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Meta-analysis in the Selection of Groups in Varieties of Citrus

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*Brazil is the largest producer of oranges (*Citrus sinensis*) in the world. The nutrient management of tree orchards is designed from experiments with a limited number of varieties. This knowledge is transferred to other varieties by diagnosing tissue nutrient composition and tree demand. Compositional data analysis has been first applied to tissue analysis of agricultural crops using centered log ratios with compositional nutrient diagnosis (CND-clr). The isometric log ratio (*ilr*) transformation is a new approach based on binary nutrient ratios and the principle of orthogonality (CND-*ilr*). We analyzed eleven nutrients: nitrogen (N), sulfur (S), phosphorus (P), potassium (K), calcium (Ca), magnesium (Mg), boron (B), copper (Cu), zinc (Zn), manganese (Mn), and iron (Fe) in leaf tissue samples across 108 commercial plots (thirty-one grow Valencia, twenty-two Hamlim, twenty Pera, and thirty-five Natal). Nutrients were partitioned between macro- and micronutrients as well as anionic and cationic species. The effect size of varieties over Valencia was quantified by the mean and standard deviation of* ilr *values across* ilr *coordinates. Specific varietal nutrient profiles and* ilr *norms were defined. The nutrient profile of orange varieties could be classified into homogeneous groups to take advantage of fertilizer trials conducted on varieties of the same group. The Aitchison distance and a perturbation vector could be instrumental for diagnostic purposes and nutrient management.*

Keywords Compositional nutrient diagnosis, fruit, nutrition, oranges

Introduction

Brazil is the leading orange (*Citrus sinensis*) producer in the world, with an area of about 850,000 ha, representing 20 percent of the global area occupied by oranges. Thus, three

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out of five glasses of orange juice consumed in the world come from Brazil (Food and Agriculture Organization 2013).

Standard nutrient values are concentrations ranges thought to be adequate for highly productive crops. It is assumed that although nutrients are interrelated, the effect of a given nutrient on crop yield depends on how close other nutrients are to their optimum value. Hence, all nutrients but the ones being diagnosed are assumed to be in sufficient but nonexcessive amounts. Nevertheless, nutrient concentration standards were criticized for not accounting for nutrient interactions (Mourão Filho 2004) because several dual and multiple interactions have been identified in plants (Marschner 1995; Mourão Filho 2004).

Beaufils (1973) addressed nutrient interactions using dual ratios in the Diagnosis and Recommendation Integrated System (DRIS). DRIS was applied to Valencia oranges in the USA (Beverly 1987a), Venezuela (Rodríguez, Rojas, and Sumner 1997), and Brazil (Mourão Filho 2005). DRIS is often viewed as complementary to nutrient concentration standards (Mourão Filho 2005). On the other hand, tissue analytical data are strictly positive data constrained to a compositional space that includes nutrient concentrations and a filling value constrained to the unit of measurement. Within that closed space, nutrient interaction whereby any nutrient addition may positively or negatively influence the level of another (Marschner 1995) is a source of resonance and spurious correlations (Aitchison 1986).

Lagatu and Maume (1935) illustrated nutrient interactions in a constrained space using closed ternary diagrams where vertices represented nutrients in proportions varying between 0 and 100 percent. Because nutrient fractions add up to 100 percent, there is at least one redundant concentration. The trivial case is a two-compositional system where the correlation coefficient between changing components is exactly minus one because any change in one component must affect the proportion of the other by exactly the same value (Thomas and Aitchison 2006). Because uncorrelated proportions are not necessarily independent, true or spurious correlations between proportions cannot be interpreted in a meaningful way (Butler, Bierman, and Marion 2005).

