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# Contribution of agrometeorology to the simulation of crop production and its applications

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**Abstract**

Weather has a significant impact on crop growth and development. This paper presents an overview of crop modeling and applications of crop models, and the significance of weather related to these applications. To account for the impact of weather and climate variability on crop production, agrometeorological variables are one of the key inputs required for the operation of crop simulation models. These include maximum and minimum air temperature, total solar radiation, and total rainfall. Most models use daily data as input, because variables at a smaller time scale are usually unavailable for most locations. It is important to define standard file formats for weather and other input data; this will expand the applicability of weather data by different models. Issues related to missing variables and data, as well as locations for which no data are available, need to be addressed for model applications, as it can affect the accuracy of the simulations. Weather generators can be used to stochastically generate daily data when data are missing or long-term historical data are unavailable. However, the use of observed weather data for model input will provide more precise crop yield simulations, especially for tropical regions. Many of the crop models have been applied towards strategic and tactical management decision making as well as yield forecasting. The predicted variability of crop yield and related variables as well as natural resource use is mainly due to the short- and long-term variation of weather and climate conditions. The results produced by the models can be used to make appropriate management decisions and to provide farmers and others with alternative options for their farming system. The crop models have been used extensively to study the impact of climate change on agricultural production and food security. Recently, they have also been applied towards the impact of climate variability and the effect of El Niño/Southern Oscillation (ENSO) on agricultural production and food security. It is expected that, with the increased availability of computers, the use of crop models by farmers and consultants as well as policy and decision makers will increase. Weather data in the form of historical data or observations made during the current growing season, and short-, medium-, and long-term weather forecasts will play a critical role in these applications. 

*Keywords:* Crop model; Decision support system; Climate variability; Climate change; Strategic application; Tactical application; Yield forecast

## 1. Weather and agriculture

Weather is one of the key components that controls agricultural production. In some cases, it has been stated that as much as 80% of the variability of agricultural production is due to the variability in weather conditions, especially for rainfed production systems (Petr, 1991; Fageria, 1992). Weather has a major impact on plants as well as pests and diseases. Before discussing the contribution of agrometeorology to the simulation of crop production, it is important to summarize the potential effect of the different weather variables on crop growth and development.

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The critical agrometeorological variables associated with agricultural production are precipitation, air temperature, and solar radiation. Air temperature is the main weather variable that regulates the rate of vegetative and reproductive development (Hodges, 1991). In most cases, an increase in temperature causes an increase in the developmental rates. At extremely high temperatures, the inverse occurs, and developmental rates slow down as the temperature further increases. Solar radiation provides the energy for the processes that drive photosynthesis, affecting carbohydrate partitioning and biomass growth of the individual plant components (Boote and Loomis, 1991). Photosynthesis is normally represented through an asymptotic response function, with a linear response at low light levels.

Precipitation does not directly control any of the plant processes. It is considered to be a modifier, that indirectly affects many of the plant growth and developmental processes. Drought occurs during periods of insufficient rainfall, while water logging occurs during periods of extensive rainfall. Drought stress in plants is a result of a combination of factors, such as potential evapotranspiration, extractable soil moisture in the rooting zone, root distribution, canopy size, and other plant and environmental factors. Drought can cause an increase or decrease in developmental rates, depending on the stage of development. In many cases, the response to drought stress is also a function of species or cultivar, as some species or cultivars are more drought-tolerant than others. Drought can also reduce gross carbon assimilation through stomatal closure, causing a modification of biomass partitioning to the different plant components. Water logging stress is caused by flooding or intense rainfall events. It can cause a lack of oxygen in the rooting zone, which is required for root growth and respiration. A decrease in oxygen content in the soil can result in a decrease in root activities, causing increase in root senescence and root death rates. The overall effect of water logging is a reduction in water uptake; the ultimate impact is similar to the drought stress effects discussed earlier.

Other weather factors that can affect crop production include soil temperature, wind, and relative humidity or dew point temperature. In many regions, soil temperature is important during the early part of the growing season, as it affects planting and germination. For winter crops, such as winter wheat, the soil temperature can also affect vernalization. Relative humidity, dew point temperature or vapor pressure deficit are similar agrometeorological factors, that express the amount of water present in the air. They affect transpiration and the amount of water lost by the canopy, causing drought stress under water-limited conditions as discussed previously. They can also influence biotic stresses, such as the presence as well as the activity of pests and diseases. At harvest maturity, both air and dewpoint temperature affect the dry down time of the harvestable product. In some cases, extreme rainfall can make a crop unharvestable, when farmers are unable to enter the field due to saturation of the top soil. Wind can also have a multiple impact on crop production. First of all, it can affect the rate of transpirational water loss by the leaves. In addition, it can affect the transport and the distribution of insects and diseases in the atmosphere, and subsequent presence in the plant canopy. Extreme wind can also affect the potential for lodging, especially for tall crops. Potential evapotranspiration is a very important agrometeorological variable. However, it is a derived value based on other weather variables, such as solar radiation, air temperature, wind speed, and vapor pressure deficit (Penman, 1948; Priestley and Taylor, 1972; Linacre, 1977). It is critical that most or all of the processes discussed here are included in a model, so that they can simulate the potential impact of weather conditions on plant growth and development and resource use.

## 2. Crop simulation models and weather

Computer models, in general, are a mathematical representation of a real-world system (Mize and Cox, 1968). In reality, it is impossible to include all the interactions between the environment and the modeled system in a computer model. In most cases, a computer model, therefore, is a simplification of a real-world system. A model might include many assumptions, especially when information that describes the interactions of the system is inadequate or does not exist. Depending on the scientific discipline, there are different types of models, ranging from very simple models that are based on one equation to extremely advanced models, that include thousands of equations. For instance, in the aerospace industry, computer models are used to design the entire structure of an airplane and simulate its operation prior to even being built. As airplanes and their interactions with the areal environment mainly deal with the laws of physics, engineering principles can be applied. However, agriculture involves biological factors for which, in many cases, the interactions with the environment are unknown. The science of plants and crops represents an integration of the disciplines of biology, physics, and chemistry. Plant and crop simulation models are a mathematical representation of this system.

