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Decision Support Tools for Avocado Fertilization & Salinity Management: Preview to the Final Project Report

Over the past five years, the California Avocado Commission (CAC) has funded a project to develop Decision Support Tools (DST) that can be used by avocado growers to better manage avocado fertilization and the effects of soil salinity on avocado yields and fruit quality. In order to research fertilization best practices, we utilized data from hundreds of trees over several years and across a transect of the major avocado production areas in Southern California.

Using advanced statistical methods and artificial neural network models, we utilized the data to decipher the patterns in leaf nutrient analysis data and determine how different elements affect crop yields. The project also examined variations in the salinity tolerance of different rootstocks and the extent to which damage caused by chloride accumulation in the foliage can be offset by managing tree nutrition.

This project is now in the final phase of data analysis, and a number of interesting and important findings are emerging from the data set. In this article we report a preview of our findings and the type of information that will be provided in the Decisions Support Tools. When successfully deployed, growers will be able to evaluate the cost-benefit of various management practices and determine how to optimize their economic return.

Deciphering Interaction of Variables Affecting Fertilization

Current recommendations for avocado tree fertilization are based on guidelines that were originally developed for citrus and have since been modified by various plant testing laboratories. While California avocado growers have utilized these guidelines with some success, it has been difficult to obtain specific avocado fertilization recommendations based on actual data linked to yield.

This is due to the high cost of leaf analysis and sampling at the block level as opposed to sampling and yield measurements for individual trees. There is also high variability in avocado yields from one year to the next due to alternate bearing, as well as high variability in the leaf nutrient status of trees within the same orchard and along the row due to microsite conditions affecting root growth, soil conditions and fertilizer distribution. Variables such as irrigation water salinity, chloride toxicity, use of different rootstocks — and the interactions between these variables — obscure the relationship between yields and leaf nutrients. Sorting out this natural variability is a huge challenge and is compounded by the fact that in many cases leaf and soil analysis reports are archived but seldom used.

Fortunately, it is now possible to solve this problem by taking advantage of powerful new statistical methods and machine learning methods to establish linkages between independent and dependent variables. These new methods allow researchers to examine the relationships between plant nutritional status and fruit yields, salinity effects on fruit quality, or irrigation water quality and soil water status on chloride toxicity.

The traditional approach to crop modeling over past decades has been to set up trials in which all vari-

