

Hydrometeorological risk assessment for crops in Chile

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ABSTRACT

This study presents a platform for climatic risk assessment for maize in Chile, a crop with a local market share of over 20% of the national cereal production. The platform uses a state of the art model for crop yield, and empirical models to simulate economic losses or crop yield deficit. The platform's goal is aiding decision makers to quantify risk in terms relevant decision variables. Uses of the platform range from the quantification of climate hazards and risks, the managing of water resources, and design of mitigation strategies, thus improving risk decisions without resorting on complex climatic models.

INTRODUCTION

In the 2015-2016 period, the combined planted surface of annual crops in Chile was 734.167 ha, of which 521.382 ha correspond to cereals (ODEPA, 2016). Within the cereal market, wheat occupy 55% of the planted surface, oat 21%, maize 20%, and rice 5%. The net maize production and the maize yield increased steadily in the 80's and 90's, as shown in Figure 1. However, the maize production has dropped severely in the last decade due to a series of extreme weather conditions, particularly high temperatures and unusual precipitations in the Biobio Region in the summer of 2011, and severe drought in the regions north of Chillan.

Considering the latest extreme climatic evens and the complexity of the crop market, the proposed computational platform aids researchers and decision makers to integrate the several layers of information required to evaluate risk, defined herein as the relative crop yield deficit. The platform 'CropYield'[®] is a Graphical User Interface developed in MATLAB (see Figures A.1 and A.2) which allows the user to import climatic databases, compute site specific climatic variables, and define crop properties for computing yield ratios and yield deficits.

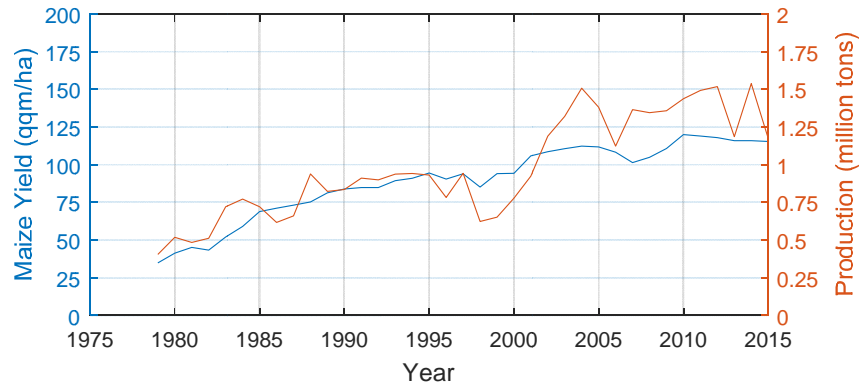


Figure 1 – Historic maize yield and maize production in Chile

Numerous studies conducted abroad have quantify agricultural risk under extreme climatic scenarios. For instance, Quijano et al., (2015) used the MSPEC model for maize and quantified the drought risk in Mexico using an event-based approach. Other studies (e.g., Yamoah et al., 2000, Hong and Wilhite, 2004) have quantified risk on maize fields based on the Standard Precipitation Index SPI. These studies and the work underway at CISGER-CHRIAM are key for evaluating the climate risk assessment, an area critical to the regional economy.

This article summarizes the methodology and data reduction techniques implemented in the platform. Results for a hypothetical maize field located in the Biobio region are presented.

METHODOLOGY

The computation of climate risk on crops assumes that the hazard, the system response, and the risk variables are independent stochastic events, which enables to treat each element separately. Given the limitations of current climate forecasting models, (e.g., local topography, spatial resolution), this study uses actual/recorded climate parameters to characterize the hazard in the area of study. This empirical hazard model is a reasonable approximation of local climate conditions and is used herein to simulate the crop response in the near-future, i.e. time spans less up to 10 years.

Hazard characterization

The platform uses records of daily precipitation, maximum and minimum temperatures obtained from gauging stations. To conduct proper statistical analysis on this database, the data gaps (data missing at random and non-existing data over large periods) were filled using local interpolation schemes, in which the missing data is computed from neighboring stations. Currently, the available methods available in the platform include the Single Best Estimators (SBE), General Mean Estimator (GME), Inverse Distance Weighting Method (IDWM), Correlation Coefficient Weighting Method (CCWM), and the Inverse Exponential Weighting Method (IEWM). An example of a raw and improved precipitation records is shown in Figure 2.

