World Journal of Fungal and Plant Biology 2 (3): 65-69, 2011
ISSN 2219-4312

Modeling of Nectarine Mass Based on Geometrical Attributes

Fereydoun Keshavarzpour

Department of Agriculture, Shahr-e-Rey Branch,
Islamic Azad University, Tehran, Iran

Abstract: In this study, eighteen linear regression models for modeling nectarine mass from some geometrical attributes of nectarine such as major diameter (a), intermediate diameter (b), minor diameter (c), geometrical mean diameter (GMD), first projected area (PA_1), second projected area (PA_2), third projected area (PA_3), criteria area (CAE), estimated volume based on an ellipsoid assumed shape (V_{Ell}) and measured volume (V_M) were suggested. Models were divided into three main classifications, i.e. first classification (outer dimensions), second classification (projected areas) and third classification (volumes). The statistical results of the study indicated that in order to predict nectarine mass based on outer dimensions, the mass model based on GMD as M = - 112.4 + 3.624 GMD with $R^2 = 0.95$ can be recommended. Moreover, to predict nectarine mass based on projected areas, the mass model based on CAE as M = - 26.46 + 4.838 CAE with $R^2 = 0.95$ can be suggested. Besides, to predict nectarine mass based on volumes, the mass model based on V_{Ell} as $M = 2.401 + 1.006\ V_{Ell}$ with $R^2 = 0.98$ can be utilized. These models can also be used to design and develop sizing machines equipped with an image processing system.

Key words: Nectarine · Mass · Modeling · Outer dimensions · Projected areas · Volumes

INTRODUCTION

Peaches and nectarines belong to the Rosaceae family and are thought to have originated in China [1]. Chinese literature dates cultivation of the peach in China to 1000 B.C. and it was probably carried from China to Persia (Iran). Peach, at one time called "Persian apple", quickly spread from there to Europe. In the 16th century, it was established in Mexico and in the 18th century Spanish missionaries introduced the peach to California, which turned out to be the most important production area after China and Italy [2]. Like other stone fruits, peaches and nectarines, both closely related [3], have a characteristic, lignified endocarp (pit or stone) that encloses the seed, a fleshy mesocarp and a thin exocarp. However, nectarine cells have smaller intercellular spaces than peaches and are, therefore, denser. In addition, they lack pubescence on the skin, which is controlled by a single gene [4]. On the basis of the separation of the stone from the flesh, peaches and nectarines can be divided into two groups: freestone and clingstone. In addition, based on the amount of softening of the flesh that occurs during ripening, peaches and nectarines can be either of a melting or non-melting type [5]. Most cultivars have yellow flesh, but white-fleshed cultivars have always been known and are being increasingly planted and currently are 30% of the plantings of the yellow flesh cultivars. The peel of both types may be highly colored due to the accumulation of anthocyanin. Peaches and nectarines with low, medium or high acid concentrations are also available [6]. Peaches and nectarines are also rich in ascorbic acid (vitamin C), carotenoids (provitamin A) and phenolic compounds that are good sources of antioxidants [7]. Currently, world production of peaches and nectarines stands at 11 million tones, with the three major producing countries being China, Italy and the United States in the Northern hemisphere and Chile, South Africa and Australia in the Southern hemisphere. All of these different combinations of fruit types, i.e. peach or nectarine, clingstone or freestone, yellow or white flesh, low, medium or high acidity, are available as freshly harvested fruit from April through September in the Northern Hemisphere and from November to March in the Southern Hemisphere [8].

Corresponding Author: Fereydoun Keshavarzpour, Department of Agriculture, Shahr-e-Rey Branch, Islamic Azad University, Tehran, Iran

Similar to other fruits, nectarine size is one of the most important quality parameters for evaluation by consumer preference. Consumers prefer fruits of equal size and shape [9]. Sorting can increase uniformity in size and shape, reduce packaging and transportation costs and also may provide an optimum packaging configuration [10-13]. Moreover, sorting is important in meeting quality standards, increasing market value and marketing operations [14-16]. Sorting manually is associated with high labor costs in addition to subjectivity, tediousness and inconsistency which lower the quality of sorting [17]. However, replacing human with a machine may still be questionable where the labor cost is comparable with the sorting equipment [18]. Studies on sorting in recent years have focused on automated sorting strategies and eliminating human efforts to provide more efficient and accurate sorting systems which improve the classification success or speed up the classification process [19, 20].

