Decision Support Tools For Management of Avocado Nutrition and Chloride Toxicity

Final Report
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Project Principal Investigator: David Crowley, Professor of Plant Soil Relations, emeritus
Report Co-author: Salvatore Campisi, postdoctoral research associate

Co-Investigators and Team Members:

Dr. Carol Lovatt, Department of Botany and Plant Sciences
Dr. Phillipe Rolshausen, Department of Botany and Plant Sciences
Dr. Mary Lu Arpaia, Department of Botany and Plant Sciences
Dr. Ariel Dinar, School of Economics

Graduate Students:

Julie Escalera, Ph.D. candidate Dept. of Environmental and Ecosystem Sciences, survey of grower methods for adoption to water scarcity, studies on root hypoxia and chloride
Jenessa Stemke, M.S. Environmental Sciences, graduated, in thesis work carried out EGAP study on effects of recycled water on avocado

Staff Research Associates

Woody Smith, Staff Research Associate (ret), Environmental Sciences
Stephen Qi, Staff Research Association, Environmental Sciences
James Sievert, Staff Research Associate (ret), Kearney Center
Toan Khuong, Associate Specialist, Botany and Plant Sciences

Moral Support and Ideas

Ruben Hofshi, Hofshi Foundation, Avocadosource.com
Wayne Brydon, California Avocado Commission
Tim Spann, California Avocado Commission
Margy Crowley, Gary Bender, Peggy Mauk, Ben Faber, Jon Dixon

Technical Support and Plant/Soil Chemical Analyses

Scott Bucy, Darrell Nelson, Fruit Growers Laboratory, Santa Paula, CA

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In this research, we have modeled the relationships between leaf nutrient concentrations and the yields of avocado trees with the aim of developing decision support tools for improved fertilization and nutrient management to increase avocado fruit yields. Using a data base of ~3500 observations in which nutrient concentration profiles and yields of individual trees were examined over several harvest seasons, we now present in our final report a refined model that predicts nutrient-yield relationships based on all possible combinations for the 11 elements that are monitored by leaf analyses. The research conducted represents an intellectual evolution of ideas on how to mine leaf and soil analysis data sets using different filters and mathematical methods to extract relationships between selected variables such as yield, fruit quality, and chloride toxicity (patent application filed, UCR 2016) Our modeling approaches involved a range of complimentary and independent methods that included artificial neural networks, Kohonen self-organizing maps, frontier/envelope analysis, and quantile regression. The ultimate product from our research is the translation of these data into working equations and lookup tables with macros that can be employed in sophisticated software for use as a decision support tool.

In the two previous activity reports, we reported specific findings on nutrient-yield response relationships for each of the individual elements required for plant nutrition. The results attained from quantile regression and envelope analyses identified target ranges for each element and the potential yield for trees having specific ranges for each leaf nutrient element. Figures and concepts generated from the results of quantile regression pointed out the need for careful filtering of the data set to model trees having high yields, but that were not in an alternate bearing mode. In any one year, 30% of the trees in an orchard may be nonproductive trees (<10 kg fruit/tree), while other trees that are in an alternate bearing mode in the same orchard may be producing more than 200 kg of fruit in a heavy-on year. Both categories of trees generate consider noise in predictive models. Alternate bearing, heavy yielding trees have a large nutrient removal in the fruit harvest one year, but may accumulate nutrients the following year during an off-cycle. Similarly, low yielding trees introduce large modeling errors. There are many reasons a tree may be producing low levels of fruit, even with optimum leaf nutrient concentrations, for example drought, poor pollination, summer heat induced fruit drop, etc. Filtering out the noisy components of the dataset through a hierarchical analysis thus enables a sharp focus on design of fertilization programs to maintain highly productive trees and possibly to help suppress alternate bearing.

One of the major challenges in this research project is the constraint imposed by modeling plant nutrient yield relationships in a manner consistent with Liebig's Law of the Minimum, which is a foundational principle in plant nutrition. In its simplest form, this law states that for any specific combination of elements, the *single element* that is most limiting must be corrected before any progress can be achieved by managing another element that is less limiting. However, the simple version of Liebig's law does not take into account the effects of nutrient excesses or phenomena such as chloride toxicity, which also impose limits to fruit production. Moreover, Liebig's law refers to total plant growth, and does not necessarily pertain to fruit production. Heavy vegetative growth can reduce fruit production, when carbon is partitioned toward canopy growth rather than reproduction. Here we refine Liebig's law to measure not only how nutrient limitations affect potential yields, but also how nutrient excesses and nutrient interactions control fruit production.

The relationships between different nutrients and avocado yields can be visualized in a number of graphic representations. One of the most powerful methods is the use of Kohonen self-organizing maps, which shows the specific combinations of conditions (leaf nutrient levels) that are associated with different yield potentials. However, in pattern recognitions models using feed-forward, artificial neural network analyses, we found that independent model runs yielded different solutions and that such models do not adequately capture the limit functions imposed by Liebig's law. More specifically, predictive ANN models allow tinkering with nonlimiting nutrients to offset yield losses imposed by nutrient excesses, whereas Liebig's law would not allow an adjustment of potassium to offset a calcium deficiency. In order to develop limit-based models, we discovered that we needed a mathematically rigorous approach to filter the data set to those trees there were the most highly productive, but not in an alternate bearing state, and then use ranking methods to identify which nutrient or nutrient interactions established the greatest constraint. In our final analysis, we show that this can be achieved by using lookup tables for pairwise nutrient interactions that simultaneously rank the constraints imposed by any and all nutrient limitations, excesses, and imbalances in leaf nutrient levels.

A major finding from our research is that much of the avocado industry in California may be over-applying some fertilizers such as nitrogen and potassium, and under fertilizing sulfur and calcium (gypsum). This finding is supported by models (high statistical confidence) that show how excesses of nitrogen, potassium, or for that matter over fertilization with any element is associated with huge losses in fruit production. Another important finding is that plant nutritional status appears to be linked to alternate bearing in avocado, and may actually be a contributing driver that sets trees into an alternate bearing pattern. This hypothesis is supported by data showing that large nutrient imbalances, e.g. between nitrogen and potassium, were mainly associated with alternate bearing trees. A third focus of this research was the study of soil salinity and chloride toxicity on avocado yields, and the extent to which this might be controlled by managing tree fertilization, soil water monitoring, and leaching practices. Results of those studies are published in several articles in the Annual Avocado journal and Grower magazine articles, and were also shared in many seminars and grower meetings over the past five years by Crowley and his Ph.D. candidate, graduate student Julie Escalera. We also have several manuscripts in preparation, including individual articles dealing with the application of data mining techniques for nutrient analyses, and a review article that examines: Crop Production Functions to Address Water Scarcity and Salinity: A literature review with focus on citrus and avocado

Many different scientists, graduate students, undergraduate student volunteers postdoctoral research associates, visiting foreign researchers from Chile, Mexico and Pakistan, contributed to this project, helping with fruit harvests, and soil and leaf sampling, or by carrying out interesting subprojects that gave new insights into topics such as the contributions of plant

growth promoting bacteria to avocado salinity tolerance, or the relationship between root hypoxia and chloride uptake. Among our research team members, we acknowledge the essential contributions of the staff research associates who kept everyone organized in carrying out different activities, namely, Woody Smith, Stephen Qi, and Toan Khuong. In the final phase of this project, all of the data analysis has come together into the final integrated models through the intellectual contributions of postdoctoral associate, Dr. Salvatore Campisi. In the latter phase of the project, we also brought in Drs. Carol Lovatt and Phillipe Rolshausen as members of our project team who contributed to detailed discussions of the data. The massive data set that enabled our high resolution modeling was through the combination of data acquired by both David Crowley and Carol Lovatt's research teams and enabled us to end our project early with return of two years funding to the California Avocado Commission. Our database construction was further supercharged through the generous support of Fruit Grower's Laboratory, who carried out hundreds of leaf analyses as a no-cost contribution to our project. The high quality analytical data provided by FGL provided the foundation data set for studying leaf chloride and nutrient interaction effects on avocado yields. Last, but not least, all of us who have worked on this project acknowledge the generosity and enthusiastic support of the avocado growers who allowed us to on their property, and facilitated this research with excellent management, and great field discussions. The California Avocado Commission supported this research, and not only provided the core research funding, but also gave excellent feedback over the years in discussions with the CAC project management team and production research committee.

Conceptual Framework and Methods:

One of the main principles of plant nutrition is Liebig's Law of the Minimum, which states that plant growth is restricted by the most limiting element. Following this concept, growth responses will not be observed by providing more of any particular limiting element unless the deficiency by the most limiting element has first been corrected. This concept is thus fundamental to predicting how multiple nutrient deficiencies affect plant growth. On the other hand, whether this law also pertains to fruit yields on perennial orchard crops such as avocado is not clear. Nutrient excesses and imbalances also affect fruit production independently of tree growth, as commonly seen when fertilization pushes tree vegetative growth at the expense of fruit production.

To better understand and predict how nutrient interactions affect fruit production by avocado trees, we have generated crop production models that utilize data mining approaches to explore how different nutrient ratios affect avocado yields. Another independent approach utilizes artificial neural network (ANN) models to examine the relationships between all nutrient elements simultaneously. Given that there are eleven elements that are required for plant growth, the possible number of element interaction combinations are in the thousands, even if simplified to conditions classifying each element deficient/sufficient (2^{11} = 2048). This large degree of freedom creates a challenge for deriving a predictive model that includes all 11 essential elements. Moreover, ANN models allow tinkering with various combinations of elements to increase yields while not fully addressing the limit threshold imposed by the most limiting element (ie., a violation of Liebig's law of the minimum).

To address these constraints, we show that this can be resolved by applying quantile regression and frontier/envelope analyses, which can be used to model the impact of nutrient limitations, excesses, and imbalances. These relationships are graphically presented as a series of figures showing the yield potentials associated with any nutrient or nutrient pair combination. The sorting function allows the most limiting conditions to be ranked and identified, and establish a top-end constraint on the yield potential that must be addressed, such that different constraints are revealed in a stepwise fashion as a grower examines how to best optimize their fertilization program. In other words, if chloride toxicity is the primary constraint, adjusting calcium/magnesium ratios or potassium levels do not provide yield benefits until the chloride toxicity is first resolved. We also examined closely those interactions that have been identified in prior research on plant nutrition for their potential effects on avocado yields. These include the element ratios for Ca/Mg, Ca/B, and Zn/P among others.

Holistic Data Mining Using Kohonen Self Organizing Maps (KSOM)

One of the most powerful tools for examining the relationships between fruit yield and all of the plant essential elements measured by leaf analysis is the use of KSOM analysis. In a KSOM, a neural network analysis is used to find the shortest possible distance between all variables simultaneously in a multi-dimensional mathematical space. The results are then shown as a set of panels in which individual panels are displayed that represent the values for each variable as individual color-coded grids. Under each panel assigned to a variable, the KSOM shows the actual values that correspond to the color range. Using a color code to represent the full range of values, the data are fully normalized with blue representing low values and red representing the highest values. By examining the panel that displays fruit yield, we see the portion of the map that corresponds to high yields, and then explore each of the other panels sequentially to see what levels of nutrients are associated with high fruit yields. Likewise we can examine alternate bearing, or low bearing trees and the nutrient profiles associated with those conditions. Conversely, we can study how high nitrogen or chloride levels affect yields by identifying the regions in those panels that represent those conditions, and then examine the same region in the yield panel to see the yields associated with specific nutrient conditions. While not practical for direct use as a decision support tool, this approach provides a holistic view of the data and serves well for mining relationships that can be examined in further detail using other data modeling approaches.

