A STOCHASTIC TEMPERATURE-BASED EMERGENCE MODEL FOR COTTON

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Abstract

A model which calculates the time distribution of emergence of cotton seedlings is described. The model is based on data collected using naturally sunlit controlled environment plant growth chambers with cold, low, medium and high temperature treatments. The actual model uses stochastic processes to predict the emergence of seedlings. The model was verified from data published by Dr. Don Wanjura.

Introduction

Mechanistical simulation models describe the development and growth of cotton plants using average weather information. Briefly described (see: Baker *et al.,*1983, Jackson *et al*., 1988, and Sequeira & Jallas, 1995), these systems are driven on a daily basis by external factors (current environment) and simulated plant status for the preceding day. Both environmental factors and plant status are used to calculate daily photosynthetic supply and demand of the cotton plant throughout the season. The modeling approach maximizes the number of causal relations present in the model and is a good representation of physiological reality. Despite their mechanistic realism and physiological detail, these models are deterministic: any variation of the driving factors leads to a unique response. These systems model an average plant, which represents a homogenous field. When these models were initially developed this choice of representing a crop as an average plant was justified because model-suggested yield improvements were easily possible, and farmers initially wanted to maximize their yield. Today, yields have reached a plateau. Further, maximum yield is no longer the producer's main objective. Each producer has his/her own objective(s) (e.g., target yield) which is an individual vision of an economic or personal optimum and which considers equipment, technical training, acceptable risk, etc. Because of the variability of the response of the plant to environmental factors, there are many ways to achieve a target yield. However, if plant variability within a field is very large then the implication of plant variability is critical for crop management. This is the reason why understanding this variability is now one of the main objectives of researchers.

The variability associated with developmental and growth rates may be due to two reasons: a phenotypic expression (intrinsic) and the interactions with the environment including other plants. Most of the variability observed in the field could be explained by the phenotypic expression differences in emergence and stand establishment. Empirical observations suggest that the first seedlings to emerge accumulate a competitive advantage over time over the other seedlings by shading them out and establishing their root systems earlier. Other stress factors will increase variability. However, stand establishment does not explain all the key sources of variation. Even a non-stressed plant will express variability when grown under optimal conditions. This suggests an intrinsic phenotypic variability. It is clear that phenotype must affect between-plant variability. For example, two plants with exactly the same genotype and growing in the same conditions will not carry all their fruits at the same location. These differences are the expression of the intrinsic phenotypic variability.

The use of queuing theory in combination with mechanistic modeling may be an alternative solution to provide crop simulation models the ability to reproduce this natural variability. Introducing queuing theory into the plant model led necessarily to an important conceptual leap because the plant model will no longer be an "average plant model". Thus, the new approach will be a field approach using a plant model as the foundation with different individual plants, which will interact with each other. Each plant will be unique, and the response of the ensemble of plants will provide the field level simulation. The queuing theory aspects can be integrated at two levels in such new systems: at the field level for the emergence process and at the plant level for the morphogenesis processes. These choices are in accordance with the assumption that: i) an intrinsic variability exists, which results only from the stochastic development of cotton sinks, even in the absence of stresses and ii) a variability exists linked to the interaction between plants and their environment.

The emergence process can be seen as an arrival process. This arrival process has an important effect on the plant-level queuing processes. The first plant arriving will be the first served, and because resources are limited it can get a principal advantage or disadvantage because of the indeterminate nature of the cotton plant. For example, the first emerged plant can avoid a future stress and take advantage of its precocity or can be in a critical stage when the stress will appear and be definitively disadvantaged.

The emergence model presented in this paper is included in the COTONS simulation model that integrates a queuing system. This emergence model was built using data from an experiment conducted at Mississippi State University in

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1997 and also by using data from the literature, specifically from Wanjura (1969, 1973).

