Developing a Web-based Pistachio Nut Growth Prediction System for Orchard Management

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Abstract. A web-based system was developed for pistachio (*Pistacia vera* L.) growers to predict nut growth from pericarp expansion through endocarp hardening, embryo development, and harvest date. Based on 3 years of data, a Gompertz nonlinear function was fitted to describe and predict growth of pistachio endocarp volume, embryo length, and shell firmness as a function of heat units for six pistachio cultivars. The web application is built on a reactive programming framework that couples a user-friendly interface with a regression engine that dynamically queries both recent and historic weather databases. The interface presents results based on a nonlinear model describing pistachio nut growth, which is the core of the system. The long-term purpose of this system is the prediction of critical growth stages to facilitate pest management, irrigation scheduling, and optimal harvest date.

Pistachio (*Pistacia vera*) is the second most economically valuable nut crop in California, USA, second only to almond (*Prunus amygdalus* L.). Pistachio nut growth has three stages: hull and shell (pericarp) expansion,; shell (endocarp) hardening; and kernel (embryo) growth. Plants have specific heat unit accumulation requirements for growth and development. Predicting pistachio nut growth and development can aid irrigation, pest management, and harvest scheduling (Goldhamer and Beede 2004; Haviland et al. 2016). Most growth models reflect and predict plant development as a function of heat unit accumulation (Godoy et al. 2008; Panta et al. 2023). Our previous research found a suitable nonlinear model to predict pistachio fruit and kernel development and indicated that the growth of nuts is a function of heat (Zhang et al. 2021). When calculating heat accumulation, the lower threshold temperature is crucial. The base temperature for heat accumulation during the growth season is crop-specific, but it is generally ≤7 °C; 5 °C was used for apple (*Malus domestica* Borkh.) in New Zealand (Stanley et al. 2015), 7 °C was used for blueberry (*Vaccinium corymbosum* L.) (Godoy et al. 2008), and 7 °C was for peach [*Prunus persica* (L.) Batch] (Marra et al. 2002). In the pistachio nonlinear model, we used 7 °C as the lower temperature limit, and the accumulation of heat units began when female trees were at 50% full bloom according to the visual estimate (Zhang et al. 2021).

Researchers have used crop models for years, but they have had limited success making them producer-friendly. Web interfaces of heat-based pest phenology models are used to predict insect pest pressure associated with integrated pest management (IPM) strategies (Damos 2015; Jones et al. 2010). The web-based decision support systems WebGro (Paz et al. 2004), which helps soybean [*Glycine max* (L.) Merr.] producers understand how different stresses interact to limit yield in their fields, and SSD Manzano, which is used for the diagnosis and control of pests in apple orchards (Mondino and Gonzalez-Andular 2019), are integrated crop management programs that consider not only disease and pest management but also weed and environmental stress. Some models have been developed to describe tree fruit and nut development (Panta et al. 2023; Salinas et al. 2019; Zhang et al. 2021); however, only a few have been converted into grower-friendly computer-aided systems. To create an effective web-based decision support tool, the model is fundamental for decision-making, and real-time temperatures are required for management (Damos 2015). Processing climate data in real time to match the frequency of updates on servers has been realized with IPM computer-aided precision support systems (Strand 2000), such as the NEWA website (newa.cornell.edu), which provides real-time decision support for fruit IPM and production and is operated and maintained by Cornell University (Carroll et al. 2017).

