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THE ROLE OF AGROCLIMATIC MODELS IN CLIMATE IMPACT ANALYSIS

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PREFACE

In 1983 IIASA initiated, with support from the U.N. Environment Programme, a two-year project on climatic impact analysis. It is being implemented by a small in-house core group with a collaborative network of 72 scientists working on 11 case studies around the world.

The overall goals of this project are first, to evaluate the impact of climatic change and variability on food grain and livestock production, and second, to assess appropriate policy responses to reduce the impacts of climate on agriculture. Each of the 11 case studies has a team of 4 to 6 scientists which includes crop-climate and economic modelers, and a high-ranking agricultural planner. Outputs from climate models (or from instrumental climatic records) are used as inputs to impact models to predict actual or potential yield responses to climatic changes. Compatibility between the case studies is ensured by using the same types of climatic scenario and similar types of impact model. To trace the "downstream" effects of yield changes, outputs from the impact models are used as inputs to economic models (e.g. farm simulations, regional input-output models). Finally, agricultural planners or ministers of agriculture are being asked to evaluate the range of policies available for impact mitigation.

The case studies are being collected together into an integrated set of climate impact assessments, the integration being achieved by methodological studies which seek to describe how different modeling approaches relate to each other. This paper by Carter, Konijn and Watts provides an overview of the use of agro-climatic models in climate impact analysis, a context against which the case study models can subsequently be evaluated.

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T.R. Carter, N.T. Konijn and R.G. Watts

1. INTRODUCTION

It would be a very convenient thing if farmers throughout the world could enjoy perfect weather and the absence of plant diseases and pests, and could grow perfect crops in perfect soils. In the real (and perhaps more exciting and interesting) world the farmer must deal with imperfect soil and variable weather, with the presence of pests and diseases, and with fluctuating markets and prices as well. The next most convenient thing to having a perfect world would be to have a perfectly predictable world. If a farmer could predict perfectly all of the factors that influence the growth of his crops and the health of his livestock, and if he could in addition predict how his crops and livestock are influenced by these factors, how markets would influence his profits, etc., then he could decide which crops to plant in any given year, or whether to plant anything at all. He could also use his perfect knowledge to decide whether and how to assist in the natural order by, for example, irrigation or the application of fertilizers.

Farmers have, of course, been trying for centuries to predict the outcome of each cropping season. Each year man and nature perform an experiment. Nature varies the rainfall, temperature, sunlight, and other weather parameters while individual farmers vary the rates of fertilizer application, planting dates, etc. The results of these experiments over many years forms the collective experience of the farmers. The pooling of this experience provides them with information about when to plant, fertilize, irrigate and harvest crops, and even when to anticipate certain kinds of disease and pest epidemics. Scientists have recently begun to streamline this process through the use of mathematical models. Crop models provide a mechanism for efficiently distilling and organizing past experience on the behavior of crops in such a way that future behavior can be predicted. The mathematical model is, of course, not the real system. It is a set of variables and mathematical relationships by which we can attempt to represent the real system. If the model is perfect, and if all the external changes are anticipated, then the model will behave exactly as nature behaves. We could then predict what nature will do and we could understand why. We can never hope to do this perfectly, of course. Instead, our task as modelers is to discover which variables are required to describe the real world adequately, and how these variables are related to one another mathematically. We will be mainly interested in the response of crops to changes in climate, and we will refer to the models discussed below as *agroclimatic models*. The purpose of this paper is to provide an overview of the role of agroclimatic models in climate impact analysis.[1]

We will approach this task in three stages. Firstly, we will describe which processes are important in determining crop production and how the farmer exploits and modifies these in order to obtain optimum yields. Secondly, we look at the types of mathematical models that are commonly used to simulate the crop production system. By concentrating on model attributes and disadvantages, we will discuss their performance in estimating crop responses to present-day conditions and assess their suitability for simulating the effects of future climatic change. As illustration, we present the results of specific experiments in which we explore the sensitivity of two models to climatic variations over a range of time periods. Finally, these features are summarized in a tabulated checklist which allows us to cross-compare the capabilities of particular models.

2. CLIMATE AND THE CROP PRODUCTION SYSTEM

Strictly speaking, any treatment of the crop production system should embrace the full range of conditions that are important in the cultivation and husbandry of crops. However, since no single model has yet been developed that incorporates all features of the system, we will restrict our discussion only to those components that we believe are pertinent in assessing the impacts of climatic change.

In this section, we have developed a scheme that is designed to reflect the reality of crop production at the plant or field level, while offering the possibility to match that reality with the conditions simulated by agroclimatic models. First, we describe crop production in terms of the influences of natural conditions on processes that determine productivity. Second, we itemize the more important requirements necessary for the development of a healthy crop and consider how the farmer attempts to modify the physical environment in order to fulfill these requirements. The importance of the timing of anthropogenic activities with respect to natural events is illustrated by combining them in the form of a farm calendar. Thirdly, the effects of crop production and the influence of technology on long-term crop productivity are discussed.

2.1. Crop Production and Climate

To be able to show the effects of climatic changes on the physical processes determining crop growth, a model should respond to at least one of the variables that help to describe the climate. No matter where crop production takes place the following conditions determine the final production level: the radiative and temperature regime, the soil water available for plant growth, the availability of plant nutrients and the interference of pests and diseases. When any of these is not considered in a model, it often means that under the actual local physical environment that particular variable does not induce annual responses sufficiently large to affect crop yields. Such an omission may become significant when longer-term climatic changes are considered.

[1]We shall focus primarily on agricultural crop models although much of our discussion is equally applicable to other plant models (such as the forest growth model reported by Kauppi and Posch, 1985).

The more important processes are illustrated in Figure 1 and have been grouped according to their parent research discipline. The implication is that for a model incorporating all these aspects in any detail, teamwork is essential.