Materials and Methods

The experiment was conducted in growth chambers during spring 1997. These closed-environment plant growth chambers used for this study are known as Soil-Plant-Atmospheric-Research (SPAR) units (Phene *et al.*, 1978). These units are used for controlled environment experiments and they have been described by Acock *et al.*, (1985), Reddy *et al.*, (1992), Reddy *et al.*, (1993). These units use natural lighting and have the capability to control ambient air temperature, vapor pressure deficit, and CO_2 concentration at predetermined set points for studies of plant growth in natural solar radiation regimes. A dedicated computer controls air temperature, CO_2 concentration, and soil watering in the SPAR units. The computer conducts continuous monitoring of all important response variables as environmental variables and plant gas exchanges. The temperature in each SPAR unit is monitored and adjusted every 10 seconds throughout the day and night. The temperature is maintained within ± 0.5°C of treatment set points. The CO_2 concentration in each SPAR unit is monitored every 10 seconds and integrated over 900 seconds intervals throughout the day and night. The CO_2 concentration is maintained within ± 10 $\mu L\ L^{-1}$ of set point (i.e., 350$\mu L\ L^{-1}$). Dew point temperature, global radiation, and quantum flux of photosynthetically active radiation (PAR) are collected every 10 s and integrated over 900-s intervals. Nine units were used for this experiment: 3 were set at 20/12°C (day/night temperature - cold), 2 other units were set at 25/17°C (low temperature), 2 units at 30/22 °C (medium temperature) and 2 units at 35/27 °C (high temperature). The units were planted on April 21, with Deltapine DP5415BT cotton seeds, in pots made of PVC pipe (0.15 m diameter, 0.67 m length) with a volume of 12 L. The growing medium was sand. Four cotton seeds were planted in each pot placed in the SPAR units. SPAR units for cold, low and medium temperature received 18 pots and SPAR units for high temperature received 24 pots. Pots were arranged to obtain a regular plant population equivalent to 18 plants/m^2 when plants will enter into competition for light. Plants were thinned to a single plant at post-emergence. Three times a day a complete Hoagland's nutrient solution was delivered to each row or pot of plants via a drip-irrigation system. Observations were continuous from planting date to the end of the experiment, which was one month after the planting date. Non-destructive daily observations included emergence rate, inter-node lengths and mainstem leaf lengths on 6 plants in each growth chamber; timing of mainstem node formation was observed on the same 6 plants per units.

Results and Discussion

Figure 1 shows cotton emergence at different temperatures. Figures 1a to 1d show the probability of emergence along the y-axis and the time since sowing along the x-axis. These results agree with results from Wanjura (1973). Development rates (e.g., organ initiation and emergence) are temperature-dependent and as temperature increases, the time between sowing and emergence decreases; emergence dispersion also decreases. A skew is observed at all temperatures in the distribution of development times. The variability observed in the emergence rate can be expressed as a function of a random variable (Sharpe *et al.*, 1977) in addition to the temperature response:

$R(T) = \varepsilon_c \tau_{(T)}$, where, ε_c is a random variable of mean $\overline{\varepsilon_c}$ and variance Φ^2 and $\tau_{(T)}$ is the mean development rate at temperature *T*.

As shown by Sharpe *et al.*,(1977), development times can be calculated from the reciprocal of the rate. The use of the reciprocal relationship is a better way to represent some biological processes because the reciprocal shows a form which represents well the skews observed in biological process distributions. The equation of the reciprocal of the normal function is:

$$f(x) = \frac{1}{x^2 a\sqrt{2\pi}} e^{-\frac{1}{2}\left[(1/x - b)/a\right]^2} \qquad (1)$$

Figure 1 shows the correspondence of the data with equation 1 at the four temperatures. Figure 2a and 2b shows the relationships between parameter *a* and *b* of the Normal reciprocal and the temperature. Values of parameters *a* and *b* are displayed along the y-axis and the temperature along the x-axis. From their fitting equations, it is possible to express parameters *a* and *b* as a function of the average temperature. Then, equation 1 can also be expressed as temperature dependent. Equations for *a* and *b* are:

$$a = 0.0054272 + 0.0000125\ \overline{T^\circ}^2 \qquad (2)$$

$$b = \frac{\overline{T^\circ}^2}{4.3767\ \overline{T^\circ} + 2182.2939} \qquad (3)$$

where $\overline{T^\circ}$ is the average temperature since the planting date.

