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Agrometeorological models for forecasting the qualitative attributes of "Valência" oranges

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Abstract Forecasting is the act of predicting unknown future events using available data. Estimating, in contrast, uses data to simulate an actual condition. Brazil is the world's largest producer of oranges, and the state of São Paulo is the largest producer in Brazil. The "Valência" orange is among the most common cultivars in the state. We analyzed the influence of monthly meteorological variables during the growth cycle of Valência oranges grafted onto "Rangpur" lime rootstocks (VACR) for São Paulo, and developed monthly agrometeorological models for forecasting the qualitative attributes of VACR in mature orchard. For fruits per box for all months, the best accuracy was of 0.84 % and the minimum forecast range of 4 months. For the relation between °brix and juice acidity (RATIO) the best accuracy was of 0.69 % and the minimum forecast range of 5 months. Minimum, mean and maximum air temperatures, and relative evapotranspiration were the most important variables in the models.

Keywords Agrometeorology . Crop model . Early prevision . Prediction . Citrus sinensis L. Osbeck

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1 Introduction

The citrus sector has a broad social and economic importance in Brazil. The country is the largest exporter of concentrated orange juice in the world (Santos et al. [2013](#page-17-0)), and the state of São Paulo produces the most high-quality oranges, mainly for juice. For every five cups of orange juice consumed in the world, at least three are produced in Brazil (Neves et al. [2012](#page-16-0)). Economics, plant-health problems, and lower juice consummation around the world (Neves et al. [2012\)](#page-16-0) have forced the citrus industry to find new alternatives for ensuring its future. Climate is the major factor influencing the yield and quality of oranges (Paulino et al. [2007\)](#page-16-0). Anticipating fruit quality before the harvest is fundamental for producers to plan their crops (Ruslan et al. [2012](#page-16-0)). This planning begins in April for the state of São Paulo, but new techniques are required to help producers and the agricultural industry to plan their activities. The "Valência" orange is a highly regarded sweet orange due to its high yield and appropriate fruit size (Pio et al. [2005\)](#page-16-0). From the industrial point of view, these oranges represent one of the pillars of agroindustry around the world due to the high quality of their juice for processing, storage, and transport (Coelho [2002](#page-16-0)).

Agrometeorological models for forecasting crop yield and quality offer an option for understanding the regional climatic conditions and requirements of orchards. These models are useful tools for planning the activities in an area and can also identify the meteorological variables that are most influential during the various phenological phases of the crop cycle.

Several agrometeorological models have been developed for estimating yield and quality for perennial and annual crops using simple or multiple linear regressions. The major difficulty in modeling is to select independent variables that provide the most information and best results. Many methods are available for this selection: forward selection, backward elimination,

stepwise selection, leaps-and-bounds regression, orthogonal descriptors, genetic algorithms, genetic populations, choosing operators, and fitness of evaluation (Xu and Zhang [2001\)](#page-17-0).

Salvo et al. [\(2012\)](#page-16-0) developed regression models as a function of climatic variables for estimating the yield of blueberries in Chile. Pedro Junior et al. ([2014](#page-16-0)) produced estimation models for soluble solids and titratable acidity of grapes for the state of São Paulo, also using regressions, as a function of growing degree days. Similarly, Nyamdorj et al. [\(2014\)](#page-16-0) developed empirical models to estimate the responses of yield and quality of blueberries in eastern Australia as a function of climatic variables.

Models have also been developed for estimating the yield and quality of oranges. Camargo et al. ([1999](#page-16-0)) developed an agrometeorological model to estimate the yield of Valência oranges as a function of a hydric factor and identified flowering and initial fruit set as the phases most sensitive to water deficit. Volpe et al. ([2002\)](#page-17-0) concluded that air temperature, represented by growing degree days, was the most influential variable for the maturation rate of Valência and "Natal" oranges from the first flowering and used this variable for developing quadratic regression models. Paulino et al. [\(2007\)](#page-16-0) have used adjusted multiple linear regressions to describe the correlation between the number of fruits per plant and meteorological variables at different phases of the Valência orange cycle. Air temperature and water deficit were the most important variables at bud formation, onset of flowering and vegetative dormancy for orchards 6–10 years of age. Moreto et al. [\(2015\)](#page-16-0) reported similar results with estimation models using multiple linear regressions as functions only of water deficit. Water restrictions during the developmental (pre-production) year had a large effect on the yield of Valência oranges, but deficits at maturity (production year) strongly affected the quality of the fruit.

Few models, however, have been developed for forecasting yield. One example, though, used linear regression to predict maize yield at Jilin, China (Matsumura et al. [2014](#page-16-0)). Yield can be forecasted in different ways. Satellites can use the normalized difference vegetation index and general circulation models to associate yield with weather forecasts. Kogan et al. [\(2013\)](#page-16-0) achieved a range of 2–3 months for predicting wheat yield in the Ukraine. Temporal series analysis (Box et al. [2008\)](#page-16-0) and using El Niño and La Niña standards are other methods. For example, Hansen et al. [\(2004](#page-16-0)) forecasted wheat yield for the pre-planting period in northeastern Australia. Statistical models can also use mean and historical climatic data. We developed monthly agrometeorological models to forecast qualitative attributes of Valência oranges $(Citrus sinensis, L. Osbeck)$ grafted onto "Rangpur" lime (Citrus limonia, Osbeck) rootstocks (VACR) for the four important producing regions of Bauru, Bebedouro, Limeira, and Matão in São Paulo and to identify the meteorological variables with the most influence on VACR quality.

