Ranking Tissue Mineral Analyses to Identify Mineral Limitations on Quality in Fruit

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Abstract. A diagnostic procedure was developed to identify mineral limitations on pome fruit quality. Fruit mineral levels were useful only when developed on a ranked or percentile (0 to 100) basis. Therefore, procedures were developed using percentile values for both leaf and fruit mineral concentration. An individual can decide which quality parameters are important and whether minimum, maximum, or intermediate values for these quality parameters are most desirable. Multiple regression is used to predict relative rankings for each quality parameter. A simple sorting program allows the operator to use these rankings to choose which categories of fruit are undesirable. It is then possible to select from among remaining lots those likely to contain fruit having the poststorage quality factors the operator considers most important. The approach is demonstrated with 2 years of data from a high-density 'Starkspur Golden Delicious' apple orchard. Selections of fruit with the best poststorage quality were based on mineral content, assuming that maximum firmness, soluble solids, titratable acidity, and yellow color were considered as most desirable. Further ranking evaluations were obtained by evaluating 6 years of data relating quality in 'd'Anjou' pears with fruit mineral concentrations. A ranking approach allows meaningful interpretation despite large differences in fruit mineral concentrations reported for different locations and years by a range of analytical laboratories. The procedure is flexible, and fruit could be categorized successfully according to several definitions of optimum quality.

Critical leaf nutrient concentrations, although useful for fertilizer recommendations (6), have limited value in managing fruit production to maintain fruit quality during storage (2, 13). Fruit composition is more strongly correlated with quality parameters (13), and fruit testing has been used successfully to predict storability (13). However, in some instances, optimum fruit composition varies among years, making interpretation of individual samples difficult (5, 12, 16, 18). Seasonal variation is especially troublesome when attempting to use fruit analyses from samples collected early in the growing season (13, 16). Correlations between early season fruit composition and quality or storage parameters are often as strong as those using lateseason analyses, but absolute critical values are less stable (13, 16). A harvest sampling produces more consistent critical levels than early sampling, but is not necessarily more predictive of storage quality (5). Preharvest mineral regression equations may not predict absolute levels of storage disorders between years due to annual variations in disorder incidence, even when highrisk fruit are correctly identified (20).

More fruit samples for analysis can be generated in the Pacific Northwest and other pome fruit-producing areas than could possibly be analyzed by a single diagnostic facility. Thus, analytical differences among commercial laboratories could produce considerable confusion and misinformation. Possible analytic differences also complicate interpretation of published research. Although large differences in critical concentrations have been reported for different seasons or locations, it is often not apparent whether differences are due to climatic and biological differences, sampling errors, analytical procedures, or to a combination of these factors.

Our goal was to express quantitatively the relationship between minerals in fruit or leaves and quality components. A survey of analytical accuracy in various laboratories and an evaluation of historical data were conducted prior to developing and testing a diagnostic procedure that minimizes analytical or seasonal differences. Since tree mineral status with regard to one yield or quality component may be unrelated to that of other components (5), a definition of optimum nutritional status will depend on which yield or quality components are most important. A flexible procedure that could categorize and rank fruit with several definitions of optimum quality was desired. A large group of commercial diagnostic laboratories then could make storage predictions or management suggestions early in the season, independent of the year.

Materials and Methods

Survey of analytical laboratories. Ground subsamples of the same oven-dried leaf tissue and freeze-dried apple tissue collected from a variety of sources were sent to 20 different analytical laboratories that routinely analyze plant tissue. Several selected laboratories received from five to 10 additional freezedried samples of apple with different mineral concentrations. Results from the 20 laboratories analyzing the same samples were tabulated and the mean, range, and SD for N, K, P, Ca, Mg, Mn, Fe, Cu, B, and Zn were recorded. Bitterpit then was predicted from the fruit mineral analysis of each laboratory using a previously derived equation. The mean, range, and SD of predicted bitterpit for all 20 laboratories then was calculated.

