of the non-seasonal AR(1) models.

	Pine	Spruce	Birch
Pine	r = 1.0 (p = 0.000) c = 137.02		
Spruce	r = 0.3993 (p = 0.000) c = 47.081	r = 1.0 (p = 0.000) c = 101.46	
Birch	r = 0.1649 (p = 0.103) c = 29.660	r = 0.4087 (p = 0.000) c = 63.257	r = 1.0 (p = 0.000) c = 236.12

Table 5. Correlations (r) and covariances (c) of residuals of the seasonal AR(1,1) models.

	Pine	Spruce	Birch
Pine	r = 1.0 (p = 0.000) c = 128.99		
Spruce	r = 0.3543 (p = 0.000) c = 39.811	r = 1.0 (p = 0.000) c = 97.865	
Birch	r = 0.1262 (p = 0.213)	r = 0.380 (p = 0.000) c = 21.300	r = 1.0 (p = 0.000) c = 55.876 c = 220.78

Cholescky decomposition of residual covariances, e_1, e_2 and e_3 were normally distributed random numbers with zero mean and variance equal to one. For the seasonal AR (1,1) models, the innovation processes were generated correspondingly from

$$
\begin{aligned}
a_{pine} &= 11.358e_1 \\
a_{spruce} &= 3.505e_1 + 9.251e_2 \\
a_{birch} &= 1.857e_1 + 5.330e_2 + 13.742e_3
\end{aligned}
\tag{7}
$$

The non-seasonal AR(1) processes were then simulated by

$$I_t = (1 - \varphi_1)\mu + \varphi_1 I_{t-1} + a_t \tag{8}$$

and seasonal AR(1,1) processes by

$$I_t = (1 - \varphi_1 - \phi_1 + \varphi_1\phi_1)\mu + \varphi_1 I_{t-1} + \phi_1 I_{t-L} - \varphi_1\phi \tag{9}$$

where
t = time
I_t = growth index
φ_1 = non-seasonal AR parameter
L = length of cycle
ϕ_1 = seasonal AR parameter
μ = mean
a_t = innovation process

4 Case Study

4.1 Case Study Problem and Planning Method

The aim in this case study was to demonstrate the effect of risk and forest owner's attitude toward risk in forest planning. Both estimated non-seasonal AR(1) and seasonal AR(1,1) models were used to produce growth scenarios. Thus one goal was to compare the use of the seasonal and non-seasonal growth scenarios.

A multi-objective planning problem under risk was defined and solved. The sources of risk were timber price and the level of tree growth. Optimal plans for different risk attitudes were analysed in several risk conditions:

A) No risk
B) Growth varies at normal level (according to estimated models)
C) Timber prices vary at normal level
D) Growth and timber prices vary at normal level
E) Growth varies at normal level and variation in timber prices is twice the normal variation

The forest holding (area 30 hectares) consisted of forty-one compartments. Most of the growing stock's total volume was composed of spruce (44 %) with the proportions of pine and birch were 33 % and 23 %, respectively. The volume of sawlog timber was 1654 m^3 (32 % of the total volume). Two-thirds of the total area was composed of stands of middle-age or mature stands. Thus the forest holding provides flexible production possibilities, and in most compartments it was easy to identify several realistic treatment alternatives for the next two 10-year periods. The forest owner aims at high incomes in both 10-year periods, but he would also like to have a lot of sawtimber stands at the end of the planning period.

The planning procedure used consisted of (1) generating growth and timber price scenarios, (2) simulating treatment schedules, (3) estimating a preference function, (4) estimating the forest owner's attitude toward risk, and (5) optimization (see Pukkala and Kangas 1996). Due to variation in tree growth and timber prices, the priority indices for each plan were calculated for all states of nature (i.e. different combination of growth and price scenarios). Thus the comparison of the alternative plans was based on the distribution of priority indices. The forest owner's attitude towards risk was modelled by specifying weights for the worst, the expected, and the best-possible priority indices. The worst and best outcomes were represented by 10 % and 90 % accumulation points of that distribution. In optimization, the maximum weighted sum of the best, expected and worst priority indices was searched for by means of a heuristic algorithm. The MONSU-program, developed by Pukkala (1993), was used as a planning and decision-support system.