One of the main goals of crop simulation models is to estimate agricultural production as a function of weather and soil conditions as well as crop management. The weather variables discussed previously, such as air temperature, precipitation, and solar radiation, are, therefore, key input variables for the simulation models. We would like to define these as primary weather input variables and to define the other input variables, including wind speed, relative humidity or dewpoint temperature, open pan evaporation, and soil temperature, as secondary weather input variables. Some scientists consider relative humidity also as a primary variable, because of its impact on plants as well as on pests, especially diseases. A critical issue is the availability of weather data to be able to run crop simulation models for a certain location or for a particular application. Especially, the secondary weather variables are measured at only a few sites. Although the primary variables are measured at most locations, solar radiation is sometimes missing. A good substitute for solar radiation is sunshine hours, which can be used to estimate solar radiation if the Angström coefficients are known. Many agricultural sites where weather stations have been installed record maximum and minimum temperature as well as precipitation at least once a day.

## 3. Weather data for modeling

### 3.1. Data sources

The national meteorological organizations, such as the National Weather Service (NWS) in the US, are the most common source of weather data for modeling applications. Unfortunately, most of these weather stations are located at airports, as their primary duty is to serve the aviation industry. In general, airports are located around large cities and the conditions at airports are not very representative for the main agricultural production regions, due to buildings, runways and other developmental structures normally found around airports. The weather stations at airports are first-order stations; both primary and secondary weather input variables are collected either manually or through automated procedures. The national meteorological organizations also operate other types of weather stations that measure weather variables. In some cases, these weather station networks are mainly located in more remote locations. For instance, in the US, the NWS maintains a Cooperative Climate Network. A volunteer observer reads the maximum and minimum thermometers and rain gauge once or twice a day, either in the morning or late in the afternoon. This provides a combined summary of yesterday's and today's weather data, although all data are reported with yesterday's date. For many of these sites, long-term records exist, going back at least 50–100 years (EarthInfo, 1998). For many European networks, weather records exist for several centuries.

The emphasis of the national meteorological organizations on serving the aviation industry and the lack of weather data for agricultural environments, has led to the development of automated weather station networks (Tanner, 1990). These networks are mainly operated by national agricultural institutes, universities, private industry and farmers (Meyer and Hubbard, 1992). The weather data collected by the weather stations of these networks have been one of the main sources for primary and secondary weather input data for crop simulation models. Unfortunately, most automated weather networks were developed during the last 10–15 years, so no long-term weather records exist. The networks, in general, are also not compatible, due to differences in instrumentation, sensor height and data logging. This makes it more difficult to use the data collected by automated weather station networks for modeling applications (Ley et al., 1994).

### 3.2. Time scale of data

The time scale of weather data used for modeling applications is also important. Many long-term weather records are based on daily observations. As a result, most crop simulation models are restricted with respect to their weather inputs, due to the lack of detailed weather data recorded at hourly or shorter intervals. They, therefore, use daily weather data as input, although they might operate internally at smaller time steps (Hunt et al., 1994). The use of weather input data reported at time intervals longer than 1 day has shown to be unacceptable for modeling applications. The use of monthly weather data for model input resulted in large under- and overestimations of yield (Nonhebel, 1994a). Several models have been developed to calculate hourly temperature values through the interpolation of the daily maximum and minimum temperature extremes, using either half-sine curves or other curve fitting techniques (Floyd and Braddock, 1984; Fernández, 1992; Ephrath et al., 1996). These hourly temperatures can then be used as input for a model, or the interpolation functions can be included in the model. For instance, the grain legume simulation model CROPGRO calculates vegetative and reproductive development at hourly time steps based on hourly temperature values, although the model uses daily maximum and minimum temperature data as input (Boote et al., 1997).

Several soil physical models that simulate a detailed soil water balance, especially runoff, drainage, and water flow, use time intervals as small as 1 s, depending on the dynamics of changes in moisture and water flow in the soil profile (De Jong and Bootsma, 1996). These models sometimes require that rainfall is presented as breakpoint data in a special precipitation file. For each rainfall or storm occurrence, both the intensity and the duration of this event are needed (Singh and Kanwar, 1995; Agnese and Bagarello, 1997; Hanson et al., 1998). Although it is beyond the scope of this paper, the accuracy of the input data has an impact on the accuracy of the simulated results (Nonhebel, 1994b, c). Also, differences in observations between different sensors that measure the same variable (Bruton et al., 1998; Llasat and Snyder, 1998) can affect the accuracy of the simulated results.

### 3.3. Data standards for crop modeling

The International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT) Project initiated an effort to define a minimum data standard for crop model applications (ICRISAT, 1984; IBSNAT, 1990a, b). This standard includes a minimum set for weather data, consisting of maximum and minimum air temperature, solar radiation, and precipitation. It also defines specific formats for the structure and the naming convention of files, including the weather files (Jones et al., 1994; Hunt and Boote, 1998). Various other modeling groups, such as the Global Change and Terrestrial Ecosystems (GCTE, 1994) Committee and the Commission on Global Change Data (CODATA) (Hunt et al., 1994; Uhlir and Carter, 1994), have adapted this file format. GCTE is especially interested in developing experimental data sets that can be used for the evaluation of various crop models for climate change applications. For these types of comparisons, it is critical that uniform file formats and data standards are defined. GCTE's effort has already led to an easy exchange of model input data between different models and has provided opportunities for collaboration between modeling groups (Semenov et al., 1996; Wolf et al., 1996; Jamieson et al., 1998). The recently established International Consortium for Agricultural Systems Applications (ICASA) (Ritchie, 1995), a collaboration between the 'De Wit School' of modelers and the IBSNAT modeling group, has led to the development of an improved set of input file standards and data formats that can be used as input data for all models, developed by both groups. Similar recommendations for data standards as well as software that use weather and other environmental data as inputs were made by Mararcchi and Sivakumar (1995). Unfortunately, they were not very successful in their implementation.