2 Material and methods

Local daily climatic data (Table 1) were obtained from automated meteorological stations. Data for precipitation (P) and minimum, mean and maximum air temperatures were organized on monthly scales for 2000–2013 for calculating potential evapotranspiration (PET) using the equation by Camargo [\(1971\)](#page-16-0) (Eqs. 1, 2, 3, 4, and 5). The models were calibrated with data for 2001–2009 and tested (validation) with data for 2010–2013.

$$
PET = 0.01 \times Q_O \times T \times ND
$$
 (1)

$$
Q_O = 37.6 \times \text{DR} \times \left[\left(\frac{\pi}{180} \right) \times hn \times \sin \Phi \times \delta + \cos \Phi \times \cos \delta \times \sin hn \right] \tag{2}
$$

$$
DR = 1 + 0.033 \times \cos\left(\frac{360 \times JD}{365}\right) \tag{3}
$$

$$
\delta = 23.45 \times \sin\left[\left(\frac{360}{365}\right) \times (JD - 80)\right] \tag{4}
$$

$$
hn = \text{ARCCOS} \left[-\tan\Phi \times \tan\delta \right] \tag{5}
$$

where Q_o is the daily solar irradiance at the top of the atmosphere (MJ m⁻² day⁻¹), DR is the relative distance from earth to sun (au, astronomic units), hn is the hour angle at sunrise (°), Φ is the latitude (°), δ: is the solar declination (°), JD is the Julian day, T is the mean air temperature ($\rm{°C}$), and \rm{ND} is the number of days of the period.

Monthly information for water deficit (DEF), water excess (EXC), soil-water storage (STO), and actual evapotranspiration (AET) were generated by the Thornthwaite and Mather [\(1955\)](#page-17-0) water-balance method with an available water capacity of 100 mm. Minimum (Tmin), mean (T) and maximum (Tmax) air temperatures, precipitation (P), relative evapotranspiration ($RET = AET/PET$), DEF , EXC , and STO were used as independent variables for developing models with multiple linear regressions (Eq.6). Only variables from the developmental year (primary phenological year) (Fig. [1\)](#page-2-0) were used for forecasting, totaling 73 independent variables (Xs) pre-selected as the most important for each region.

Table 1 Local and climatic descriptions of the regions of production

Locals	Latitude (S)	(W)	(m)	Longitude Altitude Thornthwaite (1948) climatic classification
Bauru		22° 17' 29" 49° 33' 10" 561		$C_2SB'_{4}a$
	Bebedouro 20° 56' 58" 48° 28' 45" 573			$C_2dA'a$
Limeira		22° 33' 53" 47° 24' 06" 588		$B_1rB'_3a$
Matão		$21^{\circ}36'12''$ 48° 21' 57″ 585		$B_1rB'_4a$

Fig. 1 Mean phenology of Valência oranges grafted onto Rangpur lime rootstocks in the state of São Paulo. BD bud formation, VD vegetative dormancy, FLO flowering, DIV cell division, DIF cell differentiation, CE cell expansion, E early crop harvest of Valência oranges, MID mid-crop harvest of Valência oranges, LATE late crop harvest of Valência oranges

$$
Y = a \times X_1 + b \times X_2 + c \times X_3 + \dots + LC \tag{6}
$$

where Y is the fruits per box, as BRIX, kilograms of soluble solids, ratio, acidity, fruit weight, and juice percentage; a, b, c , ... are the angular coefficients; X_1, X_2, X_3, \ldots are the selected meteorological variables; and LC is the linear coefficient.

Monthly data for RATIO (Eq. 7), fruit sugar content (BRIX) measured by refractometer, kilograms of soluble solids per box (KGSS) (Eq. 8), citric acid percentage (ACIDITY), juice percentage (%JUICE) (Eq. 9), fruits per box (FRBOX), and fruit weight (WFRUIT) of VACR oranges were obtained from local producers. For better application in the models, these data were organized as means of the two flowerings of mature orchards (more than 6 years). Orange trees usually flower twice per 2-year cycle, induced by thermal and/or water stresses, but more flowerings can occur if climatic stresses are out of season.

$$
RATIO = 'BRIX \times ACIDITY^{-1}
$$
 (7)

 $KGSS = JC \times {}^{*}BRIX \times 40.8 \times 10^{-4}$ (8)

 $\%$ JUICE = WJUICE × WFRUIT⁻¹ × 100 (9)

where JC is the juice content (L), $WJUICE$ is the juice weight (kg), and 40.8 is the box weight (kg).

The largest problem in multiple linear regressions is to select the best combination of independent variables to be combined for generate significant models. Any numeric interactive method, as the stepwise selection, has stabilization problems in local errors due to poor initial combinations. An option is to test all possible combinations (APC) when the number of independent variables is relatively small (Walpole et al. [2012](#page-17-0)).

