Original article

Predicting growth and development of the pineapple cultivar 'MD-2' with the DSSAT Aloha Pineapple Model

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Summary

Introduction – **The Cropping Systems Model-Aloha-Pineapple is a computer model that simulates pineapple growth and development and predicts final yield. The unique physiological characteristics of the cultivar 'MD-2' were added to the model to be more representative of the current and more common cultivars. The model has the potential to interpret fundamental processes related to crop response to environmental conditions in terms of growth and productivity.** *Materials and methods* – **Experimental data from 'MD-2' plants were used. The plants were grown in three environments in Costa Rica differing in temperature and solar radiation, using managed and standard agribusiness practices. Soil water and nutrients were considered non-limiting factors for growth and were uniformly controlled. Model evaluation was conducted for the prediction of phenological stage of physiological maturity using actual data from production fields of a Costa Rican pineapple export company.** *Results and discussion* – **The model was improved by adding and enhancing the simulation of five vegetative and six reproductive phenological stages. Model evaluation was satisfactory based on the statistical analysis for all experiments that were conducted.** *Conclusion* – **The modeling approach allows to simulate diagnostic agronomic indicators that can assess the effect of the environment and their interaction with agronomic management on growth and development, to predict the productivity of pineapple, and to predict the harvest date for both naturally flowering fruit and for forcing.**

Keywords
phenology, simulation, NF, harvest-index, indicator

Significance of this study

What is already known on this subject?

- The pineapple cultivar 'Smooth Cayenne' was very important for the pineapple agroindustry a few decades ago, mainly for canning, and the Aloha Pineapple Model was specifically developed for this cultivar. Currently, the most common cultivar is 'MD-2', which is mainly used for fresh fruit consumption, and has different management requirements and production conditions than 'Smooth Cayenne'.

What are the new findings?

- The physiological characteristics of the 'MD-2' pineapple cultivar were included in the Aloha Pineapple Model to create an updated version with new vegetative and reproductive phenological stages and many other traits.

What is the expected impact on horticulture?

- Improvements in the Aloha Pineapple Model can assist the pineapple agribusiness to analyze new production areas and evaluate existing ones to better predict growth, development, yield and make safe investments.

Introduction

Pineapple production across the world has doubled since the beginning of this century, making pineapple the third most important tropical fruit in the world (Leal and Coppens d'Eeckenbrugge, 2018). Costa Rica is currently the largest exporter of pineapple to both the United States and to Europe, with 'MD-2' as the dominant cultivar (Shahbandeh, 2023). The agroclimatological characteristics of the main pineapple-producing areas of Costa Rica contribute greatly to overall productivity, and the cost of land for cultivation has significantly increased. As a result, some investors have considered producing in agroecosystems with higher temperatures and solar radiation and lower elevation due to the low cost of land. However, these areas are considered marginal and are generally associated with low annual rainfall, thus requiring supplemental irrigation.

A feasibility analysis showed that the low cost of these marginal lands compensated for the irrigation investment costs required to produce 'MD-2' and that there is an advantage due to the absence of problems associated with Natural Flowering (NF). The latter was reported by Bartholomew and Sanewski (2018), who indicate that in warm tropical regions, the sensitivity to NF tends to be low because the conditions favor rapid growth, and the dry matter content remains low. However, this analysis of the return on investment and profitability was based on data from Costa Rican high-production agroecosystems.

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Although multiple agronomic practices have been undertaken to introduce the 'MD-2' cultivar in marginal areas, the projects have often been terminated for financial reasons. This lack of success demonstrates the need to understand the fundamental relationships between water, soil, plant, and environment on growth, development, and final yield of pineapple.

Accurate predictions of crop growth, development, and productivity are essential, especially with the increased emphasis on climate smart agriculture. During the 1990s, there were important advances in predicting the growth, development, harvest date, and yield of 'Smooth Cayenne' (Zhang and Bartholomew, 1993; Zhang *et al*., 1997). These improvements resulted in the development of the Aloha Pineapple model based on the maize model CERES-Maize (Jones and Kiniry, 1986). The Aloha-Pineapple Model was also integrated into the Decision Support System for Agrotechnology Transfer (DSSAT) (www.DSSAT.net) as a tool to support agricultural management (Hoogenboom *et al*., 2023; Tsuji, 1998). The original Aloha Pineapple Model was developed for the 'Smooth Cayenne' cultivar when this cultivar was predominantly used for canned fruit production. Since the original model was developed, cultivation technology has changed significantly. Therefore, the original model cannot effectively show agronomic problems and help in decision making for investment projects because of its inability to simulate the phenotypic plasticity of the pineapple plant associated with the environment.

The original model also does not include significant or useful agronomic vegetative phenological stages, and the reproductive stages are not precisely defined. Physiological maturity, which is a critical event for the fresh fruit industry because it defines the moment of fruit degreening, was predicted with criteria for the canning industry, which is very different from the physiological maturity criteria of fruit for fresh consumption.

The new Aloha Pineapple Model is based on the application of fundamental equations of plant growth physiology using weather variables as parameters of statistical regressions to predict the growth of phenological stages (V) and (R) and indicators of agronomic interest of the pineapple plant and fruit. This approach and the use of pineapple growth data from contrasting environmental conditions allows for the simulation of the phenotypic plasticity of the pineapple plant. The overall objectives of the new model are to allow for comparative monitoring by phenological stage of crop growth in the absence of growth limiting factors; to simulate and present quantitative, objective, and useful agronomic indicators for the evaluation of growth and agronomic management of pineapple; and for the model to be used as a tool for predicting the harvest date of both artificially induced and natural fruits.

Materials and methods

Experiments and data collection

'MD-2' pineapple growth data were obtained from plants grown in three contrasting environments in Costa Rica at three elevations of 90, 174, and 1,573 m a.s.l., representing different air temperature and solar radiation conditions. These sites are called Warm Zone (WZ), Typic Zone (TZ), and Cool Zone (CZ). The WZ represents very hot agroecosystems usually with productivity problems related to small fruit size where NF does not occur. The TZ represents very productive agroecosystems usually with a significant incidence of NF. The CZ is not currently a pineapple agroecosystem, but it was included in order to study pineapple response to low temperature conditions. At each location, a Davis Vantage-Pro weather station was installed with the same configuration and sensors.

