Chapter 5

Agrometeorological forecasting

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1 Overview

1.1 Scope of agrometeorological forecasting

Agrometeorological forecasting covers all aspects of forecasting in agrometeorology. Therefore, the scope of agrometeorological forecasting very largely coincides with the scope of agrometeorology itself. In addition, all on-farm and regional agrometeorological planning implies some form of impact forecasting, at least implicitly, so that decision-support tools and forecasting tools largely overlap (Dingkuhn et al., 2003; several papers in Motha et al., 2006).

In the current chapter, the focus is on crops, but attention will also be paid to sectors that are often neglected by the agrometeorologist, such as those occurring in plant and animal protection[1]. In addition, the borders between meteorological forecasts for agriculture and agrometeorological forecasts are not always clear. Examples include the use of weather forecasts for farm operations such as spraying pesticides or deciding on trafficability in relation to adverse weather. Many forecast issues by various national institutions (weather, but also commodity prices or flood warnings) are vital to the farming community, but they do not constitute agrometeorological forecasts. Some non-agrometeorological approaches do, however, have a marked agrometeorological component. This applies, for instance, to the airborne pollen capture method[2] of crop forecasting developed by Besselat and Cour (1997).

It is important to note at the very beginning of the present chapter of GAMP that operational forecasting is done for different spatial scales (Gorski and Gorska, 2003). At the lowest end, the “micro-scale”, we have the field or the farm. Data are usually available with good accuracy at that scale, for instance the breed or the variety are known, and so are the yield and the environmental conditions: soil type, soil depth, rate of application of inputs. The micro-scale is the scale of on-farm decision making by individuals, irrigation plant managers, etc.

The macro-scale is the scale of the region, which is why forecasting for a district, or a province is usually referred to as “regional” forecasting. Regional forecasts are at the scale of agricultural statistics. Regional forecasts are relevant for a completely different category of users, including national food security managers, market planners and traders, etc. At the macro-scale, many variables are not known and others are meaningless, such as soil water holding capacity.

Needless to say, the real world covers the spectrum from macro- to micro-scales, but the two extremes are very well defined in terms of customers and methods[3]. Several applications are at an intermediate scale. They would include, for instance, certain types of crop insurances, the “livelihood analysis” that is now applied in many food security monitoring systems, fire monitoring systems, etc.

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1 Plant and animal pathologists do traditionally deal with the issues, but they are not necessarily aware of the modern techniques (such as geostatistics) that are now familiar to most agrometeorologists.

2 The method applies mostly to high value and mostly wind pollinated crops such as grapes. Airborne pollen is sampled and calibrated against production in the surrounding area. The method is currently under-developed regarding the physico-physiological emission and capture of pollen by plants as a function of environmental conditions, transportation of pollens by air, the trapping efficiency including trap behaviour and effect of atmospheric agents, esp. rain.

3 Spatial scales are usually paralleled by time scales, with sampling frequencies decreasing when they refer to large areas.

Next, we should mention the links between forecasting and monitoring. Traditionally, monitoring is implemented by direct observation of the stage and condition of the organisms being monitored (type 1), or by observing the environmental conditions that are conducive (or not) to the development of organisms (type 2[4]). The second type allies mostly to pests and diseases. Surprisingly, type 1 monitoring is often more expensive than type 2 because of elevated labour costs. On the other hand, when data are collected to assess environmental conditions, we are relatively close to forecasting as data requirements naturally overlap between type 2 monitoring and forecasting.

1.2 Forecasting techniques in general[5]

There are a variety of generic forecasting methods, of which most can somehow be applied to agrometeorological forecasting as well (Petr, 1991). According to Armstrong (2001b), “judgement pervades all aspects of forecasting”, which is close to a definition which one of the authors has frequently applied to crop yield forecasting, which can be seen as “the art of identifying the factors that determine the spatial and inter-annual variability of crop yields” (Gommes, 2003a). In fact, given the same set of input data, different experts frequently come up with rather different forecasts of which, however, some are demonstrably better than others, hence the use of the word “art”.

There appears to be no standard classification of forecasting methods (Makridadis et al. 1998; Armstrong, 2001a). Roughly speaking, forecasting methods can be subdivided into various categories according to the relative share of judgement, statistics, models and data used in the process. Armstrong identifies 11 types of methods that can be grouped as

- Judgemental, based on stakeholders’ intentions or on the forecasters' or other experts’ opinions or intentions. Some applications of this approach exist in agrometeorological forecasting, especially when other variables such as economic variables play a part (for instance the “Delphi expert forecasting method” for coffee, Moricochi et al. 1995);
- Statistical, including univariate (or extrapolation), multivariate (statistical “models”) and theory-based methods. This is the category where most agrometeorological forecasting belongs;
- Intermediate types include expert systems, basically a variant of extrapolation with some admixture of expert opinion, and analogies, which Armstrong places between expert opinions and extrapolation models. This is also covered in the present chapter.

In this chapter, we consider “parametric models” to be those that attempt to interpret and to quantify the causality links that exist between crop yields and environmental factors – mainly weather-, farm management and technology. They include essentially crop simulation models[6] and statistical[7] “models” which empirically relate crop yield with assumed impacting factors. Obviously, crop-yield-weather simulation belongs to Armstrong’s Theory-based Models[8]. Non-parametric forecasting methods are those that

4 A reviewer rightly underlines the similarities between indirect monitoring (type 2) and nowcasting.
5 Definitions adopted in the present chapter may differ from those adopted in other scientific areas
6 Also known as process-oriented models or mechanistic models.
7 For an overview of regression methods, including their validation, refer to Palm and Dagnelie (1993) and to Palm (1997).
8 Armstrong considers only econometric models.

rely more on the qualitative description of environmental conditions and do not involve any simulation as such (Armstrong's Expert Systems and Analogies).

1.3 Areas of application of agrometeorological forecasts

1.3.1 Establishment of national and regional forecasting systems

There are a number of examples of institutionalised forecasting systems. As far as the authors are aware, they are never referred to as "agrometeorological forecasting systems", even if many are built around some form of agrometeorological core (Glantz, 2004). Most forecasting and warning systems in agriculture, forests, fisheries, livestock, the health of plants, animals and humans, fires, commodity prices, food safety and food security, etc. do have an agrometeorological component.

Some forecasting systems are operated commercially, for instance for high-value cash crops (coffee, sugarcane, oilpalm), directly by national or regional associations of producers. However, the majority of warning systems were established by governments or government agencies or international organisations, either because of the high costs involved (because the information serves the specific purposes of the government or organisation, e.g. for tax control systems), or because of lack of commercial interest (e.g. in food security).

On the other hand, it is striking how few integrated warning and forecasting systems do exist. Clearly, fire forecasting, crop yield forecasting, pest forecasting and many other systems have a number of data and methods in common. Yet, they are mostly operated as parallel systems. For a general overview of the technical and institutional issues related to warning systems, refer to the above-mentioned volume by Glantz.

Good examples of pest and disease warning systems can be found in Canada, where pest warning services are primarily the responsibility of the provincial governments. In Quebec, warning services are administered under the Réseau d'Avertissements Phytosanitaires (RAP). The RAP was established in 1975 and includes ten groups of experts, 125 weather stations and covers 12 types of crops. Warnings and other outputs from the RAP can be obtained by E-mail, fax or internet (Favrin, 2000).

Warning and forecasting systems have recently undergone profound changes linked with the generalisation of the internet. The modern systems permit both the dissemination of forecasts and the collection of data from the very target of the forecasts. Agricultural extension services usually play a crucial role in the collection of data and the dissemination of analyses of forecasting systems (Gommes, 2001b, 2003a). In addition to providing inputs, users can often interrogate the warning system. Light leaf spot (*Pyrenopeziza brassicae*) is a serious disease of winter oilseed rape crops in the United Kingdom. At the start of the season, a prediction is made for each region using the average weather conditions expected for that region. Forecasts available to growers over the Internet are updated periodically to take account of deviations in actual weather from the expected values. The recent addition of active server page technology has allowed the forecast to become interactive. Growers can input three pieces of information (cultivar choice, sowing date and autumn fungicide application information) which are taken into account by the model to produce a risk assessment that is more crop and location specific (Evans et al., 2000).

Before they become operational, forecasting systems are often preceded by a pilot project to fine-tune outputs and consolidate the data collection systems. A good example is provided by PAFAS (Pilot Agrometeorological Forecast and Advisory System) in the Philippines because of the number of institutional users involved. The general objectives of the proposed PAFAS were to provide meteorological information for the benefit of agricultural operations (observation and processing data) and to issue forecasts, warnings, and advisories of weather conditions affecting agricultural production within the pilot area (Lomotan, 1988).

This section emphasizes that few warning systems can properly assess the damage caused by extreme agrometeorological events to the agricultural sector. Such damage may be significant; it may reach the order of magnitude of the GNP growth. For many disaster-prone countries, agricultural losses due to exceptional weather events are a real constraint on their global economy. The indirect effects of disasters on agriculture may last long after the extreme event took place, when infrastructure or slow growing crops (e.g. plantations) were lost. The time needed to recover from some extreme agrometeorological events ranges from months to decades.

1.3.2 Farm-level applications

1.3.2.A Overview

Farmers in all cultures incorporate weather and climate factors into their management process to a significant extent. Planting and crop selection are functions of the climate and of the normal change of the seasons. Timing of cultural operations, such as cultivation, application of pesticides and fertilizers, irrigation and harvesting, is strongly affected by the weather of the past few days and in anticipation of the weather for the next few days. In countries with monsoonal climates, planting dates of crops depend on the arrival of the monsoonal rains. Operations such as hay-making and pesticide application will be suspended if rain is imminent. Cultivation and other cultural practices will be delayed if the soils are too wet. The likelihood of a frost will trigger frost-protection measures. Knowledge of imminent heavy rains or freezing rains will enable farmers to shelter livestock and to protect other farm resources. Irrigation scheduling is based on available soil moisture[9] and crop-water-use rate, both of which are functions of the weather. Farmers have always been very astute weather watchers and are quick to recognize weather that is either favourable or unfavourable to their production systems.

This traditional use of weather in farm management is significant and very important, but it is not the only use of weather information in farm management. In addition to these well-known direct effects of weather on agricultural production, weather-wise farm management includes the indirect effects of weather. Temperature determines the rate of growth and development[10] of insects, temperature and humidity combinations influence the rate of fungal infection, evapotranspiration rates determine water use rates and irrigation schedules, and radiation and moisture availability are important in the rate of nutrient uptake by crops. These effects of weather on production are not directly observable and are not the basis of a “yes” or “no” or “don’t” type of decision, but they have significant economic potential when incorporated into the farm management process (McFarland and Strand, 1994).

Consequently, regarding the importance of weather forecasting in farm management,

9 The terms “soil moisture” and “soil water content” are used interchangeably

10 Growth refers to the accumulation of biomass or weight by organisms. It is a quantitative phenomenon. Development, on the other hand, refers to the qualitative modifications that take place when organisms grow: formation of leaves, differentiation of flowers, successive larval stages of some insects etc. While this chapter deals mainly with growth forecasting, there are applications where development is receiving most attention (see 5.5).

the following aspects are crucial:

- current weather information (e.g., forecasts) must be provided routinely to the decision maker by an outside agency. Farmers cannot observe or develop all the necessary information;
- managers have to incorporate less than perfect weather information into their decision processes;
- farmers can develop and evaluate their decision processes for direct effects of weather, but must rely on outside expertise for decision support regarding indirect effects of weather.

The use of weather in farm management in developing nations is particularly valuable when the level of production inputs is increased. Virtually all the inputs that characterise increased production are weather-sensitive and most are also weather-information-sensitive. Irrigation, fertilization, pesticides, fungicides, and mechanization are all more weather-sensitive than traditional agricultural operations. In these cases, the incorporation of weather in the management process should be included in the transfer of the technology of the appropriate inputs. For example, when the use of insecticides for crop protection is implemented, the full use of weather information in pest management and the effects of weather on the application should be included in the technology transfer process.

