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Prediction of Site Index and Apple Rootstock Performance from Environmental Variables

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Abstract

Previously, we developed stability analysis models for nine rootstocks tested over 19 apple prroducing states and demonstrated significant rootstock-site interactions for cumulative yield (CY) and trunk cross-sectional-area (TCSA). A key input in these models is site index (SI), estimated from the mean over rootstocks within site. Our goal was to extend the usefulness of these models by developing further models to estimate SI for untested sites from climate variables. Prediction of SI from mean daily maximum temperature (T) and total moisture (M) (sum of precipitation and irrigation) was evaluated over five periods based on previous work and on approximate phenological phases of the apple tree over the geographic area included in this study: A = December-January (dormant), B = February-April (prebloom), C = May-June (set), D = July-September (growth to harvest), and E = October-November (post-harvest to leaf senescence), resulting in ten climate-time variables for model development. Complete records of T and M were available from 11 and 9 states, respectively. SI_{TCSA} was not significantly correlated with any T or M variable and therefore may have been influenced more by soil factors or deviations in orchard management practices than by climate. SI_{CY} was well correlated with T_C, T_D and M_C, but T_C and M_C were strongly collinear. Further model development concentrated on prediction of SI_{CY} from T variables over data from ten states (with California removed as an outlier). All one-, two-, and three-variable multiple regression models were evaluated. We concluded that SI_{CY} was best predicted from a linear relationship with T_C.

Additional index words. *Malus domestica*, climate, stability analysis, site index.

Introduction

Choice of apple rootstock is a major factor affecting tree size, growth habit, flowering precocity, yield efficiency, and suitability to orchard site. Unlike many other management decisions, choice of rootstock can only be made before planting and must be correct in order to establish a successful orchard system. A large number of apple rootstocks have been evaluated, both for performance in the propagation nursery and for effects on orchard longevity, growth, and fruiting of scion cultivars (Cummins, 1983; Ferree & Carlson, 1987; Tukey, 1964). Historically, nearly all rootstock evaluations have been conducted in a single site because of the intensive management and long-term requirements of such trials. While site environmental influences on rootstock performance have been acknowledged on an observational basis, there has been little data to quantitate these effects.

It is often assumed that rootstock performance varies on an absolute base, but not on a relative base, among different growing environments. The consequence of this assumption would be that relative ranking of rootstocks for vigor, yield efficiency, or other characteristics would remain the same across the spectrum from poor to good growing sites. The NC-140 Regional Project recently concluded an extensive apple rootstock trial conducted specifically to determine environmental effects on rootstock performance over 27 test sites distributed across North America (NC-140, 1987; NC-

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140, 1991 a, b). Data from this trial provide a unique opportunity to develop models to predict rootstock-by-environmental interactions among apple rootstocks.

A useful approach to determining environment-by-genotype interactions is the method of "stability analysis," developed by breeders of agronomic crops (Blum, 1988; Pritts & Luby, 1990). The analysis requires that a collection of genotypes be planted with replication over a range of test site environments. The performance potential of each site is characterized on a biological basis from site index (SI), the mean performance of all genotypes within a site. Linear regression models are then developed for each genotype based on SI (abscissa) versus mean performance of a given rootstock within each site (ordinate). SI is a quantitative indicator of the site potential for the plant response considered (growth, yield, etc.) and is based on biological response rather than on chemical and physical factors of the site. Using this approach, we developed stability analysis models for each of the nine rootstocks tested in NC-140 study and found evidence of significant environment-by-rootstock interactions (Olien et al., 1991). This is consistent with genotype-by-environment interactions, also called phenotype plasticity, known for annual crops (Blum, 1988; Pritts & Luby, 1990). A primary conclusion from our previous paper was that relative ranking of rootstocks should not be expected to be constant across growing sites.

The rootstock stability analysis models that we developed (Olien et al., 1991) are useful, in that they permit comparison of site-by-rootstock interactions considered in a simple graphical form. The limitation of these models is that they cannot be directly extended to predict rootstock performance in sites not included in the original study because SI cannot be calculated directly for an untested site. Currently, the NC-140 data is useful in aiding rootstock decisions for a grower orchard only if a qualitative judgment can be made that at least one of the original test sites is similar to the orchard in question. This problem could be overcome if there was a way to estimate SI for a distant site, perhaps from environmental variables. One could then enter the estimate of SI into the stability analysis models previously developed. As long as the SI estimate fell within the range of SI values of those models, an interpolated approximation of expected tree performance could be made.