Firstly, the ten growth- and timber-price scenarios (also including those with no variation) needed in the different cases were generated. Then a total of 161 treatment schedules were simulated for the forty-one compartments. Non-seasonal and seasonal growth scenarios were produced using the models of this study, whereas the price scenarios were based on the models developed by Pukkala and Kangas (1996). The same growth scenarios were used in cases B, D and E, and the same price scenarios in cases C and D. Using only ten scenarios for each source of risk (totalling 100 states of nature) was adequate for demonstration purposes and appropriate for the computation resources available.

The forest owner's priority function was estimated based on pairwise comparisons (see Pukkala and Kangas 1993):

$$P = 0.33\, p_1(Vs_2) + 0.33\, p_2(NI_1) + 0.33\, p_3(NI_2) \quad (10)$$

Sawtimber volume at the end of the 2nd 10-year period (Vs_2), and net incomes for the 1st and the 2nd 10-year periods (NI_1 and NI_2) all had the same importance. The subpriority functions (p_1, p_2 and p_3) were linear.

Functions for reflecting the forest owner's attitude toward risk were also estimated by using pairwise comparisons. The final utility (U_r) for each plan for different attitudes toward risk were computed from:

Risk avoider: $U_r = 0.79P_w + 0.12P_e + 0.10P_b$
Risk neutral: $U_r = 0.11P_w + 0.78P_e + 0.11P_b$
Risk seeker: $U_r = 0.10P_w + 0.11P_e + 0.79P_b$

P_w, P_e and P_b were the worst, the expected and the best outcomes of the priority index distribution, respectively.

4.2 Optimal Forest Plans

Similar basic results can be seen in optimal plans regardless of whether the growth scenarios were produced by non-seasonal AR(1) models (Fig. 4) or seasonal AR(1,1) models (Fig. 5). The risk avoider's and risk seeker's solutions were different even in case B, where the variation in growth was the only source of risk. When the risk attitude was neutral, the variation in growth had very little impact on the optimal plan. When two

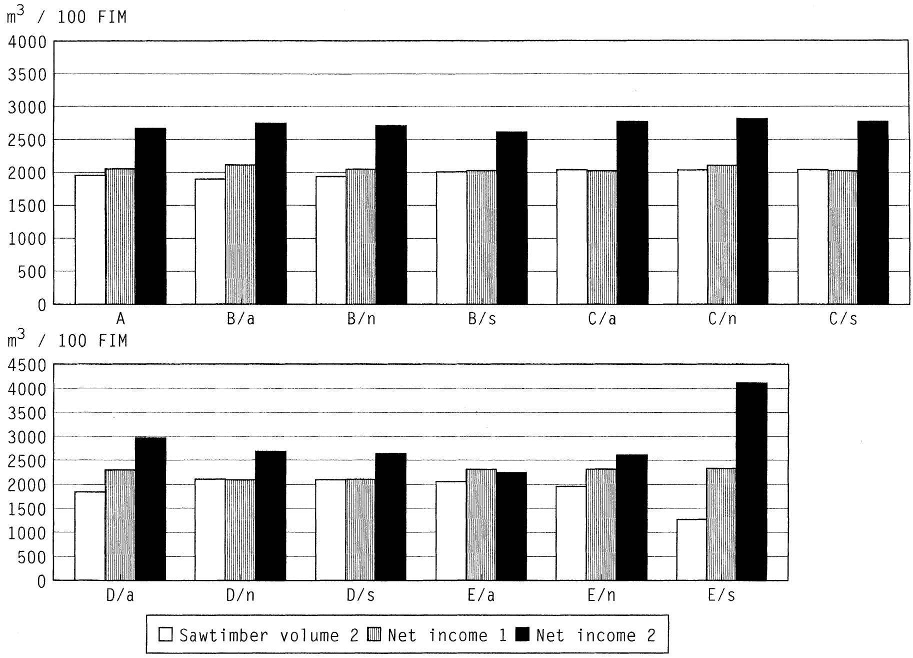

Fig. 4. Optimal solutions for risk avoider (a), risk neutral (n) and risk seeker (s) in different risk conditions when the non-seasonal growth scenarios were used. (A = no risk, B = growth varies, C = prices vary normally, D = growth and prices vary normally, E = normal growth variation and high price variation.)