Weather contingency planning for the farm level is not well developed. Swaminathan (1987) recommended that a “Good Weather Code” be developed, in addition to contingency plans that key on drought or monsoon failure. Areas that are chronically drought-prone need measures to favour moisture retention and soil conservation.

Pest management is both weather-sensitive and weather-information-sensitive. Weather sensitivity is primarily defined as the effects of wind, temperature, and precipitation on application of the pesticide. The weather-sensitive aspects of pest management are supported by the more or less conventional weather information from the mass media. If the farmer is aware of the nature of the weather-sensitivity, the existing decision processes should be sufficient. Scheduling of the times of application to avoid unfavourable winds or anticipated rains is within the farmer’s traditional use of weather information. Weather information sensitivity is primarily the optimal timing of the pesticide as a function of temperature effects on insect population dynamics and the crop growth rates. Insects are poikilothermic organisms, whose rate of growth and development is determined by the heat energy of the immediate environment. Temperature, as a measure of available heat energy, is used extensively to derive insect growth rates and development simulation model.

1.3.2.B Response farming applications

“Response farming” is a methodology developed by Stewart (1988), based on the idea that farmers can improve their return by closely monitoring on-farm weather and by using this information in their day to day management decisions. The emphasis here is on the use of quantitative current data which are then compared with historical information and other local reference data (information on soils, etc.). This is a simple variant of the what-if approach. What about planting now if only 25 mm of rainfall has been recorded from the beginning of the season? What about using 50 kg N-fertiliser if rainfall so far has been scarce and the fertiliser will increase crop water requirement and the risk of a water stress?

The method implies that, using the long-term weather series, decision tools (usually in tabular or flowchart forms) have been prepared in advance. They are based on

- knowledge of local environmental/agricultural conditions (reference data[11]);
- measurement of local "decision parameters" by local extension officer or farmer;
- economic considerations.

Crop forecasts can improve response-farming in two different ways. Firstly, the decision tables should probably be somewhat improved by using simulation models to better understand the impact of past weather on past crops. Next, models could be run on the farm to simulate possible scenarios, although this is hardly imaginable in developing countries.

In the latter, the decision-tools must be prepared by National Agrometeorological Services in collaboration with Agricultural Extension Services and subsequently disseminated to farmers. The third operation will be the most difficult in practice (WMO/CTA, 1992).

A similar concept to response farming is flexcropping; it is used in the context of a crop rotation where summer fallow is a common practice, especially in dry areas, like the Canadian prairies. Rotations are often described as 50:50 (1 year crop, 1 year fallow) or 2 in 3 (2 years crop, 1 year fallow). The term flex crop has emerged to describe a less rigid system where a decision to re-crop (or not) is made each year based on available soil water content and the prospect of getting good moisture during the upcoming growing season (Zentner et al. 1993; Peter Dzikowski and Andy Bootsma, personal communication).

Weisensel et al. (1991) have modelled the relative profitability and riskiness of different crop decision models that might be used in an extensive setting. Of particular interest is the value of information added by the availability of spring soil moisture data and by dynamic optimisation. The simulation has shown that flexcropping based on available soil moisture at seeding time is the most profitable cropping strategy. The authors stress the importance of accurate soil water content information.

1.3.2.C Farm management and planning (modern farming)

Farmers have been using weather forecasts directly for a number of years to plan their operations, from planting wheat to harvesting hay and spraying fungicides. Simulation models, however, have not really entered the farm in spite of their potential. The main causes seem to be a mixture of lack of confidence and lack of data[12] (Rijks, 1997).

Basically three categories of direct applications of forecasts can be identified:

- what-if experiments to optimise the economic return from farms, including real-time irrigation management. This is the only area where models are well established, including in some developing countries (Smith, 1992);

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11 A simple example of this could be a threshold of air moisture or sunshine duration to decide on pest risk, or a threshold of salt content of water to decide on irrigation-salinity risk. Normally, other parameters (economic) also play an important part.

12 For developing countries, one of the reviewers of this document adds the very basic "lack of electricity", lack of computers, lack of knowledge about the existence of models, not to mention the fact that models were rarely developed for the farming community.

- optimisation of resources (pesticides, fertiliser) in the light of increasing environmental concern (and pressure);
- risk assessments, including the assessment of probabilities of pest and disease outbreaks and the need to take corrective action.

Contrary to most other applications, on-farm real-time operations demand well designed software that can be used by the non-expert, as well as a regular supply of data.

In theory, some inputs could be taken automatically from recording weather stations, but specific examples are rare. A publication by Hess (1996) underlines the sensitivity of an irrigation simulation programme to errors in the on-farm weather readings.

Systems have been described where some of the non-weather inputs come from direct measurement. Thomson and Ross (1996) describe a situation where model parameters were adjusted based on soil water sensor responses to drying. An expert system determined which sensor readings were valid before they could be used to adjust parameters.

Irrigation systems have a lot to gain from using weather forecasts rather than climatological averages for future water demand. Fouss and Willis (1994) show how daily weather forecasts, including real-time rainfall likelihood data from the daily National Weather Service forecasts can assist in optimising the operational control of soil water and scheduling agrochemical applications. The authors indicate that the computer models will be incorporated into decision support models (Expert Systems) which can be used by farmers and farm managers to operate water-fertiliser-pest management systems.

Cabelguenne et al. (1997) use forecast weather to schedule irrigation in combination with a variant of EPIC. The approach is apparently so efficient that discrepancies between actual and weather forecasts led to a difference in tactical irrigation management.

We conclude this section with an interesting example of risk assessment provided by Bouman (1994) who has determined the probability distribution of rice yields in the Philippines based on the probability distributions of the input weather data. The uncertainty in the simulated yield was large: there was 90% probability that simulated yield was between 0.6 and 1.65 times the simulated standard yield in average years.

1.3.3 Warning systems, especially for food security([13])

Many warning systems target both individual and institutional users, although the main target of warnings for food security is usually governments. In many developing countries, farmers still practice subsistence farming, i.e. they grow their **own food**, and depend directly on their **own food** production for their livelihood. Surpluses are usually small; they are mostly commercialised in urban areas (the urban population constitutes about 30% of the total population in Africa). Yields tend to be low: in Sahelian countries, for instance, the yields of the main staples (millet and sorghum) are usually in the range of 600 to 700 kg/ha during good years. Inter-annual fluctuations are such that the **national** food supply can be halved in bad years or drop to zero production in some areas.

This is the general context in which food surveillance and monitoring systems were

13 Largely taken from Gommes, 1997. Although pests and diseases are not the object of this section, it is worth noting that many models developed in the general field of plant pathology can often be associated to the crop-weather models in impact assessments and warning systems. For an overview of such models, refer to Seghi et al. 1996. Most of them are typical developed country applications, where both data availability and good communications permit their implementation in a commercial farming context.

first established in 1978. Currently, about hundred countries on all continents operate food security warning systems; their name varies, but they are generally known as (Food) Early Warning Systems (EWS). They contribute to:

- informing national decision makers in advance of the magnitude of any impending food production deficit or surplus;
- improving the planning of food trade, marketing and distribution;
- establishing co-ordination mechanisms between relevant government agencies;
- reducing the risks and suffering associated with the poverty spiral.

EWS cover all aspects from food production to marketing, storage, national imports and exports down to consumption at the household level. Monitoring weather and estimating production have been essential components of the system from the onset, with an direct and active involvement of National Meteorological Services.

Over the years, the methodology has kept evolving, but crop monitoring and forecasting remain central activities:

- operational forecasts are now mostly based on readily available agrometeorological or satellite data, sometimes a combination of both. They do not depend on expensive and labour intensive ground surveys and are easily revisable as new data become available;
- forecasts can be issued early and at regular intervals from the time of planting until harvest. As such, they constitute a more meaningful monitoring tool than the monitoring of environmental variables (e.g. rainfall monitoring);
- forecasts can often achieve a high spatial resolution, thus leading to an accurate estimation of areas and number of people affected.

Due to the large number of institutional and technical partners involved in EWS, interfacing between disciplines has been a crucial issue. For instance, crop prices are usually provided as farm gate or marketplace prices, food production and population statistics cover administrative units, weather data correspond to points (stations) not always representative for the agricultural areas, satellite information comes in pixels of varying sizes, etc. GIS techniques, including gridding, have contributed towards improving links in the “jungle” of methods and data (Gommes, 1996).

1.3.4 Market planning and policy

Advance knowledge of the likely volume of future harvests is a crucial factor in market. Prices fluctuate as function of the expected production[14] (read: forecast production), with a large psychological component.

In fact, prices depend more on the production traders anticipate than on actual production. Accurate forecasts are, therefore, a useful planning tool. They can also often act as a mechanism to reduce speculation and the associated price fluctuations, an essential factor in the availability of food to many poor people.

Illustration 1 shows that the wheat prices increased from about US$ 150/ton in 1993

14 The main factors affecting prices are world production forecasts, speculation, weather, stocks and the time of the year.

to about 275 at the end of 1995. The main causes were the policy of both the United States and the European Union to reduce stocks (stocks are expensive to maintain), and the poor prospect of the 1995-96 winter wheat in the US and EU. Maize, a summer crop, was affected by “contagion”. Had the forecasts been more accurate and reliable, it is clear that the prices would have remained more stable: they culminated around May 1996, and returned to normal values thereafter.

A similar, but more dramatic situation concerned coffee prices in 1977 when they reached an all-time high due to low stocks and frost in some of the main producing areas in Brazil (Brazil produces about 28 % of the world output of which more than half comes from São Paulo and Minas Gerais).

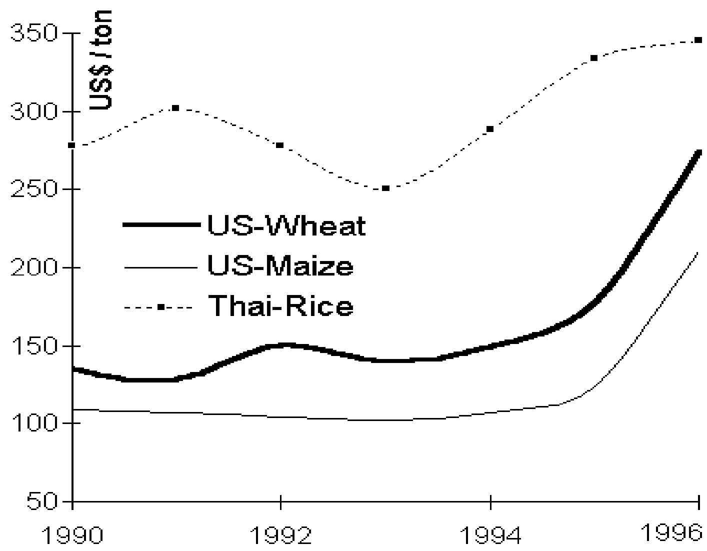

Illustration 1: variations of wheat, rice and maize prices between 1990 and 1996 (fixed 1996 CIF1 US$ prices). The tics on the X-axis represent the beginning of the respective years.

Commercial forecasts are now available by subscription. CROPCAST (CROPCAST, 1994), for instance, provides estimates not only for yields, but also for production, areas, stocks, crop condition and futures prices.

On a local scale, many food processing plants depend on production in their area, which is linked to the seasonality of production for most crops (canning of fruit and vegetables, sugar from sugar beet, cotton fibre processing, oil from sunflowers and oil palm[15], etc.). It is important to have accurate forecasts for the volume to be processed and the timing.

1.3.5 Crop insurance

Crop insurance is one of the main non-structural mechanisms used to reduce risk in farming; a farmer who insures his crop is guaranteed a certain level of crop yield or income, equivalent, for instance, to 60 or 70 percent of the long-term average. If, for reasons beyond the farmer's control, and in spite of adequate management decisions, the yield drops below the guarantee, the farmer is paid by the insurer a sum equivalent to his loss, at a price agreed before planting.