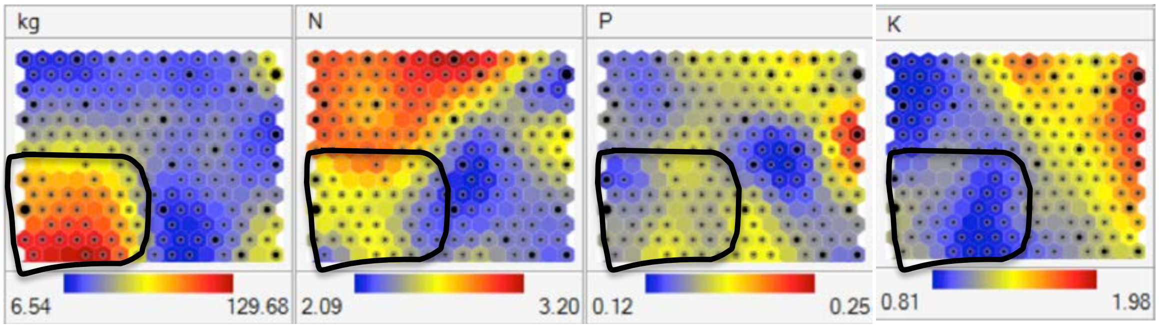
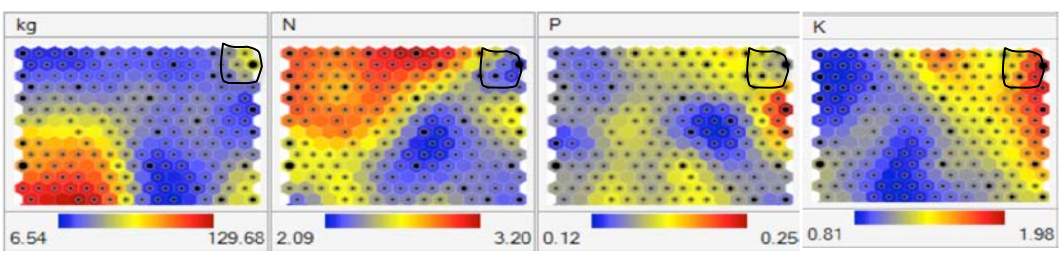


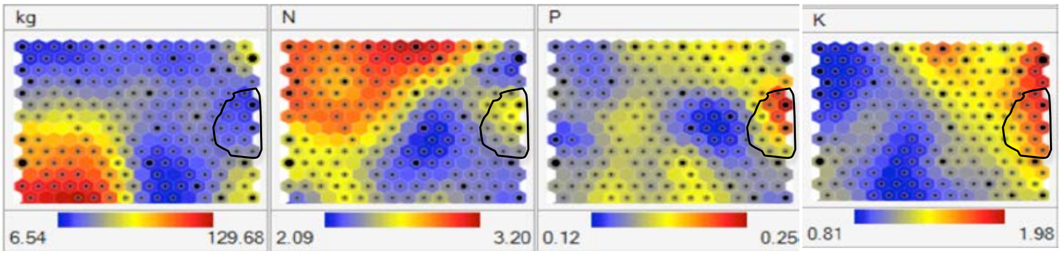
Figure 1. Kohonen self-organizing map of nutrient-yield relationships for the macroelements. Panels were extracted from a large KSOM that was constructed using all 11 nutrients. Circles highlight panel areas corresponding to high yield, but only with low levels of N, P, K. Fertilizer excesses > 2.5% N, .2 P, and 0.8-1.2% K content. Note that the highest yields are associated with low to intermediate N (2.5%), P .12-.15%, and < 1.2% K; whereas high levels of N and K are associated with low yields. Because the model is built on data from a transect of the industry, this strongly suggest many avocado growers are over fertilizing wit N and K fertilizers to the extent they may be completely lose all fruit production.

In Figure 1, above the bottom left corner of the first panel denotes having a dark red color denotes trees with up to 129 kg fruit per tree. Trees in that region have values of nitrogen ranging from 2.09 to 2.6 % N. As N levels increase to near 3%, we see yield complete yield loss to <10 kg fruit per tree. These data strongly match the same recommendations derived by completely independent quantile regression methods, and illustrates the power of KSOM methods to obtain a holistic picture of the importance of particular element or nutrient imbalance and the effect on plant yield using visual inspection alone.

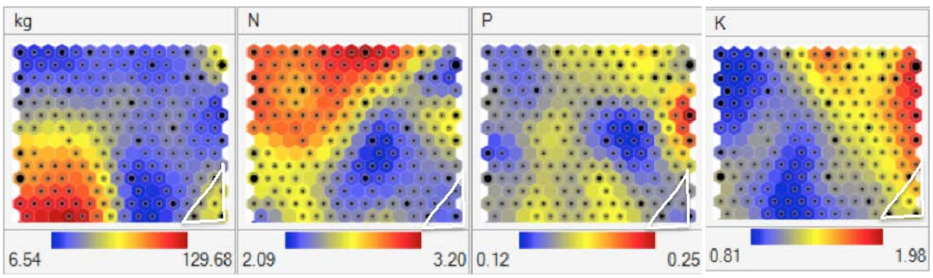
If you take a still closer look the same figure, you will also observe that there are yellow patches in the right side corners for the yield panel (circled in black), this represents a situation in the data set were good yields (yellow color) were also be obtained that were distinct from the other productive trees. Examining that same region in the N, P, K panels show those conditions: K levels are high, as long as P and N are also limiting.



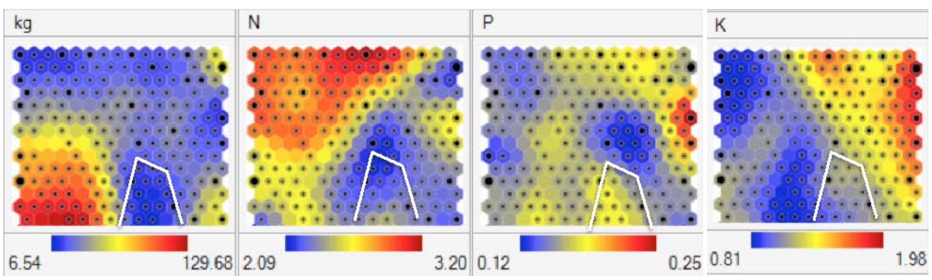
Correspondingly, when both K and P are high, and N is intermediate, fruit yields are suppressed.



Intermediate yield obtained when N is low, P is low, and K is intermediate



No yield obtained when N is low, P is high, and K is intermediate



Using the KSOM approach, we can also examine the nutrient profiles associated with trees in an off-cycle, either as a result of alternate bearing, or due to environmental factors that suppress production in any given year. In Figure 2, we see these trees represented in the first panel as the blue area representing trees producing less than 10 kg fruit.

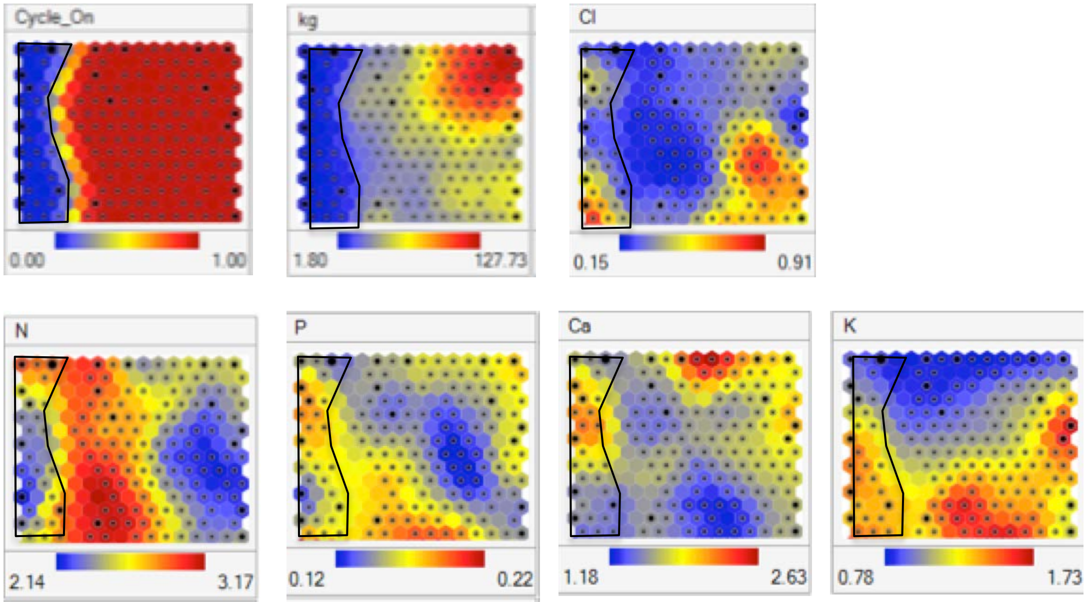


Figure 2. Nutritional factors associated with nonproductive trees / and potential driver of alternate bearing. Top left panel blue color represents nonproductive trees; Top middle, fruit yield in kg; Top right, leaf chloride; Bottom row, leaf concentrations of N, P, K, Ca, and K.

In Figure 2 above, KSOM models of nutrient profiles for non-productive trees reveal that this condition is primarily associated with trees having large nutrient imbalances among the macronutrients, or in trees experiencing chloride toxicity (Figure 2). Note that elevated leaf chloride concentrations (top right, red colored areas) are associated with generally low levels of fruit production. However, complete yield losses occur only during a combination of elevated chloride levels when combined with imbalances of the macronutrients, particularly when trees also have unbalanced N and P levels (low N and high P with elevated Cl). The analyses further suggest non-productivity may be associated with imbalanced Ca and K (high Ca, low K with elevated Cl). Altogether, the KSOM analysis reveals many different nutrient interactions that are of interest for further examination with detailed production-function models.

Hierarchical modeling of nutrient yield relationships using scatter plots, envelope analyses and quantile regression.

In the course of this research, we have carried out in-depth examination of the relationships between yield potential and each of the plant essential elements. In a hierarchical approach, we start first with an x/y plot showing the yields that are associated with increasing nutrient levels. The example provided in Figure 3 shows the x/y scatter plot for potassium. As shown in this example, the plotted data emerge as a shotgun pattern in which there are no apparent nutrient-yield relationships, and regression analysis fails to provide any statistically significant equations.

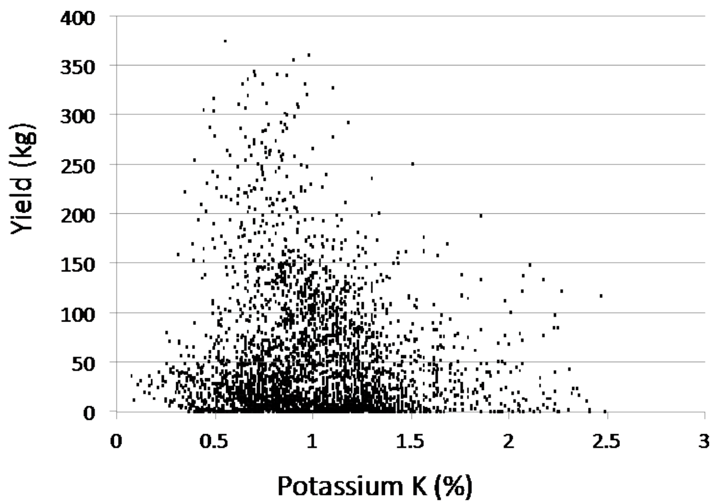


Figure 3. Scatter plot of nutrient-yield relationships for potassium.

In the second step of the hierarchical analysis, the data cloud from Figure 3 containing some 3500 observations is shown after it has been collapsed into a single vector plot, where the target levels for each nutrient are instead identified by the data symbols that vary in size and color (blue dots: nonproductive or low yielding trees; yellow circles: productive trees; large red circles, highly productive trees. Below is an example for potassium.

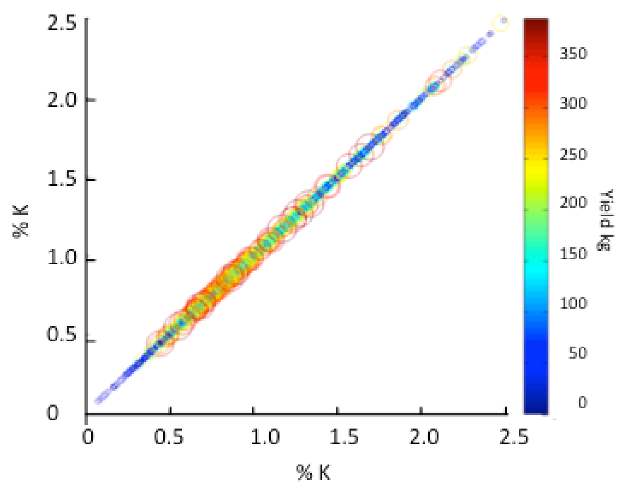


Figure 4. Univariate vector plot for potassium, high yielding trees are indicated by color and circle size. Every circle represents an independent observation (individual tree) from a transect of the avocado industry in California. Trees with high yields require 0.5 to 1.5% potassium, centering at 0.8 as a target value. More specific target levels and fertilizer recommendations will depend on levels of other nutrients and element ratios.

In the next step, we extend this approach to nutrient interactions to examine how pairwise combinations of elements correspond to yield potential. The example shown in Figure 5, below, is representative of how we can study nutrient interactions and examines the yields for trees having different potassium and phosphorus levels. The linear arrangements of the data depicting high yield trees (yellow and red circles) illustrates that high yields require potassium and phosphorus to increase concomitantly, ie. a significant nutrient interaction is evident between these nutrients. Nonetheless, there are also many nonproductive trees (small, blue circles) that also occur along this same trend line, ie. trees that are good for both P and K, but which have some other nutrient limitation or environmental constraint that has affected yield.

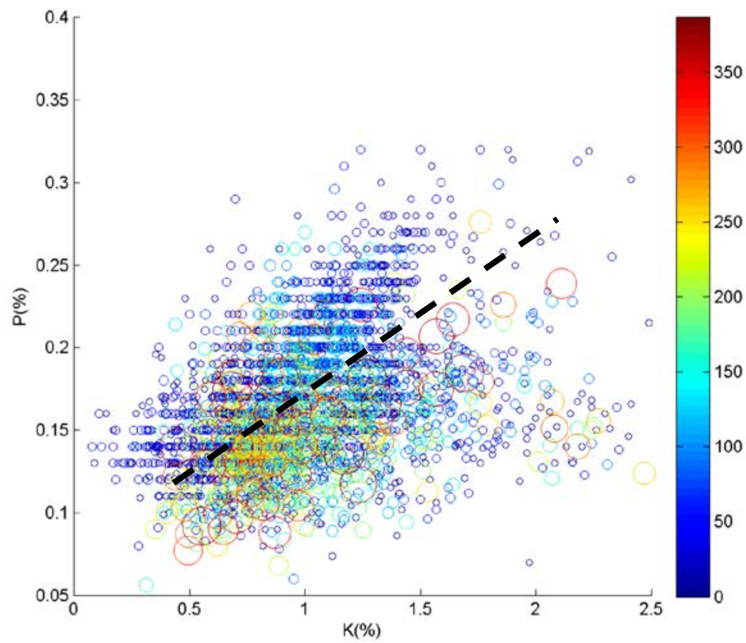


Figure 5. Scatter plot of trees with different leaf phosphorus (% P) and potassium (%K) levels. Yields associated with each observation are depicted by color and symbol size. Color bar on the right gives yield in kg/tree ranging from 0 (dark blue) to as high as 350 kg fruit per tree (dark red). Dashed trend line shows apparent relationship between P and K, in which trees with high P content need increased K levels in order to maintain productivity

While these types of plots provide good initial insight into the data cloud for nutrient yield relationships, still more detailed analysis is required to examine the distribution of trees for any particular nutrient level. Keeping with potassium as our example, Figure 6 provides an example of the next step in dissecting nutrient yield relationships. This step employs quantile regression in which the data are sorted into quantiles that represent blocks of data corresponding to a particular nutrient range. The blocks enable groups of about 300 observations into individual groups or quanta using regression models to explore how each subgroup behaves with respect to a certain characteristic such as leaf potassium content. Results using this approach were previously reported in detail in the activity reports on the macro- and micronutrients.