At all three sites, 'MD-2' was cultivated at three different planting dates, i.e., January 2021, May 2021, and September 2021, using culture bags and the same soil as substrate. The soil texture was classified as a sandy clay (sand 60%, clay 37%, and silt 3%), with a pH of 4.45, an organic carbon content of 2.39%, and nitrogen content of 0.31%. For each planting date, 10 plants were selected to determine a weekly sampling scheme of the phyllotaxy of each plant and to determine when each V-stage was reached. A new V-stage is defined when at least 50% of the 10 selected plants have reached that particular V-stage. The same criteria were also used to assess the R-stages. The description and methodology for determining the phenological stages is based on the methodology described for 'MD-2' by Vásquez-Jiménez et al. (2023).

In all cases, sucker seed was planted either on the same day that it was harvested from the "mother" plants or the next day with a fresh weight that ranged between 600 g and 650 g. The seed was obtained from the same plot of seed production from a high-tech company based in Costa Rica. Fertilizer and pesticide applications were based on standard agricultural practices of the Costa Rican industry.

When a phenological stage was completed, a sample of three plants was obtained, and the leaf area and fresh and dry weight of these plants were measured. The dry weight was obtained from each complete structure, including leaves and stem, by drying the different parts of the plants in a large forced hybrid solar dryer at the Instituto Tecnológico de Costa Rica as described in Guzmán-Hernández *et al*. (2019). The leaf area (indirect methods) was determined for each group of leaves (A, B, C, D, E, and F) according to the Sideris and Krauss (1936) leaf classification system. The basal white tissue was separated to consider only the photosynthetic green tissue in the estimation of the leaf area. Leaf area of the entire plant was calculated using the ImageJ v. 1.52a software and the methodology established by JianChang *et al*. (2011).

The leaf area and dry weight data of the vegetative phenological stages were obtained when the plants reached the following stages: First New Leaf (FNL), Leaf Cycle 1 (LC1), Leaf Cycle 2 (LC2), and Leaf Cycle 3 (LC3). Flowering induction was performed with ethephon when the third leaf cycle was reached. In R-stage we measure leaf area and dry weight at the time of harvest.

Model improvement

The study was undertaken to update the original Aloha Pineapple Model to include the 'MD-2' cultivar. The Source Code was obtained from the DSSAT Foundation (www.DSSAT.net). The first step was to modify the structure of the model, specifically the simulation of the phenological stages. A comparison between the phenological stages included in the original model and the current model is shown in Table 1. Phenology simulation is based on the scope of Growing Degree Day (GDD), resulting in the Cultivar Genetic Coefficients (CGC) for each phenological stage. The methodology used to define each CGC associated with each phenological stage was trial and error, using the Sensitivity Analysis tool (DSSAT v. 4.8). The estimated stage by the model was compared with the actual dates of each experiment in which each phenological stage was reached by at least 50% of the plant population (more details in the phenology section).

Table 1. Comparison of the original and new phases and stages of the Aloha Pineapple Model in DSSAT 4.8.

Original stage	Original definition	Current stage	Current definition	Term source code	Gdd* calibrated value
7	Start simulation to planting	11	Start simulation to planting		
8	Planting to root initiation	12	Planting to Root Initiation	TC	95
9	Root initiation to first new leaf emergence	13	Root Initiation to First New Leaf	P1	25
1	First new leaf emergence to net zero root growth	1	First New Leaf to leaf cycle 1	P2	1,150
2	Net zero stem growth to forcing	2	Leaf cycle 1 to leaf cycle 2	P3	875
		3	Leaf cycle 2 to leaf cycle 3	P4	700
		4	Leaf cycle 3 to forcing		
3	Forcing to sepals closed on youngest flowers (SCY)	5	Forcing to Open Heart	P5	815
4	SCY to first open flower	6	Open Heart to Early Anthesis	P6	530
		7	Early Anthesis to Final Anthesis	P7	630
5	Fruit growth	8	Final Anthesis to Physiological maturity	P8	2,000
6	Physiological maturity	9	Physiological maturity to Harvest	G1	90
		10	Harvest		
Genetic coefficients of the cultivar not associated with specific phenological stages.					
Potential eye number			#	G2	158
Potential eye growth rate			mg eye^{-1}	G3	28
Phyllochron interval between successive leaf tip appearances			GDD	PHINT	90

* GDD: Growing Degree Days.

There are four additional stages in the new model; three of them correspond to added leaf cycles in the vegetative stage, and one was added in the reproductive stage, where intervals between flowering stages were redefined to improve the accuracy of identification.

An equation was needed to adjust the differences in the initial weight of the vegetative seeds before predicting growth that included the increase in leaf area and biomass of each vegetative structure of the plant. The differences in the initial weight of vegetative seeds are dependent upon factors such as the origin of the seed and the methods of collection, storage, and selection of planting material. These differences are a challenge for a growth prediction model in handling the first stage, i.e., the Planting stage.

During the Planting stage, we found that the best equations to set the initial weight of the seed correspond to predictive polynomial equations that relate the total dry weight of the seed to the dry weight of each vegetative structure, to obtain a corrected value of the initial dry weight at the start of the model. The above was confirmed by a comparison between the predictions and actual results using a hypothesis test $P > 0.05$, in accordance with the validation technique developed by Sargent (2011).

Once the values of the initial variables were set, the equations were developed through a regression between the natural logarithm of the initial dry weight and the natural logarithm of the dry weight of each plant structure. Using the statistical software Infostat (Di Rienzo et al., 2018), the best equation was selected. While these equations are essential for the operation of the model, they can only accurately predict the growth and production of plants that are obtained from sucker-type seed fresh weight ranging from 600 to 650 g (65 to 75 g of dry weight per seed).

The Relative Grow Rate equation was used to predict biomass and leaf area for the following phenological stages: First New Leaf (FNL), Leaf Cycle 1 (LC1), Leaf Cycle 2 (LC2), Leaf Cycle 3 (LC3) and Harvest (HRV), The set of equations used in the source code for growth prediction are always the same both arithmetically and conceptually for each phenological stage mentioned above (see the set of equations in Equation 4). These equations are obtained from the general relative growth rate equation (Equation 1) and a regressor equation (Equation 2). The explanation of these equations is as follows:

$$RGR = \frac{Ln\left(\frac{P2}{P1}\right)}{t2-t1} \qquad \text{(Eq. 1)}$$

Where:
RGR: relative growth rate between the previous stage and the current stage;
P2: value of the variable in the current stage;
P1: value of the variable in the previous stage;
t2: time in days of the current stage;
t1: time in days of the previous stage.