We used the APC method for testing models with 1–3 independent variables from the developmental year on a monthly scale, producing 64,897 possible equations for each dependent variable (RATIO, BRIX, KGSS, ACIDITY, %JUICE, FRBOX, and WFRUIT), totaling 519,176 tested equations for each month. A routine in visual basics applications was used to develop these equations. The criteria applied for selecting the variables were the significance of the coefficients ($t < 0.05$) and regressions ($F < 0.05$), a low mean

absolute percentage error (MAPE) and a high adjusted coefficient of determination $(R^2 \text{ adj})$ (Eqs. 10 and 11).

$$
\text{MAPE}(\%) = \frac{\sum_{i=1}^{N} \left(\left| \frac{\text{Test}_i - \text{Yobs}_i}{\text{Yobs}_i} \right| \times 100 \right)}{N} \tag{10}
$$

$$
R^2 \text{ adjusted} = \left[1 - \frac{\left(1 - R^2\right) \times \left(N - 1\right)}{N - k - 1}\right] \tag{11}
$$

where Yest_i is the estimated quality attributes at year *i*, Yobs_i is the observed quality attributes at year i , N is the data number, and k is the number of independent variables at the regression.

The multicollinearity between the monthly independent variables (Tmin, T, Tmax, P, RET, DEF, EXC, and STO) were removed. Gujarati and Porter ([2011](#page-16-0)) suggested that multicollinearity was not a problem for models that only estimate, but multicollinearity can cause bias in the analysis of angular coefficients, such as in our study. The analysis of angular coefficients allows the identification of the meteorological elements with the most influence on forecasting yield and quality and the times at which they are important.

3 Results and discussion

3.1 Local climatic analysis

The Bauru (BAU), Bebedouro (BEB), Limeira (LIM), and Matão (MAT) regions have similar annual climatic characteristics but have some seasonal differences that affect yield and quality and that lead to some different responses of Valência orange crops (Fig. [2](#page-3-0)).

These regions can be divided into two groups based on temperature (Fig. [2](#page-3-0)): G_T1 represented by BEB and MAT with T between 22 and 25 °C and G_T 2 represented by LIM and BAU with T between [2](#page-3-0)0 and 23 $^{\circ}$ C (Table 2). The lowest Ts occurred in May, June, and July, the months of the phenological phases that precede flowering, such as bud formation and vegetative dormancy. Mean P was low in winter in all regions (Fig. [2\)](#page-3-0), extending into August (beginning of flowering). The northern producing regions of the state of São Paulo had similar conditions (Sentelhas [2005](#page-17-0)). The evapotranspiration demand was fulfilled between November and March (Fig. [2\)](#page-3-0) for all regions (RET > 0.9). The largest restriction of evapotranspiration occurred in August, when AET reached 40 % of PET in BEB. BAU was the only region with an excess of water during the dry period (Fig. [2](#page-3-0)). The regions could thus also be divided into two groups based on their water-balance components (DEF, STO, and EXC): $G_{\text{WB}}1$ (BAU) and $G_{\text{WB}}2$ (LIM, MAT, and BEB) (Table [2](#page-3-0)). The division for RET was the same as for water balance. The dry period is important for the flowering of orange crops and thus for quality and uniformity. Lower water availability and temperatures are major inducers

Fig. 2 Climatic characteristics of the regions for 2000–2013. a Monthly mean air temperature (°C), b precipitation and soil-water storage (mm), c relative evapotranspiration, and d water deficit (DEF) and excess (EXC)

of flowering during this phase of the crop cycle (Castro et al. [2001\)](#page-16-0).

The most important variables for inducing flowering were DEF in BEB and MAT, belonging to groups G_T1 and $G_{\text{WB}}2$, T in LIM, belonging to groups $G_T 2$ and $G_{WB} 2$, and DEF and T in BAU, belonging to groups $G_T 2$ and $G_{WB}1$ (Ribeiro et al. [2006\)](#page-16-0).

3.2 Model classification

To develop accurate agrometeorological models that could forecast the qualitative attributes of VACR with maximum range we

Table 2 Similarity groups of the water-balance components of the regions

Similarity groups					
Mean air temperature		Water Balance (STO, DEF, EXC, and RET)			
$G_{\rm T}1$	Bebedouro	$G_{\rm WR}1$	Bauru		
$(22-25 \degree C)$ Matão		(EXC until July)			
G_T2	Limeira	$G_{\rm WR}$ 2	Bebedouro		
(20-23 °C) Bauru		(EXC until April)	Limeira		
			Matão		

STO soil-water storage, DEF water deficit, EXC water excess, RET relative evapotranspiration

(mm). The water-balance components were estimated by the method of Thornthwaite and Mather ([1955\)](#page-17-0), with an available water capacity of 100 mm

tested all possible combinations of 1–3 of the monthly climatic variables (64,897 combinations) from the developmental year (primary phenological year). The combinations that showed multicollinearity (21,380) were rejected, and the remaining combinations (43,517) represented the best possible monthly models for forecasting the qualitative attributes of VACR (Fig. 3).

Fig. 3 Number of generated and tested equations for multicollinearity analyses for developing the agrometeorological models for forecasting the yield and quality of Valência oranges grafted onto Rangpur lime rootstocks as a function of the monthly climatic variables for the developmental year. n° number of models generated, n° number of models with multicollinearity between the independent variables above 0.7, and n° number of viable forecasting models

The APC method was efficient because P decreased as R^2 adj increased, and the MAPE consequently decreased (Fig. 4). We used these criteria for identifying the best models for forecasting the qualitative attributes of VACR.

3.3 Sensitivity analysis

The sensitivities of the angular coefficients of the climatic variables for the developmental year (Figs. [5](#page-5-0) and [6\)](#page-5-0) were analyzed to identify those with more influence on the RATIO and FRBOX of VACR in the regions. The juiceprocessing industries begin their planning in April, so we used this month for the sensitivity analyses. Sensitivity analyses are important to evaluate either crop-modeling approaches or the application of modeling solutions exploring combinations between local and climate conditions (Confalonieri et al. [2010\)](#page-16-0).