Recently, artificial intelligence (AI) and machine learning (ML) have been used for precision agriculture applications and the development of plant management decision-making tools (Abdulridha et al. 2020a, 2020b; Ampatzidis et al. 2017). For example, some studies have developed computer and web-based tools for disease detection and identification in fruit crops based on visual symptoms on leaves using AI (Cruz et al. 2017, 2019). Ampatzidis and Partel (2019) and Ampatzidis et al. (2020) developed a cloud-based application, named Agroview, to process, analyze, and visualize data collected from aerial [e.g., unmanned aerial vehicles (UAVs), satellites] and ground-sensing platforms using ML. Agroview is a user-friendly application that converts spectral data (e.g., multispectral and color images) to practical information. The approach can provide a plant inventory, plant volume, plant health/stress status, and plant nutrient concentration. Agroview was used as a high-throughput phenotyping tool to evaluate several citrus rootstocks and varieties during large-scale experiments in Florida, USA (Ampatzidis et al. 2019), and it can be used to predict yield (Vijayakumar et al.

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2021) and fruit quality (Ojo et al. 2021). Costa et al. (2020) used machine vision and AI to develop a tool that can automatically determine leaf stomata properties of citrus trees and potentially other crops. Costa et al. (2021) developed a computer vision tool to measure pecan nut growth to gain a better understanding of and predict the fruit growth curve. Later, the team used deep learning for object detection and semantic segmentation to estimate the area of the shuck, shell, and embryo on pecans during multiple growth stages (Panta et al. 2023). This automated tool provides a multidimensional understanding of nut development and the ability to model nut growth phenology and predict nut productions.

The objective of this research was to develop a user-friendly web-based decision support tool for growers to predict pistachio developmental stages of six cultivars planted in different locations.

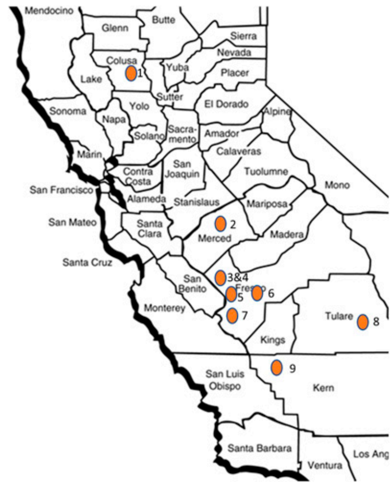

Fig. 1. Sampling locations at nine orchards in the main pistachio planting areas in Colusa, Fresno, Kern, Tulare, and Merced counties in California, USA. Location 1: 39.01°N, −122.03°W. Location 2: 37.05°N, −120.16°W. Location 3: 36.71°N, −120.48°W. Location 4: 36.69°N, −120.47°W. Location 5: 36.63°N, −120.39°W. Location 6: 36.60°N, −119.51°W. Location 7: 36.13°N, −120.10°W. Location 8: 35.94°N, −119.12°W. Location 9: 35.60°N, −119.56°W.

Materials and methods

Pistachio nut growth development models

Zhang et al. (2021) conducted a 3-year experiment (2014, 2016, and 2017) in the pistachio primary planting region of California, USA, to model its nut growth. Nuts of six pistachio cultivars, Kerman, Golden Hills, Lost Hills, Kaleghouchi, Pete1, and Aria, were collected from eight orchards distributed in north Sacramento Valley (Colusa County) and San Joaquin Valley (Fresno, Kern, Tulare, and Merced counties) (Fig. 1). Details of the geography (e.g., latitude, longitude, elevation, and soil type) and plant information (e.g., rootstock and year planted) of each location and cultivar are listed in Table 1 (Zhang et al. 2021).

The accumulation of heat units began when a visual estimate indicated 50% full bloom on female trees. Three trees of each cultivar with similar tree vigor and canopy size were selected for sampling at each location. One randomly selected cluster of nuts in each side (north, south, east, and west) was collected and 10 terminal nuts of each of the four clusters were picked for further measurement. Nuts were sampled weekly from each location from fruit set through harvest (April–September), and nut volume, shell hardness, and embryo length were measured and recorded (Zhang et al. 2021). The fitting to the multiyear and multilocation data model, four nonlinear model:three-parameter logistic model, Michaelis-Menten model, Gompertz model, and asymptotic with offset model were applied and compared through the evaluation of residual distribution, *P* value of the fixed effects on parameter values, R^2, and Akaike information criterion. The Gompertz model was selected because it fit all three growth stages (nut volume, shell hardness, and embryo length) better than the other models (Zhang et al. 2021). The Gompertz function is presented in Eq. [1]:

$$y(x) = Asym \times exp[-b \times c^x] \quad [1]$$

where y represents the expected value of each trait (nut volume, shell hardness, and embryo length), Asym is the asymptote, b translates the curve in the x axis, c determines the growth rate, and x is the accumulated heat units.