As shown in Figure 6, each nutrient range affects the distribution of trees in different production categories. The lowest number of nonproducing trees (blue) occurs for trees having ~0.8% K, whereas the highest number of exceptional trees (yellow) having from 0.88 to 0.9% K. The figures thus reveal a target range where K levels should be maintained in order to achieve the best possible yields with respect to this nutrient.

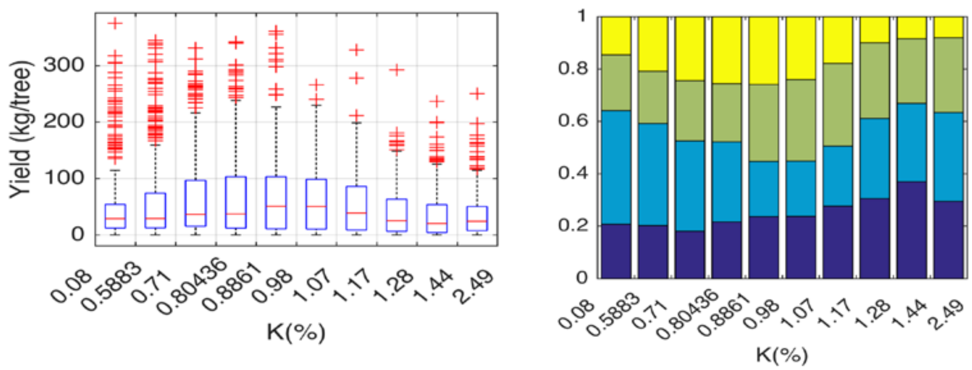
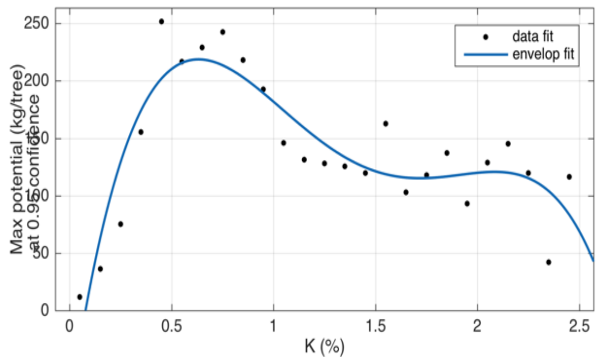


Figure 6. Quantile regression of yield-nutrient relationships for potassium. Left: Yield data are displayed on the y axis in relation to potassium levels. The blue boxes above each nutrient range represent the distribution of data for the middle 50% majority of trees having K values within a particular range for potassium. The ranges were established by examining the distribution of K values across the entire data set. Each range represents 10% increments or approximately 350 trees. Within each box, the horizontal red line indicates the median tree. The red cross symbols indicate trees that are at the highest production levels, but that are outliers from the majority group. Those trees with extraordinary high production are generally in an alternate bearing mode. The right figure provides similar information, but breaks the distribution into further categories, with dark blue corresponding to nonproducing trees, blue and green representing medium and high producing trees, and yellow corresponding to trees producing more than 200 kg fruit.

Another method that can also be applied to identify the target nutrient levels uses envelope analysis. This is a traditional method in which the data cloud is “enveloped” using regression analysis that generates a linear equation that can be used to draw a line describing the curve for the best yielding trees.



K (%) Linear model Poly4:
f(x) = p1*x^4 + p2*x^3 + p3*x^2 + p4*x + p5

Coefficients (with 95% confidence bounds):
p1 = -1.494e+06 (-2.067e+06, -9.208e+05)
p2 = 1.178e+06 (7.407e+05, 1.615e+06)
p3 = -3.27e+05 (-4.443e+05, -2.097e+05)
p4 = 3.636e+04 (2.342e+04, 4.93e+04)
p5 = -1106 (-1593, -619.5)
Goodness of fit:
SSE: 2.786e+04
R-square: 0.8566
RMSE: 35.58

Figure 7. Linear model of maximum fruit yields obtained at different concentrations of leaf potassium (% K). The equation used to generate this envelope curve is given to the right. Note the high R square value indicating excellent confidence in this production function model.

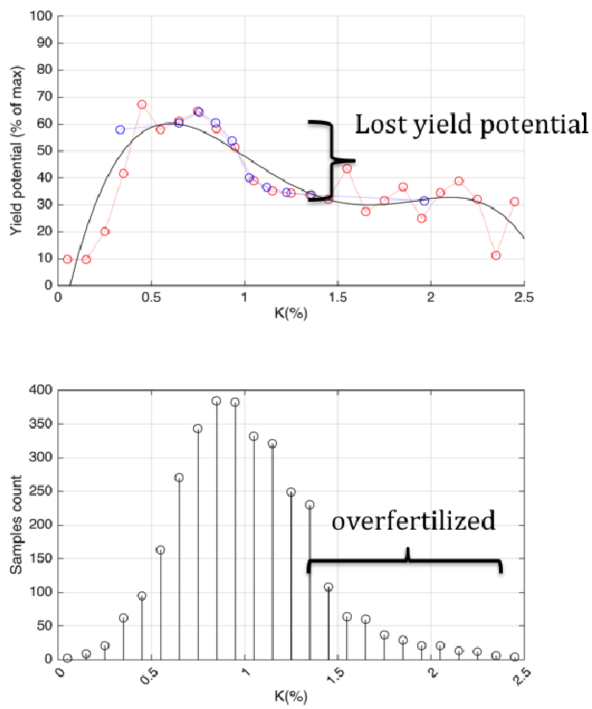


Figure 8. When the data in Figure 7 are overlaid with a plot of the distribution frequency for number of trees at each concentration; this provides a snapshot of the industry and where it is poised with respect to low yields caused by potassium over fertilization.

The envelope analysis strongly suggest that as many as 20% od growers are over fertilizing for potassium, with suppression of yield potential occurring at leaf concentrations greater than 1% K. Only 20% of trees in our study were in the optimum target value of 0.8% K. Another 20% of trees are low in K. Our models also suggest nutrient imbalances such as excessive potassium may be implicated in alternate bearing. The number of nonbearing trees in an orchard increases to 36% when leaf K levels are above 1.4%.

The above example of how we examined the effects of potassium on avocado yields has been extended to all 11 of the macro and micronutrients, and further consider the effects of chloride toxicity. (See activity reports 2016 for macronutrients and micronutrients; also provided here as Appendices 2 and 3 attached to this final report). Among the key findings submitted in our earlier reports were the detrimental effects of excessive nitrogen, and the common existence of deficiencies for calcium, magnesium, and zinc. We also quantitatively showed the effects of chloride toxicity on avocado yields and provided equations that can be used to estimate yield losses associated with salinity induced, chloride toxicity.

Putting it altogether: The Final Model

In the final year of the project, nutrient-yield response models were successfully developed for each of the 11 elements that are monitored by leaf analysis, and equations were generated to describe these functions. The final challenge in our research has been to conceptually constrain these models to Liebig's Law of the Minimum. In other words, while we can derive probabilities for different fruit production levels categories that are associated with different values of nutrients, individually for each nutrient, the hierarchical methods described above do not provide a limit function that recognizes the greatest individual constraint that should be treated first. For example, using ANN models alone, we observe the generation of models that still allow tinkering with each of the various nutrients in a manner that can offset yield losses. For example predicting yield increases if we adjust potassium when chloride toxicity is observed in the field data to be associated with complete yield loss. Under Liebig's Law, the strict definition would be that the chloride toxicity must be alleviated first before adjusting potassium would have any affect on yield. To address this issue, it became apparent that the original data must be processed using various filters to generate a high-resolution data set of those trees that representing the truly most productive trees that are not alternate, and whose nutrient profile we would like to duplicate across the orchard.

The most obvious problem with a noisy data set is that caused by trees with a high alternate bearing index that cycle through zero or low production and extraordinary yields the next year that are as high as 300 kg fruit per tree, about 10 times the fruit load on an average producing tree in California. Thus the first step in our final model development is to filter out these data from the broad data set and focus on the highly productive trees that are not in an alternate bearing state. The second step is then to generate yield-response relationships for each nutrient individually as well as for each nutrient pair combination where nutrient interactions and imbalances may either increase or decrease production with a numerical estimate of its potential effect on yield potential.

This step employs the quantile concept in which the data are robustly analyzed by generating mini data sets (quanta) that are regressed with respect to yield. A yield-potential function is than mathematically determined for each quantile and the data are placed into lookup tables for each element. Here for presentation in a graphic format, we provide 11 figures, one for each element, in which we examined all possible combinations of all of the elements, altogether comprising 482 analyses. These figures are attached in Appendix 1. Below, we describe the way in which these figures should be inspected and interpreted. The underlying data that were plotted in each figure are the same as that used to construct look-up tables by which the greatest constraint can be identified. In this manner, a computer software program / macro consisting of stepwise sorting and filtering can be used to quantitatively describe the potential yield losses associated with any particular nutrient profile that a grower wants to examine using the decision support tool.

Interesting Interactions Revealed by Hierarchical Analyses of Pairwise Nutrient Combinations

To guide the interpretation of the figures on how nutrient interactions affect avocado yield potential, some excerpts from the figures are explained in detail below. The interpretation is straightforward and corresponds to a color range where blue indicates complete suppression of productivity and increases in light shades across the spectrum from blue to yellow to indicate trees in the highest production category (Figure 9).

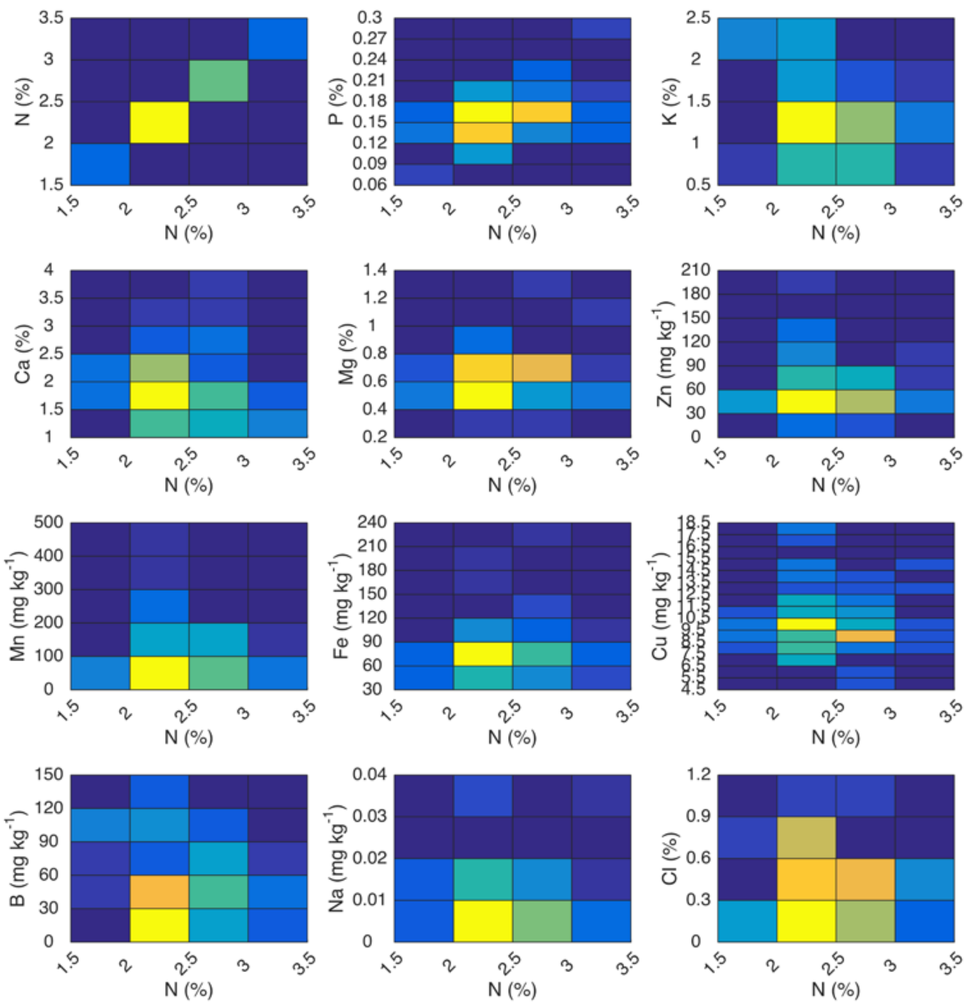


Figure 9. Production function relationships for nitrogen and 11 other elements monitored by leaf analysis; yellow indicates the nutrient range for achieving the highest level of fruit production for filtered to exclude trees with low productivity (<10 kg fruit/ tree) or high alternate bearing.