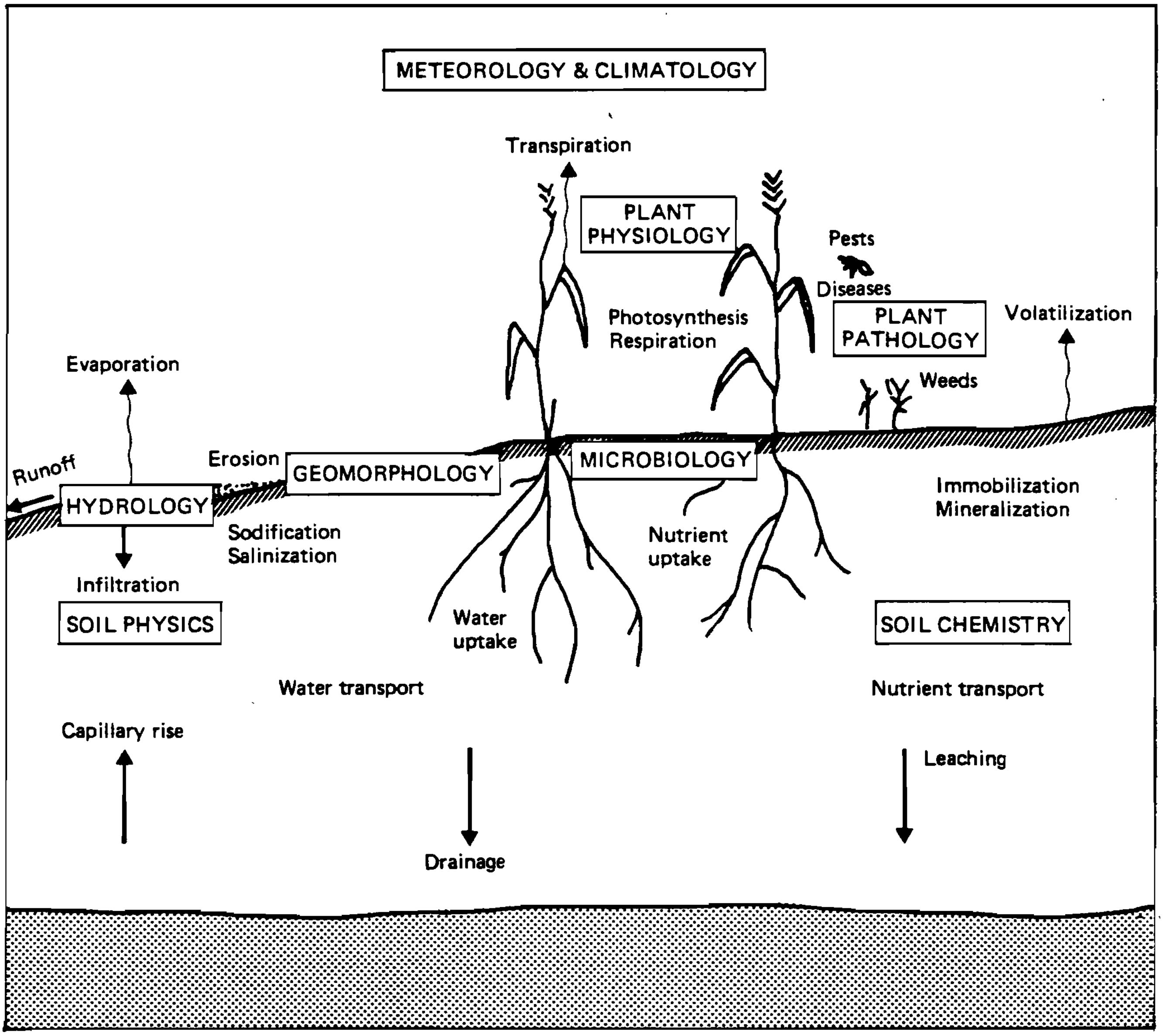


Figure 1. Physical processes in plant production.

2.2. Constructing a Farm Calendar

Some agroclimatic models relate only climatic factors to crop yield, but we will take a broader view, here, recognizing that other variables including farm management activities, do not only contribute to the level of the crop yield, but can be decisive in whether one obtains a yield at all. For example, excessive rainfall may cause a delay in planting time, or even make planting impossible, with obvious consequences for plant production. Of course, a farmer usually aims at achieving an optimal result, within the frame of his knowledge and his available options, and the weather often plays an important role in influencing his decisions.

The development of a crop and its sensitivity to the physical environment is strongly plant-type dependent. A farmer's activities are also plant-type dependent although many are common to all crops. Here, we will present an example, for a specific crop, of what can be called a farm calendar. Similar calendars exist for other crops, and these are described elsewhere in the literature (e.g. FAO, 1978; Duckham, 1963). The models we are interested in can be compared with the appropriate calendar to see whether certain important variables are included. In a later section we will offer a means to carry out this matching by way of a checklist.

Spring wheat is taken as our example. The crop has many characteristics in common with other cereals; but it differs from winter varieties in being day-neutral (i.e. its development is not influenced by day-length) and in not requiring a cold (vernalization) period before heading.

2.2.1. Crop Requirements

The development of the crop is indicated in Figure 2. Various development stages are recognized which are related to the crop's special requirements. The following are distinguished: respectively, the requirements for radiation, water, nutrients, weed control, pest control, soil conservation and temperature. These are represented over time as horizontal bars; the denser the lines in the bar the more important are the requirements.

Solar radiation stimulates a crop to convert absorbed carbon dioxide to carbohydrates (i.e. plant material) through the process of photosynthesis. During the early development of a crop, in particular, its rate of growth is strongly influenced by the amount of radiation it intercepts.

Water stress in plants is one of the most common factors limiting crop production. It is not just the annual rainfall that determines whether there is enough water available for plant growth, but the timing and distribution of rainfall, evapotranspiration and soil characteristics play a role as well, both before and during the growing season.

Of the nutrients, only the three main 'macronutrients' are distinguished, and their relative importance is staggered over the period of crop growth. Potassium tends to be more important at the beginning of the vegetative period, nitrogen following tillering, and phosphorous during heading.

The climate may play a decisive role in pest control, and activities of most of the lower organisms like fungi are triggered by humidity and temperature. As for weed control, weather conditions can affect both the competitiveness between weed cultures and with the crops.

Soil erosion is a problem in many agricultural areas. For example, during the period after plowing but before the crop has fully developed, rain can act directly on the soil surface, causing a large amount of soil loss. Rainfall of high intensity, surface runoff, or wind, together with an easily erodible soil can lead to several tens of metric tons of soil loss per hectare.

Each plant type has its typical optimum temperature range although this may vary from growth stage to growth stage. Temperatures below zero degrees Celsius do not permit growth and extremely high temperatures may also be damaging to the crop. Plants have adapted to daily fluctuations in temperature: given a sufficient supply of carbon dioxide, the higher temperatures during daylight promote a maximum photosynthesis rate, while lower nighttime temperatures reduce the losses of photosynthates by slowing down the process of maintenance respiration. For spring wheat the optimum temperature range lies between 15 and 25°C and the minimum temperature for both growth and germination is about 4°C. At ripening, the period preceding harvest, air temperatures above 18°C together with calm dry weather are optimum, leading to the minimum harvest losses.

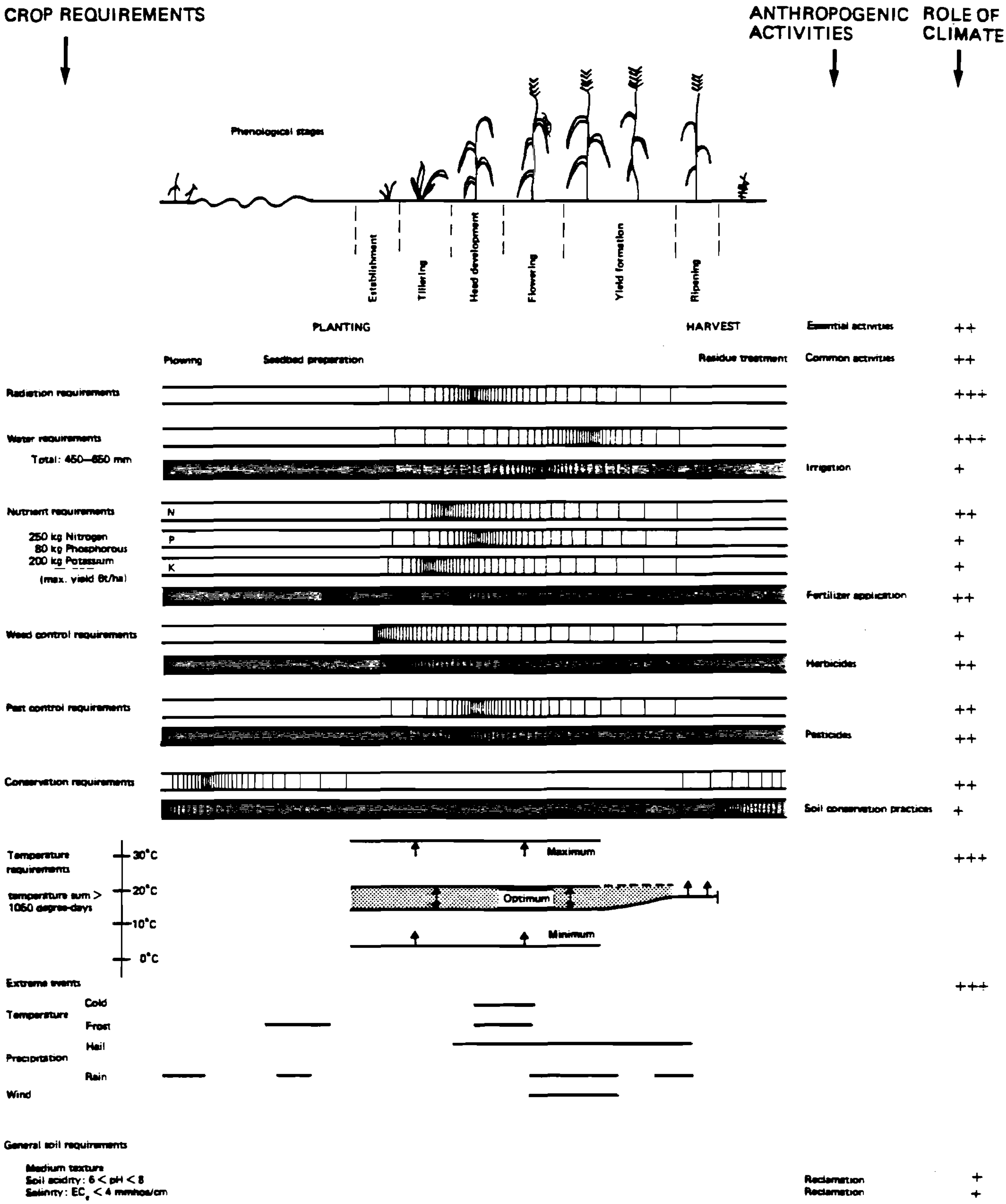


Figure 2. Farm calendar for spring wheat.