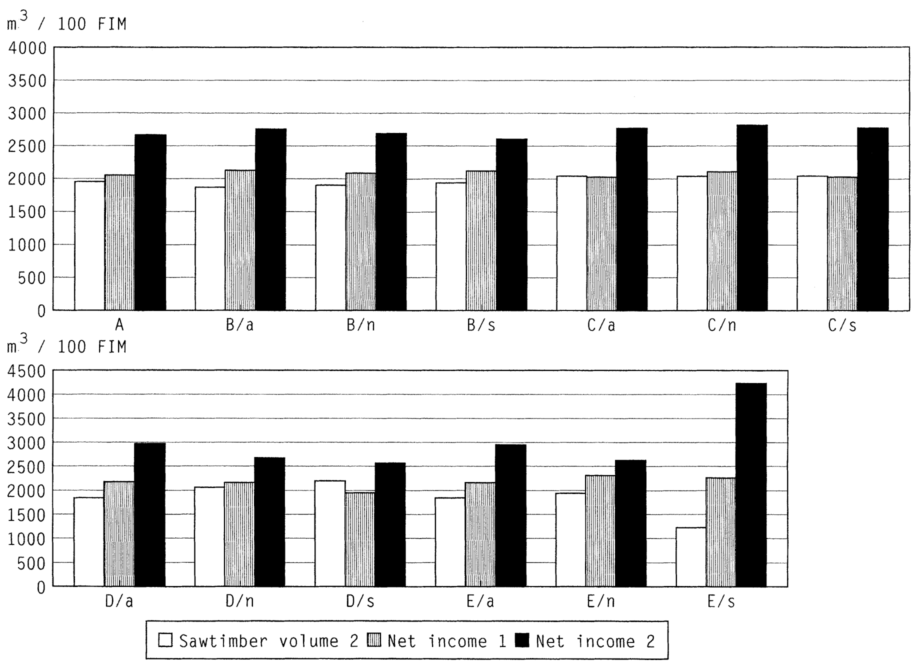

Fig. 5. Optimal solutions when the seasonal growth scenarios were used (symbols as in Fig. 4.)

sources of risk were included (D and E), the effect of the attitude toward risk was greater than in the case of one source (B and C). In the cases B and D, the attitude toward risk had some systematic impacts on the optimal solutions: sawtimber volume at the end of 2nd 10-year period increased along the level of risk taking, but net incomes decreased. With high variation in timber prices and normal variation in growth (case E), the change from risk avoider to risk seeker had radical impacts on the optimal plan. The optimum for risk seeker (E/s) means lots of regeneration cuttings during the 2nd period and giving up on high sawtimber volumes.

Optimal plans were more or less different in terms of the cutting areas. Cutting areas revealed that the different values in the optimal solutions were based on different treatments. There were no two identical plans, even though some were quite close to each other (e.g. plans A and B/n). However, the treatments revealed no systematic trends. The results (B, D and E) obtained when using seasonal growth scenarios indicated no generally greater impact on growth variation than the corresponding results based on the non-seasonal growth scenarios (cases A and C were similar due to no variation in growth). In case D, the seasonal scenarios caused greater differences between optimal plans than the non-seasonal scenarios did. According to thinnings and regeneration cuttings, the level of risk and the attitude toward risk really do have an impact on the optimal solutions.

Table 6. Correlations between the growth-index series of this study and the series presented by Mikola (1950), Tiihonen (1984) and Mielikäinen (1991).

	Length	Correlation	p-value
Scots pine			
Mikola (1950)	47	0.84	0.000
Tiihonen (1984)	39	0.78	0.000
Mielikäinen (1991)	17	0.77	0.003
Norway spruce			
Mikola (1950)	47	0.78	0.000
Tiihonen (1984)	40	0.70	0.000
Mielikäinen (1991)	17	0.60	0.011
Silver birch			
Tiihonen (1984)	40	0.75	0.000
Mielikäinen (1991)	17	0.47	0.056

5 Discussion

5.1 Material Used in Modelling

Because long-term and consistent growth index series for pine, spruce and birch were not available, new data had to be acquired for this study. The tree-ring material was measured in Pohjois-Karjala, eastern Finland, by accessing a small number of sample trees (a total of 117). Most of the measured trees were over 100 years old; thus the variation in growth obtained may be different from that revealed in normal forestry (see Mikola 1950). On the other hand, to get long-term series, old trees are needed. In fact, the first halves of the individual long-term series represented variation in tree growth at middle-age or normal final-cut age. The small number of series for the early part of the measurement period must be borne in mind.