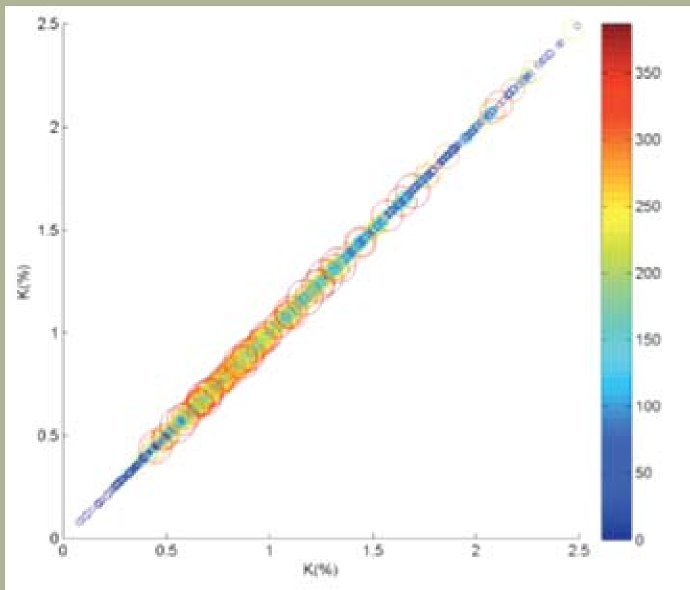

Figure 1a

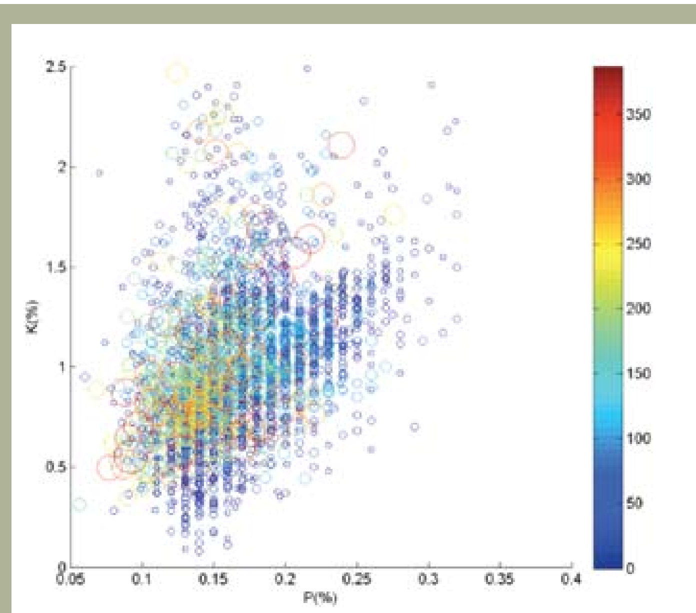

Figure 1b

Yields of avocado as affected by leaf potassium content (left, Figure 1a), or by the interaction of leaf potassium and leaf phosphorus contents (right, Figure 1b). Yields are denoted by color and size of the circles representing individual trees. Approximately 3,000 data points are included in the plots, which clearly illustrate an optimum range of 0.5 to 1.3 percent for potassium, but which centers at 0.8 percent potassium when phosphorus is at 0.15 percent.

ables are controlled except for one variable of interest, e.g. same rootstock and soil but different nitrogen fertilization amounts. In comparison, our approach has been to acquire a data set that reflects the full range of variation that occurs within the avocado industry. The DST project collected data on 15 trees per available rootstock in 12 orchards located on a transect from San Diego to San Luis Obispo. In the nutrient analysis research that is highlighted below, we included several additional unpublished data sets from Carol Lovatt that include leaf analysis and yield data for individual trees and over multiple years.

Determining Target Ranges for Nutrients

Preliminary workup of the data shows that all the data sets have similar distributions and variances, which allows us to conduct a meta analysis of the combined data. We began by identifying the nutrient yield relationships and studying the interactions between individual combinations of nutrient elements.

Figures 1a and 1b plot fruit yields as colored circles of increasing size corresponding to increasing yield and identify leaf nutrient levels that are associated with the best tree yields. Small blue circles represent low yielding trees with approximately 50 kg of fruit per tree. Large red circles represent high yielding trees with 300 kg of fruit per tree or more. Figure 1a reveals the range where a single element is optimal — in this case potassium. In Figure 1a, we see that the yellow and red circles representing high yielding trees span from 0.5 to 1.2 percent potassium, but note that the central target is ~0.8 percent for most trees.

Figure 1b plots potassium versus phosphorus in a scatter diagram. In this figure, the clustering of yellow and red colored circles show that both potassium and phosphorus should increase together to maintain high yields, with potassium at a near optimum level for most trees at 0.8 percent and phosphorus at 0.15 percent. As phosphorus increases above 0.2 percent, there are no high yielding trees, illustrating the potential for overfertilization or nutrient imbalance that causes a yield loss.

Another method of data analysis — referred to as "frontier" or "envelope" analysis — plots the frequency of trees with a specific nutrient content along with a corresponding box plot of fruit yields. This method allows us to compare the current industry yield average versus the yields that could be obtained by bringing the trees to their optimal nutrient levels for individual nutrients or nutrient ratios.

Figure 2 illustrates the relationships between leaf sulfur content and tree yields. The results clearly show that increasing sulfur to 0.55 percent is associated with a 40 lb/tree yield increase as compared to the majority of trees in the data set, which had an average of 0.33 percent leaf sulfur. While yield responses to deliberate sulfur fertilization have not been tested for avocado, these results are especially intriguing given the results many growers are observing by using sulfur burners to control soil and irrigation water pH.