Evaluation of historical data in the Pacific Northwest. Data relating mineral composition of leaves and fruit to quality pa-

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rameters after long-term storage in 'Starkspur Golden Delicious' apple were obtained from 4 years (1980–1983) of experiments where the response of six rootstocks to N, K, and B treatments was evaluated (4, 15). Mineral concentrations of leaves and fruit were analyzed throughout the growing season, and fruit were evaluated for quality and fruit disorders after 6 months in cold storage.

Data relating mineral composition of 'd'Anjou' fruit to quality parameters were obtained from two studies (1, 17) in which orchard surveys were conducted for a 3-year period in Medford, Ore. (1) and a 3-year period in Hood River, Ore. (17). Additional data relating mineral composition and cork spot incidence were obtained from field trials conducted in Wenatchee, Wash. (3, 10). In some instances, the mineral concentrations of pear fruit were measured throughout the season. In order to compare all studies, only the mineral concentration of pear flesh samples collected ≈ 115 days after full bloom were used. Pear fruit were evaluated for quality and fruit disorders after 1 to 6 months in cold storage. In some instances, fruit disorders were rated while fruit was still on the tree just before harvest.

Overview of computer procedures. A computer program was developed that used preharvest leaf and fruit mineral analyses to select fruit that were likely to have superior poststorage qualities. Since it is difficult to define fruit quality, the program operator may select the quality criteria used in a given computer selection. The following four-step process is used to categorize the most desirable fruit: 1) The operator chooses which quality parameters are most important to obtain desirable overall quality and decides if minimum, maximum, or intermediate values for these individual parameters are most desirable. 2) Concentrations for each leaf or fruit element are replaced with a percentile score (0 to 100) for all observations in the data set being evaluated. Percentile scores reflect the relative position of an element in a given observation compared with the same element from other observations in the data set. 3) Percentile scores for mineral elements are used to make poststorage quality predictions. Fruit that have undesirable storage characteristics, as defined by the operator, are identified. 4) The program then selects among remaining lots those most likely to contain fruit having the attributes the operator considered most important for storage quality.

Output from the program includes: 1) A list of samples that are likely to contain fruit lacking the storage quality components the user has identified as important. 2) A selection of fruit lots that are most likely to contain fruit suitable for long-term storage. These remaining samples are ranked with respect to decreasing desirability for long-term storage, as defined by the user.

In the apple example presented, we selected various combinations of fruit likely to be high in firmness, yellow color, titratable acidity, and/or soluble solids as most desirable. Other selection criteria may have equal or perhaps greater merit. For example, fruit high in firmness or soluble solids and low in yellow color or titratable acidity could be selected as most desirable. Intermediate ranges of desirable soluble solids content or titratable acidity also could be selected. In the pear example, we defined fruit likely to be low or high in corkspot as most desirable and undesirable, respectively. Many non-nutritional factors affect quality parameters. In the examples presented, the intent is to describe the selection approach rather than to suggest definitive relationships or any specific criterion for defining optimum quality.

Step 1: Selection of important quality parameters. The soft-

ware uses mineral content input to produce a set of predicted rankings for each quality parameter. Each individual ranking consists of a list of all samples placed in increasing order for the predicted values used to quantify each quality parameter. The operator determines how these rankings will be used in making a final selection. Fruit likely to be in any category the user defines can be either selected for or eliminated from consideration for long-term storage. The percentage of fruit to be eliminated or selected is specified by the user. For example, one could specify that fruit expected to be in the lowest 25% for the firmness parameter are undesirable.

Step 2: Percentile scores. Input into the program consists of leaf and fruit analyses from a series of samples from which predictions of storage behavior will be made. The program does not use absolute concentrations of minerals. Instead, concentrations are converted to percentile scores from which predictions are subsequently made.