Physical and geometrical characteristics of products are the most important parameters in design of sorting systems. Among these characteristics, mass, outer dimensions, projected areas and volume are the most important ones in sizing systems [21-24]. The size of produce is frequently represented by its mass because it is relatively simple to measure. However, sorting based on some geometrical attributes may provide a more efficient method than mass sorting. Moreover, the mass of produce can be easily estimated from geometrical attributes if the mass model of the produce in known [25]. For that reason, modeling of nectarine mass based on some geometrical attributes may be useful and applicable. Therefore, the main objectives of this research were: (a) to determine optimum mass model(s) based on some geometrical attributes of nectarine and (b) to verify determined mass model(s) by comparing their results with those of the measuring method.

MATERIALS AND METHODS

Experimental Procedure: Eighty five randomly selected nectarines (cv. Sunking) of various sizes were purchased from a local market. Nectarines were selected for freedom from defects by careful visual inspection, transferred to the laboratory and held at 5±1°C and 90±5% relative humidity until experimental procedure.

In order to obtain required parameters for determining mass models, the mass of each nectarine was measured to 0.1 g accuracy on a digital balance. Moreover, the volume of each nectarine was measured using the water displacement method. Each nectarine was submerged into water and the volume of water displaced was measured. Water temperature during measurements was kept at 25°C.

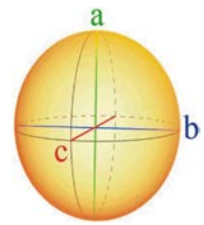

Fig. 1: The outer dimensions of a nectarine, i.e. major diameter (a), intermediate diameter (b) and minor diameter (c) by assuming the shape of nectarine as an ellipsoid

By assuming the shape of nectarines as an ellipsoid (Fig. 1), the outer dimensions of each nectarine, i.e. major diameter (a), intermediate diameter (b) and minor diameter (c) was measured to 0.1 mm accuracy by a digital caliper. The geometric mean diameter (GMD) of each nectarine was then calculated by equation 1.

$$GMD = (abc)^{1/3} \quad (1)$$

Three projected areas of each nectarine, i.e. first projected area (PA_1), second projected area (PA_2) and third projected area (PA_3) was also calculated by using equation 2, 3 and 4, respectively. The average projected area known as criteria area (CAE) of each nectarine was then determined from equation 5.

$$PA_1 = \pi\, ab/4 \quad (2)$$
$$PA_2 = \pi\, ac/4 \quad (3)$$
$$PA_3 = \pi\, bc/4 \quad (4)$$
$$CAE = (PA_1+PA_2+PA_3)/3 \quad (5)$$

In addition, the volume of ellipsoid assumed shape or estimated volume of each nectarine (V_{Ell}) was calculated by using equation 6.

$$V_{Ell} = \pi\, abc/6 \quad (6)$$

Table 1 shows some physical and geometrical attributes of the nectarines used to determine mass models.

Regression Models: A typical linear multiple regression model is shown in equation 7:

Table 1: The mean values, standard deviation (S.D.) and coefficient of variation (C.V.) of some physical and geometrical attributes of the 85 randomly selected nectarines used to determine mass models

Parameter	Minimum	Maximum	Mean	S.D.	C.V. (%)
Mass (M), g	39.3	104.1	55.8	11.6	20.7
Major diameter (a), mm	38.9	56.7	46.3	3.58	7.73
Intermediate diameter (b), mm	40.9	57.1	47.3	3.07	6.50
Minor diameter (c), mm	40.6	57.8	45.7	3.44	7.52
Geometrical mean diameter (GMD), mm	41.3	56.9	46.4	3.10	6.68
First projected area (PA_1), cm^2	13.4	25.4	17.3	2.39	13.8
Second projected area (PA_2), cm^2	13.0	25.3	16.7	2.42	14.5
Third projected area (PA_3), cm^2	13.2	25.5	17.1	2.34	13.7
Criteria area (CAE), cm^2	13.4	25.4	17.0	2.33	13.7
Estimated volume (V_{Ell}), cm^3	36.7	96.5	53.1	11.3	21.2
Measured volume (V_M), cm^3	36.6	109.7	56.0	12.3	22.0