Important results contained in the above figure are that nitrogen is optimal between 2-2.5%; at high N levels, increased P and K (balanced fertilization) is necessary to maintain productivity. In order to attain maximum yields, calcium must be maintained at 1.5 to 2%; if nitrogen goes up above 2.5%, high levels of calcium can greatly suppress fruit yield; iron must be between 60-90 ppm and deficiency becomes increasingly severe on fruit yields at high nitrogen levels; lower levels of boron near 30 ppm give best results with optimal nitrogen, intermediate levels of chloride allow better toleration of high nitrogen levels. Maintaining leaf nitrogen at 1-2.5% optimizes chloride tolerance, excessive nitrogen with high chloride completely eliminates fruit production.

The reader is encouraged to explore the figures in Appendix 1 and draw information on various nutrient interactions. Below a few more interactions are highlighted for discussion.

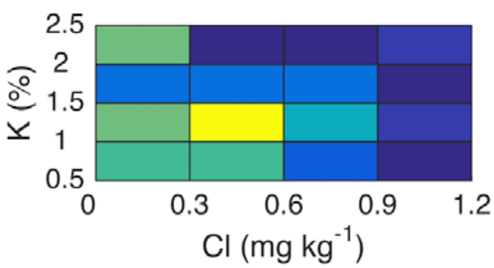


Fig. 10. High leaf potassium levels are associated with greatly reduced yields. The optimal level of potassium for increasing tolerance to chloride toxicity is at 1-1.5% K. At lower K levels below 1%, chloride toxicities have a greater impact on fruit yields.

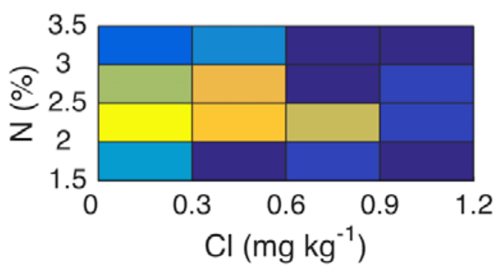


Fig. 11. Leaf nitrogen levels are very interactive with chloride toxicity in suppressing avocado yields. At low levels of nitrogen, yields are completely impaired at 0.3% Cl. Likewise, when nitrogen is greater than 2.5%. High yields under increasing chloride require maintenance of 2-2.5% N levels in the foliage.

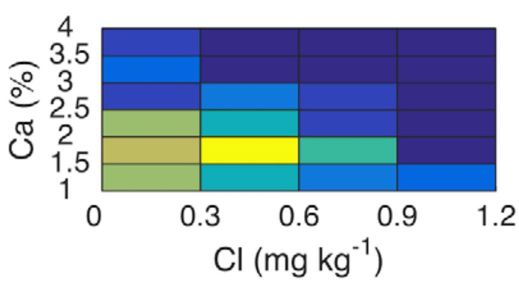


Fig. 12. It is essential to increase calcium levels to levels of 1.5-2% to maintain high productivity with increasing chloride levels caused by soil salinity. On the other hand, increasing leaf Ca to greater than 2% causes reduced yields in association with high leaf chloride.

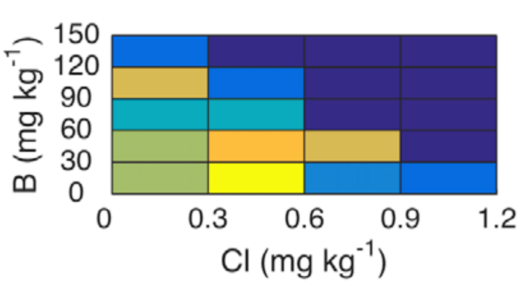


Fig. 13. Boron levels should be maintained at ~30 ppm for best tolerance to high chloride conditions. At intermediate levels of chloride, boron can be tolerated up to 90 ppm before severe yield reduction. When chloride levels are above 0.9%, leaf boron levels above 60 ppm are associated with complete yield suppression.

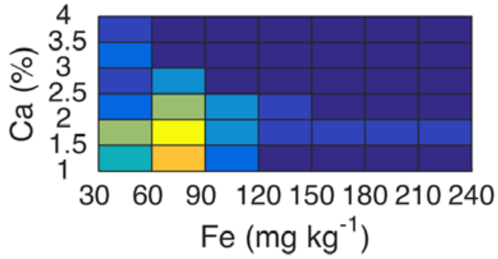


Fig. 14. The optimal level of iron in avocado leaf tissues is between 60-90 ppm, with leaf calcium at 1.5-2%. At low iron levels below 60 ppm, high levels of leaf calcium are associated with decreased yields. This phenomenon is well documented in the literature as a condition known as lime-induced chlorosis.

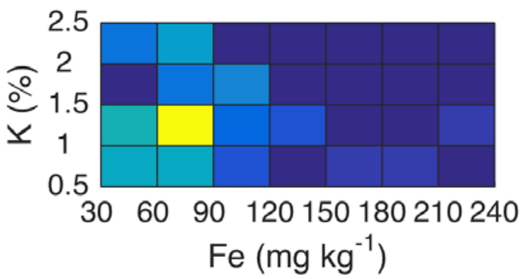


Fig 15. Excess potassium becomes particularly problematic for trees that are iron deficient with Fe below 60 ppm. Low iron and high K results in complete yield suppression. Likewise, low K and high iron.

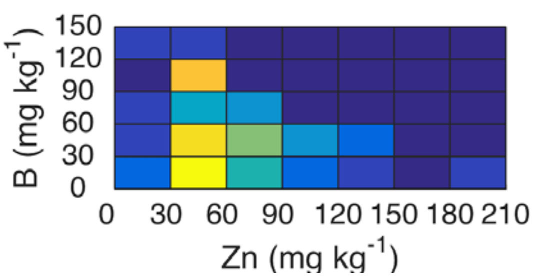


Fig. 16. High levels of boron are better tolerated when zinc concentrations are between 30-60 ppm. As zinc increases in the leaf tissue, higher levels of boron can provide better but still marginal productivity that at boron levels below 30 ppm.

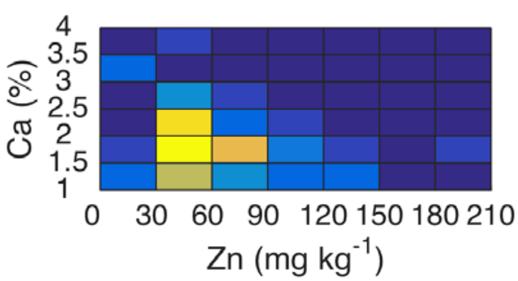


Fig. 17. At the optimal zinc level between 30-60 ppm, calcium is optimized at 1.5-2%, whereas at lower zinc levels high levels of calcium are associated with complete yield suppression, another result that, like iron, is in agreement with a diagnosis of lime induced chlorosis.

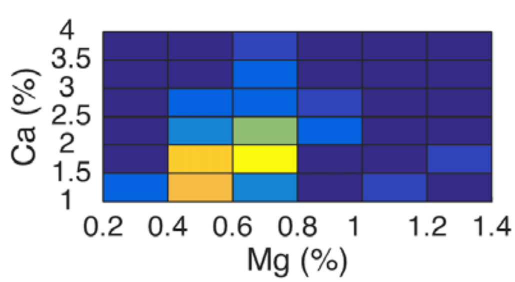


Fig. 18. Optimal calcium and magnesium levels are 1.5-2% Ca and between 0.6-0.8% for Mg. Nonetheless, as levels vary in the plant tissue, high yield potentials are best for trees maintained with a 3:1 with calcium: magnesium ratio.

Fruit Quality

During this research, exploratory analyses were also conducted on the relationships between leaf nutrient values and the ripening time of avocado. Results of our work show that chloride toxicity is associated with greatly reduced fruit shelf life (Figure 19). As shown in this 3-D plot, when fruit is removed from a cold storage and allowed to ripen, high leaf chloride levels are associated with greatly reduced ripening time as short as 0 days, thereby leading to a reduction in the amount of time available for transported and sale in the market. However, increasing appears to offset this shortened shelf life. Much more research is clearly warranted on this topic.

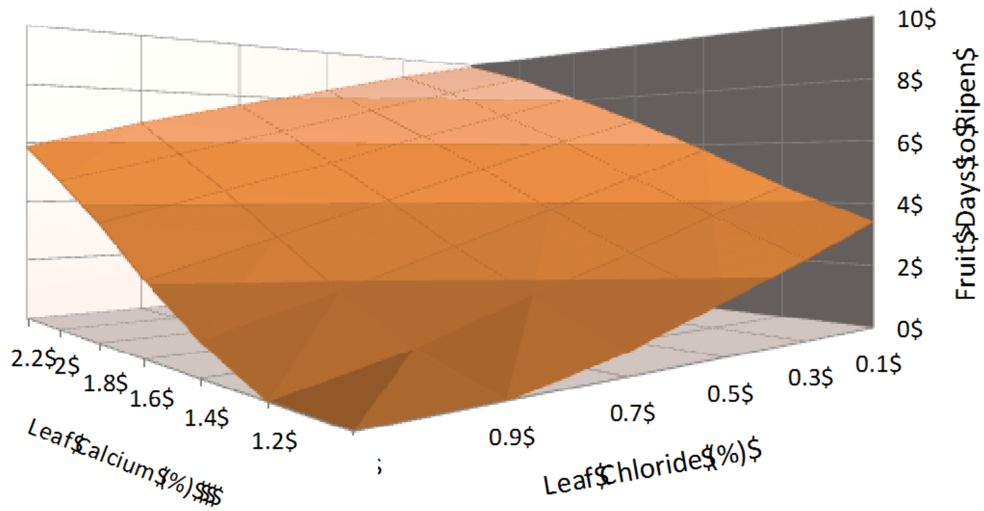


Figure 19. Interactions of leaf chloride and calcium contents as predictors of the time to ripen following cold storage of Hass avocado fruit.

Prototype Webpage for an Online Decision Support Tool

In translating the data contained in the figures to a decision support tool, one way to proceed would involve the use of software based on look-up tables in which the yield-loss predictions are calculated and examined individually for each and all of the elements. The yield loss values can then be ranked with respect to their relative impact on fruit yield potential. In the online tool, a grower would enter his data for the leaf nutrient analysis, and the underlying software would then generate a matrix with all of the nutrient ratio calculations. The resulting profile would then be sorted to identify the most limiting constraint and flag the subsequent constraints that will then need to be corrected to make specific recommendations on how to achieve the highest possible yield potential. As an alternative to the use of lookup tables, the response functions for each nutrient and element pair could be expressed through computer routines that generate yield loss values based on equations and other information about the available data, e.g., soil chemical and physical data.

A prototype interface for the decision support tool is provided below in Figure 20.

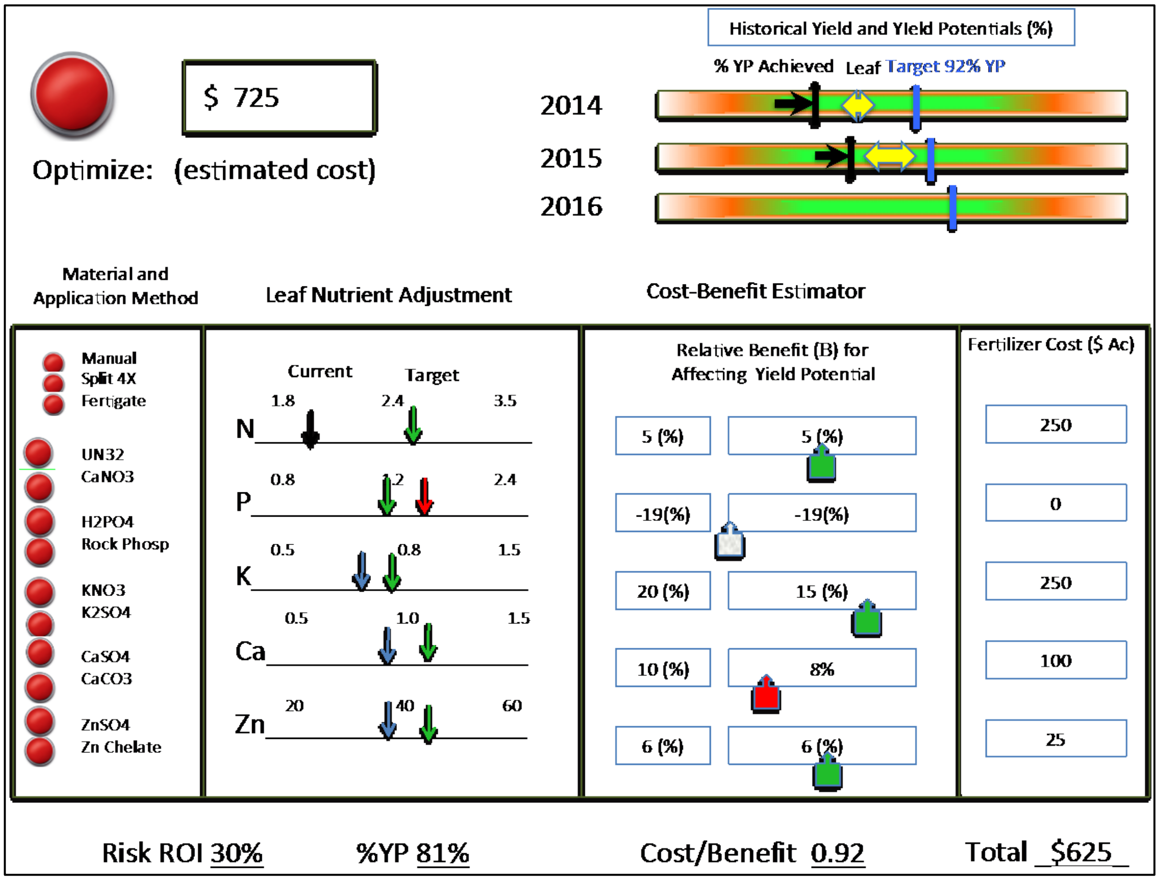


Figure 20. Draft concept for a webpage providing a decision support tool for examining nutrient yield relationships and the impacts of adjusting different nutrients to their optimum target concentrations in the leaf tissue. When combined with look-up tables for different fertilizer materials, the tool could also calculate the cost, and cost-benefit ratio. The output from this particular page would then forward into other tools where fertilizer schedules and reports can be generated.

