Is there Scope for Dynamic Crop Simulation Models in an AI World? – A View from DSSAT

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Professor and Preeminent Scholar

Global Food Systems Institute

&

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University of Florida

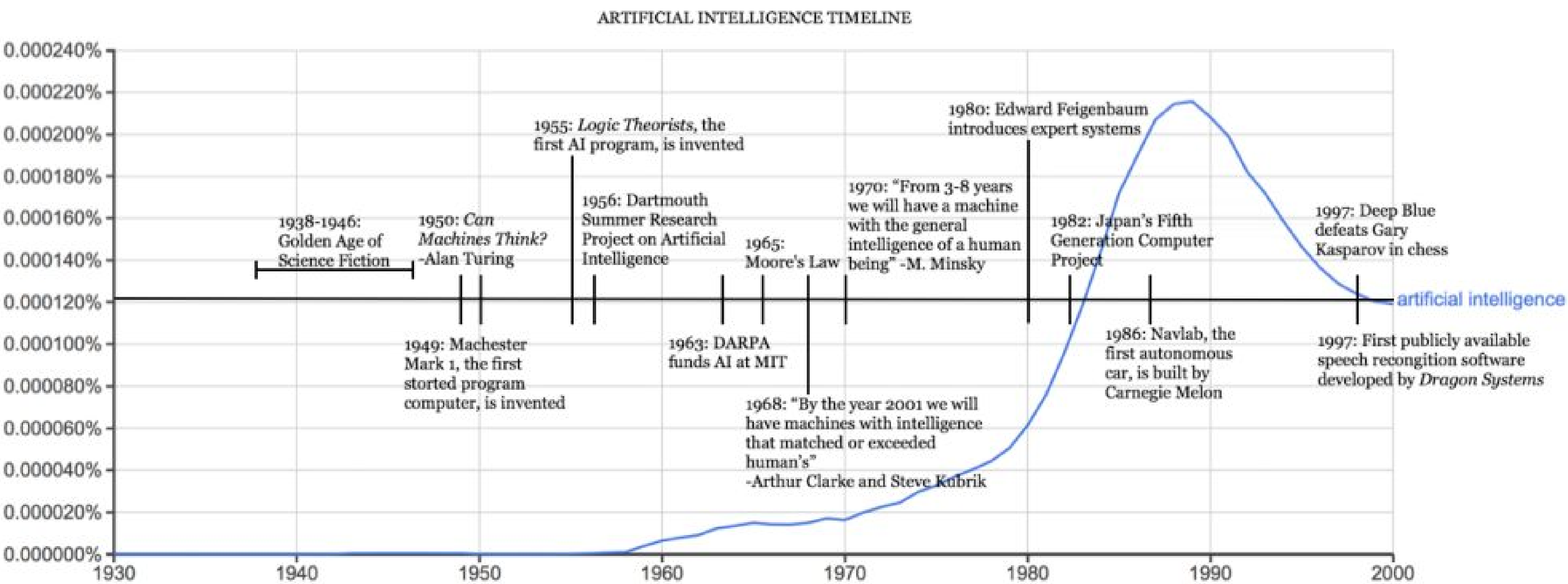
Gainesville, Florida, USA

November 14 - 16, 2023
XIII[th] STICS Users Seminar
Aérocampus Aquitaine
Latresne, France

What is Artificial Intelligence?

- Brittanica: *artificial intelligence*, the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings.
- IBM: at its simplest form, artificial intelligence is a field, which combines computer science and robust datasets, to enable problem-solving.
- Wikipedia: *artificial intelligence* is the intelligence of machines or software, as opposed to the intelligence of humans or animals.

Artificial Intelligence Timeline



Rockwell Anyoha, 2017. The History of Artificial Intelligence. Blog, Special Edition on Artificial Intelligence. https://sitn.hms.harvard.edu/flash/2017/history-artificial-intelligence/

CNN: November 11, 2023

This was a massive week for AI

By Samantha Kelly, CNN

5 minute read · Published 4:00 PM EST, Sat November 11, 2023

CNN US World Politics Business Opinion Health Entertainment Style Travel Sports Video

Justin Sullivan/Getty Images

SAN FRANCISCO, CALIFORNIA - NOVEMBER 06: OpenAI CEO Sam Altman speaks during the OpenAI DevDay event on November 06, 2023 in San Francisco, California. Altman delivered

CNN: November 11, 2023

Business / Tech

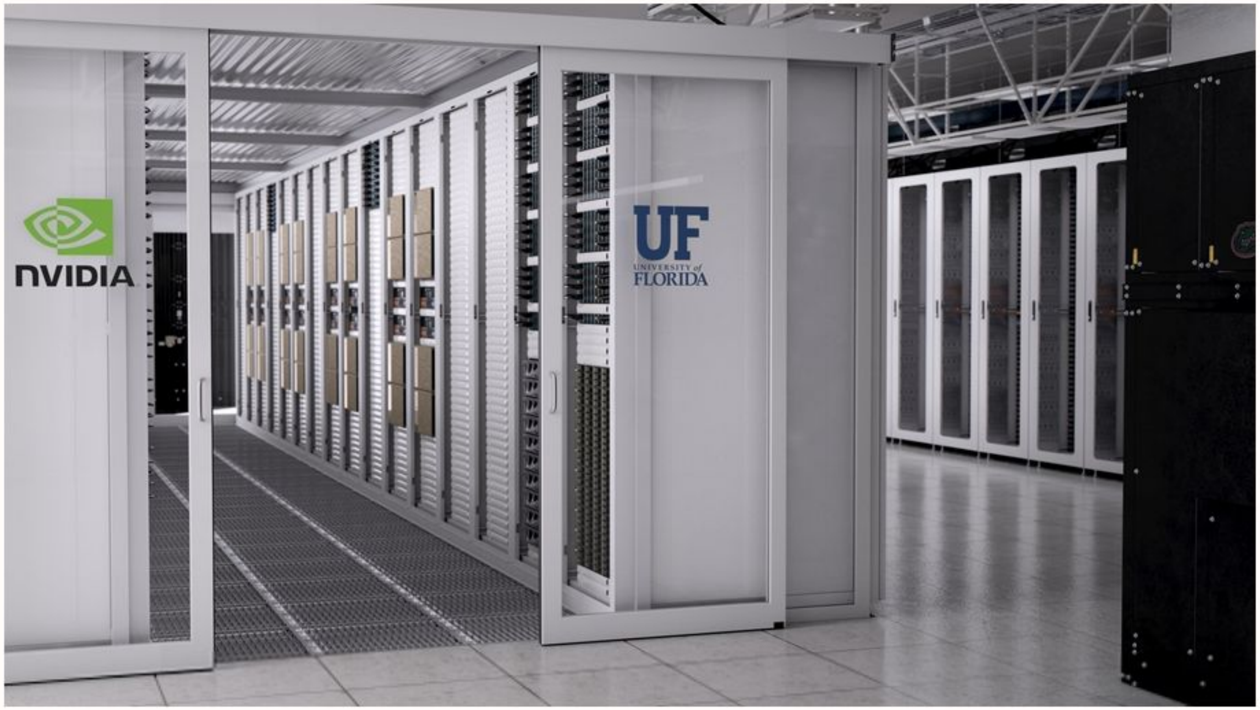
This was a massive week for AI

By Samantha Kelly, CNN
5 minute read · Published 4:00 PM EST, Sat November 11, 2023

- OpenAI hosted its first developer conference about a year after the launch of ChatGPT.
- GPT-4 Turbo, the latest version of the technology that powers ChatGPT; it now can support input that's equal to about 300 pages of a standard book, about 16 times longer than the previous iteration.
- Elon Musk's AI startup xAI unveiled a chatbot called Grok for some users of X, which he suggested has a sarcastic sense of humor similar to his own.
- Humane, a startup founded by former Apple employees, introduced its first AI wearable device called the Ai Pin.

Univ. of Florida: July 21, 2020

UF announces $70 million artificial intelligence partnership with NVIDIA

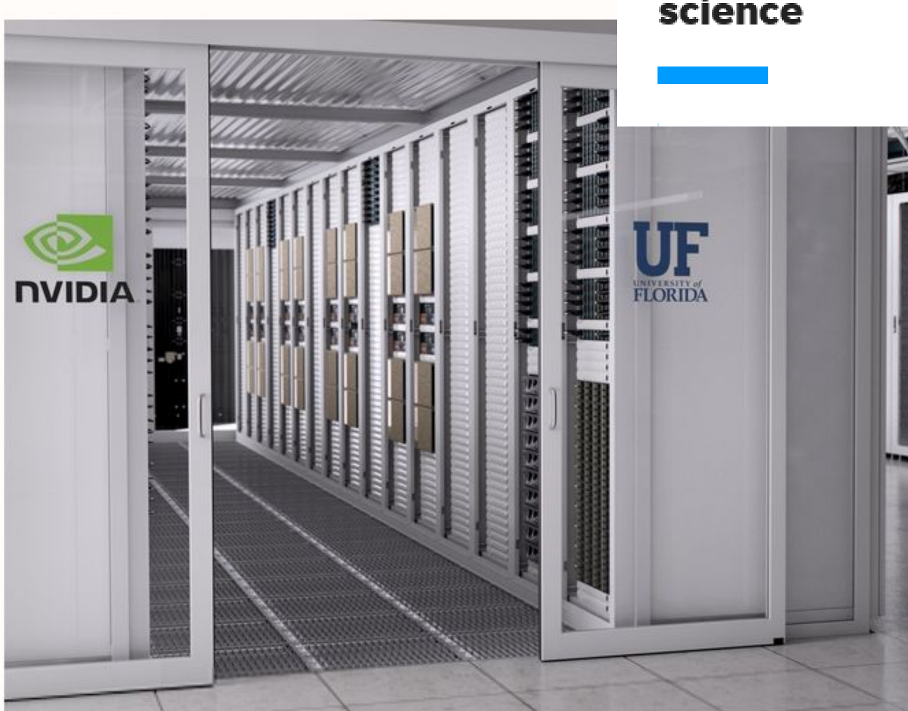


Artist's rendering of University of Florida's new AI supercomputer based on NVIDIA DGX SuperPOD architecture.

UF | UNIVERSITY of FLORIDA

July 21, 2020 & Nov 3, 2023

UF announces $70 million artificial intelligence partnership with NVIDIA



Artist's rendering of University of Florida's new AI supercomputer based on NVIDIA DGX SuperPOD architecture.

New UF building to act as hub for artificial intelligence, data science

GEM II: November 6 and 7, 2023

A symposium to share understanding and approaches to predict crop performance, accounting for Genotype by Environment by Management (GxExM) Interactions: Considering Breeder, Agronomist and Farmer Perspectives.

EVENT INFORMATION

Following on from the success of the 2022 symposium held in Brisbane, Australia, we are coordinating a second symposium designed to encourage an open and shared understanding of the importance of GxExM interactions for improving the sustainability of cropping system productivity.

The symposium will be hosted in a hybrid mode, with a combination of limited on-site participation and free online participation.

The presentations and discussions during the symposium will be recorded (whenever permission is granted) and made available online, to improve accessibility for all participants.

The organizers encourage anyone with an interest in any topics relevant to the investigation of GxExM interactions to consider participating.

If you have any questions about the format of the meeting or your potential for involvement, please contact admin@plantsuccess.org.

- Monday 6 and Tuesday 7 November, 2023
- 9:00am - 5:00pm
- The University of Florida, Gainesville, USA and online
- Submit an EOI to participate at bit.ly/GEM-2-EOI

GxExM BACKGROUND

The potential importance of GxExM interactions has been considered for many performance properties of agricultural systems. There are complex and growing pressures acting upon the global crop systems on which we depend for our livelihoods.

Universally, significant yield gaps have been identified between potential and realised on-farm crop productivity for most crop systems. Further, the sustainability of the current and required levels of crop productivity to meet the expectations of future needs are continually questioned.

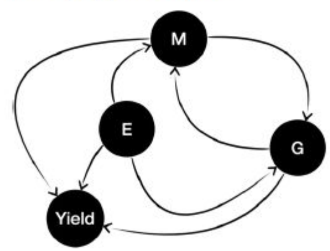
The challenges are diverse, complex and multi-faceted. Crop breeders seek to utilise available genetic resources to develop improved cultivars.

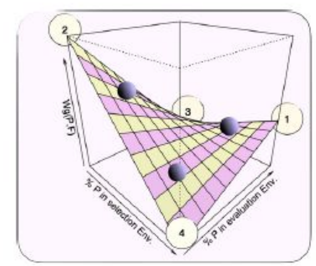
Crop agronomists seek to define agronomic management practices that will work for the improved cultivars.

Farmers seek to combine the improved cultivars with appropriate agronomic practices to achieve a target on-farm productivity while balancing short and long-term risks and rewards.

There have been and continue to be many calls for integrated efforts.

There are successful examples of integrated efforts between breeders, agronomists in partnership with farmers. A number of such efforts have emphasised the importance of considering the potential influences of GxExM interactions at multiple levels within the crop systems.





Local Organiser: Professor Charlie Messina
International Organiser: Professor Mark Cooper

Supported by:

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ARC CENTRE OF EXCELLENCE FOR PLANT SUCCESS IN NATURE AND AGRICULTURE

Ron McClendon, early pioneer in AI & agriculture

UF | UNIVERSITY of FLORIDA

Optimal Control and Neural Networks Applied to Peanut Irrigation Management

R. W. McClendon, G. Hoogenboom, I. Seginer

Abstract. *A method was developed to capture the results of a computationally intensive irrigation optimization routine through the use of neural networks. The PNUTGRO peanut crop growth simulation model was modified and incorporated into a routine to search for optimal irrigation decisions using the Sequential Control Search approach. The daily environmental conditions and crop state variables associated with these optimal irrigation sequences were used to train a*

Vol. 39(1):275-279

Estimation of Aflatoxin Contamination in Preharvest Peanuts Using Neural Networks

R. S. Parmar, R. W. McClendon, G. Hoogenboom, P. D. Blankenship, R. J. Cole, J. W. Dorner

Abstract. *The prevention and elimination of aflatoxin contamination of preharvest peanuts requires the identification of the factors involved in the contamination process and the evaluation of the effects of those factors on contamination levels. The objectives of our study were to examine the variables that affect the contamination process and to develop a model to estimate contamination levels. Artificial neural networks and linear regression models were identified as appropriate techniques to model the contamination levels. Seven years of preharvest peanut aflatoxin data were used to develop and evaluate the models. The data were randomly divided into a training set and a test set for the artificial neural network model. Artificial neural networks were developed using various network architectures and combinations of variables as network inputs.*

The inputs considered were: soil temperature, drought duration, crop age, and accumulated heat units. The accumulated heat units were computed based on threshold soil temperatures ranging from 23 to 29°C. The backpropagation algorithm with a logistic activation function for hidden and output nodes and three layers of nodes were selected as the internal neural network parameters. The most accurate results with the artificial neural network were achieved when the threshold soil temperature to compute accumulated heat units was set to 25°C and all four variables were included as inputs in a network with eight hidden nodes. The R^2-values for the training and the test sets were 0.9250 and 0.9522, respectively. Stepwise linear regression was also applied to develop a regression model for estimating aflatoxin values. The regression model was developed and evaluated for the same data sets used for the development and evaluation of the neural network model. The highest R^2-values of 0.822 and 0.809 for the training and test sets, respectively, were achieved with the regression model when all four variables were selected as input factors and accumulated heat units were computed using a threshold temperature of 29°C. This study showed that artificial neural networks can be used to estimate aflatoxin contamination in peanuts. The artificial neural networks also performed better than traditional stepwise linear regression techniques. **Keywords.** *Peanuts, Aflatoxin, Neural network.*

Aflatoxin contamination of peanuts is a recognized problem and has an adverse economic impact on the peanut industry. Aflatoxin ingestion by animals causes aflatoxicosis, a disease which produces acute necrosis, cirrhosis, and carcinoma of the liver (U. S. Food and Drug Administration Center for Food Safety and Applied Nutrition, 1992). It is assumed that humans are similarly affected as no animal species are resistant to the acute effects of aflatoxins. Susceptibility to the chronic and acute toxicity of aflatoxins depends upon several environmental factors such as exposure level, duration of exposure, age, health, and nutritional status of diet.

Several biotic and abiotic factors are involved in the process of aflatoxin contamination of peanuts. This contamination can occur before and after harvesting, however, the extent of preharvest contamination is greater than that of post-harvest contamination (Cole, 1989). Under certain environmental conditions, the fungi *Aspergillus flavus* and *A. parasiticus* develop in peanuts prior to harvest and result in aflatoxin contamination. A series of experiments conducted at the National Peanut Research Laboratory at Dawson, Georgia, has established the importance of soil temperature and drought on aflatoxin contamination of preharvest peanuts (Cole et al., 1985; Hill et al., 1983; Sanders et al., 1985). Late season drought (4 to 6 weeks before harvesting) and elevated soil temperatures (28.0 to 30.5°C) constitute favorable conditions for contamination in undamaged peanut kernels (Cole et al., 1985).

Although soil temperature and late season drought have been recognized as major factors leading to aflatoxin contamination of preharvest peanuts, their effects on the contamination levels have not been completely quantified. Thai et al. (1990) developed a model to predict aflatoxin contamination of preharvest peanuts by approximating the contamination process with a first-order kinetics model that

Article has been reviewed and approved for publication by the Information & Electrical Technologies Div. of ASAE. Presented as ASAE Paper No. 94-3562.

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The authors are **Rajbir S. Parmar**, *ASAE Member Engineer*, Research Engineer, **Ronald W. McClendon**, *ASAE Member Engineer*, Professor, Biological and Agricultural Engineering Department, University of Georgia, Athens; **Gerrit Hoogenboom**, *ASAE Member Engineer*, Associate Professor, Biological and Agricultural Engineering Department, University of Georgia, Griffin; **Paul D. Blankenship**, *ASAE Member Engineer*, Agricultural Engineer, **R. J. Cole**, Microbiologist, and **J. W. Dorner**, Microbiologist, USDA-ARS, National Peanut Research Laboratory, Dawson, Georgia. **Corresponding author:** Ronald W. McClendon, Biol. and Agric. Engineering Dept., Driftmier Engineering Center, University of Georgia, Athens, GA 30602; tel.: (706) 542-0882; fax: (706) 542-8806; e-mail: <rwmc@bae.uga.edu>.

Transactions of the ASAE

Vol. 40(3):809-813

Neural Network Models for Predicting Flowering and Physiological Maturity of Soybean

D. A. Elizondo, R. W. McClendon, G. Hoogenboom
Member ASAE Member ASAE

Abstract. *It is important for farmers to know when various plant development stages occur for making appropriate and timely crop management decisions. Although computer simulation models have been developed to simulate plant growth and development, these models have not always been very accurate in predicting plant development for a wide range of environmental conditions. The objective of this study was to develop a neural network model to predict flowering and physiological maturity for soybean* (Glycine max *L. Merr.). An artificial neural network is a computer software system consisting of various simple and highly interconnected processing elements similar to the neuron structure found in the human brain. A neural network model was used because it has the ca… of rather large and complex data bases. For this study, field-obse… experimental studies conducted in Gainesville and Quincy, Florid… considered for the neural network model were daily maximum and m… planting or days after flowering. The data sets were split into traini… sets to test the models. The average relative error of the test data s… ($n = 21$, $R^2 = 0.987$) and for date of physiological maturity predict… concluded from this study that the use of neural network models to p… promising and needs to be explored further.* **Keywords.** *Neural netw…*

Accurate predictions of plant growth and development are useful in crop management by allowing the grower to optimize the scheduling of field operations and to maximize net returns. The vegetative and reproductive development processes start as early as planting when the seed germinates, and these processes terminate at harvest maturity. The primary weather variable which controls plant development is temperature. In addition, photoperiod or the length of the daily light period can also affect reproductive development of certain species. Current simulation models have difficulty predicting development correctly for diverse

AGRICULTURAL AND FOREST METEOROLOGY

ELSEVIER Agricultural and Forest Meteorology 71 (1994) 115–132

Development of a neural network model to predict daily solar radiation

David Elizondo[a], Gerrit Hoogenboom*[,b], R.W. McClendon[c]

[a] *Artificial Intelligence Programs, University of Georgia, Athens, GA 30602, USA*
[b] *Department of Biological and Agricultural Engineering, University of Georgia, Georgia Station, Griffin, GA 30223-1797, USA*
[c] *Department of Biological and Agricultural Engineering, University of Georgia, Athens, GA 30602, USA*

Received 3 September 1993; revision accepted 29 December 1993

…lation models which predict growth, development, and yield of agro… crops require daily weather data as input. One of these inputs is daily …ich in many cases is not available owing to the high cost and complexity … needed to record it. The aim of this study was to develop a neural …an predict solar radiation as a function of readily available weather …nental variables. Four sites in the southeastern USA, i.e. Tifton, GA, …le, FL, and Quincy, FL, were selected because of the existence of long-… sets which included solar radiation. A combined total of 23 complete …ts were available, and these data sets were separated into 11 years for …d 12 years for the testing data set. Daily observed values of minimum …perature and precipitation, together with daily calculated values for … radiation, were used as inputs for the neural network model. Day-…lation were calculated as a function of latitude, day of year, solar angle, …optimum momentum, learning rate, and number of hidden nodes were … use in the development of the neural network model. After model …l network model was tested against the independent data set. Root …d from 2.92 to 3.64 MJ m^{-2} and the coefficient of determination varied … individual years used to test the accuracy of the model. Although this … was developed and tested for a limited number of sites, the results …sed to estimate daily solar radiation when measurements of only daily …n air temperature and precipitation are available.

World Academy of Science, Engineering and Technology
International Journal of Computer, Electrical, Automation, Control and Information Engineering Vol:9, No:5, 2015

Solar Radiation Time Series Prediction

Cameron Hamilton, Walter Potter, Gerrit Hoogenboom, Ronald McClendon, Will Hobbs

Abstract—A model was constructed to predict the amount of solar radiation that will make contact with the surface of the earth in a given location an hour into the future. This project was supported by the Southern Company to determine at what specific times during a given day of the year solar panels could be relied upon to produce energy in sufficient quantities. Due to their ability as universal function approximators, an artificial neural network was used to estimate the nonlinear pattern of solar radiation, which utilized measurements of weather conditions collected at the Griffin, Georgia weather station as inputs. A number of network configurations and training strategies were utilized, though a multilayer perceptron with a variety of hidden nodes trained with the resilient propagation algorithm consistently yielded the most accurate predictions. In addition, a modeled direct normal irradiance field and adjacent weather station data were used to bolster prediction accuracy. In later trials, the solar radiation field was preprocessed with a discrete wavelet transform with the aim of removing noise from the measurements. The current model provides predictions of solar radiation with a mean square error of 0.0042, though ongoing efforts are being made to further improve the model's accuracy.

Keywords—Artificial Neural Networks, Resilient Propagation, Solar Radiation, Time Series Forecasting.

I. Introduction

The ability to predict how a quantity will change in the future is a valuable ability to have, as doing so can enable the interested parties to plan accordingly. For instance, accurately predicting how stock prices will evolve can help investors to reduce risk in their investments and maximize their payoffs. Likewise, predicting commodity prices can help businesses know when to purchase certain items in bulk and

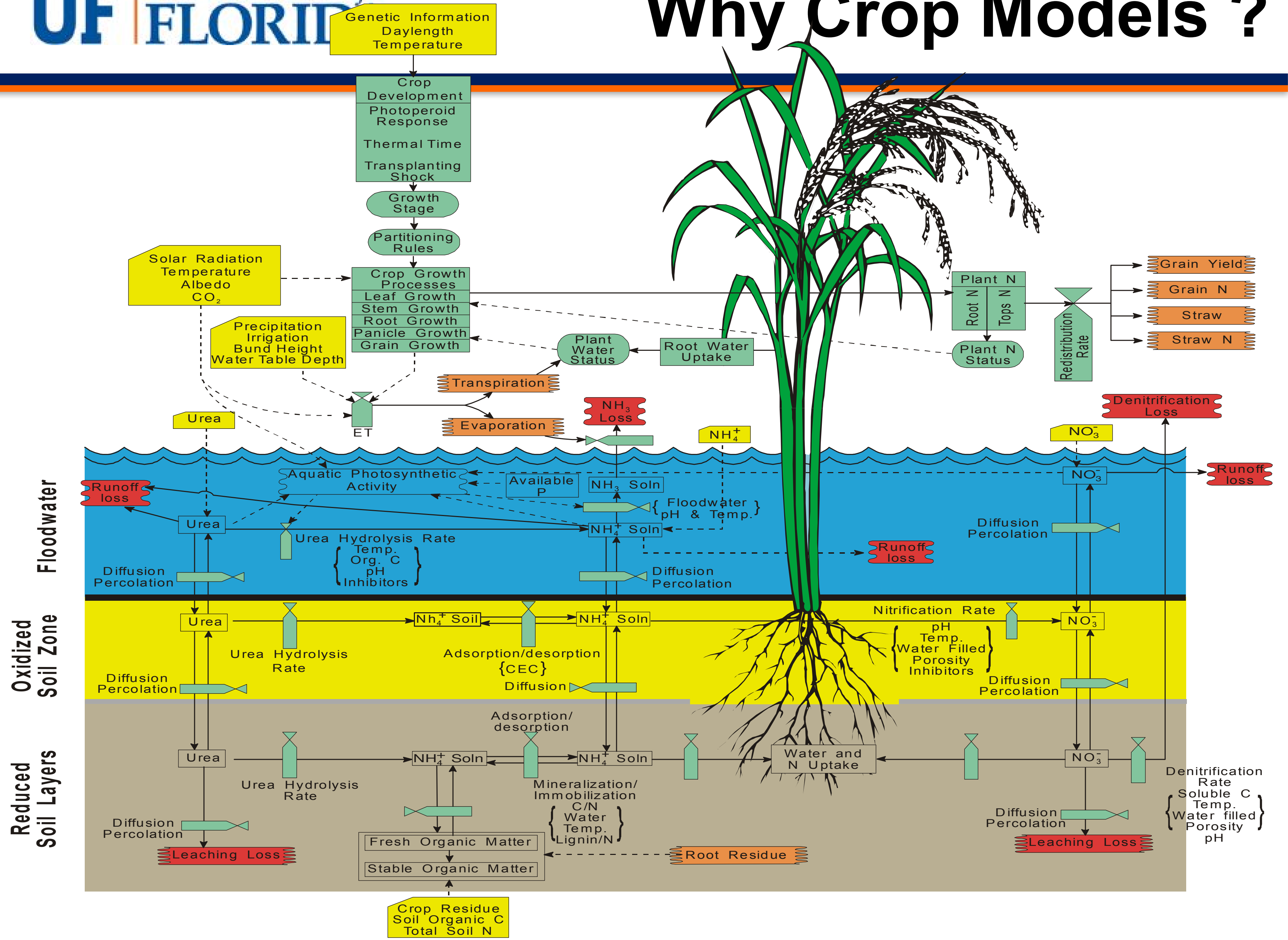
given year or the amount of energy that can be produced from a solar panel [2]-[3]. One common model for solar radiation prediction is an artificial neural network (for examples, see [4]-[6]), as these networks serve as universal function approximators [7]. Although other models and techniques exist for time series prediction such as support vector machines (SVM), hidden Markov models (HMM), dynamic Bayesian networks (DBN), and autoregressive integrated moving average (ARIMA) models, artificial neural networks (ANNs) have the advantage of accepting multiple data fields as input, rather than being limited to univariate input. Furthermore, ANNs are highly customizable in how the network can be configured (e.g. how many hidden layers/nodes, feedforward vs. recurrent, etc.) and can thus be tailored to a specific problem more readily. As solar radiation is influenced by a number of environmental and atmospheric conditions, an ANN was selected as the most appropriate model for the current study.

Direct normal irradiance (DNI) is the amount of solar radiation that will make contact with a given area under cloudless sky conditions [8]. As the actual amount of solar radiation that is measured locally has been subjected to environmental factors (e.g. cloud coverage, atmospheric gases) before it is measured, DNI can serve as a point of comparison when analyzing solar radiation data. Thus, DNI appears to be a useful field to train an artificial neural network with for the sake of predicting the actual amount of solar radiation, as the two fields should be strongly correlated. The present model utilizes a modeled DNI field in conjunction with measured solar radiation, in order to predict solar

Why Crop Models (and not AI)?

- Traditional agronomic approach:
  - Experimental trial and error

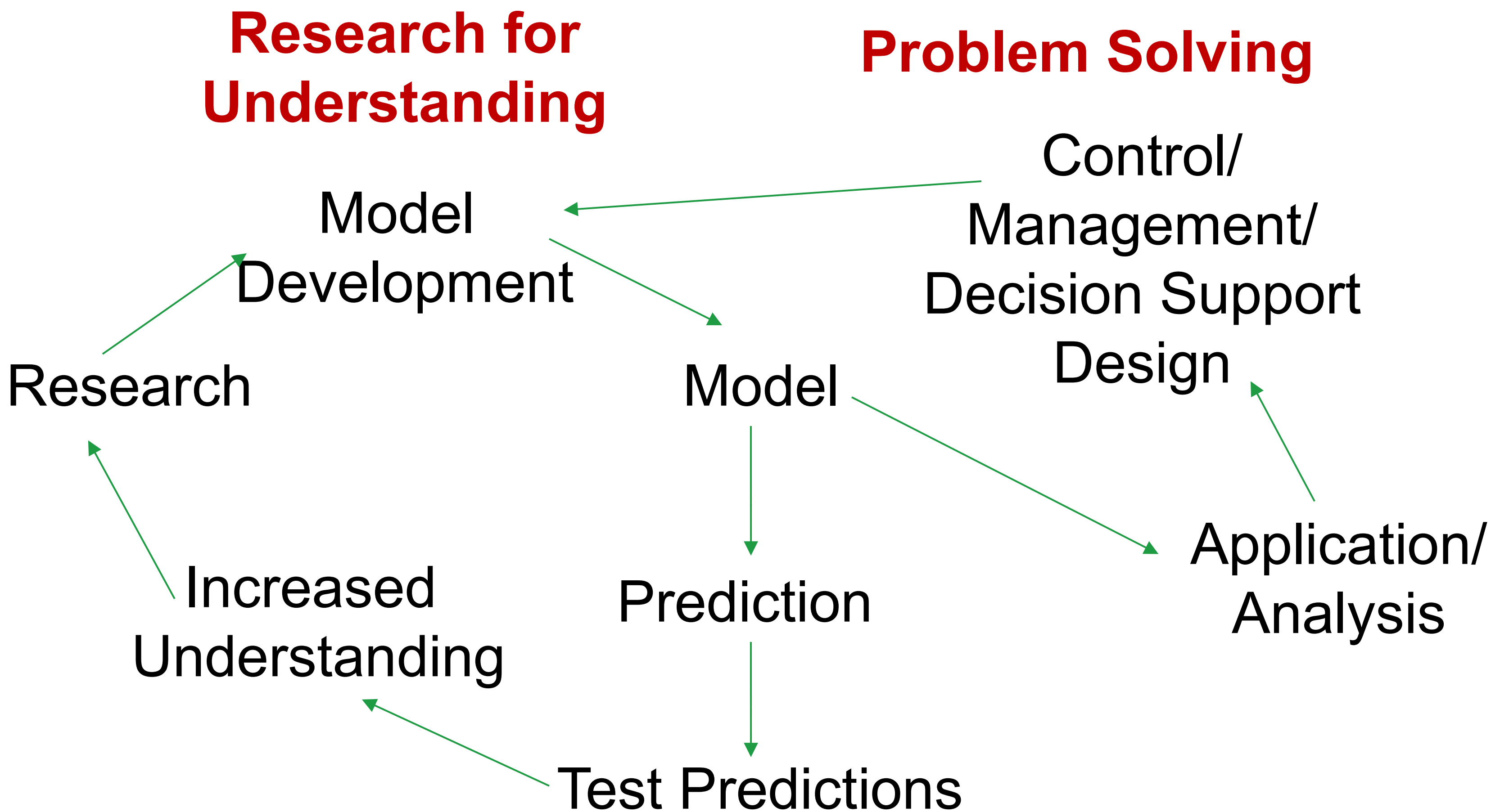
Why Crop Models ?