15 Oil palm and other palms pose a series of very specific forecasting problems due to the very long lag between flower initiation and harvest. This period usually covers 3 years and more. In addition, probably more than in other plants, qualitative factors are very critical, for instance the effect of temperature on sex differentiation (only female flowers produce seeds, thus oil). See Blaak (1997) for details.

Crop insurance schemes can be implemented relatively easily when there is sufficient spatial variability of an environmental stress (e.g. with hail), but remains extremely difficult to implement for some of the major damaging factors, such as drought, which typically affect large areas, sometimes entire countries.

One of the basic tools for insurance companies is risk analysis (Abbaspour, 1994; Decker, 1997). Crop forecasting models play a central part: when run with historical data, they provide insight into the variability patterns of yield. Monte Carlo methods play an important part in this context, either in isolation or in combination with process-oriented or statistical models. Almost all major models have been used in a risk assessment context: for instance WOFOST (Shisanya and Thuneman, 1993), AUSCANE (a sugar cane model; Russel and Wegener, 1990) and others (de Jager and Singels, 1990; Cox, 1990).

Many of the papers presented at the international symposium on "*Climatic Risk in Crop Production: Models and Management in the semi-arid Tropics and Subtropics"* in July 1990 in Brisbane are relevant in the present context.

Crop insurance is not very developed in many Third World countries and in transition economies, although the World Bank and the World Food Programme are currently setting up schemes that should considerably facilitate food security-related operations by resorting to insurance-based emergency funds. The difficulty in implementing insurance schemes to assist smallholders is best explained by the fact that many farmers live at subsistence level, i.e. they do not really enter commercial circuits. Rustagi (1988) describes the general problématique rather well. For instance, insurance companies insure a crop only if the farmer conforms to certain risk-reducing practices, e.g. early planting. The identification of the "best" planting dates constitutes an direct application for process-oriented crop-weather models. The quoted paper by Shisanya and Thuneman (1993) uses WOFOST to determine the effect of planting date on yields in Kenya.

An interesting example regarding both forecasting of the quality of products and insurance is given by Selirio and Brown (1997). The authors describe the methods used in Canada for the forecasting of the quality of hay: the two steps include the forecasting of grass biomass proper, and subsequent forecasting of the quality based essentially on the drying conditions. One of the reasons models have to be used is the absence of a structure that measures, stores and markets forage crops that is comparable to grain crops. In addition, field surveys are significantly more expensive to carry out than forecasts.

Crop forecasts used in crop insurance schemes must conform to several criteria that are less relevant for other applications:

- <u>Tamper-resistance</u>: potential beneficiaries of the insurance should not be in a position to directly or indirectly manipulate the yield estimate;
- <u>Objectivity</u>: once the methodology has been defined in precise terms, the forecasts can be calculated in an objective manner;
- <u>Special calibration techniques:</u> A "poor year" is defined as a year in which conditions are bad enough to trigger the payment of claims to insurance subscribers. A "poor year" can be defined based on at least three approaches: (1) absolute yield levels (possibly the most appropriate choice for food security), (2) a percentage of the average local yield (a "fair" choice as expectations are different in high potential and low potential areas and (3) probability of exceeding a specific yield (this usually gives "good" results in terms of statistical

significance). Rather than the statistical strength of the correlation between yield and crop weather index, it is the number of false positives (good year assessed to be poor) and false negatives (poor year assessed as good) that constitutes the most important criteria;

- Insensitivity to missing data: The best way to circumvent the occurrence of missing spatial data is to use gridded information that is not too sensitive to individual missing stations, provided sufficient data points are available and the interpolation process takes into account topography and climatic gradients.
- Publicity: Methodology has to be made available and understandable to potential subscribers of the insurance to build up mutual trust. Yield forecasts must be published regularly, for instance in national agrometeorological bulletins and other channels such as websites.

2 Variables used in agrometeorological forecasting

2.1 Overview

In agrometeorological forecasting, a statistic (e.g. yield) that is being forecast very frequently depends on a number of variables belonging to very different technical areas, from socio-economic and policy to soil and weather. The idea behind agrometeorological forecasting is first to understand what factors play a part in the inter-annual variability of the variable to forecast, and then to use the projections for those very factors to estimate future yield.

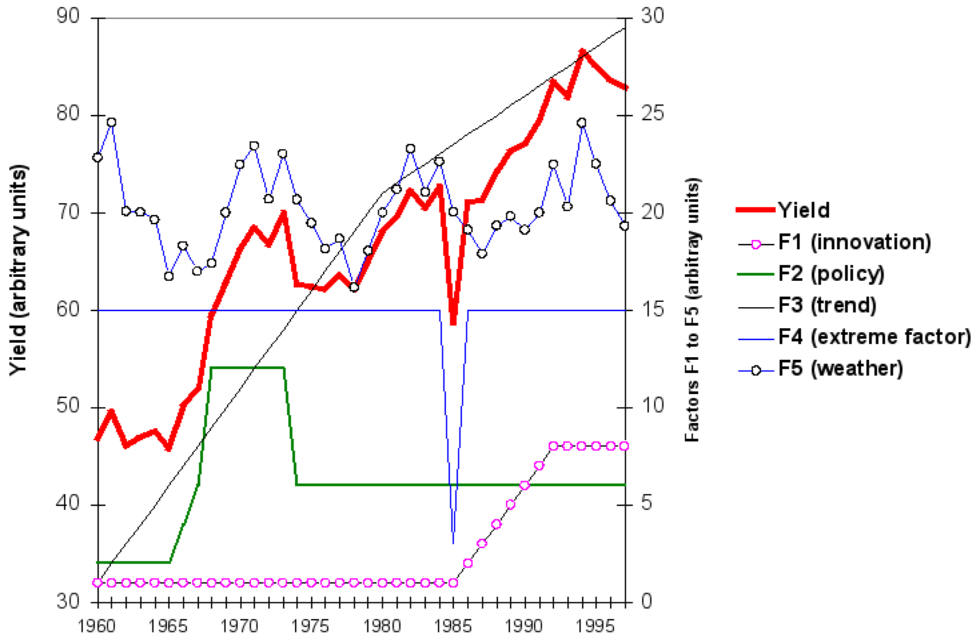

Illustration 2: A hypothetical example showing how yield depends on various factors.

A hypothetical example is shown in Illustration 2: innovation and trend are mainly associated with technology, such as breeds and improved harvesting techniques. Policy covers essentially economic decisions (such as prices) which lead producers to increase or decrease inputs or, in general, to modify management practices in response to the socio-economic environment. Extreme factors and weather are separated here for two reasons: (1) not all extreme factors are weather-related and, (2) for those that are, the mechanism of their interaction with agricultural production is rather different from the mechanisms usually at play under "normal" conditions (see 4.5).

"Weather" is supposed to remain within the normal physiological range of variations: organisms can respond in a predictable way, following well established and generally well understood patterns (e.g. photosynthesis response to light intensity, transpiration of animals as a function of atmospheric moisture content and temperature). On the other hand, "extreme" factors exceed the normal range of physiological response.

The sections below (2.2. to 2.5) provide a list of variables that are frequently used for agrometeorological forecasting. For many years, agrometeorological forecasting has resorted to raw weather variables as the main predictors. The current tendency is to focus on value-added variables, i.e. variables that have undergone some agrometeorological pre-processing using various models. Two such variables are soil moisture and actual evapotranspiration (ETA). Both are estimated using models. Soil moisture, for instance, constitutes a marked improvement over rainfall, because it assesses the amount of water that is actually available for crop growth and takes into account rainfall amount and distribution. Without entering into a discussion about indices and indicators, soil moisture can be regarded as a complex derived indicator, a value-added forecasting variable.

There is no standard method to select variables used for crop forecasting, as clearly shown by the number and variety of approaches that have been developed for agrometeorological forecasting starting in the 1950s.

The inclusion of limiting factors in the equations is characteristic of the existing methods. These factors vary in relation to crop, cultivation technique, soil and climate conditions. For example, equations for arid regions include moisture provision indices (productive water reserves in the soil, precipitation, etc.) whereas for rice (cultivated by flooding), atmospheric temperature and solar radiation values serve as the parameter. Data on crop conditions (number of stalks, leaf-surface area, plant heights) are used in an. array of methods. The majority of existing theoretical and applied yield forecast methods are based on statistical analysis of agrometeorological observation data and on correlation and regression analyses. The equations derived in these instances, should refer only to specific regions and cannot be used in others.

However, many mathematical models, in attempting to represent the complex processes of yield formation by allowing for many factors (including physiological processes, the stereometry of a crop, energetics of photosynthesis, and microflora activity in the soil), cannot be used at the present time to forecast yields in production conditions involving millions of ha (regional forecasts). The primary reason for this is the infeasibility of organizing observations of the above-mentioned complex processes. The second reason is the efficiency required for synthesizing a forecast. Some forecast models are not efficient in the use of the simple and least laborious forms of calculation, one which permits the rapid retrieval of vast amounts of information even with a limited number of predictors.

Further refinement of the existing yield forecast methods requires considerable improvements of the reference data, i.e. the agricultural statistics used for calibration, including improved maps of regional yield patterns. The extent of damage caused by pests and diseases , which is itself related to weather conditions, should be included as a correction factor.

Any deficiencies in the accuracy of agrometeorological forecasting depend on (a) how well the initial observations represent regional conditions, (b) how homogeneous the regional conditions (climate, soil characteristics, etc.) are, (c) how accurate the observations themselves are, and (d) how sensitive the model is to the variations in the agrometeorological variable being forecast (see section 3.2).

Long or medium range weather forecasting methods have not yet reached the level of accuracy desirable for operational use particularly in tropical countries. The temporal instability of some predictors does not allow the continued use of such models over a long period of time without change. The periodic revision of models has also to be viewed in the light of the possible impact of global warming and climate change on the inter-annual variability of meteorological parameters. In the case of medium range weather forecasts, accuracy level has improved potentially in extra tropical countries (see 2.5.3).

2.2 Technology and other trends

Most agricultural systems are affected by technology trends and, sometimes, variations that are short-lived and not necessarily related to environmental conditions[16]. It is stressed that some biological production system display regular variations that are endogenous or due to management practices. Some crops, for instance coffee in Kenya, display alternating pattern of high and low yields (Ipe et al. 1989.) Another essential point is that trends may be difficult to detect in the presence of very high weather variability.

Before the effect of weather conditions can be assessed, it is necessary to remove the trend (i.e. “detrend” the time series) and other non-weather factors.

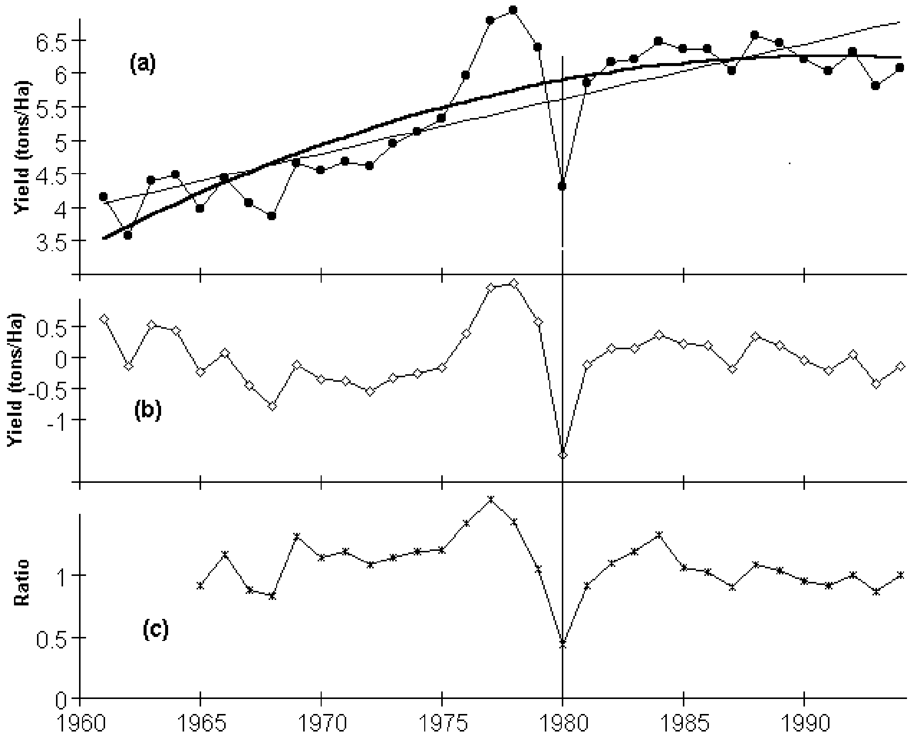

Illustration 3: Yield of total paddy in the Republic of Korea between 1960 and 1994 (based on FAO statistics). The top curve (a) indicates the actual yields with their linear and quadratic trends; the middle curve (b) is the detrended yield, i.e. the difference (residual) between actual yield and the quadratic trend; the lower curve (c) shows the ratio between the yield of year N upon the average of the 4 years from N-1 to N-4.

