Modeling Agroclimatic Systems: Guidelines and Perspectives

J.L. Steiner[1]

Abstract

Agroclimatic models offer many potential benefits including reduction of site-specific field experimentation, better interpretation of climatic limitations to crop production, evaluation of risks and benefits of proposed management practices, communication of research results, and enhanced understanding of biological and physical systems. To date, model development has far exceeded validation and implementation. Crop models range from simple, statistical models through complex, process-oriented models. Data required to support development and validation of these models are quite different, as are the potential applications. Simple models require large data sets for development and cannot be transferred outside the region for which they were developed, but utilize easily available data for implementation. Development of complex models contributes to scientific understanding and offers the potential for a wide range of applications, but requires detailed information. Intermediate level models have more manageable data requirements than the complex models and offer a greater level of transferability than simpler models, so are most promising for use in developing countries. Regardless of the complexity of the model, and regardless of whether existing models are utilized or a new model is developed, a successful modeling application must be carried out as a part of a broad approach to problem solving, which includes a clear statement of achievable goals, explicit statement of assumptions and hypotheses based on project will be conducted, careful formulation of the assumption and hypotheses into mathematical-based computer code, critical evaluation of the model outputs including validation, using independent data sets, and communication of results to the end user in a useful form.

Résumé

Modélisation des systèmes agroclimatiques—lignes directrices et perspectives : *Les modèles agroclimatiques présentent divers avantages potentiels et, entre autres, permettent de réduire l'expérimentation au champ, d'interpréter mieux les contraintes climatiques à la production, d'évaluer les risques et les avantages de pratiques d'aménagement, de mieux communiquer les résultats de recherche et d'améliorer la compréhension des systèmes biologiques et physiques. A ce jour, le développement de modèles est de loin en avance sur leur adoption et leur mise en place. La gamme va des simples modèles statistiques à ceux plus complexes et déterministes. Les données nécessaires pour développer et installer ces modèles sont bien différentes, tout comme les applications potentielles. Les modèles simples exigent beaucoup de données pour être développés et ne sont pas transférables en dehors de la région pour laquelle ils ont été générés, par contre leur mise en place requiert des données facilement accessibles.*

Le développement de modèles complexes contribue à la compréhension scientifique et offre le

1. Soil Scientist, USDA-ARS, Conservation and Production Research Laboratory, P.O. Drawer 10, Bushland, TX 79012, USA.

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potentiel d'une large gamme d'applications; leur exigence en informations précises est par contre élevée. Les modèles intermédiaires ont des exigences en données plus faciles à gérer que bien des modèles complexes, leur degré de transférabilité est supérieur à celui des modèles plus simples et par là, ils sont plus prometteurs pour les pays en voie de développement.

Indépendamment de la complexité du modèle et du fait que certains modèles existants soient utilisés ou qu'un nouveau modèle soit développé, une bonne application doit être réalisée comme un maillon d'une approche large tendant à résoudre des problèmes. Cela inclut une définition claire des objectifs à atteindre, des estimations et hypothèses qui sous-tendent le projet, une formulation attentive de ces estimations et hypothèses en code mathématique pour ordinateur. On procédera à une évaluation critique des retombées du modèle en utilisant la mise en place à l'aide de données indépendantes et la communication des résultats à l'utilisateur final sous une forme exploitable.

Introduction

The use of agroclimatic models has increased in the past several years to the extent that hundreds of agricultural models are now documented in scientific literature (e.g., France and Thornley 1984). Ambitious goals have been set in many of these modeling efforts, but researchers, as a community, are just beginning to deal seriously with the problems of how to apply models to meet specific goals and objectives in agricultural research, production, and management. The resources being devoted to model development far outweigh those being devoted to model evaluation or to model implementation, and the time has come for scientists in the agricultural research community to set clear and realistic goals for future modeling efforts.

Why Use Models?

The attractions of agroclimatic models are obvious as we deal with the complexities of cropping systems. While the suitability of current models for dealing with these complexities is not always clear, it is not possible to absorb and interrelate all the necessary factors to describe an agricultural system without the use of some type of model. Currently available models can offer the following benefits:

- reduction of site-specific, long-term field experiments;
- interpretation of climatological records in terms of production potential and limitations;
- evaluation of expected returns to soil- and crop-management practices;
- evaluation of risks associated with management practices;
- communication of research results between locations;
- enhanced understanding of biological and physical systems and their interactions; and
- conceptualization of multidisciplinary activities.