Why Models?

- Traditional agronomic approach:
  - Experimental trial and error
- Systems Approach
  - Computer models
  - Experimental data
- Understand ✉ Predict ✉ Control & Manage
  - (H. Nix, 1983)
- ✉ Options for adaptive management, risk reduction, and short- and long-term economic and environmental sustainability

Systems Approach



What is an agricultural or crop model?

- Crop simulation models integrate the current state-of-the art scientific knowledge from many different disciplines, including crop physiology, plant breeding, agronomy, agrometeorology, soil physics, soil chemistry, soil fertility, plant pathology, entomology, economics and many others.

Models and Decision Support Systems

- To provide advisories, big data products, science-based models and decision support systems to managers for improving production and product quality, optimizing resource use and reducing environmental impact.

➢ Understand different management options

➢ Provide actionable information

The DSSAT
Crop Modeling Ecosystem

www.DSSAT.net

Some Historical Notes on DSSAT

- IBSNAT Project on Food Security
- Funded by USAID from 1982 to 1993
- DATA: Minimum Data Set Concept, 1983-1986
- Initial models included the CERES-Maize, CERES-Wheat and SOYGRO soybean models.
- Data standards for compatibility of models (1986, 1994)
- DSSAT v2.1 released in 1986
- DSSAT Version 3.5 released in 1998 (after project ended)
- DSSAT Cropping System Model, DSSAT v4 released in early 2004
- DSSAT Version 4.02 in 2006, v4.5 in 2012, v4.6 in 2015
- DSSAT Version 4.7 in 2017, Version 4.7.5 in 2019
- DSSAT Version 4.8 in 2021; Version 4.8.2 released in 2023

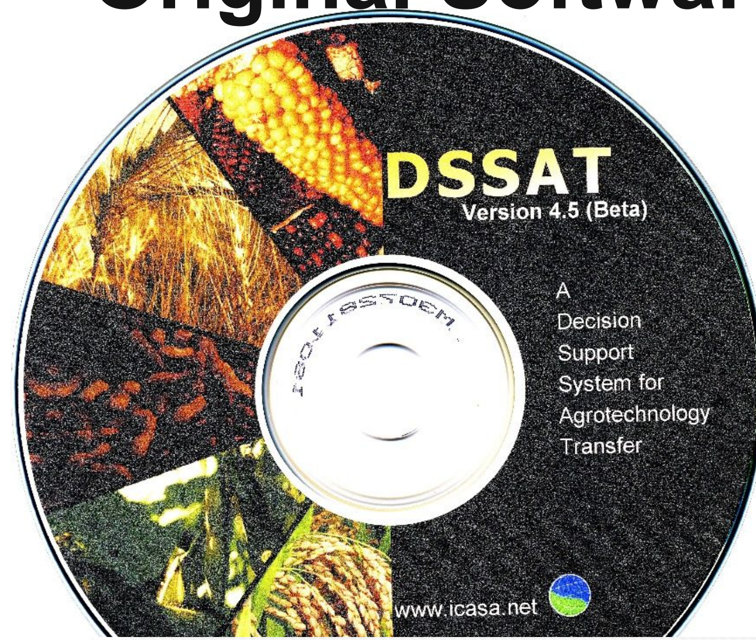
Original Software

Initial price: US $495 + shipping *costs*

Updated price: US $195 + shipping *costs*

Free download from DSSAT portal

Free download & Open Source 3-clause BSD license



Request DSSAT

DSSAT is *Free of charge*!

Request to download your own copy today!

› DSSAT Version 4.8.2 released in August 2023.

Download DSSAT v4.8.2

DSSAT is not just a software program but an ***ecosystem*** of:

- Crop model users
- Crop model trainers
- Crop model developers

- Models for the most important food, feed, fiber, fuel, and vegetable crops (42+ crops)
- Tools and utilities for data preparation
- Minimum data for model calibration and evaluation
- ICASA Data standards

- Application programs for assessing real-world problems

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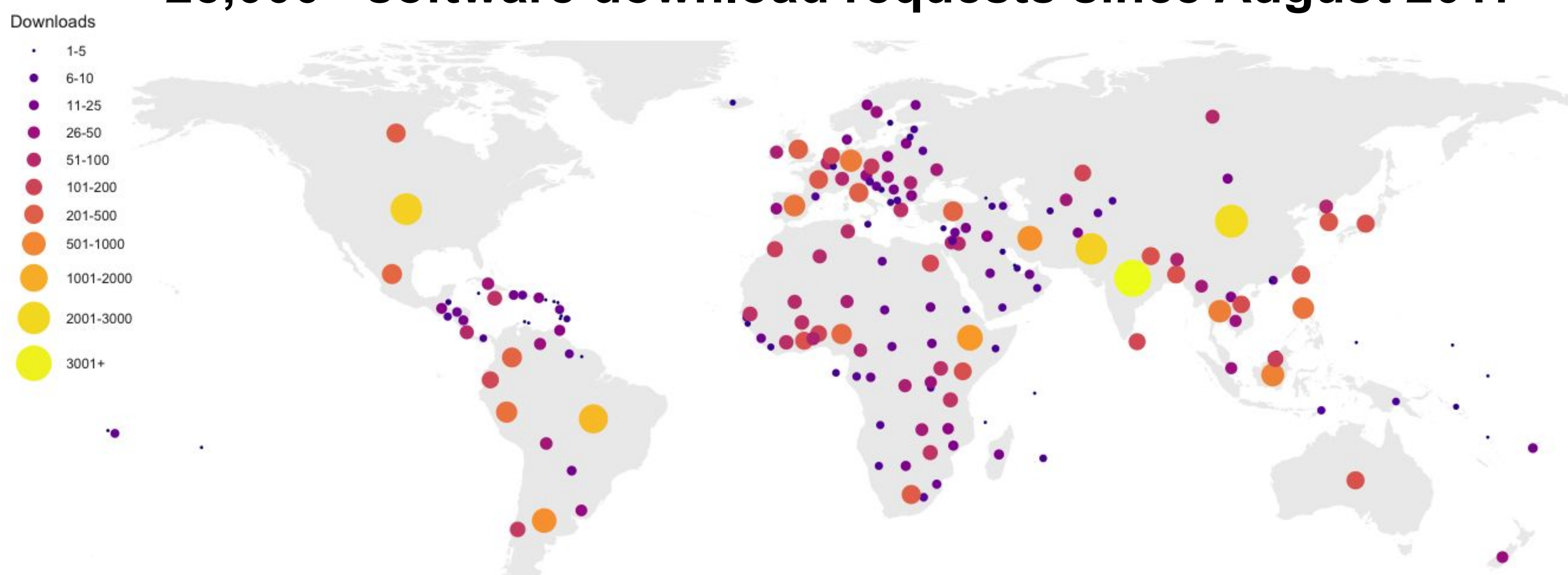
Institute for Sustainable Food Systems

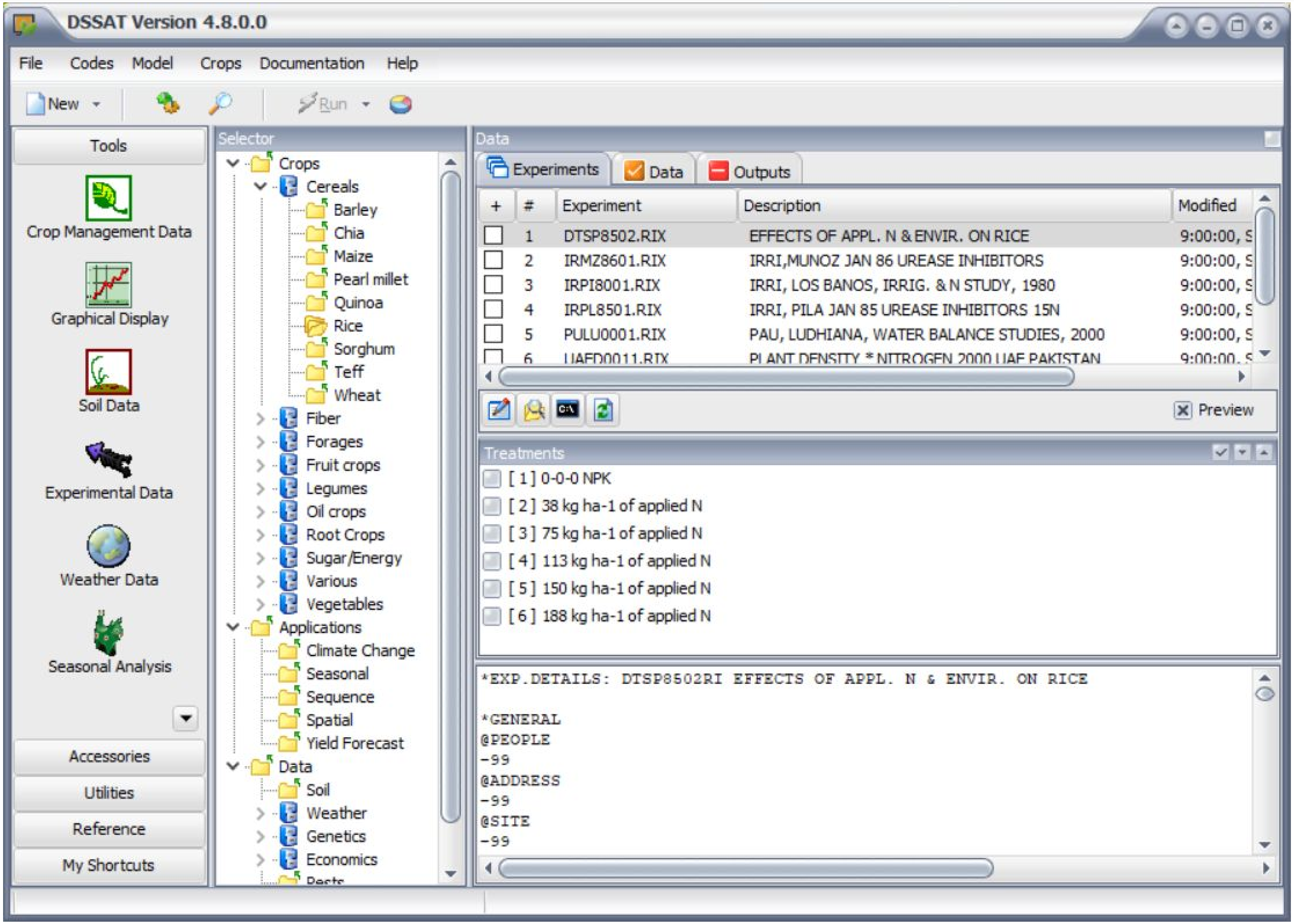
DSSAT User Community

25,000+ software download requests since August 2017



Country	Downloads	Country	Downloads	Country	Download
India	3527	Thailand	409	United Kingdom	211
China	2144	Germany	382	Italy	206
USA	1789	Spain	339	Canada	198
Pakistan	1768	Philippines	334	South Africa	195
Brazil	1224	Peru	312	France	180
Ethiopia	731	Nigeria	260	Taiwan	173
Iran	620	Mexico	244	South Korea	169
Argentina	590	Colombia	235	Australia	152
Indonesia	445	Turkey	233	Nepal	151
Countries	**187**	**Total**	**21287**		

Total DSSAT Downloads: 21287
February 09, 2023


DSSAT Version 4.8.0.0
File
Codes
Model
Crops
Documentation
Help
New
Run
Tools
Crop Management Data
Graphical Display
Soil Data
Experimental Data
Weather Data
Seasonal Analysis
Accessories
Utilities
Reference
My Shortcuts
Selector
Crops
Cereals
Barley
Chia
Maize
Pearl millet
Quinoa
Rice
Sorghum
Teff
Wheat
Fiber
Forages
Fruit crops
Legumes
Oil crops
Root Crops
Sugar/Energy
Various
Vegetables
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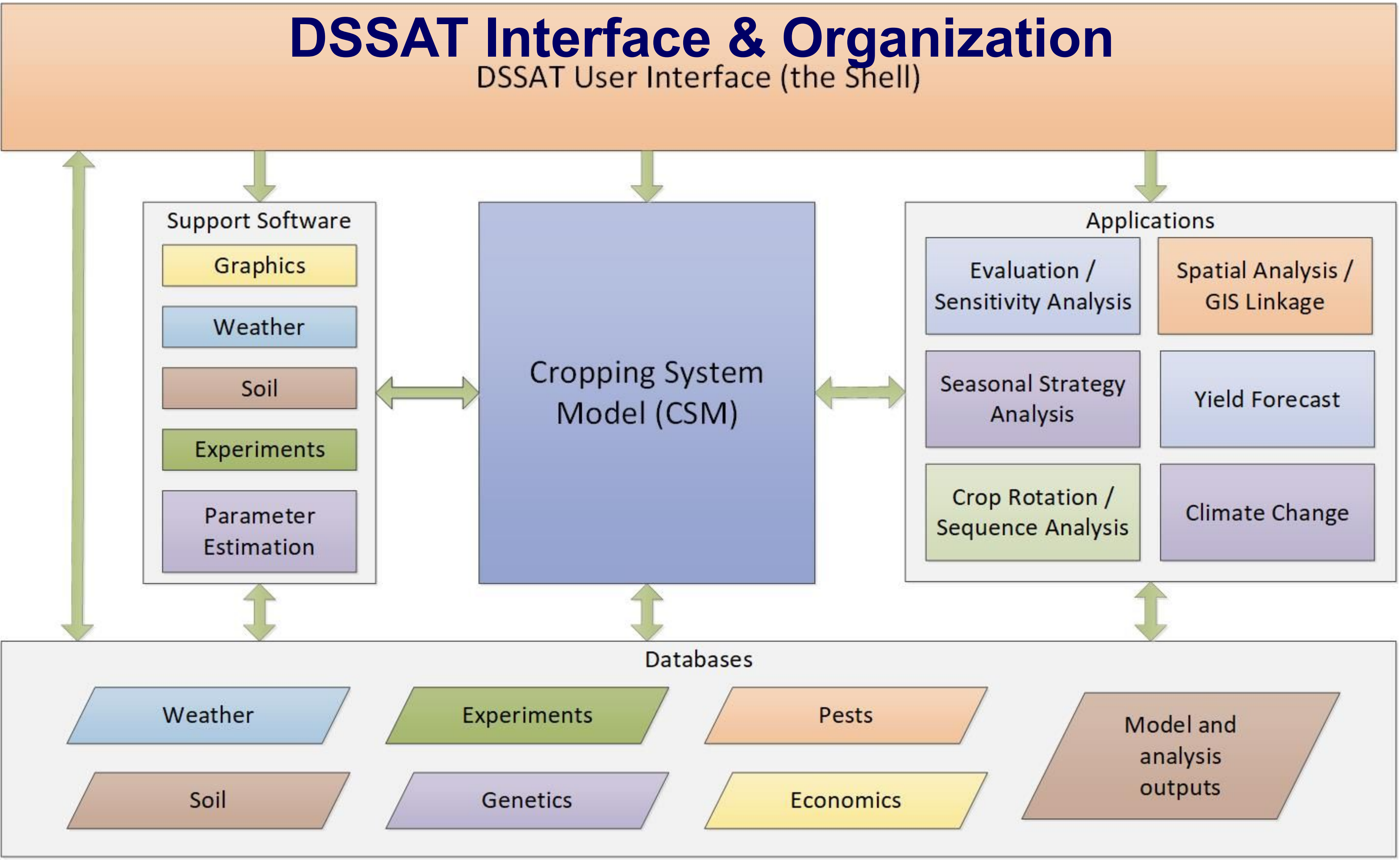
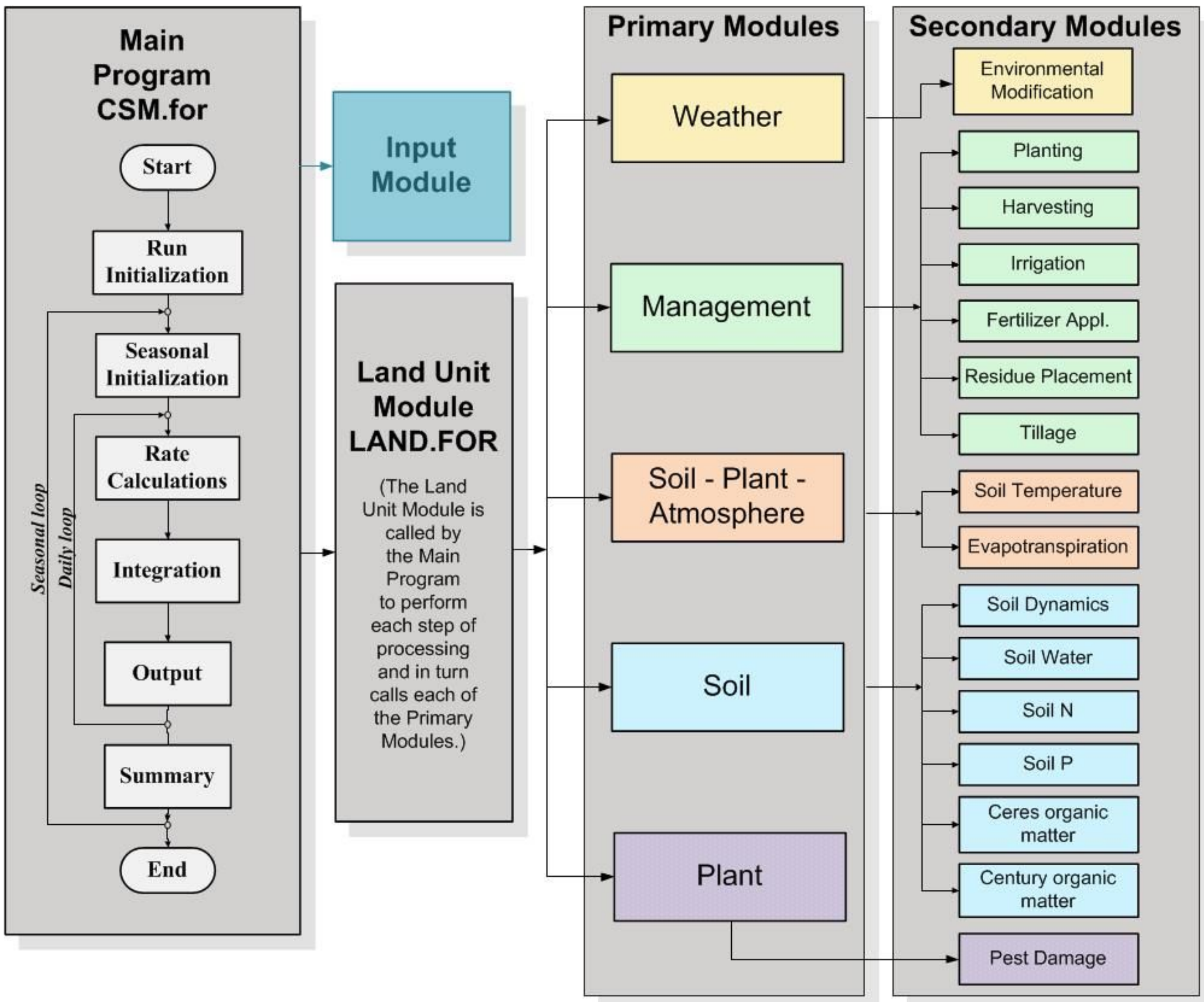
2 IRMZ8601.RIX IRRI,MUNOZ JAN 86 UREASE INHIBITORS 9:00:00,
3 IRPI8001.RIX IRRI, LOS BANOS, IRRIG. & N STUDY, 1980 9:00:00,
4 IRPL8501.RIX IRRI, PILA JAN 85 UREASE INHIBITORS 15N 9:00:00,
5 PULU0001.RIX PAU, LUDHIANA, WATER BALANCE STUDIES, 2000 9:00:00,
Preview
Treatments
[1] 0-0-0 NPK
[2] 38 kg ha-1 of applied N
[3] 75 kg ha-1 of applied N
[4] 113 kg ha-1 of applied N
[5] 150 kg ha-1 of applied N
[6] 188 kg ha-1 of applied N
*EXP.DETAILS: DTSP8502RI EFFECTS OF APPL. N & ENVIR. ON RICE
*GENERAL
@PEOPLE
-99
@ADDRESS
-99
@SITE
-99

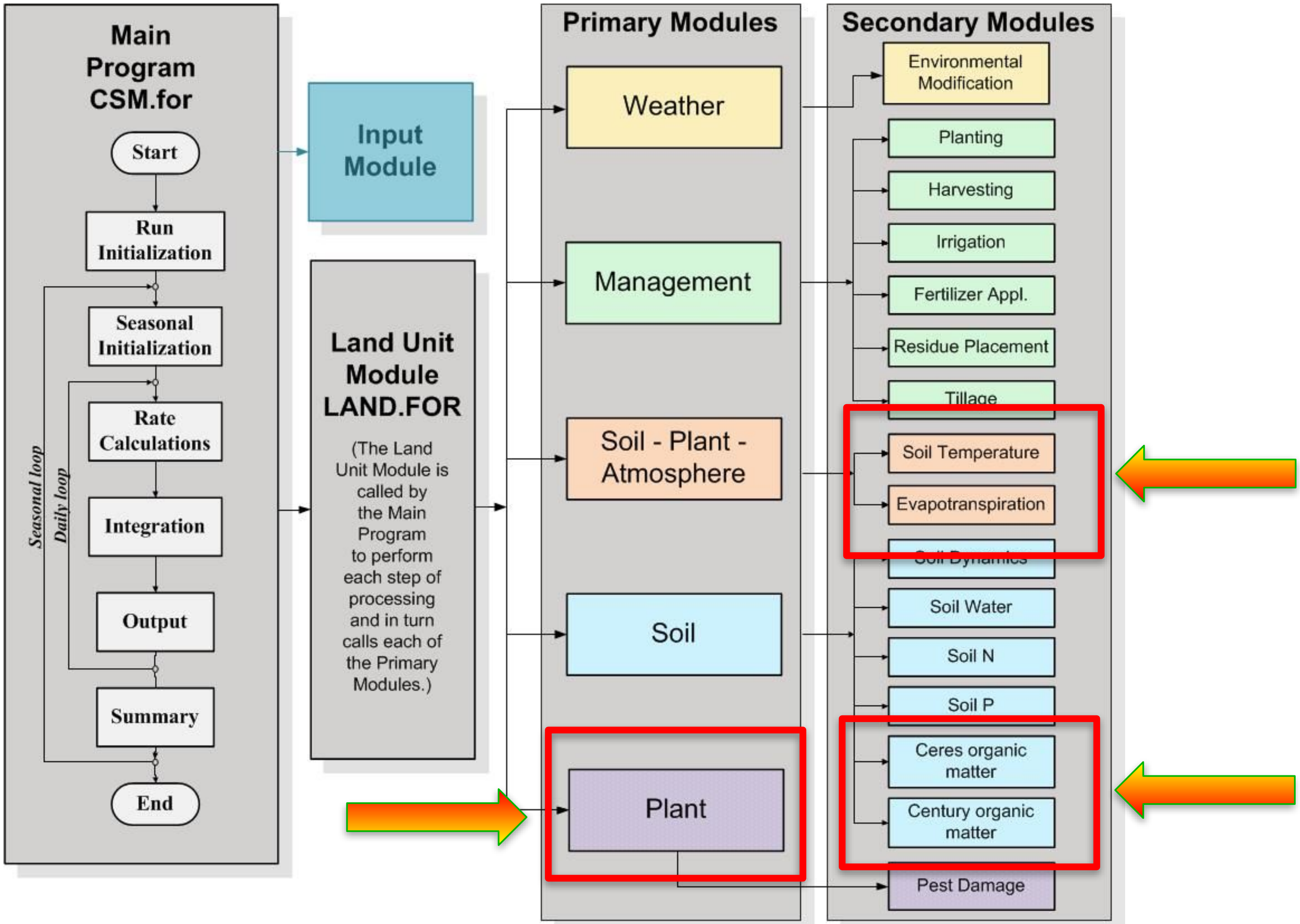
DSSAT Interface & Organization



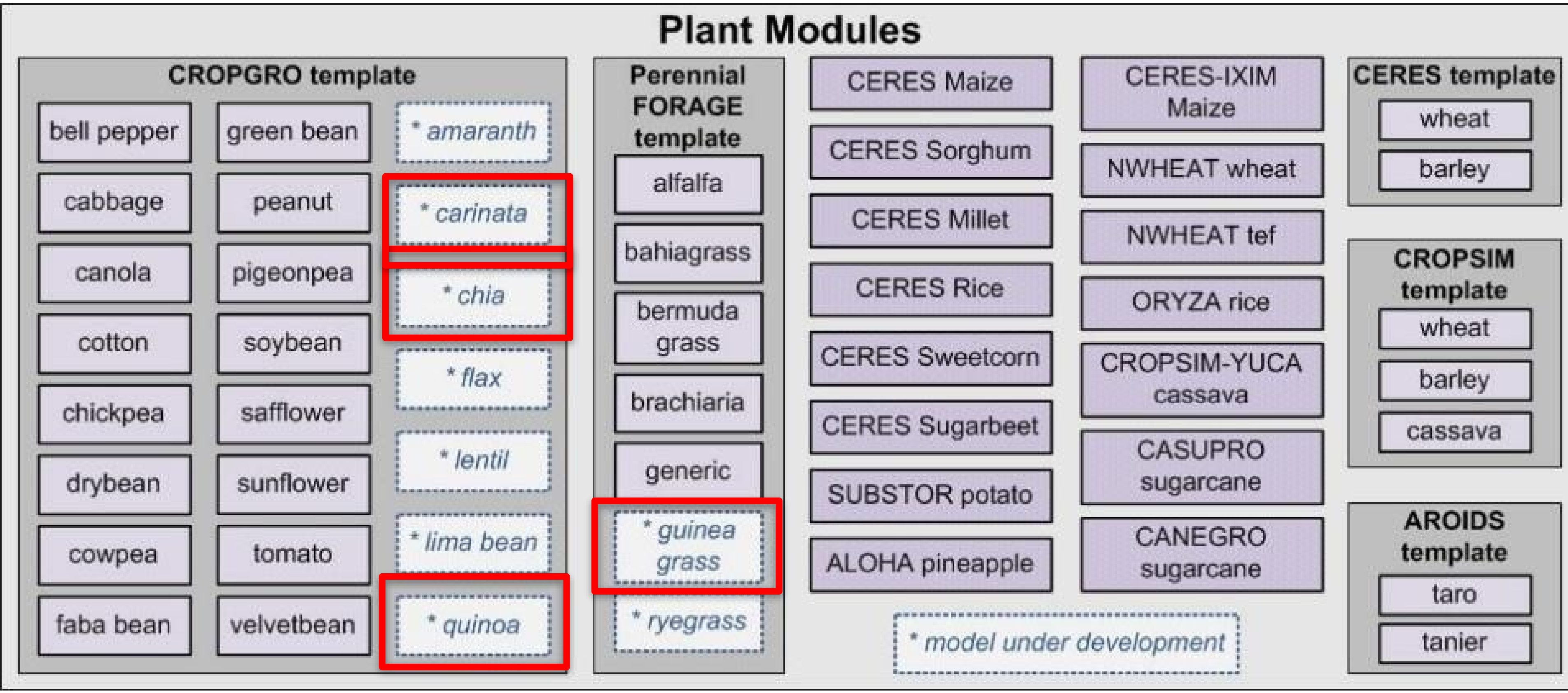
Cropping System Model (CSM) Structure



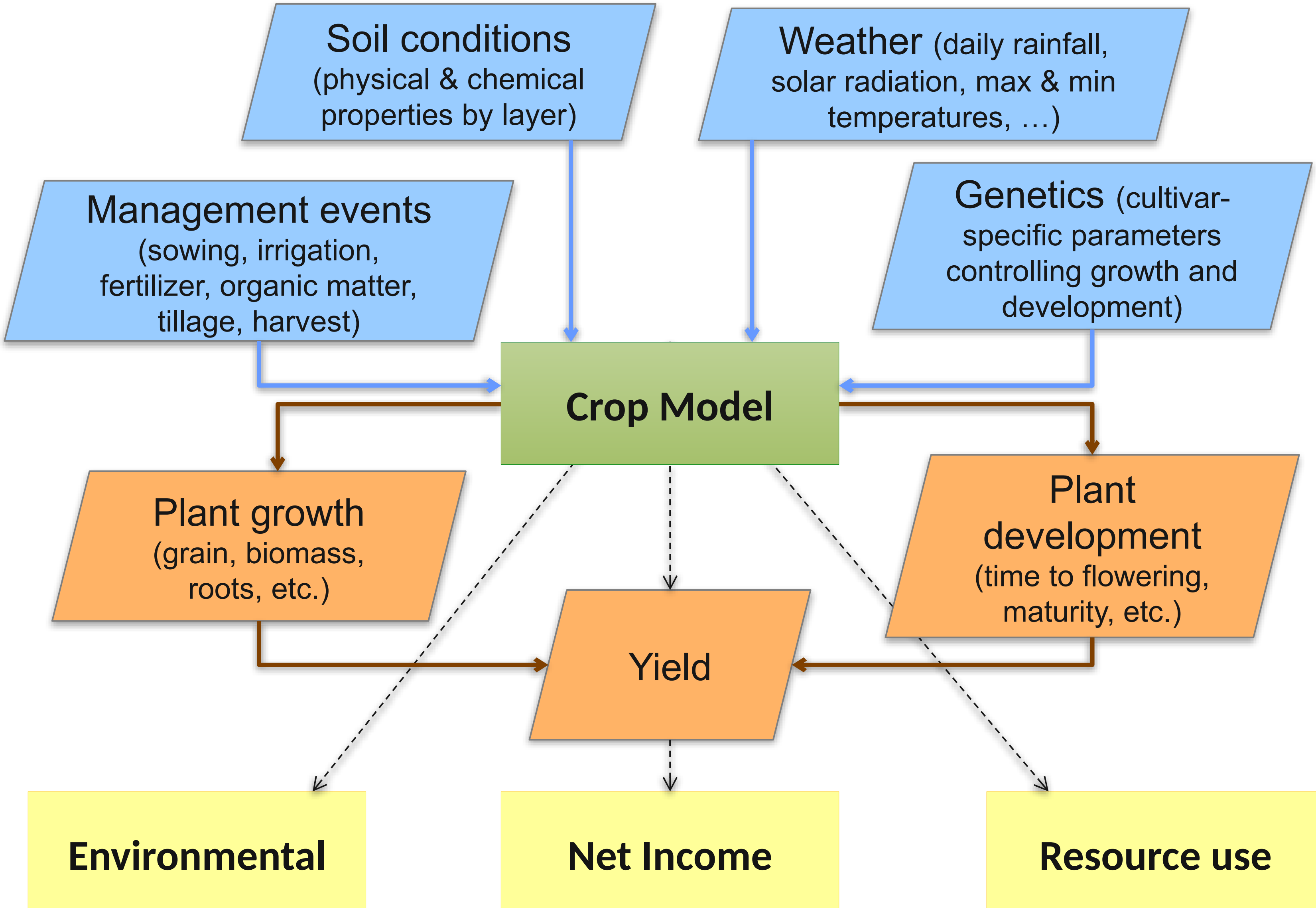
Cropping System Model (CSM) Structure



Plant Modules



Crop Simulation Model



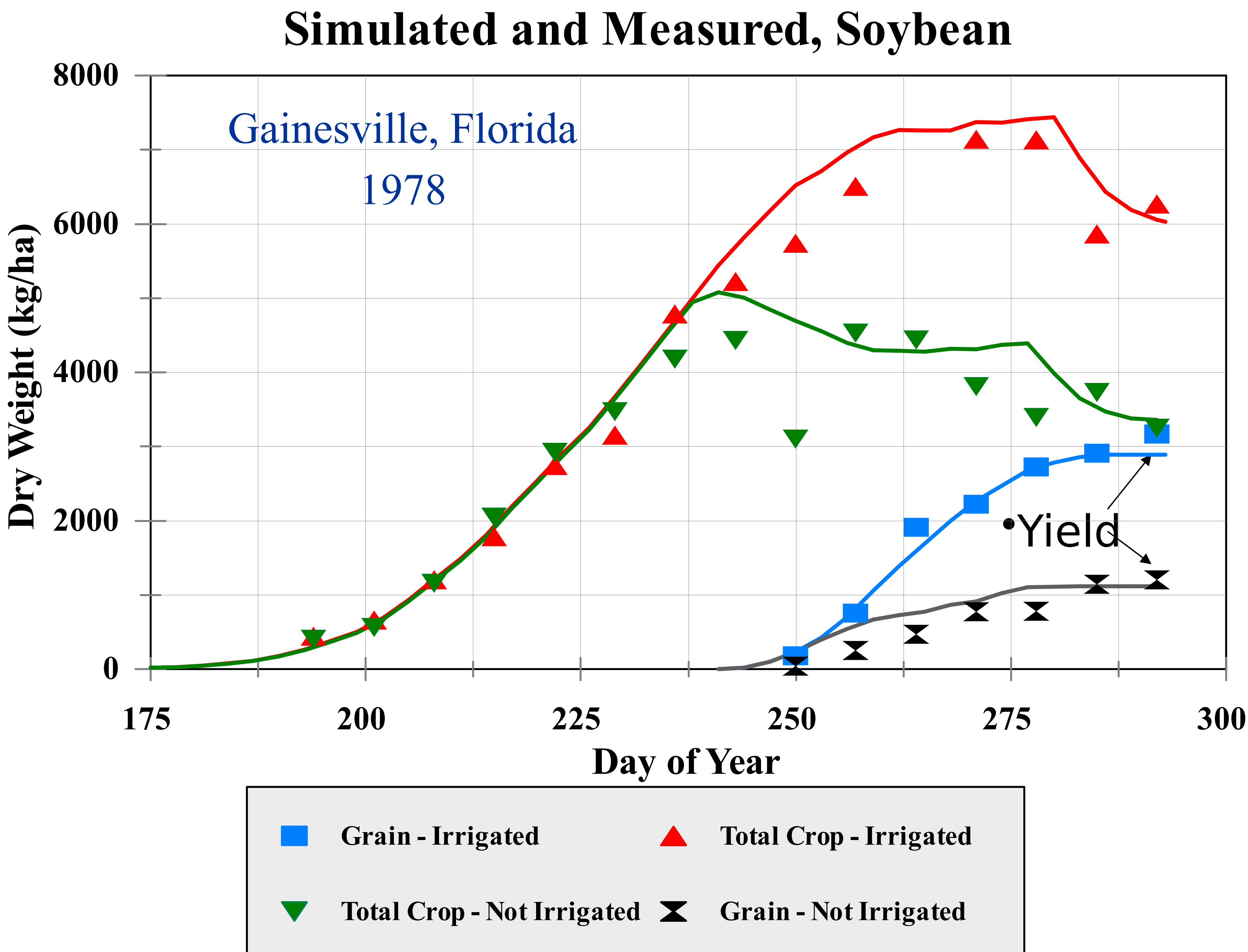
Implementation

Crop Simulation Models

1. Require information (Inputs)
   - ✓Field and soil characteristics
   - ✓Weather (daily)
   - ✓Cultivar characteristics
   - ✓Management
2. Model calibration for local variety
3. Model evaluation with independent data set
4. Can be used to perform “what-if” experiments
5. Provide actionable information for Climate Smart Agriculture