The example in illustration 3 (Republic of Korea) shows a typical upward trend due to improved technology (varieties, management, inputs) as well as the linear and quadratic trend. The coefficients of determination amount to 0.71 and 0.74, respectively. The coefficient achieved with the “best” trend model (a sigmoid, not shown) amounts to 0.80. Within the remaining 20 percent, weather accounts probably for about half.

The sharp drop in 1980 was due to severe low temperatures around the heading through early ripening stage. Tong-il varieties are high yielding hybrids that are very sensitive to abnormally cool temperatures due to the failure in pollination. In the late

16 A fundamental assumption in model building is that the behaviour of the agricultural production system is stationary or invariant over time. If this is not so, regression methods methods are generally invalid.

1970s, the weather had been mostly favourable to rice cultivation, especially to the Tong-il type (Byong Llyol Lee, personal communication). Threshold effects (such as the mentioned temperature effect) are extremely difficult to forecast by most techniques. Non-parametric methods have an advantage over other approaches in this respect.

The middle curve shows the detrended yield (using the quadratic trend). This is the yield that will be used to calibrate a regional crop forecasting model. The lower curve shows the ratio between the yield of the current year and the average of the yields of the four preceding years, assuming that the trend is not significant over such short period. The advantage of this approach is that no trend has to be determined, and no hypothesis has to be made about the shape of the trend. Some studies deal with the technology trend by predicting the difference between this year's yield and last year's yield (first order difference). As the method seems to ignore background climate, it is not further discussed here.

There is a number of methods that can be used to cope with trends. The “best” approach is, of course, to include in the forecasting model some variables that contribute to the trend, whenever independent information is available about the technology component (such as the number of tractors/ha or actual fertiliser use per ha). However, one of the main factors behind trends is the gradual change in the mix of varieties, which remains difficult to handle. In addition to the trend removal techniques illustrated above (largely drawn from Gommes, 1998a, 1998b), it is also possible to include time as a variable in statistical forecast. The number of existing empirical methods developed to handle this problem is another illustration of the fact that crop forecasting resorts a lot to the experience of the forecaster (it is “art”, as mentioned several times).

2.3 Soil water balance: moisture assessment and forecast

2.3.1 Presentation

Soil moisture content at sowing and fruiting times are closely related to emergence, growth and productivity of plants. In order to use irrigation efficiently it is necessary to know the actual amount of water required to make up the depleted portion of the soil moisture, by crop growth stages. Techniques have been developed accordingly for forecast – or assessment – of available moisture in a 1 m layer of soil at the beginning of the growing period. This is of great assistance to farm operators and agricultural planning agencies as a forecasting variable. This forecast is often based on climatological water-balance methods or empirical regression-type equations.

An assessment of moisture conditions is based on past and present climatological data (e.g. precipitation, radiation, temperature, wind) with or without the use of soil moisture measurements. An extrapolation of this current estimate into the near future is possible through the use of long-term averages or other statistical values of the above meteorological data in the water balance equation. Additionally, a soil water content forecast equation is based on a statistical analysis of recorded soil water content data related to one or several other agrometeorological variables. This approach uses, sometimes on a probability basis, the occurrence of events in the past for extrapolation in the near future. Water balance methods use the following basic equation:

$$P - Q - U - E - \Delta W = 0$$

where P is the precipitation or irrigation water supply, Q is run off, U is deep drainage passing beyond the root soil, E is evapotranspiration and ΔW is change in soil-water storage.

Each of the terms in this equation has special problems associated with its measurement or estimation. In most practical applications it is assumed that certain terms, such as Q or U, are negligible. Another assumption is that ΔW, at least over large areas and extended periods of time, can be set equal to zero. For short-term or seasonal applications an approximate value of ΔW, i.e. the soil-water storage at the beginning and end of the period under consideration, is required. Such a value can be obtained from soil moisture measurements (WMO Technical Note No. 97) but, more practically, from using climatic data in appropriate estimation techniques such as those by Thornthwaite, Penman, Fitzpatrick, Palmer, Baier-Robertson or Budyko (WMO Technical Note No. 138).

2.3.2 Soil water balance for dry land crops

An example of application of water balance approach to estimate soil moisture as well as the stress period for dry land crops is the cumulative water balance developed by Frère and Popov (1979), based on decade values of the precipitation and potential evapotranspiration. The water balance is the difference between precipitation received by the crop and the water lost by the crop and the soil through transpiration and evaporation, which is a fraction of the potential evapotranspiration. The water retrieval in the soil is also taken into account. The basic formula is as follows:

$$Si = Si - 1 + Pi - WRi$$

S_i is the water retained in the soil at the end of the decade, S_{i-1} is the water retained in the soil at the onset of the decade, P_i is precipitation during the decade, WR_i stands for water requirement of the crop during the decade.

WR_i in turn is defined as

$$WR_i = Kcr_i \times PET_i$$

In which PET_i is the potential evapotranspiration during the decade and Kcr_i indicates the crop coefficient during the decade

Regression type techniques for estimating soil-moisture or changes in the water reserves have been developed in many countries for specific crops, soils, climates and management practices. The equations used are of the form:

$$\Delta Z = aW + bT + cP + d$$

where ΔZ is the change in soil moisture of a 1 m layer of soil over a ten-day period, W indicates soil moisture reserves at the beginning of the ten-day period, T denotes mean air temperature over the ten-day period and P is the total precipitation over the ten-day period. a, b, c and d are regression coefficients.

Das and Kalra (1992) developed a multiple regression equation to estimate soil water content at greater depths from the data of surface layer, which was of the form

$$S = 0.22502\ (d-d_0) + S_0\ [1 - 0.000052176\ (d-d_0)^2] - 2.35186$$

where S is the soil moisture at depth d and S_0 is the soil moisture at or near the surface layer whose depth is d_0. This equation was fitted to the moisture data under wheat grown in India under various irrigation treatments.

2.4 Actual evapotranspiration ETA

Among the first who recognised in the mid 1950s that there is a direct link between transpiration and plant productivity was de Wit. Transpiration can be limited due to a short supply of water in the root zone, or by the amount of energy required to vaporise the water. It can be said that plant growth (biomass accumulation) is driven by the available energy, but that plants “pay” for the energy by evaporating water. This is one of the basic “dogmas” of agrometeorology.

We define the relative evapotranspiration as $Q = LE / LE_m$ and the relative assimilation as $R_{ass} = F / F_m$. LE and F are evapotranspiration and assimilation, respectively. The subscript in LE_m and F_m denotes maximum values. A plot of relative assimilation R_{ass} as a function of relative transpiration Q is close to linear when Q values are relatively high (at least $Q>0.6$). If other effects can be assumed to be constant, the relative assimilation over a day (measured as biomass accumulation) is directly related to relative evapotranspiration (approximated by ETA):

*Daily biomass accumulation ≈ K * ETA*

ETA is one of the best forecasting variables in absolute, because, as indicated above, (i) it is directly related to biomass production, but also (ii) because of its synthetic nature (it also includes radiation as one of its main driving forces); (iii) finally, the linearity between ETA and biomass assimilation has been shown repeatedly to hold across many scales, from leaf to plant, to field and to a region.

The fact that the relation between ETA and biomass accumulation persists across spatial scales derives essentially from the fact that both CO2 absorption and water transpiration take place through the same anatomic structure, the stomata. Maximum evapotranspiration (LE_m) and maximum assimilation (F_m) occur when the stomata are completely open, and both are close to zero when the stomata are closed. LE is the evaporative heat loss ($J\ m^{-2}\ d^{-1}$), the product of E, the rate of water loss from a surface ($kg\ m^{-2}\ d^{-1}$) and L, the latent heat of vaporisation of water ($2.45\ 10^6\ J\ kg^{-1}$).

It is recommended to include actual ET as one of the variables in crop forecasting methods using multiple regression. Alternatively, variables derived from ETA are also often resorted to, for instance the ratio between actual ET and potential ET (Allen et al. 1998). The Cuban early warning system for agricultural drought have been using this index because of its direct relation with crop yields (Rivero et al. 1996; Lapinel et al., 2006). There are other related indices, such as Riábchikov’s index (Riábchikov, 1976) that can be used in climate change impact assessments. As ETA can not be measured directly in most cases, it is best estimated using a water balance as explained in section 2.3.2.

2.5 Various Indices as measures of environmental variability

2.5.1 Various drought indices

2.5.1.A Overview

Drought indices can be quantified using a variety of relationships involving annual[17] climatic values and long term normals. The majority of the indices reflect the meteorological drought but not necessarily the shortage of water for agriculture. The problem of agricultural drought pertains to physical and biological aspects of plant and animals and their interactions with the environment. Since growth (biomass accumulation) is a complex soil-plant-environmental problem, agrometeorological drought indices[18] must reflect these phenomena truly and accurately

The indices can, however, provide useful variables when assessing the extent to which plants have been adversely affected by the moisture deficiency, taking into consideration supply and demand of soil water content. The soil water deficiency during the growing season may result in the partial or complete loss of crop yield. But the rainfall amount below which a reduced crop is considered drought-stricken depends on the degree to which a crop can withstand the moisture deficiency, besides stage and state of the crop. The time step used to derive the drought indices is crucial. A day or month may not be suitable. A pentad or weekly values is usually appropriate. These indices can also serve specific purposes such as irrigation scheduling, drought management, etc.

2.5.1.B Palmer Drought Severity Index

The Palmer Drought Severity Index (PDSI; Palmer, 1968) relates the drought severity to the accumulated weighted differences between actual precipitation and the precipitation requirements of evapotranspiration. The PDSI is based on the concept of an hydraulic accumulating system and is actually used to evaluate prolonged periods of abnormally wet or dry weather.

Moisture category	PDSI	Moisture category	PDSI
Extremely wet	≥ 4.00	***Incipient drought***	-0.50 to -0.99
Very wet	3.00 to 3.99	***Mild drought***	-1.00 to -1.99
Moderately wet	2.00 to 2.99	***Moderate drought***	-2.00 to -2.99
Slightly wet	1.00 to 1.99	***Severe drought***	-3.00 to -3.99
Incipient wet spell	0.50 to 0.99	***Extreme drought***	≤ -4.00
Near normal	0.49 to -0.49		

Illustration 4: Palmer drought index categories.

17 Shorter periods than annual are often .considered

18 The website of the National Drought Mitigation Center http://drought.unl.edu/ has many useful definitions and data about drought.

The index is a sum of the current moisture anomaly and a portion of the previous index to include the effect of the duration of the drought or wet spell. The moisture anomaly is the product of a climate-weighted factor and the moisture departure. The weighted factor allows the index to have a reasonably comparable significance for different locations and time of year.