These factors are essential to improve the effectiveness of our research efforts, whether it be in a high-input or a low-input agricultural system. Evaluating the array of published models to determine the suitability of specific models to specific problems is a very complex process . The objective of this paper is to put forth some observations and suggestions on model evaluations and applications to agroclimatic systems.

Agroclimatic Models

Agroclimatic models can be described at three general levels:

1. Simple, statistical models.
2. Intermediate, crop growth models.
3. Complex, process-oriented models.

Characteristics of these types of models as summarized by Norman (1981) and Stapper (1986) are shown in Figure 1. The data required to support development and utilization of these models are very different, as are the applications that can be made of the models after they have been developed and validated.

Simple Models

Simple, statistical models are primarily based on regression analysis and empirical relationships. They require a large data set to develop and cannot

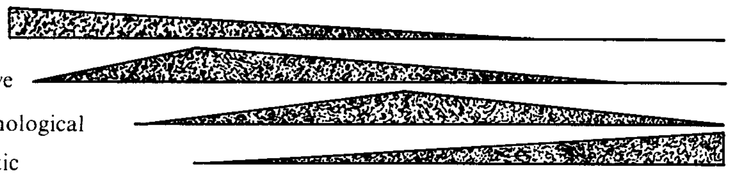
	Simple	Intermediate	Complex
Category	Emperical Crop weather	Crop growth Crop systems	Crop process
Type	Statistical static ⟶		Mechanistic dynamic
Relationships	Empirical Correlative Phenomenological Mechanistic 		
Scale	Regional	Field	m2 -> Leaf
Time step	Seasonal	Daily	Hourly
Use	Operational	Operational/Research	Research
Character	Requires data from many years to derive parameters to estimate yield	Limited scope (yield, water use, growth stage, leaf area, etc.)	Broad scope (yield, ET. soil evaporation, canopy temperature, dew, canopy profiles, soil and canopy fluxes, stomatal behavior, etc.)
	Rely on plant being good integrator of environmental effects in time and space		Integration over time and space explicit

Figure 1. Characteristics of crop models of different levels of complexity.

be applied to simulations outside the region from which they were developed. An example of a simple regression model is given in Figure 2. Jones and Hauser (1975) developed a statistical model to describe sorghum yield as a function of available soil water at planting. They used data collected over a 14-year period for model development and it is doubtful if a more complex type of model could predict yields better for the research station at Bushland, Texas, where the data used to develop the model were collected. The grain sorghum yield at Bushland is strongly related to soil water stored in the profile at planting, and assuming that average rainfall and temperature conditions prevail during the growing season, the soil water at planting is a good predictor of yield.

Figure 3 shows the performance of the simple regression model from Figure 1 in predicting the yield of grain sorghum at Bushland using data from experiments that were not used to develop the original model. Many of the data sets are distributed around the 1:1 line, with a similar amount of scatter as was seen in the original data set. However, sorghum grown during a high-rainfall season (represented by the ● symbol) yielded much more grain than would have been predicted by the model. In addition, the model cannot be used to predict yields for other locations, even those fairly close to Bushland, because all the data used to fit the model were collected at a single location. Bushland is located in a region of pronounced rainfall gradients (60 mm a^{-1} for each 100 km in the EW direction) and temperature gradients in the NW to SE direction (first and last frost dates are particularly important). Therefore, a simple empirical model, dependent on average conditions across the range of data used to fit the model would not provide valid predictions for other locations. Regression models work when average conditions prevail but fall apart during unusual growing seasons. However, it is during the unusual seasons that predictions of crop performance are needed

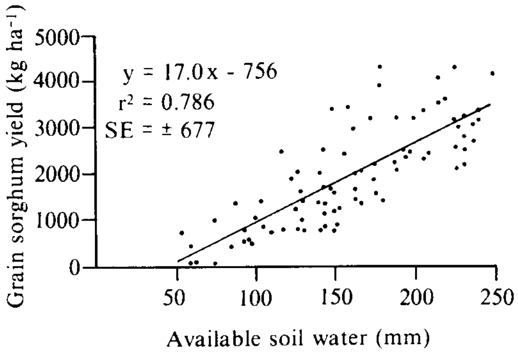


Figure 2. A simple regression model describing grain sorghum yield as a function of soil water at planting. Bushland, Texas, 1959-1972 (Jones and Hauser 1975).