### 3.4. Weather generators

It is important to use observed historical weather data for all modeling applications, except for those related to prognostic applications. However, in many cases, the availability of these weather data might be limited. Sometimes, the period of record is too short to conduct a modeling application, long periods of records are missing, or only monthly averages and totals are available. In other cases, only a few variables are recorded, such as rainfall and maximum and minimum temperatures, or in the worst case, only daily rainfall. In all these situations, weather generators can be used to generate daily rainfall, maximum and minimum temperatures, and solar radiation. A significant amount of research has, therefore, been spent on the development and evaluation of weather generators (Meinke et al., 1995).

All weather generators require some type of local climate data as input to define the monthly mean values and associated variability over time for each weather variable. The most common weather generators that have been used include WGEN (Richardson, 1981, 1985), Simmeteo (Geng et al., 1986), CLIGEN (Johnson et al., 1996) as well as various other weather simulation models (Peiris and McNicol, 1996; Duvrosky, 1997; Friend, 1998; Semenov et al., 1998). The accurate generation of precipitation, both the occurrence of an event as well as the amount, is the most difficult task, especially for tropical and sub-tropical regions (Arnold and Elliot, 1996; Schmidt et al., 1996; Jimoh and Webster, 1997). Several improvements of existing simulators that include a higher order Markov model to account for the high variability of tropical precipitation have been developed (Jones and Thornton, 1997; Schmidt et al., 1997). Several weather generators have been integrated in weather utility programs that analyze and prepare weather data for model applications, such as WeatherMan (Pickering et al., 1994). They have also been incorporated in several simulation models such as the CROPGRO and CERES models (Hoogenboom et al., 1994) or are an integral part of a modeling or decision support system (Tsuji et al., 1994; Baffaut et al., 1996).

## 4. Modeling approaches

Crop models, in general, integrate current knowledge from various disciplines, including agrometeorology, soil physics, soil chemistry, crop physiology, plant breeding, and agronomy, into a set of mathematical equations to predict growth, development and yield. Baier (1979) provided some interesting background and terminology for what he called 'crop–weather models'. The paper is based on a review for a World Meteorological Organization (WMO) expert meeting on crop–weather models, held in Ottawa, Canada in 1977. Baier (1979) distinguished between crop growth simulation models, crop–weather analysis models, and empirical–statistical models.

Crop growth models are physiologically based, in that they calculate the causal relationships between the various plant functions and the environment. The opposite would be a statistical approach, using correlative relations between all processes. Crop models can also be identified as being deterministic, in that they make an exact calculation or prediction. In this case, the opposite would be stochastic or probabilistic models, which provide a different answer for each calculation. Crop models are simulation models, in that they use one or more sets of differential equations, and calculate both rate and state variables over time, normally from planting until harvest maturity or final harvest. Some of the earliest crop simulation models simulated only photosynthesis and a simple carbon balance over time. Other processes, such as vegetative and reproductive development and the plant water balance, were added at a later date (Duncan et al., 1967; Curry, 1971; Curry and Chen, 1971; Splinter, 1974).

Ritchie (1994) identified three types of deterministic models. The first type are statistical models, which have been used to make large-area yield predictions. To develop these models, final yield data are correlated with the regional mean weather variables (Thompson, 1969a, b, 1970). On account of its many limitations, this statistical approach has slowly been replaced with the use of simple or more complex simulation models (Abbaspour et al., 1992). Mechanistic models include mathematical descriptions of most of the plant growth and development processes as they are currently known in the field of plant sciences. These models have mainly been used in research applications, and are not very practical for agricultural applications at a farm level. Ritchie's (1994) third category consists of the functional models. These models include simplified equations or empirical relationships to represent the various complex plant processes and their interactions with the environments.

The 'School of De Wit' (de Wit and Goudriaan, 1974; Bouman et al., 1996) defines four different levels or facets with respect to the evolution of plant growth models (Penning de Vries and van Laar, 1982; Penning de Vries et al., 1989). In Phase 1, temperature and solar radiation are used as inputs to simulate growth and development and to calculate potential production. Growth in this case only includes the simulation of the plant carbon balance. In Phase 2, precipitation and irrigation are added as an input, and the soil and plant water balances are simulated. In Phase 3, soil nitrogen is added as an input to simulate growth and development, the soil and plant water balance, and the soil and plant nitrogen balance. In Phase 4, other soil minerals are added as inputs as well as pests, diseases, and weeds. In this phase, the complete soil–plant–atmosphere system is simulated, including interactions with most of the biotic and abiotic components.

There are hardly any crop simulation models that currently operate at Phase 4. This is mainly due to the complexity of the soil–plant–atmosphere system. Most of the widely used crop simulation models, such as those included in the Agricultural Production System Simulator (APSIM) (McCown et al., 1996), the Decision Support System for Agrotechnology Transfer (DSSAT) version 3 (Tsuji et al., 1994; Jones et al., 1998), the Simulation and Systems Analysis for Rice Production (SARP) models (Kropff et al., 1994; Riethoven et al., 1995), and the 'School of de Wit' crop models (van Keulen and Seligman, 1987; Bouman et al., 1996), have only reached Level 3. The models in these systems simulate crop growth and development as well as the soil and plant water and nitrogen balances (van Keulen, 1982; Godwin and Singh, 1998; Probert et al., 1998; Ritchie, 1998). A few models include one or more processes at Level 4, such as the model Ecosys (Grant and Heaney, 1997) and a preliminary version of CERES (Gerakis et al., 1998); both models present a simulation of the phosphorus balance. Several models also include the option to simulate the impact of pest and disease damage (Teng et al., 1998), such as CROPGRO (Batchelor et al., 1993; Sridhar et al., 1998) CERES-Rice (Pinnschmidt et al., 1995) and ORYZA (Ehlings and Rubia, 1994). When pest and disease simulations are added to a model, additional weather variables might be needed as inputs, such as relative humidity or dew point temperature. Modeling of the interaction between crops and weeds has only been addressed at a limited scale (Kropff and Lotz, 1992; Kropff and van Laar, 1993; Oryokot et al., 1997).

