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UTILITY OF "A" HORIZON SOIL CHARACTERISTICS TO SEPARATE PEDOLOGICAL GROUPINGS, AND THEIR INFLUENCE WITH CLIMATIC AND TOPOGRAPHIC VARIABLES ON *PINUS RADIATA* HEIGHT GROWTH

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ABSTRACT

A database consisting of 299 *Pinus radiata* D. Don sample plot periodic growth data, soil measurements (mainly from the A horizon profile) gathered from within each plot, as well as relevant climatic data, was updated and revisited.

The plots were in various forests in the North Island of New Zealand. The soils relevant to the plots were grouped according to the New Zealand Soils Classification from which 11 classes can be recognised. These classes were examined by a multivariate discrimination analysis utilising A horizon soil variables as predictors. The various classes separated into two major groupings, with virtually all the classes being correctly classified for at least 75% of the data. The major discriminators were silt and clay percentage, the depth of the A horizon, organic carbon (%), and total nitrogen (%). Phosphorus (Bray or Olsen), Bray-extractable cations (calcium, potassium, and magnesium), average resistance, and soil pH had no significant effect on the separation of the classes.

These data were augmented by climatic data and attempts were made to build a predictive system for mean top height (average height of the 100 largest trees by diameter at breast height). At first, separate equations were assayed for each soil class, but insufficient replication for some soils necessitated a pooled model. A nonlinear equation was constructed that was largely unbiased over the soil classes with an approximate R^2 value equal to 0.77. The residual root of the error mean square was around 3 m. The dominant predictor variables were the age of stand when sampled, depth of the A horizon, average wind velocity, mean annual rainfall, and altitude.

The model should be used cautiously as it is very difficult to produce a predictive system of stand growth without partially confounding the effects of soils, location, and climate.

Keywords: height growth; A horizon soil features; weather variables; *Pinus radiata*.

INTRODUCTION

Hunter & Gibson (1984) described a multiple regression model to predict site index (mean-top-height corresponding to the quadratic mean of the largest 100 stems/ha by diameter at age 20) in *Pinus radiata* stands in New Zealand where the predictor variables were a combination of climatic, nutrient, and soil factors. The database from which the model was constructed consisted of 299 permanent sample plots from throughout New Zealand. Plots were chosen in which the growth data straddled age 20 and no thinning had taken place, or if there had been thinning it had occurred at least 5 years before sampling. In each plot, 10 pits were excavated with spade and auger. Litter depth and A horizon depth were measured in each pit, and soil samples were collected from the horizon for analysis, together with a pedological description based on the methods of Taylor & Pohlen (1970).

In this study the data were re-examined. The soils were re-classified and assigned to follow 10 major orders. Multivariate statistical analyses were addressed to the majority of these (as well some sub-orders) mainly using chemical concentration data acquired from the A horizon as the exploratory variables. A major objective of this study was to ascertain the degree of separation of these soil classes — to what extent are they independent or unique? A second objective was to isolate and rank the major discriminating variables. Which soil constituents contribute most to separating the classes? Which contribute little separating power? In addition, attempts were made to construct regression models to demonstrate relationships between the A horizon soil variables (together with climate and environmental variables) and stand height growth. Statistical details of these predictive equations are presented and the results are discussed.

SOIL ORDERS

Soils are generally identified and allocated to classes according to the characteristics of the entire soil profile. Use is made of diagnostic horizons, soil materials, profile forms, and other features (Hewitt 1998).

In this study the soils were grouped according to the New Zealand Soil Classification (Hewitt 1998). The classification recognizes 15 Orders at the highest level, subdivided into Groups and Subgroups. There are 10 Orders in the data here but two, Gley soils and Podzols, were insufficiently represented and were not included in the study. This left the following Orders: Ultic, Allophanic, Pumice, Granular, Pallic, Brown, Recent, and Raw soils. These can be briefly described as follows. (The figures in parentheses following each description are the number of sample plots assigned to each soil Order.)