The sensitivity analyses identified the most influential variables in the ten most accurate models for forecasting $RATIO_{APR}$ and $FRBOX_{APR}$ for each region, without considering the range. The RATIO_{APR} models had MAPEs of $2.58-$ 4.17 % for BAU, 1.86–3.52 % for BEB, 2.02–3.97 % for LIM, and 4.86–7.63 % for MAT. The accuracies of the FRBOXAPR models were 1.75–2.38 % for BAU, 5.15– 6.83 % for BEB, 1.29–3.06 % for LIM, and 4.06–11.43 % for MAT.

The most important general climatic variables for forecasting RATIO_{APR} for all regions were T_{MAX} , T_{JUL} , T_{NOV} , T max_{MAR}, T max_{APR}, T max_{JUN}, T max_{DEC}, T min_{MAY}, RET_{APR} , RET_{MAY} , RET_{JUN} , and RET_{SEP} .

All coefficients were positive for LIM, indicating that the climatic variables for this region were positively correlated with RATIO_{APR}. Tmax_{MAR} and T_{MAX} were the most important variables in the best $RATIO_{APR}$ forecast models for BEB and MAT, which have similar climatic conditions, especially temperature (Ribeiro et al. [2006](#page-16-0)). These variables had mostly negative coefficients, indicating negative correlations. RET was the most influential positively correlated variable in BAU, but $T_{\text{max}_{\text{MAR}}}$ was also important in the models but was negatively correlated with RATIO.

The angular coefficients of the $FRBOX_{APR}$ forecasting models indicated that the most important climatic variables for all regions were T_{JAN} , T_{APR} , T_{JUL} , T_{NOV} , $T_{MAX_{APR}}$, T max_{MAY}, T max_{AUG}, T max_{NOV}, RET_{APR} , RET_{JUN} , RET_{OCT} , STO_{MAX} , STO_{JUN} , DEF_{JUL} , and EXC_{DEC} . These variables can be positively or negatively correlated with VACR yield.

The variables of water availability (STO, DEF, EXC, P, and RET) in BAU were more influential in the models. Their coefficients were negatively correlated with FRBOX. RET was the most influential variable in the BEB and LIM models, with positive and negative correlations, respectively. The variables of temperature, mainly T_{JAN} and $T_{\text{max}_{\text{MAX}}}$, were most influential for MAT, with positive coefficients and a positive correlation with FRBOX.

3.4 Agrometeorological forecasting models

Agrometeorological models have demonstrated that using climatic variables for forecasting crop yields reduces the uncertainties related to the production, making agricultural activities more reliable (Hammer et al. [2000](#page-16-0)). These forecasts, when accurate, provides important information about soil and/or water management problems in agricultural areas, capturing the complexity and uncertainties and serving as a platform for making decisions and creation of farm policies (Cabrera et al. [2006;](#page-16-0) Carmona et al. [2013\)](#page-16-0). The agrometeorological models for forecasting RATIO, BRIX, KGSS, ACIDITY, %JUICE, FRBOX, and WFRUIT of VACR developed in this study were mostly highly accurate in the calibration and testing steps.

All models analyzed were significant and accurate at calibration (P≤0.050 and MAPE≤10.46 %). The models with the lowest P and MAPE (high accuracy) were WFRUIT_{NOV} and BRIX_{APR}, both for BAU. The KGSS_{APR} and JUICE_{APR} models for BEB had minimum ranges of 3 months. The $WFRUIT_{OCT}$ model for BEB had the longest range of all models, a forecast of approximately 1 year. Relationships between crop and climatic variables are more statistical than physiological the longer the forecast. Longer ranges, such as

Fig. 4 Example of the agrometeorological model classification for Bebedouro, following the criteria of accuracy (low MAPE), precision (high R^2 adj) and reliability ($P < 0.05$)

Fig. 5 Sensitivity analysis of the mean angular coefficients from the ten most accurate models for forecasting RATIO for April of Valência oranges grafted onto Rangpur lime rootstocks. a Bauru. b Bebedouro. c Limeira. d Matão

that of the WFRUIT_{OCT} model for BEB, indicate that a relationship is more statistical or of engineering.

The models for forecasting RATIO for all regions and months were accurate at testing, with a minimum MAPE of 0.69 % for August in BAU and a maximum of 7.67 % for May

in LIM (Table [3](#page-6-0)). The minimum range (5 months) for forecasting RATIO was for BEB, LIM, and MAT. The maturity index (RATIO) is the relationship between BRIX and ACIDITY, two major components for the citrus industries. RATIO has a direct impact on the price and quality of juice

Fig. 6 Sensitivity analysis of the mean angular coefficients from the ten most accurate models for forecasting FRBOX for April of Valência oranges grafted onto Rangpur lime rootstocks. a Bauru. b Bebedouro. c Limeira. d Matão

Table 3 Monthly agrometeorological models for forecasting RATIO for the state of São Paulo

The dependent variable is for the production year (year 2). Calibration and testing used monthly data from 2001 to 2009 and 2010–2013, respectively The independent variables are Tmin, T, and Tmax, minimum, mean and maximum air temperature (°C); EXC and DEF hydric excess and deficit; STO soil-water storage; P precipitation (mm); and RET relative evapotranspiration for the developmental year (year 1) BAU Bauru, BEB Bebedouro, LIM Limeira, MAT Matão,

(Ruslan et al. [2012\)](#page-16-0). Twas the most influential variable among the agrometeorological models for forecasting RATIO in all regions and months. Its angular coefficient was higher than those of the other variables. Temperature during the first semester (six first months of the year) of the developmental year were most frequent in the models for BAU and BEB, but the temperatures during the second semester were more influential for LIM and MAT.