The regression between the values of the growth rate calculated with Equation 1 for each vegetative structure against the regressor variable, Equation 2, allows for the prediction of the growth rate of each vegetative structure.

$$RV = Ln\left(GDD/\left(\frac{TMAX}{SRAD}\right)\right) \qquad \text{(Eq. 2)}$$

Where:
RV: regressor variable;
GDD: Growing Degree Day, daily average during the growth time of the phenological stage;
TMAX: average daily maximum temperature (in °C) during the growth time of the phenological stage;
SRAD: average daily total solar radiation in (MJ m^{-2} day^{-1}) during the growth time of the phenological stage.

Equations 1 and 2 are related by means of a second-degree polynomial equation. This polynomial equation consisting of logarithmic Equations 1 and 2 was included in the model source code. An antilogarithmic equation was also added that allows for the transformation of the result from the polynomial regression to a value in growth units (g or m^2).

Equation 2 represents a factor obtained from the natural logarithm of the ratio between the GDD required by the phenological stage and the ratio of the average maximum temperature (TMAX) and the daily total solar radiation (SRAD). The averages for TMAX and SRAD are calculated by the model based on the time required for each phenological phase (GDD). It is assumed that Equation 2 predicts the growth rate associated with an agroecosystem that is between the agroclimatology conditions of CZ (low temperatures) and WZ (high temperatures), which are considered contrasting and include the TZ, typical tropical environment for pineapple production.

The First New Leaf is the first stage where Equations 1 and 2 are used. In addition, Equation 3 was used because it had a better correlation for the prediction of Relative Basal White Tissue Dry Weight (RBWTDW1).

$$RGR\ modified = \frac{Ln\frac{P2}{P1}}{avGDD/(\frac{avTMAX}{avSRAD})} \qquad \text{(Eq. 3)}$$

Where:
RGR Modified: relative growth rate between the previous stage and the current stage;
P2: value of the variable in the current stage;
P1: value of the variable in the previous stage;
avGDD: average GDD obtained during the growth period of the current stage;
avTMAX: average maximum temperature obtained during the growth period of the current stage;
avSRAD: average daily total solar radiation (MJ m^{-2} day^{-1}) obtained during the growth period of the current stage.

With the regression of Equations 1 and 2, the variables RLAE1 (Relative Leaf Area Expansion), RLDW1 (Relative Leaf Dry Weight), RSTMWT1 (Relative Stem Dry Weight) are predicted, and with Equations 3 and 2, RBWTDW1 (Relative Basal White Tissue Dry Weight) was predicted.

Using Equation 4, the predicted value of the target variable was calculated.

$PLA1 = PLA12 \times EXP(RLAE1 \times (DAP3 + DAP1))$ estimate leaf area of green tissue;

$LFWT1 \quad = LFWT12 * EXP((RLDW1/1000) * (DAP3 + DAP1))$ estimate leaf green weight;

$BASLFWT1 = BASLFWT12 * EXP((RBWTDW1/1000) * (\frac{GDDFR}{(TMAXGRO/SRADGRO)}))$ estimate basal white leaf weight;

$STMWT1 \quad = STMWT12 * EXP((RSTMWT1/1000) * (DAP3 + DAP1))$ estimate stem weight (Eq. 4)

DAP3 and DAP1 define the days after planting between the Planting stage and the First New Leaf stage. The days after planting are used when the relative growth variables are calculated with Equations 1 and 2. In the variable BASLFWT1, the days after planting is not used, since RBWTDW1 was calculated with Equations 2 and 3.

Due to the non-uniformity of the seed associated with seed selection of the agroindustry, a new variable SEEDQLY was added for the prediction of the FNL stage.

$$SEEDQLY = 1 - \left(\frac{BASLFWT12}{LFWT12}\right) \times PLTPOP \qquad \text{(Eq. 5)}$$

Where:
SEEDQLY: potential factor or seed quality;
BASLFWT12: weight (g plt^{-1}) at sowing time of the basal white leaf tissue;
LFWT12: weight (g plt^{-1}) at sowing time of the photosynthetic green tissue of leaves; it does not include the weight of the basal white leaf tissue.

The variable calculated with Equation 5 was applied to the LFWT1, BASLFWT1, and RSTMWT1 variable to improve the prediction of biomass.

Upon completing its GDD, each phenological stage pushes to the next one and in turn assigns the initial value for the prediction of growth to each vegetative structure. As growth increases, the model predicts the number of leaves using the PC factor (a value between 0 and 1) that adjusts as a fraction of the phyllochron interval that occurs each day based on the TI factor (Figure 1), a polynomial equation that predicts the fraction of the phyllochron emerging by day.

The phyllochron fraction is calculated by dividing the number of leaves of each leaf cycle (LC) (13 units) and the number of days it takes to reach each respective LC, (time to P2 for LC1, P3 for LC2, and P4 for LC3). If the minimum temperature is less than the base temperature, the TI variable is set to zero. At the end of each day, the number of leaves is updated in the CUMPH variable. That is, the GDD of P2 and LC1 are reached when CUMPH = 13, LC2 and P3 are reached when CUMPH = 26, and LC3 and P4 are reached when CUMPH = 39.

The TI equation (shown in Figure 1) is the same for all leaf cycles, while the differences in the TI prediction are controlled by the PC variable, which is affected by a specific multiplier over the phyllochron interval (PHINT) based on the LC that is being predicted. We found that the specific multiplier for the PC variable is 1 for the prediction of LC1 (13 leaves), 0.9 for the prediction of LC2 (26 leaves) and 0.85 for the prediction of LC3 (39 leaves). This decrease of the multiplier is due to the fact that by increasing the number of leaves, the leaf area increases and the leaf production capacity increases, so the time to reach leaf cycle is reduced, which must be adjusted by reducing of the multiplier on the variable PC. Note how the reduction of the multiplier is 0.1 from LC1 to LC2, while from LC2 to LC3 it is 0.05, this smaller reduction

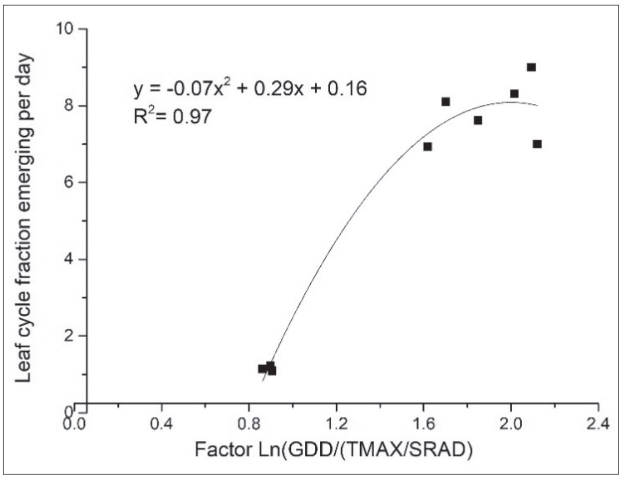

FIGURE 1. Leaf cycle fraction (TI) emerging by day. Data from experimental plots cultivated with the 'MD-2' pineapple cultivar in three contrasting environments of Costa Rica.

from LC2 to LC3 is due to the fact that at this stage the plant also allocates storage photosynthate to the stem, which does not occur in the previous stages except if the plant is predisposed to natural flowering.