It is expected that progress towards including the simulation of additional processes in the current simulation models will be slow. As models become more complex by including the simulation of more processes, the requirement to define input data for these new processes also increases (Hunt, 1994). Although model users would like to be able to simulate the complete soil–plant–atmosphere continuum, they normally have a very difficult time in obtaining the input parameters required to simulate these processes (Hunt and Boote, 1998). Computer modelers have a tendency to request input information for their simulation models that, in many cases, is not available. The lack of adequate input data requires that some of these model inputs have to be scaled back to the level at which input data are available. One of the examples is the request for hourly weather data for some models, but the existence of only daily weather data for real-world applications. Maintaining an even balance between the level and the amount of user-supplied input data (Hoogenboom, 1998) and the complexity and details of the modelled processes, will remain a delicate issue. It is also important to keep a balance between all the processes that are simulated by a model, so that they contain the same amount of details (Monteith, 1996). One needs to keep in mind that this approach might require different types of models for different applications, depending on the complexity of the problem that is being investigated (Boote et al., 1996).

One recent advancement in model development has been the change towards modularity. Although this concept has originated through object-oriented modeling (Hodges et al., 1992; Waldman and Rickman, 1996; Acock and Reddy, 1997), the trend now seems to have changed towards developing modules that can be exchanged between different modeling systems (Timlin et al., 1996; Acock and Reynolds, 1997). The APSIM system is built on the premise that the user can build a model, based on a selected set of modules that simulate the various plant and soil processes (McCown et al., 1996; Keating et al., 1997). A similar approach is also being implemented in the CROPGRO model for grain legumes (Boote et al., 1997).

## 5. Applications and weather

Crop simulation models can play an important role at different levels of applications, ranging from decision support for crop management at a farm level to advancing understanding of sciences at a research level. Weather data are the most important input data for all these applications of the simulation models. The main goal of most applications is to predict final yield in the form of either grain yield, fruit yield, root or tuber yield, biomass yield for fodder, or any other harvestable product. In some cases, associated variables, such as resource use or the impact of pollution on the environment, might also be of interest. Certain applications link the price of the harvestable product with the cost of inputs and production to determine economic returns. One application is the use of crop simulation models for policy management. As most of the applications discussed in this paper include some type of policy issue, we will not address policy applications separately. Some specific applications of models related to policy issues can be found in de Wit et al. (1987) and Rabbinge and van Latesteijn (1992). The discussion of research applications of crop models is also beyond the scope of this paper. Readers are referred to Loomis et al. (1979) and Boote et al. (1996), and others for further discussions on this topic.

In general, the management applications of crop simulation models can be defined as strategic applications, tactical applications, and forecasting applications. In strategic applications, the crop models are run prior to planting of a crop to evaluate alternative management strategies. In tactical applications, the crop models are run before planting or during the actual growing season. Both strategic and tactical applications provide information for decision making by either a farmer, consultant, policy maker, or other person involved directly with agricultural management and production. Forecasting applications can be conducted either prior to planting of a crop or during the growing season. The main objective is to predict yield; this information can be used at a farm-level for marketing decisions or at a government level for policy issues and food security decisions.

### 5.1. *Strategic applications*

In strategic applications of crop simulation models and decision support systems, the models are mainly run to compare alternative crop management scenarios. This allows for the evaluation of various options that are available with respect to one or more management decisions (Tsuji et al., 1998). To account for the interaction of these management scenarios with weather conditions and the risk associated with unpredictable weather, simulations are conducted for at least 20–30 different weather seasons or weather years (Jame and Cutforth, 1996). In most cases, daily historical weather data are used as input and the assumption is made that these historical weather data will represent the variability of the weather conditions in the future. When no long-term daily historical weather data are available, a weather generator can be used to generate daily weather variables. With the use of multiple weather years, the model will calculate one set of outcomes for each weather year. As a result, various statistical values can be calculated for each simulated variable, such as the mean and the standard deviation as well as the distribution in the form of percentiles or cumulative probability distributions. In addition, the biological outputs and management inputs can be combined with economic factors to determine the risk associated with the various management practices that are being evaluated (Gold et al., 1990; Jones, 1993; van Noordwijk et al., 1994; Lansigan et al., 1997; Selvarajan et al., 1997; Thornton and Wilkens, 1998).

#### 5.1.1. *Seasonal analysis*

In the seasonal analysis applications, a management decision is evaluated for a single season (Aubrey et al., 1998). This can include both crop and cultivar selection; plant density and spacing; planting date (Egli and Bruening, 1992); timing and amount of irrigation applications; timing, amount and type of fertilizer applications (Hodges, 1998); and other options that a particular model might have. Applications can also include investment decisions, such as those related to the purchase of irrigation systems (Boggess and Amerling, 1983). Thornton and Hoogenboom (1994) describe a special software program that was developed for seasonal analysis applications of the DSSAT crop simulation models (Tsuji et al., 1994), but can also be applied to outputs produced by other models.