Linkage between Data and Simulations

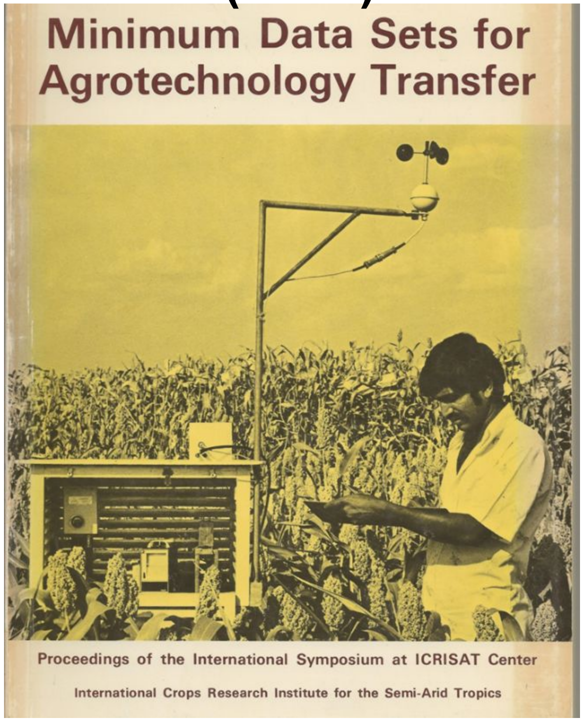
- Model credibility and evaluation
- Input data needs:
  - Weather and soil data
  - Crop Management
  - Specific crop and cultivar information
  - Economic data


Simulated and Measured, Soybean
Gainesville, Florida
1978
Dry Weight (kg/ha)
8000
6000
4000
2000
0
175
200
225
250
275
300
Day of Year
•Yield
Grain - Irrigated
Total Crop - Irrigated
Total Crop - Not Irrigated
Grain - Not Irrigated

What is a Minimum Data Set?

- Computer models require a set of input data to be able to operate.
- Different models require different sets of input data.
- Define a minimum set of data that:
  - Can be relatively easily collected under field conditions by collaborators
  - Provides reasonable answers when used as input for crop models

ICRISAT, India (1983)



ICASA Data Standards

Computers and Electronics in Agriculture 96 (2013) 1–12

Contents lists available at SciVerse ScienceDirect

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journal homepage: www.elsevier.com/locate/compag

Integrated description of agricultural field experiments and production: The ICASA Version 2.0 data standards

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ABSTRACT

Agricultural research increasingly seeks to quantify complex interactions of processes for a wide range of environmental conditions and crop management scenarios, leading to investigation where multiple sets of experimental data are examined using tools such as simulation and regression. The use of standard data formats for documenting experiments and modeling crop growth and development can facilitate exchanges of information and software, allowing researchers to focus on research per se rather than on converting and re-formatting data or trying to estimate or otherwise compensate for missing information. The standards developed by the International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT) project and subsequently revised by the International Consortium for Agricultural Systems Applications (ICASA) were of considerable value for describing experiments. However, the resulting ICASA Version 1 standards did not consider important management practices such as tillage and use of mulches, lacked descriptors for certain soil and plant traits (especially related to nutrient levels), and contained minor logical inconsistencies. The ICASA standards have evolved to allow description of additional management practices and traits of soils and plants and to provide greater emphasis on standardizing vocabularies, clarifying relations among variables, and expanding formats beyond the original plain text file format. This paper provides an overview of the ICASA Version 2.0 standards. The foundation of the standards is a master list variables that is organized in a hierarchical arrangement with major separations among descriptions of management practices or treatments, environmental conditions (soil and weather data), and measurements of crop responses. The plain text implementation is described in detail. Implementations in other digital formats (databases, spreadsheets, and data interchange formats) are also reviewed. Areas for further improvement and development are noted, particularly as related to describing pest damage, data quality and appropriate use of datasets. The master variable list and sample files are provided as electronic supplements.

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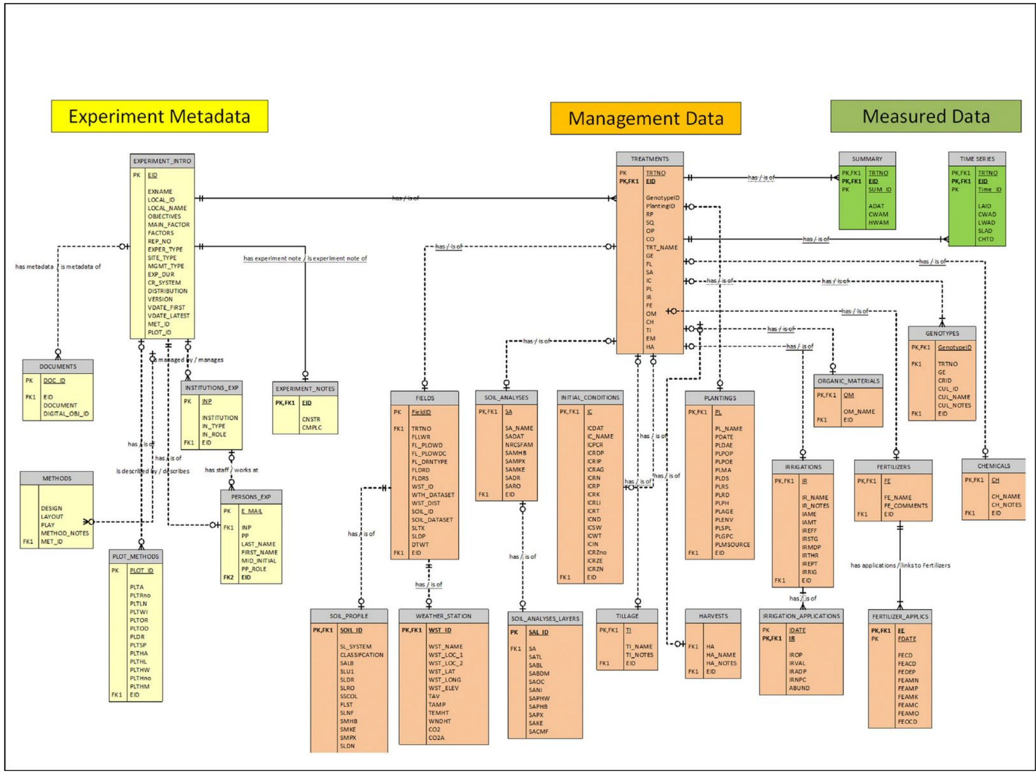
1. Introduction



Genetics in Crop Models

- Current crop models use empirical genotype specific parameters (GSPs) for cultivar environment interactions that are not linked to actual genes. These GSPs do not adequately include the genetic (G) and gene-by-environment interaction (G x E) effects on crop development, thus inherent limitations.

- Genetics in the DSSAT Cropping System Model
  - Species coefficients
  - Ecotype coefficients
  - Cultivar coefficients

- Bridging the gap between biotechnology, breeding and crop management

Statewide Variety Testing

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  - Related Links
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Commodities

Statewide Variety Testing

The UGA CAES Statewide Variety Testing program provides annual performance testing results on several commodities including canola, small grains and forage, corn and silage, and field crops.

Program Director:

John Gassett

Phone: 770-296-8268
Fax: 770.412.4734

Performance tests results 2004 and later are in PDF format and require the use of Adobe® Reader®. If you do not have this software installed, you can download Adobe® Reader® for free from the Adobe® website. To access PDF files using an iPad, iPhone or Android device, you must have an Adobe® Reader® app on your device. These apps are available free online at the appropriate app store.

Program Overview

Proper variety selection is the most important decision a farmer makes. Farmers want and need to grow the best adapted crop cultivars to be successful. But producers do not have the time or the resources to plant several cultivars to determine which are adapted to Georgia growing conditions and the best available. That's where UGA Agronomists step in to help.

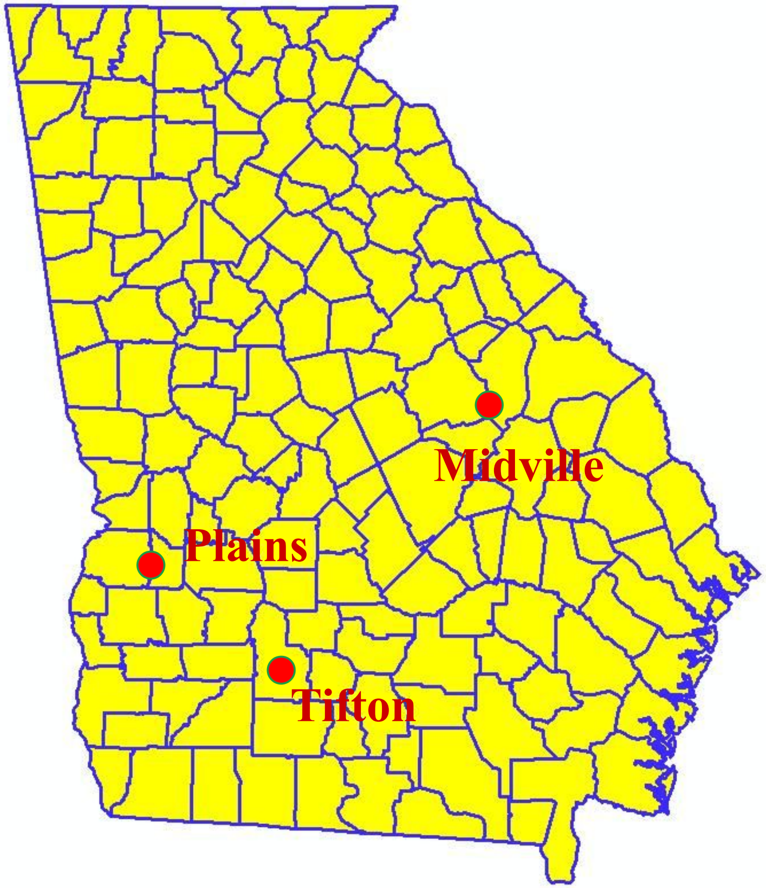
The college's Variety Testing Team does the work and research for the farmers. We perform variety research on public and private developed cultivars of corn, corn silage, soybean, peanut, cotton, grain sorghum, wheat, barley, rye, oat, triticale, canola, summer annual forages, and winter annual forages each crop year. The research is conducted within each of the seven major geographic regions of Georgia to collect agronomic data such as yield, bloom date, maturity date, test weight, height, lodging, seed size and seed shattering; also, tests for resistance/tolerance to pests and disease.

The information is published annually in five research reports which are made available to

Calibration CSM-CROPGRO

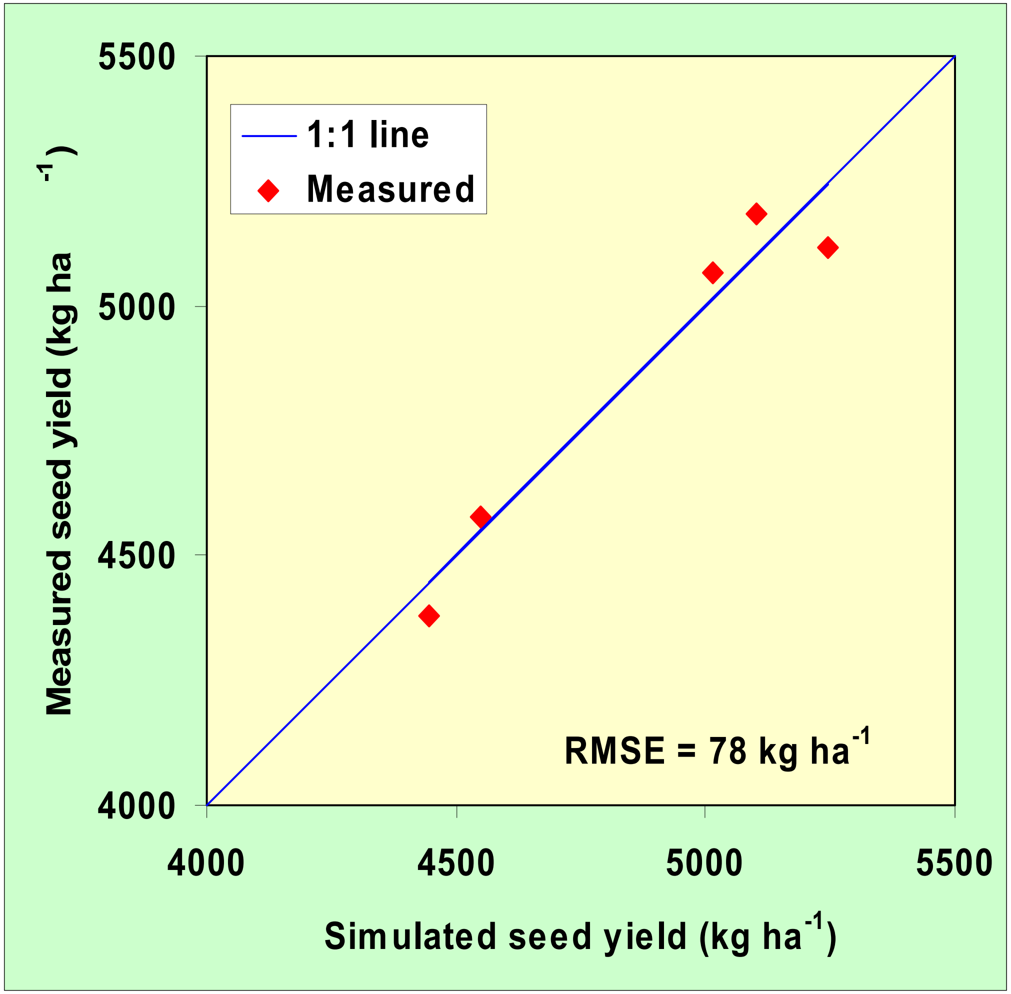
Georgia Peanut Variety Trials- Georgia Green

- “Best” variety trials selected
  - Irrigated
  - Very high yields
  - No reported pest and disease pressure
  - No reported water stress
- Selected variety trials
  Plains: 1995, 1996, 2001
  Tifton: 1994
  Midville: 1996



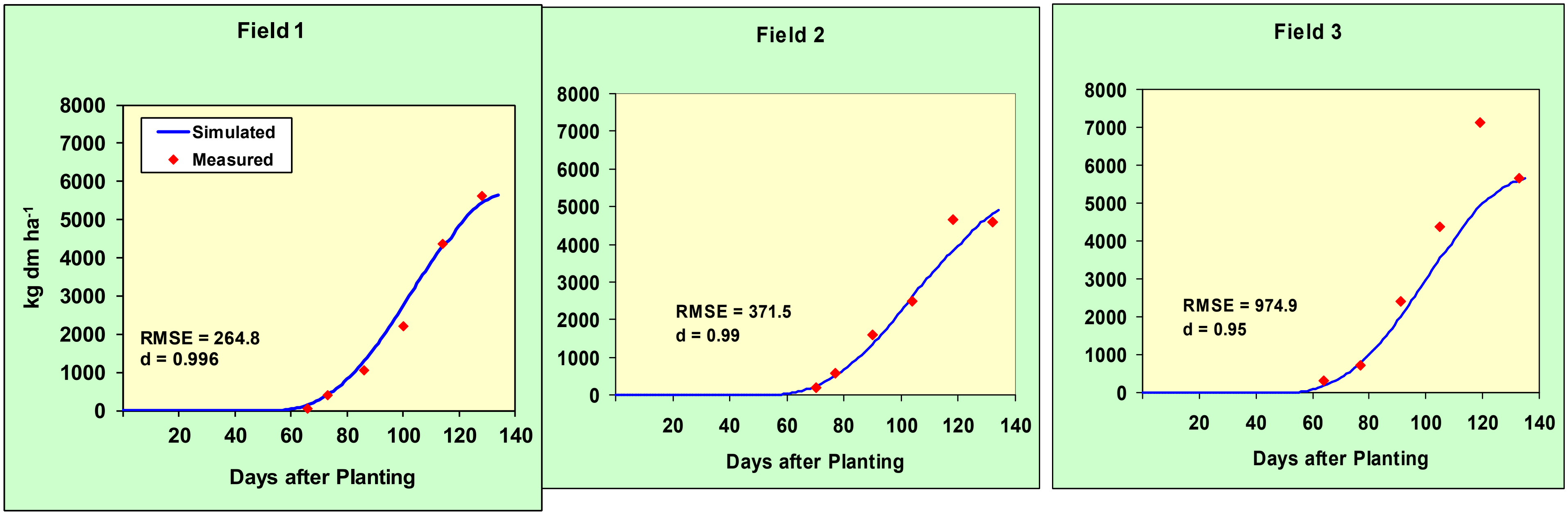
Calibration CSM-CROPGRO

Georgia Peanut Variety Trials: Calibration

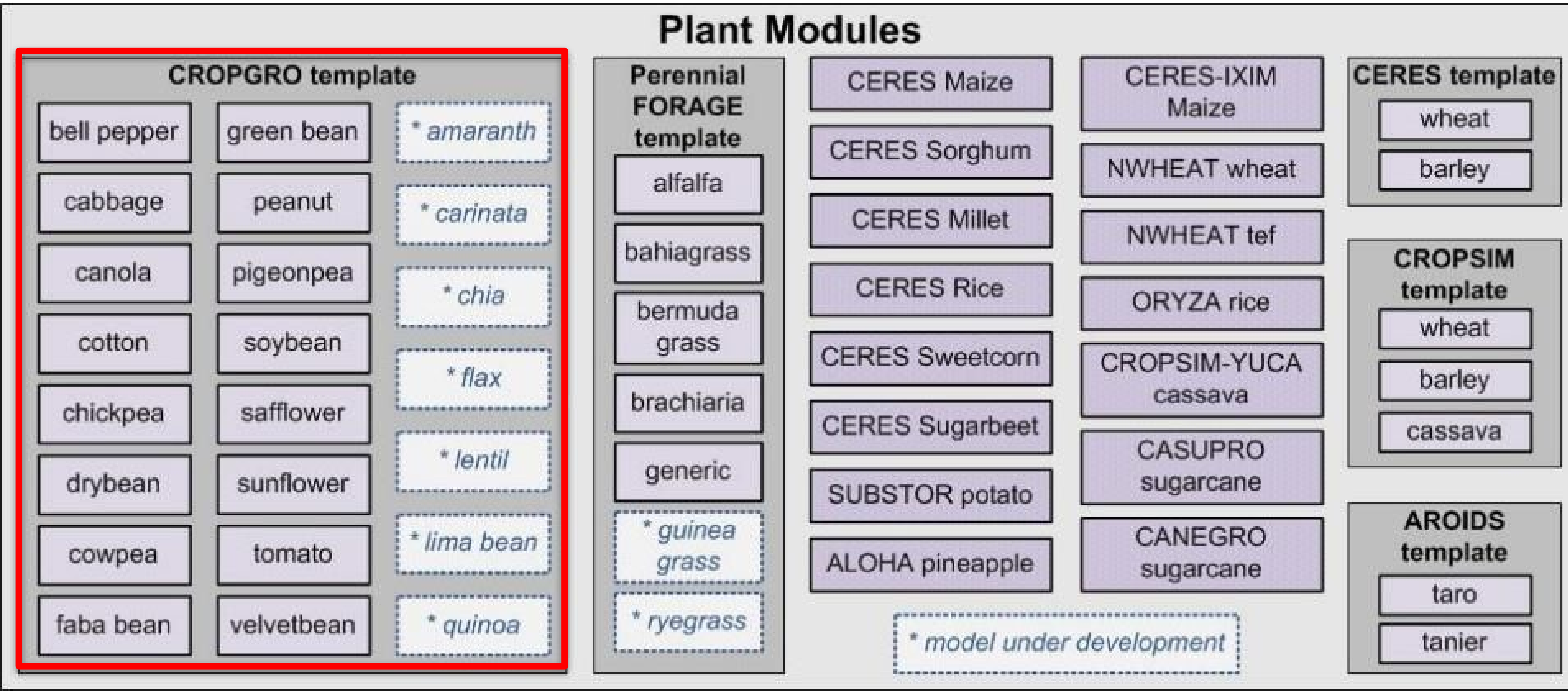


Calibration CSM-CROPGRO

Farmers' Fields (2003) : Model Evaluation



Genetics & Plant Modules



Genetic Coefficients

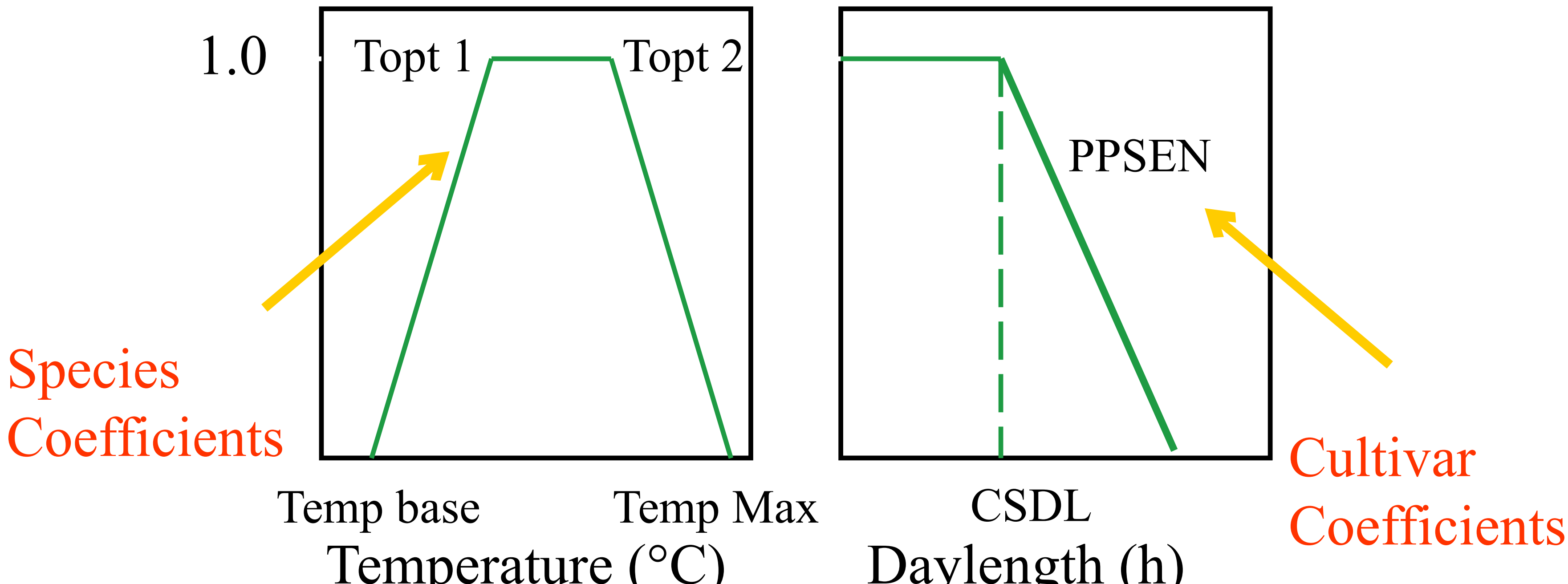
- Species parameters and functions
  - Defines the response of a crop to environmental conditions, including temperature, solar radiation, CO_2 and photoperiod, as well as plant composition and other functions and parameters.

Genetic Coefficients

- Ecotype coefficients
  - Defines coefficients for groups of cultivars that show similar behavior and response to environmental conditions.
- Cultivar coefficients
  - Cultivar and variety specific coefficients, such as photothermal days to flowering & maturity, sensitivity to photoperiod, seed size, etc.

Cropping System Model (CSM)

Simulation of plant responses to temperature and photoperiod



Model $1/d = f(T) \times f(D)$

$Stage_i = f(photothermal\ days)$

Crop Simulation Models

- Current crop models use empirical genotype specific parameters (GSPs) for cultivar environment interactions that are not linked to actual genes. These GSPs do not adequately include the genetic (G) and gene-by-environment interaction (G x E) effects on crop development. Thus, there are inherent limitations.

- A model that could predict phenotypes from genotypes would be a valuable tool for plant breeders by providing insight on target selection (Langridge et al. 2011).

Gene-based Modeling

Bridging the gap between biotechnology, breeding and crop management (and AI?)