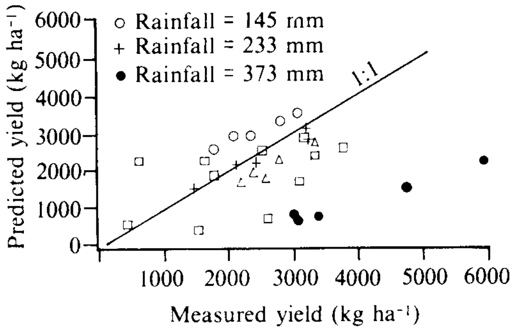


Figure 3. Evaluation of the Jones and Hauser model (Fig. 2) for predicting sorghum yields at Bushland, Texas. Data from (□) O.R. Jones, personal communication, 1973-84; (△) Unger 1984; and (•, +, O) Unger 1978 (1974, 1975, and 1976 data).

most. Thus, the use of these types of models is limited and often not practical.

Many simple crop models were developed for much broader applications than the Jones and Hauser (1975) model discussed above for illustration purposes. A useful discussion on the development of an empirical crop-weather model is given by Feyerherm and Paulsen (1986). Slabbers et al. (1979) have discussed the potential applications and evaluation of simple crop models.

Intermediate Level Models

Intermediate level models utilize descriptions of distinct processes such as photosynthesis and transpiration, which are known to be important in controlling crop growth. They generally operate on a daily time scale, because of the availability of daily climatic input data and because the knowledge of the biological and physiological processes on a shorter time scale is not adequately understood. Calculations are often made on the basis of a single plant or land area and then converted to the field level, assuming uniform soil and plant conditions across the field.

Daily growth is usually calculated in one of two ways—either the model calculates a daily net photosynthate production based on daily interception of solar radiation (e.g., Arkin et al. 1976, Charles-Edwards 1982, pp. 82-85, Gallagher and Biscoe 1978), or the model calculates photosynthesis and respiration separately, based on solar radiation and temperature, and determines net photosynthesis as the difference of the two (e.g., Baker et al. 1983, Goudriaan 1982).

Daily evapotranspiration is calculated as a function of the potential evapotranspiration (PET), crop canopy, and soil-moisture level. One of the most utilized approaches to the calculation of evapotranspiration is based on Ritchie's (1972) model, which partitions PET to crop and soil surfaces on the basis of leaf area index (LAI). Transpiration and evaporation are then calculated separately, because they are affected by different physical and physiological processes. PET rates are most often calculated by the Penman (1948) method, the Priestley and Taylor (1972) method, or using pan evaporation rates.

Crop phenology is calculated as a function of temperature or thermal units. The partitioning of dry matter is dependent on crop growth stage and is generally estimated from empirical relationships. Stress effects that are most often included in crop growth models are water stress, nitrogen stress, and, less frequently, phophorus stress. The effects of water stress on various plant processes are calculated by empirical methods, generally based on soil-water content and sometimes on PET rate. Interactions among stresses are seldom considered.

Figure 4 illustrates the application of an intermediate level model, SORGF (Arkin et al. 1976), to determine the probability of grain sorghum

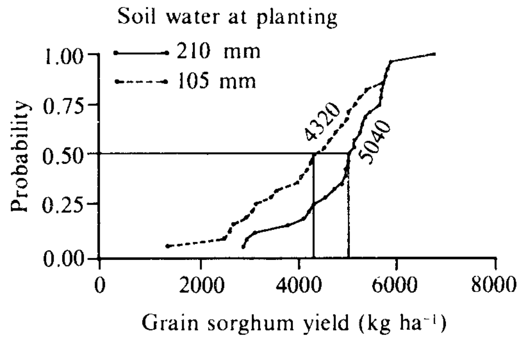


Figure 4. Use of an intermediate level model, SORGF (Arkin et al. 1976), to evaluate the effect of soil water at planting on grain sorghum yield. Bushland, Texas, 1958–1984, Pullman clay loam.

