

Harvest date estimation of ‘Gala’ apples based on environment temperature using artificial intelligence

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Received: 12 September 2022; Accepted: 23 February 2023; doi:10.4067/S0718-58392023000300272

ABSTRACT

Agroclimatic variables in different time windows were analyzed using Artificial Intelligence techniques to estimate the fruit growing season extension and harvest start date for ‘Gala’ apples (*Malus domestica* (Suckow) Borkh.) Meteorology and phenology data were collected from five orchards in Central Chile, between 2004 and 2019. The attributes derived from air temperature during the first days of fruit growing season showed the high relationship with harvest start date: The number of hours below 18 °C from full bloom to 35 d after (R = 0.9) and growing degree hours accumulated from full bloom to 45 d (R = -0.84). Different models were developed with these attributes. Simple and multiple linear regression models were the most accurate for explain the length of the total fruit growth period until harvest. The 35 d after full bloom time window was the most effective, with an $R^2 = 0.82$, for estimating harvest start date of ‘Gala’ apples. These results contribute to the apple growers demand to schedule fruit harvest and processing, especially in a climate change scenario.

Key words: Agroclimate, fruit growth, fruit phenology, *Malus domestica*, regression models.

INTRODUCTION

An estimation of the harvest date for apple trees (*Malus domestica* (Suckow) Borkh.) is decisive for logistic operations and the following post-harvest management. This is particularly relevant with ‘Gala’ apples, due to their fast ripening, extensive area planted, widely distributed throughout Chile, as it is the first apple cultivar to be harvested. Additionally, ‘Gala’ clones have shown distinctive behavior (phenology and ripening) in different microclimates in Chile (Yuri et al., 2011; 2019).

In apple trees, evidence indicates that the ripening process is determined early, in the cell division stage (Tromp, 1997; Warrington et al., 1999). This stage is characterized by the fruit growth through an increased cell number, requiring a high metabolic demand for the internal structure synthesis. Fruit T-stage has been suggested to indicate the end of this phase, and the fruit subsequently continuing to grow by increasing cell volume (Schumacher, 1989).

Environmental conditions, mainly air temperature, would strongly affect cell division stage (Bergh, 1990; Warrington et al., 1999; Stanley et al., 2000). It has been documented that the extent of the cell division stage would be directly related to total fruit growth period, from fruit set to ripening (Warrington et al., 1999; Stanley et al., 2000).

This background has been the basis for the study and models proposal for understanding and estimating apple aspects such as size at harvest (Lötze and Bergh, 2004; Reginato et al., 2019; Marini et al., 2019), soluble solids content (Biegert et al., 2021), and phenology (Kaack and Pedersen, 2010; Darbyshire et al., 2013).

Machine learning is conceived as the process by which a set of systems integrates patterns and relationships through historical information, attempting to answer a particular question. Its purpose is to suggest a model capable of effectively answering that question through a new case information (Pavón and Vega, 2016).

Several studies have reported advances in estimating the influence of climatic variables on the yield and quality of different types of crops using these tools. Using techniques such as Random Forest, Jeong et al. (2016) estimated yield of wheat, corn and potato crops using physiological and environmental variables. It has also been

shown that the use of Supervised Machine Learning techniques can improve the crop estimation accuracy compared to current manual counting techniques.

A study was carried out in Australia seeking to improve crop volume estimates in corn using a combination of agroclimatic variables and satellite information, with vegetation index and chlorophyll fluorescence. For this, Supervised Machine Learning techniques, such as artificial neural networks (ANN) were used, and these data combination predicted yields with a multiple correlation coefficient close to 0.75 (Cai et al., 2019).

The present study focused on identifying the main factors that determine the fruit growing season extension of ‘Gala’ apples, to estimate the beginning of harvest through Artificial Intelligence, which can become a support tool for growers and exporters.

MATERIALS AND METHODS

Background information

Phenology data of ‘Gala’ apples (*Malus domestica* (Suckow) Borkh.) was collected in five commercial orchards in Chile Central Zone (Figure 1), between 2004 and 2019, considering: Full bloom (FB) date (80% flowers open) and beginning of commercial harvest date (given by fruit color and flesh firmness). This information was reported by each grower.

An automatic weather station (AWS) located in each orchard recorded every 15 min readings of: Air temperature (AT), relative humidity (RH), global solar radiation (GSR), wind speed and direction, and precipitation.

Sixteen tuples were obtained, which considered FB dates, harvest start and meteorological records of the fruit growing season (Table 1).