Allophanic soils (ALLOPHANIC) occur mostly in North Island volcanic ash, and in weathering products of volcanic rocks. The soil matrix is dominated by the clay minerals allophane, imogolite and ferrihydrite. They have high phosphate retention properties. They provide a good rooting medium but are sensitive, with a pronounced loss of strength on disturbance. They are generally well drained with stable structure and are of low fertility. (37)

Brown soils (BROWN**)** are the most frequently occurring soil order in New Zealand. They occur where summer dryness is uncommon and they are usually well drained. They have stable topsoils and are of moderate fertility. Some have allophanic properties. (37)

Granular soils (GRANULAR) occur in the northern part of the North Island. They are predominantly derived from strongly weathered volcanic ash. They have a limited rooting depth and are slowly permeable. Although topsoil structures are strongly developed, workability after heavy rain is limited. Phosphate retention is high and nutrient reserves are generally low. (7)

Pallic soils (PALLIC) occur in low rainfall areas with droughty summers and moist winters. The high-density subsoils, on which water may perch, often restrict rooting depth. (9)

Pumice soils (PUMICE**)** occur in relatively young, sandy or pumiceous volcanic ashes of the central North Island. They are deep rooting soils, are well drained, but have low soil strength when disturbed and therefore their erosion potential is high. Some welded subsoils occur, particularly in southern Kaingaroa Forest, where *in situ* dense subsoils form a root barrier. Nutrient levels are low. (113)

Raw soils (RAW) lack distinct topsoil development and include young dune sands and recently eroded steep slopes. Generally they are of low fertility particularly with respect to nitrogen. (40)

Recent soils (RECENT) occur in young landscapes, including alluvial floodplains, unstable steep slopes, and slopes mantled by young volcanic ash. In this study weakly developed dune soils are also classed in this order. These soils show weak soil development and, except on steep slopes, they have deep rooting potential and good drainage. (48)

Ultic soils (ULTIC) are common in the northern North Island, and in the Wellington, Marlborough, and Nelson areas. They are strongly weathered soils with clayey subsoils. Generally they are acid soils with low nutrient levels and slow permeability. (8)

For three Orders we subdivided the data to Group level, as follows:

Recent soils, to **Sandy Recent soils** (RECENT) (27) or **Recent other Groups** (RECENT(O)). (21)

Brown soils, to **Orthic Brown soils** (BROWN) (20) or **Brown other Groups** (BROWN(O)) (17)

Pumice soils, to **Orthic Pumice soils** (PUMICE) (102) or **Impeded Pumice soils** (PUMICE(I)) (11).

The 11 divisions so formed are referred to in this paper as the Soil Classes.

“A” HORIZON SOIL DATA

The following soil variables were available for analysis, taken very largely from the A horizon (for 17 plots, mainly representing Raw soils, an A horizon was judged not to exist. For these, the topmost horizon available was substituted).

Average depth of the A horizon (cm)	(DH)
Acidity	(pH)
Percentage organic carbon	(C
and total nitrogen	(N)

Olsen and Bray phosphorus (ppm)	(OP and BP)
Bray extractable calcium (m.e.%)	(Ca)
magnesium (m.e.%)	(Mg)
and potassium (m.e.%)	(K)
Silt plus clay (%)	(SC)
Average resistance (kg/cm^2)	(R)

The basic data for each soil group are summarised in Table 1. Pearson correlations for these variables (pooled over all soil classes) show relatively few meaningful associations. Organic carbon percentage is strongly correlated to total nitrogen (r = 0.88) and the silt and clay percentage is clearly correlated to organic carbon, total nitrogen, and pH (r = 0. 59, 0.67, and –0.56 respectively). The Bray-extractable cations potassium, calcium, and magnesium are correlated to each other (r = 0.65, 0.54, and 0.59 respectively) and logically Bray-phosphorus is related to Olsen-phosphorus (r = 0.71), but all other correlations are less than 0.5, with the big majority of variables being virtually independent.