The important question is then, can SI be predicted from environmental data? There is reason to think that this is possible. Prediction of apple yield for large regions have been successfully based on average daily maximum temperatures (T_{max}) during critical monthly periods, without regard to differences in soil type or other environmental variables. Beattie & Folley (1978) tested a number of climate variables and time periods for correlation with apple yields in England and found that yield was well correlated with T_{max} during February-April (T_{FMA}) and in June (T_{Jun}), but was not correlated with solar radiation, frosts, wind, or rainfall received during any period. Subsequently, Jackson & Hamer (1980) and Jackson et al. (1983) reported that 80% of the annual yield variation of 'Cox's Orange Pippin' in England was explained by variation in average T_{max} during three periods. High yields were associated with cool T_{FMA}, warm T_{max} during the period of pollen tube growth, and warm T_{max} during early fruit development in June. Of these three periods, T_{FMA} was most closely associated with yield, excluding years of crop reduction from frost injury. T_{max} during the periods of pollination and subsequent early fruit growth became more important in years with warm T_{FMA} (Jackson et al., 1983). T_{max} during late winter-spring was also highly correlated with apple yield in the U.S. (Lakso, 1987; Mattice, 1927). Lakso (1987) reported that New York apple yields increased with warm T_{max} from harvest to leaf abscission the previous fall, cool T_{max} from mid-winter to first growth in the spring, and warm T_{max} from first growth to bloom.

Our objective in this paper was to determine if estimates of SI for cumulative yield and tree growth can be predicted from T_{max} and/or total moisture received over critical monthly periods.

Materials and Methods

Rootstocks tested were 'Ottawa 3' (O.3), 'Malling 7 East Malling-Long Aston' virus free program (M.7 EMLA), 'M.9,' 'M.9 EMLA,' 'M.26 EMLA,' 'M.27 EMLA,' 'Michigan Apple Clone 9' (MAC.9), 'MAC.24,' and 'Oregon Apple Rootstock 1' (OAR1), all grafted with 'Starkspur Supreme Delicious' as the scion cultivar (NC-140, 1991a, b). The trees were planted in 1980 and 1981 in a randomized complete block design with 10 replications. Each planting was managed uniformly according to procedures determined by the NC-140 Technical Committee.

Growth and yield data were obtained from 19 sites (one site per state or province) over a ten year period. Average daily maximum temperatures and total moisture received (rainfall plus irrigation) were recorded in nine states: Arkansas, Illinois, Iowa, Kentucky, Massachusetts, Ohio, Oregon, Virginia, and Wisconsin. California and Pennsylvania reported complete records for temperature but not moisture. Irrigation applications averaged 30 ± 5 cm water per year, but the number of years in which the trees were irrigated varied among states. Iowa and Oregon irrigated in 8 and 9 years, respectively. Arkansas, Wisconsin, Kentucky, and Illinois were irrigated in 1, 1, 2, and 3 years, respectively. Massachusetts, Ohio, and Virginia did not irrigate. Climate data were accumulated on a monthly basis (Fig. 1) and yield and trunk cross-sectional-area were reported annually (NC-140, 1991 a, b).

Cumulative yield was selected as more meaningful to long-term orchard productivity than annual yields because it includes rootstock effects on precocity and is not as affected by factors affecting fluctuations in yield among years. Similarly, final trunk cross-sectional-area was selected as a cumulative measure of vegetative growth over the ten-year evaluation period.

Sufficient climate data was collected among the test sites for preliminary simple regression analysis of a range of monthly climate variables with SI of cumulative growth and yield over the study. From these initial correlations, it was determined that monthly average and extreme minimum temperatures and total monthly solar radiation were not useful in predicting SI of growth or yield (data not presented). Based on these results, and on results of other researchers (Beattie & Folley, 1978; Jackson & Hamer, 1980; Jackson et al., 1983; Lakso, 1987; Mattice, 1927), it was decided to concentrate our efforts on average maximum temperature and total moisture as climate variables for prediction of SI.

To develop models predicting SI from the climate data, we calculated average T_{max} and total moisture over five periods, approximating developmental periods of the apple tree. These periods were dormant (December-January), prebloom (February-April), fruit set (May-June), fruit growth (July-September), and harvest to leaf abscission (October November). This resulted in ten climate variables (five T_{max} and five moisture variables) as possible predictors of SI. Abbreviations for the ten climate variables are given in Table 1.

Multiple regression models involving all combinations of temperature and moisture variables were analyzed to

Table 1. Climate variables and time periods based on approximate annual phenological periods of apple.