In terms of biomass, the Open Heart, Early Anthesis, Final Anthesis and Phenological Maturity phenological stages are not useful for agroindustry, so biomass was not estimated for these phenological stages. Therefore, leaf area, leaf, stem, and root weight follow a smooth trajectory from LC3 to harvest. The peduncle and other vegetative structures were based on the original model (Zhang *et al.*, 1997; Zhang and Bartholomew, 1993) but do not consider the agronomic indicators that are proposed in the new model.

Table 2. Statistics generated with the DSSAT GBuild 4.8 tool for: 1) Phenology: in which the precision of the calibration obtained in terms of days after planting (DAP) is compared (Observed: Obs *vs.* Simulated: Sim), both in vegetative and reproductive stages; 2) Growth: in which the precision of the calibration obtained in biomass is compared in each of the phenological stages; and 3) Specific agronomic indicators in their respective yield units are compared at the time of harvest, except Bio-Fo, which has its agronomic relevance at the time of forcing.

Variable name	Mean (Obs.)	Mean (Sim.)	Mean (Ratio)	Std. Dev. (Obs.)	Std. Dev. (Sim.)	R^2	Mean Diff.	Mean Abs. Diff.	RMSE[1]	d-Stat[2]	Used Obs.
Phenology (Days after planting)											
Vegetative stages											
RI	12.0	12.6	1.05	6.43	7.59	0.94	1	1	2.19	0.98	9
FNL	15.6	16.4	0.95	10.01	9.57	0.95	1	2	2.36	0.98	9
LC1	173	169	0.98	100.5	98.95	0.99	-4	6	7.54	0.99	9
LC2	171	169	0.99	10.41	8.67	0.78	-2	4	5.16	0.93	6
LC3	235	222	0.94	20.0	11.5	0.79	-14	14	17.7	0.77	4
Reproductive stages											
OH	43.4	41.1	0.95	8.68	9.42	0.92	-2	2	3.58	0.96	9
EA	60.9	62.0	1.02	12.8	14.5	0.95	1	3	3.73	0.98	8
FA	87.3	88.4	1.01	21.3	21.6	0.99	1	2	2.26	0.99	8
PhM	437	436	1.00	112.4	110.3	0.99	-1	3	3.79	1.00	8
HRV	440	440	1.00	110.8	111.3	0.99	0	3	3.55	1.00	8
Growth (Biomass)											
Vegetative stages											
FNL	1,030	1,035	1.01	74.4	96.7	0.00	5.5	106.2	124.7	0.36	9
LC1	2,166	2,065	0.96	236.8	213.3	0.30	-100.9	170	236.9	0.74	9
LC2	4,058	3,575	0.81	893.4	1491	0.97	-483.5	483.5	798.7	0.89	7
LC3	7,429	7,107	0.97	1,018	479	0.96	-321.6	594.5	641.8	0.83	6
Reproductive stages											
HRV	5.81	5.38	0.94	2.48	2.19	0.81	-0.43	0.97	1.16	0.94	8
Growth (Leaf count)											
LC1	13.0	12.7	0.97	0.50	1.97	0.34	-0.3	1.1	1.75	0.46	9
LC2	26.1	25.8	0.99	0.57	1.45	0.03	-0.3	1.4	1.48	0.31	6
LC3	39.0	38.8	0.99	0.68	1.75	0.00	-0.2	1.6	1.84	0.32	6
Growth (Leaf Area Index)											
FNL	0.40	0.40	1.00	0.05	0.04	0.60	0	0.03	0.03	0.87	9
LC1	0.71	0.66	0.96	0.22	0.19	0.85	-0.05	0.08	0.09	0.94	9
LC2	1.38	1.22	0.80	0.47	0.52	0.82	-0.16	0.21	0.27	0.93	7
LC3	2.21	2.19	1.00	0.31	0.22	0.30	-0.02	0.23	0.26	0.70	6
HRV	1.76	1.83	1.14	0.84	0.79	0.88	0.08	0.25	0.30	0.97	8
Specific agronomic indicators											
HI	0.77	0.81	1.05	0.12	0.11	0.70	0.04	0.06	0.08	0.89	8
Fr-p-Fr	131.4	145.7	1.15	28.5	21.5	0.61	14.3	16.2	22.8	0.80	8
Eye-w	2.28	2.57	1.13	0.76	0.84	0.88	0.28	0.29	0.41	0.93	8
Bio-Fo	5.40	5.10	0.95	2.30	2.10	0.95	-0.40	0.60	0.66	0.98	8

Definition of abbreviations: Root Initiation: RI; First New Leaf: FNL; Leaf Cycle 1: LC1; Leaf Cycle 2: LC2; Leaf Cycle 3: LC3; Open Heart: OH; Early Anthesis: EA; Final Anthesis: FA; Physiological Maturity: PhM; Harvest: HRV; Harvest Index: HI; Fruitlets per Fruit: Fr-p-Fr in units; Eye weight: Eye-w; Above ground biomass at forcing: Bio-Fo in tons ha^{-1}.

Observed: Obs.; Simulated: Sim.; Standard deviation: Std. Dev.; Difference: Diff.; Absolute difference: Abs. Diff.

[1] RMSE: Root Mean Square Error.

[2] d-Stat: The index of agreement (d) proposed by Willmott *et al.* (1985) according to the d-statistic, the closer the index value is to one, the better the agreement between the two variables that are being compared.

Model calibration

In the DSSAT Cropping System Model (Hoogenboom *et al.*, 2019; Jones *et al.*, 2003), the specific traits of a cultivar and plant response to local weather conditions are known as Cultivar Genetic Coefficients (CGC). Realistic trait physiology is currently to be considered for some crop models to link genetics more closely with crop modeling (Boote *et al.*, 2021). However, in the Aloha Pineapple Model, most of the development CGCs are based on a simpler approach, *i.e.*, Growing Degree Days (GDD).