Several standardization methods could have been used (see Visser and Molenaar 1990). Polynomial trend functions of the third order were used because they seemed to be flexible enough to remove the age-related growth trends of the different shapes and the unusually long-term variation found in some series. A more flexible trend function could have eliminated the cycles found in all the series.

Despite the deficiencies of the research material, different study areas and differences in standardization methods, the estimated growth index series were quite similar to those presented in earlier studies (Fig. 6 and Table 6). The series by Tiihonen (1984) and Mielikäinen (1991) were based on data provided by national forest inventories conducted in Finland. The series on birch in this study had higher amplitudes than the series presented by Tiihonen (1984). This may be due to the small number of measurements and the high proportion of old birches in the present study material. Correlations between the growth

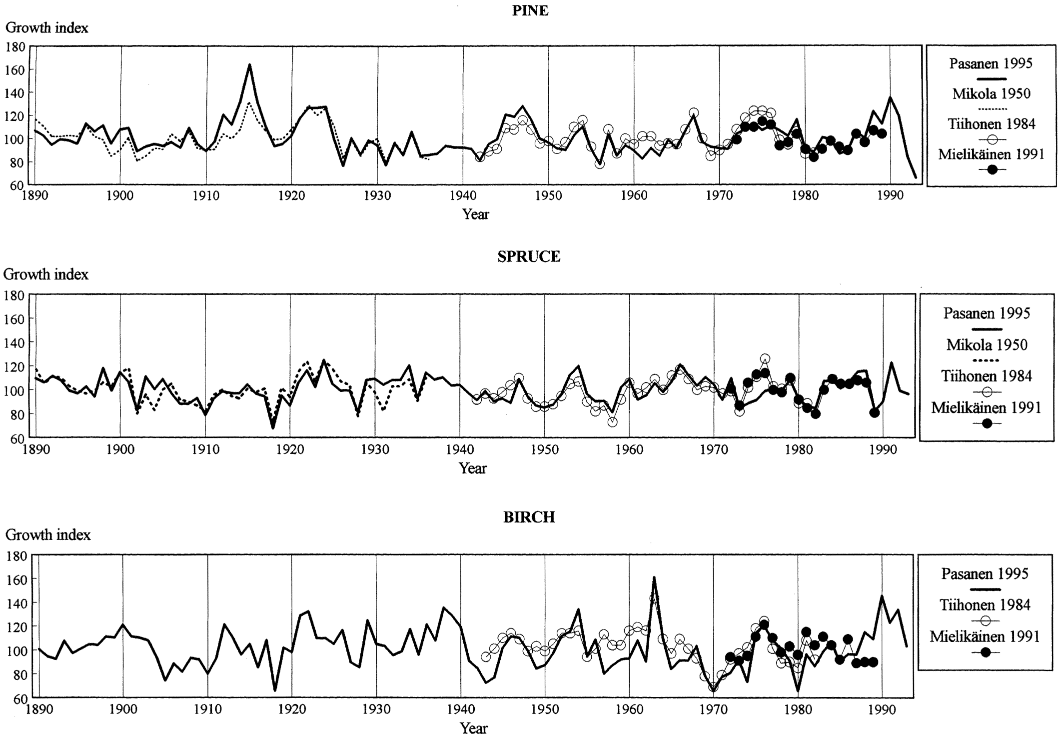

Fig. 6. Growth index series of this study (Pasanen 1995) and those of Mikola (1950, area VI), Tiihonen (1984) and Mielikäinen (1991; area II for pine and spruce and areas I, II and III for birch).

index series of this study and those of previous series were high (0.6–0.8) and significant (at 1 % risk level), except for the series on birch by Mielikäinen (1991) (Table 6).