Separate percentile scores are calculated for all important elements with respect to each quality parameter. For mineral elements known to be positively correlated with a quality parameter, mineral concentrations are ranked in ascending order and assigned a percentile score ranging from 0 (lowest) to 100 (highest). For mineral elements negatively correlated with a quality parameter, a similar procedure is used; however, the percentile scores are assigned differently. The lowest value was assigned a value of 100 and the highest value was assigned a value of 0. Thus, low- and high-percentile scores are associated with low and high values of a quality parameter, respectively. The same procedures also can be applied to ratios of mineral elements that correlate to quality parameters. Percentile scores for ratios such as N/Ca or K/Ca (19) can be calculated easily, and, in some instances, are more strongly correlated with fruit disorders or quality parameters than are individual minerals (11, 14).

Previously existing data bases consisting of quality parameters and associated leaf and fruit mineral analyses are required to identify important mineral elements and develop regression equations. Leaf or fruit minerals that are not significantly correlated with an individual quality parameter in a majority of years are not considered. Therefore "percentile scores" are developed only for leaf or fruit minerals that consistently correlate with the individual quality parameters. Either leaf or fruit mineral concentrations could be used alone if both are not available, but the accuracy of predictions for some quality parameters decreases.

Step 3: Elimination of fruit unlikely to be desirable. Stepwise multiple regression equations are developed to predict quality parameters using percentile scores as independent variables. Relative rankings (0 to 100) of dependent variables are predicted rather than the absolute values of the quality parameters. Relative rankings also can be obtained by simply averaging percentile scores for important elements or ratios. SIGSTAT software on an IBM PC was used to develop regression equations. Other software was written in BASIC. Only the four most predictive (first four steps) mineral percentile scores were used. The user can eliminate any category of fruit for one or more of the quality parameters. In the apple example, we chose to define fruit lowest (the bottom 25%) in firmness, soluble solids, titratable acidity, and yellow color (i.e., most green) as undesirable, but other selection criteria and categories are possible.

Step 4: Selection of desirable fruit among those not previously eliminated. After eliminating the undesirable fruit, the remaining fruit are ranked to select those most likely to have superior poststorage quality with regard to whatever quality parameter the operator considers most important. For example, after eliminating undesirable fruit, further emphasis can be placed on firmness, and fruit with the highest firmness rankings could be selected for long-term storage.

Program evaluation. Ideally, the entire procedure would be applied using reliable, long-established regression equations. Various combinations of pear data were selected, such that data from one location were used to develop predictive equations for the other two. A given year also was excluded from the data used to generate regression equations and then independently evaluated.

Fewer data were available to test relationships in the apple experiments. Only in 2 years were there similar sampling times and postharvest evaluations. The procedure was applied to 1980 data using 1980 regression equations, 1980 data using 1981 regression equations, 1981 data using 1980 regression equations, and 1981 data using 1981 regression equations. Data from both individual years also were tested using regression equations from the combined 2-year period.

Since all fruit were evaluated for the quality components that were predicted, it was possible to determine prediction success. Fruit that the program identified as either likely or unlikely to be of desired quality were evaluated to verify the reliability of the identification. For example, if the program assigned 25% of the pears to a high-risk category that is likely to develop corkspot, the percentage of pears that were correctly placed (actually were in the highest 25% for corkspot) was determined. Similarly, the percent of fruit that was severely misplaced (high observations placed in low category and vice versa) was also determined.

Results and Discussion

Survey of analytical laboratories. Data from the analytical laboratories revealed wide differences in the mineral concentrations reported for subsamples of the same tissue, especially with fruit concentrations (Table 1). Coefficients of variation were highest for Ca and Ca-containing ratios. Predictions of bitterpit based on fruit mineral concentration varied widely and have little value. Some laboratories reported Ca values that were high enough to predict negative bitterpit percentages. Predicted values varied from <0% to 55% for the same sample. Values obtained from the smaller group of laboratories that received more than one fruit sample also varied considerably (data not shown). However, even when absolute values for mineral concentrations varied widely, different laboratories almost always placed individual samples in the correct relative order. The results imply that, although analytical accuracy varies tremen-

Table 1. Mean, range, and coefficient of variation (Cv) for mineral analysis reported by 20 laboratories when sent subsamples of the same freeze-dried apple fruit tissue.