Compositional data intrinsically have nonnormal distribution because they are constrained between 0 and 100 percent rather than being randomly distributed in the real space between $-\infty$ and $+\infty$. Gaussian techniques should not be applied to compositional data because it is impossible that confidence intervals be less than 0 percent or more than 100 percent (Diaz-Zorita, Perfect, and Grove 2002). As a result, statistical analyses based on the normality assumption such as regression, univariate, and multivariate analyses are misleading (Butler, Bierman, and Marion 2005). In contrast, log ratios can take any real value, hence projecting the compositional space into the real space where Gaussian laws can be applied (Aitchison 1986). Tissue nutrient concentrations can be transformed into real values using techniques of compositional data analysis. Aitchison (1986) proposed that compositional data should be converted to additive (alr) and centered log ratios (clr) before running linear statistical models.

Parent and Dafir (1992) linked DRIS to compositional data analysis using the log-DRIS approach of Beverly (1987b) and clr and considered compositional nutrient diagnosis (CND)-clr as a diagnostic tool by itself. Egozcue and Pawlowsky-Glahn (2005) showed that isometric log ratios (*ilr*) are sound transformations for sequential binary partitions of components with orthonormal basis. A binary partition can be a dual ratio or product or a ratio or product involving two subcompositions within an orthogonal framework. This is appropriate for plant nutrients because two and several nutrients can be arranged into sequential binary partitions such as macro- vs. micronutrients, nitrogen plus sulphur [N + S] vs. phosphorus [P], potassium [K] vs. calcium plus magnesium

[Ca + Mg], and [Ca] vs. [Mg] (Malavolta 2006). The *ilr* coordinates are real data that avoid spurious correlations, can be tested for normality, and are analyzed by common linear statistical models. The *ilr* coordinates may thus be useful to describe nutrient profiles of orange orchards for classification and nutrient management.

Our objective was to compare the *ilr* coordinates of tissue analytical data for orange varieties grown in Brazilian orchards. We compare varieties using Manova and Anova across *ilr* coordinates. Groups of varieties are compared across *ilr* coordinates using meta-analysis (Borenstein et al. 2009). This meta-analysis procedure designated here as *compositional meta-analysis* is instrumental in forming groups of varieties with similar nutrient profiles, leading to uniform nutrient management. Knowledge from costly fertilizer trials on a given variety could be transferred to other varieties showing the same nutrient profile.

Materials and Methods

In nonirrigated orange orchards across the state of São Paulo, Brazil, we collected yield data (kg fruit ha^{-1} and kg fruit tree^{-1}) and samples with 6- to 8-month-old leaves collected from fruit-bearing shoots (third to fourth leaf from fruits) when fruits were 2–4 cm in size (Quaggio, Van Raij, and Piza 1997). The dataset comprised six rootstocks (Rangpur line, Cleopatra mandarin, Swingle citrumelo, Nonidentified, Volkamer lemon, and Trifoliate) and four canopy varieties (Valencia, Hamlim, Pera, and Natal). In each orchard, uniform areas of twenty-five trees were assessed for yield, leaf analysis, plant density, and age. Leaves were washed after collection despite seasonal fungicide applications. Leaf samples were analyzed for N, S, P, K, Ca, Mg, boron (B), copper (Cu), zinc (Zn), manganese (Mn), and iron (Fe) using standard procedures (Jones and Case 1990). The original dataset comprised 256 lines but we screened data for replications and outliers (Grubbs test). Where there were several yield measurements for the same foliar composition, we selected the median yield. The final dataset comprised 108 observations as follows: thirty-one Valencia, twenty-two Hamlim, twenty Pera, and thirty-five Natal. The compositional space (Parent and Dafir 1992) x of nutrient concentrations in the foliar orange tissue was thus described as follows:

$$x = C\ (N, S, P, K, Ca, Mg, B, Cu, Zn, Mn, Fe, F_v)\ =\ 1000g\ kg^{-1} \tag{1}$$