How does our nutrient profile optimization compare to current recommendations?

Hass Plant Tissue Analysis

Sample Area	% Nitrogen	% Phosphorus	% Potassium	% Calcium	% Magnesium	ppm Zinc	ppm Manganese	ppm Iron	ppm Copper	ppm Boron	% Sodium	% Chloride
Tree # 01	2.98	0.193	1.07	1.19	0.540	28.9	41	73	6	60.8	0.006	0.233
Tree # 02	2.88	0.144	0.983	1.36	0.628	29.3	97	161	5	25.2	0.006	0.488
Tree # 03	2.93	0.147	1.20	1.25	0.610	27.3	96	83	6	15.1	0.005	0.421
Tree # 04	3.13	0.153	0.794	1.40	0.683	22.4	67	78	3	43.2	0.006	0.416
Tree # 05	2.85	0.162	1.87	1.38	0.557	31.6	77	63	4	31.8	0.006	0.549
Tree # 06	3.02	0.158	1.52	1.20	0.513	35.3	53	71	4	19.1	0.006	0.527
Tree # 07	2.93	0.142	0.960	1.47	0.664	26.3	63	76	4	27.6	0.007	0.568
Tree # 09	2.72	0.149	0.854	1.95	0.710	29.4	54	54	4	29.8	0.006	0.245
Tree # 10	3.11	0.165	1.52	0.954	0.414	39.7	65	71	3	24.4	0.007	0.314
Tree # 11	2.54	0.138	1.15	1.25	0.617	18.8	45	63	5	27.0	0.007	0.535
Tree # 12	2.83	0.156	1.30	1.10	0.483	23.2	47	72	4	26.7	0.006	0.463
Tree # 13	2.87	0.164	0.894	1.79	0.735	31.0	54	70	5	31.1	0.005	0.543
Tree # 14	2.91	0.158	1.66	1.12	0.514	31.4	44	61	4	28.6	0.009	0.498
Tree # 15	3.07	0.149	1.09	1.23	0.463	24.5	51	75	4	25.8	0.005	0.328
Optimum Range - Average	2.2 - 2.4	0.080 - 0.44	1.0 - 3.0	1.0 - 4.5	0.25 - 1.0	30 - 250	30 - 700	50 - 300	5 - 65	12 - 100	0.0 - 0.25	0.0 - 0.25

Good Problem Low High

Note: Color coded bar graphs have been used to provide you with 'AT-A-GLANCE' interpretations.

Figure 21. Excerpt from a plant tissue analysis report showing typical results for an avocado leaf analysis. Note very high levels of nitrogen, and compare optimal ranges of other elements with those from this research.

Current recommendations for avocado in the above figure are based on recommendations that were originally generated for citrus and then directly adopted for avocado. The figure very nicely illustrates the variability that occurs in an orchard along a 3 row by 5-tree block of trees. Here leaf nitrogen levels are variable and generally excessive, both phosphorus and potassium are high to the level where yield potential has been reduced, calcium is excellent, zinc is deficient, iron is high, and copper, boron and sodium are fine. Leaf chloride levels are especially variable among the trees, the latter likely due to microsite variation in irrigation uniformity and soil leaching. Except for nitrogen, the optimum ranges in the bottom row of the table need considerable revision. As the data continue to come in through a decision support tool and analysis of massive amount of data that has been archived but never examined or interpreted. We believe that the data sequence approach that we developed for this research represents a novel method that has not been previously invented or applied for plant nutrition.

Summary

In the last phase of our project, we have focused on translating all of our results into concise models that can then be translated in the next phase of this project into an actual online decision support tool. This will require new funding support and collaborative implementation with a software company that specializes in data management and agriculture. The final deliverable for this project is this report itself, in which we describe the main mathematical relationships and conceptual framework for modeling nutrient-yield responses. This information can then be readily implemented into online decision support tools to guide avocado fertilization and tree nutrient management. We are currently in negotiations with a software company to license the hierarchical data analysis methods by which predictive models for plant yield potential can be generated. The basic science and discovery factor in this research has led the UC Office of Research to file a patent application (UC-2016-99T-1) for new intellectual property with broad relevance for improving the nutritional management of any crop that is studied using our methods.

Our methods entail a sequential process such that:

- A grower enters leaf tissue analysis data after which a macro routine generates a matrix of data describing the nutrient concentration and interaction effects that are identified in the leaf analysis profile as their potential quantitative effects on plant yields.

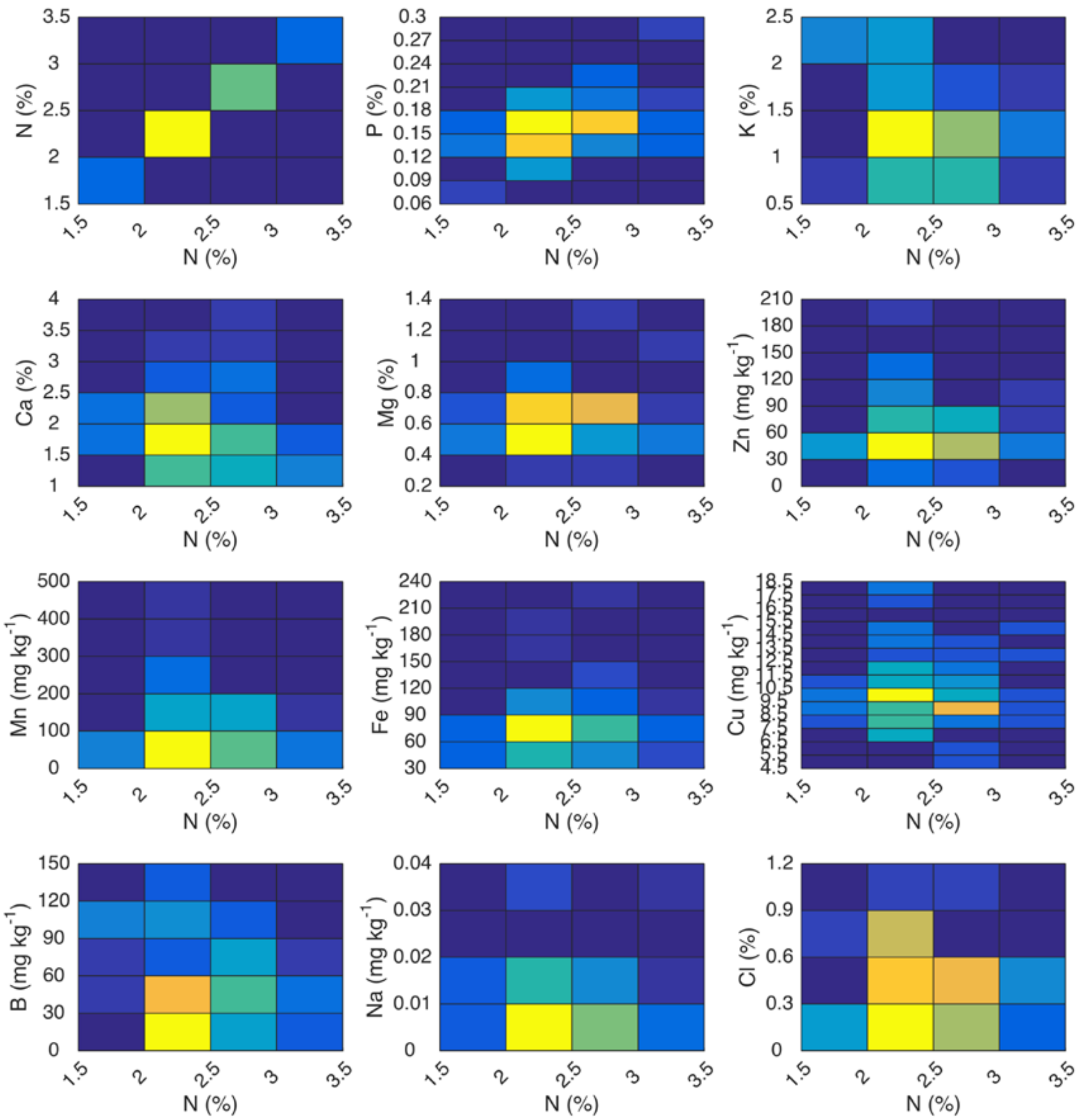
- The matrix generated above is filtered and sorted to identify trees or plants with the best performance characteristics and processed through other plant trait relevant filters (age, orchard spacing, alternate bearing) to generate a database for high resolution modeling using archived data collected over multiple years.

- Quantile regression and ANN methods are applied to identify optimal ranges for each nutrient element and data mining is carried out using Kohonen Self Organizing Maps to obtain a holistic view of soil and plant nutritional factors that affect plant yield and fruit quality. Application of neural networks to develop pattern recognition models for predicting plant yield potentials for plants having different leaf nutrient profiles to independently verify results that are obtained using quantile regressions. Cross-validation.

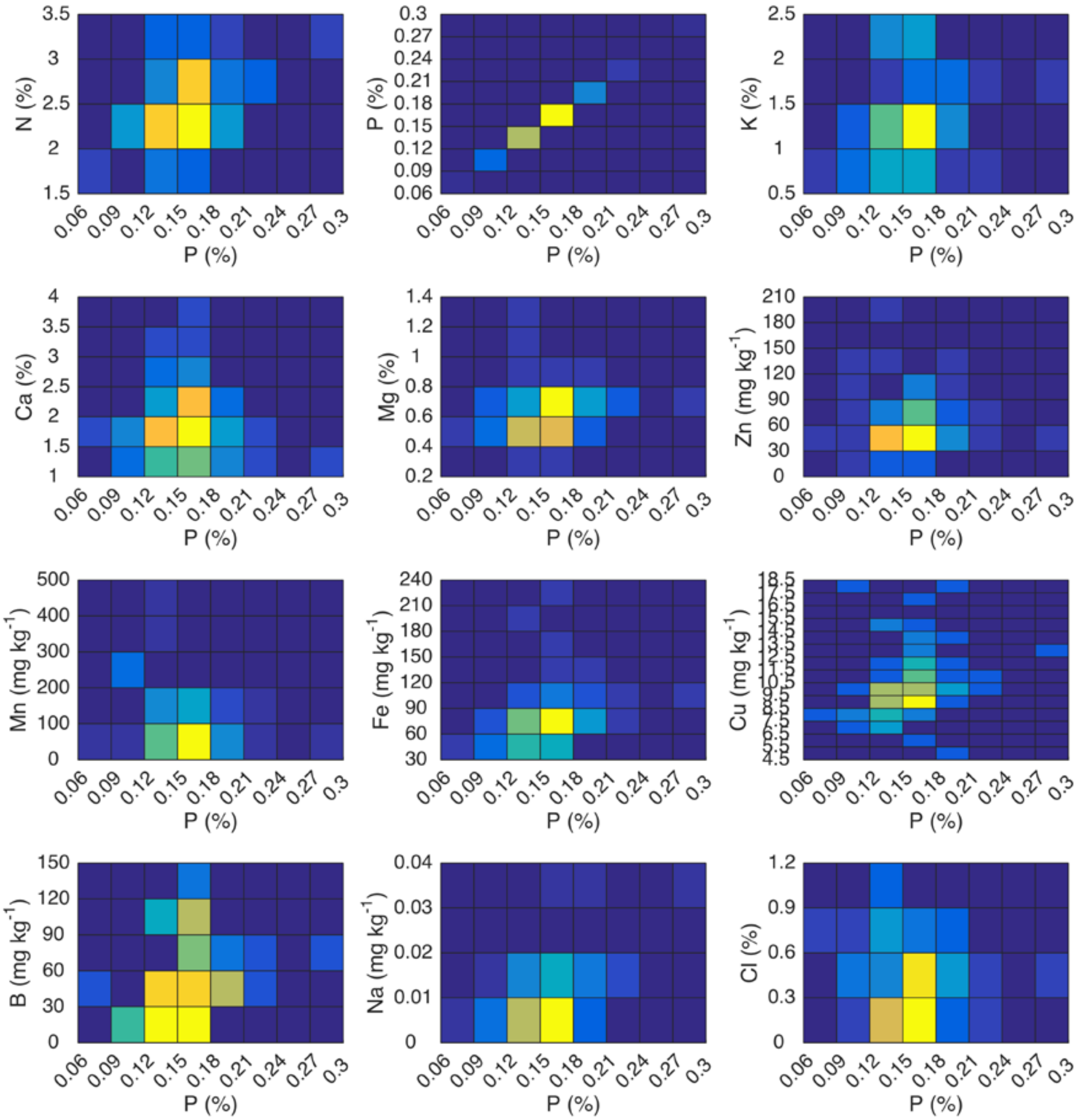
- Equations derived from the above models are generated to describe the effects of nutrient deficiencies, excesses, or imbalances on potential yield. The most constraining nutrients or interactions are then ranked by their ability to affect yield potential in order to generate a specific correction sequence that attempts to most efficiently manage plant nutrient constraints in a cost effective, stepwise fashion that is consistent with Liebig's Law of the Minimum.