The web-based decision support tool in this research was based on the Gompertz model, and the goodness of fit of this model for our datasets has been discussed previously paper (Zhang et al. 2021). The constant values of Asym, b, and c in the fitted Gompertz function for nut volume, shell hardness, and embryo length are listed in Table 2. The characteristics of nut growth (nut volume, shell hardness, and embryo length) fitted by the Gompertz model of one cultivar, Kerman, have been demonstrated (Zhang et al. 2021). Table 3 shows the predicted 'Kerman' nut growth values at different heat accumulations fitted by the Gompertz function starting at 50% full bloom.

Web application

The web application was built with the R open-source computational programming language (R Core Team 2023) using the Shiny reactive programming framework (Chang et al. 2023). Shiny is an R package that creates lightweight, standalone interactive web applications written entirely in the R programming language (Beeley and Sukhdeve 2018). Shiny web apps bind a traditional HTML5 user interface with functions written in R. When users interact with elements of the web app, reactive chains are triggered on the backend that run code and update linked objects. The architecture of the Pistachio Nut Development Decision Support Tool web app can be divided into the following four interconnected elements: user interface, prediction function, weather data, and regression engine and report generator.

User interface. The web app may be accessed at https://ucanr-igis.shinyapps.io/pist_gdd/ using any modern web browser (e.g., Edge, Chrome, Firefox) (Fig. 2). In addition to the nut development prediction calculator, the web app provides extension resources regarding how the underlying model works, photos to help users identify the biofix date (50% full bloom), instructions

Table 1. Description of collection sites and cultivars including sampling year, locations, elevation, soil type, and rootstocks of pistachio orchards used in this study (Zhang et al. 2021).

		Plant information			Geographical information			
Locations	Sampling yr	Cultivar	Rootstock	Yr planted	Latitude	Longitude	Elevation (m)	Soil type
Huron	2014	Kerman	*P. integerrima*	2006	36.13°N	−120.10°W	115.26	Panoche sandy loam
		Golden Hills	Clonal UCB1	2008				
		Pete1	*P. integerrima*	2006				
Wasco	2014	Kerman	Clonal UCB1	2005	35.60°N	−119.56°W	81.99	Kimberlina sandy loam
	2016	Golden Hills	Clonal UCB1	2005				
	2017	Lost Hills	Clonal UCB1	2005				
		Kalehghouchi	Clonal UCB1	2005				
		Pete1	Clonal UCB1	2005				
Tranquility	2014	Lost Hills	Seedling UCB1	2005	36.63°N	−120.39°W	61.28	Fresno clay
		Pete1	Seedling UCB1	2006				
Mendota (Coit Ranch)	2014	Kerman	Clonal UCB1	2005	36.69°N	−120.47°W	79.93	Panoche loam
	2016	Pete1	Clonal UCB1	2006				
	2017							
Mendota (Mitch Ranch)	2016	Kerman	Clonal UCB1	2006	36.71°N	−120.48°W	79.80	Panoche loam
	2017							
Terra Bella	2014	Golden Hills	Clonal UCB1	2006	35.94°N	−119.121°W	127.08	Centerville clay
		Lost Hills	Clonal UCB1	2006				
	2016	Kerman	Clonal UCB1	2006				
	2017							
Madera	2014	Golden Hills	Clonal UCB1	2007	37.05°N	−120.159°W	76.88	Clay hardpan
		Lost Hills	Clonal UCB1	2007				
Arbuckle	2016	Kerman	*P. integerrima*	2005	39.01°N	−122.03°W	43.00	Millholm-Contra Costa complex
	2017							
Parlier	2016	Kerman	Seedling UCB1	2008	36.60°N	−119.51°W	104.85	Hanford sandy loam
	2017	Golden Hills	Seedling UCB1	2008				
		Lost Hills	Seedling UCB1	2008				
		Kalehghouchi	Seedling UCB1	2008				
		Pete1	Seedling UCB1	2008				
		Arial	Seedling UCB1	2008				