The filling value F_v was computed by difference between 1,000 g kg^{-1} and analytical results. With eleven nutrients and F_v (D = 12) there were D-1 or 11 *ilr* coordinates. Binary partitions are made of nutrients compounded in the numerator (+) and the remainder in the denominator (–). The *ilr* coordinate is computed as follows (Egozcue and Pawlowsky-Glahn 2006):

$$x_i^* = \sqrt{\frac{r\,s}{r+s}} \ln \frac{g(x_+)}{g(x_-)} \tag{2}$$

where r and s are numbers of components in plus (+) and minus (–) groups, respectively, $g(x_+)$ is geometric mean of components in the plus group x_+, and $g(x_-)$ is geometric mean of components in the minus group x_-. The coefficient $\sqrt{\frac{r\,s}{r+s}}$ is the balance between the plus and minus groups. The *ilr* are ad hoc partitions based on a conceptual interactive model that facilitates the interpretation of the results. The sequential binary partitions were

Table 1
Ilr coordinates and filling value (F_v) of foliar nutrient composition of orange trees in Brazil

	Sequential orthonormal partitions of components													
Ilr	N	S	P	K	Ca	Mg	B	Cu	Zn	Mn	Fe	F_v	r	s	Balance
1	1	1	1	1	1	1	1	−1	−1	−1	−1	0	7	4	1.595
2	1	1	1	1	1	1	−1	0	0	0	0	0	6	1	0.926
3	1	1	1	−1	−1	−1	0	0	0	0	0	0	3	3	1.225
4	1	1	−1	0	0	0	0	0	0	0	0	0	2	1	0.816
5	1	−1	0	0	0	0	0	0	0	0	0	0	1	1	0.707
6	0	0	0	1	−1	−1	0	0	0	0	0	0	1	2	0.816
7	0	0	0	0	1	−1	0	0	0	0	0	0	1	1	0.707
8	0	0	0	0	0	0	0	1	1	−1	−1	0	2	2	1.000
9	0	0	0	0	0	0	0	1	−1	0	0	0	1	1	0.707
10	0	0	0	0	0	0	0	0	0	1	−1	0	1	1	0.707
11	1	1	1	1	1	1	1	1	1	1	1	−1	11	1	0.957

selected (Table 1) according to current knowledge on nutrient levels and both positive and negative interactions in plants (Malavolta 2006).

Nutrient interactions involving [B] vs. macronutrient, anions vs. cations, and [K] vs. [Ca + Mg] (Malavolta 2006) were translated into *ilr* coordinates for diagnostic purposes. The [Cu + Zn] vs. [Mn +Fe], [Cu] vs. [Zn], and [Fe] vs. [Mn] *ilr* coordinates are related to fungicide applications (Cu, Zn) as well as soil genesis (Mn, Fe) (Empresa Brasileira de Pesquisa Agropecuária 2006).

In compositional analysis, the difference between two compositions is computed as the Aitchison distance across *ilr* coordinates computed as follows (Egozcue and Pawlowsky-Glahn 2006):

$$d_a^2(x,y) = \sum\nolimits_{i=1}^{D-1} (x_i^* - y_i^*) \text{ and } A = \sqrt{d_a^2(x,y)} \tag{3}$$

where y_i^* is reference composition and A is Aitchison distance.

We selected orange trees that produced more than 92 kg fruit tree^{-1} for nonirrigated conditions (Rodríguez, Rojas, and Sumner 1997). On an average those orchards produced 48.5 Mg fruit ha^{-1}, in the low-yield range (40–50 Mg fruit ha^{-1}), but thirty-one orchards were in the high-yield range (>60 Mg fruit ha^{-1}) compared with irrigated orchards (Mourão Filho 2005).

The critical value of Aitchison distance for the high-yield subpopulation was obtained using the Cate-Nelson procedure (Nelson and Anderson 1984). Briefly, the scatter diagram relating a performance criterion (e.g., yield) to the Aitchison distance was partitioned into four quadrants [northwest, northeast, southwest, southeast (NW, NE, SW, SE)] and the number of points was maximized in the opposite quadrants NW and SE. The NW quadrants represented true high yielders (high yield and small A), the NE represented false high yielders (high yield and high A), the SW represented false high yielders (poor yield and low A), and the SE represented true low yielders (poor yield and high A). Using the Excel package and the chi-square homogeneity test (Hollander and Wolfe 1999), the number of successful and unsuccessful classification was compared to an equal distribution between successful and unsuccessful cases.