Appendix 1. Figures illustrating nutrient yield relationships for individual nutrient elements and in pairwise combinations with all other plant essential elements.

Nitrogen

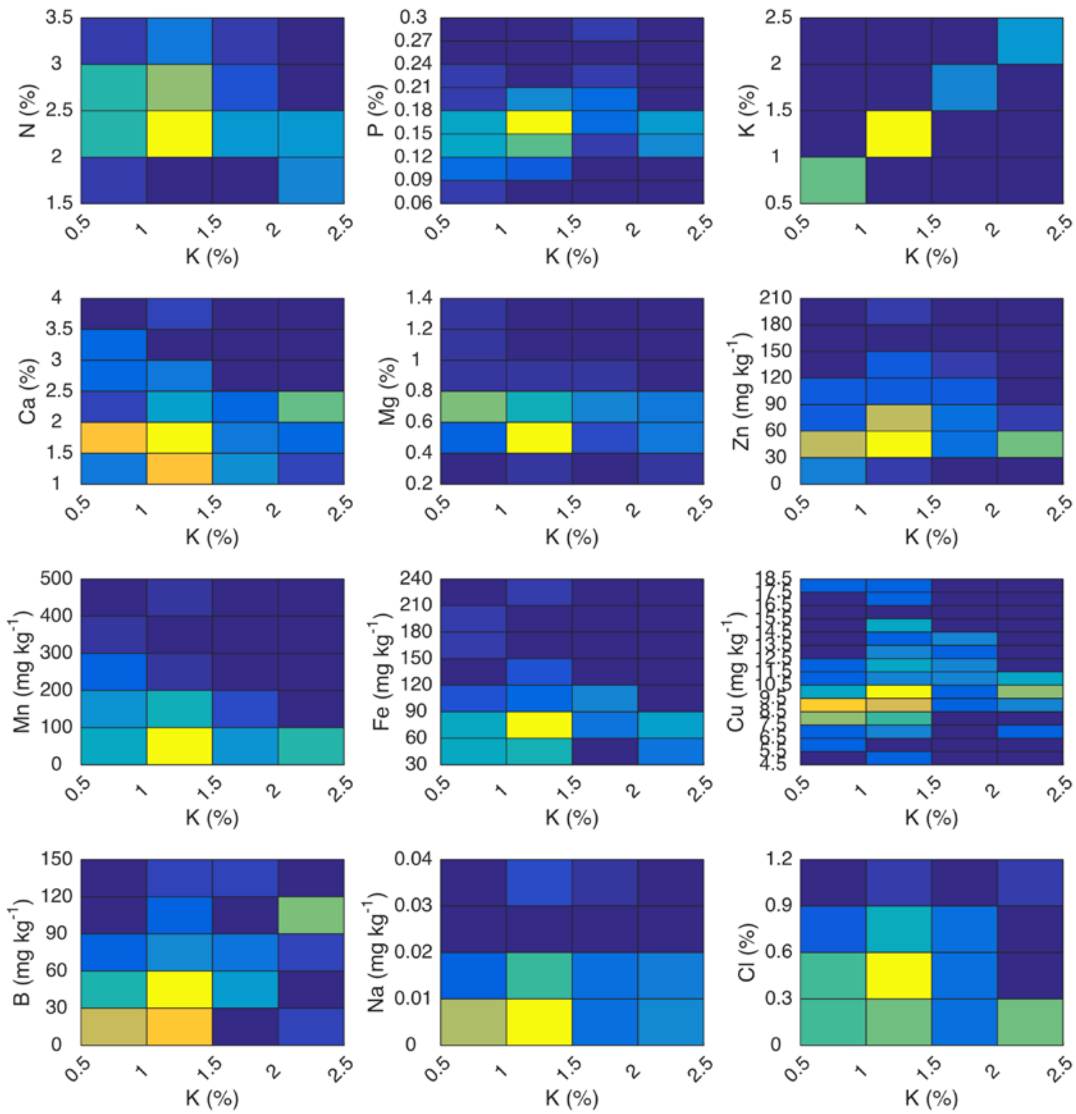


Phosphorus



N (%)
P (%)
K (%)
Ca (%)
Mg (%)
Zn (mg kg-1)
Mn (mg kg-1)
Fe (mg kg-1)
Cu (mg kg-1)
B (mg kg-1)
Na (mg kg-1)
Cl (%)

Potassium



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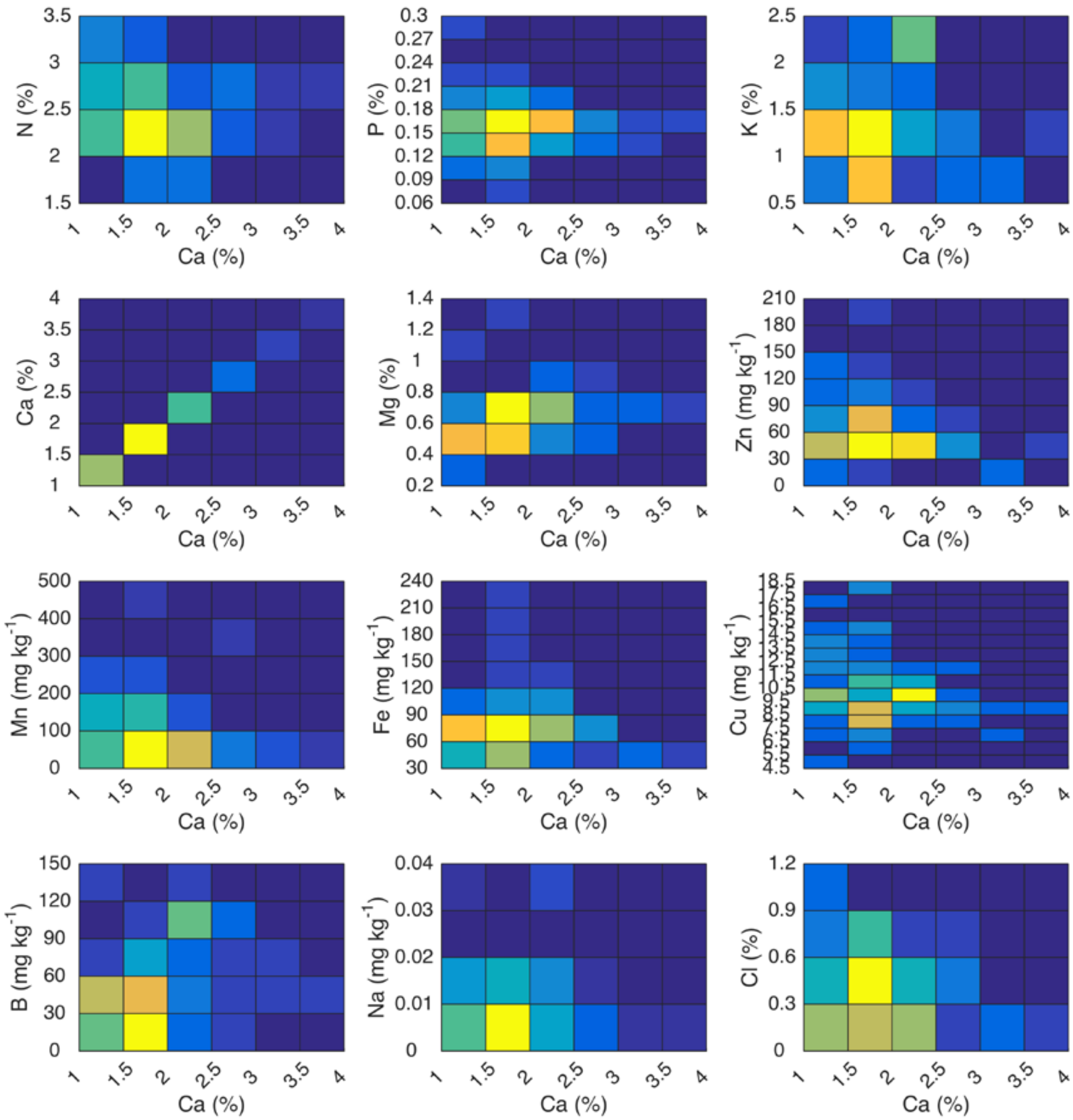
B (mg kg-1)
Na (mg kg-1)
Cl (%)
K (%)

Calciu



N (%)
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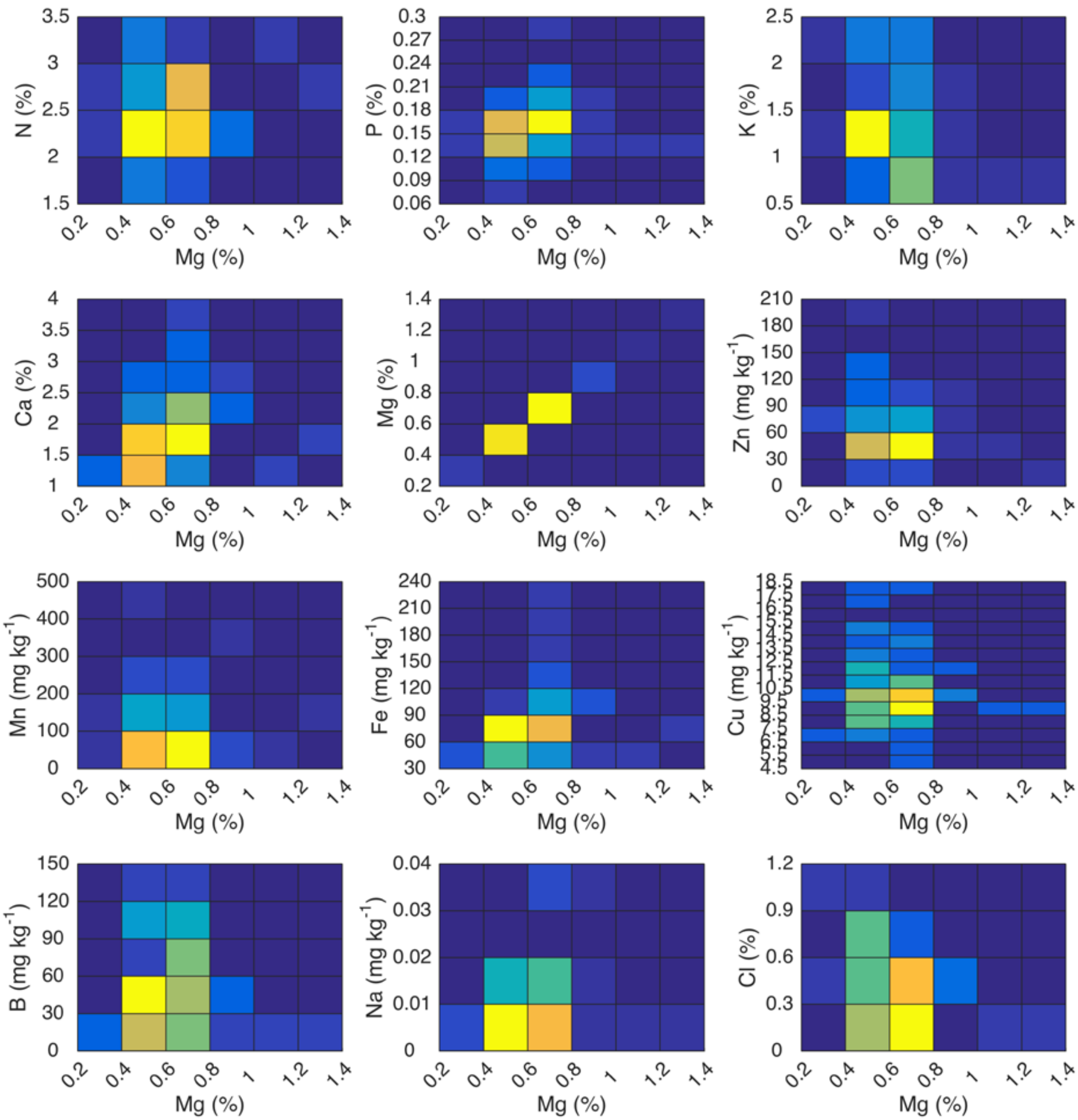
Zn (mg kg-1)
Mn (mg kg-1)
Fe (mg kg-1)
Cu (mg kg-1)
B (mg kg-1)
Na (mg kg-1)
Cl (%)
Ca (%)