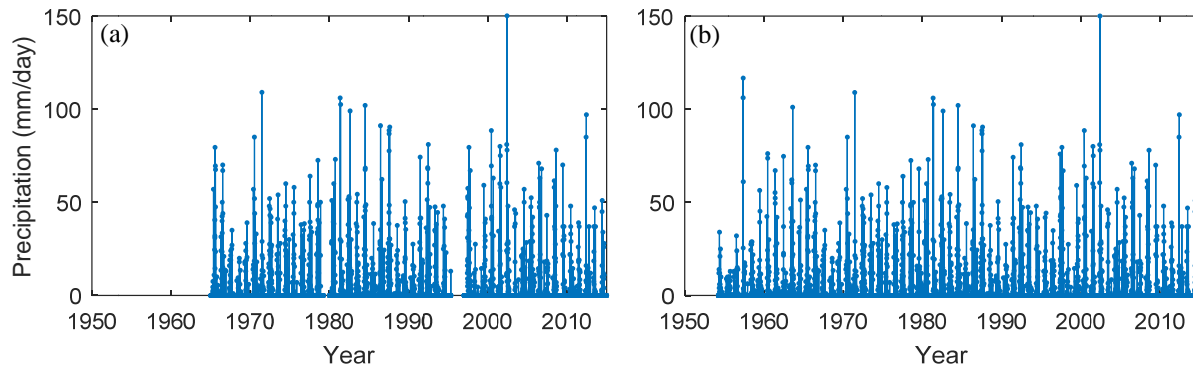


Figure 2 – Precipitation record at station “Estero Rabuco” (-71.117°, -32.851°) in the Coquimbo Region; (a) raw data, and (b) improved data. The IDWM interpolation scheme was used to compute the missing values, with data from 12 neighbor stations

For sites other than gauging stations, where no precipitation or temperature observations exist, synthetic records were generated from neighboring stations using the IDWM scheme. Conducting basic statistics over monthly periods, the frequency distribution of a climate variable can be described through a hazard curve, which relates the hazard intensity and its mean annual rate of exceedance. An example of the probabilistic analysis of precipitations is shown in Figure 3.

Crop response to water stress

The crop evapotranspiration, i.e., the simultaneous vapor removal from the ground surface (evaporation) and vaporization of liquid water in the plant surface (transpiration), is the water exchange process that controls the plant growth and yield. To quantify the effects of the climate variables in the crop evapotranspiration, this study adopted the widely accepted FAO 1998 Paper N° 56 (Allen et al., 1998). For details on the calculations of the reader is referred to source; the main features of the formulation are concisely described next.

The crop evapotranspiration under standard conditions, denoted ET_c , is the evapotranspiration of a healthy crop under optimum soil-water and fertilization conditions, in which full production is achieved. Using the single coefficient approach, ET_c is computed from climatic data and the FAO Penman-Monteith equation as $ET_c = K_c ET_o$, where K_c is the crop coefficient and ET_o is the evapotranspiration of an hypothetical grass of assumed height 0.12 m, surface resistance of 70 s m^{-1} , and albedo of 0.23. The coefficient K_c incorporates the crop characteristics, and the average effects of water evaporation in the different growing stages of the crop.

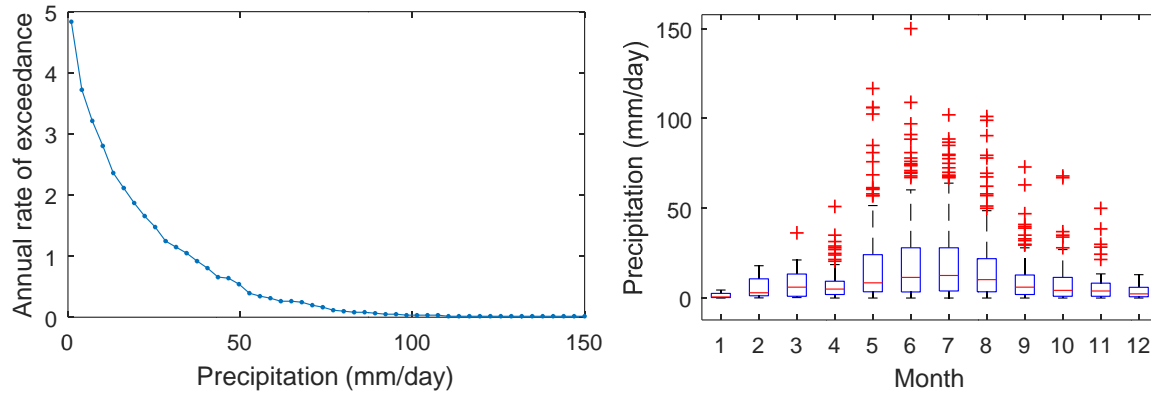


Figure 3 – Precipitation hazard analysis at station “Estero Rabuco” (-71.117°, -32.851°) in the Coquimbo Region: (a) precipitation hazard for the month of June, and (b) boxplots of daily precipitation grouped by month, the central mark is the median, the box edges are the 25%-75% percentiles, outliers are plotted individually