#### 5.1.2. *Sequence analysis*

In the sequence or crop rotation analysis, one or more crop rotations can be analyzed. In this mode, different cropping sequences are simulated across multiple years (Plentinger and Penning de Vries, 1997). It is critical that, in a crop rotation analysis, the water, nitrogen, carbon and other soil balances are simulated as a continuum. The main goal of a cropping sequence application is to determine the long-term change of soil variables as a function of different crop rotation strategies (Bowen et al., 1993, 1998; Probert et al., 1995). Several models have been specifically developed to study the long-term dynamics of nitrogen and organic matter in the soil, such as the CENTURY model (Cole et al., 1993; Gijsman et al., 1996; Yiridoe et al., 1997). One of the disadvantages of these models is that they do not predict crop yield or predict yield using very simplistic methods. Other modeling systems, such as CropSyst (Stockle et al., 1994; Donatelli et al., 1997), Ecosys (Grant, 1997), and the Erosion Prediction Impact Calculator (EPIC) (Jones et al., 1991) were specially developed to study the long-term sustainability of cropping systems. Thornton et al. (1995) present a general sequence analysis tool for crop simulation models. It has been implemented in the DSSAT suite of models (Hoogenboom et al., 1994), but can also be applied to other modeling systems.

Weather again plays a key role as input for these long-term crop rotation and crop sequencing simulations. One can use a sequence of observed historical weather data to simulate a particular long-term crop rotation. This would be applicable for evaluating the performance of a modeling system with data from long-term crop rotation trials (McVoy et al., 1995). In this case, the weather conditions observed during these long-term crop rotation trials as well as the crop management scenario would be used as inputs for the crop rotation modeling study. However, this will allow for the simulation of only one weather sequence. To account for the interaction of weather with crop rotations and to evaluate different crop rotation management scenarios, it is not possible to use historical weather data as input. Instead, a weather generator has to be used and different weather sequences have to be generated, using a different ‘seed’ or random number to initiate the weather generator at the start of each sequence of weather years.

#### 5.1.3. Spatial analysis

One of the limitations of the current crop simulation models is that they can only simulate crop yield for a particular site for which both weather and soil data as well as crop management information is available. One recent advancement is the linkage of crop models with a Geographic Information System (GIS). A GIS is a spatial data base, in which the value of each attribute and its associated *x*- and *y*-coordinates are stored. It is not within the scope of this paper to discuss the various GIS and modeling approaches. The latest state-of-the-art of linkages between agricultural models and GIS can be found in Hartkamp et al. (1999). This approach has opened a whole new field of crop modeling applications at a spatial scale, from the field level for site-specific management (Han et al., 1995; Thornton et al., 1997a) to the regional level for productivity analysis and food security (Lal et al., 1993; Stoorvogel, 1995; Engel et al., 1997; Georgiev et al., 1998).

Weather and climate play an integral part in the spatial application of crop models. As weather is measured at a weather station, it represents ‘point’ information. One can assume that the weather data collected at this site are representative for either a small area, such as a field, or a larger area, such as a district or a province. However, the latter might not be a valid assumption. If weather data are observed at more than one weather station in the region, one can interpolate the weather data between the weather stations prior to the application (Carbone, 1993). The other option is to run the crop models for the various unique areas and interpolate the results after the simulation. An important concern is the simulation for areas for which no weather or long-term climate records exist (Hutchinson, 1991). The handling of ‘spatial’ weather data for modeling applications is an important issue that has not been resolved yet. Most of the studies that have been conducted so far have dealt with handling climate variability at a spatial scale and determining spatially-based input parameters for weather generators (Hutchinson, 1995; Guenni et al., 1996; Mackey et al., 1996; Guenni, 1997; Wilks, 1998).

### 5.2. Tactical applications

In tactical applications, the crop models are actually run prior to or during the growing season to help farmers, producers, and consultants make management decisions. One of the main objectives is to integrate the growth of a crop with the current observed weather conditions, and to decide on a daily basis as to which management decisions should be made. Although we know the weather conditions for the previous days, we do not really know what the future weather conditions will be like, except for predictions provided by the weather forecasts. We have to deal with this uncertainty of weather conditions in our modeling application as well. Therefore, for any crop model run, only the weather data up to the previous day will be available. If the weather forecasts are provided in some type of quantitative format, they can also be included with the simulation. There are various methods for handling the uncertainty of future weather conditions. The first one is to use historical weather data and to run the system for multiple years. Instead of historical weather data, generated data can also be used. If multiple years of historical or generated weather data are used as input, a mean and associated error variable can be determined for predicted yield as well as for other predicted variables. Over time, the error will become smaller, as the uncertain weather forecast data are being replaced with observed weather variables. If two or more management alternatives are being compared, one can evaluate the risk associated with each management decision, using both mean and error values of each predicted variable.

Most of the tactical decisions during the growing season are related to irrigation management and nitrogen fertilizer management, because of the limitations of the crop models discussed previously (Boggess and Ritchie, 1988; Scheierling et al., 1997; Smith, 1997). Boggess et al. (1983), Swaney et al. (1983) and Fortson et al. (1989) describe various applications related to irrigation scheduling during the growing season, using the soybean crop growth simulation model SOYGRO (Wilkerson et al., 1983; Hoogenboom et al., 1992). An irrigation example of the maize crop growth model CERES-Maize (Jones and Kiniry, 1986; Ritchie et al., 1998) is presented by Epperson et al. (1993). Unfortunately, these irrigation decisions were never applied by farmers. Abrecht and Robinson (1996) present an application for tactical decision making in wheat, using the wheat crop growth model CERES-Wheat (Ritchie et al., 1998).

#### *5.2.1. On-farm management*

One of the most successful applications of a crop simulation model for on-farm management, especially related to in-season and tactical decisions, is the GOSSYM–COMAX system (Boone et al., 1993; Reddy et al., 1997). GOSSYM is a dynamic crop simulation model for cotton, and COMAX is an expert shell that handles the interactions with the user. The GOSSYM–COMAX system was developed to aid cotton farmers with their irrigation and nitrogen management decisions (Usrey et al., 1994; Staggenborg et al., 1996; Stevens et al., 1996). Other options have since been added, such as the application of growth regulators (Reddy et al., 1995b). GLYCIM, a sister model of GOSSYM that simulates soybean growth and development, was also released for on-farm applications (Reddy et al., 1995a).