Table 2: Eighteen linear regression mass models and their relations in three classifications

Classification	Model No.	Model	Relation
Outer dimensions	1	$M = k_0 + k_1\ a$	$M = -74.45 + 2.813\ a$
	2	$M = k_0 + k_1\ b$	$M = -110.0 + 3.504\ b$
	3	$M = k_0 + k_1\ c$	$M = -81.13 + 2.995\ c$
	4	$M = k_0 + k_1\ GMD$	$M = -112.4 + 3.624\ GMD$
	5	$M = k_0 + k_1\ a + k_2\ b$	$M = -111.4 + 1.070\ a + 2.486\ b$
	6	$M = k_0 + k_1\ a + k_2\ c$	$M = -101.1 + 1.566\ a + 1.846\ c$
	7	$M = k_0 + k_1\ b + k_2\ c$	$M = -113.4 + 2.312\ b + 1.308\ c$
	8	$M = k_0 + k_1\ a + k_2\ b + k_3\ c$	$M = -114.3 + 0.938\ a + 1.523\ b + 1.195\ c$
Projected areas	9	$M = k_0 + k_1\ PA_1$	$M = -23.62 + 4.598\ PA_1$
	10	$M = k_0 + k_1\ PA_2$	$M = -20.67 + 4.584\ PA_2$
	11	$M = k_0 + k_1\ PA_3$	$M = -25.01 + 4.739\ PA_3$
	12	$M = k_0 + k_1\ CAE$	$M = -26.46 + 4.838\ CAE$
	13	$M = k_0 + k_1\ PA_1 + k_2\ PA_2$	$M = -23.73 + 1.956\ PA_1 + 2.743\ PA_2$
	14	$M = k_0 + k_1\ PA_1 + k_2\ PA_3$	$M = -24.70 – 0.907\ PA_1 + 2.274\ PA_3$
	15	$M = k_0 + k_1\ PA_2 + k_2\ PA_3$	$M = -24.81 + 2.303\ PA_2 + 2.475\ PA_3$
	16	$M = k_0 + k_1\ PA_1 + k_2\ PA_3 + k_3\ PA_3$	$M = -27.65 + 1.878\ PA_1 + 0.593\ PA_2 + 2.412\ PA_3$
Volumes	17	$M = k_0 + k_1\ V_{Ell}$	$M = 2.401 + 1.006\ V_{Ell}$
	18	$M = k_0 + k_1\ V_M$	$M = 3.749 + 0.929\ V_M$

$$Y = k_0 + k_1X_1 + k_2X_2 + \ldots + k_nX_n \tag{7}$$

where:

Y = Dependent variable, for example mass of nectarine

$X_1, X_2, \ldots, X_n$ = Independent variables, for example geometrical attributes of nectarine

$k_0, k_1, k_2, \ldots, k_n$ = Regression coefficients

In order to model nectarine mass based on geometrical attributes, eighteen linear regression mass models were suggested and all the data were subjected to linear regression analysis using the Microsoft Excel 2007. Models were divided into three main classifications (Table 2), i.e. first classification (outer dimensions), second classification (projected areas) and third classification (volumes).

RESULTS AND DISCUSSION

The p-value of the independent variable(s) and coefficient of determination (R^2) of all the linear regression mass models are shown in Table 3.

First Classification Models (Outer Dimensions): In this classification nectarine mass can be predicted using single variable linear regressions of major diameter (a), intermediate diameter (b), minor diameter (c) and