Compositional analyses were conducted in R (Van Den Boogaart, Tolosana, and Bren 2010). We ran multivariate analysis of variance (MANOVA) and analysis of variance (ANOVA) in a meta-analysis using the R package. Normality was verified using the Anderson-Darling test (Aitchison 1986). Not normally distributed *ilr* data were transformed according to Yeo and Johnson (2000) and their analysis was compared to non-transformed *ilr* data to verify the robustness of the statistical analyses against nonnormal distribution. The Yeo-Johnson transformation is a power transformation that expands to the negative domain the Box-Cox transformation conceived for the positive domain only.

We made groups of varieties across rootstocks (e.g., Rodríguez, Rojas, and Sumner 1997) and tested their homogeneity using meta-analysis in R (Schwarzer 2010). Because the reference varieties were compared to each other and thus repeated in the same analysis, we divided the number of observations in the reference variety by the Box factor (Huynh and Feldt 1976), k – 1, where k is total number of varieties. Difference between varieties was determined using the random model (Borenstein et al. 2009) and t-tests. The degree of heterogeneity was measured by the I^2 statistics: heterogeneity is high if $I^2 > 0.75$, medium if $I^2 \approx 0.50$, and small if $I^2 < 0.25$ (Borenstein et al. 2009). If $I^2 < 0$, I^2 was given a value of zero.

Results and Discussion

Statistical Analysis

Like Mourão Filho (2005), we found large variations in Cu, Zn, Mn, and Fe levels possibly due to contamination by fungicide sprays (Cu and Zn) and differential soil chemistry (Mn and Fe) (Table 2). Hamlim apparently received less fungicide sprays than others. Hamlim is an early variety and it does not have multiple blooms as is the

Table 2

Statistics (mean ± standard deviation) on foliar nutrient concentration and the filling value to 1000 g kg^{-1} dry matter for orange varieties producing > 92 kg fruit $tree^{-1}$ in the state of São Paulo, Brazil (totals may be different than 1000 due to rounding error)

Component	Hamlim (n = 22)	Natal (n = 35)	Pera (n = 20)	Valencia (n = 31)
N (g kg^{-1})	28.6 ± 3.0	28.3 ± 2.8	26.3 ± 1.4	27.9 ± 2.1
S (g kg^{-1})	3.2 ± 0.7	3.0 ± 0.7	3.0 ± 0.9	3.6 ± 0.7
P (g kg^{-1})	2.0 ± 0.5	1.6 ± 0.6	1.5 ± 0.7	2.0 ± 0.6
K (g kg^{-1})	16.3 ± 3.0	12.9 ± 3.7	13.5 ± 4.5	14.8 ± 2.8
Ca (g kg^{-1})	34.7 ± 8.0	34.3 ± 7.8	34.5 ± 8.8	38.4 ± 6.4
Mg (g kg^{-1})	4.7 ± 1.5	4.0 ± 1.1	3.7 ± 1.3	5.2 ± 1.2
B (g kg^{-1})	0.095 ± 0.021	0.088 ± 0.012	0.080 ± 0.044	0.107 ± 0.045
Cu (g kg^{-1})	0.031 ± 0.035	0.055 ± 0.033	0.061 ± 0.027	0.067 ± 0.034
Zn (g kg^{-1})	0.032 ± 0.017	0.066 ± 0.041	0.070 ± 0.027	0.051 ± 0.031
Mn (g kg^{-1})	0.052 ± 0.034	0.076 ± 0.064	0.095 ± 0.052	0.095 ± 0.063
Fe (g kg^{-1})	0.144 ± 0.074	0.162 ± 0.091	0.173 ± 0.069	0.228 ± 0.084
Filling value	910.1 ± 8.6	915.4 ± 9.2	917.0 ± 13.9	907.6 ± 6.0

