Smart Farming: Computer Simulation and Predictive Model for Cassava

by

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Abstract

The diffusion of new digital technologies renders digital transformation relevant to nearly every economic activity sector, including the farming sector. Technologies like internet of things (IOT) gave to the farming sector the necessary tools to move from precision agriculture to smart farming.Precision agriculture is characterised by the use of satellite and air planes. Farmers relied on it for a precision application of pesticide and such. Nowadays with the improvement of IOT we can collect information and help farmers at a lower cost. This work tends to present smart farming architectures, a general review on smart farming architecture different levels. A useful tool of smart farming is computer simulation for crop growth. An example of computer simulation will discussed. The present work also propose a predictive model for a specific crop, cassava.

Acknowledgments

First of all, I would like to thank me, for all the hard work, my great parents for the unconditional support and my supervisors for their patience, help and tolerance.

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Chapter 1

Introduction

The advent of IOT gave to the farming sector more freedom and flexibility in acquisition and use of information related to the farm. This abundance of information open new possibilities.

1.1 Motivation

It is anticipated that by 2050 the world food supply would be lacking. The proficient cultivating at lower cost can be an answer for whitewash this issue. Furthermore, this make smart farming an alluring field of examination. Among different yields, cassava is exceptionally tolerant to corrosive soils, versatile to environmental change. It's anything but a decent supplement esteem. This load of qualities made it ideal for nations underdeveloped, and area with harsh climate. The assortment of information empowers computer simulation and the utilization of predictive models for crop development. This can help increase the harvest yield.

1.2 Problem

Cassava is predominantly utilized in underdeveloped nations. In addition it's significantly indulgent to drought. Due to it's life expectancy going from eight months to eighteen months cassava is developed under heat and humidity. these reasons caused cassava to be designated "crop for poor". Consequently there is not enough recently research about cassava. Cassava Crop modelling software is not sufficiently refreshed and is not accurate enough

1.3 Solution

I propose a modification on existing models and the addition of predictive model to the simulation. The simulation model will take into consideration soil, weather and water stress and the prediction will help with nutrient optimum application.

1.4 Methodology

The method advocated here is a thorough analyses of smart farming frameworks and the establishment of predictive crop growing model applied to cassava. Smart farming aim to the optimum application of inputs compared to the obtained output. For that reason our work will be focused on determining the best way to apply nutrient, or fertilizer for cassava growth.

1.5 Contributions

Up until now, Cassava development models center around plant response to ecological information sources, like water, solar radiation and water dissipation. Our model will foresee the ideal opportunity to begin applying supplement, and the ideal opportunity to stop it. cassava crop maximum yield is known to be sensitive to contributions at a specific level of his turn of events, after that point, except if large natural pressure the result won't change. The addition of extra supplement will not affect the maximum yield.

1.6 Outline of the thesis

Chapter 2

Related Work

2.1 Internet of Things

2.2 Big Data

2.2.1 cloud computing

2.2.2 Fog Computing

2.2.3 Edge computing

2.3 Smart farming architecture

2.3.1 Perception Layer

2.3.2 Transport Layer

2.3.3 Processing Layer

2.3.4 Application Layer

Chapter 3

Simulation Model

Cassava plant is composed of essentially three main parts. The leaves, stem and storage roots. Cassava models can be categorised in two groups. The groups are formed based on assimilate partitioning. To be more explicit the way dry matter is distributed to the various parts of the plant. The way each part growth affects the plant growth. The first category concerns models which dry matter is partitioned according to a fixed pattern. In Boerboom et al 1978, ir is established a model built on two parameters, a linear relationship between storage root dry weight and total dry weight. In [5] Gutierrez built on the previous model using theory concept for a stronger analysis. But we are not really interested in this category. The disadvantage of the fixed-pattern approach is that it takes no account of the dynamic physiological processes in the plant that contribute to the final yield, and hence the response to variable environmental conditions is limited. In fewer word the leaves short life due to environmental conditions will not affect properly the growth of the plant various part, only the leaves growth. Which is incorrect. That is a reason for a second category. One of the first models developed for this category was [6]. Crop Growth Rate (CGR) is assumed to be a constant function of Leaf Area Index (LAI) and it is a serious limitation of this model that the performance of the crop under different solar radiation and temperature conditions cannot be studied.

