Variability in flower development of Easter lily (Lilium longiflorum Thunb.): model and decision-support system

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Abstract

A model to predict the distribution of harvest dates in an Easter lily crop was validated using data from several locations. Plants were individually harvested (i.e. removed from the greenhouse for shipping) when flowers on a plant reached a minimum flower bud length. A computer decision-support system called LilyDate was developed to allow the model to be used to optimize greenhouse temperature settings to ensure that the majority of a crop is ready to harvest by a target date. To implement LilyDate, the user measures the length of the largest flower bud per plant on a sample of plants in the greenhouse, and enters the frequency of plants at each flower bud length (to the nearest cm) into the program. Based on the expected temperature and sample growth data, the software predicts a cumulative and daily distribution of when plants will be in flower. Model predictions were not biased, and the model predicted the number of days until 50 or 95% of plants were in flower with a precision of ±2 and ±3 days, respectively. The general approach to the computer system could be adapted to predict the harvest distribution for other crop species that require a consistent quantity of thermal time to harvest, and that are grown for a target harvest date. © 2000 Elsevier Science B.V. All rights reserved.

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1. Introduction

Easter lily (Lilium longiflorum Thunb.) is commercially produced as a potted plant in the US. The most important factor determining its market value is the accuracy and uniformity with which the crop flowers in time for sales prior to Easter. Plants that are not in flower immediately prior to Easter are not marketable. In contrast, plants that flower too early must be held in coolers until the market date, adding substantial production costs while reducing quality.

There are several developmental variables that the grower tracks to ensure that this process occurs with the greatest possible precision. The first of these variables is the observed ‘emergence date’, which occurs when the growing stem first breaks through the soil surface. In the weeks that follow, numerous leaves unfold from this stem. Once all but approximately five leaves unfold, the flower bud becomes visible without dissection; this event is termed ‘visible bud’. From then on, the bud elongates to 16 cm. As the bud approaches 16 cm it becomes ‘puffy’ and petals begin to open (termed ‘anthesis’).

The grower decides on a pre-determined ‘harvest’ flower bud length that indicates a plant is ready to ship. This decision on the harvestable flower length depends on the number of days prior to Easter when plants will be removed from the greenhouse and shipped to the retailer. The ‘harvest’ stage is, therefore, a specific bud length that may be 16 cm or a shorter length. Each plant is normally checked and harvested individually when a flower on the plant reaches the minimum flower bud length.

There has been considerable research effort directed towards predicting the time to flowering for floricultural species in response to greenhouse climate. These models range in complexity from thermal time (temperature-driven) models (Pasian and Lieth (1994) model of rose development), to quantification of development rate in relation to air temperature and daily light integral (Larsen and Hidén (1995) model of chrysanthemum leaf unfolding), and finally to more complex integration of responses to multiple environmental factors, for example research on poinsettia flowering by Snipen et al. (1998). Models that quantify the response of Easter lily flower development to air temperature (Erwin and Heins, 1990; Fisher et al., 1996) have been implemented in decision-support tools ranging in complexity from a simple flower bud development meter (Fisher et al., 1996) to more complex computer software (Fisher et al., 1997a). Both of these tools are used by lily growers to determine optimum greenhouse temperatures to achieve a target anthesis date.

A limitation of most existing development models for floricultural species is that they focus exclusively on the development stage averaged for all plants within a crop, and ignore variability in developmental stages within a population. Stochastic models of development rate have already been developed, however, in other research applications including vegetative bud development of balsam fir (Osawa et al., 1983) and population dynamics of Western spruce budworm, which is a lepidopteran pest species (Kemp et al., 1986). These stochastic models predict both the mean and variance in thermal time required for a population to reach different developmental stages.
In the case of commercial Easter lily production, variability in development rate is very important to profitability. The only method that the grower has to control variability is to sort plants into separate greenhouse temperature zones by stage of development and subject plants that are ahead of schedule to cooler temperatures, while providing warmer temperatures for those that are behind schedule. Making decisions regarding crop variability is difficult and growers typically experience losses due to plants flowering too early or late. Quantifying crop variability is important to ensure that the majority of plants reach anthesis in time for peak sales, and to best plan packing-labor, shipping, and cooler-space resources. While models provide an optimal vehicle for integrating this information scientifically, grower adoption of such a model depends on having the models packaged into easy-to-use decision-support tools.