case of Pera (late filing) and Valencia and Natal (intermediate production). Therefore, Hamlim gets less fungicide containing in its composition of Cu and Zn, resulting thus less absorption and contamination by these nutrients (although the leaves are washed) compared to other varieties. On the other hand, there is a wide variety of soil classes in the state of São Paulo such as Oxisols (Ustox) and Ultisols (Udults and Ustults) (Soil Survey Staff 2010). Besides differences in nutrient management of orchards, these soils cover a large spectrum of pH values and levels of oxy-hydroxides of aluminum (Al), Fe, and Mn that may impact foliar Mn and Fe levels and their interactions with other nutrients.

The Anderson-Darling normality test was significant for *ilr* 2, *ilr* 5, and *ilr* 11 ($P > 0.01$). The MANOVA showed effect of varieties across *ilr* coordinates ($P < 0.01$). The ANOVA showed similar results whether *ilr* or Yeo-Johnson-transformed *ilr* was used (Table 3).

Varieties had effects ($P < 0.05$) on *ilr* 1-4-5-7-8-9-11. Hamlim showed a greater *ilr* 1 value than others due to lower concentrations of cationic micronutrients (Table 2). The macronutrient/B and anion/cation ratios did not differ between varieties (*ilr* 2 and *ilr* 3). The anionic balance (*ilr* 4) was greater ($P < 0.05$) in Pera than in Hamlim due to P accumulation in Hamlim (Table 1). The N/S ratio (*ilr* 5) was greater in Hamlim, Natal, and Pera than in Valencia. The *ilr* 6 did not differ among varieties. The Ca/Mg ratio was greater in Pera than in Valencia due to greater leaf Mg in the latter. The *ilr* 8 was greater in Natal and Pera than in Hamlim and Valencia.

The nutrient balance expressed by *ilr* coordinates thus varied widely among varieties as shown by the ANOVA. However, the degree of varietal heterogeneity can be further explored by meta-analysis for use in nutrient-management decisions.

Table 3
Statistics (mean and standard deviation = SD) of *ilr* coordinates of orange varieties

	Mean of orange variety					
Ilr	Hamlim	Natal	Pera	Valencia	SD	Partition
1	7.483a	6.543 b	6.113 b	6.500 b	0.6508	[Macronutrients + B] vs. [Cu, Zn, Mn, Fe]
2	4.202a	4.142a	4.278a	4.162a	0.2348	Macronutrients vs. B
3	−1.084a	−1.039a	−1.087a	−1.104a	0.1241	Anions vs. cations
4	1.282a	1.459ab	1.496 b	1.345ab	0.2361	[N, S] vs. P
5	1.564ab	1.610a	1.561ab	1.466 b	0.1927	N vs. S
6	0.214a	0.062a	0.133a	0.037a	0.2621	K vs. [Ca, Mg]
7	1.422ab	1.532ab	1.587a	1.421 b	0.1909	Ca vs. Mg
8	−1.133 c	−0.613a	−0.683ab	−0.968bc	0.4237	[Cu, Zn] vs. [Mn, Fe]
9	−0.276 b	−0.161ab	−0.112ab	0.206a	0.6143	Cu vs. Zn
10	−0.730a	−0.589a	−0.449a	−0.682a	0.5667	Mn vs. Fe
11	−6.709 b	−6.626 b	−6.586ab	−6.455a	0.1841	[Macronutrients, B] vs. [Filling value]

Notes. Means followed by the same letter on the same line are not significantly different at the 0.05 level according to the Duncan multiple-range test (104 error degrees of freedom).