STATISTICAL BACKGROUND

The data were explored mainly by the statistical multivariate technique of canonical discriminant analyses (Mardia *et al.* 1979). Linear combinations

$$Z = a_1Y_1 + a_2Y_2 + a_3Y_3 + \dots + a_pY_p \quad (1)$$

are formed, where Z is called a canonical variable, Y_1 to Y_p represent the A horizon soil variables listed above, and the a_i are coefficients. The a_i are calculated in such a way that the maximum possible multiple correlation between the soil classes and Z is achieved. A series of Zs become available, each maximally correlated to the groups but independent of each other. The first canonical variate has the highest correlation, followed by the second and so on. The proportion of total variation accounted for by each combination can be estimated. Each successive canonical variate can be tested by the hypothesis that it is equivalent to zero. In practice it is useful if only the first one or two are required, and they account for a large proportion of the total variation. Canonical discriminant analysis essentially reduces dimension and highlights between-group differences (if present). Canonical functions are very similar but nevertheless distinct from classical discriminant functions (Fisher 1936, or Rao 1973) whose purpose is to allocate samples of unknown origin optimally to a set of specified groups.

METHODS AND RESULTS

The data were analysed mainly by utilising the PROC DISCRIM option of the statistical package, SAS. A test of the hypothesis that the class covariance matrices were identical was rejected ($p < 0.0001$), as measured by an approximate Chi-squared test (Morrison 1976). This strongly suggested that the various soil classes have heterogeneous variances — that is, some soil classes are more variable than others.

No less than six significant ($p < 0.0001$) canonical axes emerged. However, the first three axes explained 93% of the variation of which the first alone accounted for 72%. The axes are (the four largest coefficients by absolute value are highlighted):

TABLE 1–Basic soil data by soil class (standard deviation in parentheses)

Variable	ALLO-PHANIC	BROWN	BROWN(O)	GRANU-LAR	PALLIC	PUMICE(I)	PUMICE	RAW	RECENT	RECENT(O)	ULTIC
DH*	13 (4)	17 (7)	10 (5)	11 (3)	14 (4)	11 (2)	15 (5)	1.3 (1)	11 (5)	5 (5)	14 (4)
pH	5.6 (0.3)	5.7 (0.4)	5 (0.4)	4.9 (0.2)	5.3 (0.1)	5.4 (0.4)	5.6 (0.3)	5.9 (0.6)	5.3 (0.4)	6 (0.5)	5.1 (0.4)
C	8.6 (3)	5.0 (2)	4.6 (1)	4.9 (0.2)	4.0 (1)	6.2 (2)	4.9 (2)	1.6 (2)	4.9 (3)	1.1 (1)	10 (6)
N	0.53 (0.2)	0.37 (0.2)	0.41 (0.1)	0.3 (0.1)	0.26 (0.1)	0.2(0.01)	0.25 (0.1)	0.08 (0.1)	0.3 (0.1)	0.07 (0.1)	0.60 (0.3)
BP	4.5 (1)	9.4 (5)	9.4 (8)	2.7 (0.8)	2.6 (1)	48 (27)	30 (22)	24 (10)	9 (9)	24 (10)	7 (6)
OP	8 (6)	23 (27)	14 (19)	3 (2)	5.4 (2)	16 (10)	9.2 (6)	6.1 (3)	7 (5)	5 (3)	9 (4)
Ca	5.2 (3)	6.6 (3)	5.3 (6)	2.3 (2)	2.7 (1)	1.8 (1)	3.6 (2)	2.6 (2)	4.2 (2)	1.8 (1)	3.8 (3)
Mg	1.9 (1)	2.0(0.9)	2.0 (1)	2.1 (0.8)	2.4 (0.6)	0.5 (0.3)	1.3 (0.9)	1.5 (2)	2.4 (0.8)	0.9 (0.4)	2.6 (1)
K	0.4 (0.3)	0.4 (0.2)	0.4 (0.3)	0.2 (0.1)	0.4 (0.2)	0.3 (0.1)	0.3 (0.1)	0.1 (0.1)	0.4 (0.2)	0.1 (0.1)	0.2 (0.2)
SC	66 (9)	52 (26)	86 (9)	88 (2)	91 (6)	54 (7)	50 (13)	6.4 (5)	74 (16)	5 (4)	93 (4)
R	9 (7)	16 (8)	32 (21)	28 (6)	46 (22)	12 (6)	9 (7)	3 (7)	28 (28)	3.2 (4)	25(24)