Variable	Mean	Range	cv
Element (% dry weight)			
Ca	0.13	0.01-1.50	259
N	0.29	0.10-0.63	35
К	0.91	0.48-2.00	33
Mg	0.068	0.01-0.56	57
Elemental ratio			
N : Ca	7.22	0.42-23.00	72
K : Ca	23.40	1.30-121.00	108
Mg : Ca	1.17	0.33-7.00	77

dously among laboratories, different laboratories can make similar recommendations if results are expressed on a percentile basis.

Relationships between mineral analyses and quality in apple-general observations. For many of the fruit or leaf minerals, the mineral concentration was significantly correlated with quality parameters (4). However, even though correlations between fruit minerals and quality parameters were significant, management decisions could not be made from critical mineral concentrations in fruit tissue. Critical fruit concentrations could be defined in a given year, but would have no meaning for another year. This lack of consistency is apparent in the relationship between fruit N and soluble solids in Fig. 1. If standards from one year are applied to data from another, concentration-based fruit diagnoses are of little value. A high value in one concentration-based fruit diagnoses are of little value. A high value in one year is a low value in another (Fig. 1A). Expressing fruit N on a percentile basis eliminates seasonal differences and presents the consistent relationship apparent in Fig. 1B.

Despite drastically different fruit mineral concentrations, leaf minerals, yield, average fruit weight, soluble solids, titratable acidity, and firmness varied only slightly with year (4, 5, 15). Color was more yellow in 1981 than in 1980, but differences were relatively small (4). Over the 4-year period, large differences were observed among means for all individual fruit elements, while leaf mineral concentrations were relatively stable (Table 2). Since fruit size and moisture content were similar among years, expressing values on a fresh-weight basis did not lessen seasonal differences. Fruit N, P, Cu, and B appear to alternate between high and low values over 4 years of evaluations (Table 2). It was not possible to relate absolute fruit mineral concentrations consistently to values for quality parameters.

Elimination of plots unlikely to produce desirable fruit. The overall success of percentile-based categorizations is presented



Fig. 1. The relationship between fruit nitrogen and soluble solids in 'Starkspur Golden Delicious' apples for 1980 and 1981. Mineral content is expressed as both concentrations (A) and percentiles (B).

Table 2. Mean values for October fruit and August leaf mineral samples in trees receiving standard commercial fertilizer rates for 'Starkspur Golden Delicious' apple over a 4-year period.

		Mineral concn (% dry wt)					Mineral concn (ppm)					
Tissue	Year	N	K	Р	Ca	Mg	Mn	Fe	Cu	В	Zn	wt
Leaf	1980	2.04	1.16	0.22	1.74	0.38	57.6	168	5.27	40.5	10.08	
	1981	2.04	1.18	0.25	1.69	0.30	36.8	178	5.25	40.3	10.69	
	1982	2.15	1.17	0.25	1.32	0.31	33.8	193	5.66	35.5	9.83	
	1983	2.06	1.60	0.27	1.70	0.32	36.9	194	6.49	36.0	10.08	
Fruit	1980	0.38	0.58	0.07	0.07	0.03		13.3	0.87	19.2		145
	1981	0.17	0.69	0.10	0.06	0.02		7.6	2.97	24.1		148
	1982	0.38	0.60	0.07	0.06	0.03	2.40	24.2	1.91	19.0	0.96	142
	1983	0.07	1.16	0.14	0.04	0.06	5.08	65.4	3.57	35.0	2.26	147

Table 3. Percentage of correct (Cor) and severely misplaced prediction (SM) categorizations for various quality factors of 'Starkspur Golden Delicious' apple after storage using percentile values of August leaf and fruit minerals in regression equations for 1980 and 1981.