Meta-analysis

A heterogeneity test was provided by meta-analysis when a group is compared to a control. We selected Valencia as control because Valencia is the most documented orange variety worldwide. Criteria to make groups of varieties are the heterogeneity test (I^2) and confidence interval about the standardized mean difference. Where confidence intervals of standardized means are strictly above or below zero, group average is different than the control. Where I^2 exceeds 0.25, one variety should be removed to recover group homogeneity. Thereafter, the removed variety is compared to the control using a t-test. Results of the meta-analysis are presented in Table 4 and Figure 1 when comparing Valencia to other varieties.

The *ilr* 1, the most contrasting among orange varieties, showed that Hamlim, an early season variety, was the one where macronutrients and boron loaded most against cationic micronutrients, probably due to less fungicide applications. Pera, a late season one, was at the other end, indicating that more fungicides (Cu, Zn, Mn) had been applied probably due to differences in susceptibility to fungal diseases by the time of fruit maturation.

Nutrient status was similar across varieties for *ilr* 2, *ilr* 3, *ilr* 6, and *ilr* 10. Hamlim and Valencia formed one group while Natal and Pera formed another one for *ilr* 4, *ilr* 7, and *ilr* 8. Valencia contrasted with other cultivars for *ilr* 5, *ilr* 9, and *ilr* 11. These results show that nutrient management of Valencia may be suitable for other orange varieties across certain dimensions (i.e., *ilr* coordinates) of plant nutrition but unsuitable across other dimensions.

Nutrient Norms and Diagnosis

The nutrient management of orange orchards is based on criteria such as nutrient removal through harvest and nutrient concentration in plant tissue along with the monitoring of soil nutrient availability. Plant analysis contributes to surface soil analysis (0–20 cm) as a diagnostic tool for deep-rooted tree crops because plants

Table 4
Degree of heterogeneity (I^2) and confidence interval (CI) of standardized *ilr* coordinates of orange varieties against Valencia (groupings are proposed to reduce I^2 to zero)

Ilr	Q	I^2	C. I.	Proposed grouping (all I^2 = 0)
1	17**	0.87	−1.08 to 1.91	[Hamlim] [Valencia, Natal] [Pera]
2	4.5ns	0.56	−0.84 to 0.65	[Valencia, Hamlim, Pera] [Natal]
3	0.4ns	0	0.00 to 1.00	[Valencia] [Hamlim, Natal, Pera]
4	4.3ns	0.53	−0.45 to 1.02	[Valencia, Hamlim] [Natal, Pera]
5	0.5ns	0	0.23 to 1.24	[Valencia] [Hamlim, Natal, Pera]
6	1.2ns	0	0.04 to 1.04	[Valencia] [Hamlim, Natal, Pera]
7	1.8ns	0	0.03 to 1.03	[Valencia] [Hamlim, Natal, Pera]
8	4.6ns	0.57	−0.53 to 1.00	[Valencia, Hamlim] [Natal, Pera]
9	0.3ns	0	−1.33 to −0.32	[Valencia] [Hamlim, Natal, Pera]
10	2.1ns	0.03	−0.29 to 0.71	[Valencia, Hamlim, Natal, Pera]
11	0.0ns	0	−1.43 to −0.40	[Valencia, Hamlim, Natal, Pera]