yield with high or low soil-water content at planting at Bushland, Texas. The graph illustrates predicted yields for a 26-year period, assuming high (210 mm) or low (105 mm) available soil water at the end of the fallow period, prior to planting grain sorghum. The predicted yields for each case (high or low soil water content) were ranked and plotted to illustrate the probability of obtaining yields as great as at a certain level. The graph shows that 80% of the time, the extra soil-water content made a substantial contribution to the yield level. At the 50% probability level, the high soil-water regime produced yield predictions of less than 4300 kg^{-1}, and the low soil water regime produced yield predictions of less than 5000 kg ha^{-1}. These yields are too high for the Bushland area compared to those in Figure 2. The reasons for yield overpredictions are not yet understood, but the principle of the response to soil water is valid. Under lower soil-water regimes (e.g., different soils or annual cropping), the two curves would come together in the driest 10–20% of the years, as well as in the wettest years because the rainfall would not provide adequate water to produce a crop without a contribution from stored soil water.

De Wit and Penning de Vries (1985) present a good overview of a hierarchy of models with increasingly complex models used when more limiting factors of production are considered—from light interception and temperature to water, nitrogen, phosphorus, and other minerals. Each level of model incorporates concepts from the previous level of model and includes additional production-controlling processes.

Intermediate level models span research and operational applications. They allow researchers to interrelate knowledge from different disciplines. They have contributed considerably to the advancements of science by drawing attention of the scientists to description of processes and mechanisms, and to quantitative rather than qualitative descriptions of relationships. The data requirements are generally available, but an expert must oversee compilation of data sets to ensure high quality data. It is important to remember that there are still many empiricisms built into most of these models and few of them have been rigorously tested and validated. Norman (1981) illustrated that intermediate level models have a tendency to produce large errors.

Complex Models

Complex models have not yet reached the point of general availability. Each model is generally linked to a specific researcher or research group. The goal of this type of model is to eliminate empiricism from the model; to describe the plant canopy in physical, biological, and physiological terms. When this type of model has been developed and validated, it is extremely flexible in potential applications. Norman has applied the CUPID model to such diverse applications as analysis of canopy temperature (Norman 1979), leaf wetness (Norman and Campell 1983), and microclimate and pest management (Norman 1982). The input requirements for complex models are quite extensive, including detailed hourly climatic data, soil and plant reflectance properties, leaf size, leaf angle distribution, root distribution, plant and canopy resistances, etc.

Complex models incorporate existing knowledge about crop production systems, and contribute to the advancement of the agricultural sciences by narrowing down gaps in the existing knowledge. Use of complex models requires an active and well-supported research program to allow investigation of relationships and processes that are not well understood. They are not used in operational programs at this time because the data required to support complex models are not generally available.

Expert Systems

In future, many modeling applications will utilize 'expert systems,' which incorporate existing knowledge into computer-based systems, organized to aid in decision making (Grable, In press). Computer hardware and software are being developed, which will establish decision-making processes patterned after the human decision-making processes. The computer will make many of the 'trial and error' iterations involved in decision making, utilizing encoded rules, data bases, and user interface systems (Barrett et al. 1985). Expert systems provide a way of 'packaging' models that make them easily accessible to users and easy to interpret. The models embedded in current expert systems are generally sophisticated, intermediate-level models. An expert system, COMAX (Cotton Management expert), is currently being tested by cotton growers in the southeastern United States to aid in making management decisions, relating to in-season fertilizer application, irrigation, harvest date, and other factors (Agricultural Research Service 1986). COMAX incorporates a crop growth model called GOSSYM (Baker et al. 1983); user interface programs and built-in data bases differentiate between the 'model' and the 'expert system' that was developed specifically as a decision-making tool for farm managers.

Systems Analysis

For any modeling effort to be successful, it must be undertaken as a part of a project that has specific and achievable objectives. A model should be viewed as a tool used to achieve a goal, rather than as an achievement by itself. The overall process of solving problems by the use of a model will be described in this paper as 'systems analysis'. The essential components of systems analysis are outlined in Figure 5. As is indicated, systems analysis is an iterative procedure—the results of each effort are used to refine and improve previous steps until a satisfactory level of performance 'as initially defined by the project team' is achieved.

Setting Simulation Project Objectives

A crucial step in the problem-solving process is the statement of clear, obtainable goals.