The calibration of the model has two steps. The first is the calibration of the GDD necessary to reach a particular phenological stage based on the actual observation dates for each zone and planting date, resulting in a GDD for each CGC as defined in Table 1. The second step is biomass calibration, which is based on leaf green weight (LFWT), basal white leaf weight (BASLFWT), and stem weight (STMWT). The leaf area of green tissue (PLA) was calibrated based on the leaf area index (LAI).

The optimization process confirmed that a base temperature of 13 °C for all the V stages resulted in the highest prediction precision, while for the R stages the highest prediction precision was obtained with a base temperature of 2 °C.

1. Phenology. The calibration of the GDD defined in Table 1 was first conducted for each treatment representing all combinations of zone and planting date. Each phenological stage, one at a time, was subject to a trial-and-error evaluation using sensitivity analysis until the exact GDD was found for each phenological stage and for each Zone/Planting-Date combination with testing done using base temperatures of 0 °C to 16 °C. Subsequently, an average of the GDD for the respective phenological stage was obtained, and the result was evaluated graphically. The modified Aloha model was calibrated for the export agroindustry, which generally uses ethephon to degreening the fruit.

2. Growth. The model was calibrated for growth based on a regression generated between the Relative Growth Rate equation (Equation 1, described in the previous section) and a regressor equation (Equation 2, also described in the previous section). Equation 1 defines the total amount of growth units to be assigned to each vegetative structure according to the duration of the phenological stage, while the regressor equation (Equation 2) uses thermal time, maximum temperature, and maximum solar radiation to define the fraction of growth unit to be allocated per day. The use of these environmental variables in the regressor equation allows the model to identify different agroecosystems. Growth precision in the model depends largely on a good phenology calibration, as this calibration influences the estimation of GDDs that are the basis of the growth equations.

Model evaluation

Model evaluation requires independent data. However, the agroindustry only has data for planting dates, forcing dates, physiological maturity, and harvest dates. Therefore, the model was evaluated with a hypothesis test in Infostat of dates predicted by the model *vs.* actual dates for the sowing/physiological maturity interval.

Model application

In general terms, there are two agronomic problems or opportunities for improvement in agroindustry regarding the interpretation of production and productivity. The first one is to determine *a priori* the productive potential of new agroecosystems for pineapple production, *i.e.*, solid technical information for pre-feasibility studies, and objectively to determine the productive potential of agroecosystems already established with pineapple cultivation, *i.e.*, solid technical information to define strategies for the day-to-day management and the continuous improvement.

On the other hand, the pineapple agribusiness needs the ability to predict the harvest date of forced and naturally flowering plant. Software that could speed up and improve the precision of these estimates would be of great help.

Some of these production challenges can be addressed by defining diagnostic agronomic indicators. To assist in this process, scientific evidence of typical characteristics of plants associated with the agroecosystem like those mentioned by Bartholomew (2018) should be used, along with empirical evidence of undesirable characteristics of fruits, *i.e.*, export market criteria, associated with certain agroecosystems (Bartholomew and Sanewski, 2018). The data from the typical Costa Rican production condition (TZ site) were used in this study as a reference for ideal or desirable values of the diagnostic indicators, both for the biomass of the plants and for the number and weight of the fruitlets at the fruit level. For values that indicate a negative impact on production, the data from the WZ site were used as references, especially

Table 3. Air temperature and solar irradiance for the different zones and planting date during this study of pineapple plant and fruit development.

Zone	Planting	Temperature †			Irradiance‡ (mj m^2 day^{-1})
		Minimum	Maximum	Average	
		°C			
CZ	Jan.	14.6 (9.3 – 17.0)e	20.7 (16.8 – 24.2)d	17.5 (14.6 – 20.3)	12.3c
	May	14.7 (9.3 – 17.0)e	20.8 (16.8 – 24.2)d	17.6 (14.6 – 20.3)	11.6c
	Sep.	14.6 (9.3 – 17.0)e	20.7 (16.8 – 23.9)d	17.5 (14.6 – 20.3)	11.8c
WZ	Jan.	21.2 (15.4 – 25.9)cd	33.3 (27.8 – 37.9)a	27.0 (24.2 – 29.9)	20.0a
	May	21.2 (14.2 – 24.7)d	33.4 (27.8 – 38.1)a	27.0 (23.5 – 30.1)	20.0a
	Sep.	21.4 (14.2 – 24.5)d	32.8 (26.6 – 38.1)b	26.8 (23.5 – 30.1)	19.3a
TZ	Jan.	21.7 (15.1 – 24.3)a	30.0 (22.4 – 33.2)c	25.7 (20.7 – 28.0)	13.9b
	May	21.6 (16.2 – 24.3)ab	30.2 (22.5 – 34.4)c	25.7 (21.1 – 28.9)	14.0b
	Sep.	21.6 (16.2 – 24.2)bc	30.2 (22.5 – 34.4)c	25.7 (21.1 – 28.9)	14.2b

† Average daily data over planting-harvest growing time, in brackets, range minimum and maximum of total data of growing time.
‡ Average daily irradiance over planting-harvest growing time.
Equal letters within each column represent non-significant differences for $p < 0.05$.

those related to the biomass of the plants and HI. Empirical evidence from companies that are producing pineapple in agroecological conditions similar to the WZ site was used as a reference for undesirable characteristics of the fruit.

The agronomic indicators were included in one of the output files of the model, so that a complete list of the agronomic indicators and their respective predicted value will be available when using the model. The predicted value can be compared with real results of the farm or the agroecosystem that is being studied in order to obtain an objective basis to develop strategy to improve each of the agronomic indicators.

Results and discussion

Data collection and experiments

The use of the phenological stages as defined by Vásquez-Jiménez *et al*. (2023) and contrasting environments of the experimental plots resulted in different growth responses of the 'MD-2' cultivar required for modeling. At the same time, these stages allowed us to characterize the growth associated with a specific agroecosystem, so that the identification of the agronomic indicators of production was possible, which allows the model not only to predict growth and productivity, but also to use agronomic indicators as analytical input to interpret the specific improvement opportunities of agroecosystems.

Model improvement

1. Why RGR and not photosynthesis? The most advanced crop growth models are based on photosynthesis (Hoogenboom *et al*., 2023), but until now, the pineapple model does not have sufficient data on the dynamics of photosynthesis and dry matter partitioning to predict growth. CAM photosynthesis and related metabolism plays a major role in photosynthate allocation, but currently the data only explain different intensities of metabolism under certain controlled conditions of temperature, CO_2 concentration, and light and dark conditions (Connelly and Bartholomew, 1971; Horie *et al*., 2019; Ritchie and Bunthawin, 2010; Zhu *et al*., 1997a, b). The results from these experiments do not explain differences in photosynthetic rates for these conditions, which are needed for a robust model that simulates the dynamics of photosynthesis and dry matter partitioning. A recent study (Hartzell *et al*., 2021) proposed modeling the non-linear dynamics of CAM productivity and water use for global predictions using *Opuntia ficus-indica* and *Agave tequilana*. However, the plant genera used by these authors is very different from the *Ananas* species, and the global prediction approach is not compatible with the pineapple agroindustry, which requires site-specific information.