Extreme events that sometimes occur may not simply reduce yields, but can cause total losses. The occurrence of frost during the flowering period illustrates such an event. Lodging because of high rainfall accompanied by wind during grain formation can also lead to heavy losses. Plant breeders have come to the aid of farmers in this respect, introducing better adapted varieties like, for example, the short straw varieties that have reduced lodging in cereals.

2.2.2. Fulfilling the Requirements

For most of the crop requirements the farmer has tools to reduce any adverse effects of the environment. Thus, the requirements indicated in Figure 2 are accompanied by a bar that shows how farmers can act, given that they have the means and the sufficient know-how.

For example, the soil may not be capable of meeting the nutrient requirements, therefore, applied fertilizers may increase production, provided they are applied at the right time and in the correct way. How far those applied nutrients become available to the plant, however, is also a function of the weather. And although the farmer can to a certain degree counteract the negative effects of the weather, losses in nutrients may still occur due to leaching, fixation or volatilization.

Through suitable conservation measures, soil erosion losses can be reduced to practically nothing. The planting of wind barriers, for example, at appropriate distances and perpendicular to the dominant wind direction will often reduce losses considerably.

Ironically, many of the areas where shortage of water is a constraint on growth are also areas with a favorable radiative and temperature regime. However, if no other factor is limiting, irrigation can transform those areas into the most productive regions in the world.

2.3. Long-Term Effects of Crop Production

Throughout a crop's growth, the resources upon which it depends are themselves undergoing a continuous process of change. Moreover, these changes are not always measurable. For example, the soil texture is not likely to change significantly within a man's generation, due to the robustness of the soil minerals. In contrast, the organic matter content and composition may change considerably even within a growing season. Although anthropogenic activities play an important role in controlling the rates of some of these changes, the effect of the climate should not be underestimated. For example, the decay of organic matter is greatly influenced by fluctuating moisture and temperature conditions, suggesting that any future changes in these conditions might induce rapid responses in decay rates.

When we extend the time horizon beyond the short-term, it is important to recognize also the effects on crop production of various cropping practices, such as rotations, multiple cropping, consecutive cropping, etc. On a particular tract of land, over a series of years, any number of crops may have been grown, each uniquely affecting the long-term status of the soil. Furthermore, a change in the crop mix, due perhaps to a changing climate, might alter significantly the rates of processes such as soil degradation and erosion, maybe feeding-back to the crop system and accentuating the impact.

Finally, the rapid increases in crop yields reported from many parts of the world over the last two decades give testimony to some enormous advances in farm management practices and technology. Clearly, for as long as improvements in crop productivity are feasible, man will strive towards their attainment, through plant breeding and genetic engineering, development of new machinery and fertilizers and evolution of improved conservation techniques. These technological trends will continue to exert an important and, very likely, dominant role in future crop production.

3. MODELING THE CROP PRODUCTION SYSTEM

We can view a mathematical model as a set of input variables that affect a set of output variables through a number of mathematical relationships. In an agroclimatic model, the output variable of primary interest usually involves some measure of crop productivity (e.g. yield, biomass potential, land suitability, etc.). Input variables include climatic variables such as temperature, precipitation, windspeed, solar radiation and the like. Other environmental variables that might affect yield have already been referred to as *natural* input variables. These were distinguished from another group, labeled *anthropogenic* input variables which are associated with direct intervention by man and include, for example, irrigation and the application of fertilizers and pesticides (Figure 2).

The principal purposes of the modeling procedure are to understand the system and to develop predictive capability. Ultimately, we would like to be able to predict the consequences of changes in both natural and anthropogenic input variables. The former would tell us how natural changes will affect crop productivity. The latter would suggest to us how we might act to optimize productivity by altering anthropogenic inputs.

Before attempting to assess the characteristic features of different model types, let us consider first one of the simplest methods of relating plant growth to climate: the climate-based vegetation map.

3.1. Climate-Based Vegetation Mapping

Several schemes have been proposed which classify natural vegetation zones according to mean climate (particularly measures of temperature and moisture conditions) and there are many examples of global maps which illustrate regional vegetation patterns based on observed mean climate (e.g. Köppen, 1936; Holdridge, 1947). This approach can be regarded as correlative modeling in the very loosest sense, where a number of discrete vegetation classes are 'correlated' with climate on the basis of a sample of observations from around the world. The interest in such a procedure for climate impact analysis lies in our ability to introduce a climatic change by adjusting the values of mean climate for a region. According to the changed climatic conditions we can then 'predict' (i.e. re-map) the new vegetation pattern and can assess the impacts in terms of geographical shifts over space. Examples of the mapping of vegetation shifts include experiments using Holdridge Life Zones under a 2 x CO_2 climate (Emanuel *et al.*, 1985), and for Köppen Vegetation Zones under the climatic conditions simulated for the peak of the last ice age, 18000 years ago (Hansen *et al.*, 1984). Clearly, this type of analysis can be applied only to broad scale vegetation changes which, given the high temporal inertia of ecological systems would be measured over the long-term. Further since it is strictly a climate classification other factors such as soil properties, fire risk and species competition need to be overlaid on the basic classification in order to gain a realistic assessment of the impact of climatic change.

Vegetation maps provide a useful first approximation of the biological response to changes in climate at a continental or global scale. Experiments of the kind discussed offer a framework within which to focus our studies of crop response using agroclimatic models.

3.2. Classifying Agroclimatic Models

There are a number of excellent reviews of agroclimatic modeling in the literature (e.g. Baier, 1982; Sakamoto, 1981; Robertson, 1983) and all attempt some kind of model classification. In general, models fall into two broad classes: empirical-statistical models and simulation models.

Empirical-statistical models are developed by taking a sample of annual crop yield data from a certain area together with a sample of weather data for the same area and time period, and relating them through statistical techniques such as multiple regression analysis. This procedure is sometimes labeled a black-box approach since it does not easily lead to a causal explanation of the relationships between climate and crop yield. This description should not imply, however, that these models are developed blindly or indiscriminately. The most effective empirical-statistical models are usually the product of very careful and well-informed selection of suitable explanatory variables, based on an intimate knowledge of basic crop physiology.

Simulation models generally treat the dynamics of plant or crop growth over the growing season through a set of mathematical expressions tying together the interrelationships of plant, soil and climate processes. Some of these relationships are well-enough understood to be regarded as accepted laws of physics, chemistry and biology and are often referred to as deterministic functions (Lyons, 1982). Other processes which are either poorly understood or of secondary interest to the modeler are frequently represented by empirical functions.

Thus, no simulation model can be described as truly deterministic since all incorporate at least some empirical (black-box) elements. However, they differ from empirical crop models in their development and operation. In the latter models, the output data (such as yield) must be ***sampled*** and related to the input data in order to construct the statistical model which is to be used as a predictive tool (Figure 3a). In the simulation approach, the plant growth processes are prespecified, and output data are ***generated internally*** by the model, as illustrated in Figure 3b.