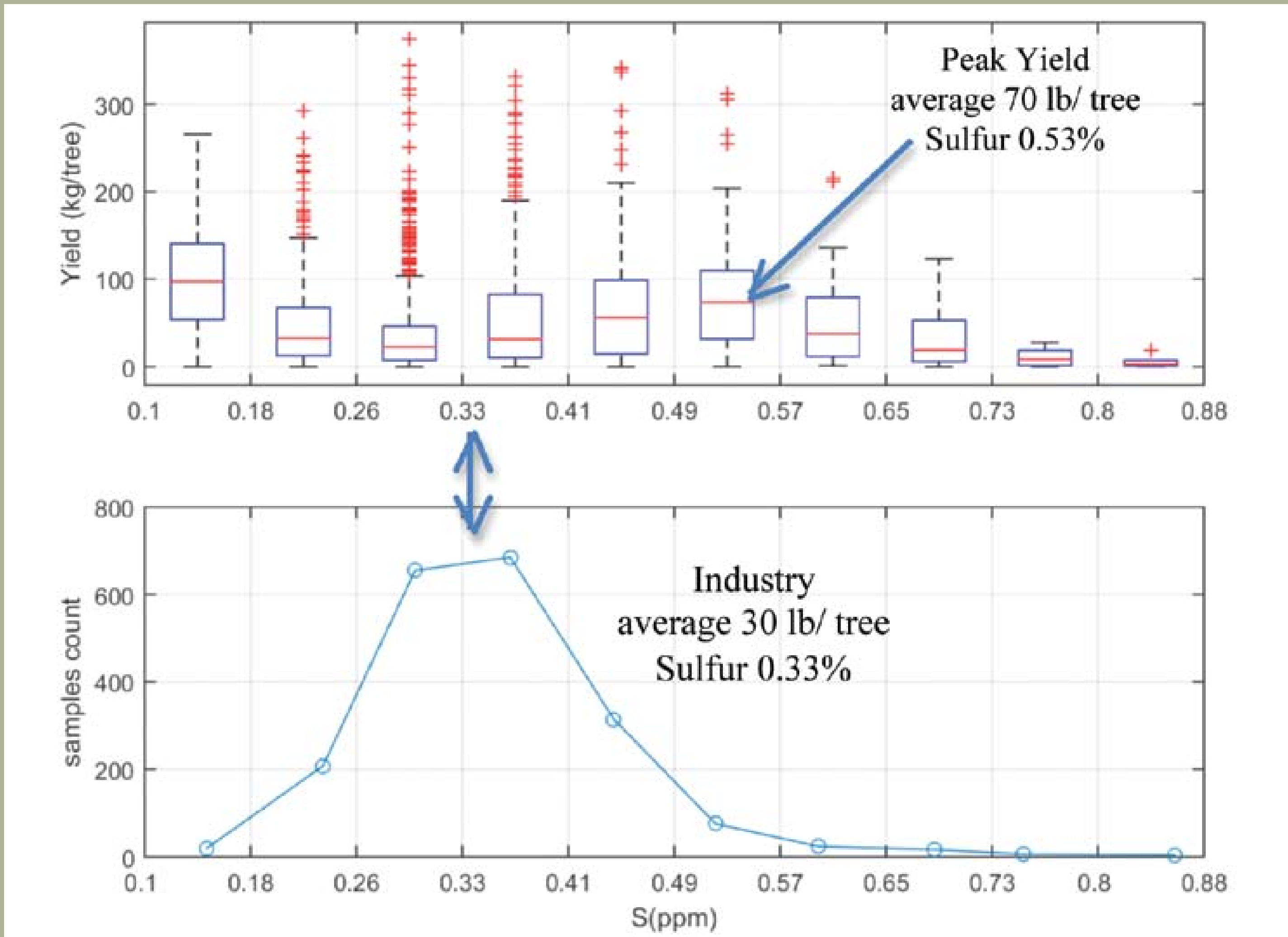

Figure 2

Frontier analysis showing box plots of yield for trees having different levels of leaf sulfur. The average yield is indicated as a red line centered in each box. The bottom plot shows frequency of trees in each sulfur level category. The majority of trees in the study had ~0.33 percent leaf sulfur, versus trees with peak yield occurring less frequently and having 0.53 percent leaf sulfur. Data suggest sulfur is limiting for most trees in this study and probably also for the avocado industry in general.

Based on analyses to date, we can now confidently provide new target ranges for leaf analyses that can be used to guide avocado fertilization programs. As shown in Table 1, the values for several elements vary substantially from earlier recommendations and current industry conditions. In general, most trees were in the optimum range for nitrogen, phosphorus, and potassium, but were deficient in calcium, zinc, manganese, boron and sulfur. We also can predict yield losses as nutrient levels exceed the optimum values.