Commercial Easter lily bulbs are vegetatively propagated and variability is, therefore, likely to be caused by environmental rather than genetic factors. Variability that is generally found in Easter lily crops is caused by variable environmental conditions, under which the bulbs were produced under field production resulting in variable bulb sizes, as well as the lack of uniformity in the greenhouse environment during forcing. Larger Easter lily bulbs tend to flower more quickly (Lange and Heins, 1990), and include more leaves compared with small bulbs (Wilkins, 1980). Growers vernalize bulbs prior to forcing, and increasing vernalization time results in more uniform flowering at the expense of flower number (Wilkins, 1980).

Fisher et al. (1997b) described a model to predict the distribution of the dates when plants reach the ‘harvest stage’ in a population of Easter lilies in response to air temperature. In this project, our objective was to validate this model using lily growth data from commercial and research greenhouses, to test how accurately the model predicted dates when 50 or 95% of flowers were ready to harvest, and to develop a computer-based decision-support system to implement the model in a format that growers can use to manage commercially-grown greenhouse crops.

2. Materials and methods

2.1. Model description

A model was developed by Fisher et al. (1997b) to predict the distribution in harvest dates for a crop of Easter lilies in relation to air temperature. The model required three inputs:

1. A vector (i.e. a list of sixteen numeric elements) consisting of the observed frequencies of plants in each of sixteen developmental stages on a particular measurement date. Element 1 in this vector is the number of plants that have not yet reached Visible Bud (and whose bud lengths can therefore not be measured non-destructively); element 2 represents the number of plants where the longest bud is between 1.5 and 2.49 cm in length; element 3 represents plants whose longest bud is between 2.5 and 3.49 cm; and in general, element \( j \) is the
number of plants with a maximal bud length of \( j - 0.5 \) to \( j + 0.49 \) cm; the last element in the vector, at index 16, is the number of plants with flower buds \( \geq 15.5 \) cm or at anthesis. Such an observed distribution would be measured on one date prior to the date at which the first plant would reach the harvest stage.

2. The bud length, \( B_f \) (cm), when a flower is determined to reach the harvest stage.

3. The expected greenhouse air temperature (\( T \), in °C) from the time when flower bud lengths were measured until plants reach the harvest stage.

Model calibration, described in detail by Fisher et al. (1997b), used published data of the development rate from Visible Bud to Anthesis for Easter lilies grown in greenhouses under 25 combinations of day/night temperatures between 14 and 30°C (Erwin and Heins, 1990), and flower bud length data were analyzed from plants grown at five average greenhouse temperatures between 15 and 28°C (Fisher et al., 1996). Analysis of bud length data from 40 plants grown in each of three greenhouses at 16.4, 18.9, and 20.9°C at the University of New Hampshire (Durham, NH, USA), and 50 plants grown in a Michigan State University (East Lansing, MI, USA) greenhouse at 20.3°C improved quantification of variability in development rate within larger experimental populations.

The thermal time, \( t_j \) (units of °C d), required for each of the \( j \) flower bud length stages to elongate from an initial average bud length \( B_j \) (equal to \( j \) cm) to a final length, \( B_f \), when the flower reaches the harvest stage, was predicted by:

\[
t_j = \frac{(\ln(B_f/B_j))}{k}
\]

where \( k \) is a parameter estimated to be 0.0029 C \(^{-1}\) d \(^{-1}\).

The model assumes that as average air temperature increases, number of days to harvest decreases. Days to harvest, \( D_j \), for flower bud length \( j \) cm at a given air temperature, \( T \), was calculated from the thermal time, \( t_j \), using:

\[
D_j = t_j \times (\min(T, T_m) - T_b)
\]

Erwin and Heins (1990) found that development rate between Visible Bud and Anthesis increased with average temperature until 26°C, but did not increase from 26 to 30°C. Air temperatures above a maximum temperature (\( T_m \), estimated at 26°C) were therefore assumed to have an equal and maximal effect on development rate, and thermal time was calculated for the calibration data sets using the x-intercept method (Arnold, 1959). \( T_b \), the ‘base temperature’, was estimated at -4.5°C.