Figure 3 shows the probability density function at 10°C and 40°C as predicted by equations 1, 2 and 3. The axes are the same as in figure 1. The trends are in accordance with what it is expected and with research reported in literature. In order to reproduce the variability observed in emergence rate, we implement the following:

- First, select a random number between {0, 1};
- Second, compute the average daily temperature, and with this average temperature compute a and b and replace them in equation 1;

- Third, compare the sum of the daily results of equation 1 with the random number: if this sum is bigger than the random number, then the plant emerges.

This new emergence model was implemented in a improved version of the GOSSYM model. This new version of GOSSYM included a new light interception/photosynthesis model, a new morphogenesis model based on the queuing theory, an architectural/plant-geometry model, and a 3D visualization tool (Jallas, 1998).

The behavior of this new plant model was examined in two ways: first, the correct expression of variability added to the appropriate functions was tested, and second, overall plant response was studied by describing high-level plant response. Thus, we analyzed the production of organs (numbers of mainstem nodes, bolls and boll weight) and yield in addition to physiological status. We used the simulation condition set used to validate the GOSSYM model (Landivar, 1987) as our "validation" benchmark. We simulated 100 plants growing on 10 consecutive rows (10 plants/row, 86000 plants/ha), and we conducted three replications with three different random number seeds. Only the results directly linked to the emergence model are presented here. These results associated to the new stochastic behaviors are described in Table 1 and in the following figures.

Table 1 shows some of the main crop characteristics as simulated by the original model and the new model. Mean values are not different; minimum and maximum values are in the expected range of values. Standard deviations express the variability simulated by the new model.

Figures 4 and 5 show the distribution of emergence and yield as simulated by the new model. Frequencies are displayed on the vertical axis and the dispersions for these two variables are displayed along the x-axis. Figure 4 shows the emergence dispersion as simulated by the new model for the 1981 data set. On the x-axis the emergence dispersion, expressed in days from the day of 50% of emergence, is plotted as vertical bars. Figure 4a shows results for each replication while figure 4b shows results for all replications pooled. The range of emergence variation is six days, and it is linked to the relatively cool spring weather conditions of 1981. For the three replications, distribution is skewed; the three replications agree with the distribution model used. Figure 5 shows the yield model's response with the new emergence sub-model as the only source of variability (i.e., without variability linked to node production or fruit abscission). Here the yield variability is due to competition for light between plants that emerge at different times. Figure 5 displays simulated yields obtained with the emergence days provided by the new system for the 1981 data set. This yield dispersion is very small, and about two-thirds of the plants have their lint production included in the same class (each class represents 0.75g of lint per plant).

Conclusion

Whereas fields often appear homogeneous, plants within a field are not identical. This field variability is important because it is the expression of the growing conditions. Plant growth is the interaction between the gene pool and the environment. Thus, it is also an indicator of the status of the environment at a given time. The status of the plant's environment is also conditioned by the history of the field, current weather conditions, and cultural practices. The farmer adjusts cultural practices based on the perception that he gets from observing his field. Thus, for a crop model to be applicable as a DSS, it must be able to correctly reproduce field variability if we want to give the farmer the correct information for decision making.

We developed an emergence model and added it into a modified version of the GOSSYM model in order to reproduce stand establishment and to allow plant competition for light. Results show that this new emergence model contributes to reproduce field variability.

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Table 1. Comparison between the original and the new model of some of the main crop characteristics.