While powerful statistical tools allow us to mine the data set for optimal ranges, the results of our analyses have revealed that there are multiple interactions between different nutrient elements. In other words, as certain nutrients go up yields can be further increased by reoptimizing other nutrients to obtain the optimum nutrient ratios. Using clever plotting methods (see Figure 1), we can visually evaluate how different combinations of two nutrients affect yields. However, the problem becomes much more complex when optimizing all of the elements at the same time. In this case, a multidimensional non-linear pattern analysis is required in which a model is trained to fit real world data, and then validated with new data that it has not seen before to determine how well the model works. Once validated, the model then becomes a working tool that can be used to predict yields based on the equation that weights the importance of each input variable to predict the output variable — in this case, yields. The ability to apply these tools for avocado modeling is very new and has been made possible by the availability of machine learning software that is used for applications such as market analysis, handwriting and voice recognition.

The DST project is the first to

use artificial neural network (ANN) models for crop modeling. Preliminary results from our first ANN models have been described in reports available on the CAC website. The major focus has been establishing leaf nutrient relationships with yield and the effects of chloride on avocado yields. However, the ANN modeling approach has many applications. For example, last year while examining the effects of salinity on fruit quality we determined that high chloride content in the fruit is associated with a greatly decreased ripening time after the fruit is removed from controlled atmosphere storage. This suggests that fruit from salinized orchards will have a much shorter shelf life. Correspondingly, we observed that increasing tree calcium levels (measured as leaf Ca content) is associated with increased ripening time and a greater shelf life. These results are now being confirmed in a repeat test of fruit from trees that have been subjected to different levels of chloride and different nutrient management regimes.

Salinity Management

Avocado is the most sensitive of all horticultural crops to salinity and a major challenge for the industry is developing recommendations for irrigation management that will save water while making use of increasingly saline groundwater supplies. In the DST project we have focused much of our data collection and analysis on the effects of chloride toxicity, which is the major hazard associated with use of saline water. To model this relationship, we installed soil probes that continuously monitor soil aeration, water availability and electrical conductivity (salinity) of the pore water solution for trees located in different soils in the DST project sites.

Our research shows that high yields can be maintained at leaf nutrient analysis values as high as 0.5 percent for leaf chloride, but this becomes increasingly difficult to achieve as irrigation water chloride levels go above 80 parts per million. We also have established that there are many nutrient interactions that affect fruit yields as chloride levels increase in the trees. One of the surprise discoveries has been that root hypoxia caused by waterlogging appears to have a major impact on the amount of chloride uptake by avocado. This has been observed in many crops, but never quantified for avocado, and illustrates the interactive effects of irrigation management and fertilizer management. These effects are still being examined in detail by Ph.D. student Julie Escalera, who is modeling soil aeration status in relation to leaf chloride content for her dissertation research.

As we complete our analyses during the final year of the project, we will continue to report additional details and findings from our modeling work and statistical analyses. It has been especially useful to bring to bear complementary statistical approaches to confirm the main results from the predictive, but much more complicated, ANN models. ANN models are especially powerful for multifactor optimization, but can also be regarded as black boxes and require careful dissection to confirm predicted relationships. Advanced statistical methods such as frontier plots allow us to see how particular interactions play out when examined closely.

The tools developed by the DST project should be of high value to avocado growers and provide an innovative new toolbox for crop modeling in general. When the DST equations are deployed, a web-based user interface will provide user-friendly toolset where yield predictions can be generated based on model software programs.

Nutrient	Optimum Range	Highest Frequency
N (%)	2.25-2.9	2.25-2.7
P(%)	0.1-0.15	0.15
K (%)	0.7-0.9	0.9
Ca (%)	1.8-2	1.4
Mg (%)	0.6-0.9	0.5-0.6
Zn (ppm)	50-80	34
Mn (ppm)	110-145	75
Fe (ppm)	55-80	55
Cu (ppm)	4-7	9
B (ppm)	38-60	25
S (ppm)	0.45-0.53	0.3-0.37

In excess	
Good	
Deficient	

Table 1

Table 1. Optimum ranges of leaf nutrient levels for avocado versus the range of elements found in most trees in a meta analysis of several avocado data sets where yield and nutrient data were available for individual trees.