2. Improvements. In addition to improving the model for the 'MD-2' cultivar, which is the most important cultivar in terms of worldwide production volume (Sanewski *et al*., 2018), the model's main improvement is the prediction of new vegetative stages with data from contrasting environments to simulate the effect of the agroecosystem on dry matter partitioning.

Our data showed significant phenotypic plasticity in the different structures of the plant, mainly between the leaves and the stem, clearly dependent on the environment where the plant was grown. The differences in the phenotypic plasticity allow us to define and build agronomic indicators associated with the different agroecosystems where pineapple is grown and understand the reason for the agronomic differences, that occur between agroecosystems such as HI, forcing quality and productivity. Therefore, for pineapple a model based on the RGR is an important step in simulating phenotypic plasticity attributed to the environment.

Model calibration

The different statistics for model calibration for phenology and growth are shown in Table 2. It also includes specific agronomic indicators that are analyzed in the final section of this paper that describes the utility of the model. The discussion is divided into two parts including the performance of the model in predicting phenology and in predicting growth.

1. Phenology. The precision of a growth prediction model depends, in part, on determining the specific moment in which the characteristic development traits are reached

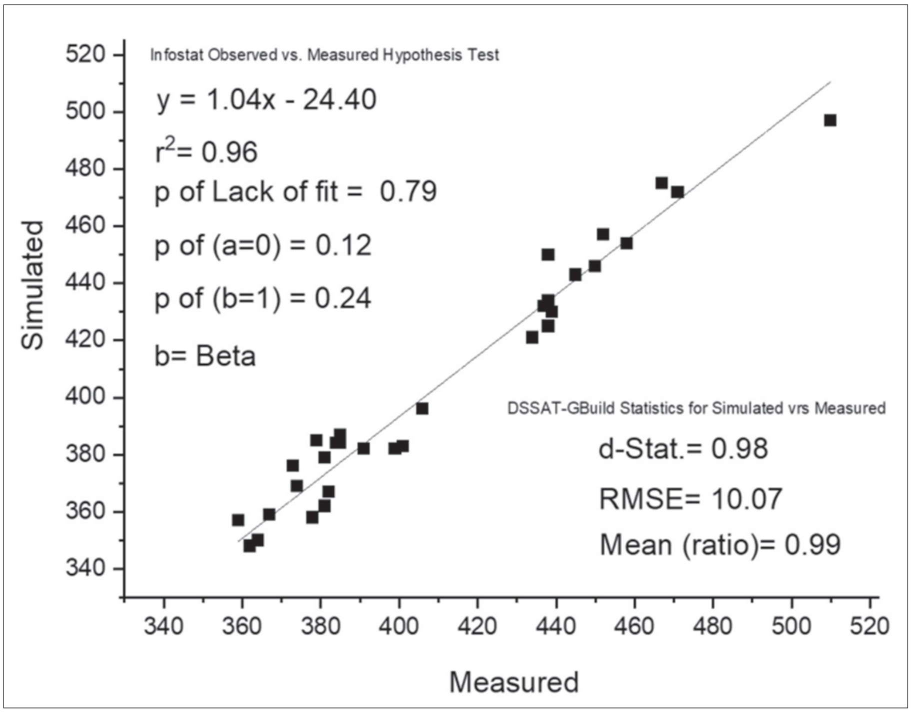

Figure 2. Simulated *vs.* measured days to physiological maturity in days after sowing for cultivar 'MD-2'. Actual data from a pineapple farm in Costa Rica that produces 'MD-2' for export.

Table 4. Example of comparative and interpretive use of model outputs (specifically agronomic indicators) *vs.* farm data. The columns Farm results and Model outputs are hypothetical but based on real empirical evidence of different agroecosystems that grow the 'MD-2' pineapple cultivar.

Agronomic indicators	Farm results	Model outputs	Additional condition (weather and field evidence)	Potential interpretation	Agronomic action
Harvest Index (HI)	<0.60	>0.70	Big plants Heavy stems WZ Like climate	Poor forcing quality. See WARNING.	Improve forcing quality
Fruitlets per fruit	<115	>140	Very large fruitlets Bracts split in half Good forcing criteria and 100% plants forced.	Poor forcing quality. See WARNING.	Improve forcing quality
Fruitlets per fruit	<115	>140	Normal size fruitlets. HI >0.7. TZ Like climate.	Growth limiting factor affecting	Detect, correct growth limiting factor. Check water balance by phenological stage. Check plant nutrition.
Physiological maturity completion several days apart	Reached	Not reached	Fruitlets per fruit <115. Very large fruitlets.	Poor forcing quality. Few fruitlets the fruit reaches physiological maturity before. Bad forcing criteria.	Improve forcing quality and forcing criteria.
Leaf cycle 3 completion	Not reached	Reached	WZ Like climate. TZ Like climate. Small plants.	Several growth limiting factors affecting.	Detect, correct growth limiting factor. Check water balance by phenological stage. Check plant nutrition. Check seed quality.
Above ground bio-mass at forcing (ton ha^{-1})	>7.0	>7.0	High level of technological management but: In farm: HI <0.60 There is never NF. In farm and model output: LAIX >2.50	WARNING: This agroecosystem tends to have low quality induction. Low productivity.	Investigate new forcing strategies. The agroindustry standard can obtain 100% induction factor but with low induction quality. Detect, correct growth limiting factor.

by the plants. The traits that were determined visually and shown in Table 1 have an accuracy of approximately one week for V-Stages and one day for R-Stages based on how often field observations are taken (Vásquez-Jiménez *et al.*, 2023). The accuracy of the model in predicting phenology (days after planting) is high, with a d-Stat > 0.93 for the V-Stages RI to LC2 (Table 2). The average values should not be considered as a reference for the duration in days of a given phenological phase, since these averages were obtained from three contrasting agroecosystems.