Quality		Regression	Selection	Plots a to unc catego	assigned lesirable ory (%)	Plots to de categ	Plots assigned to desirable category (%)	
parameter	Data	from	variables ^z	Cor	SM	Cor	SM	
Soluble solids	1980 1981 1980 1981	1980 1980 1981 1981	F ^N N, FCa, FZn, LCa FN, FCa, FZn, LCa FN, FCa, LCa, FFe FN, FCa, LCa, FFe	61* 56* 47* 80*	0* 6* 6* 0*	68* 50* 50* 76*	0* 1* 3* 0*	
Titratable acid	1980 1981 1980 1981	1980 1980 1981 1981	FCa, LCu, FK, LFe FCa, LCu, FK, LFe FCa, LCu, FN, LFe FCa, LCu, FN, LFe	66* 53* 40* 72*	0* 0* 13* 0*	53* 40 53* 71*	10* 20 0* 0*	
Firmness	1980 1981 1980 1981	1980 1980 1981 1981	FCa, LMg, FN, FMg FCa, LMg, FN, FMg FCu, FN, FFe, FCa FCu, FN, FFe, FCa	57* 63* 50* 53*	16 18 14* 15	50* 41 43* 45*	15 23 14* 9*	
Color	1980 1981 1980 1981	1980 1980 1981 1981	FCa, FN, LMg, FFe FCa, FN, LMg, FFe LN, FCu, FFe, FN LN, FCu, FFe, FN	66* 33 52* 88*	4* 16 5* 0*	72* 25 36 76*	0* 6* 6* 0*	

²Selection variables are placed in order of importance in stepwise multiple regression equations.

 ${}^{y}F = Fruit; L = Leaf.$

*Indicates that the percentage of fruit currently assigned to the category significantly differs from the 25% one would expect in a random selection.

in Table 3. Variables used for the selection process are also shown. Plots identified as being undesirable were rarely in the desirable category for any of the quality parameters. Although these categorizations are not perfect, there can be economic benefit from them. For example, a 50% correct and 12.5% severely misplaced categorization contains twice as many superior (desirable-category) fruit, and half as many inferior (undesirable-category) fruit as in a random selection, which would yield about 1/4 of the fruit in either the high (upper 25%) or low (lower 25%) category. Furthermore, desirable and undesirable categories differ significantly for quality parameters (Table 4). Desirable- and undesirable-category fruit were significantly different from the overall mean with respect to color, titratable acidity, and soluble solids. Although mean firmness values for high and low firmness categories were not significantly different from the overall mean, they significantly differed from each other. This example used leaf and fruit samples collected in August, but successful categorization was possible for some parameters as early as June (data not shown), which is in agreement with previous reports (5).

Selection of desirable fruit among remaining plots. By selecting only those fruit likely to rank high in a chosen quality parameter after eliminating those unlikely to produce desirable fruit, further improvement in the quality of stored fruit is possible. The results of several selection approaches appear in Table 4. Since quality parameters are related to each other, it is necessary to consider the effect that optimizing one parameter has on another. Making a selection to optimize firmness resulted in firm fruit without severely affecting other parameters (selection 1; Table 4). However, optimizing color, titratable acidity, or soluble solids resulted in less-desirable firmness. If the user selects a specific combination of criteria, the adverse consequence of maximizing one parameter at the expense of another is reduced. It was possible to select groups of fruit high in soluble solids and titratable acidity without reducing firmness (selection 5; Table 4). Evaluating the effect of several combined selection criteria on a given set of data may be useful in developing a selection scheme for future use.