Figure 1. Geographical location of the apple orchards studied.

Table 1. Orchard identification according to location and season with historical data.

Location	Latitude	Longitude	Seasons
San Clemente	35°31' S	71°28' W	2004-2019
Morza	34°23' S	71°02' W	2016-2017
Río Claro	35°20' S	71°21' W	2006-2017
Graneros	34°06' S	70°42' W	2018-2019
Linares	35°53' S	71°31' W	2018-2019

Methodology

The methodology includes mainly the implementation and evaluation of regression models or algorithms. With these methods it is possible to explain and represent the dependence among a response variable Y, and a series of explanatory variables X.

The methodology is based on statistical modeling, which allows all the response variables Y to be decomposed according to the explanatory variables X, as described in Equation 1:

$$Y_i = R(X_{i_1}, \dots, X_{i_m}) + \epsilon_i \quad (1)$$

where R is the function that relates the values of the response variable Y with the explanatory variables; X and ϵ_i correspond to the part of the individual i that cannot be explained by any variable.

Data preprocessing

Data cleansing and standardization is one of the fundamental tasks of Artificial Intelligence (Lomet, 2001). Data from AWS was analyzed to correct measurement units and records losses. For preprocessing, meteorological data from AWS of different orchards was processed to represent the information in agroclimatic variable.

Feature design

Attributes were defined as Agroclimatic Vector constructed by Agroclimatic Variable (calculated from meteorological data) and a Vector (time window), from FB to 25, 35, 45 and 60 d after full bloom (DAFB); Agroclimatic Vector = Agroclimatic Variable \times Vector.

From AT and HR records, daily values of the following agroclimatic variables were calculated: Growing degree days (GDD), growing degree hours (GDH), air stress index (ASI), and hours accumulation with different AT thresholds (Table 2). Meteorological attributes such as maximum, minimum, and daily mean for AT were also included.

Table 2. Agroclimatic and meteorological variable used, description and reference.

Variable	Description and units	Reference
ASI	Air stress index with “stress units” based on air temperature (AT) and relative humidity	Torres et al., 2016
GDH	Growing degree hours according to the ASYMCUR method	Anderson and Seeley, 1992
GDD	Growing degree days in base 10 °C	Stanley et al., 2000
H10	Hours with AT \leq 10 °C	
H7	Hours with AT \leq 7 °C	
H6	Hours with AT \leq 6 °C	
H12	Hours with AT \leq 12 °C	
H18	Hours with AT \leq 18 °C	
D10	Days with 5 h or more with AT \leq 10 °C	
Richardson	Chill units according to Utah or Richardson method	Richardson et al., 1974
Unrath	Chill units according to North Caroline or Unrath method	Shaltout and Unrath, 1983
ET0	Reference evapotranspiration (mm)	FAO, 2006
GSR12	Hours with global solar radiation $>$ 12 W m ⁻²	
SE	Daily solar energy (MJ m ⁻²)	
PP	Daily rain (mm)	
GOH	Growing optimal hours with AT between 20-25 °C	

Feature selection

Feature selection is a powerful tool that allows identifying the main dataset characteristics to make a prediction (Vrigazova and Ivanov, 2019). Pearson’s correlation coefficient is a test that measures the statistical relationship among continuous variables. It is used when associations are expected to act linearly. It was implemented in this study using the R programming language for explain the relationship between Agroclimatic Vectors and harvest start date, and for selecting those with a relevant correlation.

Machine learning and training and testing

Linear regression models were implemented through the Python programming language, using the Scikit-learn library (Pedregosa et al., 2011). Simple and multiple linear regression was performed. The coefficient of determination R^2 was used to evaluate the model construction. The neural network regression model was implemented through the Python programming language, using two libraries: Keras (Arnold, 2017) and TensorFlow (Abadi et al., 2016). The mean absolute error of the models was used to define the artificial neural networks (ANN) conformation and parameterization.

The training of the linear regression models was performed through the use of a *fit()* function included in the Scikit-learn library, for fitting the linear regression parameters to the data.

The neural networks training was performed through the Leave One-Out Cross Validation (LOOCV) method, which allowed to evaluate the results obtained to ensure their independence from the subdivision of the training and test data (Xu et al., 2018).