Under soil water stress conditions, the water has lower potential energy and cannot easily be absorbed by the crop roots, thus decreasing the crop productivity. The effect of soil water stress is incorporated into the formulation by multiplying the basal crop coefficient K_c by the transpiration reduction factor K_s , which is a simplified water balance model of the root zone and accounts for precipitation, irrigation, surface runoff, and deep percolation effects. The adjusted or actual crop evapotranspiration is computed as $ET_a = K_s K_c ET_o$.

Risk assessment

The risk decision variable (DV) selected for this study is the crop yield deficit, i.e., the crop yield under soil water stress conditions (Y_a) normalized by the crop yield under standard conditions (Y_c). This ratio is commonly expressed as a linear function of the relative evapotranspiration deficit (Doorenbos & Kassam, 1979), although non-linear models are also available in the literature. The linear yield deficit function takes the form given by Eq. (1), where the term K_y is the yield response factor that relates yield deficit to water use.

$$\left(1 - \frac{Y_a}{Y_c}\right) = K_y \left(1 - \frac{ET_a}{ET_c}\right) \quad (1)$$

The yield response factor is crop-specific and varies over the growing stages; a value of $K_y > 1$ indicates that the crop yield is sensitive to water deficits leading to increasing loss ratios. Since the water stress is not constant over time, a measure of the yield ratio for the entire season is determined as the product of daily yield ratios (Raes et al., 2006), as given in Eq. (2). In this expression, N is the number of days in the growing season, $K_{y,s}$ is the yield response factor of stage s (initial, middle, development, late), and L_s is the length of stage s .

$$\frac{Y_a}{Y_c} = \prod_{i=1}^N \left[1 - K_{y,s} \left(1 - \frac{ET_{a,i}}{ET_{c,i}} \right) \right]^{1/L_s} \quad (2)$$

The computation of the seasonal yield ratio involves several empirical parameters and data that is not readily available in many practical cases. Some parameters are derived from experimental analyzes, and thus carry significant uncertainty. Nevertheless, the loss ratio from Eq. (2) is a simple and straightforward method to estimate losses, and allows evaluating the relative influence of key modeling decisions, e.g., planting date, wet amount (irrigation) and wet interval.

AN ILLUSTRATIVE EXAMPLE

The methodology outlined above was applied to a hypothetical maize field located in the central valley of the Biobio Region in southern Chile. The site is located at 348 m above sea level at coordinates 36.8440°S, 71.9041°W, an area used intensively for farming. Data from seven gauging stations located within 30 km of the site were used to spatially interpolate precipitation and daily temperature values; as shown in Figure 4. These stations are administered by Dirección General de Aguas (DGA).

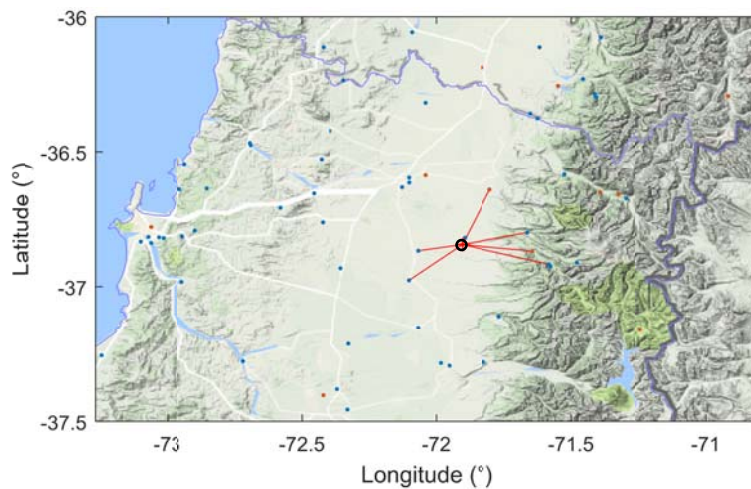


Figure 4 – Location of maize field and neighboring gauging stations

The interpolation scheme resulted in precipitation data that covers 65 years (1950 to 2014), however the temperature data covers only 55 years (1960 to 2014). One way to overcome this problem is to use the Climatological Mean Estimator (CME) scheme, which takes the average gage data for a given time interval (Teegavarapu, 2012). Boxplots of synthetic climatic data are shown in Figure 5 for complete data in the period 1960 to 2014.