BAU had the most accurate model of RATIO_{APR}, with a MAPE in the testing phase of 2.58 %, a precision $(R^2 \text{ adj})$ of 0.98, and P of 0.036. A mean RATIO of 3.32 would thus have a forecasting error of only 0.09 points. T at the end of bud formation and the beginning of vegetative dormancy (July) was the most influential variable in this model. February Tmax, Tat vegetative dormancy (July), and Tat bud formation (May) were the most influential variables for BEB, LIM, and MAT, respectively. Temperature had the most effect on RATIO in BEB (Volpe et al. [2002\)](#page-17-0). Mattheis et al. [\(1999\)](#page-16-0) found that temperature changes during plant development generally impacted flavor and fruit composition.

The models for forecasting KGSS for all regions and months were accurate at the testing stage. The minimum MAPE was 0.50 % for August in LIM, and the maximum was 12.96 % for November in BEB. The minimum range for KGSS was three months for BEB. KGSS is also used as a technological index, expressing quality. A high KGSS indicates good fruit quality (Grizotto et al. [2012](#page-16-0)). Tmax was most frequent and had high angular coefficients in BAU, BEB, and MAT in the second semester (Table [4\)](#page-8-0). T was the most important variable in the first semester in LIM.

The best $KGSS_{APR}$ model was for BAU, with a MAPE of 1.80 %, R^2 adj = 0.80 and $P = 0.039$ at the testing stage. A mean KGSS of 1.73 kg of SS per box would thus have a forecasting error of 0.03 kg of SS per box. Tmax during bud formation (April) was the most influential variable in this model. The models for BEB, LIM, and MAT were satisfactory, with Tmax influential at fruit growth (November) and at bud formation (April) in BEB and LIM, respectively. RET at the beginning of bud formation (April) was the most important variable in the KGSSAPR model for MAT, with an accuracy of 2.31 %, a precision of 0.93 and $P = 0.0004$ at testing.

The models for forecasting ACIDITY were accurate for all regions and months at testing. The minimum MAPE was 2.14 % for April in LIM, and the maximum was 17.79 % for November in BEB. The accuracy of the models decreased for forecasts near the end of the production year (end of cycle), because the models used independent variables only for the developmental year, which maximized the ranges. The minimum range for ACIDITY was 4 months for MAT and BEB. ACIDITY, %JUICE, and KGSS determine the quality of oranges (Uribe-Bustamante et al. [2013](#page-17-0)).

T and Tmax during the first semester were the most frequent variables in the ACIDITY models (Table [5\)](#page-9-0) in BEB (T), LIM, and MAT (Tmax). RET during the second semester was the most frequent variable for BAU. T during vegetative dormancy (July) and bud formation (May) were most important for forecasting ACIDITY_{APR} in LIM and MAT, respectively. Tmax and RET at bud formation (May and July) were most important in BEB and BAU.

The best $\text{ACIDITY}_{\text{APR}}$ model was for LIM, with a MAPE of 2.14 %, R^2 adj = 0.93 and $P = 0.028$ at testing. A mean ACIDITY of 2.50 % would thus have a forecasting error of 0.053 %.

The models for forecasting BRIX were accurate for all regions and months at testing. The minimum MAPE was 0.64 % for June in LIM, and the maximum was 12.10 % for November in BEB. The minimum range of 4 months for BRIX was in BEB and MAT. BRIX represents the sugar content of the juice and is commonly used for blending orange juices from different cultivars to achieve the desired BRIX of a product.

The forecasts of the BRIX agrometeorological models (Table [6](#page-10-0)) were satisfactory. T, Tmax, and Tmin were the most frequent variables among all models and months for BEB, LIM, and MAT, respectively. Temperatures during the first semester were more frequent in the models. Tmax during the second semester was the most frequent variable for BAU.

The best $BRIX_{APR}$ model was for MAT, with a MAPE of 1.38 %, R^2 adj = 0.76 and P = 0.007 at testing. A mean BRIX of 11.29° would thus have a forecasting error of 0.16°. Tmin during flowering (August) was the most influential variable in this model, again indicating that this phenological phase is very important for VACR fruit quality.

The models for forecasting %JUICE were accurate for all regions and months at testing. The minimum MAPE was 0.41 % for October in MAT, and the maximum was 10.20 % for May in BAU. The minimum range was 3 months for BEB. %JUICE (Table [7\)](#page-11-0) is a variable for both quality and yield, because more fruit will produce more juice. The models developed for %JUICE were influenced most by temperature in BEB (Tmax), LIM (Tmax), and MAT (T). RET was the most influential variable in BAU. The first-semester variables were more frequent in the %JUICE forecasting models.

The best $\%$ JUICE_{APR} model was for LIM, with a MAPE of 1.60 %, R^2 adj = 0.91 and $P = 0.007$ at testing. A mean %JUICE of 0.57 % would thus have a forecasting error of 0.00912 %. Tmin and Tmax during fruit-cell expansion in December were the most important variables in this model.