The moisture departure is the difference between water supply and demand. Supply is precipitation and stored soil moisture, and demand is the potential evapotranspiration, the amount needed to recharge the soil and run-off needed to keep the rivers, lakes, and reservoirs, at a normal level. The run-off and soil recharge and loss are computed by keeping a hydrological account of moisture storage in two soil layers. The surface layer can store one inch, while the available capacity in the underlying layer depends on the soil characteristics of the division being measured. Potential evapotranspiration is derived from Thornthwaite's method (1948).

Note, however, that Thornthwaite's method is not recommended for all climate conditions. Variants of the PDSI using Penman-Monteith potential evapotranspiration or modified water balances have also been used (Paulo & Pereira, 2006; Pereira et al., 2007; Szalai & Szinell, 2000).The index is measured from the start of a wet or dry spell and is sometimes ambiguous until a weather spell is established. Illustration 4 depicts the Palmer drought index categories. A week of normal or better rainfall is welcome, but may be only a brief respite and not the end of the drought. Once the weather spell is established (by computing a 100 percent "probability" that the opposite spell has ended), the final value is assigned. This is not entirely satisfactory, but it does allow the index to have a value when there is a doubt that it should be positive or negative.

One aspect that should be noted is that the demand part of the computations includes three input parameters - potential evapotranspiration, recharge of soil moisture, and run-off - any one of which may produce negative values. If only enough rain fell to satisfy the expected evapotranspiration but not enough to supply the recharge and run-off, then a negative index would result. If such an odd situation continued, agriculture would progress at a normal pace but a worsening drought would be indicated. Then rainfall fell below the minimum needed for agriculture, crops would suffer drastic and rapid decline because there would be no reserve water in the soil.

2.5.1.C The Crop Moisture Index

Palmer (1968) developed the Crop Moisture Index from moisture accounting procedures used in calculations of the Drought Severity Index to measure the degree to which moisture requirements of growing crops were met during the previous week. The Crop Moisture Index gives the status of purely agricultural drought or moisture surplus affecting warm-season crops and field activities and can change rapidly from week to week.

The index is the sum of the evapotranspiration anomaly, which is negative or slightly positive, and the moisture excess (either zero or positive). Both terms take into account the value of the previous week. The evapotranspiration anomaly is weighted to make it comparable for different locations and time of the year. If the potential moisture demand exceeds available moisture supplies, the index is negative. If the moisture meets or exceeds demand, the index is positive. It is necessary to use two separate interpretations because the resulting effects are different when the moisture supply is improving than when it is deteriorating.

General conditions are indicated and local variations caused by isolated rains are not considered. The stage of crop development and soil type should also be considered in using this index. In irrigated regions, only departures from ordinary irrigation requirements are reflected. The index may not be applicable for seed germination, for shallow-rooted crops which are unable to extract the deep or subsoil moisture from a 1.5 m profile, or for cool-season crops growing when average temperatures are below 12.5 °C.

2.5.1.D The Standardized Precipitation Index SPI

The SPI was designed to be a relatively simple, year round index applicable to all water supply conditions. Simple in comparison with other indices, the SPI is based on precipitation alone. Its fundamental strength is that it can be calculated for a variety of time scales from one month out to several years. Any time period can be selected, often dependent on the element of the hydrological system of greatest interest. This versatility allows the SPI to monitor short-term water supplies, such as soil moisture important for agricultural production, and longer-term water resources such as groundwater supplies, stream flow, and lake and reservoir levels.

Calculation of the SPI for any location is based on the long term precipitation record for a desired period (three months, six months, etc.). This long term record is fitted to a probability distribution, which is then transformed into a normal distribution so that the mean SPI for the location and desired period is zero (Edward and McKee 1997). A particular precipitation total is given an SPI value according to this distribution. Positive SPI values indicate greater than median precipitation, while negative values indicate less than median precipitation. The magnitude of departure from zero represents a probability of occurrence so that decisions can be made based on this SPI value.

Efforts have been made to standardize the SPI computing procedure so that common temporal and spatial comparisons can be made by SPI users. A classification scale suggested by McKee et al. (1993) is given in Illustration 5.

SPI values	Drought category
0 to -0.99	Mild drought
-1.00 to -1.49	Moderate drought
-1.50 to -1.99	Severe drought
-2.00 or less	Extreme drought

Illustration 5: SPI classification scale

The SPI has several limitations and unique characteristics that must be considered when it is used. Before the SPI is applied in a specific situation, a knowledge of the climatology for that region is necessary. At the shorter time scales (one, two, or three months), the SPI is very similar to the percent of normal representation of precipitation, which can be misleading in regions with low seasonal precipitation totals.

2.5.1.E Rainfall deciles

Gibbs and Mather (1967) used the concept of rainfall deciles to study drought in Australia. In this method the limits of each decile of the distribution are calculated from a cumulated frequency curve or an array of data. Thus the first decile is that rainfall amount which is not exceeded by the lowest 10 percent of totals, the second decile is the amount not exceeded by 20 percent of totals and so on. The fifth decile or median is the rainfall amount not exceeded on 50 percent occasions. A similar approach was implemented in a number of countries, for instance in Cuba (Lapinel et al. 1983; Lapinel et al. 1998; Lapinel et al., 2000; Lapinel et al., 2006)

The values of the decile give a reasonably complete picture of a particular rainfall distribution and knowledge of the decile range into which a particular total falls gives useful information on departure from normal. The first decile range (i.e. the range of values below the first decile) implies abnormally dry conditions, while the tenth decile range (i.e. above the ninth decile) implies very wet conditions. Das et al. (2003) used this concept to identify the different types of drought situations in India.

2.5.1.F Aridity Anomaly Index

The India Meteorological Department (IMD) monitors agricultural drought on a real time basis during the *kharif* crop season (summer crop season) for the country as a whole and during the *rabi* crop season (winter crop season) for those areas that receive rainfall during post-monsoon/winter seasons. The methodology involves computing an index known as the Aridity Index (AI) of the crop season for each week for a large number of stations, using the following formula:

$$AI = \frac{\text{Water deficit}}{\text{Water need}}$$

$$= \frac{\text{Actual evapotranspiration} - \text{Potential evapotranspiration}}{\text{Potential evapotranspiration}} \times 100$$

The departure of AI from normal is expressed as a percentage.

The following criteria are used to demarcate the area of various categories of agricultural drought.

Anomalies can be plotted on a map to demarcate areas experiencing moisture stress conditions so that information is passed on to various users. These anomalies can be used for crop planning and in the early warning systems during drought situations (Illustration 6).

Drought category	Anomaly value
Mild drought	up to 25 per cent
Moderate drought	26-50 per cent
Severe drought	more than 50 per cent

Illustration 6: Aridity Anomaly Index

2.5.1.G Surface Water Supply Index

Another index that is in use is the Surface Water Supply Index (SWSI, Shafer and Dezman 1982). This measure was formulated for use in mountainous areas where snow pack plays a significant role. Percentiles of seasonal (winter) precipitation, snow- pack, stream flow, and reservoir storage are determined separately and combined into a single weighted index, which is scaled and constrained to lie in the range -4 to +4, a typical range of the Palmer Index. The question of how to determine the weight remains open; they need to vary during the year to account for elements such as snow pack, which disappear in summer, or for elements that have small or artificially manipulated values, such as reservoir storage. How to combine the effects of large reservoirs with small relative variability and small reservoirs with large variability in the same drainage basin is also a problem. The SWSI is most sensitive to changes in its constituent values near the centre of its range, and least sensitive near the extremes.

2.5.1.H Crop Water Stress Index

Jackson (1982) presented a theoretical method for calculating a Crop Water Stress Index (CWSI), requiring estimates of canopy temperature, air temperature, vapour pressure deficit, net radiation and wind speed. The CWSI was found to hold promise for improving the evaluation of plant water stress. The use of canopy temperature as a plant’s drought indicator and stress is used by Idso, et al. (1980) to calculate the Stress Degree Day (SDD) index. The cumulative value is related to final yields.

2.5.1.I Water Satisfaction Index

Frère and Popov (1979) developed a crop-specific water satisfaction index (WSI) to indicate minimum satisfactory water supply for annual crops. At the end of the growing period, this index, which is calculated for every decade, reflects cumulative water stress experienced by the crop during its growth cycle. The WSI is a weighted measure of ETa which can be correlated with crop yield.

2.5.1.J Other water related indices

There exists a number of other water related indices[19] developed for specific applications, such as the Rainfall Anomaly Index RAI (Van-Rooy, 1965, Oladipo, 1985; Barring & Hulme, 1991; McGregor, 1992; Hu, Qi, & Feng, Song. 2002). The National Rainfall Index proposed by Gommes and Petrassi (1994) is a national index spatially weighted according to the agricultural production potential. It provides a convenient bridge to studies where national socio-economic data are considered in relation to rainfall and drought (Reddy and Miniou, 2006).

2.5.2 Remotely Sensed Vegetation Indices

The section below focuses on the classical indices developed around the NDVI (see below for definitions). However, a number of other indices are used by various authors, for instance under the name Green Leaf Area Index, Greenness, Vegetation Condition Index, Transformed Soil Adjusted Vegetation Index, Enhanced Vegetation Index, Fraction of Absorbed Photosynthetically Active Radiation (FAPAR) and many others. In addition, the “raw” satellite variables can also be used as indices (e.g. Plant Reflectance) and several

19 http://drought.unl.edu/whatis/indices.htm

indices know from crop ecophysiology, such as Leaf Area Index, are now also estimated based on satellite observations.

Satellite-based vegetation indices also vary according to the satellite being used (e.g. Gobron et al. 1999, for the MERIS Global Vegetation Index (MGVI) or Huete et al., 2002, for MODIS based indices).

Finally, it is also stressed that even if the names of the indices are similar or identical, the fact that they were obtained from different satellites using different spatial resolutions and different sensors result in variables that are not necessarily comparable. The typical NDVI is was originally obtained from the NOAA's satellites Advanced Very High Resolution Radiometer (AVHRR) starting mote than 20 years ago. Currently, we have NDVI from SPOT-VEGETATION (since 1998), EOS-MODIS (from 2000) and even from meteorological satellites such as METEOSAT Second Generation (MSG) SEVIRI NDVI (from 2004).

During periods of drought conditions, physiological changes within vegetation may become apparent. Satellite sensors are capable of discerning many such changes through spectral radiance measurements and manipulation of this information into vegetation indices, which are sensitive to the rate of plant growth as well as to the amount of growth. Such indices are also sensitive to the changes in vegetation affected by moisture stress.

The visible and near infra-red (IR) bands on the satellite multispectral sensors allow monitoring of the greenness of vegetation. Stressed vegetation is less reflective in the near IR channel than non-stressed vegetation and also absorbs less energy in the visible band. Thus the discrimination between moisture stressed and normal crops in these wavelengths is most suitable for monitoring the impact of drought on vegetation.

Aridity anomaly reports used by IMD do not indicate arid regions. They give an indication of the moisture stress in any region on the time scale of one or two weeks, and they are useful early warning indicators of agricultural drought (Das, 2000). The Normalized Difference Vegetation Index (NDVI) is defined by them as:

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{VIS}}{\mathrm{NIR} + \mathrm{VIS}}$$

where NIR and VIS are measured radiation in near infra-red and visible (chlorophyll absorption) bands.

The NDVI varies with the magnitude of green foliage (green leaf area index, green biomass, or percentage green foliage ground cover) brought about by phenological changes or environmental stresses. The temporal pattern of NDVI is useful in diagnosing vegetation conditions. The index is more positive the more dense and green the plant canopy, with NDVI values typically 0.1 – 0.6. Rock and bare ground have NDVI near zero, and clouds, water and snow have NDVI less than zero.

Moisture stress in vegetation, resulting from, prolonged rainfall deficiency, is reflected by lower NDVI values. Such a decrease could also be caused by other stresses, such as pest/disease infestation, nutrient deficiency, or soil geochemical effects. Discrimination of moisture stress from other effects does not present a problem in coarse resolution data over large areal units, as neither pest/disease attack nor nutrient stress is selective in terms of area or crop type.