- GeneGro Version 1 (1995)
  - Based on the model BEANGRO
  - 30 cultivar coefficients
  - 7 gene coefficients

- CSM-GeneGro
  - 15 cultivar coefficients
  - 7 E loci for soybean (2002)
  - 7 gene coefficients for common bean (2003)
  - Digital values (0,1)

- Gene-Base Common Bean Model (GB-CBM)
  - Quantitative Trait Locus (QTL)

Implementation I: Common bean
Known genes and their physiological responses

- Ppd Basic photoperiod response
- Hr Enhance effect of Ppd
- Fin Indeterminate vs determinate stem
- Fd Early flowering and maturity
- Ssz-1 Seed size
- Ssz-2 Seed size
- Ssz-3 Seed size

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CSM-GeneGro-Common bean

Examples of genotypes specified for cultivars






Cultivar	*Ppd*	*Hr*	*Fin*	*Fd*	Ssz1	Ssz2	Ssz3
Redkloud	0	0	0	0	1	1	1
Calima	1	0	0	0	1	1	1
Pinto UI114	1	1	1	1	1	0	1
Jamapa	0	0	1	0	0	0	1
Porrillo S.	1	0	1	0	0	0	1
Fleetwood	1	0	0	0	0	0	0
Seafarer	0	0	0	0	0	0	0

Coefficient determination in CSM-GeneGro

- Select genes that have a physiological effect
- Use regression analysis to quantify effects of genes on individual cultivar coefficients
- Gene effects that are not significant are eliminated
- Remaining cultivar coefficients are assumed to be constant

Examples of gene effects assumed in model

- *Two genes, no interaction*:

  Physiological time from flowering to emergence

  EM-FL = 26.853 + 3.306*Fin - 4.497*Fd

  $R^2 = 0.46^{**}$

- *Two genes that interact (epistasis):*

  Photoperiod sensitivity

  PPSEN = 0.001 + 0.023**Ppd* + 0.062**Ppd***Hr*

  $R^2 = 0.47^{**}$

Version 2.0
Field data for modeling (2005):

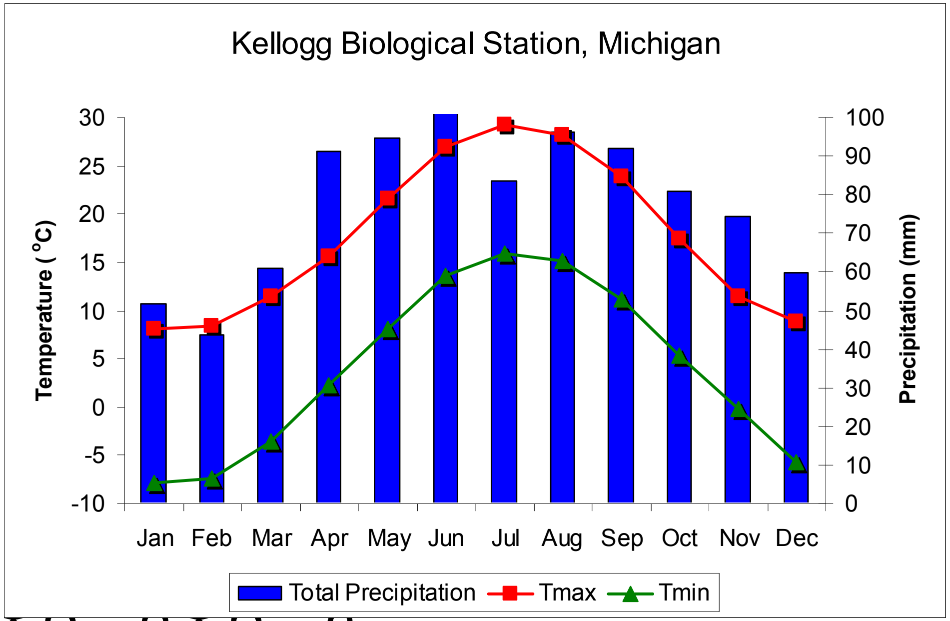
- 46 cultivars
- Various treatments
  - Irrigation
  - Row spacing
  - Planting dates
- Calibration data
  - 10 trials:
    - USA, Mexico, Colombia, Canada
  - 177 observations
- Evaluation data
  - 26 trials:
    - USA, Mexico, Colombia, Canada
  - 333 observations

Evaluation data set - RMSE

Variable	CROPGRO	GeneGro
Days to anthesis	4.3	5.0
Days to maturity	5.7	6.0
Grain yield (kg/ha)	1020	1070
Above ground wt. (kg/ha)	2180	2120
Unit grain wt. (mg)	0.08	0.12

Kellogg Biological Station, Michigan

- Planted on July 9
- Rainfed
- Kalamazoo Loam
- 73 years of weather data
  - 1930 – 2002
- 96 genotypes
  - Ppd * Hr * Fin * Fd * Ssz1 * Ssz2 * Ssz3
  - 128 potential combinations: 2^7
  - eliminate ppd * hr



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CSM-GeneGro-Common Bean

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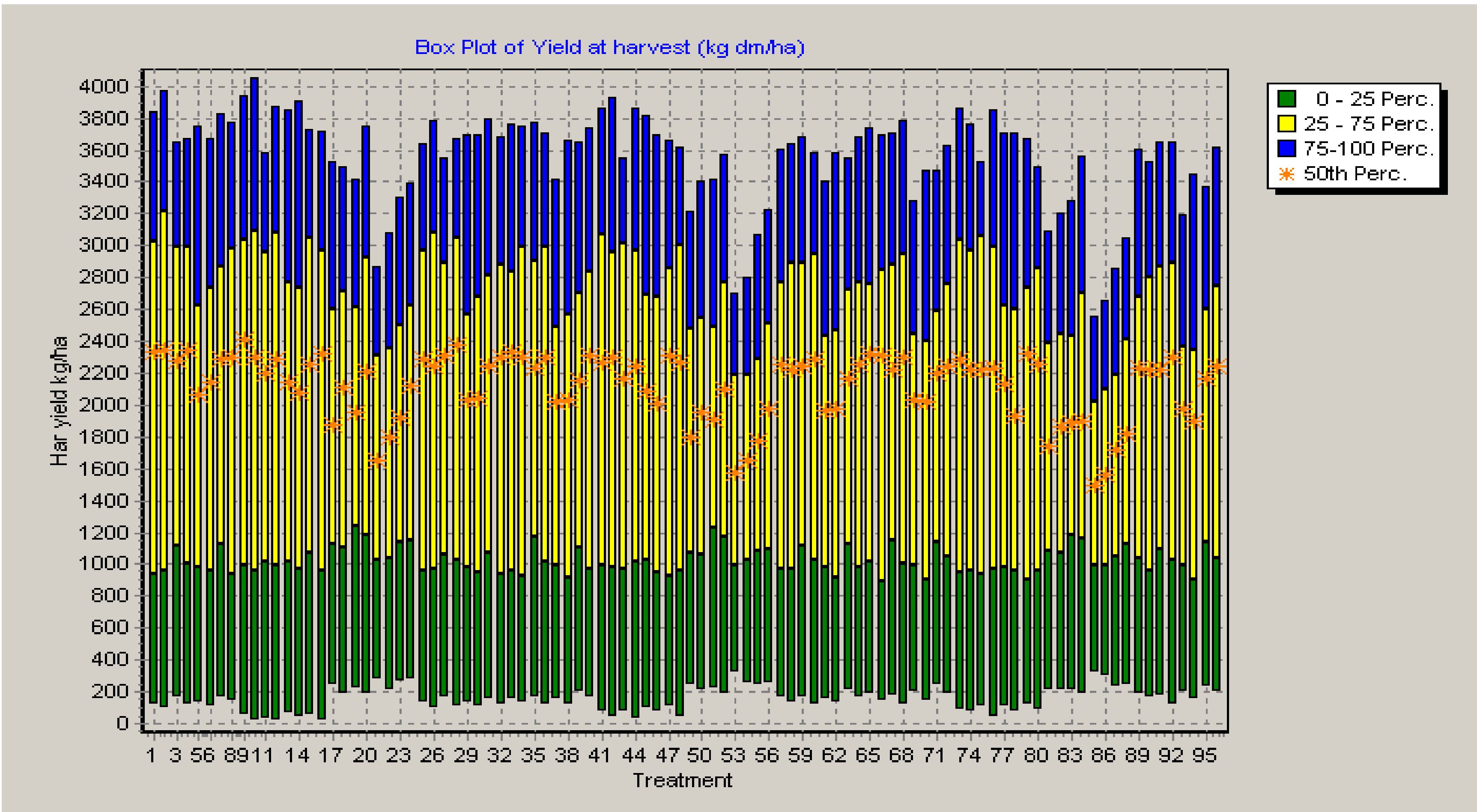
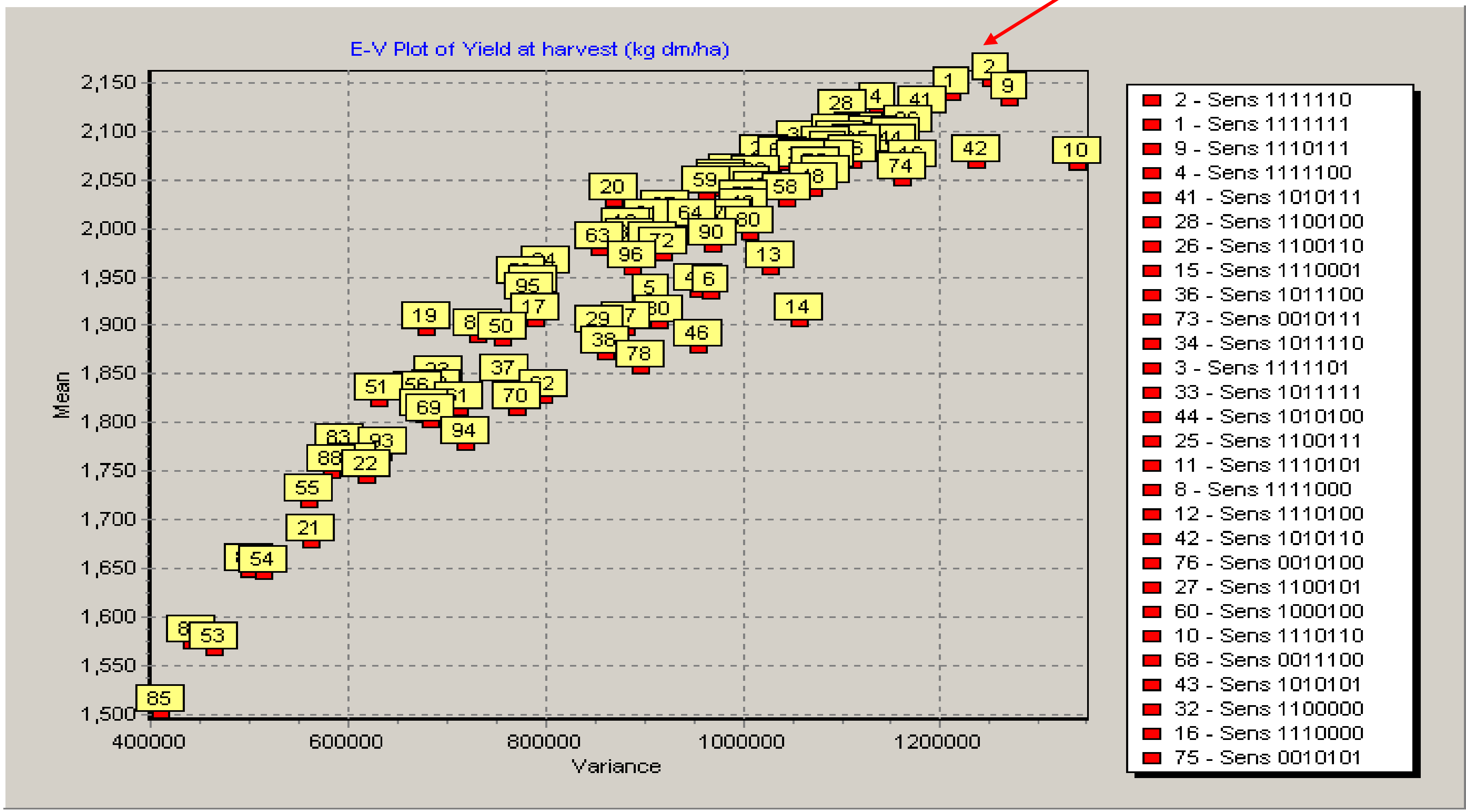
Median Yield



CSM-GeneGro-Common Bean

Mean Yield vs Variance

1111110
ssz3 recessive



Yield Performance

- Kellogg Biological Station, Michigan
  - 1111110 (Genotype 2)
  - 1111111 (Genotype 1)
  - 1110111 (Genotype 9)
- Twin Falls, Idaho
  - 1110111 (Genotype 9)
  - 1111110 (Genotype 2)
  - 1110110 (Genotype 10)
- Prosser, Washington
  - 1110110 (Genotype 10)
  - 1110111 (Genotype 9)
  - 1111110 (Genotype 2)
- Critical Genes
  - Fd: early versus late flowering
  - Ssz3: seed size

Predicting time to flowering for dry bean based on QTL and Environmental Variables

G3 Genes | Genomes | Genetics

INVESTIGATION

A Predictive Model for Time-to-Flowering in the Common Bean Based on QTL and Environmental Variables

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ABSTRACT The common bean is a tropical facultative short-day legume that is now grown in tropical and temperate zones. This observation underscores how domestication and modern breeding can change the adaptive phenology of a species. A key adaptive trait is the optimal timing of the transition from the vegetative to the reproductive stage. This trait is responsive to genetically controlled signal transduction pathways and local climatic cues. A comprehensive characterization of this trait can be started by assessing the quantitative contribution of the genetic and environmental factors, and their interactions. This study aimed to locate significant QTL (G) and environmental (E) factors controlling time-to-flower in the common bean, and to identify and measure G × E interactions. Phenotypic data were collected from a biparental [Andean × Mesoamerican] recombinant inbred population ($F_{11:14}$, 188 genotypes) grown at five environmentally distinct sites. QTL analysis using a dense linkage map revealed 12 QTL, five of which showed significant interactions with the environment. Dissection of G × E interactions using a linear mixed-effect model revealed that temperature, solar radiation, and photoperiod play major roles in controlling common bean flowering time directly, and indirectly by modifying the effect of certain QTL. The model predicts flowering time across five sites with an adjusted *r*-square of 0.89 and root-mean square error of 2.52 d. The model provides the means to disentangle the environmental dependencies of complex traits, and presents an opportunity to identify *in silico* QTL allele combinations that could yield desired phenotypes under different climatic conditions.

KEYWORDS
Phaseolus vulgaris
mixed-effects model
multi-environment trial
G × E interactions

Linear Mixed-Effects Statistical Model

- Time to Flower = μ + G ij + E j + (G*E) ij + ε ij

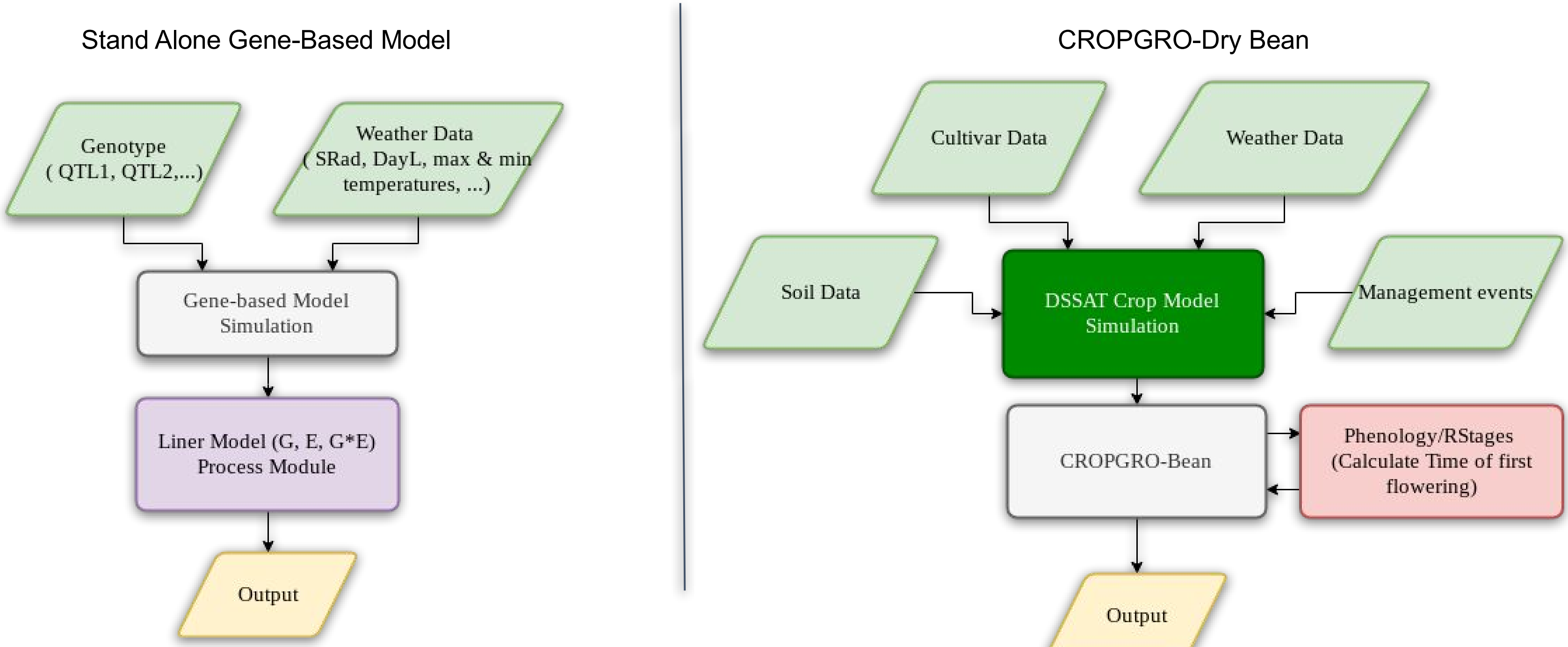
```
!-------------------------------------------------------------
!       The dynamic gene-based mixed effects linear model, Bean
!-------------------------------------------------------------
       RFij = RFmean                                    &
      + 5.85339e-04 * (TMAX - Tmaxm)                    &
      + 5.20694e-04 * (TMIN - Tminm)                    &
      - 1.58858e-03 * (DAYL - DLm)                      &
      - 8.59106e-05 * (SRAD - Sradm)                    &
      + 9.26783e-04 * TF(1)                             &
      + 1.25430e-03 * TF(2)                             &
      - 6.69171e-04 * TF(4)                             &
      - 3.51446e-05 * TF(5)                             &
      + 5.66365e-04 * TF(6)                             &
      - 4.13906e-04 * TF(7)                             &
      - 2.20600e-04 * TF(8)                             &
      - 4.63511e-04 * TF(9)                             &
      - 2.71880e-04 * TF(10)                            &
      + 3.41766e-04 * TF(11)                            &
      - 1.60067e-04 * TF(12)                            &
      + 2.87046e-04 * TF(1) * TF(2)                     &
      - 5.12084e-05 * (SRAD - Sradm) * TF(12)           &
      - 1.36551e-04 * (DAYL - DLm)   * TF(1)            &
      + 9.93241e-05 * (TMAX - Tmaxm) * TF(5)            &
      - 1.00970e-04 * (TMIN - Tminm) * TF(3)            &
      - 6.85350e-04 * (DAYL - DLm)   * TF(3)
```

```
!-------------------------------------------------------------
!     Limit rate of development to positive values;
!       initial value=0.0. When SumRFij first reaches 1.00,
!       flowering will occur
!-------------------------------------------------------------
      SumRFij = SumRFij + RFij*1.0
```

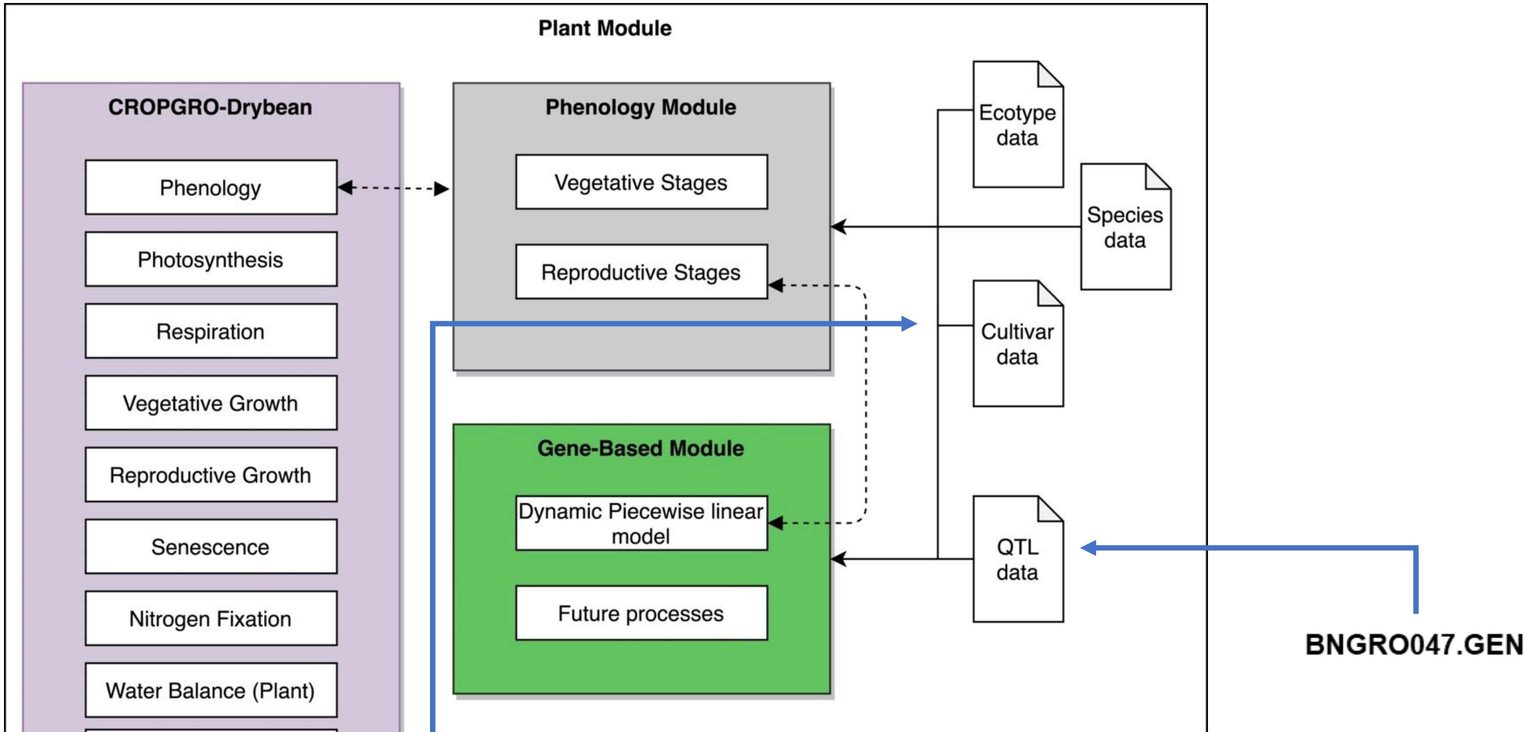
- Based on linear mixed effects models developed by Mehul Bhakta et al.,
- Rate of Development toward first flower in Common Bean, using G, E, and G x E inputs

Stand Alone Model vs CROPGRO-Dry Bean

- Basic flow of Stand Alone Model and CROPGRO-Bean for predict first flowering



Gene-Based Model Integration diagram

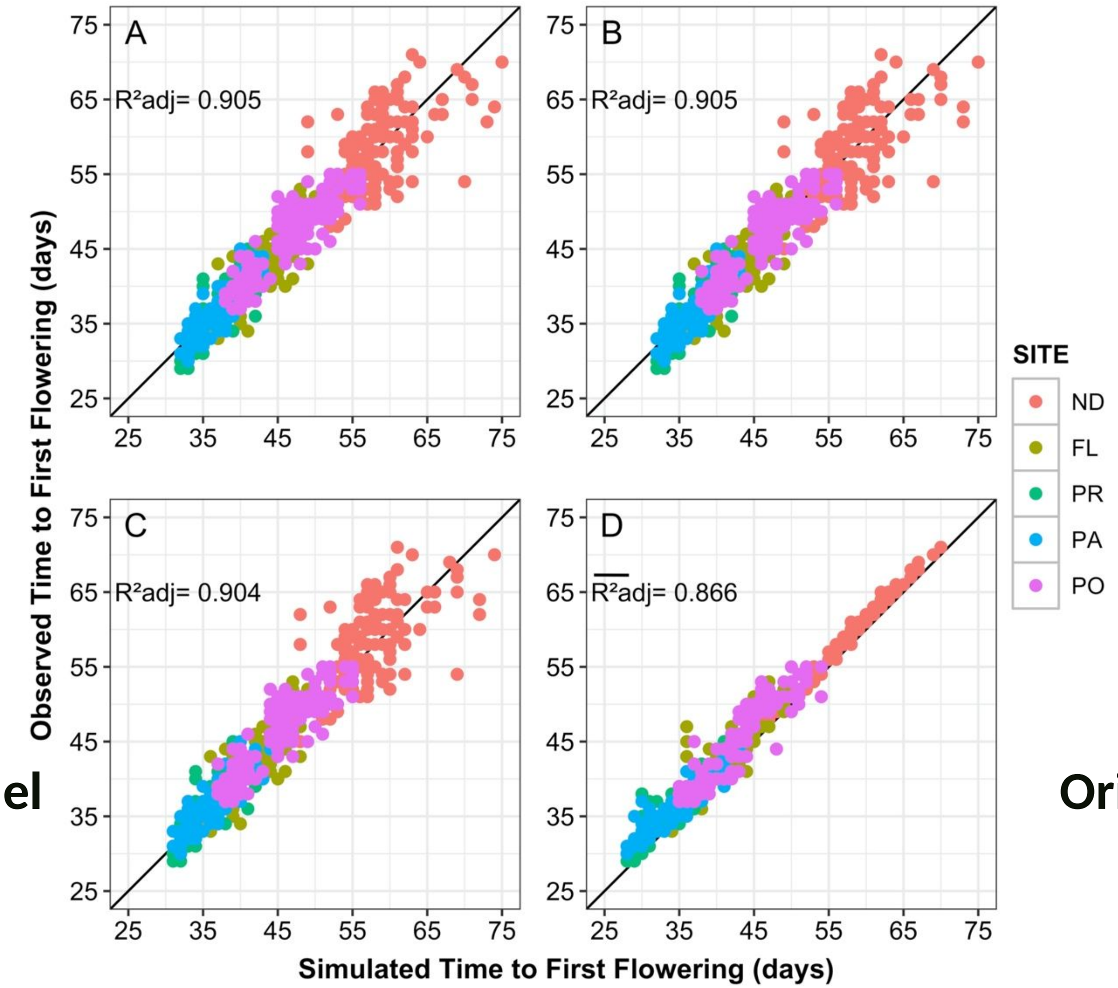


@VAR#	VRNAME..........	TF1	TF2	TF3	TF4	TF5	TF6	TF7	TF8	TF9	TF10	TF11	TF12
CALIMA	Calima-RIJC	1	1	1	1	1	1	1	1	1	1	1	1
JAMAPA	Jamapa-RIJC	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
RI-020	RIJC Line 020	1	1	-1	-1	-1	-1	-1	-1	1	1	-1	-1
RI-022	RIJC Line 022	-1	-1	1	1	-1	-1	1	-1	1	-1	-1	-1
RI-232	RIJC Line 232	-1	-1	-1	-1	-1	-1	1	1	1	-1	-1	-1
RI-252	RIJC Line 252	1	1	1	1	-1	-1	1	-1	1	1	1	1
RI-257	RIJC Line 257	1	1	1	1	-1	1	1	-1	-1	-1	-1	-1
RI-262	RIJC Line 262	-1	-1	-1	1	-1	-1	1	-1	1	-1	-1	-1
RI-316	RIJC Line 316	1	1	-1	-1	-1	-1	-1	-1	-1	-1	-1	1
RI-339	RIJC Line 339	-1	-1	-1	-1	-1	-1	1	-1	1	-1	1	1
RI-347	RIJC Line 347	-1	-1	-1	-1	-1	-1	1	1	1	1	-1	1
RI-358	RIJC Line 358	-1	-1	1	1	-1	-1	1	1	-1	-1	-1	-1
RI-374	RIJC Line 374	1	1	-1	-1	-1	-1	1	-1	-1	1	-1	-1

Multi Environment Phenotyping (5 sites)

- **Citra, Florida**
  - Avg. Temperature: 32/18 °C
  - Day-Length range: 12:30 – 13:30 h
- **Prosper, North Dakota**
  - Avg. Temperature: 27/13 °C
  - Day-Length range: 15:20 – 15:53 h
- **Palmira, Colombia**
  - Avg. Temperature: 29/19 °C
  - Day-Length range: 11:56 – 11:58 h
- **Popayan, Colombia**
  - Avg. Temperature: 23/13 °C
  - Day-Length range: 12:08 – 12:11 h
- **Isabela, Puerto Rico**
  - Avg. Temperature: 29/19 °C
  - Day-Length range: 11:30– 12:35 h

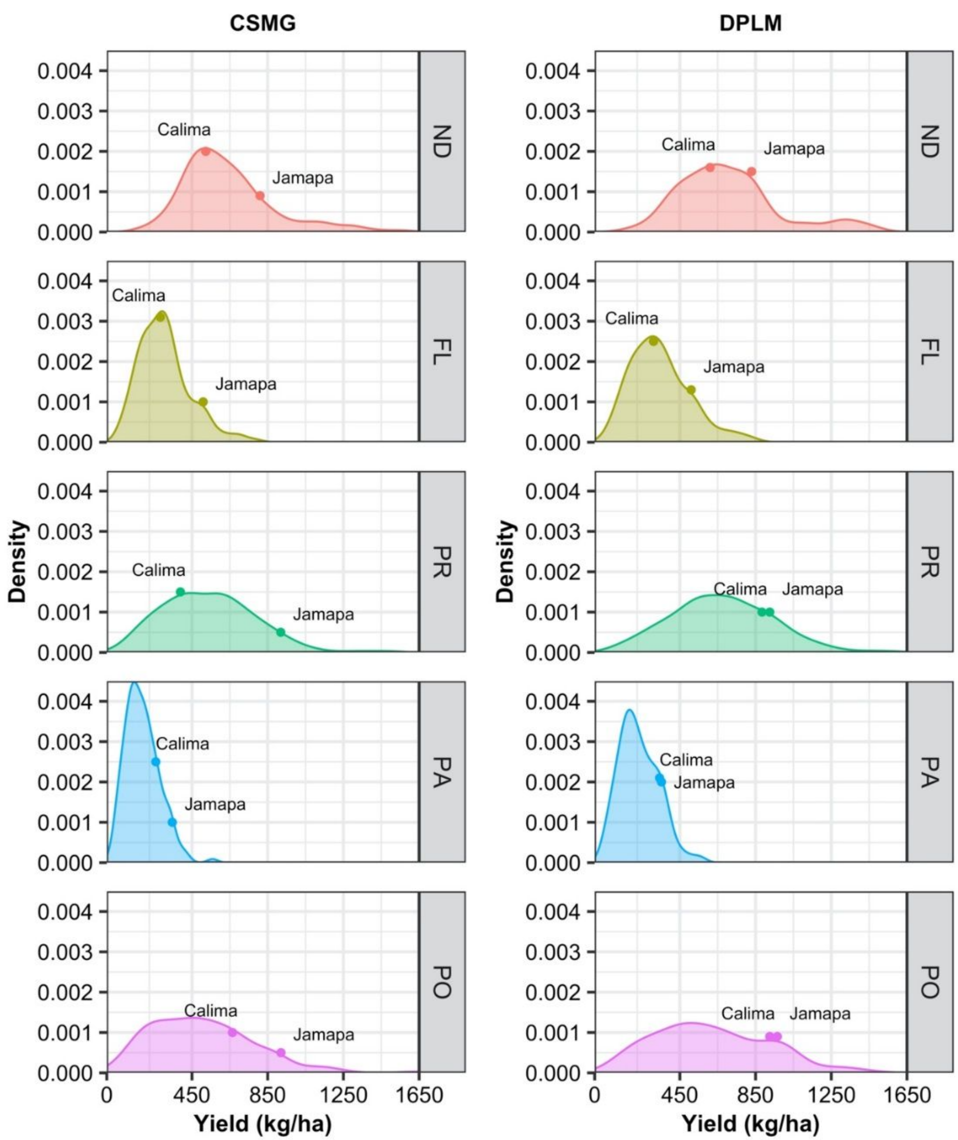
Predicted versus Observed Flowering



Gene-based Model

Original Model

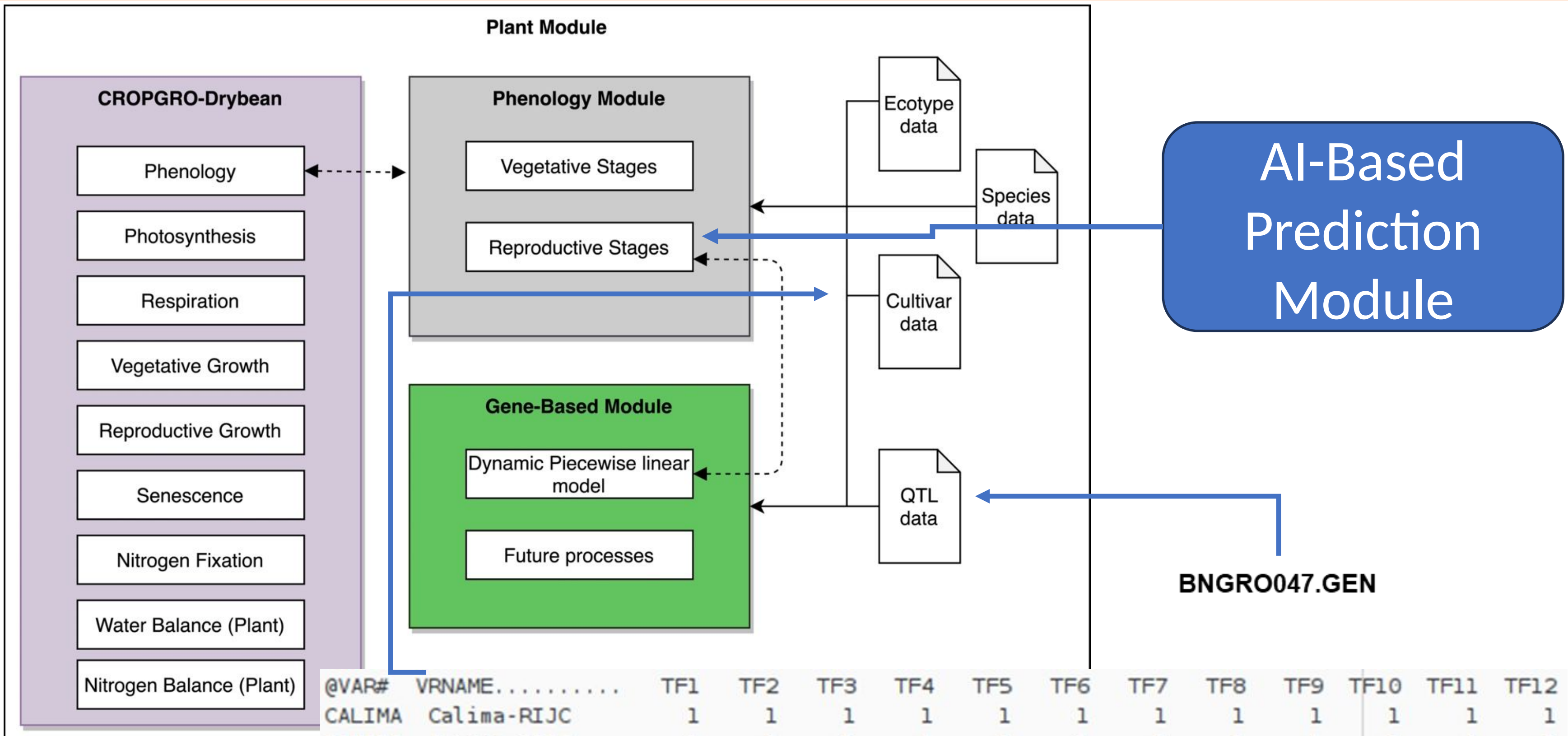
Final Simulated Yield



Original Model

Gene-based module integrated into the Main Model

Gene-Based Model Integration diagram



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CALIMA	Calima-RIJC	1	1	1	1	1	1	1	1	1	1	1	1
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RI-020	RIJC Line 020	1	1	-1	-1	-1	-1	-1	-1	1	1	-1	-1
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RI-232	RIJC Line 232	-1	-1	-1	-1	-1	-1	1	1	1	-1	-1	-1
RI-252	RIJC Line 252	1	1	1	1	-1	-1	1	-1	1	1	1	1
RI-257	RIJC Line 257	1	1	1	1	-1	1	1	-1	-1	-1	-1	-1
RI-262	RIJC Line 262	-1	-1	-1	1	-1	-1	1	-1	1	-1	-1	-1
RI-316	RIJC Line 316	1	1	-1	-1	-1	-1	-1	-1	-1	-1	-1	1
RI-339	RIJC Line 339	-1	-1	-1	-1	-1	-1	1	-1	1	-1	1	1
RI-347	RIJC Line 347	-1	-1	-1	-1	-1	-1	1	1	1	1	-1	1
RI-358	RIJC Line 358	-1	-1	1	1	-1	-1	1	1	-1	-1	-1	-1
RI-374	RIJC Line 374	1	1	-1	-1	-1	-1	1	-1	-1	1	-1	-1