Agrometeorological models for forecasting FRBOX developed in this study were strongly dependent on temperature, but at least one model relied on water-balance components (DEF, EXF, and STO) for its forecasts. The FRBOX test models were highly accurate for all months and regions, with a minimum MAPE of 0.84 % for September in BAU and a maximum of 19.52 % for September in MAT. The minimum range for FRBOX was 4 months for BEB and LIM.

Table 4 Monthly agrometeorological models for forecasting kilograms of soluble solids per box (KGSS) for the state of São Paulo

The dependent variable is for the production year (year 2). Calibration and testing used monthly data from 2001 to 2009 and 2010–2013, respectively The independent variables are Tmin, T, and Tmax minimum, mean, and maximum air temperature (°C); EXC and DEF hydric excess and deficit; STO soil-water storage; P precipitation (mm), and RET relative evapotranspiration for the developmental year (year 1)

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			Table 5 Monthly agrometeorological models for forecasting citric acid percentage (ACIDITY) for the state of São Paulo	
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The dependent variable is for the production year (year 2). Calibration and testing used monthly data from 2001 to 2009 and 2010–2013, respectively The independent variables are Tmin, T, and Tmax minimum, mean and maximum air temperature (°C); EXC and DEF hydric excess and deficit; STO soil-water storage; P precipitation (mm); and RET relative evapotranspiration for the developmental year (year 1).

Table 6 Monthly agrometeorological models for forecasting sugar content (BRIX) for the state of São Paulo

The dependent variable is for the production year (year 2). Calibration and testing used monthly data from 2001–2009 and 2010–2013, respectively The independent variables are Tmin, T, and Tmax minimum, mean and maximum air temperature (°C); EXC and DEF hydric excess and deficit; STO soil-water storage; P precipitation (mm), and RET relative evapotranspiration for the developmental year (year 1)