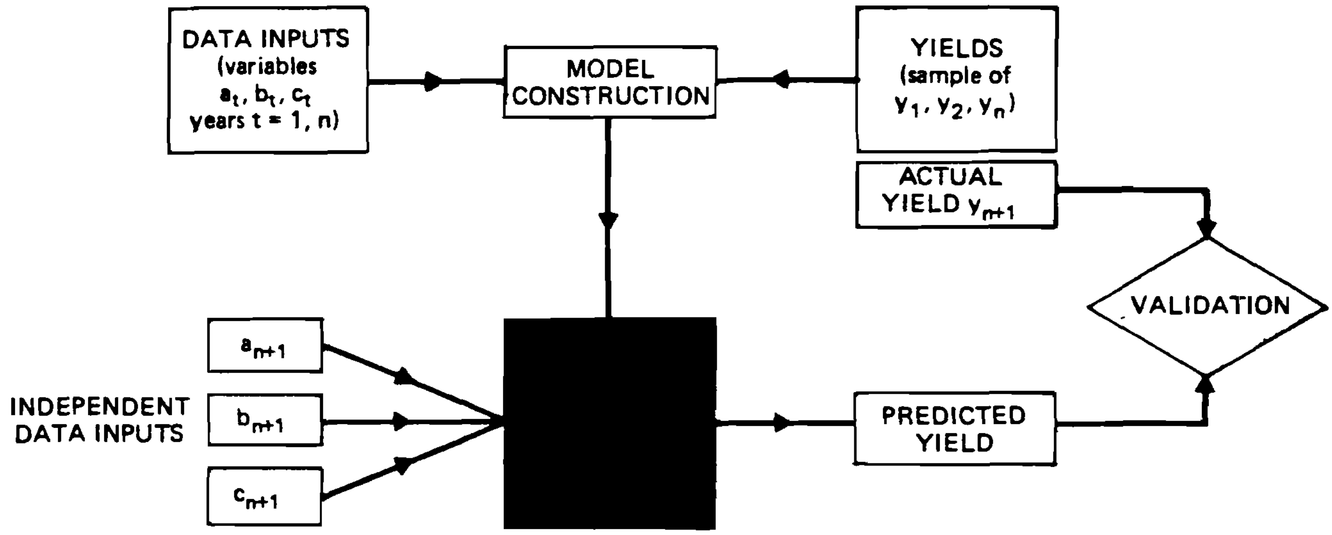
3.3. Evaluating the Utility of Agroclimatic Models

We can evaluate a model according to the following general criteria: objectives, logistics, assumptions and sources of error, and validation.

3.3.1. Objectives

In general, models are constructed in order to satisfy certain objectives. These are bound to condition what levels of detail and explanation are required in developing the model. As a simplification, empirical statistical models are built for the sole purpose of yield prediction; simulation models offer a means to analyze as well as to estimate yield. These differences in modeling objectives should become more apparent in the following discussion.

a) Empirical/statistical



b) Simulation

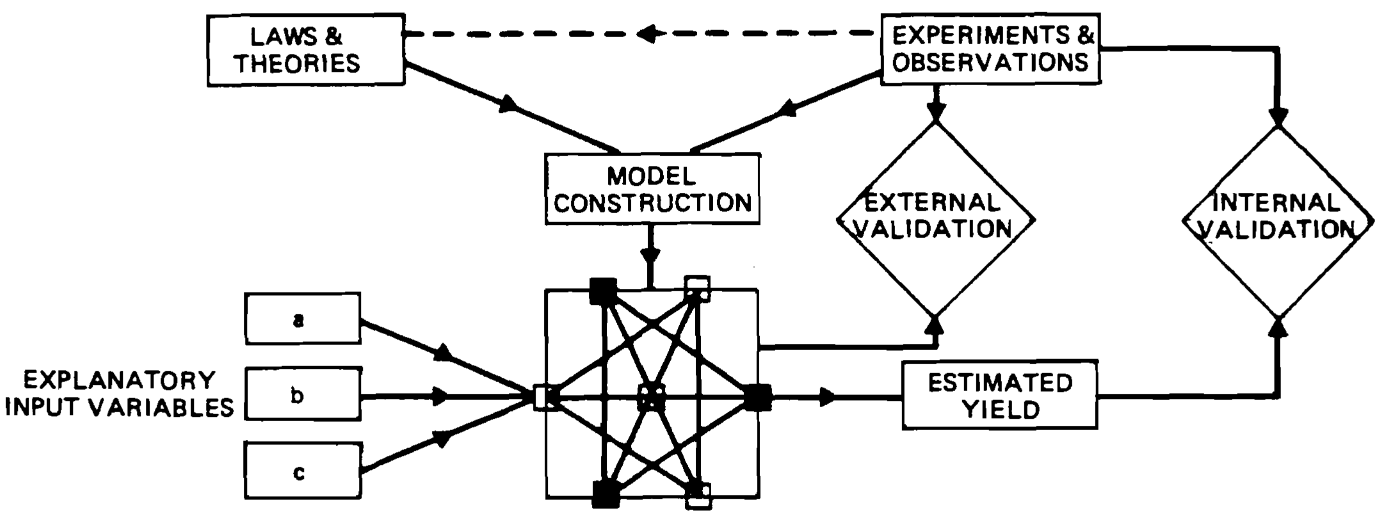


Figure 3. The construction, operation and validation of a) an empirical/statistical (black-box) model and b) an interactive simulation model (schematic).

3.3.2. Logistics

It is probably true to say that a model is only as good as the data set upon which it is based. Adequate data are required first, for constructing the model algorithms, second, for running the model (i.e. as inputs) and third, as independent objective measures against which to validate model outputs. In considering the effects of climatic change one important concern is for a model to be capable of responding to those annual fluctuations over several decades that are characteristic features of most regional climates.

In general, with fewer and simpler model variables one can expect a longer time series of data and a more straightforward and rapid calculation process. Most empirical-statistical models are constructed to meet this objective, both for the purpose of simplicity and to avoid the statistical problem of inflated correlation coefficients due to a high number of explanatory variables (Sakamoto, 1981). Continuing this line of reasoning, it is no surprise that some of the most effective statistical models have been developed in areas where crop growth and yield are governed by a *single* major weather factor (e.g. temperature and hay yields in Iceland, Bergthorsson, 1985).

For an empirical treatment of a more complex system, data bases may become prohibitively large, and in this situation the explanatory, simulation approach might be a viable substitute since some of the variables can be generated internally by the model. However, data requirements are normally greater for simulation models anyway, given the short time-steps frequently employed. Moreover, such fine scale data are seldom available over long time periods imposing a formidable restriction on the applicability of many simulation models for the analysis of climatic fluctuations on a decadal basis.

An additional logistical advantage of most empirical models lies in their prediction of yields for quite large regions. Thus, climatic data are often regional averages derived from a number of sites, any one of which need not necessarily provide a continuous record. Conversely, simulation models tend to be site-specific, requiring a single, unbroken run of data for all variables.

3.3.3. Assumptions and Sources of Error

In a perfect model, all variables contributing to the growth of a crop would be represented exactly and connected with an unbroken logic. However, because current understanding of plant processes is so imperfect, modelers must adopt a pragmatic approach, selecting only those variables thought to have a significant influence on crop growth, and where the interrelationships between these variables cannot be represented, even as empirical functions, assumptions must be introduced which are based on the modelers' experience and judgement. The effectiveness of a model, for whatever purpose it is designed, invariably rests on the nature and validity of its assumptions. Although each model has its own unique set of assumptions, some are common to most models.

Many of the weaknesses of empirical models, in particular, can be attributed to their statistical assumptions. In the classical linear regression analysis, it is assumed that variables are independent. Unfortunately, few of the climatic variables that impact on crop yield are *not* related to each other and further, many are also related to themselves over time (i.e. autocorrelated). These problems of *multicollinearity* usually result in regression coefficients with large, unstable variances. In addition, the relationships between crop yields and climatic variables are rarely linear. Where they are modeled as such, this can also lead to inflated variance, and the resulting coefficients may be unstable to the extent that their sign can change with the addition of new observations (Biswas, 1980).

One potential solution for reducing collinearity is to combine intercorrelated variables into an *agroclimatic index*. Surrogate variables such as these have been used to represent soil moisture information or heliothermic conditions and can be related directly to yields (e.g. Williams, 1985).

A third, simplifying assumption, which pervades most models but may have a greater influence in the empirical-statistical type, concerns the *interpolation* and *extrapolation* of values. Since most models are developed and 'tuned' using functions pertaining to an observed range of present-day conditions, it is likely that interpolation will be the dominant procedure employed in model runs conducted under 'normal' conditions. However, altering the climate may introduce values outside the modeled range. Thus prediction becomes speculation as we must extrapolate the functional relationships in order to estimate response. This unsatisfactory procedure merely re-emphasizes the need to develop models over the *greatest possible range of observed conditions*.

A fourth assumption, which affects both model types but in different ways, involves the inclusion of *management practices and technology* as explanatory variables (see Section 2.3.). In simulation models these are either included as explicit input variables, or specified as constants. In the latter case, this assumption may restrict the model's effectiveness in estimating long-term effects of technological change.