Month	Approximate phenological stage	Mean daily maximum temperature (°C)	Total moisture received (mm)
Dec.-Jan.	Dormancy	T_A	M_A
Feb.-Apr.	Late winter to prebloom	T_B	M_B
May-June	Bloom through fruit set	T_C	M_C
July-Sept.	Fruit growth to harvest	T_D	M_D
Oct.-Nov.	Postharvest to leaf fall	T_E	M_E

determine which of the ten climate variable-period combinations best predicted SI for cumulative yield (SI_{CY}) and for trunk cross-sectional area (SI_{TCSA}). Calculations were performed using SAS (SAS Inst, Cary, NC). Variables were selected and models were compared based on coefficient of determination, the F statistic and its associated probability level, analysis of residuals, and Mallows Cp statistic (Mallows, 1973). "Jackknifing," a method of model verification and analysis of regression residuals, was also used to compare models (Lachenbruch and Mickey, 1968).

Results & Discussion

Selection of critical temperature and moisture variables from nine states. The first goal was to determine which of the ten climate variables were significantly related to SI_{CY} and SI_{TCSA} by developing simple linear regressions and estimating correlations over the nine states with complete temperature and moisture data (Table 2). SI_{TCSA} was not adequately predicted by any of the variable combinations. This surprised us, since one would expect vegetative growth to be highly dependent on temperature and moisture. Lack of correlation was not due to insufficient variation in SI_{TCSA}, which varied from 35 cm^2 (Massachusetts) to 87 cm^2 (Illinois) over the nine sites (Olien et al., 1991). We conclude that other factors, perhaps related to soil (texture, drainage, fertility, etc.) or interactions of soil and climate variables were more limiting to growth than were T_{max} or total moisture over the geographic range of this study. The positive implication of this result is that rootstock effect on tree size may not be significantly affected by differences in T_{max} and total moisture between test sites and grower orchards. This conclusion will need to be tested in future studies.

Unlike tree size, SI_{CY} was negatively correlated with T_C, T_D, and M_C, significant at P = 0.003, 0.008, and 0.004, respectively (Table 3). Based on pre-

Table 2. Correlation of temperature and moisture variables with site index for cumulative yield and trunk cross-sectional-area of nine rootstocks. Data from nine states (Ark., Ill., Iowa, Ken., Mass., Ohio, Ore., Vir., and Wis.).

	Site index variables			
	Cumulative yield/tree		Final trunk cross-sectional-area	
Predictor variables	r	Probability	r	Probability
T_A	-0.25	0.513 ns	+0.25	0.447 ns
T_B	-0.46	0.211 ns	+0.25	0.441 ns
T_C	-0.85	0.003 **	+0.28	0.400 ns
T_D	-0.81	0.008 **	+0.22	0.488 ns
T_E	-0.53	0.140 ns	+0.37	0.295 ns
M_A	+0.23	0.552 ns	-0.05	0.867 ns
M_B	-0.04	0.918 ns	-0.00	1.000 ns
M_C	-0.85	0.004 **	-0.22	0.489 ns
M_D	-0.43	0.249 ns	-0.08	0.719 ns
M_E	-0.07	0.860 ns	-0.16	0.582 ns

vious reports (Beattie and Folley, 1978; Jackson and Hamer, 1980; Jackson et al., 1983; Lakso, 1987; and Mattice, 1927), we expected SI_{CY} to be closely and negatively correlated with T_B, but correlation of SI_{CY} with T_B was significant only at P = 0.21 (Table 3).

Since both T_C and M_C were highly correlated with SI_{CY}, the next step was to determine if M_C was necessary in developing a predictive model for SI_{CY}. When T_C was regressed on M_C these two variables were found to be highly collinear, with r = +0.64, with P = 0.064 (Fig. 2). T_{max} and total moisture were also highly correlated in the dormant and prebloom periods (r = 0.78 and 0.72, P = 0.013 and 0.029, respectively)

Table 3. Correlation of cumulative yield site index with themperature variables in one-, two-, three-variable multiple regression models. Data from tne states (Ark., Ill., Iowa, Ken., Mass., Ohio, Ore., Penn., Vir., and Wis.; excludes California).