	Original Model	New Model Mean	STD	Min	Max
Emergence	05/10	05/10		05/08	05/14
# of Nodes	22	22.47	1.76	19	28
# of Bolls	9.44	7.69	2.21	3	15
Plant height (cm)	102.11	102.82	18.24	82.94	131.81
Yield (kg/ha)	975.98	942.78	127.77	518.88	1238.05

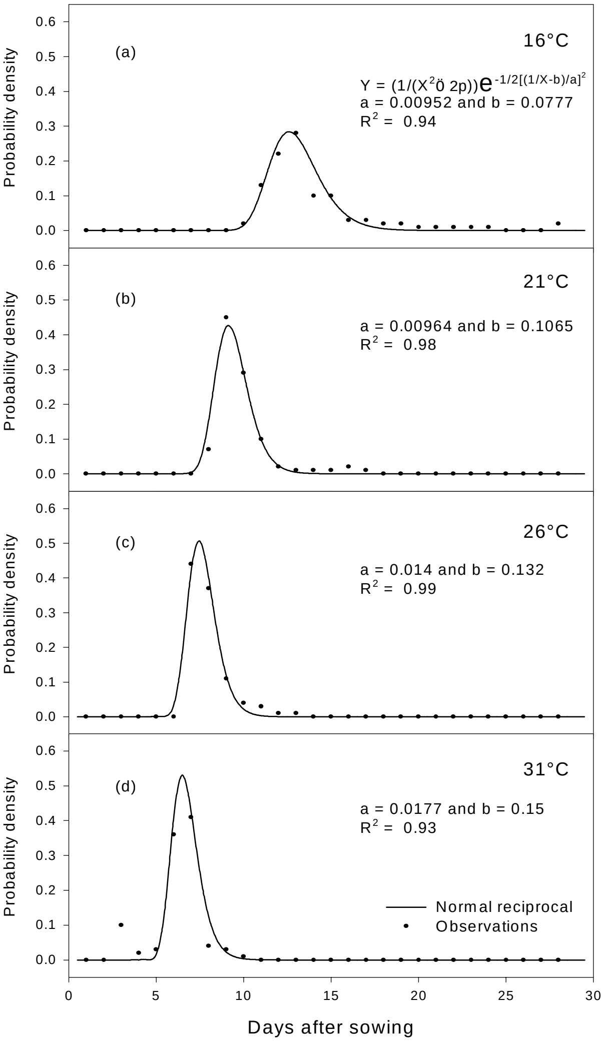

Figure 1. Emergence PDF in function of temperature. Solid line shows adjustment with the normal reciprocal function (equation 3.8).

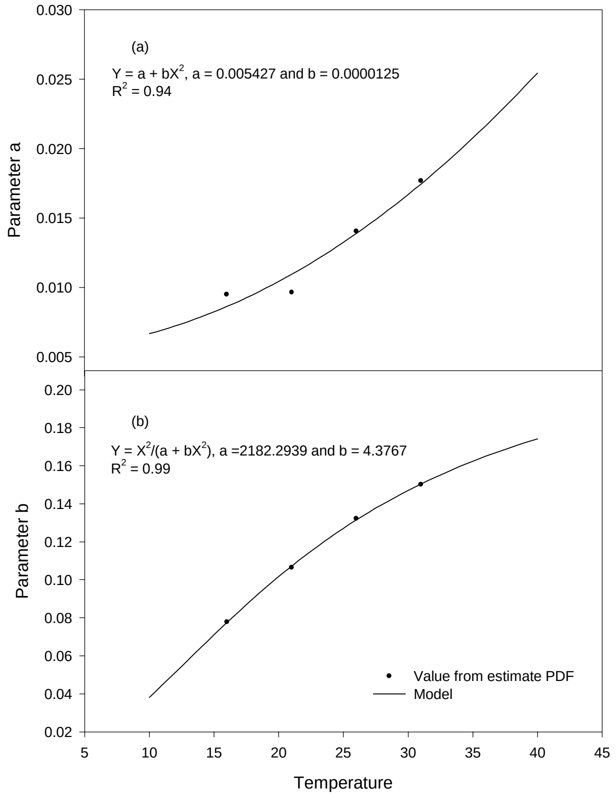

Figure 2. Relationship between parameters a and b and the temperature.