Empirical-statistical models often treat technological change as a time trend based on yield statistics over a relatively long period of time. This procedure has two disadvantages. First, it relies upon the subjective separation of technological trends from those that can be attributed to the environment (including climate). Secondly, as in the case of simulation models, a future scenario requires some assumptions about the extrapolation of the technology trend.

Finally, *sporadic climatic events* such as hail storms, floods, late or early frosts can often have devastating effects on crops. While simulation models generally make allowance for these episodic events through the use of critical tolerance levels, empirical-statistical models often do not, and this can have implications in the analysis of longer-term climatic change (see Section 3.4.1.).

We have given short descriptions here of some of the more important model assumptions and sources of error. More complete discussions of these and others can be found in the reviews by Sakamoto, 1981; Baier, 1981, 1982; Biswas, 1980 and Katz, 1979.

3.3.4. Validation

The ultimate test of any model is to assess how closely its estimates of real world conditions correspond to actual measured observations. The whole credibility of a model's forecast of crop response rests on the rigorous testing of its sensitivity and verification of its outputs against independent observations.

A *sensitivity analysis* can tell us a lot about the inherent stability of a model, its effective range of operation and its potential applicability to climatic change experiments. In essence, a sensitivity analysis seeks to evaluate a model's responses to incremental changes in magnitude of each input variable (both singly and in combination). These adjustments should be distributed such that the extreme values lie well outside the observed natural range. A similar procedure is employed for those mechanisms, including feedback processes, that are generated internally. In this way, we can gain insights into:

a) the physical realism of the modeled relationships over a wide range of conditions;

b) the relative importance of the various types of external forcing;

c) the relative influence of each modeled variable in determining model outputs; and

d) some of the model's limitations, including information concerning (i) the conditions under which the model breaks down, and (ii) which of its coefficients are potentially unstable, under what circumstances and with what effect (e.g. see Katz, 1979).

In order to appraise its performance, it is necessary to *validate* a model's estimates against observed data. This procedure has a number of attendant difficulties, not least the problem of securing adequate data for its implementation. The types of data required for validation depend to a large extent on the nature of the model's predictions.

As a minimum requirement, the outputs from an empirical-statistical model should be verified against at least ten years of independent crop yield data, reflecting a variety of conditions. Ideally, these should be different bodies of data from those used to construct the model, and for the same time period, in order to test the model's common applicability. However, because of the area-specific nature of most statistical models (due in part to their general neglect of variables such as soils, drainage and management that are often highly heterogeneous over space) this form of cross-validation is rare. Model results are usually compared with observations from the same area but for a different time period (Figure 3a).

For simulation models, the problems are slightly different. Firstly, the data requirements are usually very much greater than for statistical models. A proper validation procedure should include not only a comparison of modeled outputs with real conditions, but also the verification of each and every internally derived value (Figure 3b). In some instances, however, it may be either impractical or even technically impossible to measure a particular variable.

Secondly, to restate the need for internal validation, let us consider some possible validation outcomes. For example, a perfect correspondence of observed with predicted outputs such as yield can, when taken in isolation, mask an internal cacophony of errors. Conversely, where the internal validation is apparently good, the output estimates may be discordant. This condition might be explained by the cumulative effect of small, seemingly inconsequential structural errors, or by the omission of important explanatory variables from the model, or indeed by a combination of the two effects.

Finally, in validating any type of model, care should be taken to ensure that the independent observations being used are totally compatible with the model estimates. Efficient scrutiny of the data may uncover unforeseen peculiarities to which a model may or may not be sensitive (such as the introduction of irrigation to an area, the replacement of a crop hybrid, or a change in the total area under the crop).

3.4. Agroclimatic Models in Climate Impact Analysis

In the late 1960s and early 1970s, when modelers first began to address the problem of examining crop responses to possible future climatic change, many conducted their experiments using models that were not always appropriate for the task. Most models had been constructed either as predictive tools for estimating year-to-year yields, or as research tools to investigate detailed crop-environment interrelationships during a typical growing season. Now, over a decade later, it has become increasingly clear that by extending the time horizon of study beyond the immediate short-term (for which many models are tuned) we run into a whole set of fresh problems. These can be grouped into two categories: (i) problems relating to the validity of model relationships and (ii) difficulties concerning which methods to adopt in simulating climatic change.

3.4.1. Model Relationships

All facets of the natural environment are undergoing a continuous process of change. Over short time periods, in situations where rates of change are relatively slow, their effects may be imperceptible. Thus, for the purposes of modeling short-term crop response they can often be parameterized as constants. However, in a consideration of longer-term climatic changes, over periods ranging from decades to centuries, these processes may exert an influential and possibly dominant role in crop growth. It is therefore important to incorporate these effects in models, at least on an annual updated basis. Examples include changes in soil properties (see Section 2.3.) and the natural adaptation of certain plant species to stressful weather.

As a result of readjusting model parameters many of the functional relationships, adequate in describing short-term processes, may become invalid and require re-evaluation (Wigley, 1984). Moreover, a change in climate may alter the importance of critical threshold values for crop growth (e.g. a climate warming might reduce markedly the risk of cold damage to a cereal crop but may increase the probability of heat stress; and see Rosenberg, 1982). Further, if a crop is especially vulnerable to the effects of episodic events then it is of critical importance that such events should be modeled effectively, for any change in their frequency may have dramatic consequences.

Finally, attendant on, and possible contributing to climatic change could be factors such as atmospheric, soil and water pollution. However, for modelers to simulate the direct crop responses to such complex problems as increased atmospheric carbon dioxide concentrations, or acid precipitation, is placing a rather large onus on their skills if we consider the prevailing uncertainties existing within these fields. Nevertheless, there have been several recent attempts, albeit not within a formal model framework, to quantify the direct effects of carbon dioxide on crop yield (e.g. Rosenberg, 1981; Waggoner, 1983).

3.4.2. Model Runs for Future Climate

A first consideration for modelers wishing to simulate the effects of future climatic change is how best to quantify that change. There exist predictions of change simulated by a suite of global climate models of varying type and complexity, predictions based on using past climatic anomalies as analogs of future conditions, and predictions generated stochastically and/or synthetically. The temporal and spatial resolution of these predictions varies widely, and it is this consideration which is a major determining factor in the selection of an appropriate scenario as an input to a particular model.

One method of improving the 'compatibility of scales' where the resolution of the predicted climate variables is too coarse for input into an agroclimatic model, is to generate a synthetic set of finer-scale data. Methods exist for generating daily temperatures from monthly means (e.g. Brooks, 1943), for adjusting weekly precipitation by allocating fixed proportions of the weekly total to particular days (e.g. Stewart, forthcoming), and for stochastic simulation of daily weather data (e.g. Richardson, 1981; Mearns *et al.*, 1984). Alternatively, instead of improving the resolution of the input data, another more common compromise is to run the impact model at a coarser resolution. The possible errors involved in this procedure are discussed more fully in Section 4.

A final consideration when running a climate impact scenario concerns how models handle a climatic change. This can be approached on two levels. First, a model's simulation of year-to-year crop response may be *static* or *dynamic*.

Briefly, a scenario using a static model usually involves the input of one set of changed climatic means (averaged over several decades) with the output assumed to represent mean response over the same period. The procedure is suspect, however, for in reality it is very rare for a period-averaged climate to resemble any one of the constituent years of weather within that period (particularly in the case of precipitation). Moreover, the crop yield estimated for a 'mean climate' year can be quite different from crop yield estimates calculated for each year and averaged over the whole period (see, for example, Table 1, Section 4.1.).[2]

Thus, a more satisfactory scenario is one which treats climate as a variable, dynamic entity, and models year-to-year fluctuations both for the present day and future climatic regimes. Of course, a static-type model can be used for this purpose by repeating individual runs for varied inputs. However, it is more efficient (and elegant) if a model can collect the separate sets of input data together and conduct multiple runs in a single operation. Year-to-year variability about a future climatic mean can be simulated by generating synthetic data, and some of the more sophisticated models have this capability built-in. Under conditions of 'stable' climate, model runs of this kind should normally be conducted over a period of several decades in order to simulate equilibrium conditions.