* DH = average depth of the A horizon (cm); pH = acidity; C = percentage organic carbon
N = percentage total nitrogen; BP = Bray phosphorus (ppm); OP = Olsen phosphorus (ppm)
Ca = Bray-extractable calcium (m.e.%); Mg = magnesium (m.e.%); K = potassium (m.e.%)
SC = silt plus clay (%); R = average resistance (kg/cm^2)

$$Z_1 = \mathbf{2.33SC} - \mathbf{0.35N} + \mathbf{0.45C} - 0.17BP + 0.27OP + \mathbf{0.79DH} + 0.13pH + 0.16K - 0.15Ca - 0.15Mg + 0.04R \quad (2a)$$

$$Z_2 = -\mathbf{0.76SC} - \mathbf{0.77N} + \mathbf{1.47C} + 0.26BP + 0.27OP + \mathbf{0.88DH} + 0.43pH + 0.41K - 0.39Ca - 0.45Mg - 0.18R \quad (2b)$$

$$Z_3 = -\mathbf{0.71SC} + \mathbf{1.96N} - \mathbf{0.49C} - 0.04BP - 0.21OP - 0.17DH + 0.23ph - 0.02K + 0.18Ca - \mathbf{0.29Mg} + 0.13R \quad (2c)$$

The terms have been defined in the section on A horizon soil data.

The first (and major) axis 2a separates the soil classes very largely through the percentage of silt plus clay present and, to a lesser extent, through the A horizon depth. The second axis 2b is dominated by the effects of organic carbon percentage but also suggests an interaction of total carbon percentage and A horizon depth against nitrogen and silt plus clay percentage levels. The third axis 2c is very substantially a direct effect of total nitrogen.

The mean Z scores for the first two canonical variates for each soil class were calculated and are plotted in Fig. 1. The corresponding circles represent 95% confidence regions (see Mardia *et al*. 1979, p. 344). (Note that the axes utilise standardised variables with a mean of zero and standard deviation of one and so the data given in Table 1 are not directly comparable.) The various radii reflect the different replication available for each soil class. The various soil classes split into two discrete clusters are shown in Fig. 1, with Raw soils and Sandy Recent soils spatially very distant from the rest of the soil classes. Within the larger cluster, two smaller groupings are evident — (a) Impeded Pumice, Pumice, Brown, and Allophanic soils, and (b) Recent, Ultic, Pallic, Orthic Brown, and Granular soils, respectively. Orthic and Granular soils are virtually identical, as too are Pallic and Ultic soils. Conversely, there is some evidence of Impeded Pumice soils differing from Orthic Pumice soils.

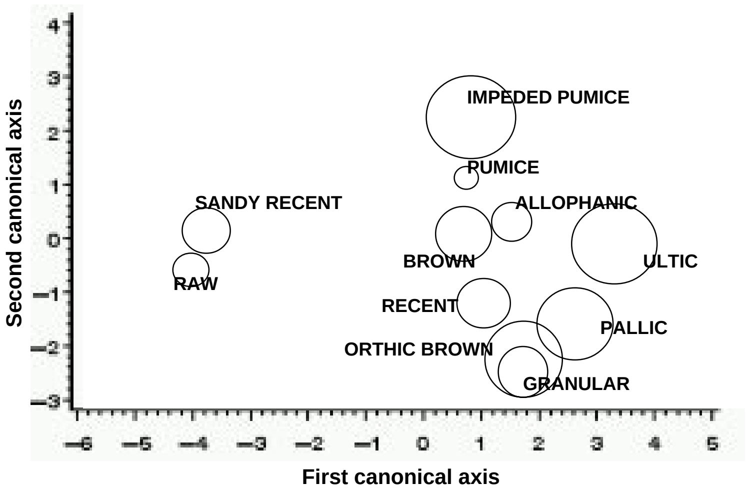

FIG. 1–Plot of the first and second canonical means for the 11 soil classes

A set of discriminant functions based on a squared distance measure (Rao 1973) were constructed, but individual class dispersion matrices were utilised rather than a single pooled variance-covariance matrix. From these, the percentages of data correctly allocated to their parent soil class were calculated (Table 2). Overall these percentages reflect an excellent allocation rate, with only the Brown and Recent soils showing a higher degree of variation.