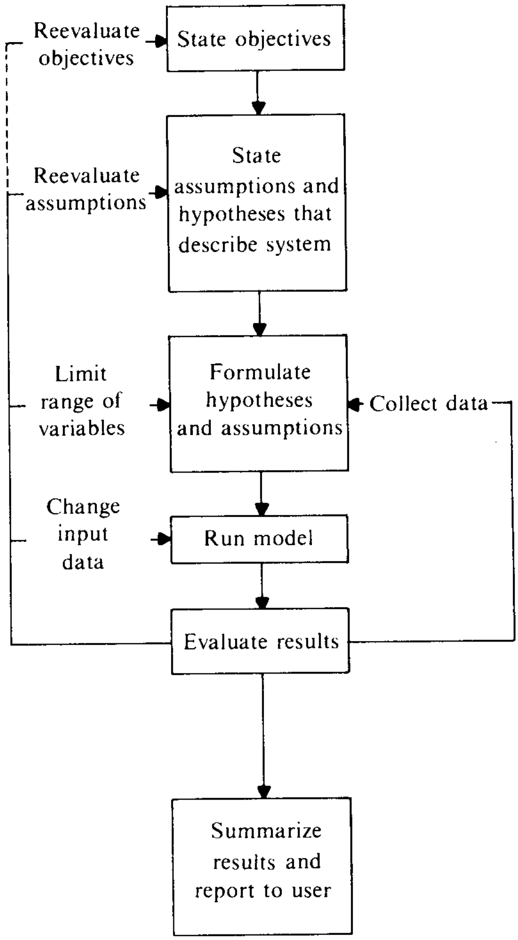


Figure 5. Schematic diagram of systems analysis including model development.

A group that sets a goal to 'stop soil erosion' or to 'end world hunger' will not achieve those goals in the foreseeable future. Instead their efforts might become so diffuse and the possibility of achieving their goal so hopeless that very little will actually be accomplished. Several components are necessary for goal setting. First, it is necessary to identify and then maintain active, two-way communication with the end user throughout the project. A model written to provide information about maize yields to a national agricultural ministry will be very different from a model which is written to provide information to a farmer. It is important to be realistic in evaluating available resources including people, money, data, and facilities, and to specify a time frame for the completion of various stages of the project. An additional factor that is often omitted is the specification of required performance levels of the model and the evaluation techniques. An example of this might be that the model should be able to predict regional maize yields to the Agricultural Ministry within 25% of actual yields, 9 years out of 10, with a lead time of four weeks before harvest begins. If the goals are set keeping these criteria in mind, then the modeling group will be able to determine when they have met their goals and finished the project.

This goal-setting step should include the active participation of the end user, i.e., the research team that will be putting the model together, and the administrative hierarchy which will be overseeing the project.

State Hypotheses and Assumptions

Once the objectives of the project are stated, then the process of trying to accomplish those goals can begin. At this point, the hypotheses and assumptions under which the team will be working should be clearly stated. In order to do this in a manner that will lead naturally into a modeling effort, the problem should be broken down into manageable subunits. The assumptions and hypotheses associated with each subunit must first be set out in specific and quantifiable statements, and then interactions among the various subunits must be defined. Rather than stating that 'growth is related to water use of plant', a more usable hypothesis would be that 'the daily dry-matter production of the crop decreases from some upper limit as transpiration for the plant on that day'. McKinion and Baker (1982) listed important hypotheses and assumptions that were identified and then incorporated into a cotton growth model.

As was the case in setting the overall objectives of the project, active participation at all levels from administrative through scientific to user levels is necessary to adequately define the assumptions and hypotheses under which the project will be conducted.

Formulate Hypotheses and Assumptions

Formulation of hypotheses is the process of expressing ideas stated verbally in a mathematical form. The process of formulating hypotheses and assumptions associated with the project may be quite time consuming. However, a logical sequence of steps should be followed just as in the previous phases. The first step is to graph the interesting relationships using existing data or knowledge. Locating and evaluating the usefulness of available data requires considerable knowledge of the subject matter. After looking at the data in a graphical form, each hypothesis should be rewritten in an appropriate numerical form that describes the shape of the curve indicated by the points on the graph and the equations solved to obtain the coefficients associated with each equation (Ross 1981). In many cases, the dependent variable (unknown) of one equation will be used as the independent variable (known) of another equation. There are many statistical hazards associated with this procedure, but they are unavoidable in many types of model building. Consultation with a statistician at this point may produce a more valid and stable model (Chanter 1981). Equations must then be translated into computer code for solution.