The second level of approach to climatic change considers whether we should model change as *step-like* or *transient*. If we accept that long-term climatic change is likely to involve a gradual process of change, then we should appreciate the dangers of treating change as an abrupt perturbation, for not only is such a climatic change rather unrealistic, but the model responds to the change as if it were part of the year-to-year variability. Thus, longer-term processes such as soil adjustments are not allowed time to react (unless changed equilibrium conditions are simulated). Unfortunately, all too many model experiments have been conducted using this 'sudden shock' approach and the modeling of transient changes (whether linear, exponential or cyclic) has been largely neglected. Reasons for this may include the requirement for large input data sets and considerations of computer time.

4. EXPLORING MODEL SENSITIVITY TO CLIMATE: TWO EXPERIMENTS

Our eventual major interest, as modelers, will be in predicting the effect of climatic change on future crop yield. In order to do this, we will need to know the future distribution of the various climatic variables over both space and time. Clearly, the prediction of daily weather events over an entire season will not be feasible in the near future, if, indeed, it is ever possible (Lorenz, 1968). Predicting seasonal, or even monthly averages smoothed over large areas, however, seems a goal that might be achieved in the not too distant future. It will be very nice if this kind of time and space averaged input data can be used in agroclimatic models with some assurance that reasonably accurate crop yields will be predicted.

The nature of this problem brings out very nicely the idea that the effects of time and space resolution are not entirely independent. Rainfall, for example, tends to be a highly localized phenomenon in both time and space. Averaging rainfall over either time or space hides the variability of the true signal, and this variability might be a very important factor in crop growth and yield. On the other hand, real rainfall data are seldom available on less than a daily averaged basis, and then only at specific sites. The rainfall in a given cropping region might vary appreciably over both space and time. If we average over space, does it make sense not to average over time? It is also perhaps worth pointing out that empirical-statistical models generally attempt to correlate crop yield with monthly, seasonally, or even annually averaged temperature, precipitation and the like. Can this ever be expected to be a reasonable approach? In what detail must we know and specify the input variables in an agroclimatic model in order to have a reasonably good chance of predicting the effects of these variables on crop yield? Must we use daily or even hourly data, or can we use monthly or seasonal or annual averages?

[2] It should be noted, however, that this effect may not be so important for models operating with a timestep exceeding one month.

The yield of a particular crop depends upon many climatic variables, such as rainfall, temperature, sunlight, and their seasonal variations. In addition to climate directly, yield depends upon a variety of chemical and physical properties of the soil; for example, its permeability, acidity, and available nutrients. These properties can change in response, for example, to precipitation changes, with time constants of many years. These long term changes might affect yield. In fact the sensitivity of yield to long term climatic change might be very different from the sensitivity to year to year variations.

In the light of the above, it might be useful to use agroclimatic models to explore both ends of the time scale. We present here the results of two sets of numerical experiments through which we explore the effect of temporal resolution of the input precipitation on yield, and the difference between short-term and long-term sensitivity of yield to climatic change.

4.1. Experiment 1. The Temporal Resolution of Input Data and Its Effect on Yield

The first set of experiments was performed with a crop production model described by Konijn (1984). The model was chosen strictly on the basis of its availability and on its suitability for performing the experiments described below. The model estimates crop yields based on characteristics that describe the physical environment (including the climate). The data for these experiments were taken from the Stavropol region of the USSR. Only one soil type was considered and the growth of the chosen crop, oats, was assumed not to be limited by diseases, pests, or shortage of nutrients.

The model was first run for each of the 12 years, 1971-1982, using ten day averaged rainfall data for each year. Next, the ten day rainfall data in each year were averaged by threes to obtain thirty day averages. The model was then run with the same time step as before, but using thirty day averaged rainfall as input data. An ensemble average of the ten day rainfall data was also created by averaging each ten day period over the entire twelve year data set. A similar ensemble average set was created from the thirty day averages. The model was run with these ensemble averaged precipitation data.

The results are summarized in Table 1. The yield computed using the ten day and thirty day rainfall input data differ by less than 3% in half the cases. In no case do they differ by more than 10%. In most, but not all, cases the use of thirty day averaged data (smoothing the data) results in higher yields. The yield resulting from the use of the ensemble average precipitation data (again, smoothing) is higher than the average yield over the twelve year period. This is especially true of the ten day data.

We have chosen three years for closer examination. The precipitation data for these years (1971, 1975, and 1982) are shown in Figure 4. The solid lines are ten day averaged and the dashed lines thirty day averaged precipitation. The beginning and end of the growing season are marked by arrows on the horizontal (time) axis. Table 2 shows, for the same three years, the total dry weight assimilation broken down into four plant components: leaf, root, stem, and grain.

1982 was a relatively wet year during the growing season, and the grain yield was high. Smoothing the precipitation data (using the thirty day average) resulted in a 5.1% higher predicted yield. The variability of the ten day rainfall data is much higher than that of the thirty day data. When very high rainfall occurs during a ten day period, the runoff can be considerable. This water is effectively lost from the system. During 1982 the variability was especially high during the early and middle parts of the growing season. This is reflected in the fact that the leaf dry weight, which develops mainly during this period, is nearly 10% higher for the thirty day

Table 1. Comparison of grain yields of oats estimated using precipitation data averaged over 10 day and 30 day time-steps. Data refer to the period 1971-82 at Stavropol, U.S.S.R.

	Grain Yield (kg/ha)		
YEAR	10 Day	30 Day	% Difference
1971	1458	1472	1.0
1972	2797	2855	2.1
1973	3201	3307	3.3
1974	2956	2978	0.7
1975	2623	2552	-2.7
1976	3420	3745	9.5
1977	4750	5099	7.3
1978	4711	4523	-4.0
1979	2257	2273	0.7
1980	3099	3328	7.4
1981	2865	2781	-2.9
1982	4240	4455	5.1
12 Yr Avg Yield	3165	3281	
Ensemble Average Rainfall Data	3449	3434	

averaged data than for the ten day averaged data.

For the 1975 case, averaging over thirty days instead of ten days results in a *lower* predicted grain yield. Leaf, root, and stem dry weights are all slightly *higher*, however, (see Table 2). The reason for this is the following: Although the ten day averaged precipitation is, of course, less smooth than the thirty day average values, there are only two ten day periods during which precipitation exceeds 40 mm. Thus, the smoothing of precipitation input, and the resulting decrease of runoff, should not greatly increase the efficiency with which the plants can use the moisture. On the other hand, during the last two ten day periods of the growing season, the particular way in which the averaging was done resulted in the fact that a very dry ten day period outside the growing season was used to compute the last thirty day averaged data. The precipitation during the last twenty days of the growing season was thus underestimated in the thirty day averaged case.

The very low precipitation during the 1971 growing season resulted in the smallest grain yield of any of the twelve years studied. Variability of precipitation was also low. In no ten day period did the precipitation exceed 30 mm, and in only three cases was it less than 10 mm. Hence, values obtained from model runs using ten and thirty day precipitation averages differed by less than 1%.

Instead of continuing our experiments by running the model for longer and longer time periods, we have plotted grain yield (computed using ten day averaged precipitation) against seasonally and annually averaged precipitation for each of the twelve years (Figure 5). There is a quite good correlation between yield and seasonally averaged precipitation, but only a very weak one for the case of annually averaged precipitation. The annually averaged precipitation in 1971 and 1982 were almost identical, but in 1971 the rain fell mostly outside the growing season, whereas in 1982 it was distributed through the growing season with the larger