Table 2. Constant values of Asym, b, and c according to the Gompertz model for predicting pistachio nut volume, embryo length, and shell firmness of 'Kerman' based on multiyear and multilocation data (Zhang et al. 2021).

Nut growth	Asym	b	c
Nut volume	3036 (mm^3)[i]	5.9	1.0
Shell hardness	23.9 ($lb{\cdot}3\ mm^{-2}$)[ii]	6.0	1.0
Embryo length	19.2 (mm)[iii]	35.4	1.0

[i] $1\ mm^3 = 6.1024 \times 10^{-5}\ inch^3$.
[ii] $1\ lb{\cdot}mm^{-2} = 645.16\ lb{\cdot}inch^{-2} = 0.4536\ kg{\cdot}mm^{-2}$. The penetrometer needle used to determine firmness is 3 mm in diameter. The data were the reading values obtained using the device. The unit was $lb{\cdot}3\ mm^{-2}$.
[iii] 1 mm = 0.0394 inch.

for using the prediction calculator, interpreting the outputs, and using the results for orchard management. There is also a web form for submitting feedback and asking questions.

The user interface presents the model parameters and output settings in a simple interface that performs well on a range of screen sizes. The user first selects their location either from an interactive map or by entering longitude and latitude coordinates. Then, they select their pistachio cultivar, biofix date, end date, and percentage of the maximum asymptote to highlight in the output (default value of 90%). They may also select a range of years to use as the historical baseline for comparison purposes and proxy for the rest of the season.

Prediction function. The prediction function is based on the best selected nonlinear model, the Gompertz model. This function can be represented as follows:

$$z(x) = 100exp[-b \times c^x] \quad [2]$$

where b and c are constants calculated by the selected model and x is the total thermal unit starting from the user input start date (50% full bloom date) to the end day (prediction date) collected from. Constant values (i.e., b and c) are different for the prediction function of

Table 3. Identify pistachio nut volume, shell hardness, and embryo length of 'Kerman' as functions of heat accumulation and measurement starting at 50% full bloom.

	Heat accumulation (units)									
Nut growth	250	500	750	1000	1250	1500	1750	2000	2250	2500
Nut volume (mm^3)[i]	1202	2770	3009	3033	3036	3036	3036	3036	3036	3036
Shell hardness ($lb{\cdot}3\ mm^{-2}$)[ii]	0.9	3.9	8.8	13.8	17.8	20.4	22.1	23.0	23.6	23.9
Embryo length (mm)[iii]	0.0	0.0	0.7	4.3	9.8	14.3	16.9	18.3	18.9	19.2