This step of the systems analysis process differs from the other steps in that it must be conducted by people with specific scientific, technical, mathematical, statistical, and/or computing skills. If the team responsible for conducting the project is lacking in some of these skills, it can reasonably seek assistance from persons who have the necessary expertise (i.e., mathematicans, statisticians, systems analysts), and who have not been involved in setting the overall goals and defining the hypotheses and assumptions of the project. However, it is essential that at least one person be reasonably familiar with all levels of the project, including the system being modeled, the data sets available for model building, and the basic formulation procedures.

Make a Run of the Model

Initial runs of the model should be made at a fairly early stage to evaluate the reasonableness of the overall approach taken and to identify areas that require or would respond most to additional efforts. To make a run of the model, someone who knows the system well must assign initial values to variables and assign values to the identified constant. Scientists who have been involved in the formulation of the model and end users of the model are likely to provide the most reasonable initial input values.

Evaluate Model Output

Once the earliest output of the model is obtained, the process of improvement and refinement begins. The first step, commonly referred to as 'debugging' involves checking that the computer code is working on the calculations which the programmers intended it to work on according to the hypotheses outlined by the project team. The next step is to verify that the results of the simulation make sense according to existing knowledge about the system, e.g., that predicted yields fall within a reasonable biological range or increase with increasing water or nutrient availability. It is likely that several iterative steps will be required before a reasonable prediction is made by the model. If the results of the simulation do not appear reasonable, there are several possible options. Sets of initial values for variables and constants can be tried to best describe the conditions of simulation. If no set produces a reasonable result, then the formulation of the project hypotheses should be examined. Perhaps inappropriate equation forms were used to describe the data. Some of the variables may need to be limited to a specific range of values (e.g., $0.0 < x < 1.0$) so that an equation may make physical or biological sense. Inadequate data may have been used to describe the process of interest. Field or controlled-environment experiments may have to be designed to collect the necessary data to describe certain relationships needed in the model.

The model predictions should be compared to independent field data to validate the predictions. A sensitivity analysis should be made to determine the degree of accuracy necessary in the input variables. If change in an input variable results in large changes in the model prediction, then that variable must be measured accurately. In models with many subroutines, each important relationship may need to be validated separately so that the model may reasonably predict the performance of the crucial processes.

If all the relationships taken separately seem reasonable, and the model still fails to produce reasonable results, the hypotheses and assumptions under which the project is being conducted, or even the overall objectives of the project, should be reexamined and restated if necessary. Although the early evaluation processes may be carried out by programmers and technical people, in the later evaluations, the entire team must be involved.

Summarize the Project Results

Once the model is performing at the level that was originally specified in the objectives, the necessary simulation analysis should be conducted, summarized, and communicated to the end user.

Using Existing Models in Systems Analysis

Needless to say, the above process is time consuming and a considerable amount of expertise and resources are necessary to develop a model. When possible, it would help to utilize an existing model to accomplish a different set of objectives other than those for which it was originally written. When using an existing model, a group should use the same basic steps as described above, but the procedure can often be expedited by using an existing model as outlined in Figure 6. Once the project objectives are clearly defined, then one or more models should be identified that may be suitable for use in the simulation. The next step is to analyze each model in question quite thoroughly.

First the assumptions and hypotheses that are incorporated into the model should be identified to make sure they do not limit the model from the application in question. It is important to analyze all the assumptions incorporated in all the subroutines before using the model. This procedure is greatly facilitated by communication with the developer of the model. Sometimes, well written documentation of the model is available, but this is the exception rather than the rule. Certain parts of most models are much better documented than others. In some cases, documentation may describe earlier versions of the model that have since been modified, sometimes extensively. If most components of a model seem acceptable for the desired application but a few assumptions or hypotheses seem inappropriate or wrong, then modifi-