TABLE 2–Percentage of data correctly allocated to their respective soil class

Allophanic	92	Impeded Pumice	100
Brown	59	Raw	74
Orthic Brown	90	Recent	66
Granular	100	Sandy Recent	96
Pallic	100	Ultic	100
Pumice	77		

PREDICTION OF MEAN TOP HEIGHT

The construction of yield models for mean top height (average height of the largest 100 trees/ha by diameter at breast height) required five of the soil classes to be dropped because there was insufficient replication to test for lack of bias. Thus, this section of the study is limited to Allophanic, Orthic Brown, Pumice, Raw, Recent, and Sandy Recent classes.

The growth data are copious with over 2800 growth records, the majority of which, however, represent repeated measures in time on the same sets of trees. Such data are clearly auto-correlated. This can cause tests of hypotheses in regression analyses to be compromised through spuriously deflated standard errors (West *et al*. 1984; Woollons 1998). Accordingly, the data were reduced to only one growth measurement per sample plot, thus eliminating the temporal dependence. The actual growth measure retained for each plot corresponded as much as possible to the age when each plot was sampled for soil characteristics. This gave an age range between 12 and 40 years. In contrast to Hunter & Gibson (1984), it was decided to include sampling age as a predictor variable and model mean top height rather than site index *per se*; preliminary analyses suggested several of the soil variables were somewhat correlated with stand age.

Initial attempts to model stand top height in terms of stand (sampling) age and the A horizon variables were not especially successful, their contribution appearing minimal. Later, it was realized that this approach was too simplistic on at least two grounds:

(a) Other factors, climatic or topographical in nature, were likely to contribute to stand height growth;

(b) Different factors may well contribute to height growth on contrasting soils.

Accordingly, it was decided to augment the soil data with the altitude data for each plot, as well as adding climate data obtainable from the BIOCLIM database and program (Wahba & Wendelberger 1980; Hutchinson 1984; Nix 1986). These data were not available to Hunter & Gibson, who relied on simple extrapolated figures from nearest-neighbour weather stations. Basic climate data available included mean annual rainfall (mm), mean estimated wind speed (km/hour), and mean annual temperature (°C). BIOCLIM also provides estimates of evaporation and solar radiation but we decided not to utilise these because they are not measured at most New Zealand weather stations, and thus are likely to be poorly estimated.

However, attempts to build individual equations for each soil type quickly revealed other problems. Only the Pumice group had substantial replication and the range of data available for other soil classes tended to be very narrow, limiting the efficiency of regression analyses. Attempts were made to put the classes into three bigger groupings as shown by the discriminant analysis above, but these too were not entirely satisfactory. Finally, we returned to a pooled model, but took especial care to check the goodness-of-fit of the equations for each soil class.

To build the model, we invoked the PROC NLIN routine from the SAS statistical package. The basic sigmoid log-reciprocal (Schumacher 1939) model

$$H = \exp(\beta_0 + \beta_1 / T) \tag{3}$$

where H = mean top height (m)
T = age (of sampling) in years
β_0, β_1 = parameters, estimated by non-linear least squares

gave a highly significant fit to the data, with a residual mean square of 16.96 and an approximate (Ratkowsky 1990) multiple correlation $R^2 = 0.58$. Plots of residual values, however, showed the model to be badly biased with respect to several soil classes.