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$%$ JUICE (J)		P value	Calibration		Testing	
			MAPE $(\%)$	R^2 adj	MAPE $(\%)$	R^2 adj
April						
BAU	$J = 0.0005 P_{\text{OCT}} - 0.371 \text{ RET}_{\text{APR}} - 0.071 \text{ RET}_{\text{JUL}} + 0.832$	0.008	1.69	0.94	3.04	0.82
BEB	$J = 0.010$ Tmin _{IIII} - 0.020 Tmax _{FFB} + 0.001 EXC _{DFC} + 1.065	0.025	2.12	0.79	3.21	0.98
LIM	$J = 0.012$ Tmin _{MAR} + 0.013 Tmin _{JUL} + 0.002 DEF _{MAY} + 0.236	0.006	2.52	0.85	1.60	0.91
MAT	$J = -0.031 T_{\text{FEB}} - 0.039 T_{\text{JUN}} + 0.001 \text{ DEF}_{\text{APR}} + 2.025$	0.018	3.01	0.75	2.57	0.98
May						
BAU	$J = -0.005$ Tmin _{JUN} + 0.002 DEF _{MAY} + 0.001 STO _{OCT} + 0.530	0.056	1.29	0.79	10.20	0.58
BEB	$J = 0.008$ $T_{\text{SEP}} + 0.014$ $T_{\text{max}FEB} + 0.0002$ $P_{\text{JAN}} - 0.180$	0.009	1.05	0.88	1.66	0.93
LIM	$J = -0.014$ Tmax _{JUN} – 0.007 Tmax _{AUG} + 0.0002 P_{SEP} + 1.155	0.039	1.29	0.66	1.89	0.89
MAT	$J = -0.008$ Tmin _{JUN} + 0.014 Tmax _{FEB} + 0.001 P_{MAX} + 0.088	0.004	1.45	0.87	2.58	0.98
June						
BAU	$J = -0.019$ Tmax _{JAN} – 0.0003 P_{JUL} + 0.0001 P_{DEC} + 1.233	0.041	0.92	0.83	0.54	0.96
BEB	$J = 0.012$ Tmax _{AUG} – 0.001 DEF _{AUG} + 0.001 STO _{JUL} + 0.169	0.046	1.51	0.72	1.18	0.89
LIM	$J = -0.004$ Tmin _{DEC} + 0.0004 P_{SEP} + 0.0002 STO _{JUL} + 0.599	0.036	1.13	0.67	0.59	0.88
MAT	$J = -0.010$ T max _{OCT} + 0.0003 P_{MAX} + 0.040 RET _{SEP} + 0.881	0.010	1.18	0.81	0.73	0.96
July						
BAU	$J = 0.005 T_{\text{MAX}} - 0.007 T_{\text{min}_{\text{JAN}}} - 0.002 T_{\text{min}_{\text{AUG}}} + 0.629$	0.006	0.21	0.95	0.82	0.95
BEB	$J = 0.017 T_{JUN} - 0.001 \text{ DEF}_{OCT} + 0.001 \text{ STO}_{SEP} + 0.226$	0.049	1.40	0.71	1.44	0.84
LIM	$J = -0.006$ Tmin _{MAR} $- 0.010$ Tmax _{DEC} $+ 0.0004$ STO _{SEP} $+ 0.997$	0.016	0.82	0.76	0.61	0.96
MAT	$J = -0.014 T_{JUN} + 0.0003 STO_{JUN} + 0.0003 STO_{NOV} + 0.819$	0.008	1.04	0.83	0.66	0.92
August						
BAU	$J = 0.004$ Tmin _{MAY} – 0.012 Tmin _{JUL} – 0.0002 STO _{NOV} + 0.649	0.028	0.45	0.87	0.78	0.81
BEB	$J = 0.012$ Tmax _{JUN} + 0.0002 EXC _{DEC} + 0.001 STO _{MAY} + 0.154	0.026	1.23	0.79	1.39	0.86
LIM	$J = 0.011$ Tmax _{FEB} – 0.0001 $P_{\text{MAR}} + 0.0003$ EXC _{DEC} + 0.242	0.004	0.59	0.87	0.79	0.86
MAT	$J = 0.018$ T_{SEP} – 0.0001 P_{FEB} + 0.0005 STO _{OCT} + 0.189	0.039	2.09	0.66	0.92	0.81
September						
BAU	$J = -0.008 TOCT - 0.005 Tmin_{SEP + 0.006 Tmin_{DEC} + 0.723$	0.027	0.56	0.87	0.95	0.83
BEB	$J = 0.0001$ EXC _{JAN} – 0.0003 EXC _{DEC} + 0.0009 STO _{OCT} + 0.575	0.002	0.44	0.95	0.72	0.99
LIM	$J = -0.022 T_{APR} + 0.003 T_{min_{MAX}} + 0.0001 EXC_{FEB} + 1.058$	0.010	0.68	0.81	0.81	0.90
MAT	$J = 0.006$ Tmax _{SEP} – 0.010 Tmax _{OCT} + 0.0002 STO _{JUN} + 0.719	0.006	0.89	0.84	0.51	0.83
October						
BAU	$J = -0.012 T_{APR} - 0.014 T_{minJUL} - 0.073 RET_{APR} + 1.010$	0.017	0.38	0.91	0.67	0.95
BEB	$J = 0.003$ Tmin _{JUN} + 0.001 STO _{OCT} – 0.0005 STO _{NOV} + 0.561	0.012	0.77	0.86	1.04	0.96
LIM MAT	$J = 0.004$ Tmin _{JUL} + 0.015 Tmax _{JAN} – 0.0003 P_{MAR} + 0.133 $J = 0.003$ Tmin _{SEP} – 0.007 Tmin _{NOV} + 0.0004 STO _{OCT} + 0.627	0.009 0.005	0.94 1.28	0.82 0.86	2.29 0.41	0.98 0.95
November						
BAU	$J = 0.005$ $T_{\text{AUG}} - 0.018$ $T_{\text{max}_{\text{MAR}}} - 0.009$ $T_{\text{max}_{\text{DEC}}} + 1.417$ $J = 0.005$ Tmax _{SEP} + 0.006 Tmax _{OCT} + 0.001 STO _{AUG} + 0.166	0.041	0.94	0.83	0.84	0.89
BEB LIM		0.004 0.021	0.48 1.33	0.92 0.74	2.13 0.77	0.89 0.99
MAT	$J = -0.004$ Tmin _{JAN} - 0.0002 EXC _{FEB} + 0.093 RET _{OCT} + 0.585 $J = 0.010 T_{\text{SEP}} + 0.005 T_{\text{max}_{\text{JAN}}} + 0.0003 EXC_{\text{MAR}} + 0.147$	0.041	1.27	0.65	2.15	0.76
December						
BAU	$J = 0.0003$ DEF _{JUN} = 0.0004 STO _{JUL} + 0.116 RET _{APR} + 0.507	0.046	0.57	0.82	0.51	0.98
BEB	$J = -0.012 TJUL + 0.0003 PJAN + 0.0001 PDEC + 0.714$	0.025	0.73	0.79	2.22	0.92
LIM	$J = 0.001$ STO _{JUN} – 0.151 RET _{MAY} + 0.658	0.008	1.80	0.73	4.19	0.88
MAT	$J = 0.016$ Tmax _{AUG} + 0.001 P_{MAX} – 0.0005 P_{JUN} – 0.023	0.003	1.05	0.88	9.91	0.72

The dependent variable is for the production year (year 2). Calibration and testing used monthly data from 2001–2009 and 2010–2013, respectively The independent variables are Tmin, T, and Tmax minimum, mean and maximum air temperature (°C); EXC and DEF hydric excess and deficit; STO soil-water storage; P precipitation (mm); and RET relative evapotranspiration for the developmental year (year 1)

Table 8 Monthly forecast agrometeorological models of fruits per box (FRBOX) for the State of São Paulo

The independent variables are Tmin, T, Tmax minimum, mean, and maximum air temperature (°C); EXC and DEF hydric excess and deficit; STO soilwater storage; P precipitation (mm); and RET relative evapotranspiration, referents to the developmental year (year 1) and the dependent variable is referent to the production year (year 2). Calibration and testing used monthly data from 2001 to 2009 and 2010–2013, respectively

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Table 9 Monthly agrometeorological models for forecasting fruit weight (WFRUIT) for the state of São Paulo	

. BAU, Bauru; BEB, Bebedouro; LIM, Limeira; MAT, Matão. The independent variables are Tmin, T and Tmax, minimum, mean and maximum air temperature (°C); EXC and DEF, hydric excess and deficit; STO, soil-water storage; P, precipitation (mm) and RET, relative evapotranspiration for the developmental year (year 1). The dependent variable is for the production year (year 2). Calibration and testing used monthly data from 2001–2009 and 2010–2013, respectively

The most influential variables for $FRBOX_{APR}$ were Tmax and Tmin for BEB, T during the first semester for LIM and T during the second semester for BAU (Table [8](#page-12-0)). BEB presented all the developmental year, first and second semesters, with important variables on the forecast of FRBOX of VACR.

