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A decision support system for rainfed agricultural areas of Mexico

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ABSTRACT

Rural inhabitants of arid lands constantly face a lack of sufficient water to fulfill their agricultural and household needs. In this situation they have to take quick and precise decisions about how to cope with the situation. Moreover, there is not readily available technical information to support their decisions regarding the course of action they should follow to handle the agro-climatic risk. In this paper a computer model (soil water balance model) is described to assess the impact on crops yields of rainfall shortages in dry lands in Mexico. The model is linked to a knowledge based database where a farmer may find readily available information to support cropping decisions. The knowledge base activates when the computed average crop yield is less than the 50% of the expected crop yield. The knowledge base provides information on risk, potential crops, and the geographical location (counties) where the crop may succeed. Also, it provides a technology to increase water productivity under limited availability situations. Further, the model can evaluate the impact of a climate change scenario (IPCC B2). Other inputs to the model being equal, the user may shift the model to run the climate change scenario and to compare the outputs of the model to assess the climate change impact on future crops yields.

1. Introduction

Developed countries are characterized by a large population that has exited the rural sector. Mexico, despite public policies to increase the annual GDP, still has about 28% of the total population linked directly or indirectly to the rural sector. Also, land tenure for most of these dryland farmers is characterized by high climate uncertainty and the lack of support to prevent or to cope with this risk (Sanchez Cohen et al., 2011).

Capacity constraints are often coupled with weak harmonization and coordination of policy, legal and regulatory frameworks between the sectors competing for land and natural resources. Also, there are often weak institutions in charge of coordinating land issues, including those tasked with implementing National Action. There is a need for synergies among these strategies, including agriculture strategies and action plans (FAO, 2013).

Mexico, like many other countries in the world, faces great water challenges. In fact, water is the most important impact of climate change that should be addressed in its relation to the water cycle, water pollution, water scarcity, poor water administration, lack of resources for research and technological development, and lack of environmental planning (Arreguin Cortes et al., 2011).

Rainfed areas in Mexico account for 14 million hectares where around 23 million people live and are located in places where there is little climatic information or are ungagged at all. The severe drought that has impacted northern Mexico in the past several years as well as other parts of the country, has forced decision makers to look for improved tools and procedures to prevent and to cope with this natural hazard. Computer models that simulate

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crop growth and estimate crop yields are a powerful tool for decision taking and planning when properly used. Achieving potential crop yields under irrigated conditions depends on following agronomical recommendations regarding planting dates, use of suitable seeds, and pests and diseases control; on the other hand, for estimating crop yields under rainfed conditions one must to add rainfall uncertainty to the above constraints. This uncertainty may be accounted for using stochastically driven water balance models where rainfall patterns are estimated based on statistics that define the behavior of the rainfall historical data (Sanchez-Cohen et al., 2014).

Dryland farmers face uncertainty every year about what to do or lack of knowledge regarding what alternatives they have to prevent or to adapt to the imposed risk by climate uncertainty or variability.

The objective of this paper is to present a stochastic decision model (water balance model) for dry lands in Mexico whose outputs are linked to readily available technology to cope with climate risk aiming to support farmers decision taking at farm level. Besides farmers, technicians, agronomy professionals and decision takers at different levels of decision are also the aim of this research work.

2. Research approach

2.1. Soil water balance description

Soil water balance assesses the soil water content at a given time and it may be defined as the amount of water held in the soil at that time. The soil water balance relies on the soil water storage capacity in the root zone which, for the purpose of modeling, is determined by soil texture and plant growth stage. In rainfed agriculture planning and analysis, it is desirable that this balance be done on a daily basis as a way to identify dry or wet spells that impact crop yields.

A crop growth simulation model must therefore keep track of the soil moisture potential to determine when, and to what degree, a crop is exposed to water stress. This is commonly done with the aid of a water balance equation, which compares incoming water in the rooted soil with outgoing water for a given period of time, and quantifies the difference between the two as a change in the amount of soil moisture stored. The purpose of soil water balance calculations is to estimate the daily value of the actual soil moisture content, which influences soil moisture uptake and crop transpiration and then, based on this balance, to compute the effect on crop yield.