Table 3: Mass models, p-value of model variable(s) and coefficient of determination (R^2)

	p-value										
Model No.	a	b	c	GMD	PA_1	PA_2	PA_3	CAE	V_{Ell}	V_M	R^2
1	2.16E-27	---	---	---	---	---	---	---	---	---	0.76
2	---	2.70E-38	---	---	---	---	---	---	---	---	0.87
3	---	---	4.60E-30	---	---	---	---	---	---	---	0.79
4	---	---	---	3.01E-54	---	---	---	---	---	---	0.95
5	2.52E-07	3.16E-18	---	---	---	---	---	---	---	---	0.90
6	1.05E-16	---	2.34E-19	---	---	---	---	---	---	---	0.91
7	---	2.08E-18	3.37E-10	---	---	---	---	---	---	---	0.92
8	6.39E-09	1.28E-10	9.55E-12	---	---	---	---	---	---	---	0.95
9	---	---	---	---	4.92E-44	---	---	---	---	---	0.90
10	---	---	---	---	---	3.42E-47	---	---	---	---	0.92
11	---	---	---	---	---	---	1.34E-47	---	---	---	0.92
12	---	---	---	---	---	---	---	2.28E-57	---	---	0.95
13	---	---	---	---	3.61E-05	2.17E-08	---	---	---	---	0.93
14	---	---	---	---	0.000495	---	3.97E-37	---	---	---	0.92
15	---	---	---	---	---	2.83E-07	1.09E-07	---	---	---	0.94
16	---	---	---	---	1.87E-06	0.230047	6.35E-09	---	---	---	0.95
17	---	---	---	---	---	---	---	---	1.18E-75	---	0.98
18	---	---	---	---	---	---	---	---	---	5.20E-60	0.96

geometrical mean diameter (GMD) of nectarine or multiple variable linear regressions of nectarine diameters. As indicated in Table 3, among the first classification models (models No. 1-8), model No. 4 had one of the highest R^2 values (0.95). Also, the p-value of independent variable (GMD) was 3.01E-54. Based on the statistical results model No. 4 was selected as the best model of first classification. Model No. 4 is given in equation 8.

$$M = - 112.4 + 3.624\ GMD \tag{8}$$

Second Classification Models (Projected Areas): In this classification nectarine mass can be predicted using single variable linear regressions of first projected area (PA_1), second projected area (PA_2), third projected area (PA_3) and criteria area (CAE) of nectarine or multiple variable linear regressions of nectarine projected areas. As showed in Table 3, among the second classification models (models No. 9-16), model No. 12 had one of the highest R^2 values (0.95). Moreover, the p-value of independent variable (CAE) was 2.28E-57. Again, based on the statistical results model No. 12 was chosen as the best model of second classification. Model No. 12 is given in equation 9.

$$M = - 26.64 + 4.838\ CAE \tag{9}$$

Third Classification Models (Volumes): In this classification nectarine mass can be predicted using single variable linear regressions of estimated volume calculated from an ellipsoid assumed shape (V_{Ell}) or measured volume (V_M) of nectarine. As indicated in Table 3, between the third classification models (models No. 17 and 18), model No. 17 had the highest R^2 value (0.98). In addition, the p-value of independent variable (V_{Ell}) was 1.18E-75. Once more, based on the statistical results model No. 17 was chosen as the best model of third classification. Model No. 17 is given in equation 10.

$$M = 2.401 + 1.006\ V_{Ell} \tag{10}$$

CONCLUSIONS

To predict nectarine mass (M) based on outer dimensions, the mass model based on geometrical mean diameter (GMD) as $M = - 112.4 + 3.624$ GMD with $R^2 = 0.95$ can be recommended. Moreover, to predict nectarine mass based on projected areas, the mass model based on criteria area (CAE) as $M = - 26.46 + 4.838$ CAE with $R^2 = 0.95$ can be suggested. Besides, to predict nectarine mass based on volumes, the mass model based on estimated volume calculated from an ellipsoid assumed shape (V_{Ell}) as $M = 2.401 + 1.006\ V_{Ell}$ with $R^2 = 0.98$ can be utilized. These models can also be used to design and develop sizing machines equipped with an image processing system.