Predictor variables	R^2	Probability	Mallow Cp statistic	Model coefficients[z] a (kg)	b (kg/°C)	c (kg/°C)	d (kg/°C)
Single variable correlations:							
T_A	0.04	0.2700	15.860	146	-4.93		
T_B	0.20	0.1098	12.290	206	-7.22		
T_C	0.78	0.0008	-0.212	526	-16.18		
T_D	0.63	0.0036	2.392	608	-17.54		
T_E	0.35	0.0409	8.758	282	-10.50		
Two-variable models:							
T_A, T_C	0.83	0.0021	0.405	599	3.86	-19.74	
T_C, T_E	0.82	0.0023	0.523	596	-23.34	7.20	
T_B, T_C	0.81	0.0029	0.823	583	3.97	-20.27	
T_A, T_D	0.79	0.0047	1.515	802	6.39	-25.50	
T_C, T_D	0.78	0.0046	1.554	471	-22.59	7.76	
T_B, T_D	0.76	0.0071	2.215	797	7.30	-27.35	
T_D, T_E	0.72	0.0127	3.300	747	-26.68	7.59	
T_A, TE	0.66	0.0221	4.634	470	14.59	-27.10	
T_A, T_B	0.56	0.0557	7.256	400	26.28	-34.00	
T_B, T_E	0.45	0.1219	10.153	308	5.17	-16.15	
Three-variable models:							
T_A, T_B, T_C	0.84	0.0085	2.131	601	9.72	-7.53	-17.39
T_A, T_C, T_D	0.83	0.0098	2.323	648	4.53	-16.06	-5.19
T_A, T_B, T_E	0.83	0.0103	2.388	571	31.42	-23.13	-21.00
T_A, T_C, T_E	0.83	0.0102	2.391	600	2.92	-20.85	1.99
T_B, T_C, T_E	0.82	0.0109	2.506	598	0.90	-23.14	6.07
T_C, T_D, T_E	0.82	0.0110	2.513	609	-22.49	-1.38	7.49
T_B, T_C, T_D	0.81	0.0131	2.775	623	4.69	-17.57	-4.16
T_A, T_D, T_E	0.80	0.0165	3.147	758	9.64	-20.12	-7.83
T_A, T_B, T_D	0.79	0.0185	3.346	777	10.98	-6.37	-22.66
T_B, T_D, T_E	0.76	0.0285	4.210	802	7.03	-27.73	0.62

[z]Model coefficient a = intercept. Coefficients b, c, and d are associated with succeeding terms in the model, in the order listed under Predictor Variables.