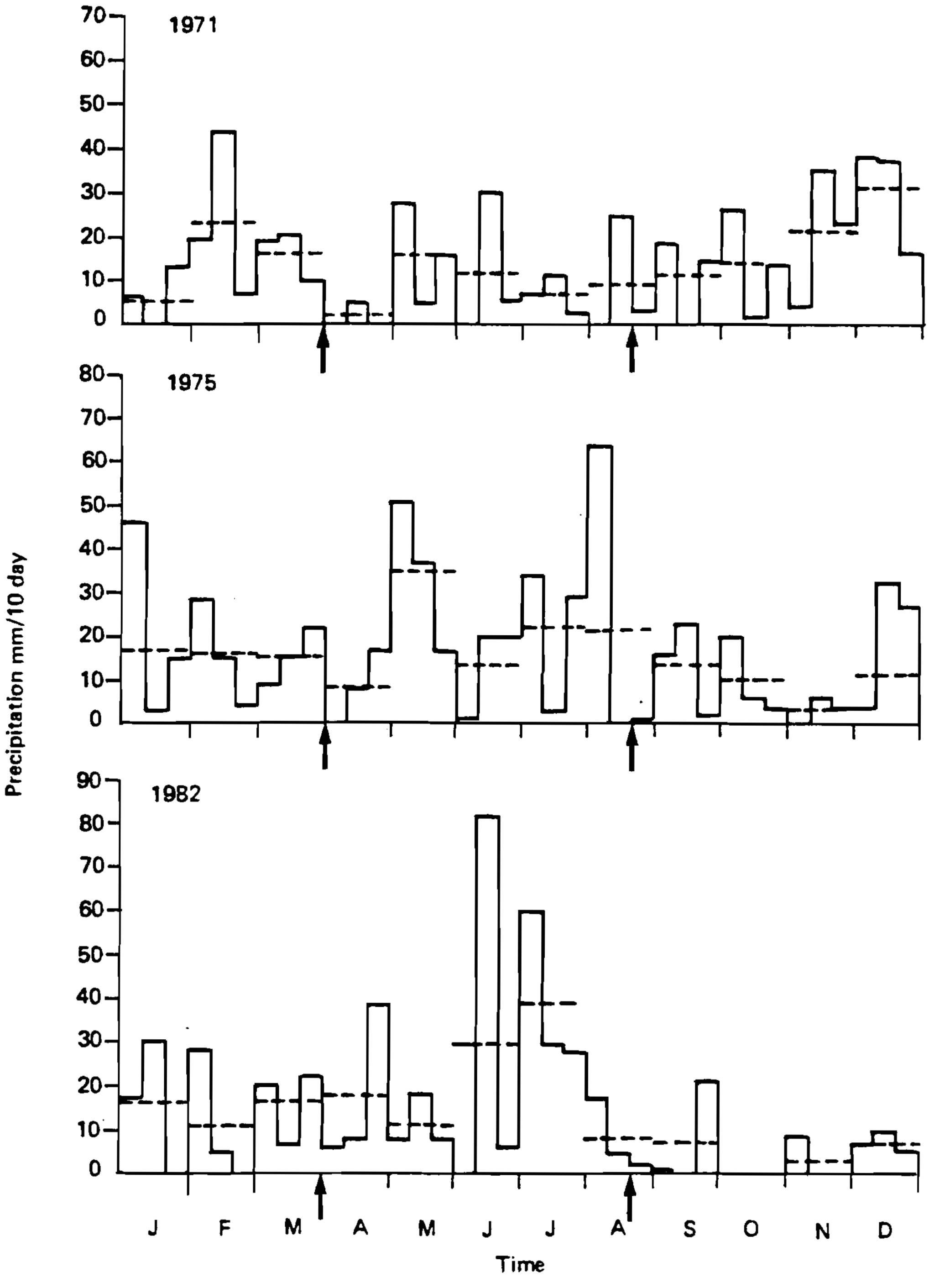


Figure 4. 10 day (solid lines) and 30 day (dashed) averaged precipitation (mm) at Stavropol for the years 1971, 1975 and 1982.

Table 2. Dry matter production of oats (kg/ha) divided into four basic plant components. Estimates are for three years (1971, 1975 and 1982) and for 10 day and 30 day precipitation averages.

YEAR	DRY MATTER PRODUCTION (kg/ha)				PRECIPITATION (mm)	
(Avg Period)	LEAF	ROOT	STEM	GRAIN	ANNUAL	GROWING SEASON
1971 (10 day)	1029	351	995	1458	511.0	136.8
1971 (30 day)	1055	355	1005	1472		
1975 (10 day)	1366	499	1367	2623	778.0	301.0
1975 (30 day)	1421	509	1392	2552		
1982 (10 day)	1889	687	1865	4240	498.0	314.0
1982 (30 day)	2079	705	1943	4455		

portion falling in the last half, when the grain was forming. It seems clear from Figure 5 that (as would be intuitively expected) the year to year change in annual precipitation is not a very good measure of predicted crop yield. On the other hand, the correlation with precipitation during the cropping season is surprisingly good.

We are, of course, fully aware that we have tested the response of a model of nature and not nature itself. If one finds that ten day, monthly, or seasonal rainfall data can be used with nearly equal accuracy in an agroclimatic model, it cannot automatically be concluded that the same is true in nature. Nevertheless, the results give us cause for hope that this very convenient state of affairs might be true. Obviously, it would be very interesting to repeat these experiments with a model that could incorporate daily or even hourly rainfall data.

4.2. Experiment 2. Comparing Short-Term and Long-Term Sensitivity of Yield to Climatic Change

In order to explore this question we use the results of some experiments previously reported by Watts (1983). The experiments were performed using the VNIISI model, an environmental model that contains both crop growth and soil components (Pitovranov *et al.*, 1984). The crop model uses only annually averaged climate data, but the soil model has the advantage of allowing soil characteristics to evolve over very long time periods. It is therefore unique in that it can be used to explore the relative values of long- and short-term changes of yield in response to climatic change. The sensitivity of the model to temperature and precipitation changes was examined in the following way. First the soil and geography in the model were fixed to represent approximately the Great Plains of the United States (plains, loamy sand). Nitrogen fertilizer application was fixed at 50 kg/ha and phosphorus at 10 kg/ha (similar to current fertilizer use on wheat in Kansas). The model allows for local temperature to be changed as an input. Long-term average precipitation values can also be specified, but the model itself imposes a stochastic

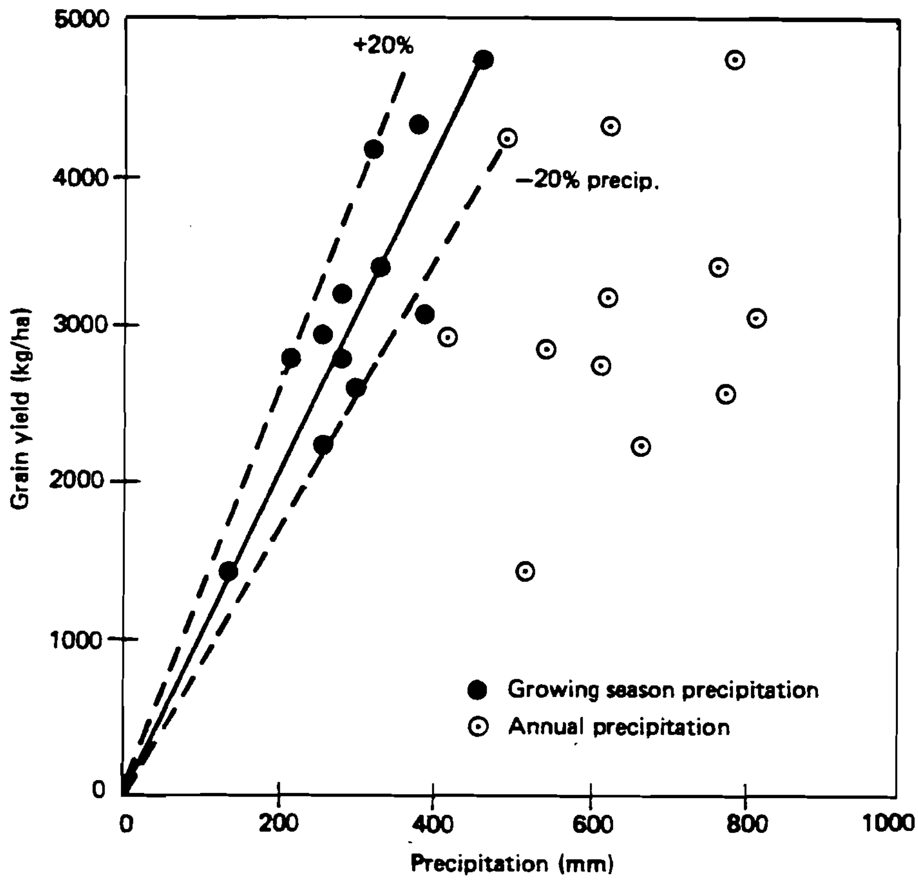


Figure 5. Plots of modeled oats yield against seasonally and annually averaged precipitation. Yields were computed using 10 day averaged precipitation.

variation of precipitation about the average value. A temperature and precipitation value was chosen and the model run until a statistical steady state was reached. Average yield and the variations of precipitation and yield about the average were recorded. The experiment was then repeated for another set of average temperature and precipitation data.