Eqs. (1) and (2) predict the average thermal time to harvest, \( t_j \), for an individual lily plant with its longest flower bud at \( j \) cm. Fisher et al. (1997b) also quantified variability in thermal time for all \( j = 2 \) to 16 stages until harvest for a population of lilies. The standard deviation, \( s_j \), of \( t_j \) in Eq. (1) for each \( j \) stage was modeled using a linear function (Eq. (3)):

\[
s_j = c + dB_j
\]

with parameters \( c \) and \( d \) estimated at 63 and -3.2°C/d cm. Eq. (3) was combined with Eqs. (1) and (2) to predict the mean and standard deviation of harvest dates for each \( j \) stage.
The cumulative proportion $P_j(t)$ of plants at development stage $j$ that would reach anthesis by thermal time $t$ was expressed as a function of the mean $t_j$ and standard deviation $s_j$ in the thermal time of anthesis for each developmental stage

$$P_j(t) = f(t, t_j, s_j)$$

(4)

where $f$ was the normal cumulative distribution function.

Because it is not feasible to measure flower bud lengths on every plant in an Easter lily crop (which can exceed 100,000 plants) the model predicts the total harvest distribution based on a sample of measured flowers. The number of plants $n(t)$ in the population that would be predicted by the model to be at the harvest stage by thermal time $t$ was quantified by

$$n(t) = \sum_{j=2}^{16} \frac{n_j}{n_s} \cdot n_T \cdot P_j(t)$$

(5)

where $n_j$ was the total number of plants sampled that were at stage $j$, $n_s$ was the total number of plants sampled and $n_T$ was the total number of plants in the population. Time of harvest was not predicted for plants at stage $j = 1$, i.e. that were not yet at the Visible Bud stage.

Fig. 1 illustrates the distribution for timing of harvest predicted from Eq. (5), assuming 100 plants had flowers at each of the $j = 2–15$ stages (2, 3, …, 15 cm long flower buds) when measured at day zero, and were subsequently grown at 20°C from day zero until harvest at 16 cm. The model predicted that buds that were initially longer would reach anthesis sooner, and with less variability, than flower buds that were less mature (i.e. shorter) on day zero.

Fig. 1. Predicted harvest distributions for 100 plants at flower bud development stages ranging from $j = 2$ (2 cm flower buds) to $j = 15$ (15 cm flower buds) on day zero, assuming that all plants were grown at 20°C. For visual clarity, only $j = 2, 4, 6, 8, 12$, and 15 are displayed.
2.2. Computer decision-support system

The model was packaged as a decision-support system called LilyDate. It was implemented using spreadsheet software (Microsoft Excel) to allow Easter lily growers to predict the distribution of anthesis dates for a lily crop (Fig. 2). Information entered by the user include a descriptive crop name, the observation date, flower bud lengths for the sample of plants, and the number of plants in the entire crop. An expected average temperature until anthesis is entered, and can be changed by the user to run ‘what if’ scenarios to investigate the effect of air temperature on the anthesis distribution. Temperatures entered into LilyDate are limited to between 14 and 30°C, because the model was calibrated with data in this range of temperatures. By changing the expected air temperature, the user can select a temperature that will result in an acceptable proportion of the crop ready to harvest by a target date.

The user specifies the minimum bud length \(B_f\) in Eq. (1)) required to harvest a plant, and enters the frequency of plants at each flower bud length (to the nearest cm) from a sample of plants into LilyDate. Based on the expected temperature and sample growth data, the software predicts a cumulative and daily distribution of harvest dates for the entire crop. LilyDate also reports when the median harvest date is predicted, and when 95% of the crop will be ready to harvest.
2.3. Validation of predicted harvest distribution

The model was tested against data from lilies grown in four different greenhouses in order to validate the model against data that were independent in time and location from the original model calibration. In all locations, air temperature was logged with a thermistor placed 30 cm above canopy height. Fifteen-minute average temperatures were averaged over 24 h to calculate ADT.

University of California at Davis (‘UCD’) population: ‘Nellie White’ Easter lily bulbs (grade 8/9, i.e. 20–23 cm in circumference) were case-cooled at 4.5°C in redwood sawdust from October 31 1995 until December 12 1995, when they were potted in 15 cm diameter pots with UC Mix (1 peat:1 sand:1 redwood sawdust) and were moved to a UCD greenhouse. Plants were grown at a soil temperature of 16–18°C until January 15, and 20–22°C air temperature until immediately prior to the Visible Bud stage. Plants were then randomly separated into three groups of 40 plants and were moved into three greenhouses with different ADT (16.4 ± 0.6°C, 18.9 ± 0.2°C, and 20.9 ± 0.4°C) (mean ADT is reported ± 95%). On five dates (March 14, 17, 21, 25, and 29, 1996) the length of the longest flower bud was measured on each plant, and the date when flower buds reached 16 cm in length was checked daily.