Progressively, other predictor variables (when justified) were added to the basic model (3) until a new model emerged:

$$H = \exp(\beta_0 + \beta_1 / T + \beta_2 \mathrm{Ialt} + \beta_3\,\mathrm{rain} + \beta_4 \mathrm{wind} + \beta_5 \log(\mathrm{DH} + 1)) \tag{4}$$

where alt = stand altitude (m)
rain = mean annual rainfall (mm)
wind = average windspeed (km/hour)
DH = average depth of the A horizon
I = a dummy variable: I = 0 if the soil class is Raw or Sandy Recent; I = 1 otherwise

and $\beta_0 = 4.0402$ $\beta_1 = -15.7394$ $\beta_2 = -0.000107$ $\beta_3 = 0.000075$ $\beta_4 = -0.0190$ $\beta_5 = 0.0624$

All the coefficients were significantly different from zero, as judged by approximate 95% confidence limits. The residual mean square was 9.33, an increase in precision of 45% relative to (3), and the approximate R^2 value was = 0.77. Considerable care was taken to ensure that other functional forms of (4) did not give a lesser error mean square, or that other transforms of the predictor variables gave superior predictive ability. We also explored whether the canonical variate scores from 2(a) to 2(c) represented relevant predictor variables, but none were significant. The single most-effective predictor variable (aside from sampling age) was depth of the A horizon, followed by wind, rain, and altitude. A histogram of the residuals from Model (4) for each soil class is given in Fig. 2; predictions are substantially unbiased for all the soil classes.

To utilise Model (4) effectively it is important to input correct predictor values for a specific soil class. The model may well behave erratically if inappropriate inputs are entered. These average figures are given in Table 3; the values in parentheses are standard deviations.

DISCUSSION

The canonical discriminant analysis is very efficient in separating the various soil classes and helps considerably in understanding the A horizon variables that are important in causing