All the obtained growth index series seemed to be reliable enough for further use, although the reliability and validity of the series on birch were not so good. The series represent the average variation in tree growth in forests based on mineral soils in Pohjois-Karjala, eastern Finland, and to some degree in forests in southern and central Finland, due to uniformity with the compared series. According to Mikola (1950) variation in tree growth is uniform over large areas of Finland. On the contrary, Henttonen (1984) found considerable differences between growth-index series obtained from different locations, but many of the series referred to were based on data collected from thinned stands.

5.2 Models

Non-seasonal AR(1) models were adequate for producing growth scenarios. The AR(1) coefficient was smaller for spruce and birch than for pine. This result is not in contradiction with the theory of variation in tree growth. Seed production by conifers consumes a lot of energy and decreases the growth of pine during two successive years (flowering and maturing) but in spruce mainly during one year (Pukkala 1983). The greater coefficient (greater variance as well) of pine is partly caused by the fact that spruce needles live longer than pine needles, and thus pine is more sensitive to an individual year's effects than spruce is (see Mikola 1950). Although birch can set aside the nutrient reserve of the foliage, it is clear that variation in growth between successive years is then more affected by random factors than is the case with conifers.

Henttonen (1984) found also non-seasonal

Table 7. Results of the test simulations of the processes.

	Mean	Standard deviation	Correlation (pine)	Correlation (spruce)	Correlation (birch)
Non-seasonal AR(1) processes					
Pine	97.6...105.6	14.6...17.7	1	0.15...0.53	0.08...0.31
Spruce	99.0...102.4	10.9...13.2		1	0.54...0.65
Birch	96.8...102.7	12.3...17.2			1
Seasonal AR(1,1) processes					
Pine	0.54...0.65	13.1...15.6	1	0.26...0.48	–0.13...0.23
Spruce	98.5...101.7	9.1...13.1		1	0.19...0.60
Birch	95.4...104.0	15.4...18.8			1