REFERENCES

1. Salunkhe, D.K. and B.B. Desai, 1984. Postharvest Biotechnology of Fruits. CRC Press, Boca Raton, FL, pp: 168.

2. La Rue, J., 1989. Introduction. In: J.H. La Rue and R.S. Johnson (Eds.), Peaches, Plums and Nectarines: Growing and Handling for Fresh Market. University of California Division of Agriculture and Natural Resources Publication 3331, pp: 1-2.
3. Brady, C.J., 1993. Stone fruit. In: G. Seymour, J. Taylor and G. Tucker, (Eds.), Biochemistry of Fruit Ripening. Chapman and Hall, London, pp: 379-404.
4. Lill, R.E., E.M. O'Donaghue and G.A. King, 1989. Postharvest physiology of peaches and nectarines. Hort. Rev., 11: 413-452.
5. Lester, D.R., W.B. Sherman and B.J. Atwell, 1996. Endopolygalacturonase and the Melting Flesh (M) locus in peach. J. Am. Soc. Hort. Sci., 121: 231-235.
6. Genard, M., M. Reich, P. Lobit and J. Besset, 1999. Correlation between sugar and acid content and peach growth. J. Hort. Sci. Biotech., 74: 772-776.
7. Byrne, D.H., 2002. Peach breeding trends. Acta Hortic., 592: 49-59.
8. Lurie, S. and C.H. Crisosto, 2005. Chilling injury in peach and nectarine. Postharvest Biology and Technology, 37: 195-208.
9. Rashidi, M., M. Malekiyan and M. Gholami, 2008. Egg volume determination by spheroid approximation and image processing. World Applied Sciences Journal, 3: 590-596.
10. Sadrnia, H., A. Rajabipour, A. Jafary, A. Javadi and Y. Mostofi, 2007. Classification and analysis of fruit shapes in long type watermelon using image processing. International Journal of Agriculture and Biology, 9: 68-70.
11. Rashidi, M. and K. Seyfi, 2007. Classification of fruit shape in cantaloupe using the analysis of geometrical attributes. World Applied Sciences Journal, 3: 735-740.
12. Rashidi, M. and K. Seyfi, 2007. Classification of fruit shape in kiwifruit applying the analysis of outer dimensions. International Journal of Agriculture and Biology, 9: 759-762.
13. Rashidi, M. and M. Gholami, 2008. Classification of fruit shape in kiwifruit using the analysis of geometrical attributes. American-Eurasian Journal of Agricultural and Environmental Sciences, 3: 258-263.
14. Wilhelm, L.R., D.A. Suter and G.H. Brusewitz, 2005. Physical Properties of Food Materials. Food and Process Engineering Technology. ASAE, St. Joseph, Michigan, USA.
15. Rashidi, M. and K. Seyfi, 2008. Determination of cantaloupe volume using image processing. World Applied Sciences Journal, 2: 646-651.
16. Rashidi, M. and K. Seyfi, 2008. Determination of kiwifruit volume using image processing. World Applied Sciences Journal, 3: 184-190.
17. Wen, Z. and Y. Tao, 1999. Building a rule-based machine-vision system for defect inspection on apple sorting and packing lines. Expert Systems with Application, 16: 307-713.
18. Kavdir, I. and D.E. Guyer, 2004. Comparison of artificial neural networks and statistical classifiers in apple sorting using textural features. Biosystems Engineering, 89: 331-344.
19. Kleynen, O., V. Leemans and M.F. Destain, 2003. Selection of the most effective wavelength bands for 'Jonagold' apple sorting. Postharvest Biology and Technology, 30: 221-232.
20. Polder, G., G.W.A.M. van der Heijden and I.T. Young, 2003. Tomato sorting using independent component analysis on spectral images. Real-Time Imaging, 9: 253-259.
21. Malcolm, E.W., J.H. Toppan and F.E. Sister, 1986. The size and shape of typical sweet potatoes. TRANS. A.S.A.E., 19: 678-682.
22. Marvin, J.P., G.M. Hyde and R.P. Cavalieri, 1987. Modeling potato tuber mass with tuber dimensions. TRANS. A.S.A.E., 30: 1154-1159.
23. Khojastapour, M., 1996. Design and fabrication method of potato sorting machine according to Iran conditions. M.Sc. thesis, Tehran University, Iran.
24. Carrion, J., A. Torregrosa, E. Orti and E. Molto, 1998. First result of an automatic citrus sorting machine based on an unsupervised vision system. In: Proceeding of Euro. Agr. Eng., 1998. Olsa. Paper 98-F-019.
25. Rashidi, M. and K. Seyfi, 2008. Modeling of kiwifruit mass based on outer dimensions and projected areas. American-Eurasian Journal of Agricultural and Environmental Sciences, 3: 14-17.