[i] $1\ mm^3 = 6.1024 \times 10^{-5}\ inch^3$.
[ii] $1\ lb{\cdot}mm^{-2} = 645.16\ lb{\cdot}inch^{-2} = 0.4536\ kg{\cdot}mm^{-2}$. The penetrometer needle used to measure firmness is 3 mm in diameter. The data were the reading values obtained using the device. The unit was $lb{\cdot}3\ mm^{-2}$.
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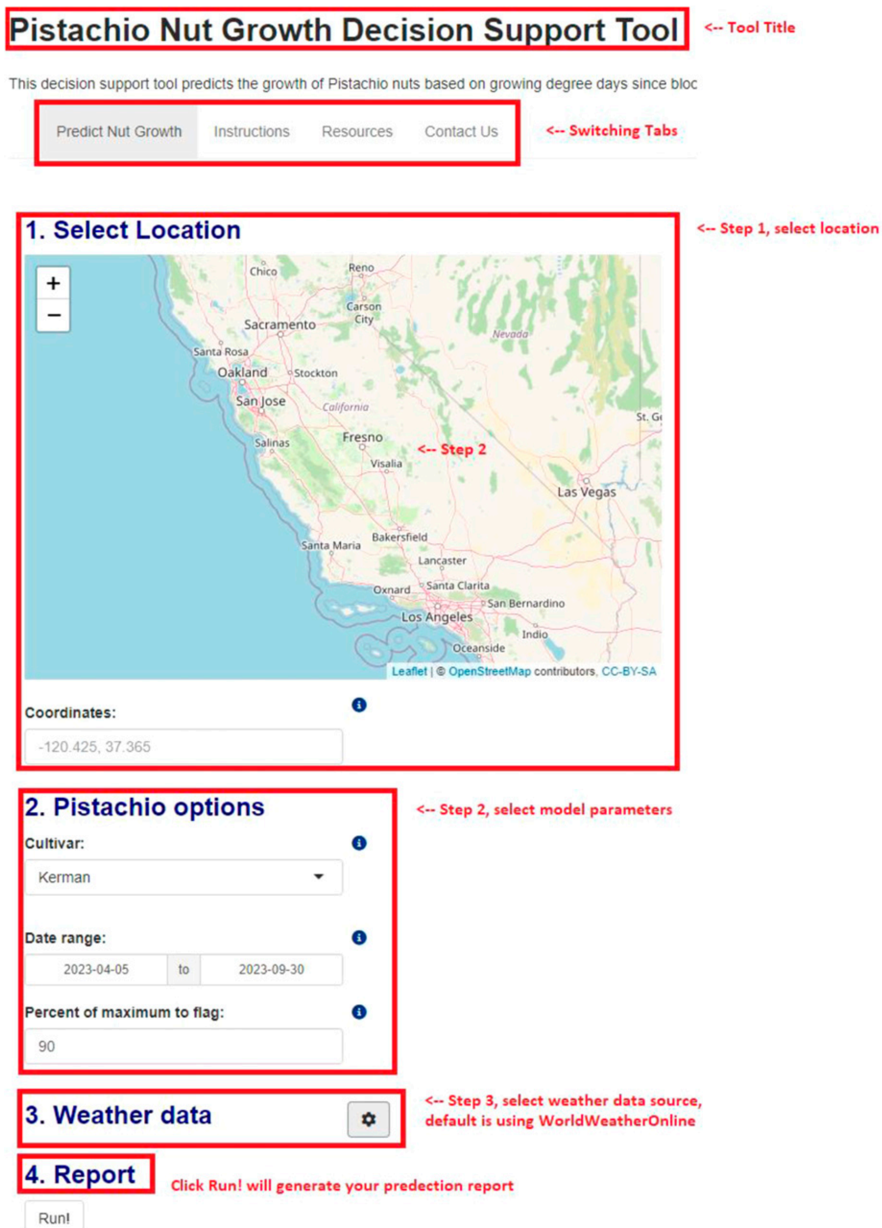

Fig. 2. Overview of the pistachio nut development decision support tool (Tool Title) website. All components are circled in red. Switching tabs include "Predict Nut Growth" (the main tool page), "Instructions" (detailed contents about the tool), "Resources" (supplemental reading materials), and "Contact Us," which includes a survey for the Pistachio Nut Development Decision Support Tool. Users are required to follow three steps to generate a new report (NOTE: clicking the i icon will pop the instructions). Step 1: input or select coordinates. Users can input the geography coordinates or click the map to select the location. Step 2: enter the model parameters. The default cultivar is Kerman. Change the date range to match your date. Step 3: select the weather data source. The default weather data source is "World Weather Online." Click "Run!". A report will be generated.

nut volume, shell hardness, and embryo length (Table 2).