The model took no account of temperature, solar radiation, or water stress effects, and although branching was an integral part of the model, control of this characteristic was not included. [7] extended [6] concept of CGR as a function of LAI to take into account the effect of light, temperature, and water stress. Dry matter allocation was based on empirical relationships derived from data of [8] for the cultivar MAusl0, including effects of temperature, photoperiod, and leaf and shoot sink size. Leaf senescence was calculated by multiplying a potential senescence rate by temperature, water status, or shading modifiers. Using this Australian model for other environment, will require a good amount of calibration. See fig 2 for a visual understanding of the model.

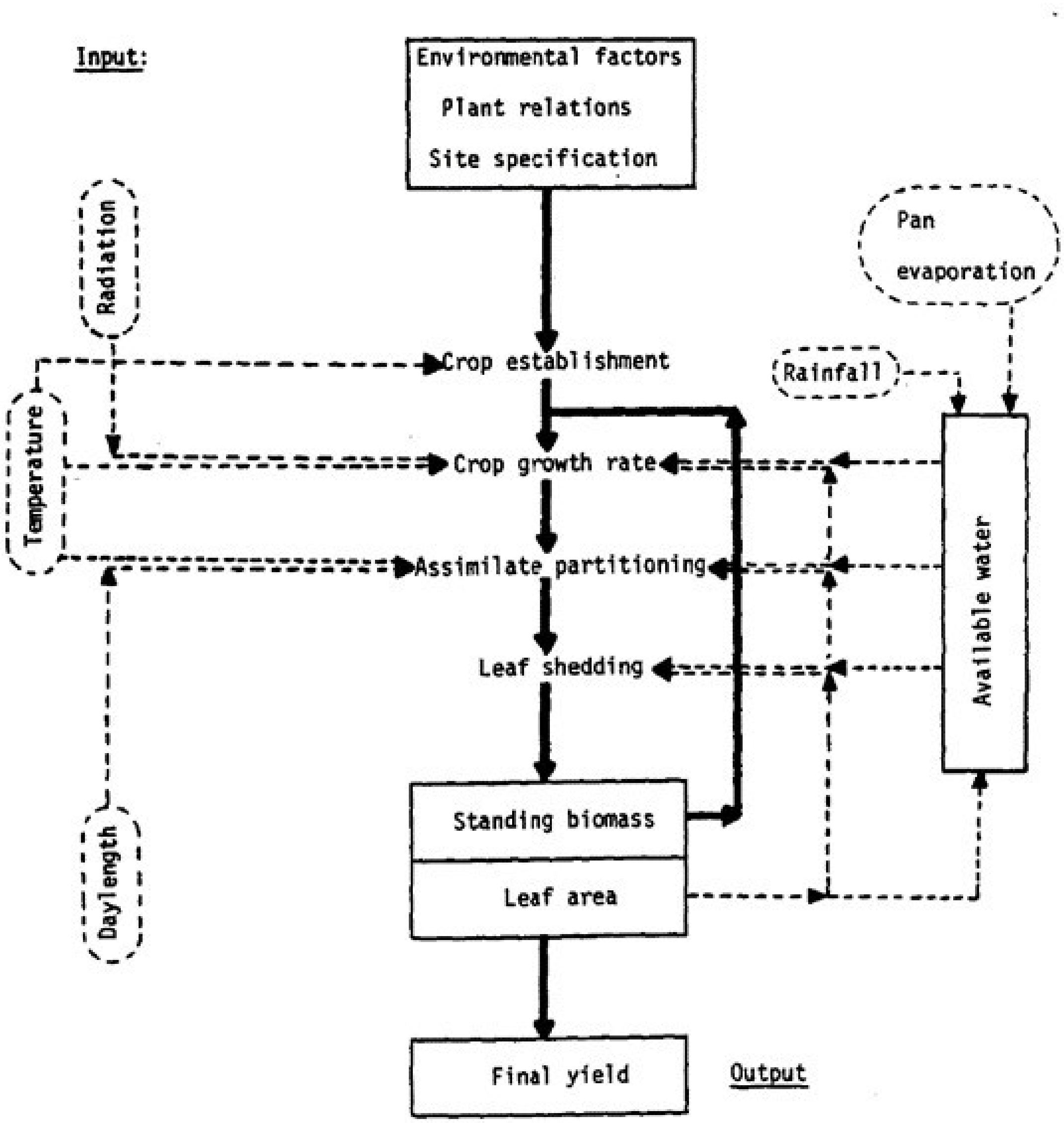
Most of the deficiencies in earlier models were well taken care of in the cassava simulation model GUMCAS [3]. Maximum potential CGR, a varietal character, is included in this model for calculating dry matter production. The effect of stress due to solar radiation, temperature, and water deficit on CGR has been computed with the help of multipliers, as in the case of the Fukai and Hammer model [7]. So far, we asserted the model based on groups and chronologically. And we have noticed that newer publications tend to improve previous models. In that trends [9] SIMCAS is a model built to help take into consideration nutrient supply. So far, we were taking into consideration environmental factors that we can not really control (except for irrigation). This model helps to reduce moisture, nitrogen, and potassium wastages, and to maximize yield by applying the required amounts at the proper time. The model also calculates stresses due to shortages of moisture, nitrogen and potassium on crop growth and yield.