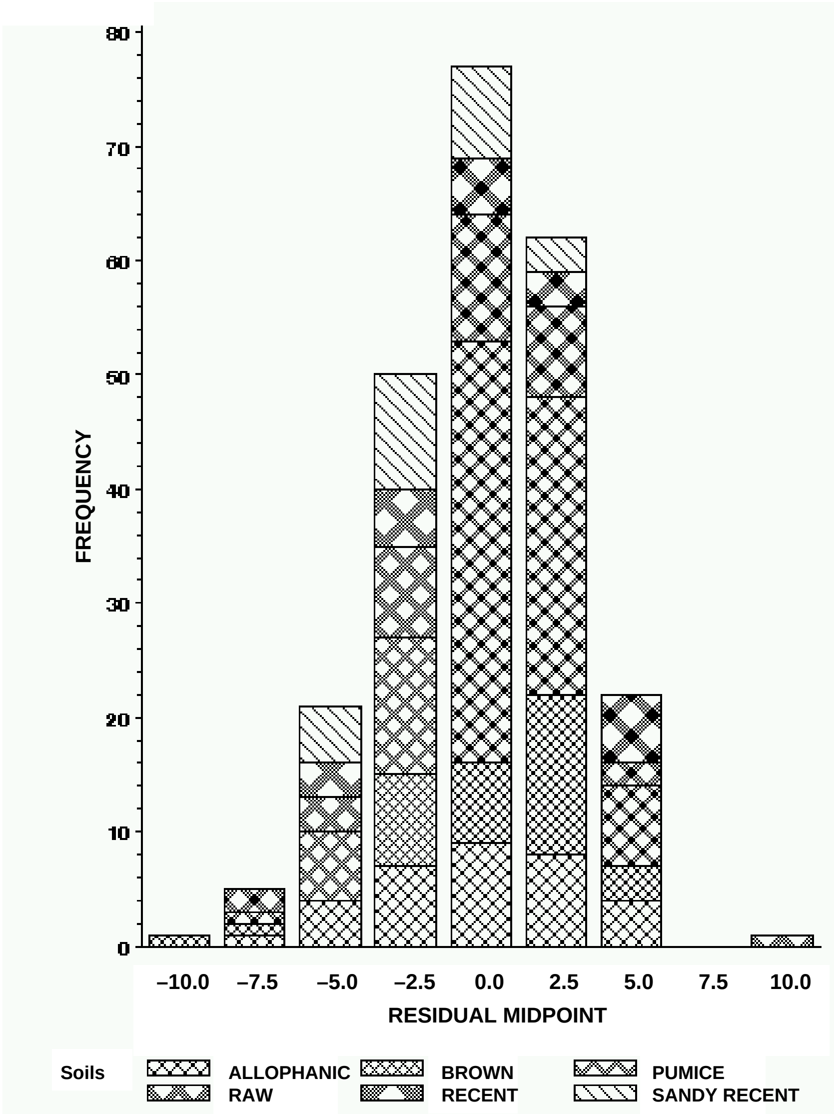

FIG. 2–Histogram of the residuals from Model (4) for the various soil classes

TABLE 3–Predictor variables for the modelled soil classes (standard deviations in parentheses)

Soil class	Altitude (m)	Annual rainfall (mm)	Wind (km/h)	A-horizon depth (cm)
Allophanic	315 (138)	1907 (319)	12.5 (1.5)	13.0 (4)
Brown	210 (105)	1781 (248)	12.4 (1.4)	10.0 (5)
Pumice	384 (122)	1587 (208)	7.9 (1.5)	15.0 (4.5)
Raw	77 (84)	1203 (267)	10.8 (1.5)	1.3 (1.2)
Recent	285 (115)	1600 (349)	12.6 (2.4)	11.0 (5)
Sandy Recent	60 (72)	1255 (288)	10.7 (1.7)	5.1 (5)

these differences. We do not, however, suggest that similar analyses should become standard methods for classifying soils. Soils are a product of soil-forming factors: parent material, climate, topography, vegetation, and time. The A horizon characteristics represent only one facet of a complex system.

The major separating variables are logically the silt plus clay percentage, the A horizon depth, and percentages of organic carbon and total nitrogen. The silt plus clay percentage expresses important soil physical and chemical characteristics for long-term tree growth. Clay and silt enable the soil profile to hold water. Dominance of the clay fraction also influences the penetrability of the soils, and the propensity of the soil to become anaerobic under conditions of poor drainage. Soil physical properties as informed by the silt plus clay percentage can be modified by the presence of soil organic matter (SOM) and here characterised by soil carbon and soil nitrogen concentrations. The presence of SOM influences the soils' air and water content by providing for good soil aggregation, acting as a malleable soil-cementing agent. Soil depth is important in forestry as tree roots explore for nutrients over decades compared with months for agriculture, and in doing so can make effective use of nutrients present in low concentrations. The Pumice soils, with their relatively low soil nitrogen status compared with the Allophanic and Brown soils, have soil depth to compensate.

Whereas the carbon : nitrogen ratio is important in agriculture as the determinant of nitrogen availability (mineral nitrogen), the carbon : nitrogen ratio is less important in forest soils than the soil nitrogen content as trees have the ability to access the soil nitrogen pool through mycorrhizal symbioses competing directly and successfully with the soil microflora.

The height prediction formula is noteworthy largely for containing environmental variables at the expense of soil characteristics; in particular, the absence of phosphorus might seem surprising. In fact, the Hunter-Gibson dataset was deliberately constituted with plots where phosphorus fertiliser was not required for maintaining tree nutrition and, more generally, the majority of the forests sampled were thrifty and generally devoid of major nutrient deficiencies. Approximate critical soil nutrient levels below which tree growth may be impaired are given in Table 4. A comparison of these levels to those in Table 1 shows that most of the soil class values are well above the threshold standards. These might well explain the lack of soil variables in the height model.