The stage dependent parameters used for maize in the risk simulation were obtained from Allen et al., (1998). These parameters include the length, the crop coefficient, and the yield response factor for each stage; these factors are considered conservative for the purpose of crop yield assessment. The maximum root depth was defined as 1.7 m

and the depletion fraction (for $ET \approx 5$ mm/day) was defined as 0.55. The underneath soil is a low plasticity clay or Loam. In southern Chile, the planting date of maize takes place between September and December and the harvest is near the 120th day of growth, i.e., near the 10th day of the late stage.

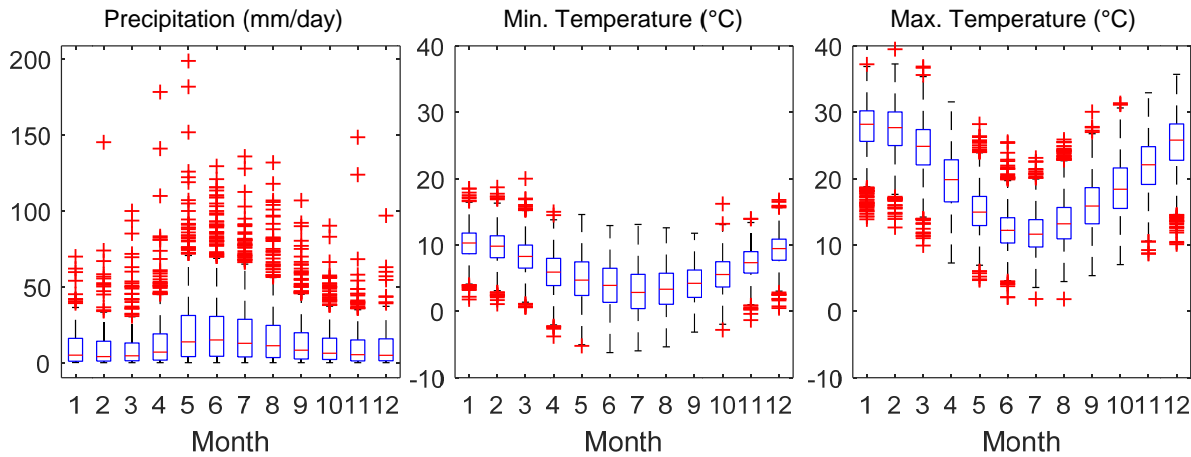


Figure 5 – Synthetic data of monthly precipitation and temperature

The yield ratio given by Eq. (2) was computed for each season using the proposed MATLAB platform, resulting in 55 loss values. The frequency distribution of the yield deficit (or risk decision variable) is shown in Figures 6 and 7 for two sets of parameters. Figure 6 shows the effect of alternative irrigation schedules, and Figure 7 shows the influence the planting date. Naturally, since maize is an annual crop, the annual rate of exceedance of any crop outcome is a value between 0 and 1.

In this example, from Figure 6 is apparent that an adequate irrigation plan significantly improves the productivity. For instance, in rainfed maize a yield deficit up to 50% occur in average once a year, whereas a maize field irrigated with 10 mm of water every 5 days (throughout the whole growing season) experiences similar deficits 0.22 times per year, or equivalently, once every 4.5 years.

Table 1 – Stage dependent maize parameters (Allen et al., 1998)

Parameter	Growing Stage			
	Initial	Crop development	Mid-season	Late season
Length of stage, L (days)	30	30	50	30
Crop Coefficient, K_c	0.3	1.05	0.6	2
Yield response factor, K_y	0.4	1.5	0.5	0.2

The influence of the planting date on the crop yield deficit is less dramatic, but nonetheless important. Notice that the growth period of maize is approximately 4.5

months, with a mid-season that lasts 50 days. If crops are planted on the beginning of October or November, they spend all their mid-season in the between December and February, the time of the year with least precipitations and highest temperatures. This aspect is reflected on yield deficit curves shifted to the right (more losses) compared to the crops planted on early September or early December.