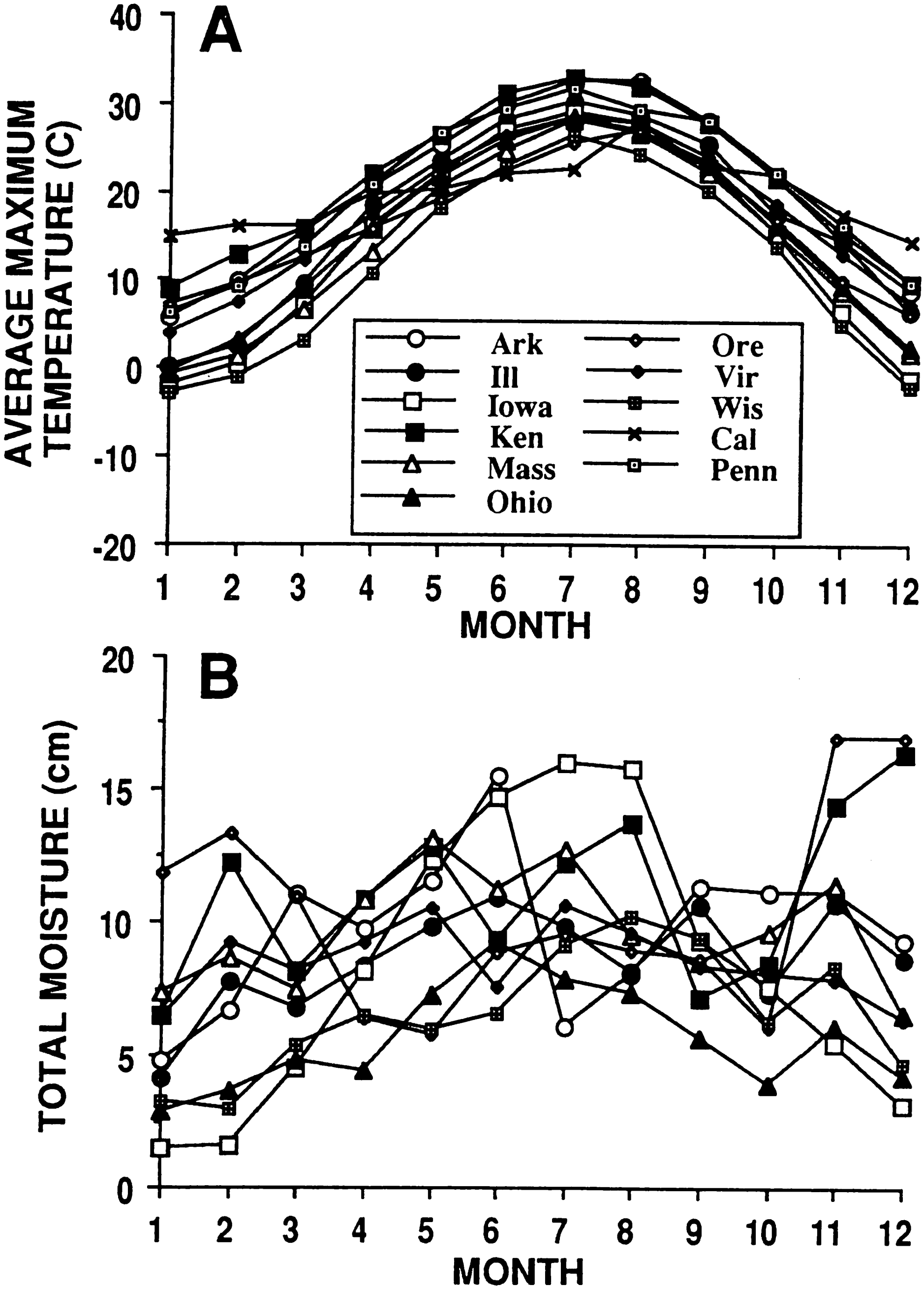

Figure 1. (A) Mean maximum temperature by month for sites in eleven states (Ark., Calif., Ill., Iowa, Ken., Mass., Ohio, Ore., Penn., Vir., and Wis.) and (B) total moisture for study sites in nine states (Ark., Ill., Iowa, Ken., Mass., Ohio, Ore., Vir., and Wis.) over 10 years (1980-1990). Total moisture is the sum of precipitation and irrigation.

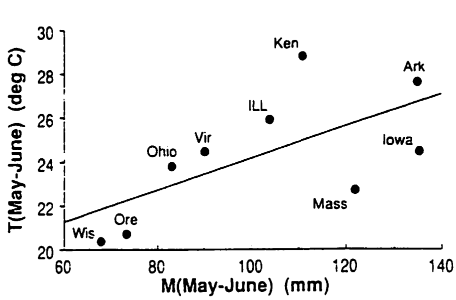

Figure 2. Collinearity of mean of daily maximum temperatures during May-June (T_C) with total moisture received over the same period (M_C) over ten-years in test sites in nine states (Ark., Ill., Iowa, Ken., Mass., Ohio, Ore., Vir., and Wis.).

and marginally correlated during the postharvest period ($r = 0.56$, $P = 0.12$). T_{max} and total moisture were not correlated during the grow period ($r = 0.03$, $P = 0.82$). Based on the close relationship of T_C and M_C and the general association of T_{max} with total moisture across the other periods, it was decided that further model development need only consider temperature variables. This decision strengthened our data base since we were then able to include two additional states (California and Pennsylvania) which had complete data for temperature but not moisture.

Selection of temperature variables from eleven states. In the second stage of model development, association of SI_{CY} with the five T_{max} variables was reexamined using all eleven states. Simple correlation coefficients were significant for SI_{CY} only with T_C ($r = -0.77$, $P = 0.006$) and T_D ($r = -0.724$, $P = 0.012$). However, plots of the data indicated that California had a major effect on these relationships and did not fit the pattern of the other states

Table 4. "Jackknife" verification of the eight best fit models predicting site index for cumulative yield (SI_{CY}) from temperature variables.

State excluded from model	Observed cumulative yield site index (kg/tree)	Models Predicting SI_{CY}[z]							
		(C)	(D)	(AC)	(CE)	(BC)	(ABC)	(ACD)	(ABE)
		Predicted SI_{CY} (kg/tree)[y]							
Ark	70.6	82.6	54.2	87.1	87.6	90.0	82.1	111.7	65.9
Ill	118.0	105.3	113.9	97.5	106.3	93.7	102.3	98.0	94.4
Iowa	73.8	135.6	149.0	131.8	147.5	131.6	148.6	131.7	170.3
Ken	95.3	43.3	51.4	51.2	40.3	49.8	48.4	51.9	81.8
Mass	164.9	158.4	154.3	151.8	154.5	148.1	158.4	150.4	171.0
Ohio	157.5	139.6	145.6	129.9	132.0	135.7	118.9	130.5	104.5
Ore	201.6	187.3	158.7	272.6	226.9	278.6	273.1	272.0	237.3
Penn	46.0	80.6	95.9	87.1	98.2	80.9	106.6	103.1	105.5
Vir	145.8	127.6	135.5	135.8	136.7	133.6	136.7	138.4	131.3
Wis	192.5	197.4	193.7	183.3	187.3	182.0	189.9	183.0	196.8
$\Sigma(\text{deviation})^2$:		8948	12560	13850	13116	14542	18580	16626	17963