California commercial populations 1 and 2 (‘CA1’ and ‘CA2’): Flower bud lengths were measured on ‘Nellie White’ Easter lily plants (bulb grade 8/9) in a block of 100 plants (greenhouse ‘CA1’) or 108 plants (greenhouse ‘CA2’) arranged on greenhouse benches in two locations in coastal California. Plants in the two locations were case-cooled in redwood sawdust for 1000 h at 4.5°C, and each batch originated from different bulb suppliers. After planting, mean date of Emergence above the media surface was December 11 1995 (CA1) or December 26 1995 (CA2), and the Visible Bud stage occurred, on average, on February 20 and 22 in CA1 and CA2, respectively. The length of the longest flower bud on each plant was measured in both locations on March 6 and 13, and again on March 18 in CA2. Plant maturity was checked daily for when the longest flower bud reached 16 cm (CA1) or 13 cm (CA2) in length (the final bud lengths that indicated when a plant reached the harvest stage for the two locations).

Michigan (‘MI’) commercial population: Flower buds were measured on March 6 and 19 1998 for a sample of 200 ‘Nellie White’ lilies (bulb grade 7/8) growing in a Grand Rapids, Michigan greenhouse. The sample was located in a row of single plants along the middle of a bench running the length of a commercial greenhouse containing 80 000 plants. Plants had been cooled using the CTF (controlled temperature forcing) method where bulbs were planted in 15 cm diameter pots in MetroMix 510 (Scotts, Marysville, Ohio) media, were rooted in a greenhouse for three weeks, and were subsequently cooled from October 30 to December 14 at 4.5°C in a controlled environment chamber. After removing plants from the cooler, mean date of Emergence above the media surface was January 3, and the Visible Bud stage occurred, on average, on February 24. The length of the longest flower bud on each plant in the sample was measured on March 6 and 19. Harvest of each individual plant in the entire crop of 80 000 plants occurred when a flower bud on
the plant reached 13 cm in length, and the number of plants harvested each day from the entire crop was recorded. Harvest occurred every day of the week except Sunday.

Flower bud length data from each location was entered into LilyDate, and the predicted dates when 50 and 95% of plants reached 16 cm (UCD and CA1) or 13 cm (CA2 and MI) were compared against the observed timing of 50 and 95% flowering, using linear regression. Model precision was calculated by calculating 95% confidence limits for the model error (observed–predicted days to the median or 95% harvest date) by the 0.025 $t$-statistic.

3. Results

In the UCD experiment, as temperature increased, both median time to harvest and variability in harvest dates decreased. For example, from the first measurement date on March 14, 24 days were required until the median harvest date occurred at 16.5°C, 18 days at 19.2°C, and 15 days at 21.4°C. The duration from when the first 5% until the last 5% of plants were at harvest in each temperature treatment was 11, 9, and 7 days for 16.5, 19.2, and 21.4°C, respectively. These observations were predicted by the model with an accuracy of ±1 day for the median date, and ±2 days for the range from the first to last 5% of plants at harvest. Because standard deviation in development time to harvest is quantified by the model in terms of thermal time, the model predicts decreasing chronological variability as temperature increases, similar to that observed in the UCD population.

There was greater variability in the CA1 population than CA2, with a range in 17 days from the first 5% to last 5% of plants at harvest in CA1 compared with 9 days in CA2, and variances were statistically significantly different using a variance ratio test ($P < 0.01$). During the experimental period, the variability in CA1 caused considerable management problems for the grower, who lacked a cooler facility for the earliest plants, and resulted in a significant loss of saleable plants. The model predicted the median harvest date within one day of observed at CA1 and CA2, and the range from the first to last 5% of plants at harvest with an accuracy of ±3 days.

In the MI population, a sample of 200 plants was used to predict harvest dates for the entire 80,000 plants, whereas in other locations the bud measurements and harvest date were recorded on the same group of 40–108 plants. The model predicted the median harvest date at MI two and zero days late for measurement dates March 6 and March 19, respectively. The first 5% to last 5% of plants to reach harvest date were predicted from the two measurement dates to be spread over a range of 16 and 13 days, compared with an observed 16 days.

There was no statistically significant bias in the model, i.e. the slopes equalled one and the intercepts equalled zero for regressions of predicted versus observed days until 50% (Fig. 3(A)) or 95% (Fig. 3(B)) of plants were ready to harvest. Model error (scatter around the predicted = observed lines in Fig. 3) was not affected by days from measurement to harvest. Predictions of the number of days until 50 or
95% of plants were ready to harvest with 95% confidence intervals of $\pm 1.8$ and $\pm 2.9$ days, respectively.