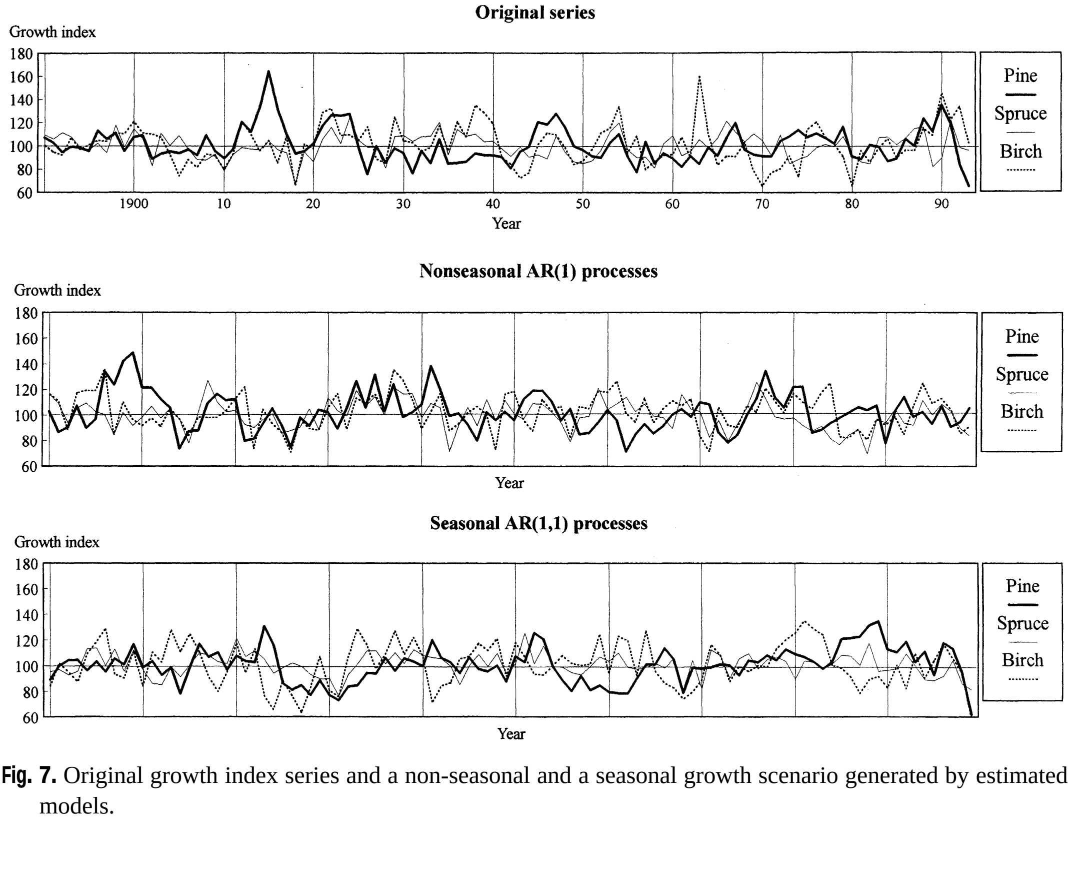

Fig. 7. Original growth index series and a non-seasonal and a seasonal growth scenario generated by estimated models.

AR(1) models to fit well with the average tree-ring index series of Scots pine and Norway spruce. The AR(1) models based on series from Koli (Pohjois-Karjala, eastern Finland) were compared to the non-seasonal AR(1) models obtained in this study. In the case of pine, the AR(1) parameters were similar (Henttonen 0.59, present 0.56), but the standard deviation of the residuals was smaller in this study (Henttonen 15.42, present study 11.77). For spruce, the AR(1) parameters were different (Henttonen 0.55, present study 0.30), whereas the standard deviations of the residuals were closer (Henttonen 11.57, present study 10.12). Monserud (1986) concluded the ARMA(1,1) model to be generally best for the analysed individual tree ring series. Visser and Molenaar (1990) found the AR(1) models to fit well for Norway spruce, but emphasized that their AR(1) models were in fact approximately the same as the ARMA(1,1) models found by Monserud (1986).

Boman (1927) found 7, 11, 21, 35 and 70 year periodicities of growth for Scots pine in Finland. Mikola (1950) also discussed different cycle lengths in growth (11, 17, 23 and 35 year cycles). In this study, adequate seasonal AR (1,1) models were found for each of the three tree species. The models could not be supported by any special theory due to the lack of current research on possible periodicity in growth, but the 7-year cycle for pine was not a new result (see Boman 1927). In addition, a complicated model fitting "too" well with the observed series has to be used with special care to avoid serious errors. The seasonal models were presented and used in the case study to provide tentative evidence about seasonality in growth and to test the effects of seasonality on optimal solutions. The idea of forecasting growth cycles has been mentioned by Mikola (1950) and it is clear that more research is needed in this field.

Studying the long-term variation in growth requires long-term series. Thus, two old Scots pines (used also for the mean growth-index series) were used to find out long-term cycles. A logarithmic trend function was used in the standardization in order to include all periodicities into an index series. Significant seasonal parameters were found at cycle lengths of 14, 20, 27, 36 and 41 years. Further research with additional data on old trees (more than 200 years) should be carried out in order to obtain more profound knowledge about the existence of these long waves. If middle- or long-term fluctuations really do exist, they should be taken in to account in forest planning as well as in climate-change research.

In the course of this study, some individual tree-ring index series for each of the three tree species (a total of 11 series, lengths of 99 years) were modelled also in order to check whether the single-tree models were similar to the models for the average series. The standard deviations of the residuals were clearly (30 %–100 %) higher compared to the deviations in the cases of the average series. AR(1) models were adequate for all series, but the coefficients were more or less different in each cases. Suitable MA(1) or MA(2) models were also found for all the series. Cycles of different lengths were clear in most series. None of the series was found to behave as an ARMA(1,1) process.

5.3 Using the Estimated Models

It must be borne in mind that the original growth indices and the generated ones are realisations of the same stochastic processes (Fig. 7). A total of ten correlated growth scenarios (length 100 years) were generated by computer to test the applicability of the non-seasonal and seasonal AR models for real use. The means, standard deviations and correlations (Table 7) were logically compared to the values of the original series. Thus, the main aim of this study appears to ha been reached.