[z]Regression model variables:
Model C: $SI = a + b\,(T_C) + \text{error}$.
Model D: $SI = a + b\,(T_D) + \text{error}$.
Model AC: $SI = a + b\,(T_A) + c\,(T_C) + \text{error}$.
Model CE: $SI = a + b\,(T_C) + c\,(T_E) + \text{error}$.
Model BC: $SI = a + b\,(T_B) + c\,(T_C) + \text{error}$.
Model ABC: $SI = a + b\,(T_A) + c\,(T_B) + d\,(T_C) + \text{error}$.
Model ACD: $SI = a + b\,(T_A) + c\,(T_C) + d\,(T_D) + \text{error}$.
Model ABE: $SI = a + b\,(T_A) + c\,(T_B) + d\,(T_E) + \text{error}$.

[y]Predicted site index for cumulative yield from planting over ten years (SI_{CY}) calculated from the models indicated. Each model (within columns) was regressed iteratively excluding each state one state at a time. Thus, actual SI_{CY} for Arkansas is compared with SI_{CY} predicted by each model with Arkansas excluded from the model. The process was repeated for each state. Residual deviations of predicted and actual SI_{CY} were then squared and summed over all states for each model. Lowest sum of squared deviations indicates best predictive model.

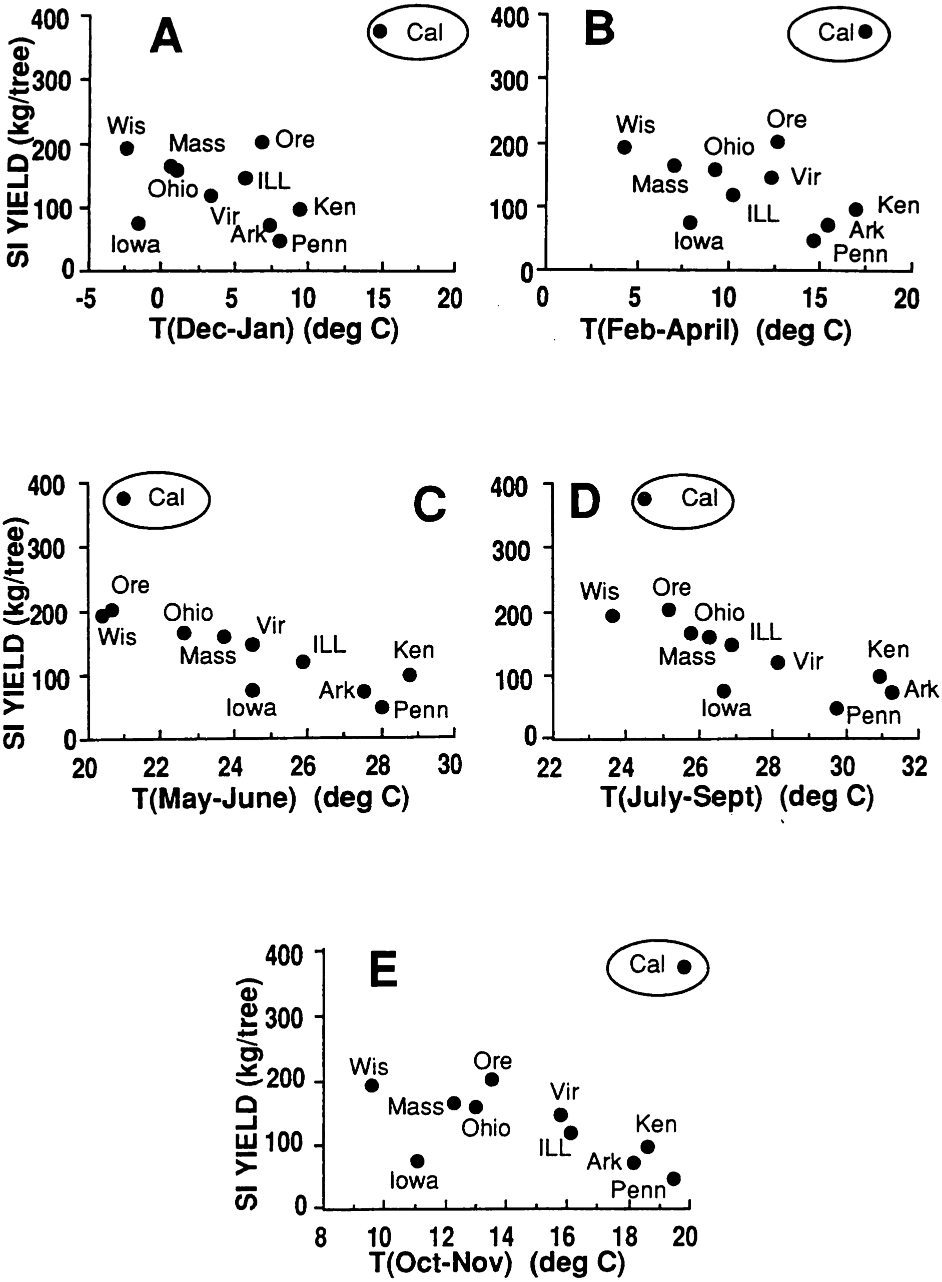

Figure 3. Relation of cumulative yield site index (SI_{CY}) to mean maximum temperature over five phenological periods for nine rootstocks over sites in eleven states (Ark., Calif., Ill., Iowa, Ken., Mass., Ohio, Ore., Penn., Vir., and Wis.): T_A = December-January; T_B = February-April; T_C = May-June; T_D = July-September; and T_E = October-November. California is circled, indicating excessive residual sums of squares from regression models.

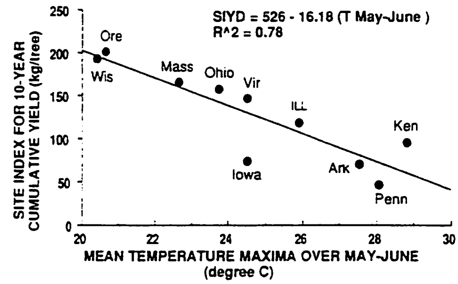

Figure 4. Prediction of SI_{CY} from mean of daily maximum temperatures during May-June (T_C) based on data from sites located in ten states (Ark., Ill., Iowa, Ken., Mass., Ohio, Ore., Penn., Vir., and Wis.). Model fit to observed data by least squares regression.

(Fig. 3). Over all five of the T_{max} variables, regression residuals for California were 3.0 to 5.7 times larger than the average absolute value of residuals for the other ten states. In subsequent analysis without California, residuals for Pennsylvania were 3 to 5 times the remaining 9 states for T_A, T_B, and T_E, but were small for T_C and T_D. It was decided that Pennsylvania should be retained in the data set since T_C and T_D were two best predictors of SI_{CY} up to this stage.