Relationship between mineral analyses and quality in 'd'Anjou' pear. Color, firmness, storage rots, and corkspot were re-

Table 4.	Mean values	after stor	rage for	firmness,	soluble a	solids,	color,	and	titratable	acidity	for	'Starkspur	Golden	Delicious'
apple in	various comp	outer sele	ctions us	sing 1981	regression	n equat	ions o	n 198	30 data.			-		

	Mean firmness (N) for		Mean soluble solids (°Brix) for		Mean cold	or (1–5) ^z r	Mean acidity (meq·liter ⁻¹) for	
Selection	Eliminated	Selected	Eliminated	Selected	Eliminated	Selected	Eliminated	Selected
Selection	Iruit	Irun	Ituit	Ituit	IIult	itult		Irun
1) Eliminate low firmness Select high firmness	95.1	101.7	9.79	9.14	2.92	3.21	21.7	21.4
2) Eliminate green color Select yellow color	99.6	86.8*	8.87*	9.80	3.60*	2.67*	18.2*	23.3*
3) Eliminate low acid Select high acid	97.1	95.8	9.73	9.98	2.90	2.70*	19.1*	26.2*
 Eliminate low soluble solids Select high 								
soluble solids	101.4	96.0	8.52*	10.30*	3.41*	2.77	19.37	22.7
5) Eliminate low acid & low firmness								
Select high								
soluble solids	96.1	97.8	9.76	10.15*	2.91	2.72	20.4	24.4*
Over-all mean								
no selection	98.	3	9.3	8	3.0	6	21.	2

 $^{z}1 =$ yellow; 5 =green.

*Indicates that mean values for the selection are significantly different than the overall means (P < 0.05).

lated to fruit mineral composition, as previously reported (1, 17). Although we evaluated these data with regard to several quality components, and various sorting schemes could be derived, only corkspot incidence is described in detail. In some years at some locations, fruit Ca, K, Mg, K : Ca ratios, or Mg : Ca ratios also were strongly related to the disorder. However, N : Ca ratios were most consistent across all years and locations. The N : Ca ratio of the fruit was significantly related to corkspot incidence in 5 of the 6 years. The N : Ca values in the Hood River 1985 sampling were generally low and not related to corkspot incidence. Average corkspot incidence for samples with N : Ca ratios within a given range is presented in Table 5. It has been our experience that although corkspot incidence can vary considerably for high-Ca fruit, it is rarely severe (>3%) in fruit with a N : Ca ratio <4.0 or Ca levels >8 mg Ca per 100 g of fresh weight. However, these levels are attained only rarely, and predicting corkspot incidence for fruit that are not in a lowrisk category is not possible. Fruit with N : Ca ratios between 6.5 and 8.0 had an average corkspot incidence that varied between 3% and 22%. Similarly, fruit with N : Ca ratios between 8.0 and 12.0 had an average incidence of corkspot that varied between 0.5% and 35%. Fruit with high N : Ca ratios can be

either relatively low in corkspot incidence (Wenatchee 1981) or extremely high (Medford 1975 and 1976). It may be possible to select a threshold value associated with minimum risk, but predictions of corkspot incidence above this threshold are not appropriate.

Comparisons between locations could partially involve sampling and analytical differences. Years of data collection with standardized sampling and evaluation procedures would be required to evaluate fully seasonal and geographical differences commonly reported in the literature. However, this sampling may not be necessary. It is more reasonable simply to rank different lots of fruit with regard to relative hazard and make storage decisions accordingly. Corkspot incidence, Ca concentration, N: Ca ratio, corkspot hazard ratings, and prediction success are presented in Table 6. Irrespective of the source of differences, expressing values on a percentile basis consistently identifies the most- and least-desirable fruit for a given location and year, regardless of the regression equation used. Simpler approaches using a ranking of N : Ca ratios also can consistently identify relative corkspot hazard. Superior fruit (low in corkspot) usually were correctly assigned to the desirable category, and inferior fruit (high in corkspot) usually were correctly as-

 Table 5. Average percentage of incidence of corkspot for d'Anjou' pears for samples with N

 : Ca ratios within a given range.