Crop Model Applications

- Diagnose problems (Yield Gap Analysis)
- Precision agriculture
  - Diagnose factors causing yield variations
  - Prescribe spatially variable management
- Irrigation management
- Water use projection
- Soil fertility management
- Plant breeding and Genotype * Environment interactions
- Yield prediction for crop management

➢ ***Can we do the same with AI Prediction?***

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Meta analysis on the evaluation and application of DSSAT in South Asia and China

205 papers published from January 2010 – February 2022

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Invited Articles (Silver Jublee Publication)

Meta analysis on the evaluation and application of DSSAT in South Asia and China: Recent studies and the way forward

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ABSTRACT

The Decision Support System for Agrotechnology transfer (DSSAT) is a global modelling platform that encompasses crop models for more than 40 different crops. The models have been used extensively throughout the world, including South Asia and China. From the web of science database, we reviewed 205 papers that were published from January 2010 to February 2022 containing examples of the evaluation and application of the DSSAT crop simulation models. In South Asia and China, more than 50 traits and variables were analyzed for various experiments and environmental conditions during this period. The performance of the models was evaluated by comparing the simulated data with the observed data through different statistical parameters. Over the years and across different locations, the DSSAT crop models simulated phenology, growth, yield, and input efficiencies reasonably well with a high coefficient of determination (R^2), and Willmott d-index, together with a low root mean square error (RMSE), normalized RMSE (RMSEn), mean error (ME) or percentage error difference. The CERES models for rice, wheat and maize were the most used models, followed by the CROPGRO models for cotton and soybean. Grain yield, anthesis and maturity dates, above ground biomass, and leaf area index were the variables that were evaluated most frequently for the different crop models. The meta-analysis of the data of the most common simulated variables (Anthesis, maturity, leaf area index, grain yield and above ground biomass) for the four com-

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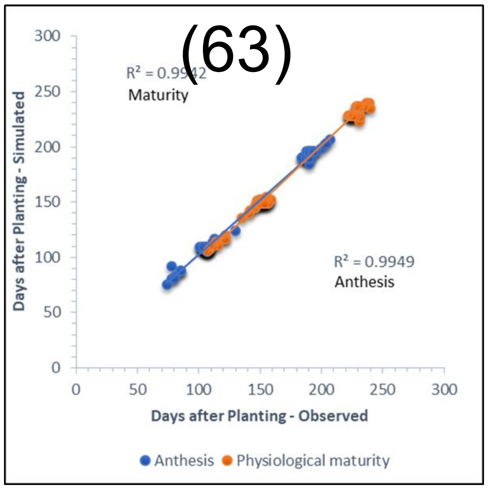
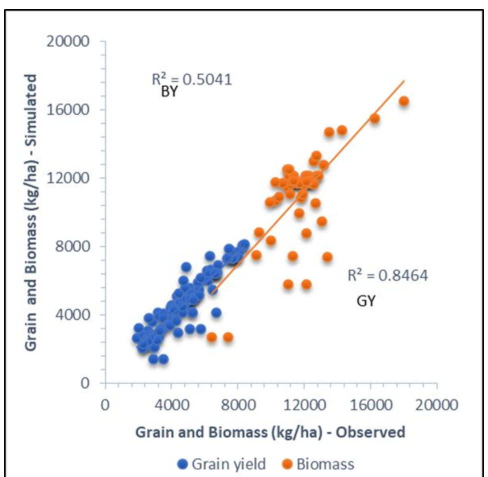
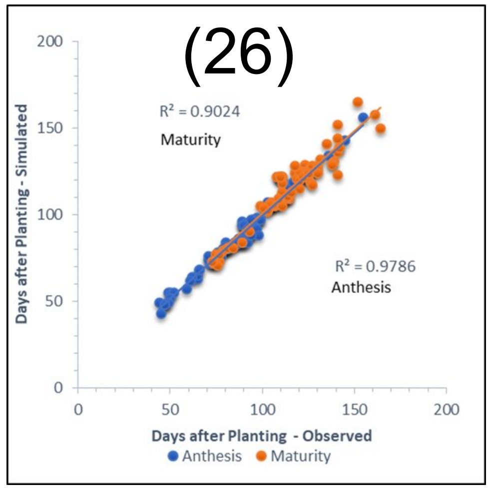
Meta analysis on the evaluation and application of DSSAT in South Asia and China: Recent studies 2010-2022

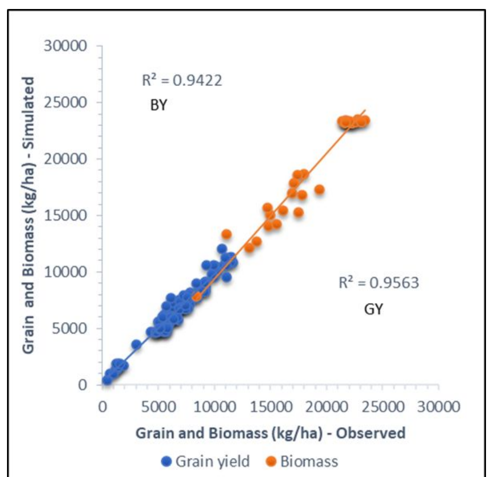
Ceres-Wheat (63)



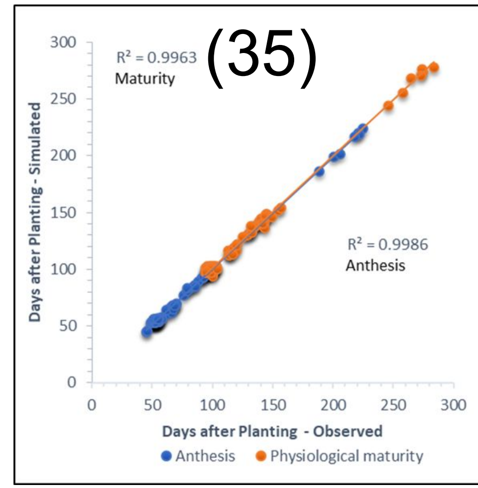


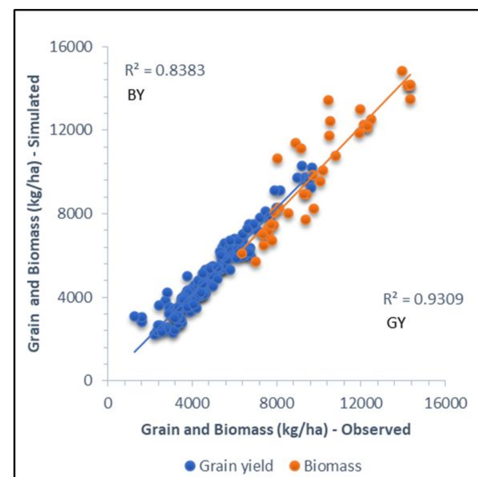
Ceres-Rice (26)





Ceres-Maize (35)





Low input systems model intercomparison

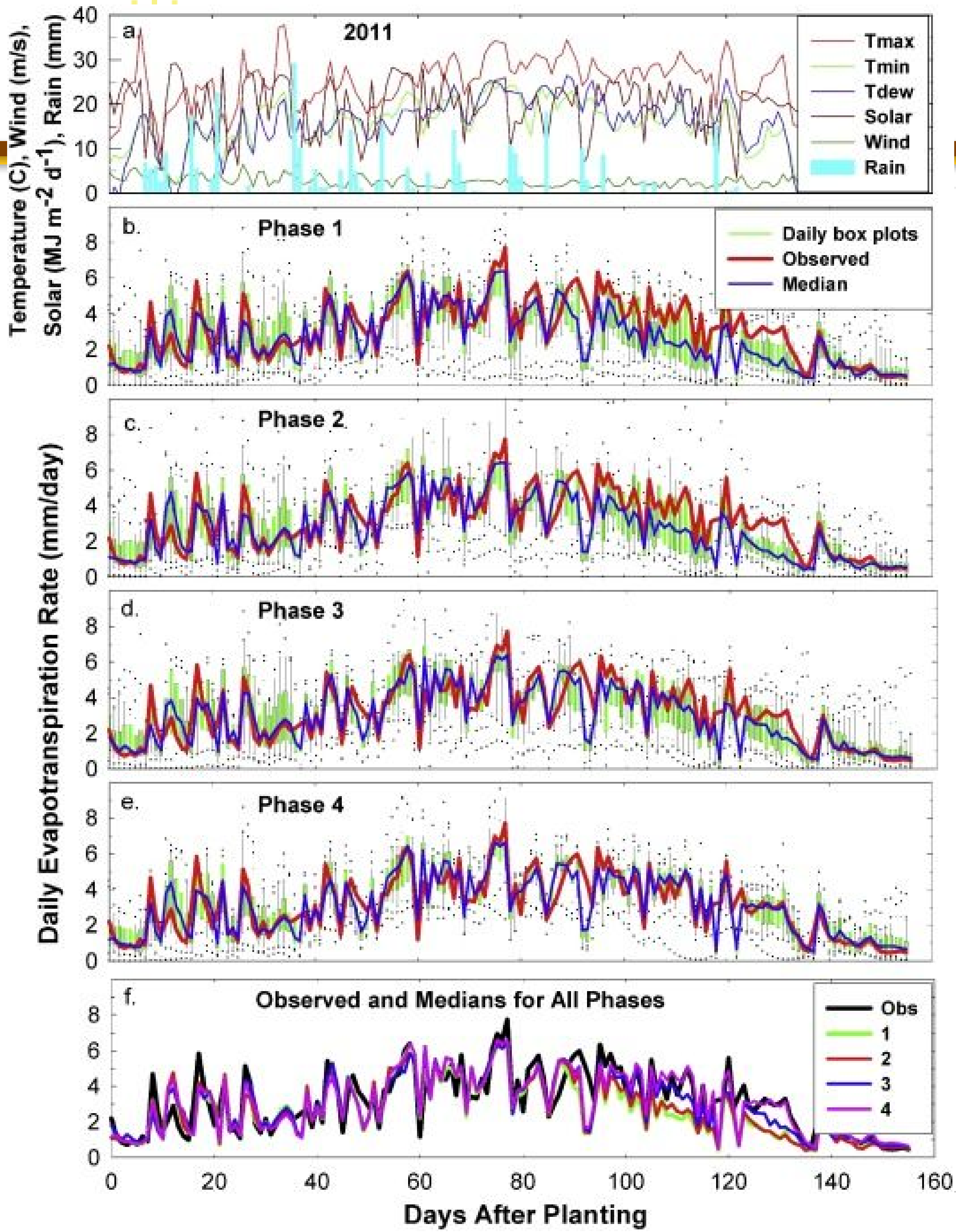
Global Change Biology

PRIMARY RESEARCH ARTICLE | Full Access

Modelling climate change impacts on maize yields under low nitrogen input conditions in sub-Saharan Africa

Gatien N. Falconnier, Marc Corbeels, Kenneth J. Boote, François Affholder, Myriam Adam, Dilys S. MacCarthy, Alex C. Ruane, Claas Nendel, Anthony M. Whitbread, Éric Justes, Lajpat R. Ahuja, Folorunso M. Akinseye, Isaac N. Alou, Kokou A. Amouzou, Saseendran S. Anapalli, Christian Baron, Bruno Basso, Frédéric Baudron, Patrick Bertuzzi, Andrew J. Challinor, Yi Chen, Delphine Deryng, Maha L. Elsayed, Babacar Faye, Thomas Gaiser, Marcelo Galdos, Sebastian Gayler, Edward Gerardeaux, Michel Giner, Brian Grant, Gerrit Hoogenboom, Esther S. Ibrahim, Bahareh Kamali, Kurt Christian Kersebaum, Soo-Hyung Kim, Michael van der Laan, Louise Leroux, Jon I. Lizaso, Bernardo Maestrini, Elizabeth A. Meier, Fasil Mequanint, Alain Ndoli, Cheryl H. Porter, Eckart Priesack, Dominique Ripoche, Tesfaye S. Sida, Upendra Singh, Ward N. Smith, Amit Srivastava, Sumit Sinha, Fulu Tao, Peter J. Thorburn, Dennis Timlin, Bouba Traore, Tracy Twine, Heidi Webber ... See fewer authors

First published: 06 July 2020 | https://doi.org/10.1111/gcb.15261 | Citations: 2



ET intercomparison

Agricultural and Forest Meteorology

Volume 271, 15 June 2019, Pages 264-284

Simulation of maize evapotranspiration: An inter-comparison among 29 maize models

Bruce A. Kimball [a], Kenneth J. Boote [b], Jerry L. Hatfield [c], Laj R. Ahuja [d], Claudio Stockle [e], Sotirios Archontoulis [f], Christian Baron [g, h], Bruno Basso [i], Patrick Bertuzzi [j], Julie Constantin [k], Delphine Deryng [l, m], Benjamin Dumont [n], Jean-Louis Durand [o], Frank Ewert [p, q], Thomas Gaiser [q], Sebastian Gayler [r], Munir P. Hoffmann [o, s], Qianjing Jiang [t], Soo-Hyung Kim [u], Jon Lizaso [v], Sophie Moulin [w], Claas Nendel [p], Philip Parker [x], Taru Palosuo [y], Eckart Priesack [z], Zhiming Qi [t], Amit Srivastava [q], Tommaso Stella [p], Fulu Tao [y, A], Kelly R. Thorp [a], Dennis Timlin [B], Tracy E. Twine [C], Heidi Webber [p, q], Magali Willaume [k], Karina Williams [D]

Phased calibration – from "blind" to "full" calibration

Fig. 1. (a.) Weather variables (maximum and minimum air temperature, dew point, solar radiation, wind speed, rainfall) during 2011, a "typical" rainfall year. (b.) Box plots of daily evapotranspiration (ET) where the lower and upper limits of the box indicate the 25th and 75th percentile of ET values simulated by 29 maize growth models, respectively, the lower and upper whiskers indicate the 10th and 90th percentiles, and the points are outliers. Observed values and the median values from the 29 models are also shown. The simulated values in this plot came from Phase 1, a "blind" test whereby the modellers were only given weather, phenology, management, and soils information, but no crop response data. (c.) Same as (b.) except for Phase 2 whereby the modellers were given leaf area index data for all eight years. (d.) Same as (c.) except for Phase 3 whereby the modellers were given the observed ET, yield, soil water content at 10 cm, and other data for 2011. (e.) Same as (d.) except for Phase 4 whereby the modellers were given the all the ET, yield, growth, and soil water data for all eight years, as well as options for handling a water table. (f.) Observed daily ET values as well as the median simulated ET values for Phases 1, 2, 3, and 4.

AgMIP The Agricultural Model Intercomparison and Improvement Project

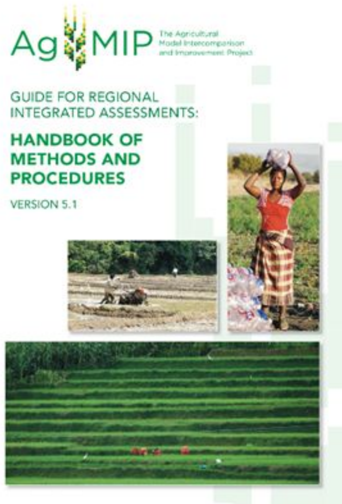
Core Questions for Regional Integrated Assessment

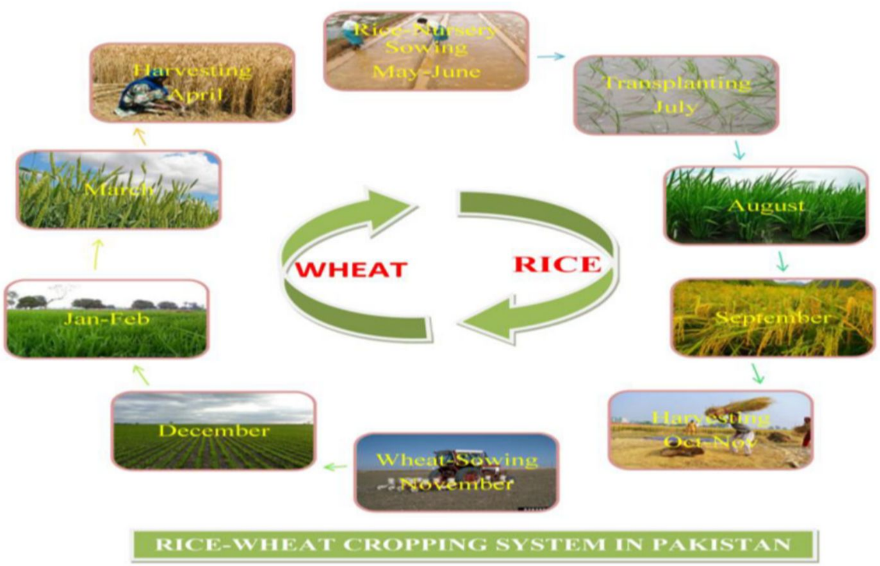
1. What is the sensitivity of current agricultural production systems to climate change?
2. What are the benefits of intervention in current agricultural systems?
3. What are the impacts of climate change on future agricultural production systems (without adaptation)?
4. What are the benefits of climate change adaptations?




Climate Change

Example Study Punjab, Pakistan under the auspices of the AgMIP Project





Punjab, Pakistan

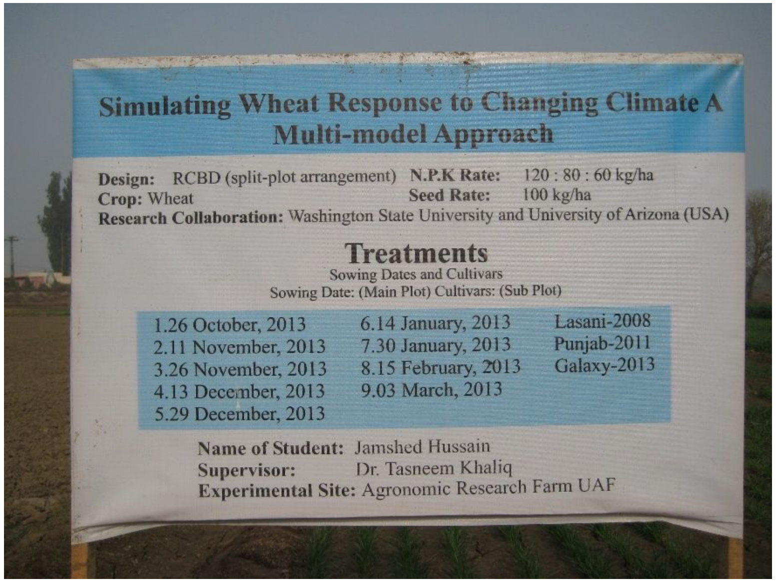
- The Rice-Wheat cropping system is the breadbasket of Punjab, Pakistan and Punjab, India
- The Punjab is the largest agricultural production system in South Asia, covering 13.5 m ha
- 20% of the world population depends on its agricultural production

(source Ashfaq et al, 2015)

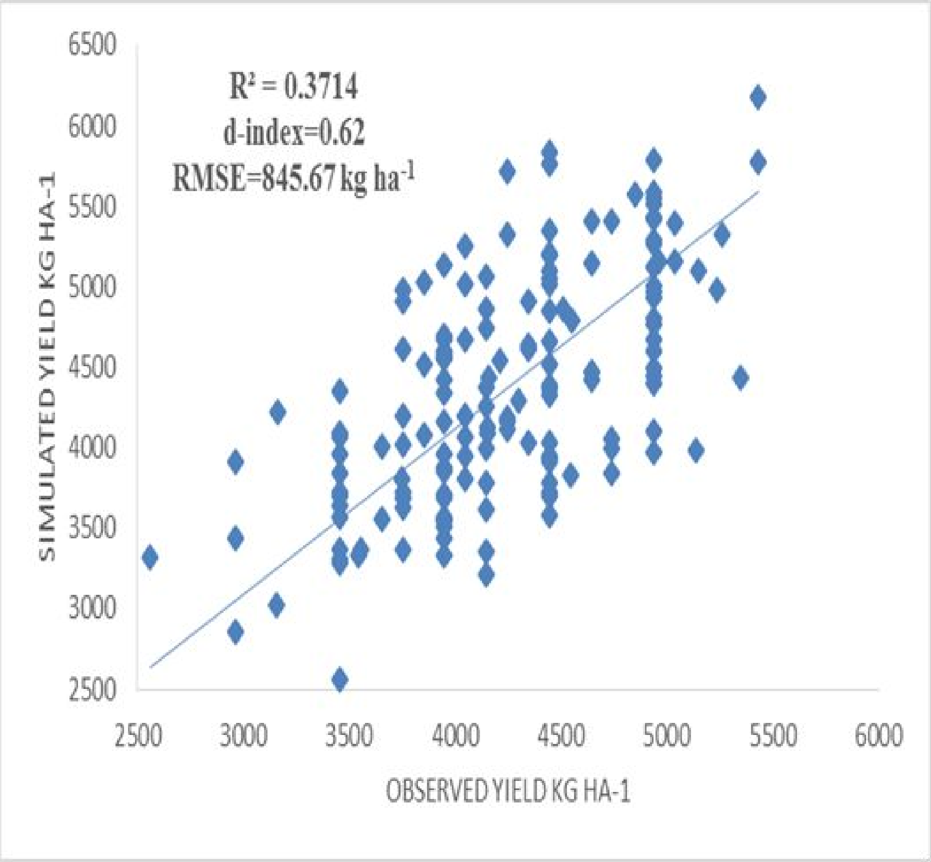
Punjab, Pakistan

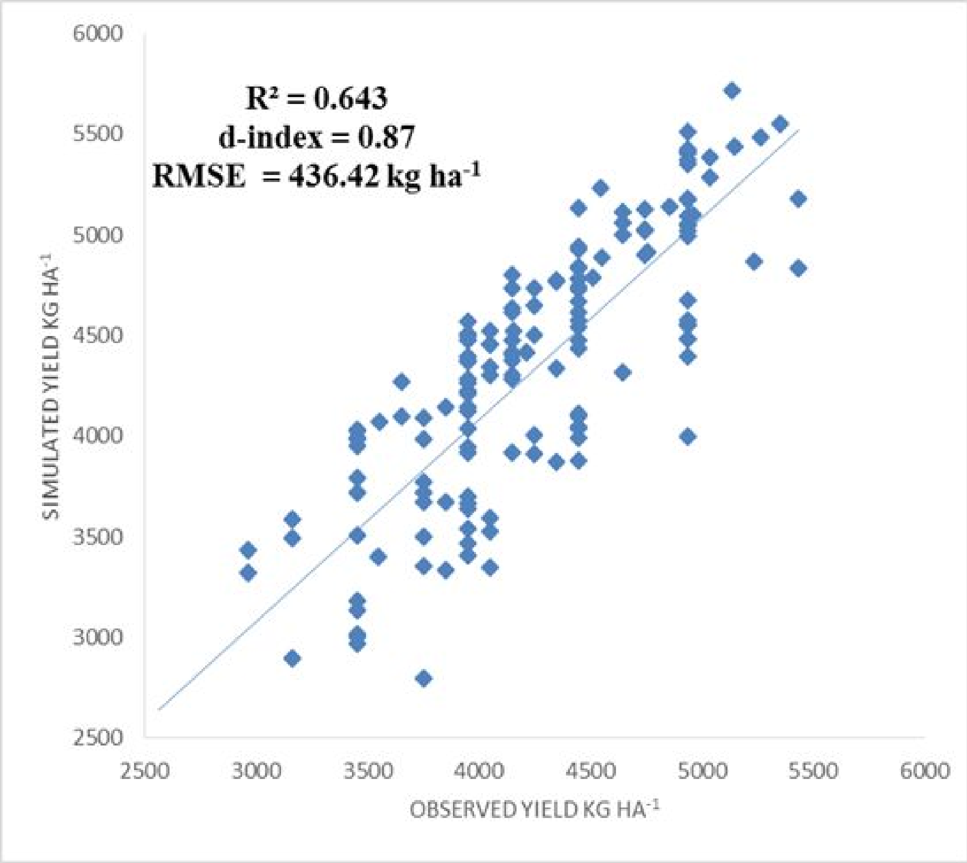
- Data from three experiments were used for rice & wheat model evaluation
- Yield and socio-economic data were collected by surveying 155 farmers in five districts of Punjab
- Two crop models (DSSAT and APSIM) were used to assess climate change impact and adaptation
- Five General Circulation Models (GCMs) under RCP 8.5 were used to generate future weather data
- Economic model (TOA-MD) was used to quantify the climate vulnerability and adaptation strategies in the study area

Research for Crop Model Evaluation



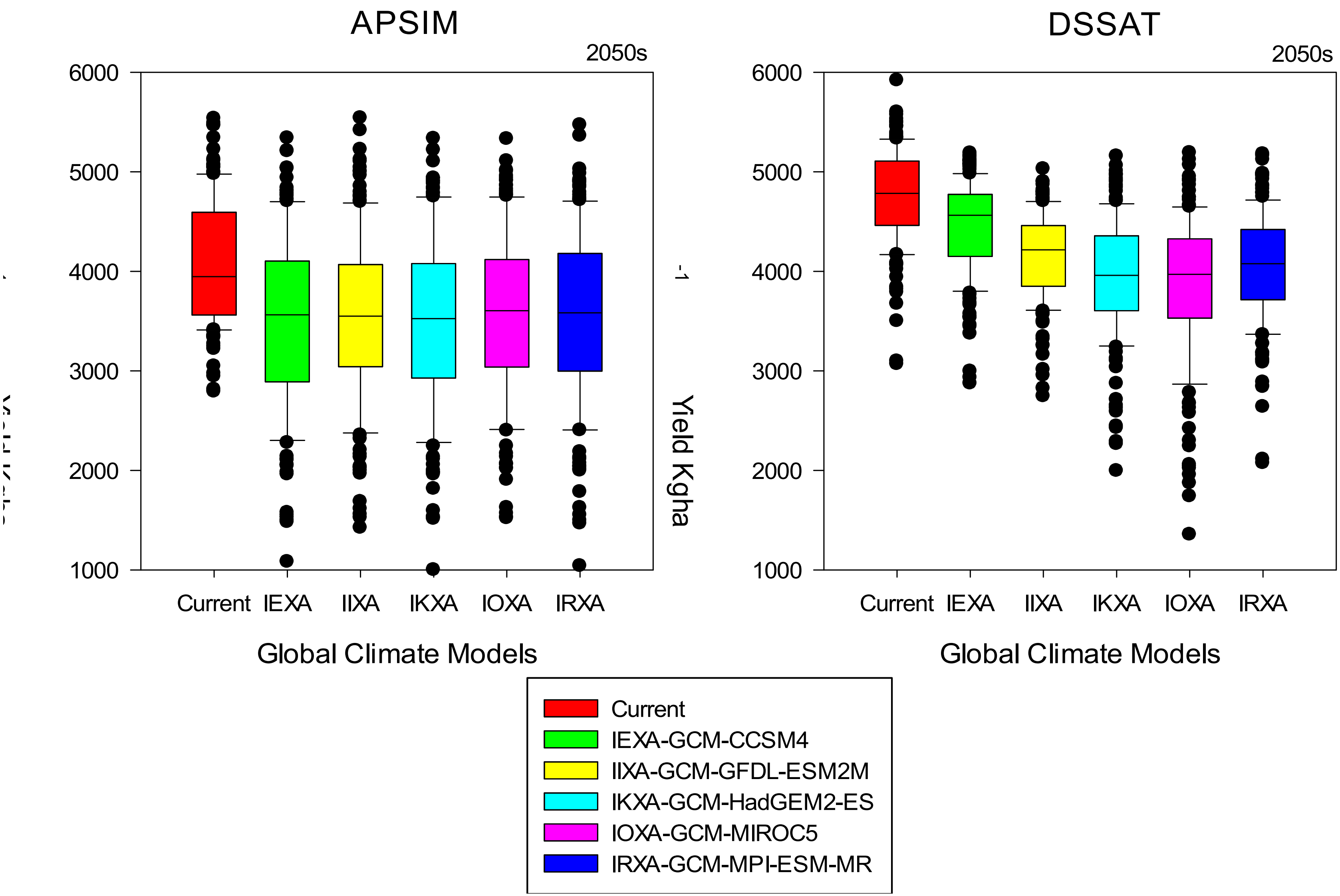
On-Farm Wheat Model Evaluation



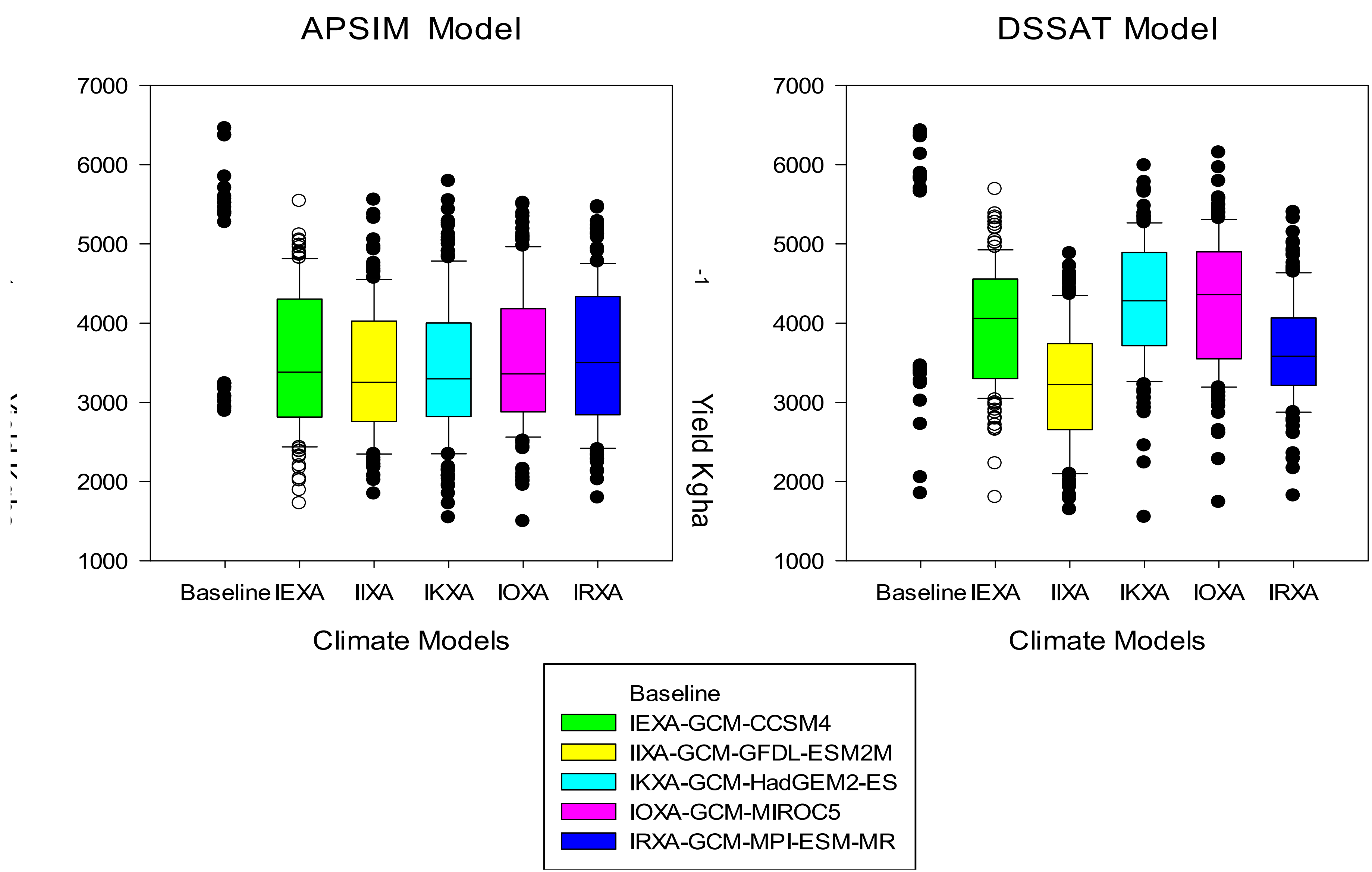


APSIM **DSSAT**

Climate Change Impact on Wheat (source Ashfaq et al, 2015)



Climate Change Impact on Rice (source Ashfaq et al, 2015)



Climate Change Impact on Rice-Wheat Production

- Results of DSSAT and APSIM for 155 farms with 5-GCMs in the wheat-rice region of Punjab-Pakistan:
  - Mean yield reduction for rice was 15.2% for DSSAT and 17.2% for APSIM
  - Mean yield reduction for wheat was 14.1% for DSSAT and 12% for APSIM

Climate Change Adaptation

- Planting of wheat should be 15 days earlier than present
- 25% increase in planting density for wheat
- Use of 20% more fertilizer in wheat
- Decrease the number of irrigations by 25%
- Agro-climatic advisory services for farmers (Early Warning System)
- Selection of improved cultivars (Short lag phase, Early canopy development, Enhance Leaf Area Duration etc.)