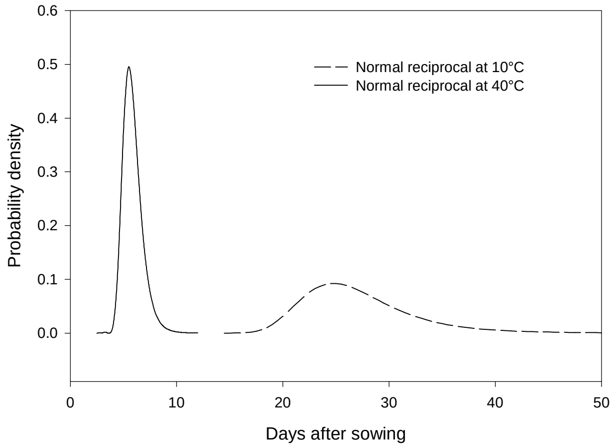

Figure 3. Emergence PDF at 10°C and 40°C as modeled with the normal reciprocal function.

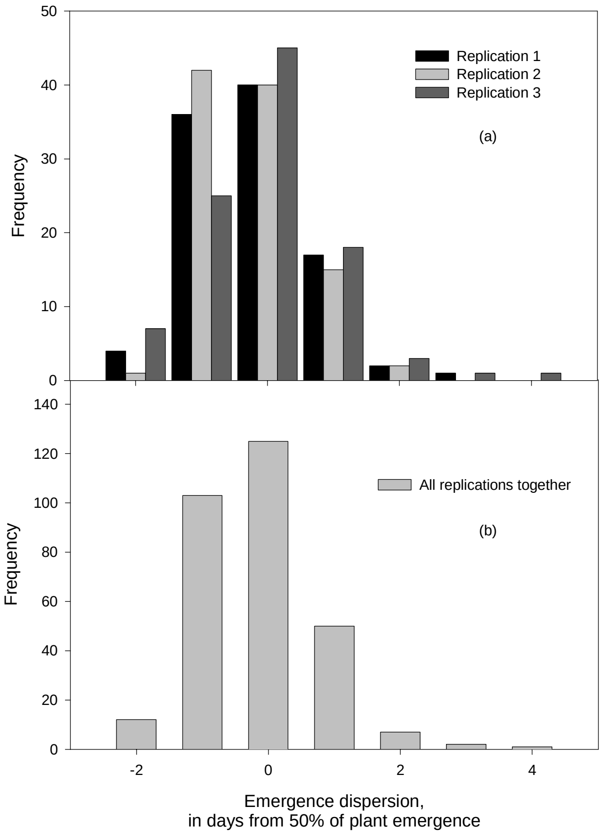

Figure 4. Distribution of emergence divergence from mean, in days from 50% of emergence.

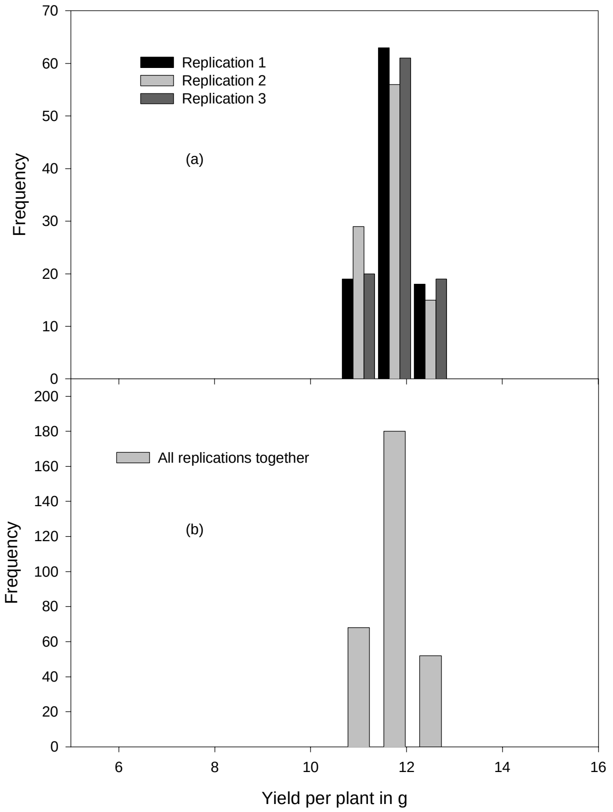

Figure 5. Distribution of yields simulated with the integration of the new emergence model only.