Final model development based on ten states. Final model development now focused on the ten selected states, with the goal of predicting SI_{CY} from one or more of the T_{max} variables. Multiple regression models were developed involving combinations of temperature variables. None of the T_{max} interaction terms were significant in any of the multiple regression models. The multiple regression models were then re-examined with main effect terms only. Coefficient of determination (R^2), F and probability for F, Mallow's Cp statistic, and the model parameter coefficients are presented in Table 3 for all one-variable models and the ten best two- and three-variable main effect models. T_C was clearly the best predictor of SI_{CY} ($r^2 = 0.77$ with $P = 0.0008$), followed by T_D and T_E. T_B and T_A were not good single-variable predictors of SI_{CY}. Five of the two-variable and nine of the three-variable models had higher values of R^2 that the best single-variable model (Table 3).

Mallow's Cp statistic has been used to select among models when all have relatively good apparent predictive value (Mallows, 1973). The Cp statistic is a comparison of the residual sum of squares of a model containing p parameters (including the intercept) to a model containing all possible parameters, with correction for degrees of freedom differences in the models. A well fit model is indicated by a Cp value less than p. In our case, lowest value of p - Cp was obtained for T_C as a single variable model, but p - Cp of a number of the models were also low (Table 3). The simplest model is generally selected among a number of models that have good predictive value, and this would lead us to accept the single variable T_C model. However, models predicting annual apple yields developed by previous authors (Beattie and Folley, 1978; Jackson and Hamer,

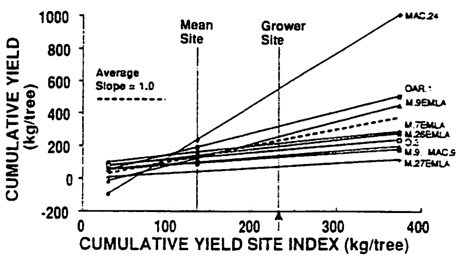

Figure 5. Stability analysis models for nine apple rootstocks illustrating dependence of 10-year cumulative yield on site index of 19 sites (data from Olien et al., 1991). Regressions models are shown only over the range of data obtained. For a hypothetical grower site (not in the original trial), an estimate of Site Index is calculated from average daily temperature for May-June (T_C) by Eq. [1] developed in this paper. Expected performance of these nine rootstocks at the grower site is indicated at intersections of the rootstock regression lines with the vertical line above the arrow.