It exists two types of models, statistical and process-based. So far, we have been talking about process-based model. The research has shown that there is possibility to combine statical model and Process-based models. In [10] we see an example with maize which combination reached a higher accuracy than the other types of models took individually. they compared predictions of a simple process-based crop model (Soltani and Sinclair 2012), a simple statistical model (Schlenker and Roberts 2009), and a combination of both models to actual maize yields on a large, representative sample of farmer-managed fields in the Corn Belt region of the United States. We have seen in the case of cassava models, they use both, statistical model to establish well the relationships between the different processes[7]. So far, our study led us to the understanding of the process-based software reproduction [11]. It is a platform in multiple languages, but the upside is that it provides tutorial on how modify and integrate new models.

3.1 Statistical model

3.2 Process-based model

3.3 Model Example



This model has been implemented and has been inspired by Fukai et al 1979.

3.3.1 Initialization

The initialisation part is made of two subsections. The first subsection is the initialisation of all environmental conditions. Because the model is made on a weekly base, we need a second initialisation to set the crop establishment parameters or better known as the plant onset.
The first initialisation require 52 set of values (representing 12 months, 52 weeks of growth) of all environments inputs. The environmental inputs will be assessed once. The parameters took in consideration are solar radiation (Sr), air temperature, rainfall, pan evaporation and day length (D). In order to determine the day length, we need the culture location and latitude. The pan evaporation is necessary to establish soil water balance, and for that we also specify the following soil parameters for the three first soil layer: depth, average bulk density, field capacity, wilting point and moisture content.
The second initialisation represent the crop establishment. It has been verified that the minimum accumulated temperature needed for establishment is 16.7 . For our crop to start growing we need to calculate the heat sum. When the heat sum reach 16.7 then the plant onset is met.

$$heat\_sum = \sum_{n=1}^{m} \sqrt{T - 16}$$

$$heat\_sum \geq 16.7$$

$$m : number\ of\ minimum\ week\ required\ for\ establishment.$$

For example a constant temperature of 25°C will take 6 weeks for establishment.
We do not take into consideration the water stress before onset. At establishment we assume that leaf area index (LAI) is set at 0.5, the stem is at 7, the petiole at 5, the lamina at 20, tuber at 0, planting piece at 37 and a total dry matter at 69.
And then we make a loop for 52 iteration of the following blocs.