Magnesium



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Cl (%)
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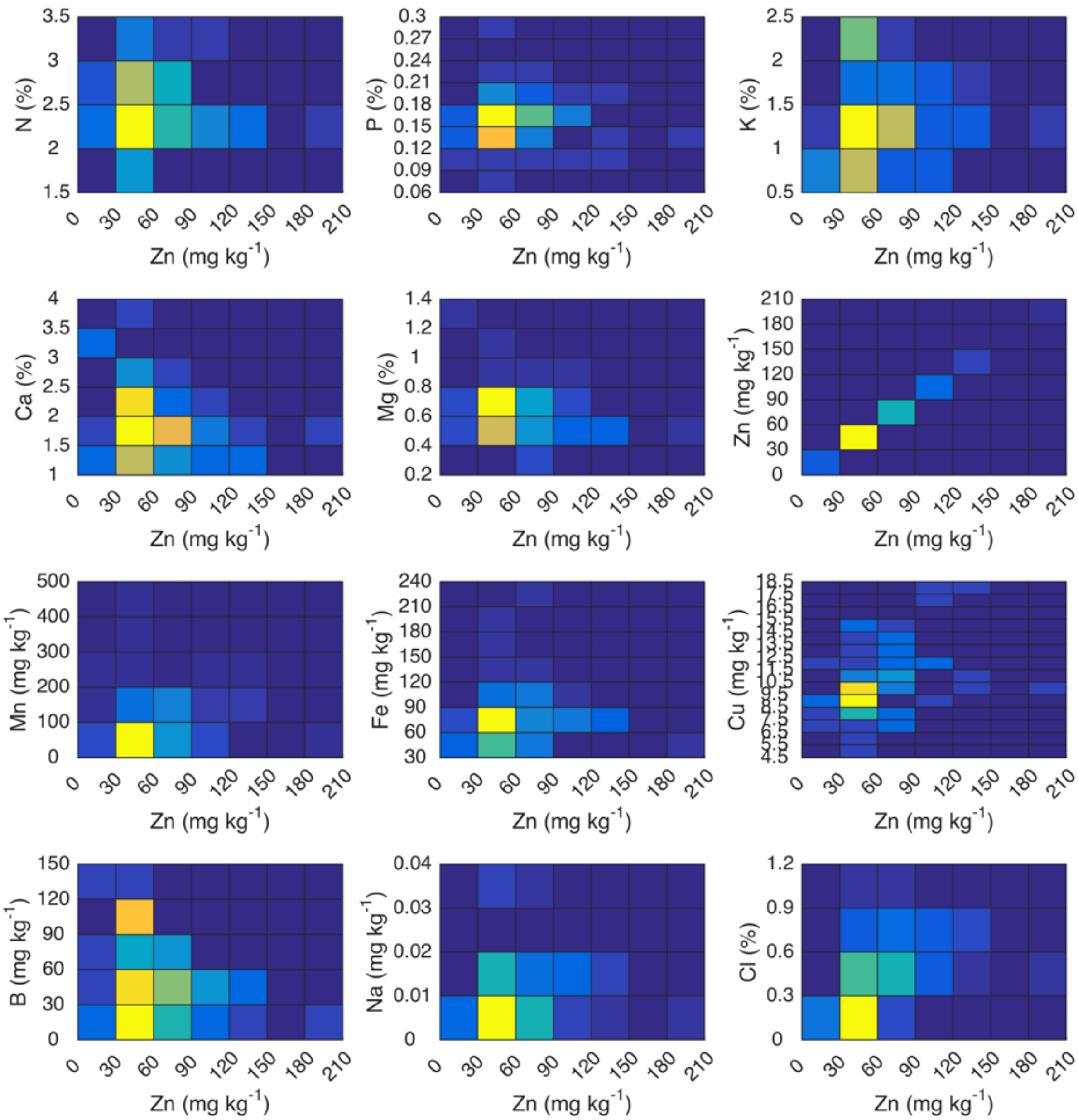
Zinc



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Fe (mg kg-1)
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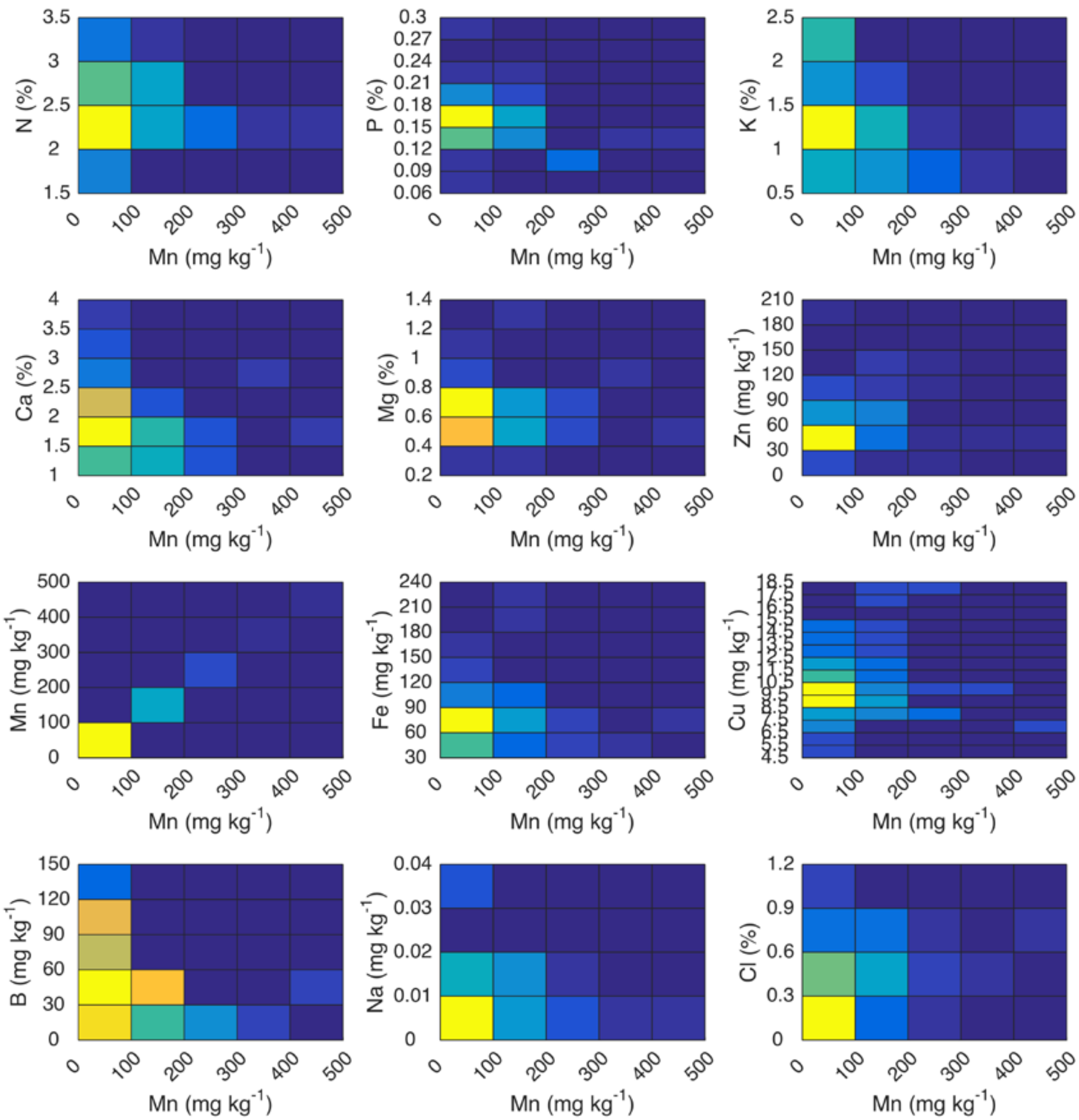
Cl (%)
Zn (mg kg-1)

Manganese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Fe (mg kg^{-1})
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Na (mg kg^{-1})
Cl (%)
Mn (mg kg^{-1})
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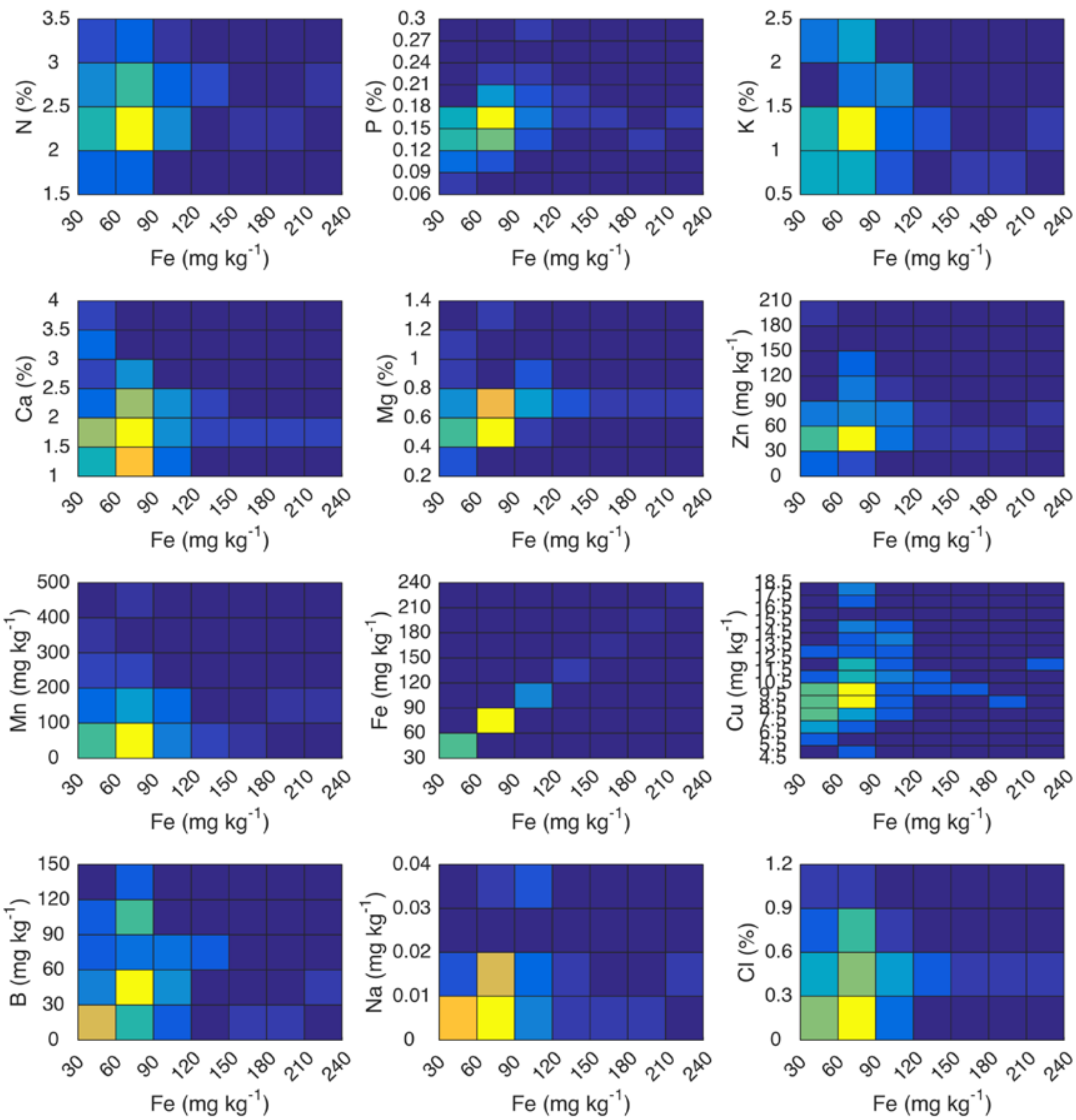
Iron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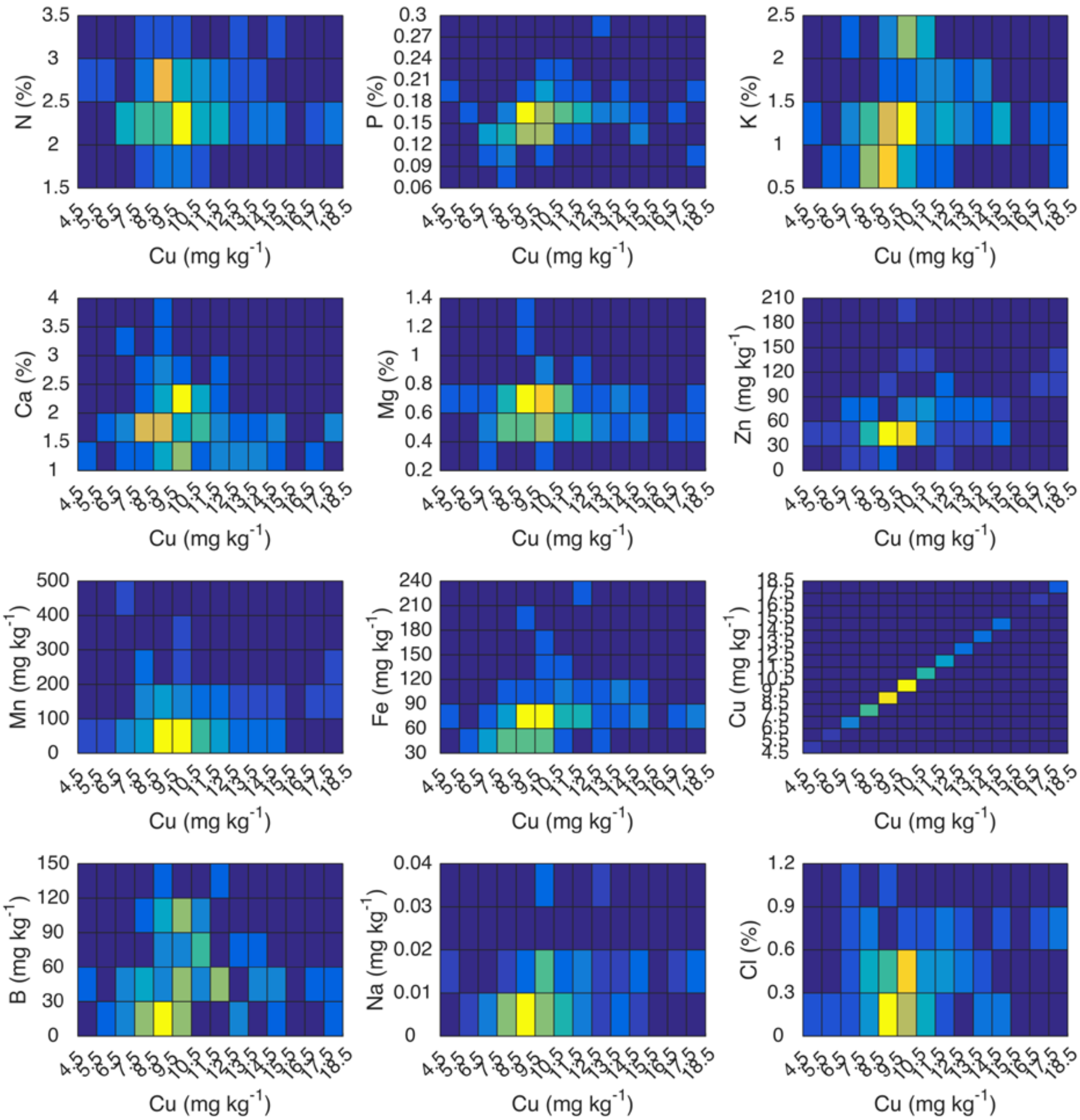
Na (mg kg-1)
Cl (%)
Fe (mg kg-1)