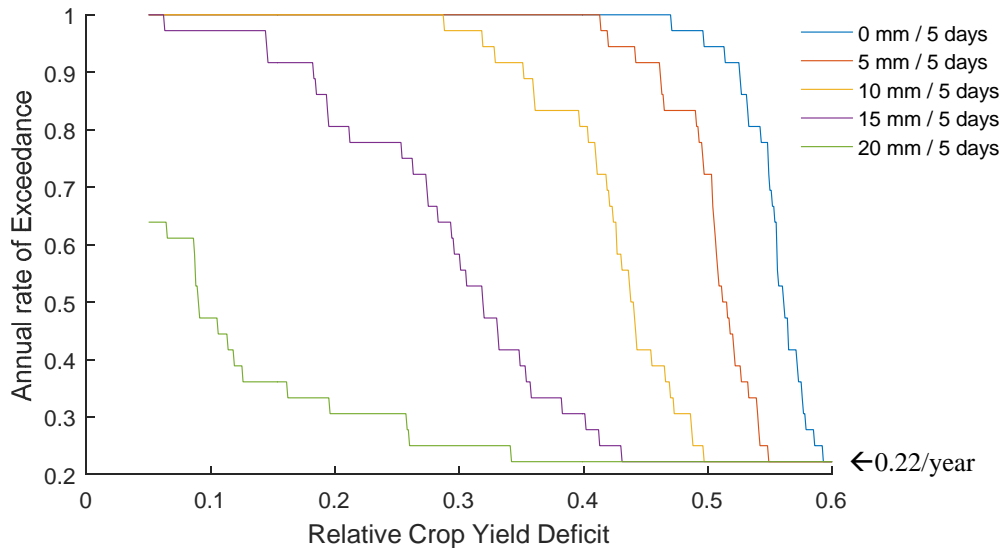


Figure 6 – Annual rate of exceedance of the crop yield deficit for different irrigation schedules. Planting date taken as October 1st of each year

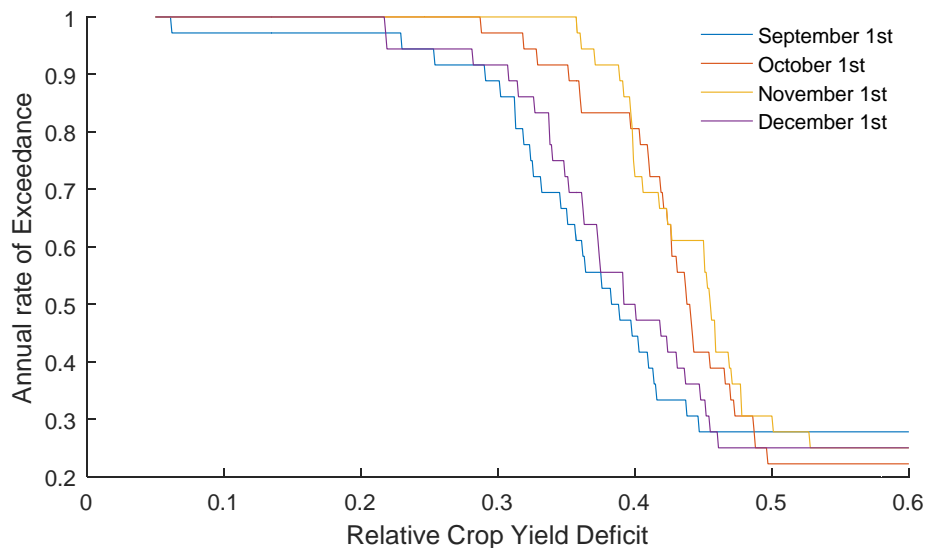


Figure 7 – Influence of the planting date on the yield deficit rate of exceedance. The assumed irrigation schedule was set at 10 mm in 5-day intervals

CLOSING REMARKS

The methodology implemented in the platform CropYield systematically integrates the climatic variables, a validated model for crop response to water stress, and a simple linear model for crop yield deficit, which allows communicating risk decision variables in a simple way, even for an audience not familiarized with formal risk analysis principles. Given the significance of maize production for the regional economy and the uncertain consequences of future extreme climatic scenarios, this platform is a versatile tool to aid in the risk evaluation and the design risk-based mitigation strategies.