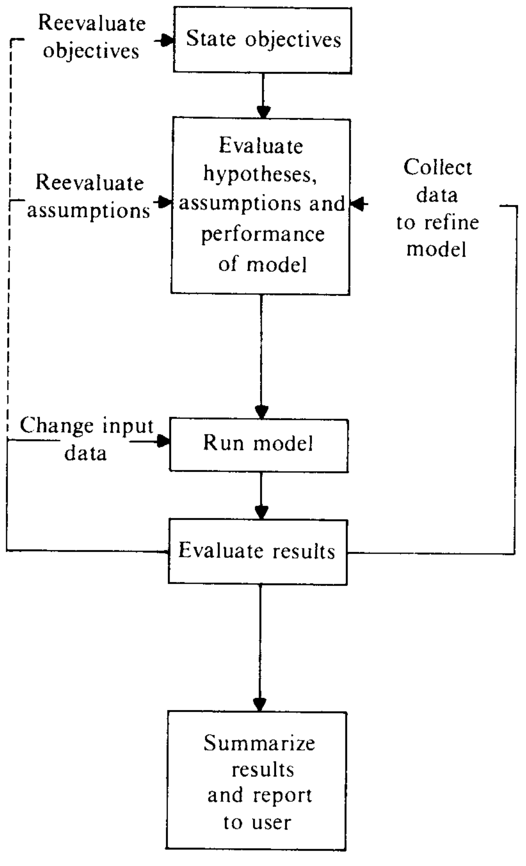


Figure 6. Schematic diagram of systems analysis using existing models.

cation of certain subunits of the model may be possible without developing a new model. Danneker (1984) discussed in some detail the evaluation of two published models—an empirical, regression based model (Hodges and Kanemasu 1977) and an intermediate level model (de Wit et al. 1978)—for use in yield prediction programs and climate-yield potential analysis. He was not satisfied with predictions of either model, so in order to use one of them, he would be required to reevaluate the assumptions built into the models. In this case, the tested models could not be used 'off the shelf', but improvement of the existing models might save a lot of time compared to developing an entirely new model for the desired application.

By the time a model is published and distributed to other users, the developers almost certainly will have verified that it performs reasonably well, i.e., it provides plausible answers. However, before the model is used for other applications, its performance should be evaluated using independent data sets, i.e., data sets that were not used in the model development or calibration procedure. The validation data sets should cover a wide range of conditions to ensure stable model performance as was illustrated by Slabbers et al. (1979). With intermediate to complex models, validation of the subcomponents rather than validation of the entire model is often necessary (Bell 1981).

In another type of model evaluation, a sensitive analysis of the input variables needs to be done to know how sensitive the model is to a particular input variable in order to evaluate the quality of the input data required for simulation work. Terjung et al. (1982) describe a sensitivity analysis of the input variables to an evapotranspiration model.

The model developers or an independent group may have already conducted validation tests on the model. If not, this should be done before the model is utilized for simulation work. In most cases, the model must provide not only a plausible, but a reasonably accurate answer. The validation process defines the confidence with which you can accept the accuracy of the answers provided by the model.

When using a properly validated model, simulation analysis can progress fairly quickly to the stage of making the initial runs. At this point, the performance of the model is evaluated, and through an iterative procedure, the initial input values and formulation of the hypotheses are modified, if necessary. Satisfactory performance of the model should be expected relatively quickly. The project team can then complete its simulation, and report the results to the end user.

Data Requirements and Availability

In order for any type of model to contribute to an agricultural research or development project, it is essential that good data sets be available. Historical data sets are essential for model development and validation. Ongoing data collection is essential for model improvement and operational programs where prediction of current or future production is desired.

Development of large-scale, statistical models requires data collected over long periods of time and from many locations. These types of data are seldom available in areas that have only recently been developed for agricultural production. The necessary agronomic data sets are seldom available to model new agricultural production techniques or strategies. Climatic data can be generated stochastically using climate models such as those described by Richardson (1981, 1982) to extend evaluation of management practices over long periods of time. However generated climatic data cannot be used for model development.

Complex models require a very technical, well-funded research program to support their development. Use of complex models requires detailed, accurate, and precise input, so data sets must be collected and monitored by highly trained technical staff and specialists. It is important for the development of complex models to continue, but they do not offer the potential for current applications. The models at this time are research-, not applications-oriented, and the payoff for their development may be far in the future.

Intermediate level models offer the combined benefit of a manageable data requirement and a greater level of transferability than simpler models. Within the broad category of intermediate level models, a wide range of model types is available for different applications. Developing agricultural programs can take advantage of existing models by concentrating on validation of models for the desired applications and modification of existing models, where necessary.

Acknowledgment

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