		Average percentage of incidence of corkspot N : Ca range									
Location and Year	3.5	3.5-4.5	4.5-5.5	5.5-6.5	6.5-8.0	8.0-12.0	12.0				
Medford 1975	*	4 (6) ²	1 (8)	8 (10)	22 (29)	30 (24)	36 (22)				
Medford 1976	*	*	*	10 (11)	15 (11)	35 (53)	73 (23)				
Wenatchee 1980	0 (20)	0 (20)	1 (50)	*	*	0.5 (10)	* ′				
Wenatchee 1981	*` ´	2 (12)	1 (12)	2 (33)	3 (12)	4 (31)	*				
Hood River 1983	*	* ´ ´	* ´	* ` ´	* ` ´	4 (13)	10 (87)				
Hood River 1985	3 (38)	2 (40)	7 (17)	*	*	* ` ´	*`´				

²Values in parenthesis indicate percentage of samples falling within a given range. *Indicates < 2% of the total samples fell within range.

Table 6. Average corkspot incidence, mineral composition of fruit, corkspot hazard ratings, and success of prediction categorizations for 'd'Anjou' pears.^z

	<u> </u>				<u>.</u>	
<u></u>	Med	Medford		atchee	Hoo	d River
	1975	1976	1980	1981	1983	1985
Average corkspot						
incidence (%)	25	42	0.6	2.9	12	3
Least affected fruity						
Ca (mg/100 g)	7.25	7.39	5.60	6.70	4.78	16.31
N : Ca	7.71	6.25	3.70	5.09	12.30	3.49
Corkspot hazard ^x	26	25	40	25	18	53
Most affected fruit						
Ca (mg/100 g)	5.24*	5.24*	5.30	5.70*	2.40*	15.89
N:Ca	13.34*	11.50*	5.95*	8.07*	24.00*	3.99
Corkspot hazard	72*	85*	78*	79*	77*	58
Prediction success (%)*						
1975 Equation	75*	74*	75*	66*	75*	32
1976 Equation	71*	78*	75*	50*	70*	22
1980 Equation	64*	70*	75*	66*	73*	30
1981 Equation	70*	71*	75*	66*	73*	17
1983 Equation	65*	73*	75*	50*	70*	24
N : Ca ratio	50*	81*	75*	50*	75*	40
Severely misplaced (%)						
N : Ča ratio	0*	3*	0*	0*	0*	20

²Data from Hood River and Medford were collected from orchard surveys; data from Wenatchee was obtained from a field trial where treatments altered mineral composition and corkspot incidence.

^yLeast and most affected categories are defined as the groups of fruit with the lowest (bottom 25%) and highest (top 25%) incidence of corkspot for a given location and year. An exception is Wenatchee 1980, which, due to the large proportion of unaffected fruit, is divided into affected and unaffected groups.

*Corkspot hazard ratings are the means for the percentile rankings of the N : Ca ratios in either least-affected or most-affected categories.

"Regressions equations were derived from ranked values of fruit flesh N and Ca concentrations in each individual year.

*Indicates that value significantly differs from the same value for unaffected fruit. It also indicates that the percentage of fruit correctly assigned to the high-risk category significantly differs from the percentage one would expect in a random selection.

signed to the undesirable category. Fruit were very rarely severely misplaced with superior fruit placed in an undesirable category or inferior placed in a desirable category. Ranking approaches were unsuccessful only at Hood River in 1985. Corkspot incidence was relatively low, Ca levels were high, N : Ca ratios low and were not related to mineral composition. The 1985 Hood River sampling was the only year where the majority of samples would have been above a threshold level. Although a threshold value (N : Ca = 3.5 or 4.0) could be assigned below which corkspot is not likely to occur, this value is almost never achieved. Furthermore, the overall relationship between N : Ca ratio and corkspot incidence obtained by combining the 5 years of data where significant relationships were obtained individually is not statistically significant (r = 0.06). The amount of disorder occurring above a low-risk threshold depends on year and cannot be predicted by N : Ca ratios. In Fig. 2, relative (percentile) N : Ca ratio is plotted against relative (percentile) corkspot for the 5 years where there was a statistically significant relationship. The relative severity of corkspot incidence can be predicted with N : Ca ratios in fruit tissue. Desirable fruit (lowest 25% in relative corkspot) never were found with a percentile (N : Ca) score > 75 and undesirable fruit (highest 25% in relative corkspot) never were found with a percentile score < 25 (Fig. 2). The data imply that it should be relatively simple to initiate a fruit sampling program in any of three pear-growing areas regardless of season, location, or analytical differences that are likely to occur. It may be desirable to evaluate more than one quality parameter. For example, in the 1983 Hood River evaluations, pears that were categorized as unlikely to develop poststorage corkspot required more time to ripen.