Finally three more indices characterizing moisture (VCI), thermal (TCI) and vegetation health (VT) conditions were constructed following the principle of comparing a particular year's NDVI and Brightness Temperature (BT) with the entire range of variation during extreme (favourable/unfavourable) conditions. Since the NDVI and BT interpret extreme weather events in an opposite manner (for example, in case of drought, the NDVI is low and BT is high; conversely, in a non drought year, the NDVI is high while the BT is low), the expression for TCI was modified to reflect this opposite response of vegetation to temperature.

The VCI and TCI were defined as:

$$VCI = 100 \times \frac{(NDVI - NDVI_{\min})}{(NDVI_{\max} - NDVI_{\min})}$$

$$TCI = 100 \times \frac{(BT_{\max} - BT)}{(BT_{\max} - BT_{\min})}$$

where NDVI, $NDVI_{max}$ and $NDVI_{min}$ are the smoothed weekly NDVI, its multi-year absolute maximum, and minimum, respectively; BT, BT_{max}, and BT_{min} are similar values for BT. The VCI and TCI approximate the weather component in NDVI and BT values. They change from 0 to 100, reflecting variation in vegetation conditions from extremely poor to optimal. In drought years leading to yield reduction, VCI and TCI values drop below 35 (Kogan, 1997). This level was accepted as a criterion for drought detection. The VCI and TCI were also combined in one index (VT) to express their additive approximation of vegetation stress, as shown by equation

$$VT = \frac{(VCI + TCI)}{2}$$

With the development of the validation data set, some weights will be assigned to the VCI and TCI indices.

2.5.3 El Niño Southern Oscillation (ENSO) indices

2.5.3.A Overview

In addition to the indices of agricultural drought, a number of general indices have been developed. These are really indices of the degree to which the weather has been abnormal. They do not attempt to include the biological uncertainties which arise when one tries to derive an index which relates to the specific agricultural or hydrological effects of a period of abnormally dry weather. Even so, a general drought index, properly interpreted, can be very useful for agricultural purposes (WMO, 1975).

2.5.3.B ENSO indices as good predictors for future rainfall

The current state of drought forecasting scenarios suggests strongly that some of the ENSO-based seasonal prediction methods, and methods based on other Sea Surface Temperature (SST) anomaly patterns, can be used in several regions (Australia, E and S. Africa, etc.) for skilful seasonal rainfall prediction and thus for crop forecasting. However, significant efforts are required to provide skilful drought predictions in a form that users can readily apply to crop forecasting.

2.5.3.C Statistical forecasts of sea surface temperature

Even for regions with a strong ENSO influence, the historical record shows a less than perfect relationship between SST and anomalies in precipitations: precipitation anomalies typically show a consistent ENSO relationship in 75-80 percent of the ENSO episodes during the last century. However, even the best performing statistical SST prediction schemes have cross-validated correlations between observed and predicted tropical eastern Pacific SST of 0.8-0,9 for two seasons ahead in the northern summer through fall. Thus if the anomaly correlation of the given regional precipitation with the observed SST is 0.8 in strong ENSO years, we might reasonably expect to make predictions of precipitation with anomaly correlations of 0.6-0.7 during such years - i.e., in about half of all years. The average correlation over all years will be substantially less; this is consistent with experience (Barnston and Smith, 1996). At this relatively low level of overall skill, precipitation forecasts are best couched in terms of probabilities.

However, one of the main limitations of ENSO-based seasonal prediction schemes is that, ENSO is active in its warm or cold phases only about half the time. Since 1990, there have been thirty warm and nineteen cold episode years, according to the Southern Oscillation Index-based criterion of Ropelewski and Jones, 1987. The close relationship was noticed between the southern Oscillation Index (SOI) and central equatorial Pacific sea surface temperature anomaly during most of the twentieth century. If precipitation were skilfully predictable during all such ENSO episodes, but not otherwise, drought prediction would only be possible about half the time. However, crops must be planted and water resources managed every year. However, ENSO is not the only factor influencing many drought-prone regions.

2.5.3.D Prospects for improved forecasts: a case study for Australia

Although the El Niño-Southern Oscillation is a major influence on Australian climate and provides a mechanism for predicting some aspects of droughts, considerable improvement would be needed for the forecasts to reach an acceptable level of skill at all times of the year, and for all of the country. As noted earlier, the effect of the El Niño-Southern Oscillation is clearest in eastern and northern Australia. Further work is needed to provide a system that adequately forecasts rainfall in southern and western parts of the country. More crucially, the El Niño-Southern Oscillation does not provide much skill in prediction around the start of winter (February-June), when many farmers are preparing for planting. Most of Australia's crops are winter cereals, so information about winter and spring rainfall, available before planting, is crucial, if farmers are to profit from insights into the El Niño-Southern Oscillation.

2.5.3.E Applying El Niño forecasts to agriculture

Since the 1982-3 El Niño, the influence of this phenomenon on Australian climate has become well recognised. A computer package, 'Australian RAIN-MAN', developed by the Queensland Department of Primary Industries and the Bureau of Meteorology, allows farmers and others to investigate the likely consequences of particular phases or trends of the SOI on rainfall at thousands of locations. When this information is combined with readily available current SOI values, users can prepare their own seasonal climate forecasts.

The availability of forecasts does not necessarily mean that they will be used to change decisions or, even if they are, that the resulting decisions will lead to increased profit or less risk. There must be careful evaluation of how the forecasts might be used.

Hammer et al. (1996) investigated the value of El Niño-Southern Oscillation-based forecasting methodologies to wheat crop management in northern Australia by examining decisions on nitrogen fertiliser and cultivar maturity using simulation analyses of specific production scenarios. The average profit and risk of making a loss were calculated for the possible range of fixed (i.e., the same each year) and tactical (i.e., varying depending on the El Niño-Southern Oscillation-based seasonal forecast) strategies. The technical (forecast-based) strategies would have led to significant increases in profit (up to 20 per cent) and/or reduction in risk (up to 35 percent) of making a loss. The skill in seasonal rainfall and frost predictions, based on the El Niño-Southern Oscillation, generated the value from using tactical management. This study demonstrated that the skill obtainable in Australia was sufficient to justify, on economic grounds, their use in crop management. Presumably these forecasts could also be useful in drought management decision making, for instance in determination of appropriate stocking rates on pastoral properties (McKeon et al. 1990).

2.6 Heat supply forecast

Heat supply forecast is required in the case of certain heat-loving plants to assess the most likely thermal conditions during the next growing season. Thermal conditions indicated mostly by GDD (Growing Degree Days) during the growing season are useful for arriving at any strategic decision in the case of many major crops like soya bean, maize, wheat etc. (particularly temperate crops). It is also useful in taking precautionary measures against insect pest and diseases attack on crops, for irrigation scheduling at critical growth stages, for prediction of harvesting time, for the drying of seeds to the required moisture content and for marketing fresh products. Finally, GDD is an essential variable to estimate the development stage of plants, pathogens such as fungi and insects.

In the region encompassing the sub-tropics and the mountainous areas of the tropics, total effective air temperatures (the temperature total over a period with mean diurnal temperatures higher than 10°C) are commonly used as agroclimatic indices for heat assurance characteristics during the growth of winter growing crops. In order to estimate the degree of heat assurance in the region over the growing season and to compare this assurance among the different areas in the geographical cultivation range, the relationship between total effective temperature ($T_{tot.eff}$) in the 10-20°C range and overall total temperature higher than 10°C ($T_{>10}$) can be calculated (Chirkov, 1979).

This relationship, over a total effective temperature range of 600-1800°C has a non linear nature and is expressed by means of the equation

$$T_{tot.eff} = 6.74\ T_{>10} + 140\ ;\ R = 0.94$$

Using this equation, it is easy to estimate effective heat resources in the geographical cultivation range.

For the purpose of estimating heat resources in the continental areas of a moderate-climate region, as well as in the subtropics, a correction is introduced over the duration of the frost-free period, which is shorter in this region than the period with a temperature higher than 10°C.

2.7 Potential biomass and reference yield

Potential biomass is mentioned in the current context because crop forecasting methods regularly require a variable to express the local yield potential. This can be solved using several techniques. The easiest approach is to use average yield, when time series and cross sectional data are used for calibration. Other authors prefer to use the local "yield potential", i.e. the yield that could be achieved in the absence of limiting factors. This "yield potential" is often expressed as the Net primary Production Potential, or NPP. [20]

There exist a number of more or less empirical equations relating NPP with major limiting environmental factors such as rainfall or radiation. One of the most famous equations developed by Monteith in the 1970s is known as the "production ecology equation". It applies a chain of "efficiencies" (factors) to gradually convert extra-terrestrial radiation to global radiation to photosyntetically active radiation (PAR) to radiation actually absorbed by vegetation (e.g. crops) and stored as chemical energy in biomass. The production ecology equation has been very widely used for many applications (Binkley et al., 2004; Allen et al., 2005; Economo et al., 2005; Lindquist et al., 2005).

An interesting equation is given by Uchijima and Seino, the "Chikugo" model, very useful for tropical areas where temperature is not limiting. It involves several terms of the water balance, i.e. radiation and rainfall:

$$NPP = 6.938\ 10^{-7}\ H \exp\left[-3.6\ 10^{-14}\ (H/Prec)^2 \right]$$

Uchijima and Seino use Budyko's "radiative dryness index" (RDI) defined as the ratio H/(L.Prec) between H (the annual net radiation) and the product of L and Prec, L being the latent heat of vaporization of water and Prec annual precipitation. RDI expresses how many times the available energy can evaporate the rainfall. The equation shows the Chikugo model in SI units[21]: NPP is the Net primary Productivity in g (DM) m^{-2} $year^{-1}$, H in J m^{-2}, Prec in mm (equivalent to kg m^{-2}). The equation applies over the crop growing period.

20 A word of caution about NPP: NPP is seen in the current context as ecological production potential (Net primary Production Potential), which differs from the net primary "agricultural" productivity. The factor that converts total dry biomass (roots, stems, leaves, grain) to grain, fiber, sugar... is know as harvest index H. H is usually in the range between 0.2 and 0.5.

21 L, the latent heat of vaporization of water disappears from the equation because it is a constant absorbed in the other constants. It is given explicitly in the original publication of the Japanese scientists.

3 Implementation of yield forecasts in practice

3.1 Data requirements

The data required for agrometeorological forecasting falls into two broad categories: (i) the input data that are required for each forecast, and (ii) data to calibrate and assess the model (see section 4.2). In the case of crop forecasting, this second category of data must include yield data; it may also include other crop data such as phenology, biomass, and leaf area index (LAI). Although crop yield data have already been discussed in some detail, two issues should be emphasized. Firstly, the availability of these data is absolutely crucial if a forecasting system is to be reliable. Secondly, controlled environment experiments and agricultural yield trials play an important role in understanding crop growth and the interaction between genotype and environment. However, the gap between yields obtained in these circumstances and those obtained in the growers' fields is significant. There is a clear need for good quality measurements of regional and local level yields.

Input data requirements depend upon the forecasting method used. Simulation models (i.e. process-based, or equivalently, mechanistic, models) usually require daily inputs of temperature, radiation and rainfall as a minimum. Information on the soil type, crop variety and management techniques are also required, although the level of detail depends upon the model used (see section 4). The spatial scale on which the model operates is particularly relevant here. For example, point-based models can be run using meteorological station data as long as the station is within or very close to the area where the crop is grown. At the other end of the modelling spectrum, models which simulate crop growth over larger areas require weather inputs that are representative of that area.