The best $FRBOX_{APR}$ model was for LIM, with a MAPE of 1.29 %, R^2 adj = 0.97, and $P = 0.023$ at testing. A mean FRBOX of 280.58 would thus have a forecasting error of 3.62. T and Tmax at bud formation and vegetative dormancy (June and July) were the most influential variables in the $FRBOX_{APR}$ model in LIM, indicating that VACR yield was dependent on the initial developmental stages of the plant. Paulino et al. ([2007](#page-16-0)) found significant correlations between the number of fruits per plant and T max and T in April and June for orchards 3–5 years old and in May and July for orchards older than 6 years.

WFRUIT is directly related to FRBOX: fruit size increases as the number of fruits per box decreases. The WFRUIT models (Table [9](#page-13-0)) were accurate among all regions and months, with a minimum MAPE of 1.48 % for June in BAU and a maximum of 16.61 % for October in MAT. The minimum range was 4 months for LIM. T was the most important variable for LIM and MAT, RET was the most important variable for BAU, and Tmax and Tmin were the most important variables for BEB, all during the first semester of the developmental year.

The best $WFRUIT_{APR}$ model was for BAU, with a MAPE of 2.52 %, R^2 adj = 0.95 and $P = 0.002$ at testing. A mean WFRUIT of 0.16 kg would thus have a forecasting error of 0.004 kg. RET at bud formation and vegetative dormancy (April and July) was the most important variable in the WFRUIT forecasting model for BAU.

The qualitative attributes (Tables [3,](#page-6-0) [4,](#page-8-0) [5](#page-9-0), [6](#page-10-0), [7,](#page-11-0) [8](#page-12-0) and [9\)](#page-13-0) were most influenced by temperature, indicating that this climatic factor was most important to VACR fruit quality for all regions. RET was also important. Transpiration in citrus plants occurs throughout the year and is influenced by rootstock, cultivar, vegetative growth and corresponding phenological phases (Vellame et al. [2012](#page-17-0)). Paulino et al. [\(2007\)](#page-16-0) found a positive effect of VACR evapotranspiration on yield during the phases of flowering, fructification and fruit growth.

3.5 Model forecasting performance

The forecasts of the monthly agrometeorological models developed in this study performed well. A comparison of independent data for FRBOX and RATIO for all months of 2010– 2013 (Fig. 7 and Fig. 8, respectively) has shown that the forecasts were highly precise. The minimum R^2 adj was 0.80 for FRBOX in LIM and 0.98 for RATIO in MAT.

Fig. 7 Accuracy analysis of the monthly models for forecasting FRBOX using independent data from 2010 to 2013. a) Bauru, b) Bebedouro, c) Limeira and d) Matão

3.6 Overview of climatic parameters during the crop cycle

We conducted a combined analysis of the four regions to summarize the meteorological variables and their effects on the qualitative attributes of VACR (Fig. [9\)](#page-15-0). The criteria used were the frequency of the variables in the models and the angular coefficients. Tmax was the most important variable during flowering (August) and was positively correlated with BRIX and FRBOX. Tmax in August was negatively correlated with WFRUIT, T in August and February was negatively correlated with RATIO and ACIDITY, respectively. The meteorological variables that influenced %JUICE and KGSS were in equilibrium during the developmental year, having positive and/or negative correlations with these qualitative variables of VACR.

Fig. 8 Accuracy analysis of the monthly models forecasting RATIO using independent data from 2010 to 2013. a) Bauru, b) Bebedouro, c) Limeira and d) Matão

Fig. 9 Overview of the meteorological elements influencing the qualitative attributes of 'Valência' oranges grafted onto 'Rangpur' lime rootstocks in the areas of production in the state of São Paulo. a) RATIO,

b) kilograms of soluble solids, c) citric acid, d) sugar content, e) juice percentage, f) fruit weight and g) number of fruits per box

DEF was the most important water-balance component for VACR qualitative attributes. DEF at bud formation (April) and vegetative dormancy (July) was most important in the forecast models for $BRIX_{MAX}$ and $FRBOX_{APR}$ in MAT and BAU, respectively. DEF did not have a large influence in BEB, with the lowest coefficients in the models that used it. The angular coefficients for $FRBOX_{\text{H,N}}$ in LIM indicated that RET was the most influential variable during fruit growth (October), followed by DEF during vegetative dormancy (July).

Paulino et al. (2007) reported similar results and noted that the number of fruits per plant was significantly correlated with DEF in LIM from July to September of the developmental year.

The models were generally accurate for all four regions. The RATIO, KGSS and WFRUIT models were best for BAU, the ACIDITY, %JUICE and FRBOX models were best for LIM and the BRIX model was best for MAT.

4 Conclusions

Testing all possible combinations for selecting the variables and the use of multiple linear regressions were efficient for developing models to forecast the qualitative attributes of 'Valência' oranges grafted onto 'Rangpur' lime rootstocks for four regions in the state of São Paulo in Brazil.

Accurate models as functions of climatic variables were developed for all months. The minimum forecasting ranges were five months for RATIO, four months for FRBOX, BRIX, ACIDITY and WFRUIT and three months for KGSS and %JUICE for all regions.

Minimum, mean and maximum air temperature and relative evapotranspiration were the most important variables in the models. Water deficit was the most influential waterbalance component on the qualitative attributes of 'Valência' oranges.

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