The accuracy of model predictions at each of the four sites, quantified as the relation between the predicted and observed harvest date distributions for the earliest bud measurement date (14–25 days before the median harvest date), showed slight differences (Fig. 4). Under research conditions, at the UCD site, model predictions were most accurate. In the commercial sites, errors in the predicted harvest date were more apparent, with both CA1 and CA2 populations approaching 100% harvest several days before the date predicted by the model.

Figure 3. Relationship between the observed number of days after flower buds were measured until (A) 50%, and (B) 95% of plants were ready to harvest. Data are combined from the four locations. Solid lines represent a perfect model fit, i.e. observed = predicted number of days to the harvest stage.
Fig. 4. Predicted and observed distributions of harvest for (A), (B), and (C) the University of California at Davis (UCD) populations at three average daily temperatures, (D) the CA1 population, (E) the CA2 population, and (F) the MI population. Time is represented as days after flower buds were measured.

4. Discussion and conclusions

The predictive model provided information on the distribution of harvest dates for a crop of Easter lilies with an accuracy of ±2–3 days. Model predictions could be successfully extrapolated at the commercial MI site from a sample of 200 plants to a crop of 80,000 plants growing in a single greenhouse. To identify the minimum sample size for the MI crop, we ran 500 additional model simulations, where bud lengths from 100 randomly selected subsamples of 150, 125, 100, 75, or 50 plants out of the original sample of 200 plants were entered into the model. The model
correctly predicted the median harvest within ±1 day for all sample sizes except where only 50 plants were sampled (±2 days). Predicted duration from when the first 5% until the last 5% of plants were harvested was ±3 days of observed duration for 150, 125, or 100 plants, but was within ±4 days for 75 or 50 sampled plants. A sample size of 100 plants therefore had the same precision as 125, 150, or 200 plant samples.

Potential sources of model error at MI were as follows: (1) no plants were harvested on Sundays; (2) not all plants may have been harvested at exactly the final harvest bud length ($B_f$) because of differences between workers and the need to complete orders; and (3) the sample was not randomly distributed in space and may not have accurately represented the entire crop.

The model is reasonably simple, driven only by air temperature and observed variability in flower bud measurements. Adding other variables that affect lily plant tissue temperature in lily, and possibly plant development rate, such as radiant energy exchange and vapor pressure deficit (Faust and Heins, 1998), may improve model precision. Heins et al. (1982a,b), however, found that light intensity between the visible bud and anthesis stages had little or no effect on lily development rate or flower quality. Differences between sites found in the present study may have been caused by differences in the plant material from multiple years and suppliers. Implementation of the decision-support system would be more difficult with increasing complexity of input variables.

The validation experiments indicate that the LilyDate program could be used by growers as part of their strategy for managing variability. The model can be implemented 2–3 weeks before harvest begins to provide an estimate of median and 95% harvest dates. This information can be used to decide whether to change average greenhouse temperature in order to move the distribution back or forward in time. The displayed range in harvest dates from the first to last few plants also indicates the need to move early- and late-developing plants to cool or warm greenhouses, respectively, and also when cooler space is likely to be needed. Larger greenhouse operations may produce lilies from several bulb suppliers, grow more than one bulb size, and use several greenhouse temperature zones. An improvement of the program would be to combine distributions for several crops of lilies within one operation, in order to provide an overall harvest distribution for the entire business. Given that moving plants to warm or cool greenhouses is a key aspect of managing variability, the ability to combine several harvest distributions in the model would also show the best way to divide and manage a non-uniform crop. It may also be possible to configure the program so that it recommends an optimum temperature to meet a desired outcome, rather than relying on experimention with ‘what if’ scenarios.

Although most development models currently used in floriculture are designed to predict mean flowering date, management of variability and the distribution of flowering in an entire crop are important production factors faced by growers. Crop variability is particularly important for any crop that is grown for a target harvest date. The general approach used for LilyDate can be applied to other crops, using a model that: (1) accepts measured development stages on a sample of plants
at an immature stage before flowering occurs; (2) uses either the frequencies of plants at each stage or individual plant measurements (rather than a single average number for the entire sample) as input; and (3) predicts the resulting distribution of the harvest stage by combining the predicted time from each immature stage to flower.

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