Satellite data are a useful source of large-area information for crop modelling. In addition to providing up-to-date rainfall estimates, they provide vegetation indices that can be used to derive Leaf Area Indices (LAI). This, in turn , may be used to assess the performance of the crop model and update predictions. Meteorological forecasts must be used where projections into the future are required. These vary in character depending upon lead time and on spatial scale. For example, forecasts up to approximately ten days can be deterministic, whereas monthly and seasonal forecasts should consider chaos theory and therefore are often expressed probabilistically. Chapter 4 contains more information on weather and climate forecasting.

Simulation models and satellite data are complementary. Firstly, because remote sensing can contribute to estimating surface agrometeorological variables (Gommes, 2001a). Secondly, satellite inputs are currently used in crop modelling (Seguin, 1992; Nieuwenhuis et al. 1996; Stott, 1996; Cleevers and van Leeuwen, 1997). In spite of current shortcomings of the proposed methods, there is little doubt that with improving spatial and spectral resolutions, progress will be made in the area of water balance components (soil moisture) and biomass estimations (especially the above-mentioned LAI and conversion efficiencies).

Early attempts to use satellite data in crop forecasting focused mainly on Vegetation Indices (VI), i.e. satellite-derived indices that are related to living green biomass (see 2.5.2). While the qualitative use of VIs has become routine in many countries, their quantitative use in crop yield forecasting has remained disappointing, due to well understood factors. It is suggested that one of the largest potentials for VIs and other satellite inputs such as cloud information lie in their use as auxiliary variables for stratification, zoning and area averaging of point data in combination with GIS and geostatistics.

In many circumstances, particularly in many developing countries, fields tend to be small and irregular in size and shape, crops are often mixed, etc. so that the sensors measure essentially a mix of crops and natural vegetation. It is then generally assumed that crops follow greenness patterns similar to vegetation. This is a reasonable assumption in areas where vegetation shows marked seasonality, for instance in semi-arid areas. Many of the difficulties listed disappear at higher spatial resolutions.

Weather radar-derived rainfall and imagery from microwave satellites are now commonly available to the operational agrometeorologist. Microwave imagery provides estimates of superficial soil moisture. Together, the two sources have the potential to improve soil moisture estimations and, therefore, forecasts as well.

Whatever the source of data - observations, estimates, forecasts or a combination - it is important to recognise the associated measurement error and its impact on the agrometeorological forecast. This is the subject of section 3.2 below.

3.2 Calibration and sources of error

Model calibration is the comparison of model output with reference values, usually actual yield, or some qualitative feature of an agricultural product, such as protein content of hay or tannin concentrations in wine. Errors are usually discovered during calibration, and it is one of the objectives of calibration to reduce them.

The term “calibration” is used mainly[22] for simulation models and it does not necessarily cover the same concept nor criteria for different authors (for a more detailed discussion, see Gommes, 1998a). Accuracy, precision and sensitivity to changes in inputs are some of the criteria that are taken into consideration. The comparison of the model outputs with the real world is done for variables that are proxies in most instances, i.e. simulated water uptake by roots cannot be compared with actual uptake rates, because such rates are unknown[23]. As soil moisture is accessible to observation, simulated soil moisture is compared with actual soil moisture. Unfortunately, actual soil moisture can depend on factors that are not taken into account by the simulation model, and in many cases, calibration, while necessary, does not ensure that the model describes the actual soil-plant-atmosphere interactions.

In addition, reference data are often from experimental fields, most of which are very different from farmers’ fields where, in particular, yields are significantly lower than in experimental farms. For the purpose of crop regional forecasting, there used to be only one yardstick: regional yields as provided by National Statistical Services. This is the reason crop forecasts are eventually calibrated against statistics and, strictly speaking, crop forecasts predict agricultural statistics. They also incorporate all errors and biases present in the Statistics.

There is, however, a potential source of calibration data that, to the knowledge of the authors, has never been implemented, i.e. the original crop cutting data that are the basis of many area and yield estimates produced by National Statistical Services. If NSSs could georeference the point yield measurements, they would offer a unique and unbiased

22 The term is also used for the calibration of sensors and instruments, the geometric correction of satellite images, and in several other areas.

23 They can be observed, but in a very complex experimental setting.

source of calibration data.

We have stressed elsewhere the importance of using models only at the scale for which they were developed. This hold particularly in regional forecasting where statistical crop-weather models found their first applications. The EC crop forecasting system is based on a non-crop specific version of WOFOST (Dallemand and Vossen, 1995; Vossen and Rijks, 1995; Supit, 1997) run with daily data interpolated to large pixels (50 x 50 Km), which is subsequently calibrated against agricultural statistics. For Europe, Vossen and Rijks list the main methodological issues as

- a change of scale;
- a limited precision of input information, in particular the fact that the weather data do not necessarily represent the main cropping areas, uncertainties regarding phenology, etc. We could add the fact that inputs are no longer real data but spatial averages;
- some missing data, for instance rooting depth (this factor is rarely critical in some humid climates where water supply is usually sufficient);
- insufficient spatial resolution of inputs ;
- insufficient knowledge of agro-pedo-meteorological growth conditions and yield for the various regions of Europe;
- poor timeliness of some of the inputs.

It is suggested that an additional point could be mentioned, perhaps the most important one: the very long “distance” between the raw weather data and the final yield estimate at the regional scale. The “distance” would be measured in terms of pre-processing (indirect estimation of radiation, area averaging for many variables, etc.) and processing by the internal machinery of the models. It is suggested that many process-oriented models are too complex for regional applications. Sensitivity analysis normally refers to model parameters, not to the input data, in particular the weather data which are “given”. It would nevertheless be most interesting to artificially contaminate the input data with a random factor or increasing magnitude to see what fraction of estimated detrended yield can actually be assigned to weather.

The section below discusses some sources of errors that commonly affect regional crop forecasts. They include:

- observation errors in the primary environmental and agronomic input data;
- processing errors in the input data, including transmission and transcription;
- biases introduced by processing: many models and forecasting methods are run with a mixture of actual (observed) and estimated data, i.e. missing data that were estimated using models, other methods or expedients. Many inputs are now more and more derived indirectly from remote sensing or weather radar. The conversion of the sensor reading to a physical environmental variable (radar rainfall, radiation) is error prone;
- spatial “scale” errors. Actual forecasts often have recourse to data with different spatial scales, such as points (stations), polygons (soil features), pixels of varying sizes (radiation, rainfall), administrative units (agricultural statistics);

- Temporal scale errors. In some cases daily-mean inputs of weather may not be enough to resolve key crop processes (see section 5.6.1). Also weather forecasts tend to have greater error the longer the lead time;
- errors in eco-physiological crop parameters are relevant mostly for simulation models. They are also subject to scale errors: for instance, it is unlikely that the mesophyll resistance to water vapour diffusion measured in the lab can be applied to a field let alone used for a whole district;
- simulation model errors due to either structural model errors (i.e. incomplete or incorrect representation of the relevant processes) or accidental model errors (i.e. bugs in the computer implementation of models);
- errors due to non-simulated factors (pests, weather at harvest). There exist models to asses their impact (e.g. Debaeke and Chabanis, 1999), but those models are themselves subject to errors ;
- errors in the agricultural statistics used for the calibration;
- calibration errors (choice of statistical relation between crop model output and agricultural statistics). This applies particularly when the data exhibit a trend that is not captured by the crop model. In this situation, assuming a linear or curvilinear trend may result in different forecasts;
- errors in the “future data”, i.e. the weather or climate forecasts used for computing crop forecasts proper;
- “second order errors”: assume that a correct forecast is made at the time of planting. Farmers may base their management decisions on the forecast: if they expect, for instance, that prices will drop because of large volume of production is anticipated, they may decide to use less fertiliser. As a result, although the original forecast based on historical data was correct, the use of the forecast in management has resulted in a larger than anticipated error (underestimate of production). Second order errors are one of the reasons why forecasting methods have to be recalibrated annually.

Conflicts between results of different forecasting techniques do occur frequently: in most real-world situations, several forecasts are available from different sources and methods. The situation is often resolved rather empirically (final forecast is average of forecasts!) or using “convergence of evidence”, i.e. if two methods out of three agree, the third is discarded (refer to “Combination of methods”, 4.4).

When a forecast is made over an extended period of space and/or time, these sources of errors are manifest as errors in the mean yield (over time or space) and errors in the magnitude of variability in yield. Even when the mean and variability of yield is correctly simulated, the spatial and/or temporal distribution of yield may be incorrect. Root mean square error in yield estimation can be broken down into these three components in order to improve the understanding of the sources of errors (see e.g. Challinor et al., 2004).

4 Basic agrometeorological forecasting approaches

4.1 Empirical statistical relations

4.1.1 Introduction

Agrometeorological yield forecasting using a multiple regression always starts with a table of data containing yields and a series of agrometeorological and other variables which are thought to determine the yields. An example of such a table is given below (Illustration 8) with data from Malawi. Such tables are often referred to as the "calibration matrix."

A regression equation (usually linear) is derived between crop yield and one or more agrometeorological variables, for instance

$$\text{Yield}=5+0.03\text{Rain}_{\text{March}}-0.10\,T_{C,June}$$

with yield in tons ha^{-1} , March rainfall in mm and June temperature in °C. Beyond its simplicity, the main advantages of the equation are the fact that (1) calculations can be done manually, (2) data requirements are limited and (3) the ease of derivation of the equations using standard statistical packages or a spreadsheet.

An example of a statistical potato yield forecast is shown in illustration 7 below.

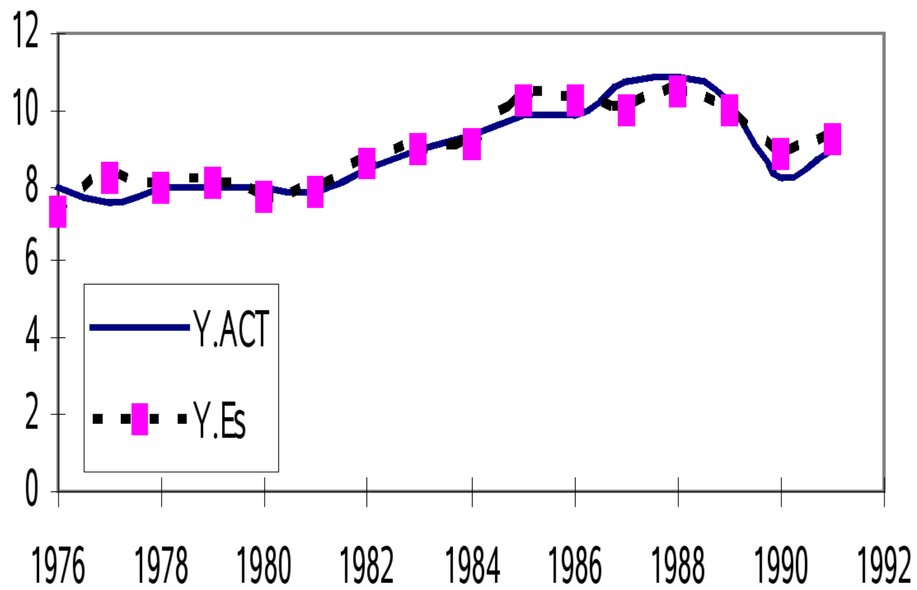

Illustration 7: comparison of actual yields (T/ha) of autumn potato (Y.act) with estimated yields (Y.Es) in Egypt (Giza area). Y.Es was obtained through a regression equation between yields (ordinate), September and October maximum temperatures and solar radiation (from Dawod, 1996)

The main disadvantages of regression models are the poor performance outside the range of values for which they have been calibrated, i.e. their inability to yield correct values in the event of extreme factors (see section 5.4). This is why multiple regression “models” potentially lead to nonsensical forecasts. The equation above, for instance, suggests that low March rainfall (a negative factor) could be corrected by below zero temperatures in June (frost), which obviously does not make sense. Another disadvantage is the need to derive a series of equations to be used in sequence as the cropping season develops.