Cotton is a high cash crop that requires many inputs during the growing season. Therefore, optimizing the crop inputs, using either crop simulation models, expert systems, or other decision support systems, can significantly benefit a farmer. Many other crops, especially those grown under rainfed conditions, require hardly any inputs during the growing season. Therefore, the application of crop simulation models as a tactical management tool does not provide much benefit for farmers, except for possibly the management of pests and diseases. Unfortunately, the transfer of the GOSSYM–COMAX technology to the private sector was not successful, although most of the farmers who ran the system seemed to have learned from their use and application on their farm. In general, farmers do not want to pay for weather-related services, including the access and use of crop simulation models.

In the area of pest and disease management, especially integrated pest management (IPM), the application of models has been shown to be very profitable. Most IPM models do not include a crop model component that predicts yield and they are, therefore, not considered crop simulation models. However, in many cases, they include degree day calculators to determine the actual stage of a crop (Pusey, 1997). As the application of pesticides is rather expensive, farmers are interested in minimizing the application of pesticides, both from an economic viewpoint as well as from an environmental viewpoint. In the early 1980s, a system to spray for pests and diseases in winter wheat was developed in The Netherlands (Rabbinge and Carter, 1984; Zadoks et al., 1984). This system, called EPIPRE, was extended to other countries in Europe, although there was a significant difference in climatic conditions between these countries (Zadoks, 1989). Unfortunately, the discussion of successful IPM models for on-farm management is beyond the scope of this paper (Coulson, 1992; Berry, 1995; Ende et al., 1996; Rabbinge and van Oijen, 1997).

The United Soybean Board (USB), an American farmers' organization responsible for managing soybean checkoff funds, recently sponsored a project for the development of a soybean decision support system for on-farm applications, based on the CROPGRO-Soybean model (Boote et al., 1997). PCYield is a tactical management decision tool that allows a farmer to make irrigation decisions and provides an expected yield (Jacobson et al., 1997). It requires current weather data from either a soybean field or farm as input and uses 10 years of historical weather data from a local weather station for the remainder of the growing season. A private company has shown interest in PCYield. During the 1997 and 1998 growing season, it conducted preliminary evaluations with various soybean producers. Based on the interest shown by farmers, a PCYield for maize based on the CERES-Maize model (Ritchie et al., 1998) has been developed and extension of PCYield for other crops is currently being discussed. One of the main advantages of this company is that it can provide local weather data via one of its subsidiaries, Weather Services International (WSI). WSI is one of the main commercial weather data suppliers in the US. It has developed a technology that allows it to provide daily weather data at a 2 km grid level for the entire US. Both the weather data as well as the simulations are delivered via the Internet. It is expected that delivery of weather data via the world wide web as well as the operation of simulation models via the world wide web will be new agrotechnologies for the near future (Georgiev and Hoogenboom, 1998, 1999).

### *5.3. Forecasting applications*

The application of crop simulation for forecasting and yield prediction is very similar to the tactical applications discussed previously. However, in the tactical decision application, a farmer or consultant is mainly concerned about the management decisions that are made during the growing season. In the forecasting application of the crop models, the main interest is in the final yield and other variables predicted at the end of the season. Most of the national agricultural statistics services provide regular updates during the growing season of total acreage planted for each crop as well as the expected yield levels. Based on the expected yield, the price of grain can vary significantly. It is important for companies to have a clear understanding of the market price so that they can minimize the cost of their inputs. Traditionally, many of the yield forecasts were based on a combination of scouting reports as well as statistical techniques. However, it seems that crop simulation models can play a critical role in crop yield forecasting applications if accurate weather information is available, both with respect to observed conditions as well as weather forecasts (Nichols, 1991; Abawi et al., 1995).

The weather data for yield forecasting applications is handled in a manner very similar to the one for the weather data for tactical decision making applications. During the actual growing season, the current weather data up to the previous day are used as input. For the remainder of the season, either historical weather data or generated weather data are used (Duchon, 1986). In some cases, some type of short-term or long-term weather forecast might be available, which can be used to modify the weather data inputs to represent future conditions. Most weather forecasts are available in a qualitative format, and the crop models actually require weather inputs in a quantitative format. More work will be needed to transform the weather forecasts, both short-term and long-term forecasts, into a format that can be used by crop simulation models.

One of the most recent applications of models for yield prediction is for the Famine Early Warning System (FEWS). FEWS is currently being implemented for Africa, especially the drought prone areas in the Sudan-Sahelian countries. Thornton et al. (1997b) describe a prototype application to predict yield for millet production in Burkina Faso, using the CERES-Millet model. Due to the lack of current weather data, especially precipitation, decadal data had to be transformed into daily rainfall data. Most of the research related to the prediction of food security has concentrated on improving the local weather forecasts (LeComte, 1994). However, it will be important to link the crop simulation models to the local short- and long-term weather forecasts. This will improve the yield predictions and provide policy makers with advanced yield information to help manage expected famines and other associated problems.

The Department of Science and Technology (1990) in India has developed a very strong program in medium-range weather forecasting and agrometeorological services. It currently is in the process of linking the medium-range weather forecasts with crop simulation models. It is expected that the Center for Medium-Range Weather Forecasting will be able to provide crop model-based yield forecasts and recommendations that can be used by local extension personnel and farmers (Gadgil et al., 1995).