From a graphical representation of the data, it seems there was no significant relationship between Bray-extractable phosphorus and foliar phosphorus. It is therefore not surprising

TABLE 4–Approximate critical values for various soil nutrients

Nutrient	Critical soil value	Reference
Nitrogen	0.1%	Hunter *et al*. (1986)
Phosphorus	5–12 µg/g	Ballard *et al*. (1971); Ballard (1978)
Potassium	0.2–0.4 cmol/kg	Ballard *et al*. (1971); Ballard & Pritchett (1976); Ballard (1978)
Calcium	Not determined	Ballard *et al*. (1971)
Magnesium	0.7 cmol/kg	Ballard (1978); T.Payn & S.Olykan (pers. comm.)

that Bray phosphorus is not a significant factor here in the relationship between tree height and soil factors. This is not to say that phosphorus is unimportant as a driver of growth; it is important, but Bray extraction is not a good measure of the soils’ capacity to supply phosphorus in situations (as here) where it is not limiting growth.

The lack of statistical relationships between pine growth and extractable cation status is also not surprising. The cation pool represents a “static” measure of availability, more related to short-term than to long-term measures. For pine plantations, cation flux should be more related to availability than cation pools. Soil pH can vary dramatically across the New Zealand pine plantation estates, from as low as pH 3.6 on West Coast pakihi soils to around pH 5.5 on the pumice soils, and to pH 7 on soils derived from limestone. At the higher pH values, iron chlorosis can be a problem but apart from pH-induced nutritional problems at high pH, pH level *per se* does not affect tree growth.

It is of interest that increasing windspeed has been shown here to have a significant influence on height growth, with higher windspeeds producing shorter trees. Wind is known to affect tree growth and shape through a variety of mechanisms (Grace 1977), not all of which are well understood. Wind is also an important factor in the energy and water balance budgets of tree canopies. With increasing windspeed, boundary-layer resistance decreases and, where other factors do not limit stomatal conductance, transpiration or evaporation from wet surfaces also tends to increase. This might imply that increasing windspeed should increase productivity. However, enhanced evapo-transpiration also increases soil moisture deficit. Therefore, the relationship between wind and growth is not straightforward. To fully explore the observed relationship between wind and height growth, more detailed analysis using site-specific data would be required.

This study was based on a dataset that is probably unobtainable today. The data were gathered for the objective of isolating nutrient, soil, and climatic factors that contribute to top height (at age 20) *P. radiata* production in New Zealand. When first encountered this may appear reasonably straightforward. In hindsight, we believe the most important finding in this study is that, in fact, the objective is very difficult, if not impossible to achieve, at least not without a degree of confounding. We have not attempted to compare our equation to that of Hunter & Gibson for several reasons. The datasets are not comparable; some measurements have been lost, and the climatic data used here were not available 20 years ago. Moreover, the response variables are not compatible.

Because *P. radiata* stands are established on a variety of soils of greater or lesser fertility, we initially wanted to build a set of models for each of the major soil groupings, anticipating that different factors could well govern height growth on contrasting soil classes. In the event we have resorted to a pooled model because ultimately there was no choice. Any empirical model depends upon a quantity of data to provide an adequate estimate of experimental error. For several of the soil classes, there were simply insufficient growth plots to contemplate individual models. Some soils tend to be tightly located in space so that the climatic and topographical variables are near constants. Obviously, it would have been better to secure more data for some classes but this did not occur. Adoption of the pooled model is not ideal. It is conceded that this action may have masked to some extent the true effects of soil and climate, and their influence on height growth. On the other hand, spatially (and within most of the soil classes) the sample plots are fairly well spread. This gives some confidence that the confounding of soil and climate should not be severe.

The height prediction equation we have constructed has been shown to be reasonably unbiased over the soil classes. For the reasons we have outlined earlier, we believe the predictor variables to be very logical, and plausible from both statistical and physiological viewpoints. Doubtless, however, there will be some *P. radiata* forests where the model will not perform well or the predictor variables are not relevant. These points lead us to emphasise that Equation (4) is presented neither as a mechanistic formulation explaining *P. radiata* height growth nor as a global predictive tool. It is operable for the soil types listed above and no more. The dummy variable is used in conjunction with altitude since it is essentially a constant near to zero for the Raw soils and Sandy Recent soils. Usage with all the soil classes produces a spurious curvilinear relationship with top height.

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