Policy Brief

Food Security in Punjab, Pakistan

Adapting rice-wheat farming to climate change

Harvesting rice in Pakistan.

Policy Brief
June 2014

Key Messages Punjab, Pakistan

Adaptations using different crop varieties and management practices can help reduce projected losses and poverty rates caused by increases in temperature and greater rainfall extremes.

CLIMATE

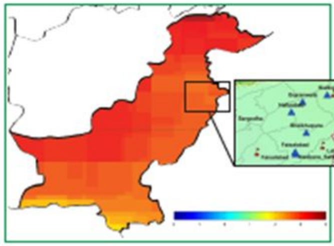
- **Climate change in the Pakistan Punjab** region is already occurring with **temperature increases of up to 1°C,** record-breaking floods, and drought.
- Temperatures are **projected to increase an average of 2°C** by 2050.
- **Heavy rainfall** and **increasing flooding** may occur during the wet seasons; **dry seasons could get drier.**

IMPACTS

- **Major losses of irrigation water** for the Punjab area could result from Himalayan glacier melt.
- **Yields** trends of rice, wheat, and cotton **have recently plateaued,** partly due to changes in climate.
- **Rice yield losses** could range from **8-30%** and **wheat yield losses** could range from **6-19%** by 2050.
- Poverty might increase by about 6% due to climate change in the Punjab by 2050.

ADAPTATIONS

- The **adaptation package** evaluated consisted of new varieties, earlier sowing dates, increase in fertilizer, and higher sowing density.
- The models predict that the **majority of farmers** would likely **adopt** the simulated adaptation packages.
- **Additional adaptations could be tested** to understand how to mitigate the negative impacts of climate change.



Adaptations Tested

The adaptation package included improved cultivars, changes in cropping patterns, improved farming practices, water management, fertilizer subsidies, diversification, and irrigation policies.

Impacts to Livelihood

Poverty could possibly be reduced from about 35% to about 13% through use of the adaptation package under climate change conditions by the 2050s.

RESULTS

By the 2050s, average annual temperature in Punjab, Pakistan is likely to **increase by about 2°C.** Increased dryness in the dry season, coupled with a higher number of heavy rain events in the wet season may result in more flooding. Overall the region is expected to become slightly wetter than at present.

Without changes to the current production system, **70-80% of small-holders could suffer losses** and the **poverty rate* could increase by 4-8%.**

Adaptations that greatly improved simulated outcomes for farmers in the 2050s included:

Sowing improved cultivars

Increasing sowing density - up to 30% for wheat and up to 15% for rice

Shifting sowing date earlier - about 15 days for wheat and 5 days for rice

Increasing fertilizer - up to 25% for wheat and 15% for rice.

RECOMMENDATIONS

Utilize the integrated assessment methodology to demonstrate how stakeholders and researchers can work together to address variable and changing climate.

Prioritize current adaptation strategies for testing of longer-term sustainability and effectiveness.

Explore adaptations that improve overall food security across diverse communities – design and test adaptations for at-risk farm systems, but also for successful farm systems.

*Poverty Line = US $1.25/person/day.

CLIMATE CHANGE IMPACTS on farms in Punjab, Pakistan

What is the sensitivity of CURRENT agricultural production systems to CLIMATE CHANGE*?

74% of farms could be **negatively affected** due to climate change†

*Climate change was simulated for RCP 8.5 with 5 GCMs.
†Mean of 69-83% - projections from 5 GCMs and 2 crop models.

What is the impact of CLIMATE CHANGE on FUTURE* agricultural production systems?

66% of farms could be **negatively affected** due to climate change†

*Future development changes by 2050s consisted of trends in number of people in household, non-agricultural income, yield, price of outputs, and production costs.
†Mean of 57-78% - projections from 5 GCMs and 2 crop models.

What are the benefits of FUTURE ADAPTATIONS* to CLIMATE CHANGE?

93% of farms could **benefit** from **adaptation** to climate change†

*Adaptation package tested included improved cultivars, changes in cropping patterns, improved farming practices, water management, fertilizer subsidies, diversification, and irrigation policies.
Adaptation benefits for some farms are not cost-effective.
†Mean of 92-94% - projections from 5 GCMs and 2 crop models.

Climate Change for Punjab Pakistan by 2050s

- Temperature projected to rise everywhere.
- Heavy rainfall is projected during the wet seasons, increasing the chances of flood.
- Dry seasons could get drier.

Participating Institutions: University of Agriculture, Faisalabad – Pakistan, Washington State University, USA, Pakistan Meteorological Department, Islamabad - Pakistan, Baha-ud-Din University, Multan - Pakistan, COMSATS University, Vehari – Pakistan

AgMIP receives major support from the UK Department for International Development's UKaid, in partnership with the US Department of Agriculture Agricultural Research Service

Crop Yield Forecasting Using the CCAFS Regional Agricultural Forecasting Toolbox (CRAFT) in the Oromia Regional State of Ethiopia

Kindie Tesfaye, Esayas Lemma, Robel Takele, Vakhtang Shelia , Addisu Dabale,

Pierre C. Sibiry Traore, Gerrit Hoogenboom, Dawit Solomon

GHACOF 56, August 26, 2020

Greater Horn of Africa Climate Outlook Forum

International Maize and Wheat Improvement Center

INTERNATIONAL CROPS RESEARCH INSTITUTE FOR THE SEMI-ARID TROPICS

ግብርና ሚኒስቴር MINISTRY OF AGRICULTURE

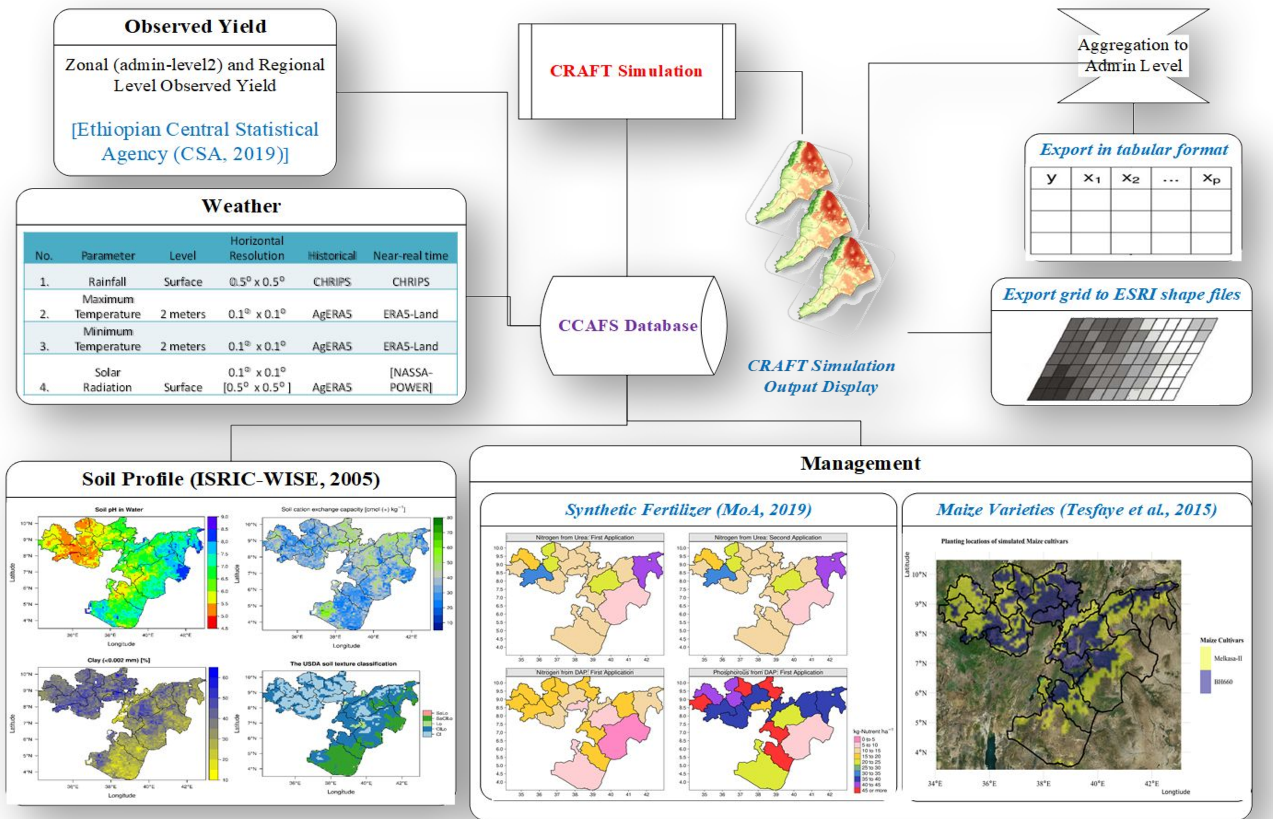
UNIVERSITY of FLORIDA

CGIAR

RESEARCH PROGRAM ON Climate Change, Agriculture and Food Security

CCAFS

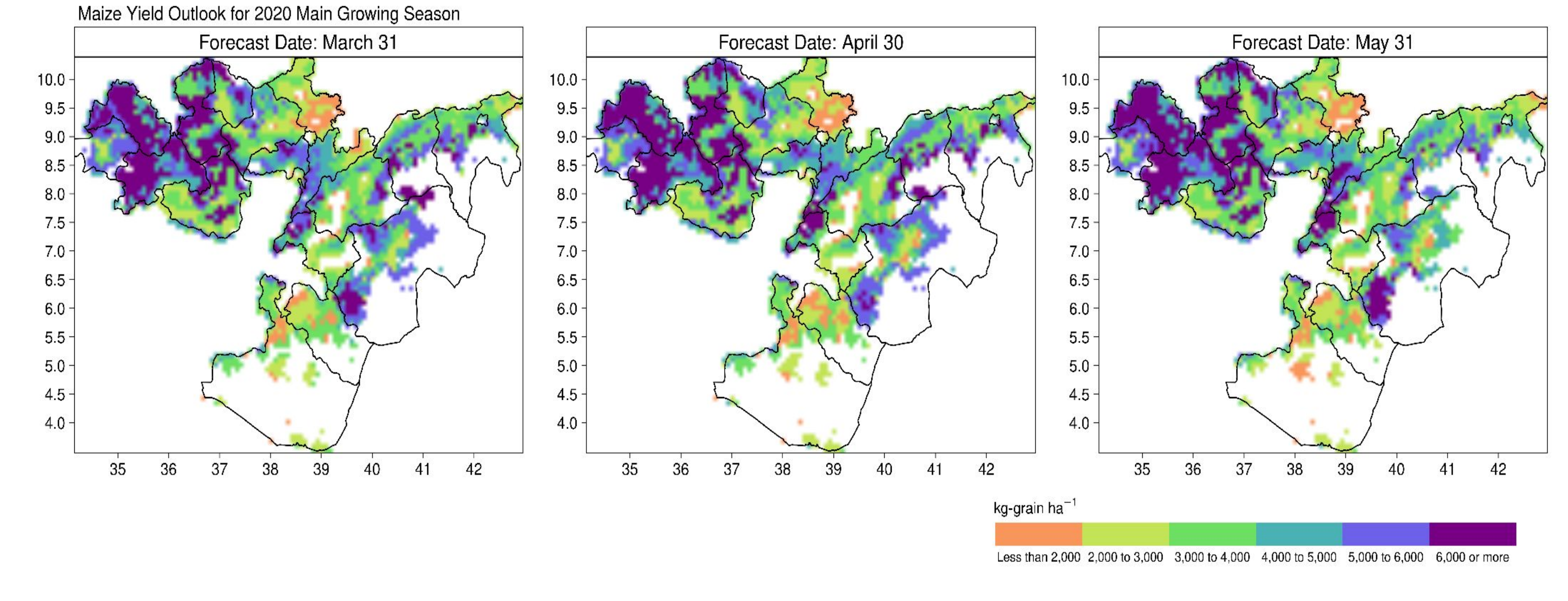
Model inputs and outputs



No.	Parameter	Level	Horizontal Resolution	Historical	Near-real time
1.	Rainfall	Surface	0.5° x 0.5°	CHIRPS	CHIRPS
2.	Maximum Temperature	2 meters	0.1° x 0.1°	AgERA5	ERA5-Land
3.	Minimum Temperature	2 meters	0.1° x 0.1°	AgERA5	ERA5-Land
4.	Solar Radiation	Surface	0.1° x 0.1° [0.5° x 0.5°]	AgERA5	[NASSA-POWER]

CIMMYT International Maize and Wheat Improvement Center
ICRISAT INTERNATIONAL CROPS RESEARCH INSTITUTE FOR THE SEMI-ARID TROPICS
ግብርና ሚኒስቴር MINISTRY OF AGRICULTURE
UF UNIVERSITY of FLORIDA
CGIAR
RESEARCH PROGRAM ON Climate Change, Agriculture and Food Security
CCAFS

Forecast:



CIMMYT International Maize and Wheat Improvement Center
ICRISAT International Crops Research Institute for the Semi-Arid Tropics
ግብርና ሚኒስቴር Ministry of Agriculture
UF University of Florida
CGIAR
Research Program on Climate Change, Agriculture and Food Security
CCAFS

Spatial Yield Forecast for Ethiopia

- Normal-to-above average maize production is expected for the 2020 main growing season

- On average, 4301 – 4345 kg/ha of grain yield could be obtained from maize fields over Oromia regional state.

  – Maize production: 5.3 MMT tons (2020 forecast)
    4.6 MMT tons (2018 reported)

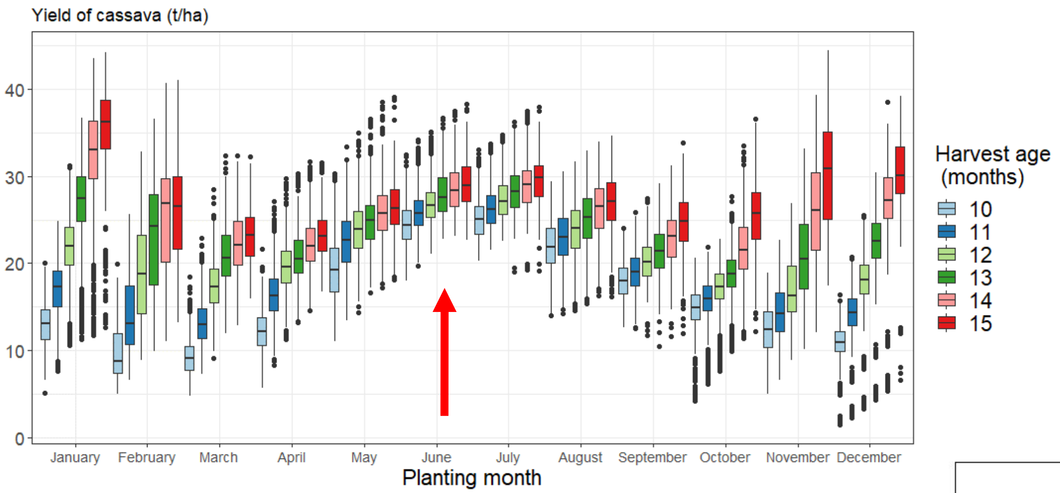
- Slightly poor performance by the crop model lower yield environments

African Cassava Agronomy Initiative (ACAI) project

Project funded by the Bill and Melinda Gates Foundation

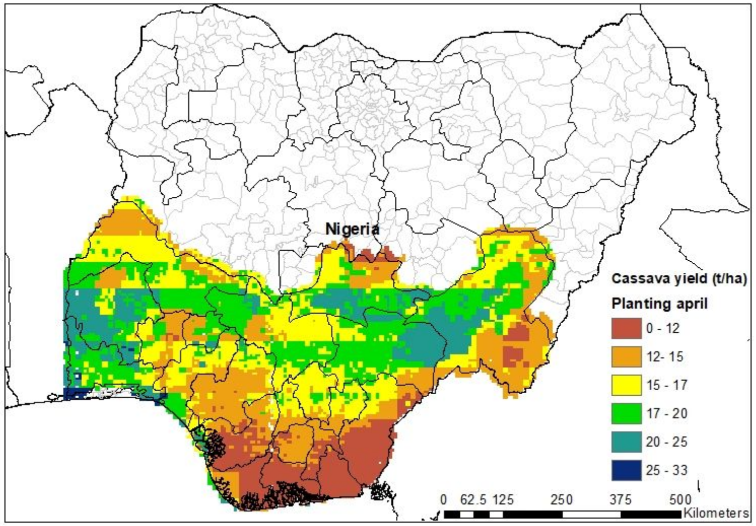
Modeling cassava as part of the agronomic decision support service for smallholder growers in Africa

African Cassava Agronomy Initiative (ACAI) project



DSSAT*

Estimated cassava yield (t/ha) under different planting and harvesting months in Nigeria.



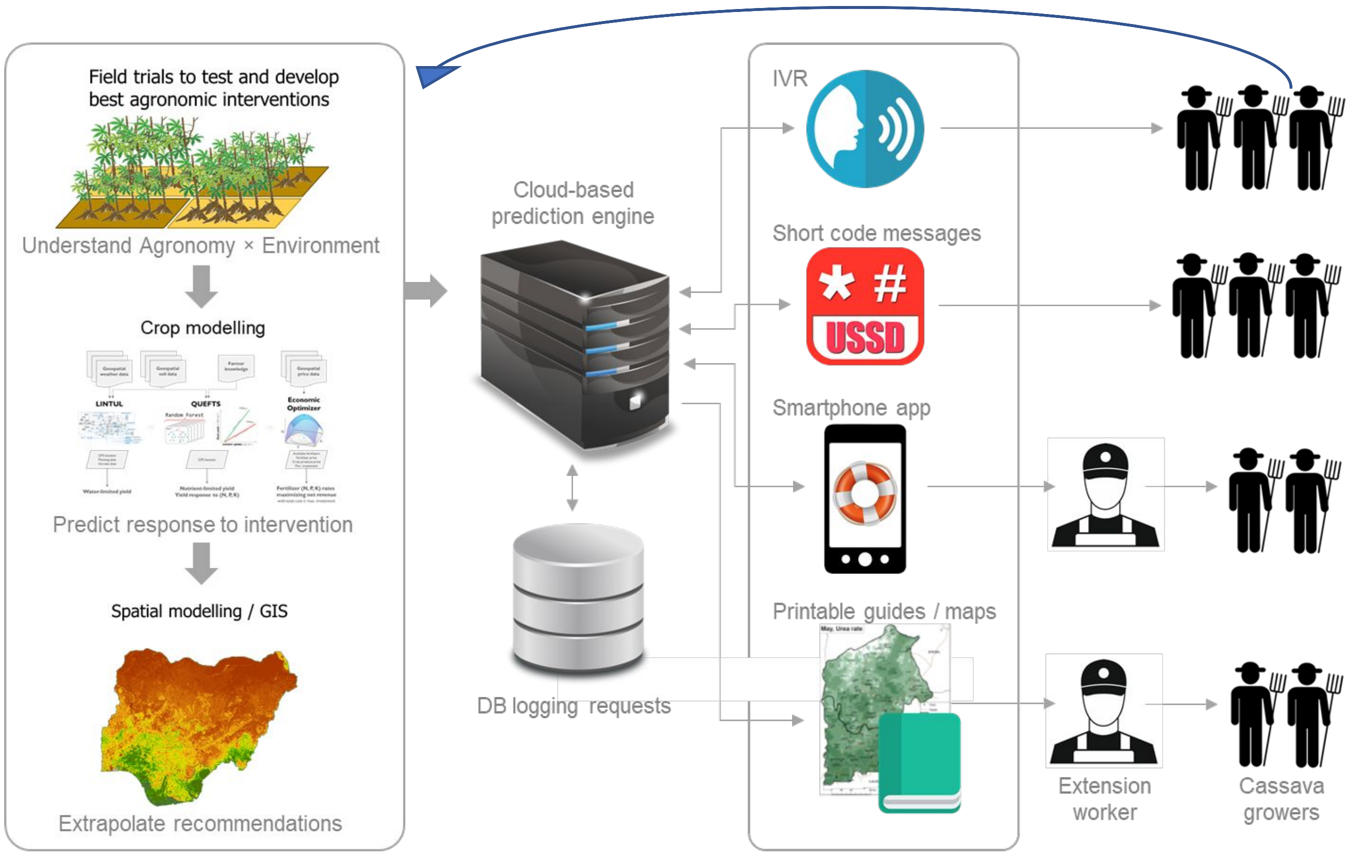
Spatial layer of estimated cassava yield (t/ha) for April planting with harvesting age of 10 months.

*Decision Support System for Agrotechnology Transfer (DSSAT)

African Cassava Agronomy Initiative (ACAI) project

Akili✉ smart *Kilimo*✉ agriculture

developing and delivering tailored agronomy recommendations to cassava growers



www.iita.org | www.cgiar.org | www.acai-project.org

Crop model applications at larger spatial scales

Crop model requires a lot of data

Heterogeneity of cropping systems, crop management practices

Data not easily available at the required temporal and spatial resolution

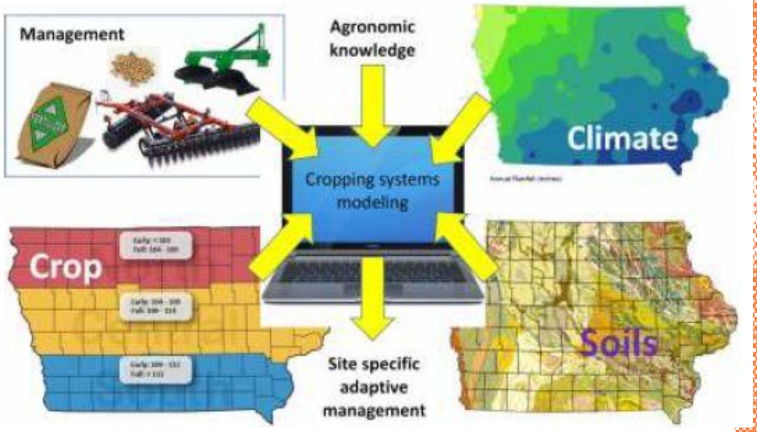
Data collection approaches:

- Multi-site-year field experiments
- Expert Interviews
- Extensive literature review
- Local and public data sources

Challenges:

➢Extensive time, effort, and resources

➢May be relevant to a specific region



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Efficient parameterization approaches: use case from Senegal

1. Rice simulation in Delta Region, Senegal River Valley

Fig. Location of Senegal (in green) in Africa

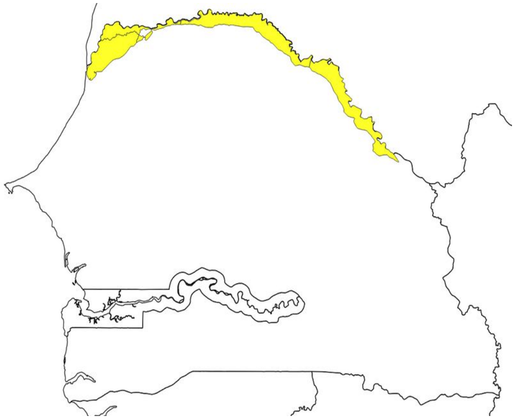


Fig. Senegal River Valley (in yellow)

Fig. Rice fields in the Delta region within Senegal River Valley

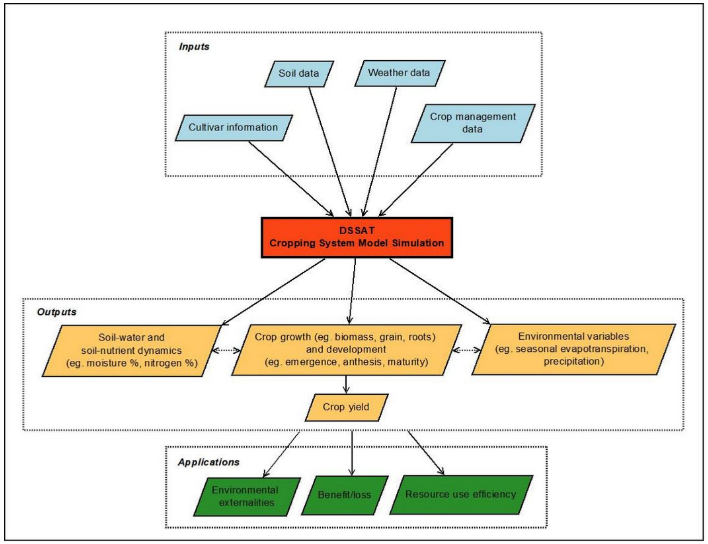


Fig: Overview of the inputs for DSSAT-Cropping System Model and some of its outputs and applications.

164 Simulation POINTS

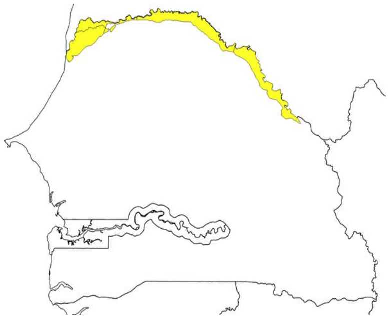


Fig. Senegal River Valley (in yellow)

Fig. Simulation points at 5-arc min resolution (~ 9 km)

Data collection approaches:

- Multi-site-year field experiments
- Expert Interviews
- Extensive literature review
- Local and public data sources

Environmental input data

Daily Weather

- NASA POWER: Solar radiation, Tmax and Tmin (www.power.larc.nasa.gov/)
- CHIRPS: Rainfall (https://www.chc.ucsb.edu/data/chirps)

Soil

- Global High-Resolution Soil Profile Database
- Harvest Choice Soil Database

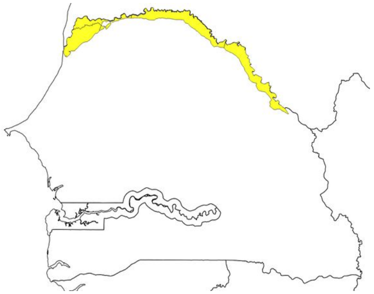


Fig. Senegal River Valley (in yellow

Management and genetics input data

Cultivar and Management practices

- Expert interviews
- Machine reading
- Remote sensing

Machine Reading System

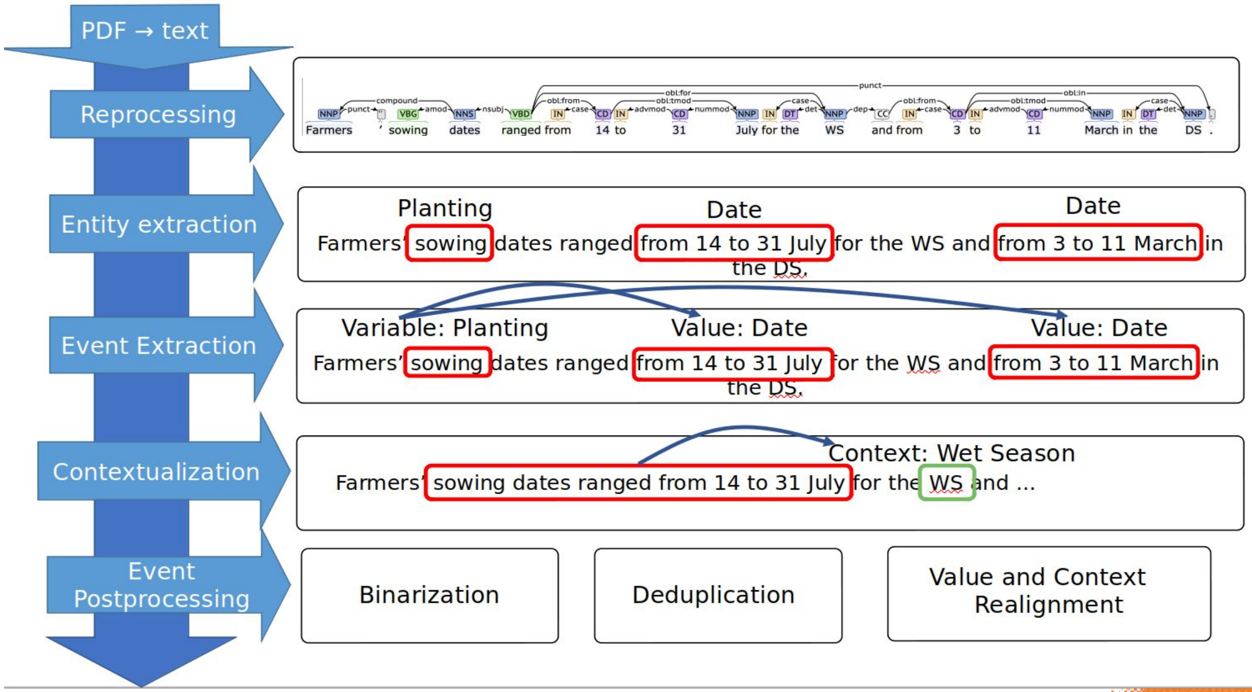
Allows users to automatically extract information from scientific papers and reports

The system is built using the rule-based information extraction framework

Involves preprocessing (pdf to text conversion and text preprocessing) and post-processing (redundancy filtering, binarization, etc) components.