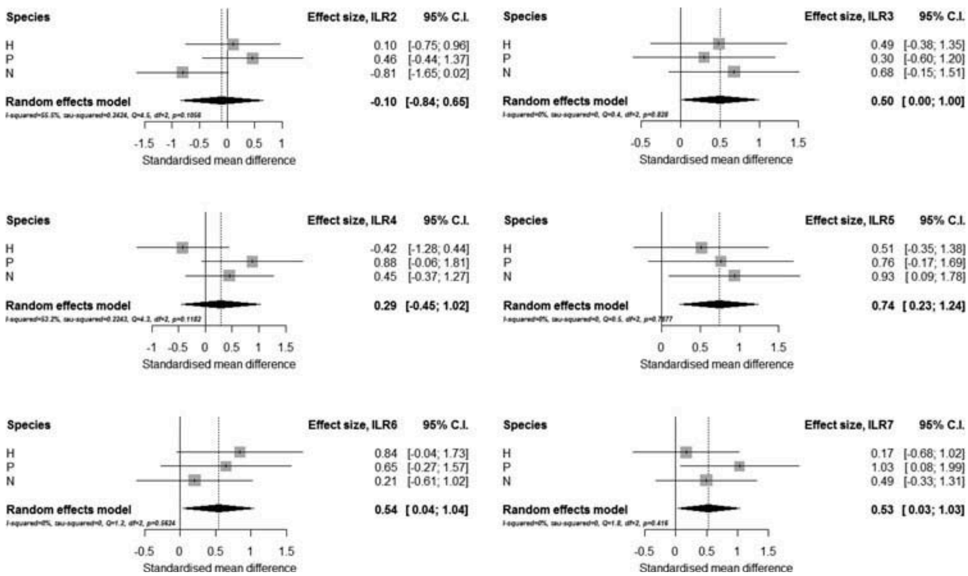

Figure 1. Forest plots of the meta-analysis of *ilr*2 to *ilr*7 across orange varieties (H = Hamlim; P = Pera; N = Natal) against Valencia.

access nutrients in the soil profile more than would be found through usual soil analytical procedures (Smith, Asher, and Clark 1997). Furthermore, in the case of N, for which methods of soil analysis lack consistency in diagnosis (Cantarella, Mattos, and Van Raij 1994), citrus leaf N analysis has been used as a criterion for evaluating its availability (Quaggio, Cantarella, and Van Raij 1998). Leaf nutrient diagnosis requires a standardized sampling method, routine analytical methods, standard nutrient values, and an interpretation of analytical results that should be free from bias for fertilizer recommendations (Kenworthy 1983).

Nutrient norms for the reference composition (y_i^*) were derived from mean *ilr* values where effect sizes were homogeneous across varieties (Table 5). The *ilr* 4 to *ilr* 7 coordinates were critical for macronutrient management. Natal and Pera required a greater [N, S] to [P] ratio than Hamlim and Valencia (*ilr* 4). Target value for the [N] to [S] ratio (*ilr* 5) was found to be lower for Valencia than others. Although balance between K and divalent cations was the same across cultivars, the [Ca] to [Mg] ratio was lower in Hamlim and Valencia.

The Aitchison distance was computed between a given composition (x_i^*) and the reference one. If the Aitchison distance across the selected set of *ilr* values exceeded a critical value, the diagnosed composition was declared imbalanced. We excluded *ilr* 1 and *ilr* 8 to *ilr* 11 because cationic micronutrients were more related to soil genesis and disease control than plant nutrition. The critical A value was found to be 0.47 for yields exceeding 154 kg tree^{-1} (Figure 2). With an average plantation density of 357 tree ha^{-1}, high yielders produced more than 55 Mg fruit ha^{-1}, close to 60 Mg fruit ha^{-1}, considered as high yield level by Mourão Filho (2005). True high yielders and true low yielders made up 64 percent of this classification (sixty-nine successful and thirty-nine unsuccessful cases for classification). Compared to an equal distribution of 50 percent successful and 50 percent unsuccessful cases and using a chi-

Table 5
Proposed nutrient norms using median values for homogeneous varietal groupings with zero I^2

	Mean of orange variety			
Ilr	Hamlim	Natal	Pera	Valencia
1	7.483	6.521	6.113	6.521
2	4.182	4.182	4.182	4.182
3	−1.084	−1.084	−1.084	−1.084
4	1.314	1.478	1.478	1.314
5	1.564	1.564	1.564	1.466
6	0.098	0.098	0.098	0.098
7	1.422	1.560	1.560	1.422
8	−1.051	−0.648	−0.648	−1.051
9	−0.137	−0.137	−0.137	−0.137
10	−0.636	−0.636	−0.636	−0.636
11	−6.606	−6.606	−6.606	−6.606