Two statistical correlation measures were used to evaluate the performance of the models. Mean absolute error (MAE) measures the absolute difference between the prediction and the real value, based on the standard equation of this correlation measure (Chai and Draxler, 2014) and was calculated according to Equation 2:

$$MAE = \frac{1}{n} \sum_{i=1}^n |Y_i - X_i| \quad (2)$$

Mean squared error (MSE) measures the difference between the prediction and the real value considering the number of data used (Jeong et al., 2016) and was calculated by Equation 3:

$$MSE = \frac{\sum_{i=1}^n (Y_i - X_i)^2}{n} \quad (3)$$

where, Y_i represents the observations in the test data sets, and X_i the predictions.

RESULTS AND DISCUSSION

Feature selection

The Agroclimatic Vectors used in this study showed a high correlation and codependence among them (Figure 2). The attribute H18 showed $R = 0.9$ for 35 DAFB and GDH showed $R = -0.84$ for 45 DAFB, when related to the response variable Y (harvest start date).

Attributes at 35 DAFB Vector showed four significant linear relationships, including: H18 ($R = 0.90$), GDD ($R = -0.88$), GDH and daily AT mean ($R = -0.85$). The Attributes at 25 and 60 DAFB showed only one significant relationship.

Pearson's correlation results show that Attributes with the highest R values correspond to those derived from the AT recorded during the four DAFB Vectors (Figure 2). Simple linear regression, multiple linear regression and ANN models were estimated with these Attributes.

The regulatory role of temperature in fruit development and growth is well known, as it determines the speed of biochemical processes. These reach its maximum rate with AT range between 20 and 30 °C (Rom, 1996).

An increase of mean AT since FB to harvest date resulted in a shorter fruit growing season for 'Fuji' and 'Gala' apples, analyzing different growing sites and seasons (Argenta et al., 2022), and for 'Conference' pears, comparing growing seasons (Lysiak, 2022). Argenta et al. (2022) noted that the effect of site on the growing season length was greater for 'Gala' than 'Fuji' apples, indicating a cultivar and/or maturation date of fruit response to spring temperature.

Our results agreement with studies that related apple ripening progress to AT in the first weeks of fruit growth (Tromp, 1997; Warrington et al., 1999). Moderate AT conditions post fruit set have been associated with a longer cell division stage, resulting in an extended total fruit growth period (Stanley et al., 2000). These thermal conditions post bloom have effect on cell number and size, leading to denser apples (Atkinson et al., 2001). In warmer spring areas, a more accelerated and shorter cell division period is observed resulting in suboptimal develop of fruit structural components, especially membranes and cell walls (Tromp, 1997; Atkinson et al., 2001; Lachapelle et al., 2013). This would lead to an accelerated drop of ripening indices than in colder areas (Tromp, 1997; Warrington et al., 1999). Accelerated ripening of 'Gala' apples in warm areas could compromise postharvest shelf life, especially when harvesting is delayed in expectation of red coloration (Yuri et al., 2019).