The results are shown in Figure 6. (Many runs for various soil types, fertilizer application rates, and geographic regions were made, and the results were all qualitatively similar to those shown.) The solid lines show the steady state variations of yield with (average) precipitation for various temperatures. The slopes of these lines represent the long-term sensitivities of yield to precipitation changes at various temperatures. The dashed lines represent variations of yield caused by the year to year variation of precipitation. The two are clearly not the same. In fact, for the cases of T = 9°C, and T = 7°C with P = 670 mm/yr, the *signs* of the sensitivities are different.

Some interesting inferences can be drawn from this numerical experiment. Short- and long-term sensitivities of agroclimatic models (and, by inference, real systems) can be very different. Many models, in particular, empirical-statistical models, measure only short-term sensitivities. In analyzing and attempting to predict crop yield change due to long-term climatic change *both* are important.

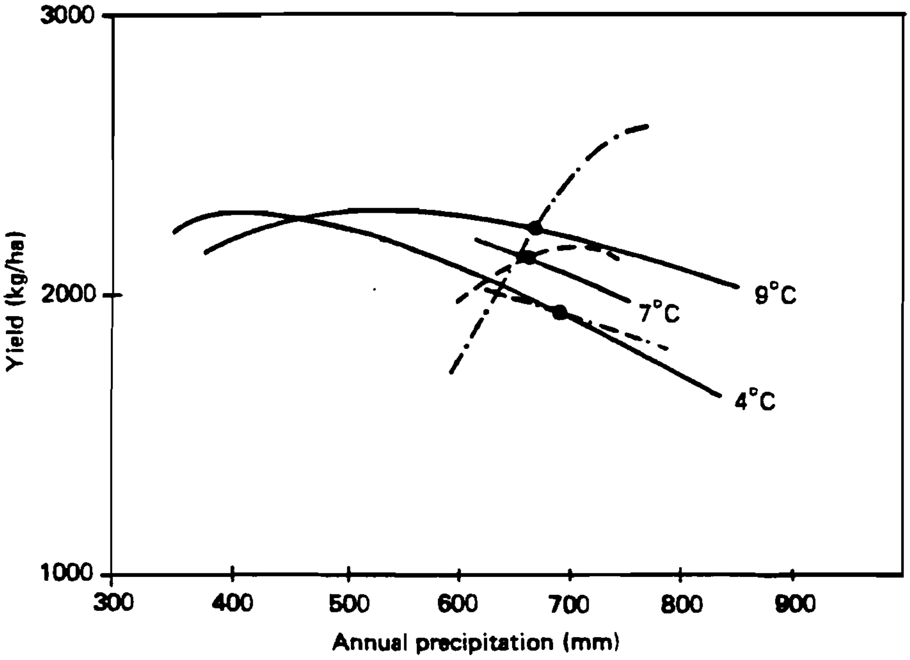


Figure 6. Long- and short-term sensitivities for wheat yields (nitrogen fertilizer, 50 kg/ha; phosphorus fertilizer, 10 kg/ha).

Long-term changes in climate, in temperature and precipitation, say, quite obviously might affect average crop yields. It appears from the present results that the sensitivity to short-term climatic variations, i.e., the short-term sensitivities, also change when long-term climatic change occurs. Variability of interannual temperature and precipitation is also expected to change in response to long-term climatic change. If a given climate change caused both these variabilities and the associated short-term sensitivities to decrease, the variability of crop yields might decrease substantially, and this could be very important for regions of marginal agriculture (Parry, 1976). On the other hand, increases in both variabilities and short-term sensitivities could prove disastrous to marginal agriculture, even if long-term average yields increased.

5. AGROCLIMATIC MODEL CHECKLIST

The preceding discussion has addressed a number of questions concerning agroclimatic models and their applicability in climate impact analysis. Table 3 is an attempt to fit together some of these points in the form of a model checklist. This allows us to make our own assessment of a particular model on the basis of its component parts and its operation.

5.1. Model Components

Three classes of model components are depicted:

a) *Data inputs* — a list of variables which can be input directly although some may be derived internally by the model. These can be natural or anthropogenic inputs.

EXPLICIT MODEL VARIABLES			PRESENT DAY CONDITIONS							CLIMATIC CHANGE				RESPONSE OPTIONS
			MODEL-SPECIFIC VARIABLE	TEMPORAL RESOLUTION					RESPONSE TO SPORADIC EVENTS	STEPLIKE		TRANSIENT		ADJUSTMENT OF MODEL VARIABLE
				YEAR	MONTH	SUB-MONTH	DAY	INTER-ANNUAL VARIATIONS		STATIC MEAN	DYNAMIC EQUILIBRIUM	STATIC MEAN	DYNAMIC EQUILIBRIUM	
NATURAL INPUTS	SITE													
	CLIMATE	TEMPERATURE												
		PRECIPITATION												
		SUNSHINE/ RADIATION												
		EVAPORATION												
		WINDSPEED												
		HUMIDITY												
		CO_2												
	SOIL	SOIL WATER												
		NUTRIENTS												
		SOIL STRUCTURE												
		EROSION												
		SALINITY												
		pH												
	EXOGENEOUS YIELD-REDUCING FACTORS	PESTS & DISEASES												
		WEEDS												
ANTHROPOGENIC INPUTS	LAND MANAGEMENT PROCEDURES	FERTILIZERS												
		IRRIGATION												
		SOWING & HARVEST												
		TILLAGE												
		HERBICIDES & PESTICIDES												
	CROP SELECTION	CROP TYPE												
		CROP STRAIN												
DERIVED OUTPUTS		LAND EVALUATION												
		RELATIVE PRODUCTIVITY												
		AGRICULTURAL YIELD												
		POTENTIAL YIELD												
		PARTITIONED YIELD												

Table 3. An agroclimatic model checklist.

b) *Site specifications* — indicating whether a model is site- or area-specific (if it is not, see 5.2.c).

c) *Derived outputs* — ranging from suitability indices to detailed crop yield components.

5.2. Model Operation

We have identified three features important in running a model:

a) *Simulation of present-day conditions* — indicating the time-step used during the growing season, whether variables are updated from year to year, and the capability for responding to sporadic events such as frosts, floods, etc.

b) *Simulation of climatic change* — whether this is modeled as a step-like change of mean values or of a distribution of values; or as a transient change of the mean or of a distribution.

c) *Response option* — indicating whether it is possible to adjust model inputs i.e. to simulate the choices of response that a farmer might face.

In general, the scheme attempts to include first those variables that are more commonly modeled, so that the incorporation of variables towards the bottom of each list indicates an increased level of model sophistication. Likewise, entries towards the right of the tableau indicate a more detailed, higher resolution simulation capability.

6. CONCLUSIONS

In this paper we have attempted to outline some of the techniques that can be employed to assess the impact of climatic change on crop production. We have proceeded from the premise (for which we present numerous supporting examples) that fluctuations in climate can induce significant biophysical responses in agricultural crops, affecting both the quality and quantity of the harvestable product. It is is these "first-order" responses to climate that form the focus of our discussion, but clearly these may constitute only the initial link in a chain of economic and social repercussions cascading through the farming system and beyond.

There exists a broad spectrum of approaches for examining first-order crop responses to climatic variations, which we have grouped under the heading of agroclimatic models. Each has been developed to reflect certain features of the crop production system, a system that we have characterized in the form of a farm calendar. We have stressed that most agroclimatic models were developed with a contemporary application in mind. The evaluation of crop responses to climatic change, particularly longer-term changes of an amplitude lying well outside the present range, introduces new dimensions of complexity to the modeling procedure. This merely serves to spotlight the importance of detailed and thorough sensitivity testing and validation of models. Without these, and bearing in mind the inevitable uncertainties associated with each stage of the climate impact "cascade", the credibility attached to estimates of crop response could be cast in serious doubt.

From the results of the two sensitivity experiments, we have illustrated how:

a) It may not be necessary to operate models at the most detailed (and costly) time resolution if satisfactory results can be obtained using a longer time-step.

b) The short-term response of crops to a particular climatic anomaly may be quite different to the response over a longer period.

Finally, we have presented a method of assessing an agroclimatic model, by means of a checklist. As well as incorporating traditional model characteristics, the checklist also considers how a model handles climatic change and whether input variables can be adjusted to represent possible farming responses to this change.

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