Weather data. Two periods of weather data are needed to run the prediction model: observed temperatures from the biofix date to the present date and forecast temperatures from the present date to the end of the analysis (typically harvest). Recent weather and the 10-d forecast are accessed from a REST (REpresentational State Transfer) API (application programing interface) service provided by World Weather Online (https://www.worldweatheronline.com/). Beyond the 10-d forecast, the historic average for the location of interest is used as a proxy for the rest of the season because the reliability of deterministic weather forecasts is limited to 8 to 10 d (Zhang et al. 2019). The historic baseline for the location of interest is extracted from the Livneh dataset, which comprises gridded weather variables interpolated from meteorological stations for the period from 1950 to 2013 (Livneh et al. 2015). The Livneh data are hosted on Cal-Adapt (Thomas et al. 2018) and accessed via a REST API using the caladaptR package (Lyons and R Development Core Team 2022a).

Regression engine and report generator. To run the prediction function, after retrieving weather data, the web application computes daily heat units for the past and future temperature data. Heat units are computed using the simple average degree day method (Lyons and R Development Core Team 2022b) using a base temperature of 7 °C. The fitted Gompertz curve is computed with the coefficients for the selected cultivar, which is then used to identify the dates when the required quantity of accumulated heat units are reached for the user's preferred threshold value. Results are presented to the user in a series of interactive charts and a table of predicted dates for the nut development milestones.

Results and discussion

After a user enters the location, cultivar, date range, and percent asymptote, the inputs are verified to prevent errors. Clicking the "Run" button triggers a reactive function that retrieves weather data, computes the thermal units, computes the regression curves, and generates output. Figures 3 and 4 present an example of the prediction results displayed on the web interface in a text table and a linear plot, respectively.

The design allows users to predict different cultivars (Fig. 2). As discussed, the Gompertz model ideally fits pistachio nut growth. Our previous research (Zhang et al. 2021) showed that only the fixed effect of a cultivar had a significant effect on all three constants (Asym, b, c) for all three traits (nut volume, shell hardness, embryo length) in the Gompertz model, which demonstrated that the Gompertz model can predict pistachio nut growth by cultivar. The combination of site and year are the random samples of the population; therefore, if the models are well-fitted, then they can be used to predict pistachio nut growth of the six cultivars across different locations and years. The interface can be used by growers in different locations in California, USA, because the data are used to fit the data covering most pistachio planting areas.

The nuts sampled can only approach the asymptote, maximum nut volume, firmness, and embryo length. Therefore, the estimated thermal units necessary to reach 90% of the maximum value are recommended in this model. However, users can select the "percent of maximum to flag" (Fig. 2). Because this website can predict up to 10 d ahead, this system can help growers predict harvest dates up to 10 d in the future. The ability to predict harvest could avoid late season navel

Fig. 3. Reporting. All components are circled in red. The input summary shows the response after users input the required information and follow the steps. Step 1: input or select coordinates. Step 2: enter the model parameters. Step 3: select the weather data source in Fig. 2. In the graphic view, the orange curve is the current season thermal unit accumulation calculated based on the current year weather, the blue curve is thermal unit accumulation for 10 d based on 10-d weather prediction, and the green curve shows the historical average thermal unit accumulation using previous years' weather data and the historical data range selected by users. The result summary "nut development milestones" is the prediction result of 'Kerman' nut growth. "Percent max" is the percentage of maximum value. Figure 4 demonstrates 90% of the maximum values predicted by the Gompertz model. Values are volume, firmness, and embryo length at 90% of model predicted maximum values. The predictions are for 10 d. If the prediction date (current date + 10 d) is earlier than the date when nuts reach 90% of maximum growth, then the "estimated date" in the table "nut development milestones" will show "beyond analysis end date."