#### 5.3.1. Remote sensing

Accurate application of crop simulation models requires, in many cases, some type of evaluation of the model with locally collected data. Especially for yield forecasting, it is critical that yields are predicted accurately, as policy decisions related to the purchase of food could be based on the outcome of these predictions. One option is to use remotely sensed data, that are being used to estimate yield, based on a greenness index (Smith et al., 1995). A more advanced application would be to link physical remote-sensing models with crop simulation models (Bouman, 1992). With this approach, the simulated biomass can be adjusted during the growing season, based on remotely sensed or satellite data, and yield predictions can be improved based on these adjusted biomass values (Bouman, 1992, 1995; Maas, 1993; Baumgardner, 1994). One of the limitations of this linkage is that simulations are point-based applications, while remotely-sensed data are spatially based (Guerif and Duke, 1998). This problem is similar to the spatial applications of the crop models discussed earlier. There still seems to be a gap in collaboration between crop modelers and scientists with expertise in remote sensing (Moran et al., 1995; Carbone et al., 1996). For future applications in yield forecasting, it will be critical that the weather forecasts, remotely sensed information, and the crop simulation models are closely integrated in effective forecasting tools for yield prediction, famine early warning and other potential food disasters.

## 6. Climate change and climate variability

The variability of our climate and especially the associated weather extremes is currently one of the concerns of the scientific as well as the general community (Climate Research Committee, 1995). The application of crop models to study the potential impact of climate change and climate variability provides a direct link between models, agrometeorology and the concerns of society. Early reports related to the impact of climate change used surveys of climatologists and agricultural scientists (National Defense University, 1978). As climate change deals with future issues, the use of general circulation models (GCMs) and crop simulation models provides a more scientific approach to study the impact of climate change on agricultural production and world food security compared to surveys (Curry et al., 1990a; Kaiser and Drennen, 1993; Matthews et al., 1995; Rosenzweig et al., 1995; Downing, 1996; Goudriaan, 1996). Similarly, the issue of climate variability, especially related to the variation in sea surface temperature (SST) of the Pacific Ocean or El Niño/Southern Oscillation (ENSO), has opened an area where crop simulation models also can play an important role. They can potentially be used to help determine the impact on agricultural production due to ENSO and recommend alternative management scenarios for farmers that might be affected, thereby mitigating the expected impact of ENSO.

### 6.1. Climate change applications

The early generation of crop simulation models were not intended for use in climate change applications. One of the main reasons is that most models did not respond to changes in the carbon dioxide concentration of the atmosphere. The models were also developed to only simulate the effect of weather conditions similar to the local environments where they were originally evaluated. As a result, many of the relationships incorporated in the models could not handle any temperature extremes, either high or low temperatures, which were being predicted by the climate change scenarios. Modifications, therefore, were made in various models, such as EPIC (Stockle et al., 1992b) and the CERES-Maize and SOYGRO models (Peart et al., 1988). A special DSSAT was developed to handle issues related to climate change (Hoogenboom et al., 1995). More research is still needed to evaluate the performance of the models for these types of conditions. Very limited information is available with respect to modeling the impact of climate change on pests, diseases and weeds (Goudriaan and Zadoks, 1995).

In most climate change applications, long-term historical weather data are used as input for the crop models. In general, at least 30 years of historical weather data are preferred to represent annual weather variability; different climate change scenarios can then be applied to these data records. The simplest approach is to assume a fixed climate change and to modify the data with a constant number, such as an increase or decrease of 1, 2, 3°C etc. for temperature. Similarly, rainfall and solar radiation can be changed with a certain percentage, such as an increase or decrease of 10, 20, 30% etc. These changes are then applied to the daily weather data and the crop simulation models are run with these modified inputs. A more realistic approach is to use the outputs from the GCMs to modify the historical weather data (Robock et al., 1993). The predictions of the GCMs in general can represent both current and future climate conditions as well as the expected climate change. The GCM predictions normally only provide monthly changes, which are in absolute terms for temperature and in relative terms for solar radiation and precipitation. These GCM predictions are again applied to the historical weather data and the modified historical weather data are used as input for the crop simulation models (Curry et al., 1990b; Mearns et al., 1992). The models can then be run, using various climate change scenarios. These include the standard historical weather data, the standard historical weather data and a doubling of the $CO_2$ concentration, GCM-modified historical weather data, and the GCM-modified historical weather data and a doubling of the $CO_2$ concentration. In addition, different GCM scenarios can be created with different GCMs (ANL, 1994). Some recent applications include the use of weather generators, rather than using historical weather data, to generate climate change scenarios (Riha et al., 1996; Mearns et al., 1997). In this case, one can account for both the mean change as well as the change in variability. The latter might especially be critical with respect to precipitation.

There are various issues related to the climate change scenarios, predicted by the GCMs, and the actual implementation in crop simulation models. There are several GCMs, developed by different climate groups in various countries, and some models have different versions, based on when they were released. Unfortunately, each climate model predicts a different climate change scenario. Several GCM models do not predict the local climate very well, so some type of GCM model evaluation is needed with local climate data (Mearns et al., 1995b; Alexandrov et al., 1999). Another concern is that the spatial scale of most GCMs is rather large. In some cases, the scale of one climate or grid cell might cover more than one political or climatic district or region. As a result, the same climate change scenario has to be applied to weather data, collected at weather stations that are located at different sites (Bardossy, 1997). This makes it especially difficult to predict the impact of climate change at a regional level, unless some major assumptions are made. Another problem is that the GCMs provide a monthly climate change prediction. As the crop models operate with daily weather data inputs, the monthly change needs to be interpolated over time to be able to apply the climate change scenario from the GCM towards the daily weather data required for the crop models. One final issue relates to the change in rainfall patterns and rainfall frequency that could occur because of climate change (Mearns et al., 1995a). This can especially be important in the arid and semi-arid tropics, where most production is water-limited (Sivakumar, 1992). The current GCMs only predict a change in rainfall amount and not in rainfall distribution, such as the start of the rainy season, the end of the rainy season, and the distribution of wet and dry spells.