3.3.2 Leaf area index (LAI)

To calculate daily the LAI we use leaf Lamina dry weight and create a polynomial extrapolation of specific leaf area.

$$LAI = lldw \cdot sla$$

where
lldw: leaf lamina dry weight
sla: specific leaf area.

3.3.3 Soil Water Balance

In the plant growth, the environmental conditions like water availability, pan evaporation can add stress on the plant. So determine the amount of stress these conditions add, we calculate a stress index (SI). The stress index is function of the potential extraction and potential transpiration.

$$SI = \frac{Pt - Pex}{Pt}$$

Where
Pt: Potential transpiration
Pex: Potential extraction
Note: SI should always be positive. If the result is negative which means that Potential extraction is superior to potential transpiration, we assume $SI = 0$. In that case there is no water stress on the crop.
The soil evaporation is needed to calculate the potential transpiration. It is related to the ground cover proportion and days separating rainfalls.
The ground cover proportion is:

$$scov = 1 - e^{(-K \cdot LAI)}$$

where
K=0.8
and LAI is calculated daily

From this we can obtain the potential soil evaporation:

$$PE = epan \cdot (1 - scov)$$

where
epan: pan evaporation
With this information we use Ritchie procedure to determine the soil evaporation amount. The soil evaporation amount helps to determine if the soil dry or not. According to this factor the potential transpiration calculus method may change To calculate the potential transpiration we deduce:

$$Pt = epan \cdot scov$$

For a dryer soil surface we take another path:

$$Pt = epan \cdot Gcov$$

where

$$Gcov = 1 - e^{(-cf \cdot LAI)}$$

$$For\ this\ particular\ case\ cf = 1$$

We should keep in mind that the root depth start at 70 cm at establishment and is increase by 7 cm each week until the maximum depth of the third layer, which is approximate at 120cm. With this information in mind we can calculate the uptake, "the amount of moisture that can be extracted. The sum gives the potential extraction.

$$Pex = \sum_{n=1}^{3} UPTAKE_i$$

$$UPTAKE_i = \alpha_i \cdot (PAWP_i)^{\beta}$$

Where i is for i^{th} layer, We calculate the uptake for each soil layer.
$\beta = 1.67$
$\alpha_1 = 3.2$; $\alpha_2 = 5.6$; $\alpha_3 = 6.7$
$PAWP_i$ is the plant available water proportion for each layer.

3.3.4 Crop Growth rate

The crop growth rate (CGR) is a function of LAI,solar radiation and temperature. Under optimum conditions which mean $temperature > 24^{\circ}C$ and solar radiation $> 22MJ \cdot m^2$, the i deal CGR is as follow:

$$ICGR = a - b \cdot e^{(-c \cdot LAI)}$$

Where
$a = 21.7$; $b = 20.5$; $c = 0.27$

Because ideal conditions do not really exist, the model need to take into consideration the stress induced by water, temperature and radiation. For that reason we did a polynomial extrapolation to determine the multiplier index for each parameter. with this update, the CGR functions change.

$$CGR = PCGR \cdot (tm \cdot rm \cdot wsm)$$

Where
tm: temperature index multiplier
rm: radiation index multiplier
wsm: water stress index multiplier

3.3.5 Assimilate distribution

After CGR we estimate the assimilate distribution among the different organs. This distribution is affected by temperature, day length, LAI and water stress index.The water stress polynomial extrapolation is unique for assimilate distribution. This relationship is expressed as follow:

$$DRS = [0.011T + 0.0136LAI + 0.0637 \cdot (D - 10)] \cdot wsm \cdot fm$$

Where:
DRS:Distribution ratio to shoot
T: Temperature
D: Day length

wsm : water stress multiplier
fm: fertilizer multiplier

$$fm = 0.65$$

if no fertilizer is applied and

$$fm = 1$$

if there is fertilizer

Chapter 4

Predictions

4.1 Data acquisition

4.2 Data analysis

Chapter 5

Implementation

Chapter 6

Conclusion and Recommendation

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