Machine Reading System

- Supply papers and reports
- Convert pdf to text
- Tokenization (text into words and sentences)
- Entity (variables of interest) extraction
- Event extraction (assigns value to variables)
- Add Context
- Post-processing



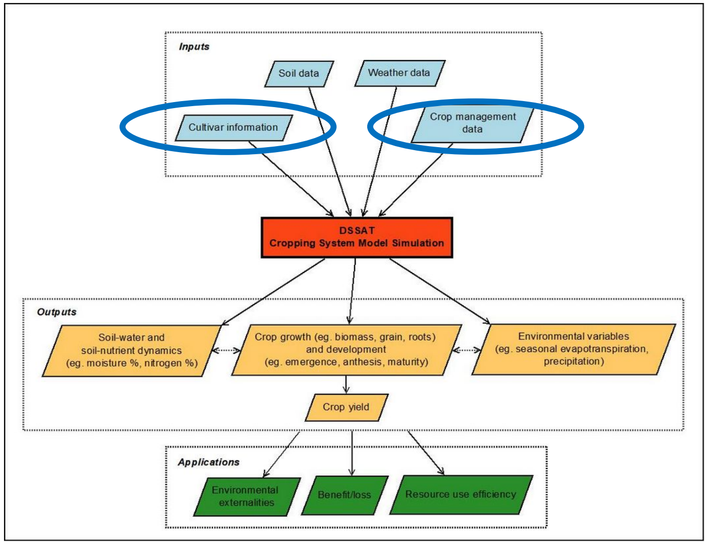
Cultivar Information

PropertyAssignment	N/A	2000	planting	Sahel 108	N/A	wet season	0	**medium duration**
PropertyAssignment	N/A	2000	planting	Jaya	N/A	wet season	0	**medium duration**
PropertyAssignment	N/A	2000	planting	Sahel 202	N/A	wet season	0	**medium duration**
PropertyAssignment	Nakhlet	from 4 to 7 November	planting	Jaya	N/A	N/A	0	**129 days**
PropertyAssignment	N/A	from 4 to 7 November	planting	Jaya	N/A	N/A	0	**109 days**
PropertyAssignment	N/A	N/A	harvesting	Jaya	N/A	N/A	0	**20 days**
PropertyAssignment	N/A	N/A	planting	Jaya	urea	N/A	0	**50 days**
PropertyAssignment	Rosso	1970-1984	N/A	Sahel 108	N	wet season	0	**11 days**
PropertyAssignment	Rosso	1970-1984	N/A	Jaya	N	wet season	0	**1 day**
PropertyAssignment	Rosso	1970-1984	N/A	Sahel 108	N	wet season	0	**10 days**
PropertyAssignment	N/A	N/A	planting	rice	N/A	N/A	0	**shortcycle**
PropertyAssignment	N/A	N/A	planting	Sahel 108	N/A	N/A	0	**125 days**
PropertyAssignment	Senegal R	From May to June	natural_di	Rice	N/A	dry season	0	**120 days**
PropertyAssignment	Podor	1995	planting	indica	N/A	wet season	0	**short duration**
PropertyAssignment	Podor	1995	planting	indica	N/A	wet season	0	**slender grain**
PropertyAssignment	Podor	1995	planting	Aiwu	N/A	wet season	0	**short duration**
PropertyAssignment	Podor	1995	planting	Aiwu	N/A	wet season	0	**slender grain**
PropertyAssignment	Podor	1995	planting	I Kong Pao	N/A	wet season	0	**short duration**

Planting window

PlantingDate	N/A	from 29 February to 1 April in the 2012DS	planting	rice	N/A	2012DS	0	**from 22 August to 26 September in 2011WS**	**2011-08-22 -- 2011-09-26**
PlantingDate	N/A	from 5 to 23 March in the 2013DS	planting	rice	N/A	2012DS	0	**from 29 February to 1 April in the 2012DS**	**2012-02-29 -- 2012-04-01**
PlantingDate	N/A	from 22 August to 26 September in 2011WS	planting	rice	N/A	2012DS	0	**from 5 to 23 March in the 2013DS**	**2013-03-05 -- 2013-03-23**
PlantingDate	Rosso	early November	planting	Jaya	N/A	1999WS	0	**between 7 and 22 July**	**XXXX-07-07 -- XXXX-07-22**
PlantingDate	N/A	the end of November	planting	Sahel 202	N/A	2000WS	0	**between 19 July and 4 August**	**XXXX-07-19 -- XXXX-08-04**
PlantingDate	N/A	before 29 July	planting	N/A	N	N/A	0	**before 29 July**	**XXXX-XX-XX -- XXXX-07-29**
PlantingDate	N/A	before 29 July	planting	N/A	N	2000WS	0	**before 29 July**	**XXXX-XX-XX -- XXXX-07-29**
PlantingDate	N/A	2000WS	planting	N/A	N	2000WS	0	**before 29 July**	**XXXX-XX-XX -- XXXX-07-29**
PlantingDate	N/A	1998WS	planting	N/A	N/A	2000WS	0	**after 29 July in the 2000WS**	**2000-07-29 -- XXXX-XX-XX**

Machine Reading and Inputs to DSSAT



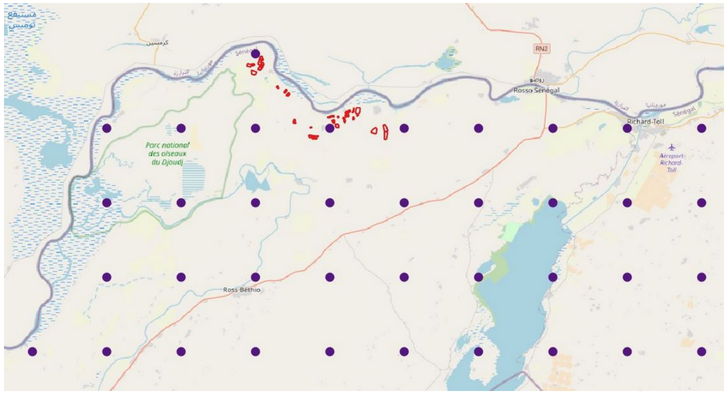
Overview of the inputs for DSSAT-Cropping System Model and some of its outputs and applications.

Management and genetics input data

<u>Cultivar and Management practices</u>

- Expert interviews
- Machine reading
- Remote sensing

- Growing season
- Cultivars
- Cultivar characteristics
- Planting window
- Fertilization strategies
- Yield range


Gridded weather and soil data at 5 arc-min resolution

Management and genetics input data

<u>Cultivar and Management practices</u>

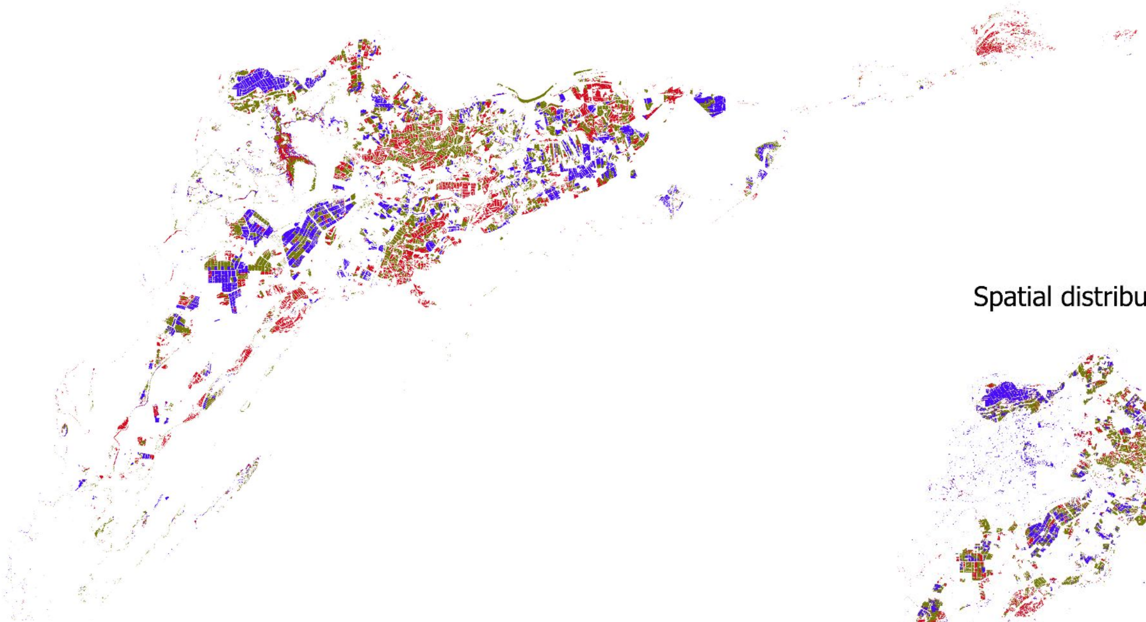
- Expert interviews
- Machine reading
- Remote sensing

When and where flooding happened?

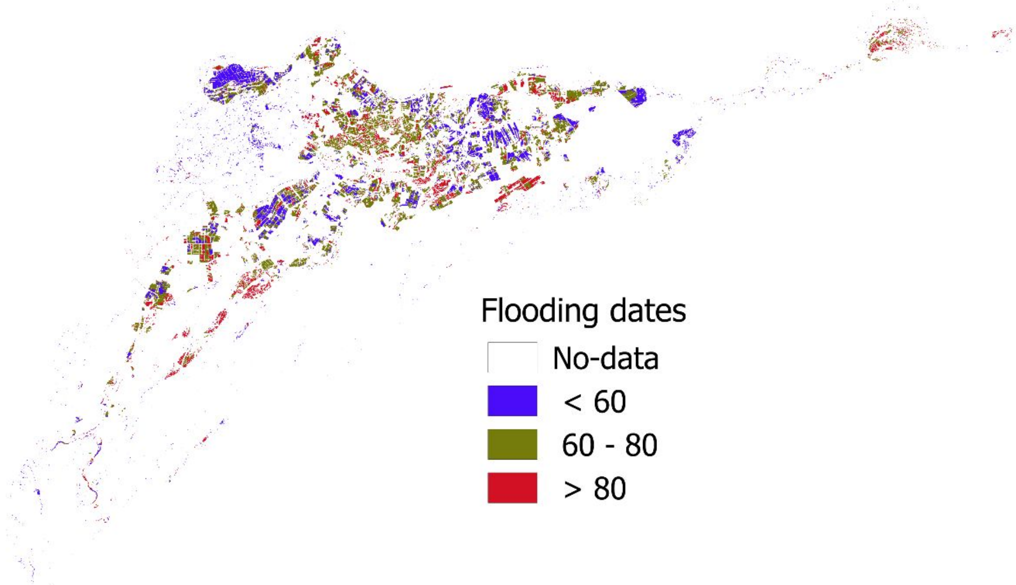

Plots near Ronkh region in Senegal River Valley- 2019

Flooding maps

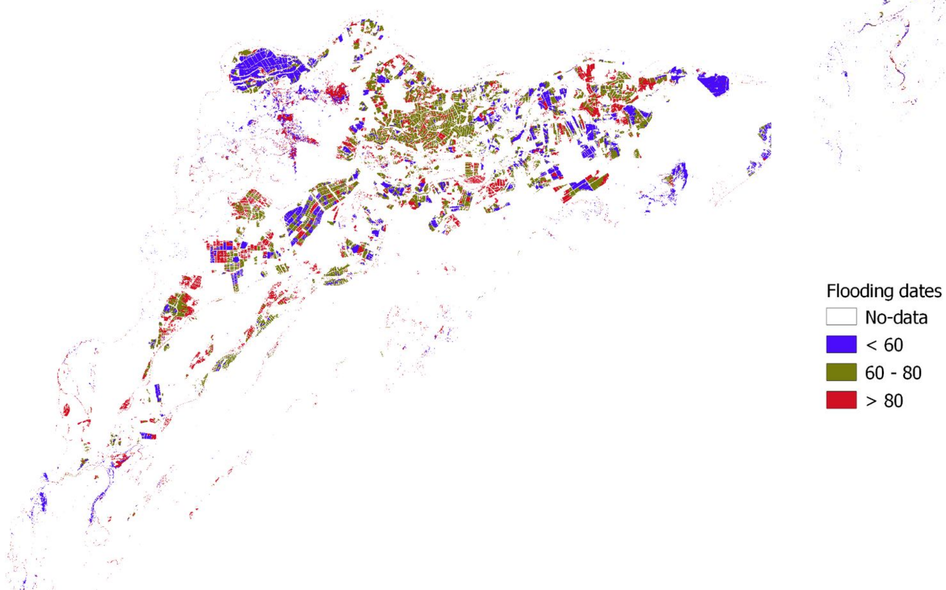
Spatial distribution of flooding events in 2020



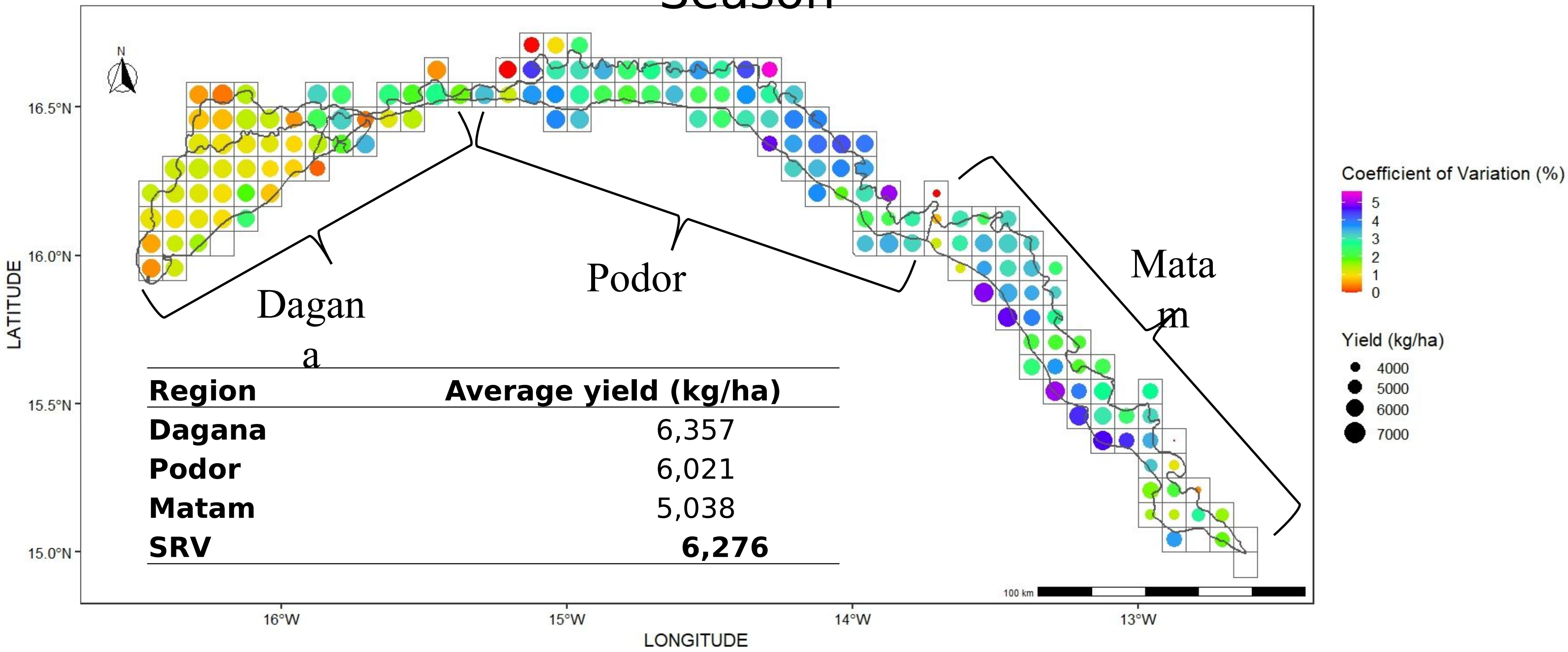
Spatial distribution of flooding events in 2022



Spatial distribution of flooding events in 2021

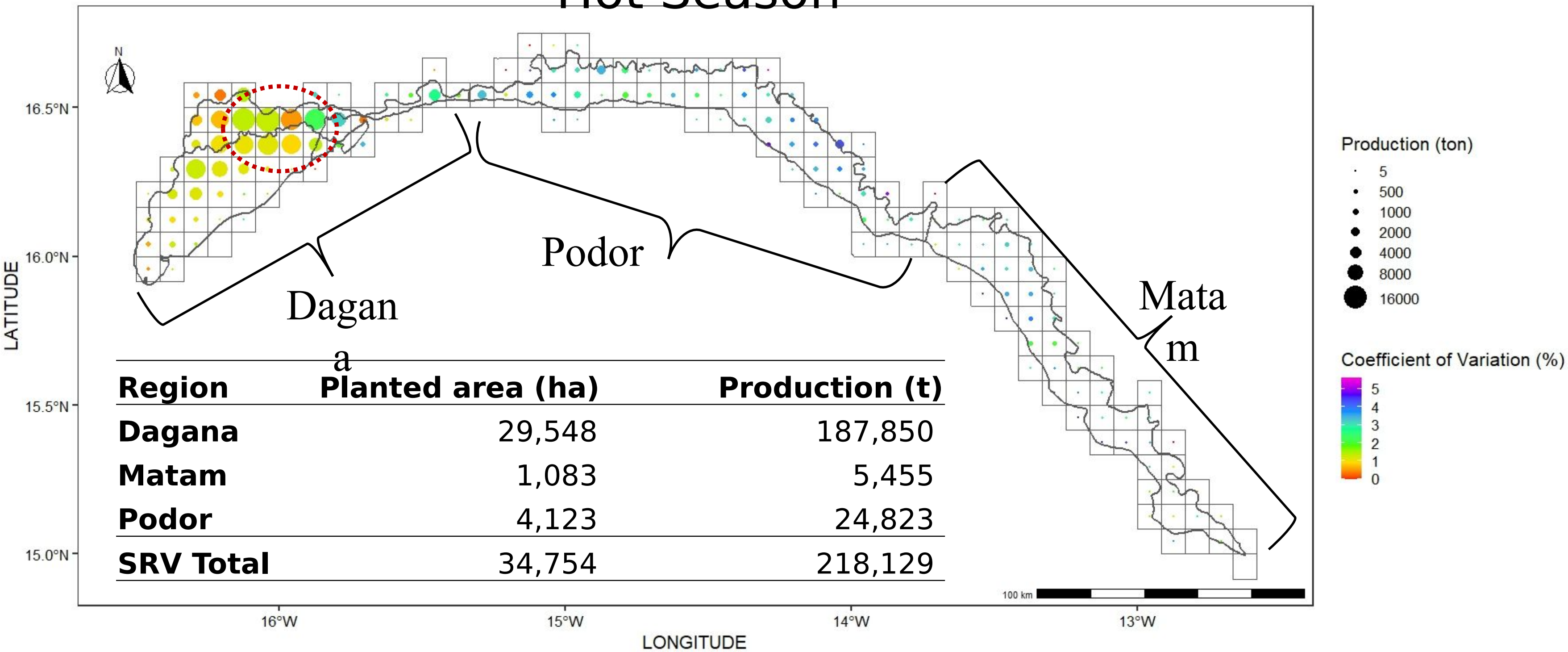


Senegal River Valley (SRV)
Yield Forecast on July 1, 2022, for Rice for the Dry Hot Season



Region	Average yield (kg/ha)
Dagana	6,357
Podor	6,021
Matam	5,038
SRV	**6,276**

Senegal River Valley (SRV)
Production Forecast on July 1, 2022, for Rice for the Dry Hot Season



Region	Planted area (ha)	Production (t)
Dagana	29,548	187,850
Matam	1,083	5,455
Podor	4,123	24,823
SRV Total	34,754	218,129

Hybrid Approach:

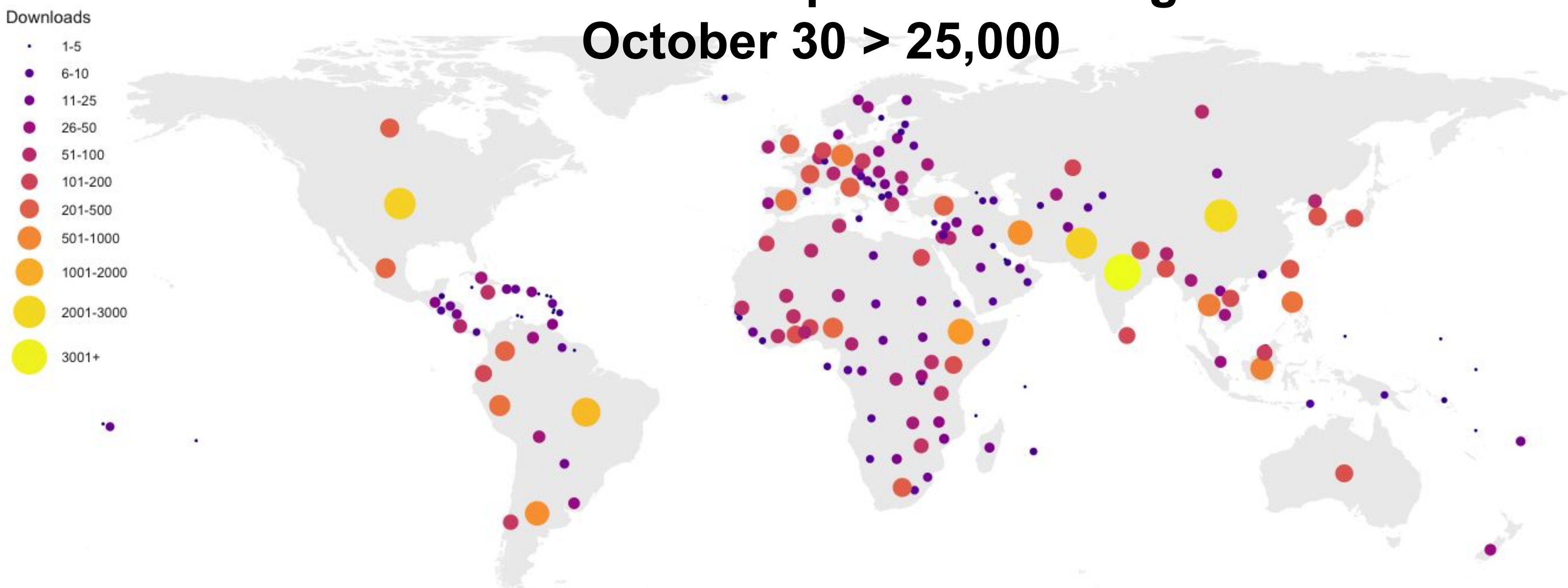
- AI & Machine learning
- Remote Sensing
- Crop Modeling

UF UNIVERSITY of FLORIDA

DSSAT User Community

Software download request since August 2017

October 30 > 25,000



Country	Downloads	Country	Downloads	Country	Download
India	3527	Thailand	409	United Kingdom	211
China	2144	Germany	382	Italy	206
USA	1789	Spain	339	Canada	198
Pakistan	1768	Philippines	334	South Africa	195
Brazil	1224	Peru	312	France	180
Ethiopia	731	Nigeria	260	Taiwan	173
Iran	620	Mexico	244	South Korea	169
Argentina	590	Colombia	235	Australia	152
Indonesia	445	Turkey	233	Nepal	151
Countries	**187**	**Total**	**21287**		

Total DSSAT Downloads: 21287
February 09, 2023

Perennial Forage Model-Alfalfa

Published online August 2, 2018

BIOMETRY, MODELING, AND STATISTICS

Adapting the CROPGRO Model to Simulate Alfalfa Growth and Yield

Wafa Malik,* Kenneth J. Boote, Gerrit Hoogenboom, José Cavero, Farida Dechmi

ABSTRACT

Despite alfalfa's global importance, there is a dearth of crop simulation models available for predicting alfalfa growth and yield with its associated composition. The objectives of this research were to adapt the CSM-CROPGRO Perennial Forage Model for simulating alfalfa growth and yield and to describe model adaptation for this species. Data from six experimental plots grown under sprinkler irrigation in the Ebro valley (Northeast Spain) were used for model adaptation. Starting with parameters for *Bracharia brizantha*, the model adaptation was based on values and relationships reported from the literature for cardinal temperatures and dry matter partitioning. A Bayesian optimizer was used to optimize temperature effects on photosynthesis and daylength effects on partitioning and an inverse modeling technique was employed for nitrogen fixation rate and nodule growth. The calibration of alfalfa tissue composition was initiated from soybean composition analogy but was improved with values from alfalfa literature. There was considerable iteration in optimizing parameters for the processes outlined above where comparisons were made to measured data. After adaptation, the Root Mean Square Error and d-statistic of harvested herbage averaged across 58 harvests (yield range: 990–4617 kg ha^{-1}) were 760 kg ha^{-1} and 0.75, respectively. In addition, good agreement was observed for Leaf Area Index (LAI) (LAI range: 0.1–6.7) with d-statistic of 0.71. Simulated belowground mass was within the range of literature values. The results of this study showed that CROPGRO-PFM-Alfalfa can be used to simulate alfalfa growth and development. Further testing with more extensive datasets is needed to improve model robustness.

Core Ideas

- Alfalfa is the main forage legume in crop livestock systems worldwide.
- There is still a scarcity of perennial crop models for alfalfa simulation.
- Regrowth and herbage yield depend on reserves, seasonal temperature and daylength.
- A systematic procedure was followed to develop species and cultivar parameters.
- CROPGRO-PFM-alfalfa is available in the latest DSSAT model version (4.7).

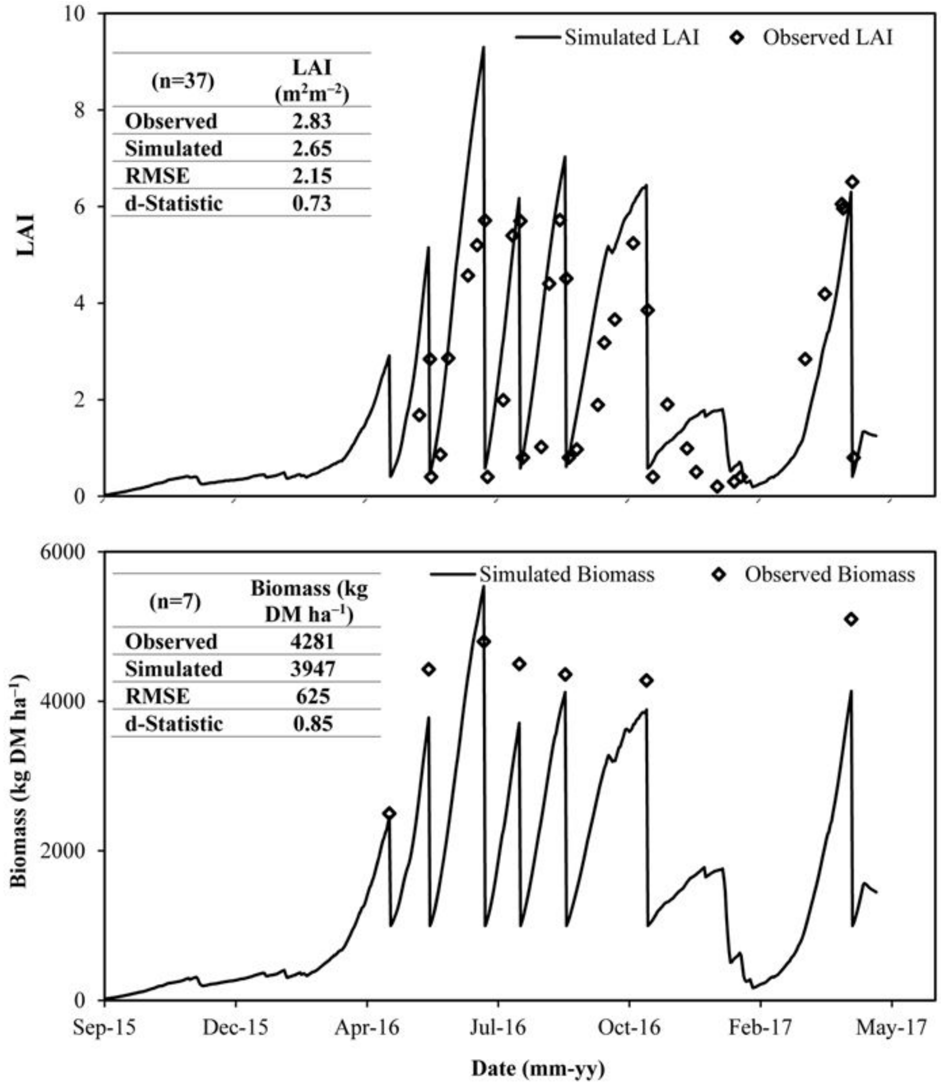
Published in Agron. J. 110:1777–1790 (2018)
doi:10.2134/agronj2017.12.0680
Available freely online through the author-supported open access option

ALFALFA (*MEDICAGO sativa* L.) is the main forage legume in crop livestock systems worldwide, with the greatest amount of feed proteins per unit area among the forage and grain legumes (Huyghe, 2003). Changes in forage yield and nutritive value due to climate change are likely to affect the agronomic, economic, and environmental performance of dairy farms. It has been estimated that two-thirds of the potential yield of major crops is usually lost due to adverse growing environments (Bajaj et al., 1999). Accurate prediction of alfalfa yield and growth stages is important in scheduling management practices such as sowing dates, pesticide applications, irrigation scheduling, and cutting frequency or grazing. Timely management can greatly increase the quantity and quality of harvested alfalfa (Sanderson et al., 1989). Crop models can be useful tools for management and decision making in crop production systems by attempting to schedule critical growth stages during the most favorable environmental conditions (Charles-Edwards et al., 1986). Furthermore, computer simulation models after calibration and validation with experimental data provide yield prediction and allow for studying the influence of management strategies and environmental factors on crop growth and development without conducting costly field experiments (Barnes et al., 1988). When physiological processes are well understood, they can be synthesized with crop models, which then become important tools in research by assisting decisions in breeding programs and for soil and crop management, as well as being useful in future climate change assessment (Asseng et al., 2013).

Over the past few decades, several simulation models have been specifically developed for alfalfa. The first alfalfa model SIMED (Holt et al., 1975; Schreiber et al., 1978) is a crop growth model that takes into account dry matter partitioning among leaves, stems and roots. It incorporated most physiological processes but not the regrowth process after cuttings and does not include nonstructural carbohydrates. The second alfalfa model developed was ALSIM (Fick, 1981) which had

W. Malik, F. Dechmi, Agrifood Research and Technology Centre of Aragon (CITA), Soil and Irrigation Dep. (EEAD-CSIC Associated Unit), Avda. Montañana 930, 50059 Zaragoza, Spain; K.J. Boote, Dep. of Agricultural and Biological Engineering, Univ. of Florida, Gainesville, FL 32611; G. Hoogenboom, Institute for Sustainable Food Systems, Univ. of Florida, Gainesville FL 32608; J. Cavero, Dep. of Soil and Water, Estación Experimental de Aula Dei (CSIC), Avda. Montañana 1005, 50059 Zaragoza, Spain. Received 1 Dec. 2017. Accepted 26 Apr. 2018.
*Corresponding author (wmalik@cita-aragon.es).