The case study demonstrated the impacts of risk and forest owner's attitude toward risk in an optimal forest plan when variation in growth and timber prices were included in the planning process. The results support previous conclusions that deterministic plans may differ clearly from plans including risk and attitude toward risk (see Pukkala and Kangas 1996). Even in the case where variation in growth was the only source of risk, the optimal plan was different for the risk seeker and the risk avoider. The use of seasonal growth scenarios caused no clearly greater impacts on the optimal forest plans compared to the situation when non-seasonal models were used.

Non-seasonal and seasonal AR models were selected for generating growth scenarios in the case study. The cross-correlations of the original series were taken into account using the covariances of the residuals. Although the original tree-ring material was measured in Pohjois-Karjala, the models can be used for generating growth scenarios in southern and central Finland due to the uniformity of the original series with the compared series. The periodocity of growth requires further research. If long waves are significant and easy to model, these will be important in forestry research in general as well as in practical forest planning.

However, it must be borne in mind that variation in growth and timber prices are not the only sources of risk. Errors in inventory data and models, the occurrence of forest damage, and even the objectives of the decision maker, include uncertainty. Much research work is needed to integrate the various sources of risk successfully into forest planning.

Acknowledgements

This study is the author's Master's thesis. I wish to thank Dr. Timo Pukkala and Dr. Juha Alho for supervising my research work. I also wish to acknowledge Dr. Joann von Weissenberg for the instruction she provided me in the writing of the manuscript in English, and Dr. Jyrki Kangas for his valuable comments. The Finnish Forest and Park Service and Enso Oy permitted me to acquire the tree-ring data from virgin forest stands on their lands.

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Total of 25 references

Appendix 1. Growth indices for Scots pine, Norway spruce and birch from 1890 to 1993, estimated for Pohjois-Karjala, eastern Finland.

Year	Pine	Spruce	Birch	Year	Pine	Spruce	Birch	Year	Pine	Spruce	Birch
1890	107	110	101	1925	99	105	105	1960	90	109	93
1891	103	106	95	1926	76	99	117	1961	83	92	108
1892	95	111	92	1927	100	100	89	1962	92	95	90
1893	99	108	107	1928	86	81	85	1963	85	106	161
1894	99	99	97	1929	98	108	125	1964	99	98	110
1895	96	97	101	1930	94	109	105	1965	92	107	84
1896	113	103	105	1931	77	104	103	1966	107	121	91
1897	106	94	104	1932	96	108	95	1967	120	112	91
1898	111	118	111	1933	86	109	99	1968	97	104	103
1899	96	99	110	1934	106	121	117	1969	93	111	79
1900	108	115	121	1935	85	93	96	1970	92	105	66
1901	109	106	111	1936	86	115	121	1971	91	92	77
1902	89	83	110	1937	87	109	108	1972	104	110	81
1903	93	111	108	1938	94	110	135	1973	108	85	92
1904	95	101	93	1939	92	104	129	1974	114	89	74
1905	94	109	74	1940	92	104	120	1975	108	92	114
1906	97	97	89	1941	91	98	91	1976	111	99	121
1907	92	88	82	1942	81	91	85	1977	107	102	108
1908	109	88	93	1943	95	99	73	1978	102	100	102
1909	96	93	92	1944	99	91	77	1979	117	108	91
1910	90	79	80	1945	121	93	102	1980	91	93	66
1911	98	93	93	1946	119	89	111	1981	89	87	96
1912	121	99	121	1947	128	109	110	1982	101	85	86
1913	112	97	110	1948	117	95	99	1983	99	107	99
1914	133	97	96	1949	100	87	84	1984	87	108	107
1915	164	104	105	1950	97	85	87	1985	89	101	90
1916	132	97	85	1951	92	88	97	1986	106	107	97
1917	111	94	108	1952	90	97	111	1987	100	115	96
1918	94	68	66	1953	103	113	115	1988	123	116	115
1919	96	95	102	1954	111	120	134	1989	113	83	109
1920	103	87	98	1955	91	97	94	1990	135	90	145
1921	118	106	129	1956	78	90	109	1991	119	123	123
1922	127	116	132	1957	104	91	80	1992	84	99	134
1923	126	102	110	1958	85	81	87	1993	66	97	103
1924	128	125	110	1959	94	102	92				