Copper



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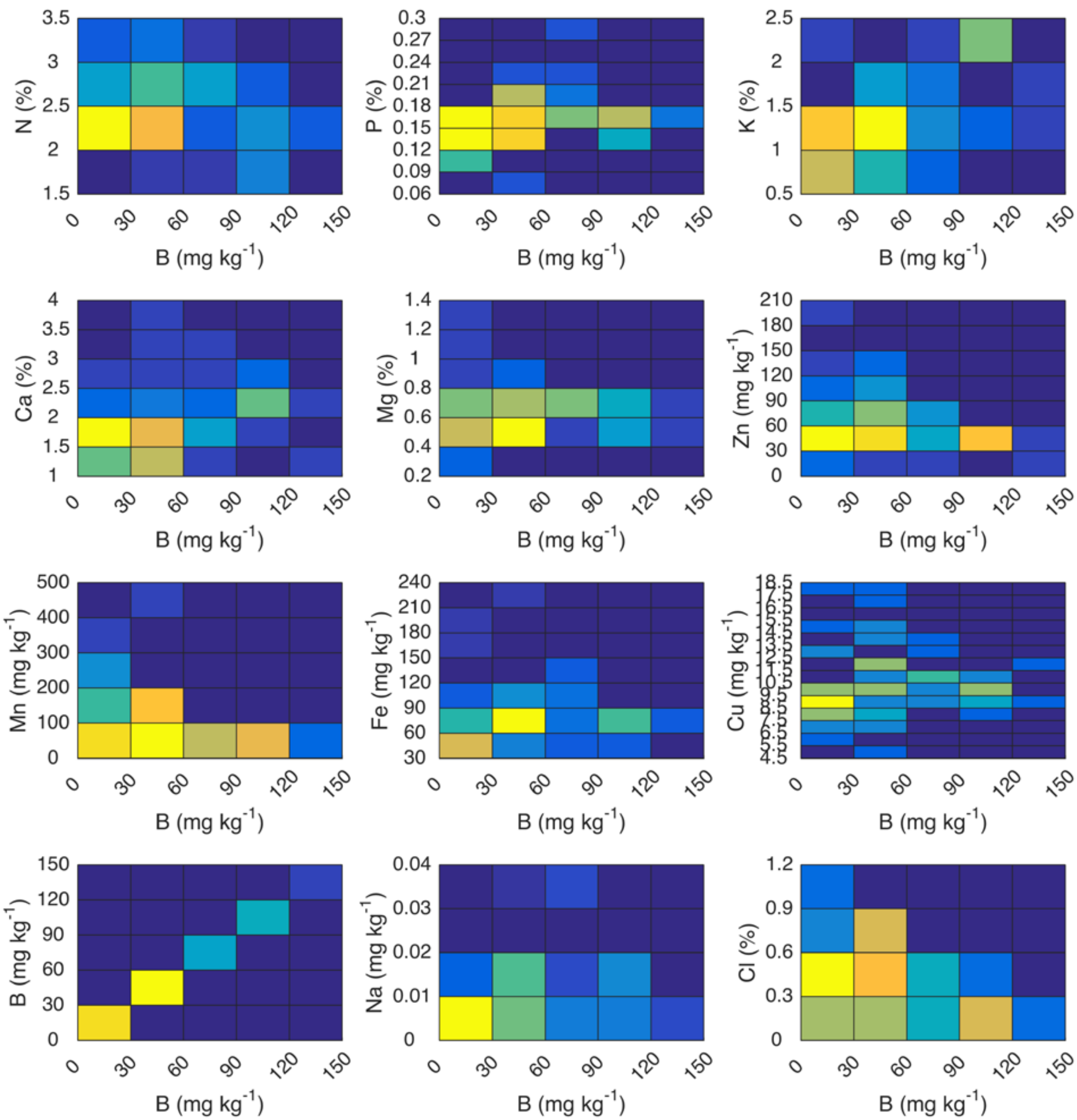
Cl (%)
Cu (mg kg-1)

Boron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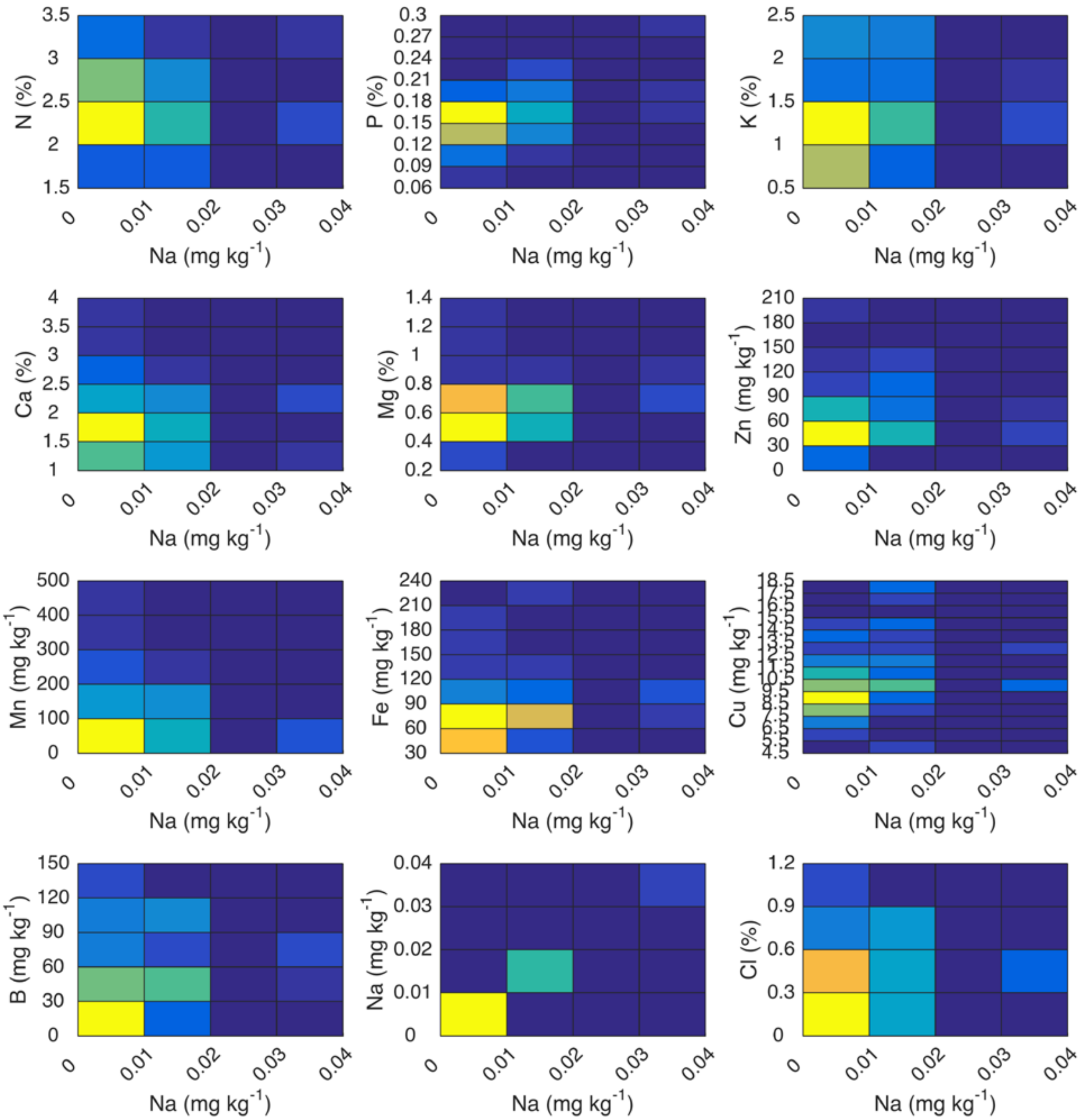
Cl (%)
B (mg kg-1)
0 30 60 90 120 150

Sodium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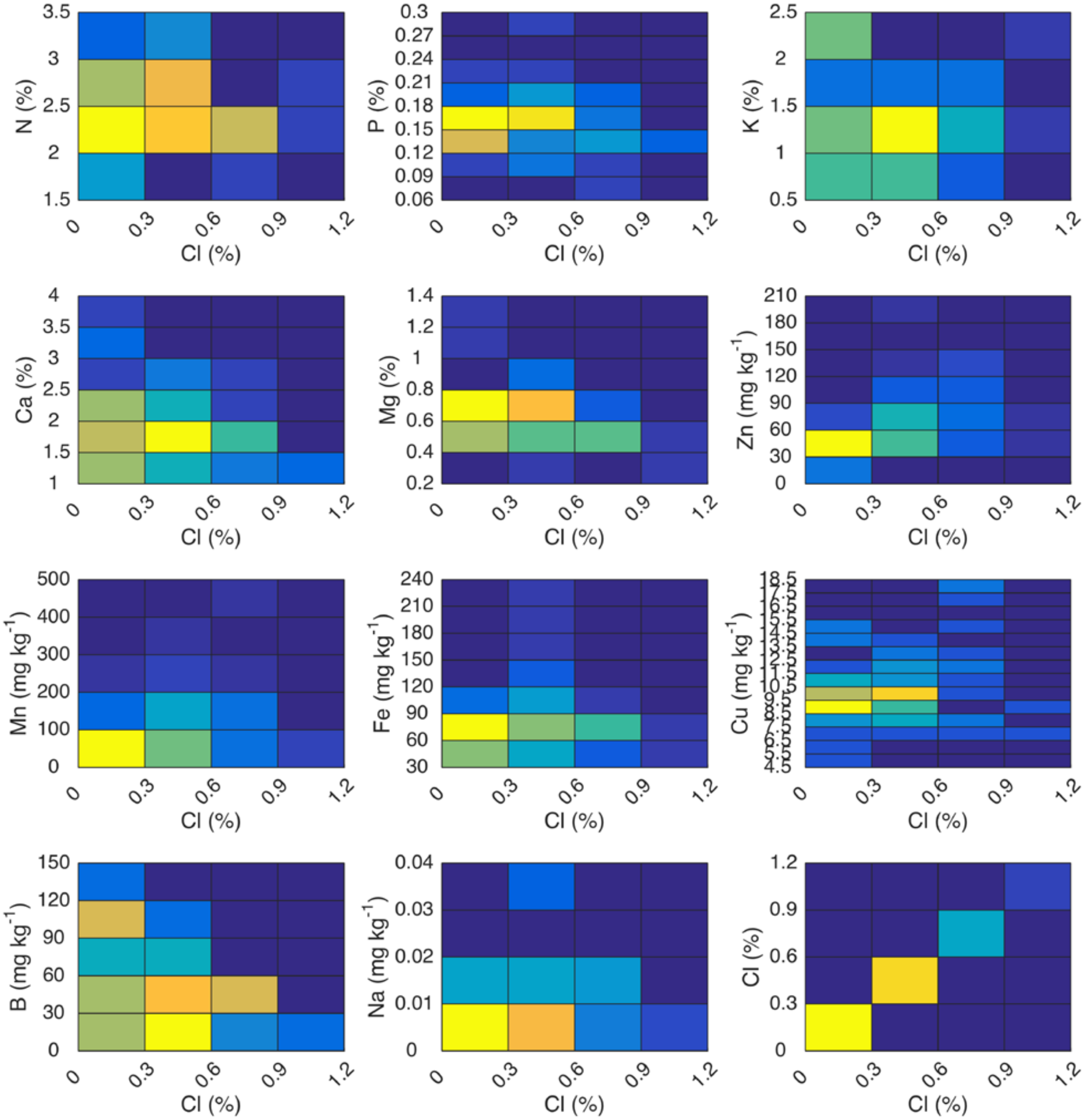
Cl (%)
Na (mg kg-1)

Chloride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Cl (%)