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APPENDIX

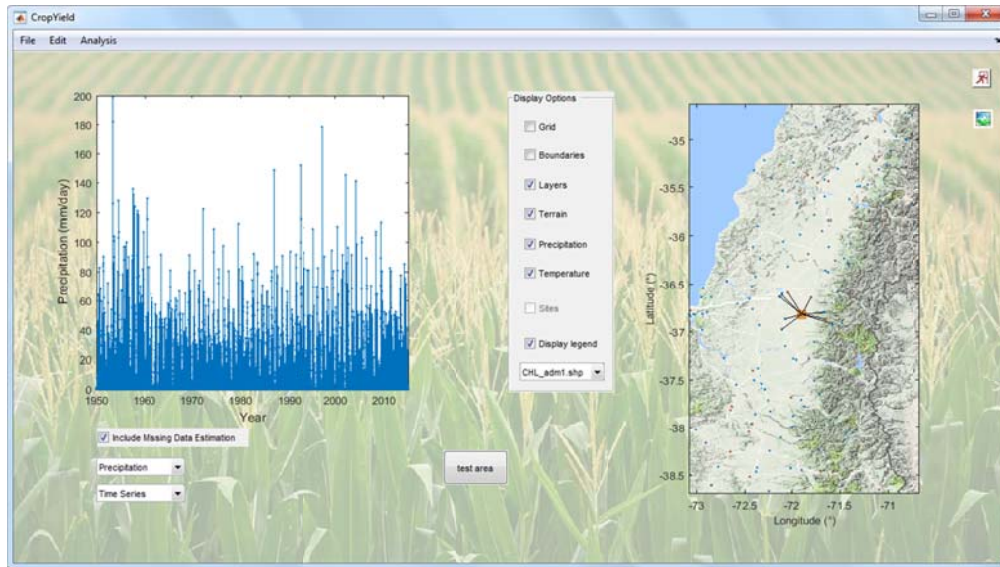


Figure A.1 – Main module of the MATLAB platform CropYield[®]

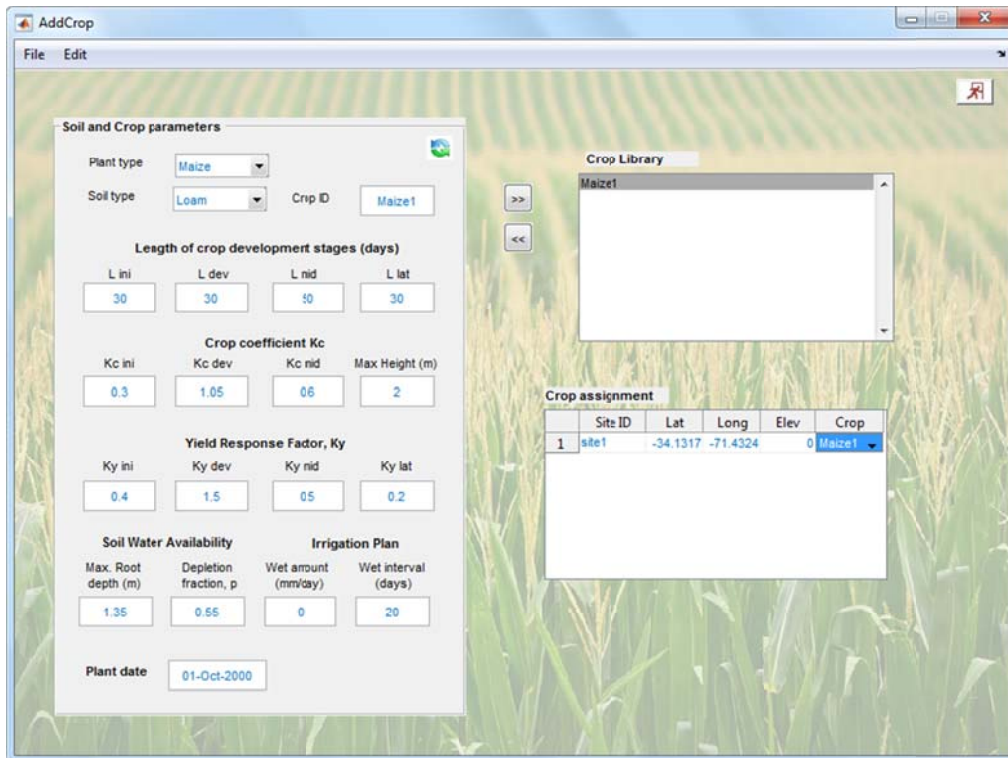


Figure A.2 – Crop parametrization module of the MATLAB platform CropYield[®]