When the statistic that compares simulated or measured values involves predicting the accuracy of a variable with a predefined fixed value, for example all 13 leaves in LC1 (such as Std. Dev, r^2 and dStat), the statistic value may not reflect the accuracy of the model. In a review of statistical indices for the evaluation of the performance of crop models, Saldaña-Villota and Cotes-Torres (2021) concluded that the coefficient of determination is not a useful statistic and that the root mean square error is preferred. The conclusion of these authors is clearly reflected in the cases mentioned above, or when the value to be predicted corresponds to the initial value of a variable. In these specific cases, the best statistic to check the accuracy of the model is the root mean square error.

For example, the standard deviation of both the simulated and measured values of around 100 days in the LC1 *vs.* LC2 or LC3 phenological stage (Table 2) is high. This is because at the CZ site this stage took around 310 days, at the TZ site it took about 104 days, and at the WZ site it took about 93 days. However, because NF occurred at the CZ site, the phenological stages LC2 and LC3 were not reached. Therefore, the standard deviation is less than 15 days (two weeks) since the calculation is composed only of data from the TZ and WZ sites.

During the calibration of the V-Stages, the base temperature that provided the best fit between simulated *vs.* measured values was 13 °C, while it was 2 °C for the R-Stages. This difference in base temperatures between vegetative and reproductive phenological stages found for these three environments demonstrates the pineapple's high phenotypic plasticity, which is reflected in the high demand for photoassimilates by the inflorescence and infructescence.

The use of data from contrasting conditions results in a more robust model. For example, in the cold zone the leaf area is smaller because the partitioning to the stem is greater compared to the warmer zones. Stem dry matter is much higher for low temperature conditions than for warm areas and it has a significant effect on the HI. To simulate the phenotypic plasticity of a pineapple cultivar correctly, two or more climatic conditions must be considered while they should be significantly different from each other. Since the prediction equations follow a polynomial projection, the model assumes that the phenotypic plasticity of the cultivar will be correctly simulated based on the weather conditions.

High phenological precision is needed in order to predict ripening and harvest dates to ensure shelf life and to meet agroindustry volume production requirements.

The R-Stages Open Heart, Early Anthesis, and Final Anthesis were calibrated to serve as reference points to predict the harvest date or physiological maturity of the fruit (with special interest in NF). The precision of the calibration between simulated *vs.* measured values was high (Table 2) ranging from a d-Stat of 0.96 to 0.99.

In the pineapple agroindustry, the prediction of physiological maturity of the NF fruit is critical for harvest and marketing (Bartholomew, 2014). The three R-Stages, *i.e.*, OH, EA, and FA, can be agronomically estimated by sampling to determine the occurrence date for each of the stages and then basing the prediction of NF physiological maturity on the dates for the other stages. In other words, to predict the physiological maturity date of NF with the model, the natural induction date must first be predicted.

The precision of the calibration between simulated *vs.* measured values for Physiological Maturity and Harvest was very high with a d-Stat value of 1 (Table 2), as expected from the high precision of the previous R-Stages. It also confirms the usefulness of using these stages for model calibration.

2. Growth. The differences between measured biomass and leaf area at the different V-Stages in CZ were visible to the naked eye. These values were also significantly different from those measured in TZ and WZ, mainly due to the low temperature. The differences between the minimum and maximum temperatures and irradiance at the three zones (Table 3) were found to be statistically significant ($P < 0.05$). In most of cases the differences between the biomass and leaf area between TZ and WZ were less evident to the naked eye, but the values were statistically different ($P < 0.05$) in most cases.

The model was slightly less accurate in simulating growth with values for d-Stat that were around 0.83, except for FNL which had a d-Stat value of 0.36 and LC1 which had a d-Stat value of 0.74 (Table 2).

The d-Stat value for biomass in the FNL phenological stage between simulated *vs.* measured values is low because the data points cluster around the same value. The linearity assumption (Ratner, 2009) between the observed and simulated values of the biomass variable in stage FNL was not met. Therefore, other statistical analyses should be considered to evaluate the accuracy of simulated values when compared to observed values. The value of the Mean Ratio statistic was 1.01 for biomass, which means that there is a high similarity between the simulated and observed values. Due to the short time between sowing and the FNL stage, the average value for biomass correctly represents all study sites. However, due to the short time between sowing and the FNL stage, the non-uniformity of the seed can skew the observed data and alter the precision of biomass estimation. This imprecision in the observed values at the beginning is mitigated with the use of the SEEDQLY variable (see Equation 5 in Materials and methods), but its effect is better reflected from the next stage LC1.

The relatively low d-Stat value of 0.74 for biomass in the LC1 stage between simulated *vs.* measured values is due to an underestimation of the biomass in two samples from the September sowing. This underestimation occurs when there is a lack of uniformity in the weight of the sampled seeds, but it does not imply that there is a problem with the simulation. Because during the LC1 stage the partitioning of dry matter is mainly directed at the production of new leaves and the number of leaves is close to the estimate Mean Ratio of 0.97 between simulated *vs.* measured values (Table 2), we concluded that the differences between simulated and observed values for biomass during LC1 are more related to the uniformity of seed weight at sowing and not the actual simulation of biomass. Uniformity during sowing is a problem because the pineapple seed is asexual or vegetative and uniform seed selection is an issue to be resolved in the pineapple agroindustry (Vásquez-Jiménez *et al.*, 2023).

There are no data for LC2 and LC3 for this zone because in CZ the plants were induced naturally prior to LC2, and because flowering interrupts the production of new leaves in the pineapple plant (Bartholomew, 2018).

The prediction of the foliar cycles will always be close to the fixed values of 13, 26, and 39 leaves for the corresponding leaf cycles LC1, LC2, and LC3. Both the simulated and observed values are oriented towards the same predetermined fixed value, and the assumption of linearity will not be met (Ratner, 2009). Therefore, the best statistics to evaluate precision between simulated *vs.* measured values for the variable number of leaves in each leaf cycle are the Mean Ratio, which is greater than 0.97 in all cases, and the RMSE, which is less than 1.84 in all cases (Table 2).

The data show a high prediction precision for LAI. Although in most cases the r^2 and d-Stat statistics have high values that are close to 1, they are not objective comparisons of the predicted and observed data for LAI. The values are close to 1 primarily due to the effect that the CZ site has on the dispersion of the data. The high contrast in the data is because of poor leaf development for the 'MD-2' plants under low temperature conditions with respect to the TZ and WZ sites (see Table 3). The best comparisons for this variable are again Mean Ratio and RMSE; the Mean Ratio between simulated *vs.* measured values is close to 1 and the RMSE is low at 0.27 (Table 2).