1980; Jackson et al., 1983; Lakso, 1987; and Mattice, 1927) led us to expect that T_B and T_E would also be important variables, in addition to T_C. We did not want to eliminate these additional variables from our final model too hastily. Model verification would provide an independent basis to decide among the best-fit models.

"Jackknifing" is one approach to subdividing a data set for purposes of model verification (Lachenbruch and Mickey, 1968) where an adequate independent data set does not exist. In this approach, each of the eight best-fit models from Table 3 was recalculated iteratively, leaving one state out at a time. The SI_{CY} value for the omitted state is estimated based on a model calculated from data for the remaining states. This estimated value of SI_{CY} is then compared to the actual value of SI_{CY} observed for that state. The process is repeated for each state. Deviations of actual and estimated SI_{CY} were then squared and summed across all states. The lowest sum of squared deviations is associated with the model best predicting SI_{CY} (Table 4). On this basis, the T_C single variable model again stood out as the best predictor of SI_{CY}. The second best model was based on T_D, and the third best on T_C and T_E. It is worth noting that two less commonly used approaches (Cp statistic and Jackknifing) provided a basis for model selection where traditional regressions statistics (R^2 and probability of F) did not lead to a clear conclusion.

We concluded that the optimum model for prediction of SICY from temperature data in this study was a single variable model based on T_C:

$$SI_{CY} = 526 - 16.18(T_C), \qquad [1]$$

with SI_{CY} expressed as kg/tree and T_C as °C (Fig. 4). This model explains 78% of the variability in SI_{CY} regressed on T_C with a probability of significance of $P = 0.0008$. The importance of T_C suggests that average daily maximum temperatures during the period of pollination and early fruit development was the most limiting factor in determining cumulative yields in North America.

In using Eq. [1], it should be remembered that the ten states included in this model are concentrated in the northeast quadrant of the country (roughly Iowa to Massachusetts and Wisconsin to Arkansas). Application of Eq. [1] to states outside this region would need to be evaluated. For example, rootstock performance in Oregon was consistent with Eq. [1], but California did not fit the SI_{CY}-T_C pattern of the other ten states.

Use of predicted SI in stability analysis models. After predicting SI for a grower site from Eq. [1], the next step is to incorporate this value into the stability analysis models developed previously (Olien et al., 1991). The linear regression models fitted for each rootstock and performance variable are characterized by two parameters. The first parameter is average performance of a given rootstock at the average site, that is the predicted average performance of a rootstock at the SI grand mean over all sites tested. The second parameter, the slope of the regression line through this point, is an indication of the stability or sensitivity of the rootstock by environment interaction, relative to the other rootstocks tested. The steeper the slope, the less stable is performance of a given rootstock across sites. A slope of 1.0 is the average stability of the rootstock population considered. A slope flatter than 1.0 has greater than average stability. In general, greater stability across sites is correlated with lower genotype potential at the average site (Blum, 1988; Pritts & Luby, 1990).

The stability analysis models developed previously for CY were all highly statistically significant (Olien et al., 1991) and are presented graphically in Fig. 5. SI values predicted for a grower site by Eq. [1] can be used as the abscissa value on the stability analysis graphs as long as predicted SI falls within the range of SI values for the sites tested in developing these models. Reading up along the ordinate will then give a first approximation of what the cumulative yield per tree would be for each of the nine rootstocks if grown in the untested grower site. Cumulative yield per ha can be approximated by multiplying estimated CY by trees/ha.

The NC-140 is conducting a series of apple rootstock trials subsequent to the 1980/81 trial (used as the data base here). If a constant "internal standard" group of five to six rootstock clones were included in all NC-140 rootstock trials, it would be possible to make comparisons among trials. The inclusion of an internal standard set of rootstocks in future trials would greatly aid the development and verification of rootstock performance models. For example, SI could be calculated from the performance of the internal standard rootstock clones and plotted against the mean performance of all rootstocks in the same trial or across trials.

The predictive models developed here are a beginning and need further expansion and refinement to include other regions, rootstocks, and environmental variables. Our primary conclusion from the present work is that combining stability analysis models with prediction of SI from environmental variables has potential as a decision aid for making rootstock recommendations.

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