Examples from the literature further support the use of a relative (percentile) basis of expression for fruit analyses. Yearto-year variations in the apple mineral concentrations in the United Kingdom have been reported recently by Perring and Holland (9). Even though relative differences in treatment effects were consistent, two-fold differences in the average Ca concentration of 'Golden Delicious' apple fruits were reported between years in the Pacific Northwest (8). In Fig. 3A, fruit Ca was consistently associated with bitterpit in every year, as reported by Van der Boon (18). However, when mean bitterpit was plotted against mean Ca concentration for each year, no long-term relationship between mean Ca levels and bitterpit could be obtained (Fig. 3B). We viewed Ca concentration as moderating the severity of bitterpit occurrences whenever Ca concentrations are less than an almost unattainable threshold of 35 mg per 100 g of dry matter. We replotted relative (percentile) Ca vs. relative bitterpit to create a consistent relationship (Fig. 3C). An evaluation of a plot's Ca status and successful placement of fruit into high- and low-risk categories then could be made. In other examples, the amount of disorder associated with a particular level of fruit Ca varies with the year, even when thresh-



Fig. 2. Relationship between the percentile rank N : Ca ratio vs. percentile rank corkspot in 'd'Anjou' pears (1975 to 1983 data).

old levels are consistent (16). Although blossom end rot occurred in tomatoes with the lowest Ca concentration in each of 2 years, a high Ca concentration in tomatoes for one year would have been of similar magnitude to a low Ca concentration in another (7). Similar observations are likely to occur with other quality parameters.

Using percentile scores as independent variables is not always necessary. Predictions using mineral concentrations as independent variables followed by a ranking of predicted dependent variables sometimes can produce useful categorizations. However, when individual elements vary widely among years or among analytical laboratories, the relative importance of a given component in a multiple regression equation is distorted. Results are often different from evaluations that use ranked mineral content as independent variables. When mineral concentration is expressed on a percentile basis, laboratories with drastically different absolute concentrations still produce similar predictions.

Although absolute values for quality parameters could not be predicted with a percentile scheme, relative rankings may have commercial value. A packer must deal with the current year's crop; therefore, identifying superior or inferior lots of fruit may assist marketing and management decisions, regardless of whether the crop as a whole is above or below average. If an individual orchard consistently obtains an unfavorable relative position, it may reflect a need for management changes. Gains likely could be made in striving for an advantageous relative position. With sophisticated instrumentation and computer-assisted diagnostic capability, a large number of samples could be evaluated and interpreted before harvest.

We conclude that the approach described here is useful in



Fig. 3. Relationship between the percentage of bitter pit in 'James' Grieve' apples and the Ca concentration in the fruit (size 70-75 mm) [data after Van der Boon (18)]. (A) Plots of Ca level vs. bitter pit in all years. (B) Plot of average Ca level vs. average bitter pit for each individual year. (C) Plots of percentile rank Ca level vs. percentile rank bitter pit in all years.

interpreting fruit mineral concentrations when seasonal and analytical variations produce values that are otherwise unusable. The only requirement is that the elements being evaluated are consistently correlated with quality parameters and that analytical laboratories can correctly determine relative mineral concentration. Consistent critical values are not necessary and evaluations are not dependent on a single definition of optimum quality. Although ranking procedures show promise, evaluating more data is required to verify the usefulness of ranking procedures over a variety of conditions in a commercial setting.

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