A computer program was written for the simulation model in Fortran 90 and then it was migrated to a Delphi platform to facilitate building a user-friendly interface. For the purpose of this paper, the water balance is defined as:

$$\Delta S_i = \Delta S_{i-1} + [Pp + Q + \delta]_i - [\mathrm{Eta} + \mathrm{Qo} + Z]_i \tag{1}$$

where ΔS_i is the current soil water content (L), Pp is the daily precipitation (L), Q is runoff to the cropped area expressed as water depth (L), δ is the soil capillarity, Eta is the crop maximum evapotranspiration ($\mathrm{L\,T^{-1}}$), Qo is the runoff out of the cropped area (L), and Z is deep percolation (L). The subscript "i" refers to the timing, (i.e. t_{i-1} is the previous day).

In most dry lands it is difficult to find the water table near the soil surface and also in shallow soils that characterizes drylands in Mexico, it is not common to have deep soils; so based on this, δ is dropped from Eq. (1).

2.2. Rainfall computation under actual climate scenario

The main characteristic of the water balance method in this paper is the stochastic process used to compute rainfall amounts and occurrence under both actual and climate change scenarios (Scenario B2 of the Intergovernmental Panel on Climate Change, IPCC). Within the model, daily rainfall is simulated using a Markov chain-exponential model in which precipitation occurrence is described by a first-order Markov chain and the amount of rainfall for those days on which rainfall occurs is based on an exponential distribution of daily rainfall amounts (Sanchez-Cohen et al., 1997, 2014):

$$F_{x1}(x) = P(x_1 \leq x) = 1 - e^{-\lambda x} \tag{2}$$

where parameter λ = inverse of daily precipitation (Hanson et al., 1975). The first-order Markov chain utilizes two states defined by the transition probabilities:

$$p_{ij}(n) = P(X_n = jIX_{n-1} = i); \quad i,j = 0,1; \; n = 1,2,\ldots 120 \tag{3}$$

where state 0 signifies a dry day and state 1 signifies a wet day and:

$$p_{i1}(n) = 1 - p_{i0}(n); \quad i = 0,1 \tag{4}$$

Thus these transition probabilities define four possible states as follows: P_{00} – the probability of a day being dry given that the previous day was dry; P_{01} – the probability of a day being dry given that the previous day was wet; P_{10} – the probability of a day being wet given that the previous day was dry; and P_{11} – the probability of a day being wet given that the previous day was wet (Sanchez-Cohen et al., 1997). Both Markov chain and exponential distribution parameters may be computed for selected periods from daily rainfall data using methods described by Woolhiser and Roldan (1986) and by Wilks (1995).

Once the distribution parameters have been defined, the simulation procedure consists of generating a random number between 0 and 1 to determine whether or not precipitation occurs on any given day utilizing Eqs. (3) and (4). If rainfall does occur, another independent random number is generated and transformed to compute the amount of precipitation according to Eq. (2) (Sanchez-Cohen et al., 1997).

2.2.1. Intergovernmental Panel on Climate Change Scenario (IPCC)

As a result of the need for regional projections to evaluate the integrated impacts of climate change to a regional scale, downscaling dynamic and statistical techniques have been developed which reduce some of the bias in General Circulation Models (GCM) as well as their spatial limitations. The term scale reduction or transformation is a relatively recent one aiming to describe a series of techniques that correlate atmospheric variables with local or regional variables (Hewitson and Crane, 1996). This is widely used in climate modeling due to its relatively rapid application and reduced computational need compared to the dynamic rescaling approach of the GCM. Essentially, the regional climate is considered to be conditioned by the global scale climate as $Y = F(X)$, where Y is the predictand or local variable being rescaled (i.e. temperature or rainfall), X is a series of predictive atmospheric variables of global scale (sea level pressure, relative humidity, etc.) and F is a linear or non-linear transfer function.

Within the proposed model under climate change scenario, downscaled variables (temperature, maximum and minimum) are used to rescale transition matrix probabilities for computing time and amounts of rainfall according Eqs. (2)–(4) and to recalculate the soil water balance and to compute crop evapotranspiration. Table 1 shows a comparison between transition probabilities for a given climate station under both a current and future scenario (IPCC B2).

Figs. 2 and 3 show the general steps to rescale local climate databases expanding the method highlighted by the dark gray rectangle shown in the second row of the left hand side of Fig. 1 (IPCC). The chosen IPCC scenario for computing climate variables