For natural flowering, the number of leaves is more important than the weight of the plant and the chronological age. Despite the cold climate for the CZ site (Table 3), there was no natural flowering for more than 400 days for the first planting date and more than 330 days for the second planting date. For both planting dates the incidence of NF began between LC1 and LC2. Flowering is artificially induced as part of the technical operations in the pineapple industry and normally occurs during LC3. To determine the correct time for forcing, it is better to use the leaf cycles instead of fresh weight. Depending on the weather conditions, fresh weight can vary and bias the technical forcing criteria, but leaf cycles are a precise and consistent measure (Vásquez-Jiménez *et al.*, 2023).

In determining the final Harvest stage, the model predicts biomass with a high precision, while the same is also true for yield (Table 2). The planting density is not calibrated in the model, so the estimation of productivity is based on the average weight of the fruit and a plant density of 13,333 Plt ha^{-1}. Therefore, any comparison should be made based on this density.

Model evaluation

The data from an export company were used for independent model evaluation for the prediction of the maturity date. The data simulated by the model and the measured data from a commercial farm were evaluated through a hypothesis test in Infostat. The null hypothesis was accepted ($P>0.05$), and there was no statistical difference between the simulated and measured values. This evaluation was further confirmed with a d-Stat value of 0.98 (Figure 2).

Model application

We found that our research confirmed the reports of Bartholomew (2018) regarding pineapple plant characteristics (larger plants and greater leaf area) and its agronomic consequences with a low harvest index for very warm climates associated with agroecosystems. We also identified “agronomic production indicators” that can be used as a diagnostic tool for agroecosystems to guide the production of ‘MD-2’. These indicators can be used to make production budgets compatible with the production potential of agroecosystems, reduce the environmental impact of production practices based on financial pressure, and potentially prevent project closure by using solid data generated by the model to develop sustainable management practices.

A summary of some agronomic indicators and their potential applications are described in Table 4.

Once both the statistically representative field data and the model prediction data are known, an analysis can be conducted. For example, if the farm HI is less than 0.6 and the model predicts an HI greater than 7.0, while at the field level the plants are large, the stems are heavy, and the weather is similar to that indicated in Table 3 for the WZ site, it is likely that there is poor quality forcing in that agroecosystem. If the above-ground biomass at forcing indicator (ton ha^{-1}) is greater than 7.0, in general that agroecosystem has a tendency to decrease the induction quality, which, if not corrected, will result in a low productivity. The induction factor and the quality of induction are concepts that have been well defined (Bartholomew and Sanewski, 2018), but the induction quality is normally not considered by the pineapple agroindustry.

Table 4 shows two cases where both the actual field results and the model outputs for fruitlets per fruit are the same, but a review of additional conditions provides different information. In the first case, the fruitlets are so large that the bracts are divided, giving the fruit an ugly general appearance. If the producer assumes that forcing occurred at the right time, the most likely problem is the quality of forcing, since the plants developed adequately. Although there was sufficient leaf area to produce large fruit, the fruit is small with few fruitlets per fruit. In the second case, the fruitlets have a normal weight, the HI can be higher than 7.0, and the climate is similar to that indicated in Table 3 for the TZ site. In this case it is likely that there is a limiting factor such as water, nutrition, soil preparation, *etc*. Since the weather conditions are conducive to producing large fruits, there is no reason to suspect a poor quality of induction. The fruits should have a greater number of fruitlets, but they do not because they are only producing the number of fruitlets that the weight of the plants and leaf area are capable of filling, implying that the plants have a low weight and little leaf area due to a limiting factor. This condition could also be due to poor agrotechnological practices or forcing that was carried out prematurely.

The two previous examples show some of the agronomic indicators that are included in the model and the potential for analysis and application. Agronomists with experience in ‘MD-2’ pineapple cultivation should be able to use all the agronomic indicators that are simulated by the model. The model can also be used as a tool for investment decision-making for new pineapple production projects. In this case the agronomic indicators of the model can be used to analyze an agroecosystem for possible investment, such as a pre-feasibility study, or to infer potential opportunities for specific improvement in the technical and operational management of established projects.

The model also predicts the harvest date, which can be used to budget production volumes of fruit for price and delivery negotiation. The R-Stages offer the possibility of associating a natural flowering date to estimate the dates of physiological maturity of the plants that flower naturally, which is helpful in coordination and logistical planning.

In the case of forcing fruit, the model predicts the harvest date based on the forcing date, using the Weatherman tool (also available in DSSAT v. 4.8) to first obtain a projection of the climate variables necessary so that the model can work with future dates.

To predict the harvest date of naturally flowering fruit, it is first necessary to conduct field sampling to accurately identify the date on which any of the R-stages are met prior to physiological maturity. This date will be the reference to use in the prediction. Through subsequent trial and error, forcing dates are tested until a forcing date is obtained that adjusts or predicts the date of the reference R-stage. Once this date is found, the predicted harvest date will automatically be the searched harvest date of the naturally flowering fruit.

Model potential

We have demonstrated and discussed the most important findings of the study, among which we emphasize the capacity of the model for simulation of phenotypic plasticity of the ‘MD-2’ cultivar as response to the environment. Based on the differences in growth and plant characteristics associated with phenotypic plasticity, the model can be used to define diagnostic agronomic indicators. These can then serve as a tool for analysis, agronomic interpretation, and definition of management strategies for agroecosystems under pineapple production. However, this required to limit the study to some very specific and controlled research conditions. Other relevant potentials of the model that are independent of any limitations is its ability to predict the harvest date of both artificially induced fruit and naturally flowering fruit.

Limitations and recommendations for model improvement

This study shows the potential for the model to be a useful tool for the pineapple industry, especially for the ‘MD-2’ cultivar. Future research could further enhance the model’s potential by using different types and weights of seeds. Other areas for model improvement would be the simulation of the effect of sowing density, since only one sowing density was used in this study for growth calibration. Components that need additional research include the effect of simulating limiting factors especially water and nitrogen.

Conclusion

The model improvements made resulted in more accurate phenology prediction and growth prediction. However, the accuracy of phenology prediction is greater than the accuracy of growth prediction. The degree of accuracy in predicting growth depends on improvements or changes in the seed selection and standardization paradigm by the pineapple agroindustry at the time of planting. The synthesis and demand for photo assimilates in pineapple are very different between vegetative and reproductive phenological stages, which is reflected in two highly contrasting base temperatures of 13 °C for V-stages and 2 °C for R-stages. One of the main benefits of the improved model is that it can provide agronomic indicators that facilitate the agronomic characterization of agroecosystems and the visualization of management strategies aimed at mitigating the harmful effects of the environment on productivity.

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