One of the first projects to study climate change and its potential impact in the US was sponsored by the United States Environmental Protection Agency (Smith and Tirpak, 1989; Adams et al., 1990). This project was later expanded to study the impact of climate change at a global level (Rosenzweig and Parry, 1994; Rosenzweig et al., 1995). Both projects used the DSSAT suite of crop models. They were also used in the PAN-EARTH project, which studied the impact of climate change in developing countries (Harwell, 1993). The EPIC model was used extensively to study the impact of climate change on agricultural production in the Missouri–Iowa–Nebraska–Kansas (MINK) region (Stockle et al., 1992a; Easterling III et al., 1993; Rosenberg, 1993). One of the most recent studies is the United States Country Studies Program, which includes assessments of vulnerability to climate change and options for adaptation, especially for those countries that are the most vulnerable to the potential impact of climate change (Sathaye et al., 1997).

It is impossible to provide a comprehensive review of all studies associated with climate change and the potential impact on agricultural production and food security. Unfortunately, most of the results of these studies are not conclusive. On account of the interaction of temperature, precipitation and $CO_2$ on plant growth and development, yield predictions differ depending on the GCM climate change prediction, local climate at a site, and the management scenario applied. It is expected that developing countries will be impacted the most, mainly due to the lack of adequate financial resources needed to adapt the management scenarios of local farmers.

### *6.2. Climate variability and El Niño applications*

The connection of the Southern Oscillation episodes with El Niño was not identified until the late 1960s (Rasmusson and Wallace, 1983). Most of the applications of crop simulation models towards the impact of ENSO on agricultural production have been conducted in Australia (Rimmington and Nicholls, 1993; Hammer et al., 1996; Meinke and Hammer, 1997) and Zimbabwe (Cane et al., 1994; Philips et al., 1998). It is expected that the potential impact of El Nino in other regions will be studied in the near future, especially for the most vulnerable countries. There are many opportunities for potentially successful application of the crop models, because a possible occurrence of an ENSO event can be predicted at least 6 months in advance. The crop models can be run, using historical weather years that are representative for ENSO events. Alternative management scenarios can be evaluated with the models to identify those scenarios that can reduce the potential impact (Frenken et al., 1993; Iglesias et al., 1996). The optimum scenarios can then be presented to farmers to provide them with various options to adapt their crop management regime for the current growing season.

System for Analysis, Research and Training (START) has been very active in studying the impact of climate variability on agricultural productivity and food security in the tropics. Most countries in the tropics are very vulnerable, due to the strong correlation between weather conditions and agricultural production. Manton et al. (1997) and Sivakumar (1997) recommended various applications of crop simulation models to study the impact of climate variability on crop productivity in the Asian Monsoon region and tropical Sub-Saharan Africa. Gadgil et al. (1999a, b) presented an example for India, using the peanut model PNUTGRO. It will be important to develop forecasting systems for these regions that link climate models and crop simulation models and to provide products that can be used by both farmers and policy makers to help reduce the expected impact. This concept of linking crop simulation models and weather forecast products is very similar to the system discussed previously for famine early warning.

## 7. Future issues

The application of crop simulation models has become more acceptable in the agricultural community during the last few years. For any application of a crop model, weather data is one of the key inputs. It will be critical that weather data continue to be collected for all regions where agricultural production is an economic source of income. To account for spatial weather and climate variability, denser weather station networks might be needed. It will also be important that data are collected at daily intervals, but preferably more frequently, and that at least the primary set of variables needed for crop modeling are included. As automated weather stations are becoming more common in both developed and developing countries, it will be crucial that standards are developed for weather station equipment and sensors, installation, and maintenance. It will also be important that a uniform file format is defined for storage and distribution of weather data, so that they can easily be exchanged between agrometeorologists, crop modelers, and others using the crop simulation models. Easy access to weather data, preferably through the Internet and the world wide web, will be critical for the application of crop models for yield forecasting and tactical decision making. For large area and regional yield predictions, the issues of weather data interpolation and data gaps need to be addressed.

It seems that there have been no significant advances in the development of new crop simulation models during the last decade. Instead, crop models have been evaluated and applied for a wide range of environmental conditions and management scenarios, including issues related to climate change and variability. Existing crop models are being improved, but at a slow pace. More efforts are needed to improve the current crop models and add the simulation of processes that are important for agricultural practices in both developed and developing countries. Although most models have been developed for only one or two specific applications, it will be critical for modeling groups to collaborate, given the limited amount of resources available for model improvement. An open source code policy and easy exchange of crop models and modules will aid in the overall improvement of the models.

There still seems to be a large gap between the products, generated by crop simulation models and decision support systems, and the application of these products by potential users. These users can range from farmers, consultants, extensionists to local, regional or national policy and decision makers. Although some models might continue to operate for research purposes only, it is important that models become a more effective decision support tool. Therefore, a concerted effort is needed to narrow the gap between the researchers and those who work directly with farmers, consultants and others associated with agribusiness. Private industry can possibly play a partial role in this venture. At the same time, it is of crucial importance that the models maintain their credibility. One or two bad examples or case studies will negatively impact any potential for future applications of the crop models.

The distribution and maintenance of crop modeling products for on-farm applications should be handled by the private sector in order for it to be economically sustainable. However, it is critical that researchers are involved in the development of modeling concepts as well as the evaluation of their models and decision support systems for on-farm applications. The most successful applications might be those in which the actual models reside with researchers, and the application shell or product resides with the private sector.

Crop simulation models will never be a substitute for experimental data collection. Field data continue to be needed for model evaluation as well as for improvement of the models. However, as our society becomes more computerized, there will be more scope for the application of crop simulation models to help provide guidance in solving real-world problems related to agricultural sustainability, food security, the use of natural resources and protection of the environment. Agrometeorology will be a critical component of all these applications to help understand the impact of weather variability and the uncertainty of future weather conditions.

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