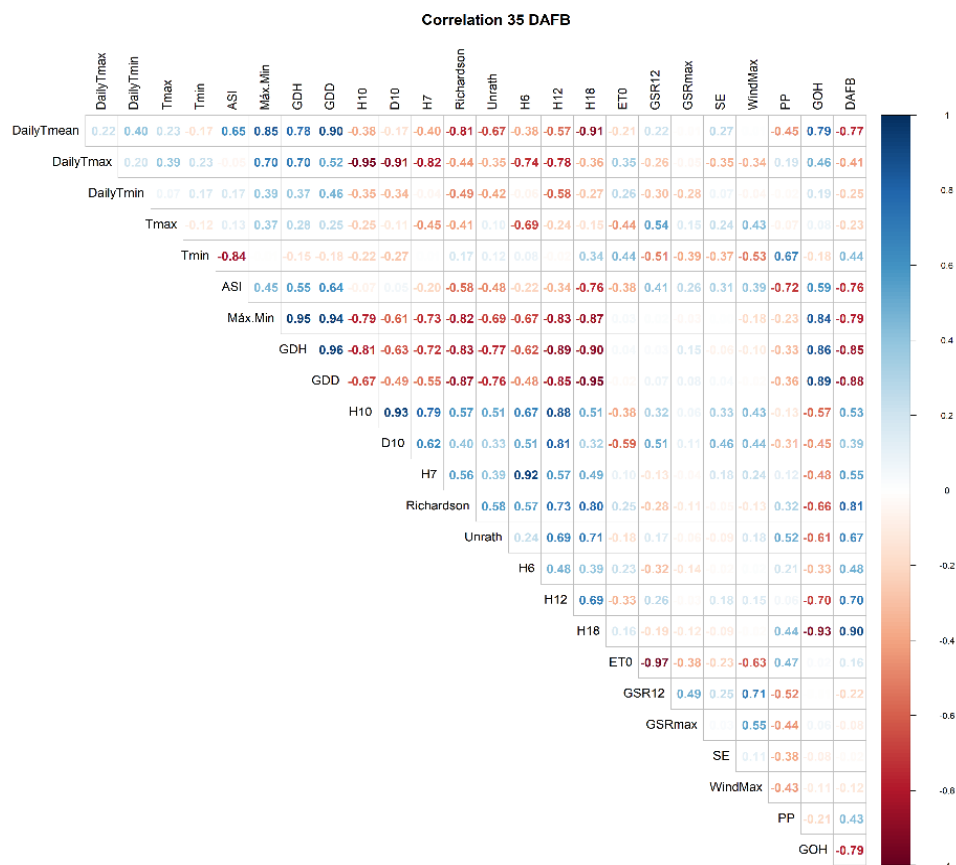


Figure 2. “Pearson correlation”, the image shows the R of the correlations among the explanatory variables (X) and the response variable (Y) at 35 d after full bloom (DAFB). DailyT_{max}: Maximum daily temperature; dailyT_{min}: daily minimum temperature; T_{max}: maximum temperature; T_{min}: minimum temperature; ASI: air stress index; Max.Min: maximum temperature of daily minimum temperatures; GDH: growing degree hours; GDD: growing degree days; H10: hours with air temperature (AT) ≤ 10 °C; D10: days with 5 h or more with AT ≤ 10 °C; H7: hours with AT ≤ 7 °C; Unrath: chill units according to Unrath method; H6: hours with AT ≤ 6 °C; H12: hours with AT ≤ 12 °C; H18: hours with AT ≤ 18 °C; ET0: reference evapotranspiration; GSR12: hours with global solar radiation > 12 W m⁻²; GSR_{max}: SE: daily solar energy; Wind_{max}: maximum daily wind speed; PP: daily rain; GOH: growing optimal hours with AT between 20-25 °C.

According to the AT importance in tree fruit physiology, time-thermal accumulation systems have been proposed, such as GDH (Anderson and Seeley, 1992) and GDD; both considering a base T° (4 °C for GDH and 10 °C for GDD). The GDD has proved to be more effective when the input is limited with a maximum T° threshold, although it would not be useful during spring, since AT rarely exceed 30 °C.

Based on this background, it was expected a high correlation between GDH and GDD at cell division phase with the length from FB to harvest start. The number of hours of AT below 18 °C (H18) can be considered in the same kind of time-thermal variables, since it is equivalent to the exposure of hours with AT above 18 °C.

Rodrigues et al. (2022), calculating GDD accumulation for each phenological stage from dormant bud to ripe fruit of several seasons, founded that GDD quantity varied and can be estimate according with the chilling hours accumulation in dormancy. Chill and heat accumulation interaction should be addressed in future work, beyond the estimation of bloom date, as has been proposed (Pope et al., 2014; Kaufmann and Blanke, 2019).

Training and testing

The Attributes with the higher R values of the 35 and 45 DAFB were used to generate simple linear regression models (Figure 3). The model at 35 DAFB showed an MSE = 3.84 with an $R^2 = 0.8$, and at 45 DAFB an MSE = 5.82 with an $R^2 = 0.7$. The linear training model result indicated that H18 was the most stable Attribute for estimating the harvest start date at 35 DAFB. A combination of the Attributes with the highest R at 35 and 45 DAFB reduce the MAE (Table 3). However, the MAE reduction is mainly explained by the contribution of Attributes at 35 DAFB (GDD and H18).