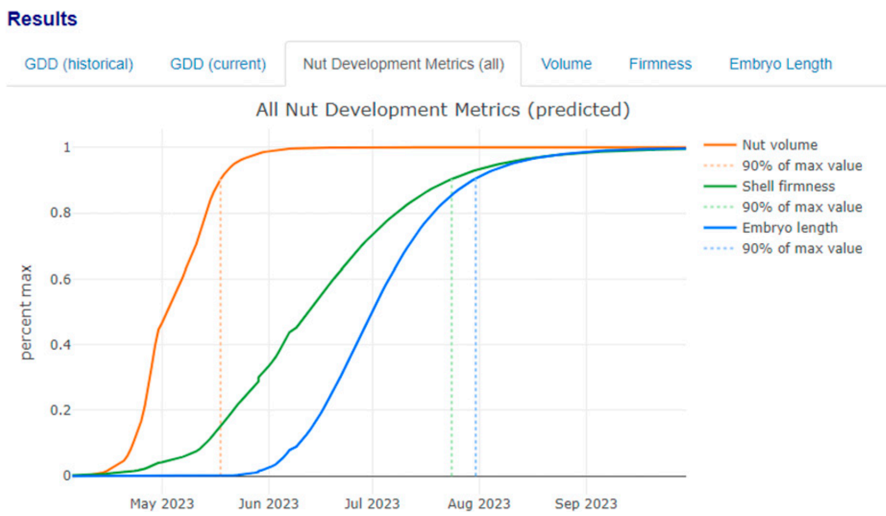

Fig. 4. Predicted pistachio nut growth including volume, firmness, and embryo length based on the Gompertz model (Zhang et al. 2021), current year weather, and 10-d predicted weather. Values pointed out using dotted lines are expressed as a percentage (90%) of the model's maximum values. The orange curve and dotted line represent nut volume, the green curve and dotted lines represent nut firmness, and the blue curve and dotted line represent embryo length.

orangeworm (*Amyelois transitella*) infestation, which is now the most serious pest problem for California pistachio, and allow better insecticide application timing. It causes direct damage and spreads the endemic fungus *Aspergillus flavus*, which generates the potent liver carcinogen, aflatoxin (Doster and Michailides 1994). The ability to predict harvest time also facilitates efficient scheduling with the harvesting contractor and processing plant.

Previous research demonstrated that the mechanism of shell split is a function of the physical force exerted on the shell suture by kernel growth (Polito and Pinney 1999). Nonsplit nuts have less commercial value. Our research (Zhang et al. 2018) of nut split rate revealed a strong relationship between nut split and heat based on the coefficient of determination (R^2 = 0.822). The results also demonstrated that nut split as a percentage of 'Kerman' nuts sampled at 2000 heat units increased ∼60% with an additional 600 heat units. With additional data, the percentage of nut split could be added to the model, further enhancing the value for harvest prediction.

In many plants disease identification and decision systems, the pictures, descriptions, and links between diseases and characteristics are defined and inserted for web inquiries (Mondino and Gonzalez-Andular 2019; Pertot et al. 2012). This provides users with a visual guide and convenient method of prediction. However, at this time, no visual parameters (e.g., pictures of nuts) have been included in this model because the parameters measured were growth parameters. Further coding work could be designed to provide users with this information when a visible parameter, perhaps shell split width, can be incorporated into the model.

Conclusion

Pistachio nut growth, including nut volume, shell firmness, and embryo length, were fitted to the Gompertz model. Using local historical data and the growth curve predicted by the Gompertz model, a web interface was developed that can predict the nut growth of six different pistachio cultivars. With this user-friendly interface, growers, consulting companies, and researchers only need to input cultivar, bloom date, and field location to predict the nut growth volume, embryo length, and shell firmness of pistachio fruit. Heat units were used for these predictions. In the future, new technologies that incorporate the gathering of real-time data (e.g., soil, water, and light) and machine learning will be used to improve the predictive ability of the existing model.

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