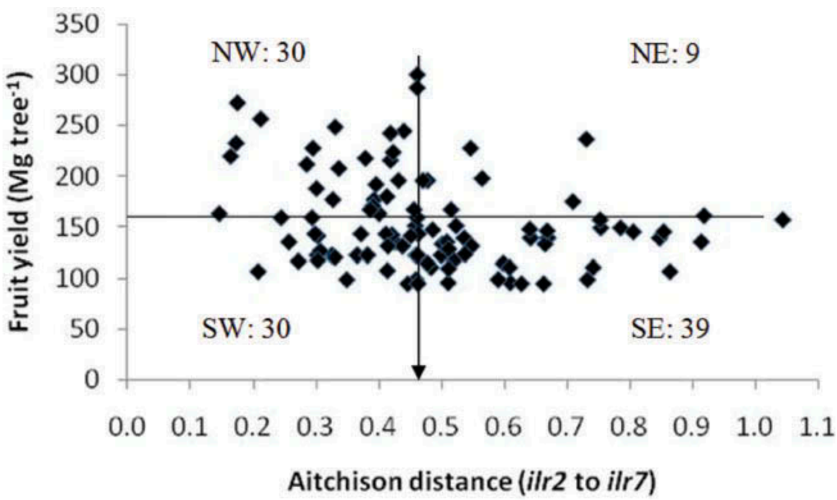

Figure 2. Cate-Nelson partitioning of the relationship between the Aitchison distance across *ilr2* to *ilr7* and fruit yield of orange orchards in the state of São Paulo, Brazil (number of observations per quadrant in parentheses).

square homogeneity test (Hollander and Wolfe 1999), the null hypothesis was rejected $(x_1^2) = 3.93$, $P < 0.05$). Hence, the critical Aitchison distance of 0.47 showed diagnostic potential to detect nutrient imbalance in orange orchards. However, independent fertilizer trials must be conducted to ascertain the critical Aitchison distance of 0.47.

Since the Aitchison distance can be decomposed into *ilr* differences [Eq. (3)], the main cause of imbalance is shown by the greatest *ilr* difference while the direction of imbalance is shown by the sign of that difference. To correct the most imbalanced nutrients, composition of the diagnosed tissue can be perturbed until the Aitchison distance falls below 0.40.

In compositional data analysis, a perturbation is a multiplicative operation whereby the original composition x is converted into a perturbed composition X through perturbation vector u as follows (Aitchison 1986):

$$X = \mu \oplus x = c\left(x_1 \mu_1, \ldots, x_D \mu_D\right) \tag{4}$$

where c is the closure operator. Tissue composition can be varied for nutrients contributing most to *ilr* differences from *ilr* norms using a perturbation vector u to identify the most deficient nutrients. Compositions are changed by vector u until proper Aitchison distance is recovered, that is, below critical value. Nutrient management is adjusted by applying a source of deficient nutrients at the rate and timing sought appropriate to re-establish nutrient balance.

Conclusions

Sequential binary partitions provided a framework for nutrient profiles based on current knowledge in plant physiology and pathology and in soil genesis. The nutrient profile of Valencia differed from others for *ilr* 3 and *ilr* 5. The varietal nutrient profiles were similar for *ilr* 2-6-7-8-9-10-11. Hamlim and Valencia showed *ilr* 4 and *ilr* 7 nutrient profiles different from Natal and Pera. On the other hand, the *ilr* coordinates involving cationic micronutrients may reflect differential applications of fungicides and hence the degree of varietal requirement for best management of fungal diseases. The nutrient profile of orange varieties could be classified into homogeneous groups to take advantage of fertilizer trials conducted on varieties of the same group. The Aitchison distance and a perturbation vector could be instrumental for diagnostic purposes and nutrient management.

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