Abbreviations: CP, crude protein; DM, dry matter; LAI, leaf area index; N_2, dinitrogen; RMSE, root mean square error; SLA, specific leaf area; SLW, specific leaf weight; TB, base temperature; TM, maximum (failure) temperature; TO1, first optimum temperature; TO2, second optimum temperature.



CROPGRO-Strawberry

Scientia Horticulturae 291 (2022) 110538

Contents lists available at ScienceDirect

Scientia Horticulturae

journal homepage: www.elsevier.com/locate/scihorti

ELSEVIER

Development and improvement of the CROPGRO-Strawberry model

Alwin Hopf[a,*], Kenneth J. Boote[a], Juhyun Oh[b,c], Zhengfei Guan[b,c], Shinsuke Agehara[c,d], Vakhtang Shelia[a], Vance M. Whitaker[c,d], Senthold Asseng[a,#], Xin Zhao[d], Gerrit Hoogenboom[a,e]

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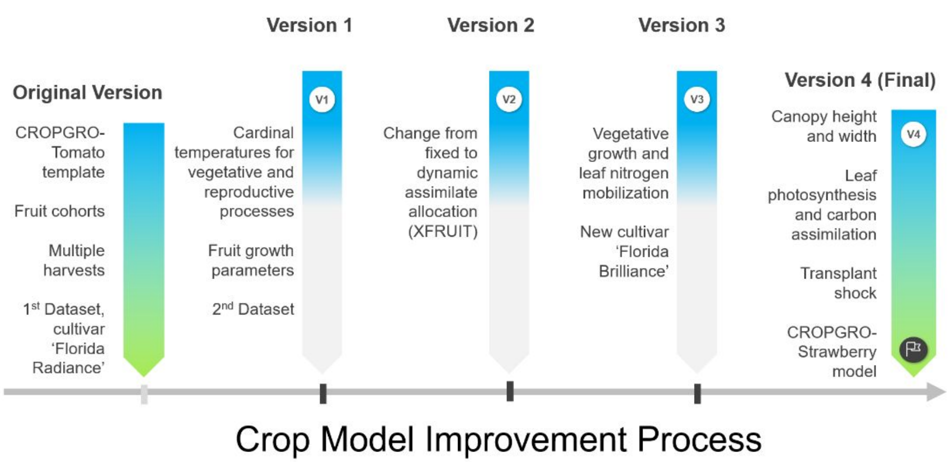
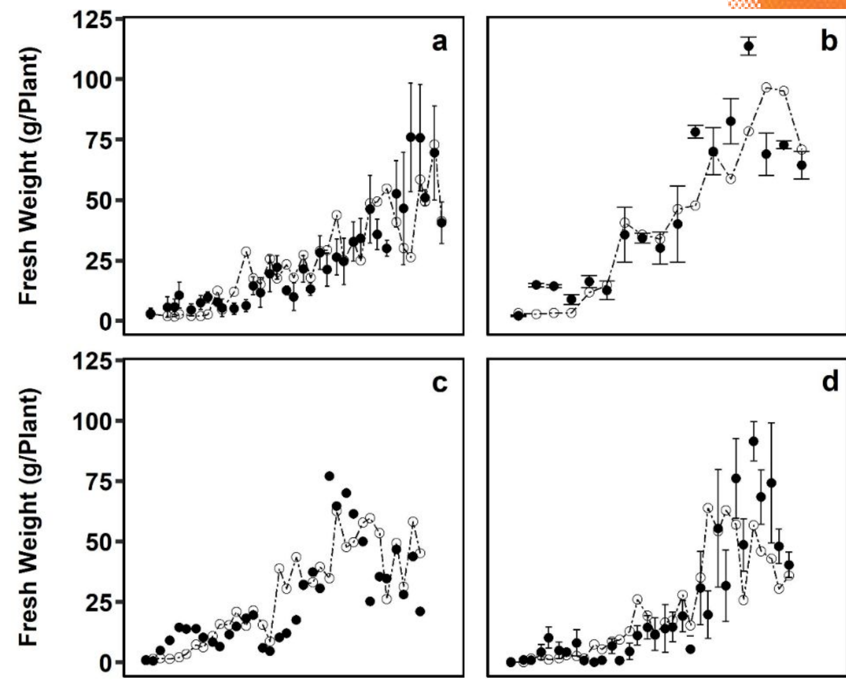
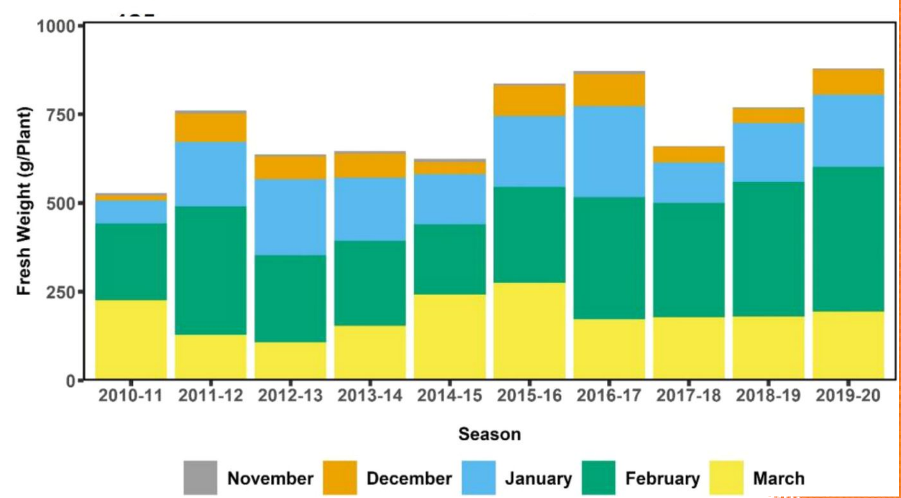
[d] Department of Horticultural Sciences, IFAS, University of Florida, Gainesville, 32611, FL, USA
[e] Institute for Sustainable Food Systems, IFAS, University of Florida, Gainesville, 32611, FL, USA







Time Series Calibration

CULTIVAR COEFFICIENT ESTIMATOR FOR THE CROPPING SYSTEM MODEL BASED ON TIME-SERIES DATA: A CASE STUDY FOR SOYBEAN

ASABE Research

Emir Memic[1,*], Simone Graeff[1], Kenneth J. Boote[2], Oliver Hensel[3], Gerrit Hoogenboom[2,4]

[1] Cropping Systems and Modeling, University of Hohenheim, Stuttgart, Germany.
[2] Department of Agricultural and Biological Engineering, University of Florida, Gainesville, Florida, USA.
[3] Department of Agricultural and Biosystems Engineering, University of Kassel, Witzenhausen, Germany.
[4] Institute for Sustainable Food Systems, University of Florida, Gainesville, Florida, USA.
[*] Correspondence: emir.memic@uni-hohenheim.de.

HIGHLIGHTS
- Software was developed for estimation of DSSAT CSM-CROPGRO-Soybean cultivar coefficients.
- Phenology-related coefficients were estimated based on observed phenological events.
- Growth-related cultivar coefficients were estimated based on time-series observations.
- Cultivar coefficients were optimized based on single- and multiple-experiment data sets.

ABSTRACT. *The Decision Support System for Agrotechnology Transfer (DSSAT) is one of the most popular software solutions for predicting crop growth and yield while capturing the effects of management practices and interactions between the crop and the environment. Accurate estimation of the crop cultivar coefficients that govern in-season growth and development is critical for correct yield estimates. The manual cultivar coefficient estimation process is time-consuming and results in user-dependent, subjective optimums that are difficult to reproduce. Typically, end-of-season observations (point-based) are used for estimating dynamic in-season biomass accumulation rates. The objective of this study was to develop a time-series estimator (TSE) capable of using multiple in-season observations for estimating the coefficients that define in-season growth and biomass partitioning. Using the TSE, cultivar coefficients were estimated based on multiple in-season observations of leaf area index (LAI) and shoot, leaf, and grain dry matter weights. The cultivar coefficients were estimated from single- and multiple-treatment (seasons and locations) in-season observations. This was done for two cultivars for six management × environment combinations. Estimated multiple-treatment based cultivar coefficients were evaluated with an independent data set and compared to DSSAT standard (manual) coefficients and the cultivar coefficients estimated with the GLUE method. The average normalized root mean squared error (nRSME) for LAI and shoot, leaf, and grain weights was 26% lower for one cultivar and about the same for the other cultivar when compared to the DSSAT standard. Because GLUE uses end-of-season point-based cultivar coefficient estimation, the grain weight over time was underestimated in earlier phases and more accurate toward harvest. The TSE-estimated cultivar coefficients based on 346 in-season observations across multiple target variables and six experiments more accurately reflected in-season growth and grain weight without compromising final grain weight predictions.*

Keywords. *CROPGRO-Soybean, DSSAT, Genetic coefficients, Normalized root mean square error minimization, Time-series observations.*

A wide range of crop models have been developed for various purposes, such as yield prediction, evaluation of agricultural input management, and assessment of the long-term impacts of agricultural management practices on soil and environmental degradation (Boote et al., 2010; Ewert et al., 2015; Rötter et al., 2015; Tsuji et al., 1998). In general, these models are capable of predicting crop growth and quantifying yield-limiting factors (Hoogenboom et al., 2019a; Thorp et al., 2010) while capturing the effects of crop management (fertilizer, sowing date, sowing density, etc.) and interactions between crops and the environment (soil, weather, etc.) (Jones et al., 2003). The Decision Support System for Agrotechnology Transfer (DSSAT) is a conceptual and practical solution for capturing many important factors that affect production of more than 40 crops (Hoogenboom et al., 2019a). Within DSSAT, the Cropping System Model (CSM) CROPGRO-Legume (Boote et al., 1998) simulates crop growth and development from planting to harvest on a daily basis (carbon and nitrogen balances) throughout the vegetative and reproductive stages with different biomass and yield accumulation rates.

Submitted for review on 6 December 2020 as manuscript number ITSC 14432; approved for publication as a Research Article by the Information Technology, Sensors, & Control Systems Community of ASABE on 18 May 2021.

Transactions of the ASABE

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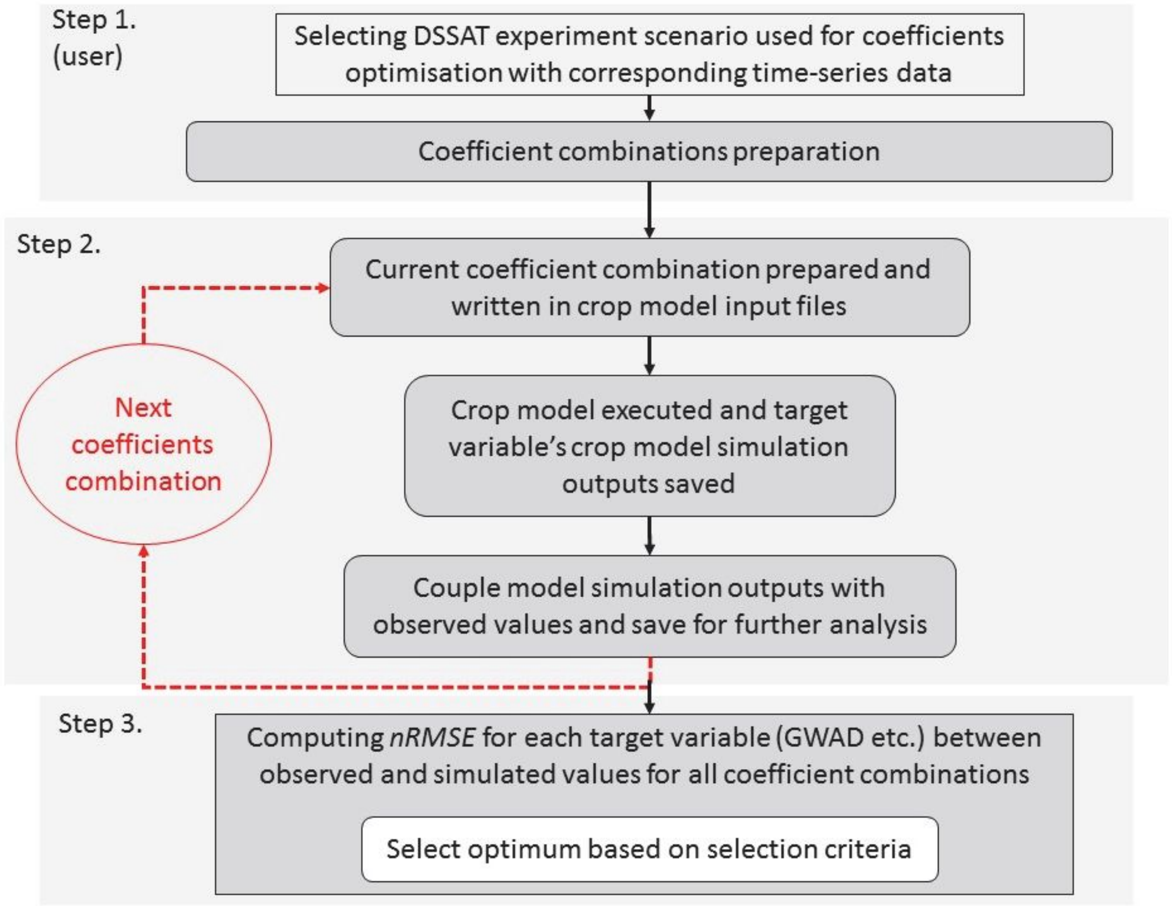

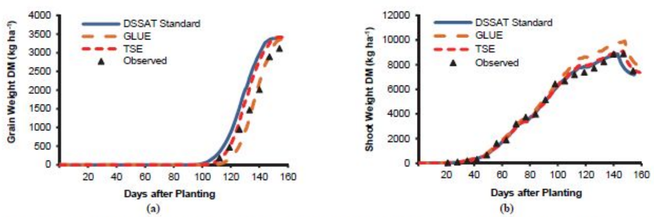

Figure 5. Time-series graphs showing simulation results for (a) grain weight and (b) shoot weight of Bragg cultivar using three optimization approaches (DSSAT standard, GLUE, and TSE). "Observed" is the Gainesville 1976 experiment data, which were not used in the cultivar coefficient estimation process.

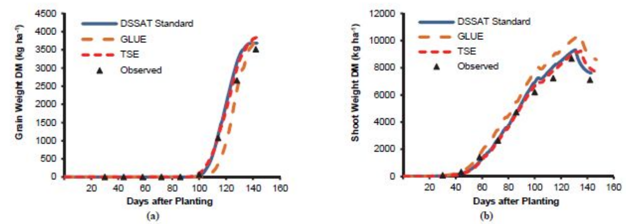

Figure 6. Time-series graphs showing simulation results for (a) grain weight and (b) shoot weight of Williams cultivar using three optimization approaches (DSSAT standard, GLUE, and TSE). "Observed" is the Iowa 1990 experiment data, which were not used in the cultivar coefficient estimation process.

Coupling Pests and Diseases

Coupling a Pest and Disease Damage Module with CSM-NWheat: A Wheat Crop Simulation Model

Thiago Berton Ferreira[1,*], Willingthon Pavan[2], José Mauricio Cunha Fernandes[3], Senthold Asseng[4], Fabio Antunes de Oliveira[5], Carlos Amaral Hölbig[6], Diego Noleto Luz Pequeno[1], Genei Antônio Dalmago[3], Alexandre Lazaretti Zanatta[6], Gerrit Hoogenboom[5]

[1] International Maize and Wheat Improvement Center (CIMMYT), Texcoco, Mexico.
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[3] Embrapa Trigo, Passo Fundo, Rio Grande do Sul (RS), Brazil.
[4] Department of Life Science Engineering, Technical University of Munich, Freising, Germany.
[5] Department of Agricultural and Biological Engineering, University of Florida, Gainesville, Florida.
[6] Graduate Program in Applied Computing, University of Passo Fundo, Passo Fundo, RS, Brazil.
[*] Correspondence: t.berton@cgiar.org.

Highlights
- CSM-NWheat, a DSSAT wheat crop model, was coupled with a pest module named PEST.
- The coupled model can simulate the impact of pest and disease damage on wheat crops.
- Pest damage is expressed in daily steps by communication links called coupling points.
- Coupling points are linked with state variables at which pest damage can be applied.
- Field pest-scouting reports and linear interpolation are used to compute damage rates.

Abstract. *Wheat is one of the most important global staple crops and is affected by numerous pests and diseases. Depending on their intensity, pests and diseases can cause significant economic losses and even crop failures. Pest models can assist decision-making, thus helping reduce crop losses. Most wheat simulation models account for abiotic stresses such as drought and nutrients, but they do not account for biotic stresses caused by pests and diseases. Therefore, the objective of this study was to couple a dynamic pest and disease damage module to the DSSAT model CSM-NWheat. Coupling points were integrated into the CSM-NWheat model for applying daily damage to all plant components, including leaves, stems, roots, and grains, the entire plant, and to the assimilate supply. The coupled model was tested by simulating a wheat crop with virtual damage levels applied at each coupling point. Measured foliar damage caused by tan spot (*Pyrenophora tritici-repentis*) was also simulated. The modified model accurately estimated the reduction in leaf area growth and the yield loss when compared with observed data. With the incorporation of the pest module, CSM-NWheat can now predict the potential impact of pests and diseases on wheat growth and development, and ultimately economic yield.*

Keywords. *Biotic stress, Decision support, DSSAT, Model coupling, Yield loss.*

Wheat (*Triticum aestivum* L.) is one of the most important cereals in the world and is produced both as a human food and as a feed for livestock. Demand for wheat is expected to increase with the rise in the global population (Singh et al., 2016). Modern wheat cultivars developed by private and public wheat breeding programs often exhibit an extensive geographic adaptation (Braun et al., 2010). Depending on the mega-environment, wheat yield and quality are constantly at risk due to numerous pests, including insects, nematodes, and diseases (Oerke, 2006; Farook et al., 2019). The rapid evolution of wheat agrosystems in recent decades has led to a large variation and variability of crop losses due to insect pests and plant pathogens (Shewry, 2009; West et al., 2014). Damage due to biotic stresses is estimated to be responsible for 10.1% to 28.1% of the global production losses (Savary et al., 2019).

With computational advances during the past 30 years, decision support systems have been used in agriculture to help evaluate farm management and to assist with complex decision-making (Boogaard et al., 1998; Keating et al., 2003; Hoogenboom et al., 2019a; Tsuji et al., 1998). The Decision Support System for Agrotechnology Transfer (DSSAT) computes the soil-plant-atmosphere dynamics to predict crop development and can help decision makers with identifying improved management responses (Jones et al., 2003; Hoogenboom et al., 2019b). The Cropping System Model (CSM), which is the main modeling engine of DSSAT, simulates yield for more than 42 crops and has three different

Submitted for review on 19 March 2021 as manuscript number ITSC 14586; approved for publication as a Research Article by the Information Technology, Sensors, & Control Systems Community of ASABE on 23 August 2021.

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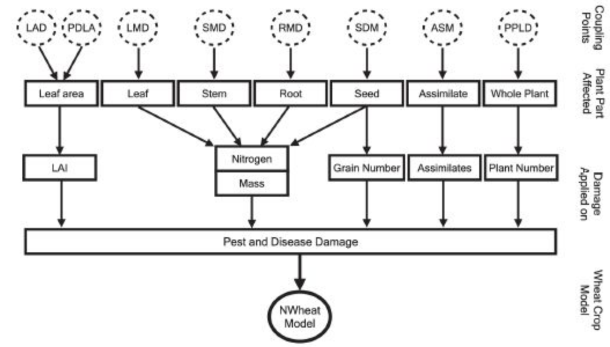


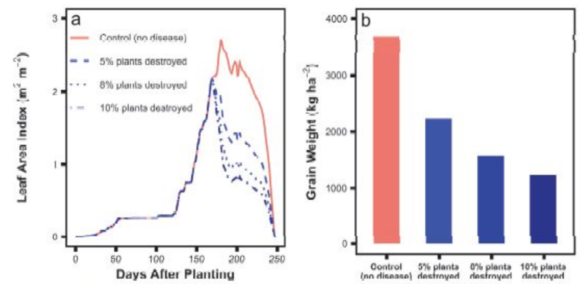
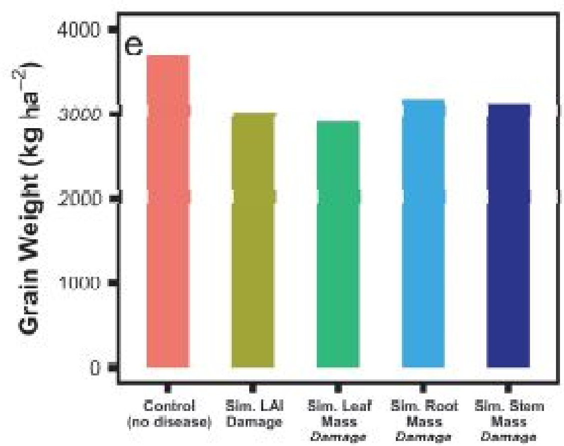


Figure 4. Sensitivity of the CSM-NWheat module coupled with the disease module to simulate the effects on (a) LAI and (b) yield when 5%, 8%, and 10% of the plants are removed.



Capacity Building & Training

DSSAT 2024

International Training Program

Assessing Crop Production,
Water and Nutrient Management,
Climatic Risk and Environmental
Sustainability with Simulation Models

May 20 - 25, 2024

A Joint Training Program of
DSSAT Foundation
University of Florida
Global Food Systems Institute
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DSSAT FOUNDATION

Capacity Building & Training

Capacity Building

Train the Trainers

Methodology for simulating crop production, water and nutrient management, climate risks and environmental sustainability in DSSAT

Czech University of Life Sciences Prague

Assoc. Prof. Vera Potopová

Digital edition: ČZU – 2023

Metodika simulace produkce plodin, hospodaření s vodou a živinami, klimatických rizik a environmentální udržitelnosti v DSSAT

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Dr. Kenneth J. Boote
Mgr. Marie Musiolková, Ph.D.

Katedra agroekologie a rostlinné produkce
Fakulta agrobiologie, přírodních a potravinových zdrojů
Česká zemědělská univerzita v Praze

Zemědělské a biologické inženýrství
Floridská univerzita (University of Florida, UF) ve Spojených státech amerických

Lektoroval: doc. Dr. Mgr. Vera Potopová
Jazyková korektura: Mgr. Marie Musiolková, Ph.D.

Odborní recenzent: doc. Petr Hlavinka, Ph.D. (Ústav výzkumu globální změny AV ČR, v.v.i.)

Grafický design: Iradion Jachiu

Vydala: Katedra agroekologie a rostlinné produkce, Fakulta agrobiologie, potravinových a přírodních zdrojů, Česká zemědělská univerzita v Praze, Kamýcká 129, 165 00 Praha-Suchdol

Rok vydání: 2023

ISBN 978-80-213-3254-6

https://home.czu.cz/potop/uvod

Metodika simulace produkce plodin, hospodaření s vodou a živinami, klimatických rizik a environmentální udržitelnosti v DSSAT

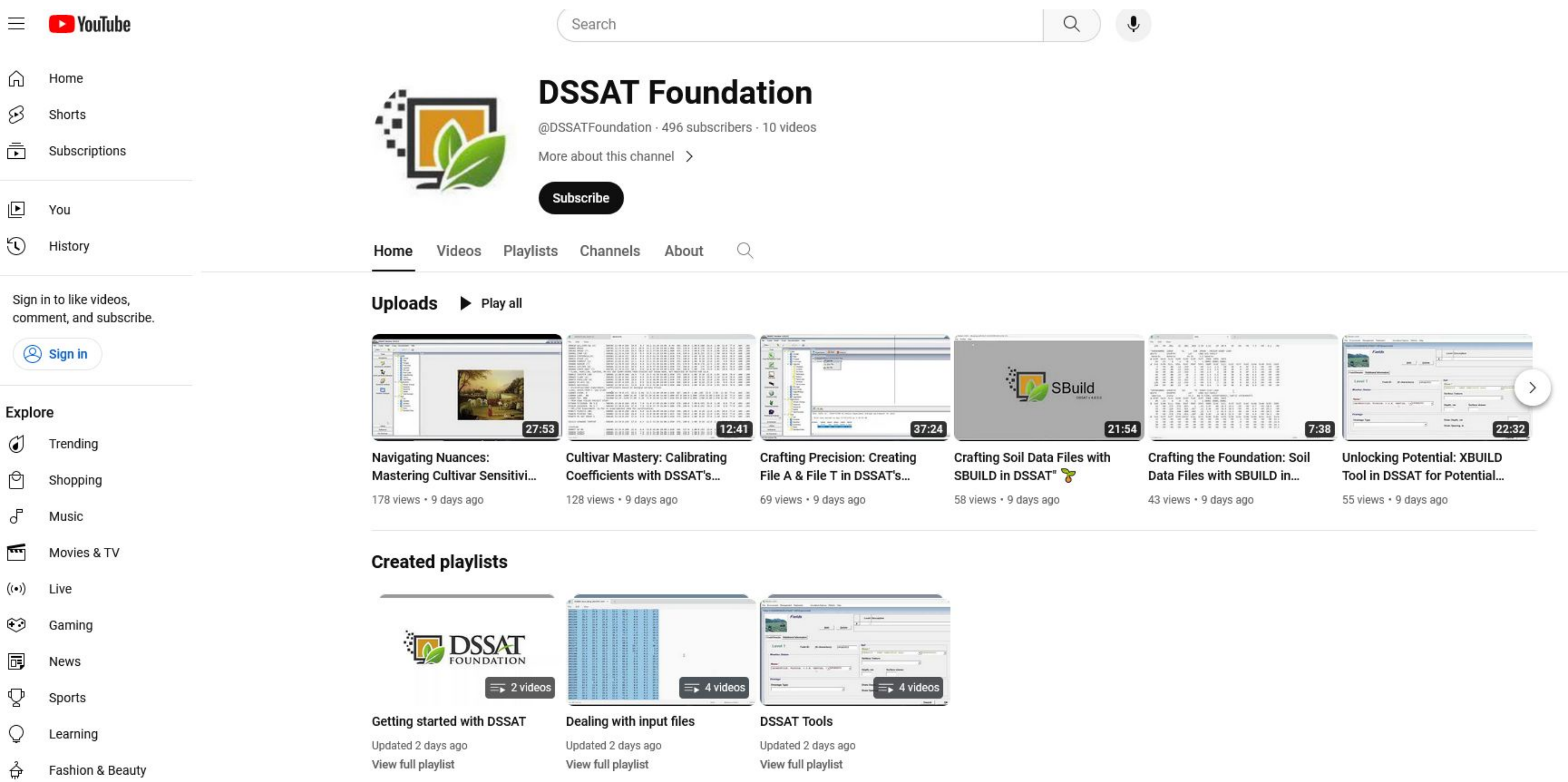
Česká zemědělská univerzita v Praze

Vedoucí autorského kolektivu
doc. Dr. Mgr. Vera Potopová

Digitální vydání: ČZU – 2023

On-line training

DSSAT YouTube Channel



DSSAT Hackathon

20th Development Sprint @ UF, January 8–12, 2024

18th Development Sprint @ UF, January 17–20, 2023

17th Development Sprint @ UC Davis, July 25-29, 2022

Cooperator Interaction

26th Annual Open Forum on Crop Modeling and Decision Support Systems
Monday, October 30, 2023 @ 7:30 pm

25th Annual Open Forum on Crop Modeling and Decision Support System

If you are attending the ASA-CSSA-SSSA 2022 International Annual Meeting in Baltimore, Maryland, come and join us at the DSSAT Open Forum where we will exchange what's new on crop modeling research, collaboration opportunities, and development on data and tools.

- **Date:** November 7, 2022
- **Start Time:** 7:30pm
- **End Time:** 9:00 pm
- **Location:** Room 312, Baltimore Convention Center

Monday, November 8, 2021

7:30 PM - 9:30 PM

Salt Palace Convention Center - 151 DEF

Description

The DSSAT Foundation Open Forum is an informal discussion and information exchange on the advances of crop modeling and decision support systems. The forum also provides an opportunity to discuss the developments of the DSSAT community.

DSSAT Portal *www.DSSAT.net*

What is DSSAT?

Decision Support System for Agrotechnology Transfer (DSSAT) is software application program that comprises dynamic crop growth simulation models for over 42 crops. DSSAT is supported by a range of utilities and apps for weather, soil, genetic, crop management, and observational experimental data, and includes example data sets for all crop models. The crop simulation models simulate growth, development and yield as a function of the soil-plant-atmosphere dynamics. DSSAT has been applied to address many real-world problems and issues ranging from genetic modeling to on-farm and precision management, regional assessments of the impact of climate variability and climate change, economic and environmental sustainability, and food and nutrition security. DSSAT has been used for more than 30 years by researchers, educators, consultants, extension agents, growers, private industry, policy and decision makers, and many others in over 187 countries worldwide. Learn more...

23 OCT

New DSSAT Foundation YouTube Channel

By Fabio Oliveira • October 23, 2023 • News & Event • Comments Off

The DSSAT Foundation now has a YouTube channel to assist the user community with informative videos about the download system, installation procedures and how to manage the DSSAT tools and application programs. To access the YouTube Channel please click the link below. Do not forget to hit the subscribe button, leave your like and comments [...]

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16 OCT

Bilateral Project Between Ankara University and the University of Florida on Capacity Building

By Fabio Oliveira • October 16, 2023 • News & Event, Past Workshops, Workshops • Comments Off

Ankara University, in collaboration with the University of Florida, developed a project entitled "Capacity Building on the Dissemination of the Use of Agro-technological Decision Support Systems in Agriculture." The project has been funded by the US Embassy in Türkiye under the auspices of a US-Türkiye bilateral Program. The project team includes seven scientists from Ankara [...]

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- University of Florida
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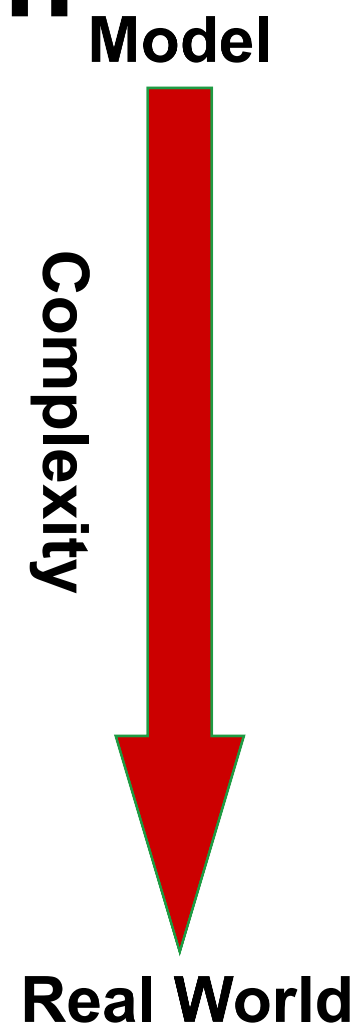
Modeling Limitations?

Agricultural Production

- Potential production
- Water-limited production
- Nitrogen-limited production
- Nutrient-limited production
- Pest-limited production
- Other factors
  - Intercropping
  - Economics
  - Food quality
  - Human decisions



Opportunities

Crop Modeling – Fact or fiction?
Environment * Management * Genotype
Economics

- Computer simulation model:
  - "A mathematical representation of a real-world system"
- Requires careful evaluation for local conditions
- Requires "accurate" input data
- ***Opportunities for Hybrid modeling, integrating AI with crop models***

Questions?

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