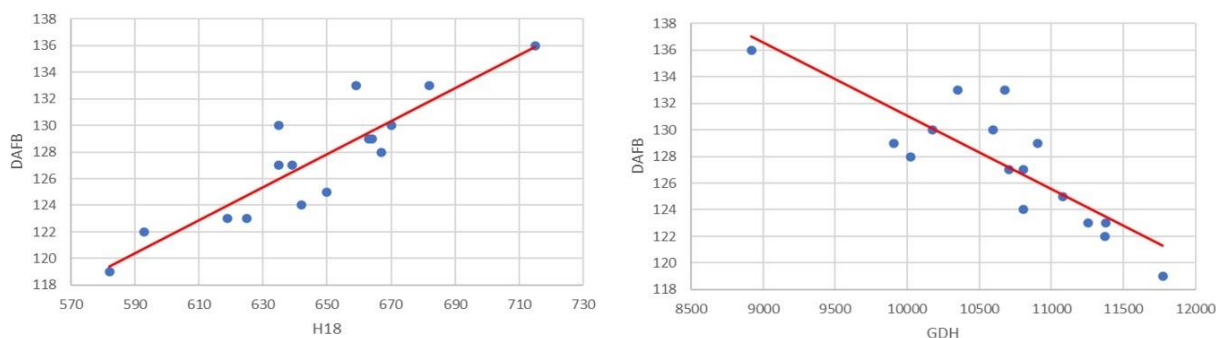


Figure 3. Linear regression for the 35 d after full bloom (DAFB) Vector (left) with number of hours of air temperature below 18 °C (H18), and at 45 DAFB with growing degree hours (GDH) (right).

Table 3. Vectors, attributes, mean absolute error (MAE) and coefficient of determination (R^2) of the linear regression training models. *Attribute at 35 d after full bloom (DAFB); **Attribute at 45 DAFB. AT: Air temperature; GDH: growing degree hours; GDD: growing degree days; H18: hours with AT ≤ 18 °C; GOH: growing optimal hours with AT between 20-25 °C.

Vector	Agroclimatic attributes	MAE	R^2
35 DAFB	Daily AT mean, GDH, GDD, H18	3.60	0.82
45 DAFB	GDH, Richardson, GOH, H18	5.02	0.74
Combination	GDD*, H18*, GDH**, Richardson**	3.50	0.83

Artificial neural networks

The parameterization of the artificial neural networks (ANN) was generated using 20% of the data set, with a 4.3 error rate. Finally, the ANN model was defined with three layers and 5500 iterations.

The LOOCV method was used to training the model. At both, 35 and 45 DAFB the ANN showed lower results than the multiple linear regression models. However, the 35 DAFB Vector showed the lower MAE and higher R^2 (Table 4).

Table 4. Artificial neuronal network training model results. MAE: Mean absolute error; DAFB: days after full bloom; AT: air temperature; GDH: growing degree hours; GDD: growing degree days; H18: hours with AT ≤ 18 °C; GOH: growing optimal hours with AT between 20-25 °C.

Vector	Agroclimatic attributes	MAE	R^2
35 DAFB	Daily AT mean, GDH, GDD, H18	5.92	0.70
45 DAFB	GDH, Richardson, GOH, H18	7.11	0.65

Based on the high correlation of the Attributes used in the study, the linear regression models presented best results over ANN, due to the direct and inversely proportional relationship among Agroclimatic Attributes and the extension of the fruit growth period until harvest. Thus, the selected Attributes would allow harvest start prediction model.

CONCLUSIONS

Artificial Intelligence techniques allowed recognizing the Agroclimatic Variables and the most relevant Vector in days after full bloom (DAFB) to estimate harvest start for ‘Gala’ apples.

The Attributes selected through Pearson’s correlation agreed with research on apple phenology and physiology. The diverse Agroclimatic Variables derived from air temperature presented the closer relationships with harvest start for ‘Gala’ apples. The number of hours below 18 °C in the first 35 DAFB was the most relevant Agroclimatic Vector. Simple and multiple linear regression models were the most accurate in predicting the harvest start of ‘Gala’ apples.

The findings of this study contribute to growers to program fruit harvesting and processing, especially in the uncertain scenario due to climate change. Future models for fruit grower industry based on Artificial Intelligence techniques should consider agroclimatic variables and fruit physiology.

Author contributions

Conceptualization: J.A.Y., A.S. Methodology: Y.G., A.S. Software: Y.G. Validation: Y.G. Formal analysis: Y.G., A.S. Investigation: Y.G., A.S. Resources: J.A.Y. Data curation: Y.G. Writing-original draft: Y.G., A.S. Writing-review & editing: J.A.Y. Visualization: A.S. Supervision: J.A.Y. Project administration: J.A.Y. Funding acquisition: J.A.Y. All co-authors reviewed the final version and approved the manuscript before submission.

Acknowledgements

The authors would like to acknowledge the Fundación para la Innovación Agraria (FIA) through the project “Indicadores nutricionales y agroclimáticos para la producción de cerezas de alta calidad bajo cubiertas plásticas: una estrategia de adaptación microclimática” (PYT-2019-0352) for the support.

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