EPA-RDP	Yield (Kg/Ha)	YEAR	WRSIfin mm	DEFflow mm	DEFrip mm	ETAveg mm	WEXini mm
LINTHIPE-THIWI_LIFIDZI-1996	104	1996	86.4	0	-47.2	89.5	110.1
KABWAZI-THIWI_LIFIDZI-1996	109	1996	87.3	0	-43.1	88.7	112.9
KARONGA_CENTRAL-KARONGA-1997	110	1997	95.6	-2.4	-2.8	73.6	113.2
NAMPEYA-KAWINGA-1997	121	1997	89.1	-8.7	-14.5	86.9	129.3
MITOLE-CHIKWAWA-2005	128	2005	44.5	-227.8	-107.7	119.4	59.5
MITOLE-CHIKWAWA-1995	152	1995	33.6	-335.9	-91	113.7	35.9
MBEWE-CHIKWAWA-1995	160	1995	33	-335.9	-91	114.3	48.6
MIKALANGO-CHIKWAWA-2005	169	2005	42.4	-246.4	-101.2	118.6	60.9
MBWADZULU-MANGOCHI-1995	184	1995	61.7	-112	-81.3	103.7	48.6
LIRANGWE-SHIRE_HIGHLANDS-2005	199	2005	59.5	-120.9	-91.8	106.1	50.1
NASENGA-MANGOCHI-1995	230	1995	71.7	-72.2	-62	96.5	34.6
NAMPEYA-KAWINGA-2005	251	2005	84	-43	-26.2	103.4	34.1
NANYUMBU-KAWINGA-1998	258	1998	84	-44.8	-19.5	91.6	32.1
LISUNGWI-MWANZA-1995	260	1995	47.8	-216.5	-99.6	110.9	96.8
DOLO-CHIKWAWA-2005	266	2005	48.6	-217.4	-86.2	117.4	52.8
MPATSA-NSANJE-2005	271	2005	65.4	-130.2	-53.9	110.4	39.4
MULANJE_SOUTH-MULANJE-2005	272	2005	87.4	-27.9	-22	94.4	34.1
MAGOTI-NSANJE-1995	278	1995	52.5	-173.8	-50.8	109	43.5
MPINDA-PHALOMBE-2005	298	2005	74.2	-53.5	-45.9	91.3	26
MAKHANGA-NSANJE-2005	301	2005	50.7	-211.5	-77.8	117	55.5
CHIKWEO-KAWINGA-1998	302	1998	88	-25	-13	88.4	40.1
NASENGA-MANGOCHI-1998	305	1998	82.6	-60.2	-17.4	94.1	43.2
ULONGWE-BALAKA-1997	328	1997	76.5	-2.4	-41.3	99	178.9
MULANJE_WEST-MULANJE-2005	333	2005	85.5	-22.1	-32.3	91.6	44.8
MAKHANGA-NSANJE-1995	345	1995	47.5	-207.7	-52.4	110.5	58.8
NTONDA-SHIRE_HIGHLANDS-2005	347	2005	49.1	-194.1	-93.2	110	51.5
KALAMBO-CHIKWAWA-1995	352	1995	37.5	-294.6	-107.8	114.6	99.4
PHALULA-BALAKA-2005	360	2005	70.6	-68.6	-68.4	99.1	47.5
NTUBWI-ZOMBA-2005	366	2005	68.5	-79	-67.5	95.9	31.4
MPATSA-NSANJE-1995	368	1995	65	-110.5	-38.1	107.7	18.1
NANYUMBU-KAWINGA-2005	368	2005	77.3	-58.1	-46.8	99.9	34.1
MAGOTI-NSANJE-2005	374	2005	55.9	-181.3	-70.7	115.1	44.8
MPINDA-PHALOMBE-1995	376	1995	93.7	-7.4	-16.8	82.5	33.4
KALAMBO-CHIKWAWA-2005	379	2005	57.7	-140.6	-104	122.9	62.2
MIKALANGO-CHIKWAWA-1995	388	1995	36.6	-290.2	-71.2	112.4	23.2
KASONGO-PHALOMBE-2005	391	2005	84	-24.4	-31.9	88.1	16.7

Illustration 8: some lines from a typical calibration matrix (the actual lines amount to 1360). The data are for different RDPs ("regions") and EPAs ("districts") during the years from 1995 to 2005 in Malawi. For instance, the two first lines are for the EPAs of Linthipe and Kabwazi in 1996 (both in Thiwi Lifidzi RDP). Lines 5 and 6 are both for Mitole in Chikwawa, but for different years. The variables are: the yield of local MAIZE (“local”stands for unimproved varieties), the year, the Water satisfaction index at harvest time, water deficit at the time of flowering, water deficit at the time of ripening, actual evapotranspiration ETA during the vegetative phase and water excess during the initial phase (germination).

Crop forecasting is as much art as science: with the same input data, some experts produce reliable and stable methods, while others come up with equations[24] which the

24 Whether multiple regression “models” are models at all is open to debate. If the explanatory variables are actual factors that influence yield (such as sunshine or soil moisture), it may be argued that the multiple

experienced eye can discard at first glance. Nonsensical equations can be produced when the blind application of statistics prevails over common sense and agronomic knowledge.

4.1.2 "Golden rules" of regression forecasting and good practice advice

The present note tries to summarise some of the considerations which the crop forecaster should keep in mind when deriving multiple regression equations (so-called Yield Functions) which will eventually be used for forecasting crop yields. The process by which the coefficients of a yield function are derived are known as calibration[25]. The rules below are purely empirical or based on common sense:

- Use only variables which are known to be meaningful for the crop under consideration. When there are good reasons to suspect that the response of crop production to a given variable is not linear, use a quadratic term in addition to the linear term.
- Retain only those variables for which the coefficients are significantly different from 0. This is to say that the regression coefficients must be significantly larger (absolute values) than their standard errors. This can be tested statistically (ratio of coefficient to its error), but common sense is usually enough.
- The sign of the coefficients must correspond to what is known about the response of the crop to the variable considered. This applies also to the quadratic terms.
- The coefficients must be spatially coherent, which is to say that they must vary smoothly over adjacent districts
- The quality of a regression equation is given, in addition to the statistics (R, R^2, coefficients significantly different from 0), by the average error of estimated yields.
- Trends MUST be removed before carrying out the regression work proper. The trends need not be linear.
- Be aware of the fact that there are two types of variables: continuous-quantitative ones (e.g. minimum temperature affecting crops through night-time respiration) and qualitative ones (e.g. male sterility induced by high temperatures) .
- Always use a variable which stands for the local yield potential
- A yield function does not have to be linear. In some cases, a multiplicative function can be more appropriate.

In addition, it is good practice to...

- Compute the correlation matrix between all variables to get a better feel for the redundancy of the information;
- Plot the yield against time, to get an idea of the shape of the trend and decide on

regression equations qualify as models. However, if the equations use variables (predictors) which describe environmental conditions but do not influence yields (such as NDVI), the equation is not, strictly speaking, a model.

25 Roughly, calibration of "statistical" models can be seen as the equivalent of "validation" of process oriented models

which function should be used for the time trend;

- Run a Principal Components analysis on the calibration matrix to realise how redundant your data set actually is, and to identify the most important factors. Run the PCA twice (1) excluding the yield as a variable, to get a feel for the variable groupings and redundancy and (2) with yield to identify the variables which are associated with the yield, as well as those that are irrelevant;
- Pay attention to the fact that the weather variables may play a secondary rôle, and ignore them altogether. For coffee in Mexico, it was shown that the most important variables influencing yields included altitude above sea level, number of weeding rounds, age of the plantation and type of smallholding (Becerril-Roman and Ortega-Obregon, 1979);
- After removing the trend, plot de-trended yield against each individual variable to see the shape of the regression curve and the strength of the statistical correlation, if any relation is clearly non-linear, add a quadratic term[26] to account for curvilinearity;
- As far as possible, ignore redundant variables and multicollinearity, or use the regression through a principal component analysis. Always prefer techniques with (manual or "automatic") addition of variables to techniques with deletion of variables;
- Use techniques to ensure the stability of the coefficients (randomly or systematically eliminating up to 50% of the observation points of the time series);
- Use jack-knifing to determine the actual accuracy of the method;
- Yield functions become often obsolete after a couple of years because of changing environment and farming practices. Unless conditions remain stable over time, yield functions need to be recalibrated regularly!

4.2 Crop simulation models[27]

Process-oriented crop simulation models are deemed to be the most accurate and the most versatile of models in that they attempt to describe a crop's behaviour (physiology, development) as a function of environmental conditions. They tend to be less sensitive to "new" situations, i.e. situations that did not occur during the period used to "train" the model.

Crop simulation models, however, are sometimes not suitable for operational regional crop forecasts, for a variety of reasons, in particular their complexity. A corollary of the complexity is the arbitrariness of many parameters when models are run in regional forecasting mode.

26 For instance, if the plot of yield against W_Ex_Flor (Water Excess at the time of flowering) looks like a saturation curve (i.e. yield levels off at higher W_Ex_Flor values), use both W_Ex_Flor and W_Ex_Flor² as a regression variable.

27 For the sake of completeness, we also mention gene-based models. In the words of White and Hoogeboom (2003) "advances in genomics suggest the possibility of using information on gene action to improve simulation models, particularly where differences among genotypes are of interest". See also Boote et al., 2003.

To illustrate the complexity, note that the current versions of leading models such as EPIC, CERES and WOFOST use about 50 crop characteristics, around 25 parameters to describe soils, plus 40 or so management and miscellaneous parameters. In comparison, the daily weather variables which actually drive the models are usually just 5 or 6 (rainfall, minimum and maximum temperatures, wind speed, radiation and air moisture[28]). The, at internal variables used by WOFOST amount to about 260, of which half are crop variables, 30% are soil variables and 20% are weather variables (including all the astronomic variables like day length, extraterrestrial radiation, etc.).

Output variables can, in principle, be any of the internal model variables. The EPIC manual, for instance, lists 180 between input parameters and output variables. In comparison, CropSyst uses “only” 50 input parameters.

All process-oriented models more or less openly use ad hoc variables to force the models to behave like the experimental data. It is not always easy to decide which variables are ad hoc without digging deeply into the operation of the models, which is possible only with the models for which detailed documentation and often the source code is available. The ad hoc variables are sometimes grouped under a category of “miscellaneous” variables, or they have names like “reduction factor”, “adjusted rate”, “correction factor” or “coefficient of crop yield sensitivity to water stress”. For example, the 1995 EPIC User’s Guide (Mitchell et al. 1995) has a “factor to adjust crop canopy resistance in the Penman equation” and a “nitrogen leaching factor”.

Most of the simulation models were developed as research tools: they apply at the field scale. When simulation models are used to forecast crops, they must therefore be run at the scale to which they apply, i.e. basically a “point”.

To use models at the regional scale, three basic approaches are available:

- operating models with regional input data that are regional (spatial) averages of point data. Due to the heterogeneity of the input data, and the non-linear relationships between model inputs and outputs, this method is prone to aggregation error (Hansen and Jones, 2000). Beyond a certain spatial scale, which will depend upon the spatial heterogeneity of the region (climate, topography, soils), aggregation of inputs such as solar radiation and rainfall can lead to significant error (Baron et al., 2005). Indeed, some models may have inputs which are not available on that scale (e.g. average number of grains per spike). Relatively simply process-based models can, however, produce accurate results using spatially averaged data (e.g. Challinor et al., 2004);
- many authors run crop simulation models on a grid, i.e. they interpolate all model inputs to a common grid (Braga and Jones, 1999). This applies mainly to crop parameters and to weather data, as soil characteristics are usually available as maps from which model inputs (such as soil characteristics) can easily be read. This is the approach followed by the EU MARS programme (Genovese, 1998; Boogaard et al., 2002; Rojas et al., 2005);
- models can be run at a limited number of stations (mostly weather stations) where most required inputs are actually available. Once the station yield has been computed, it is subsequently spatialised (gridded, rasterised) so that a regional average can be computed. This is the approach usually followed by FAO (Gommes, Snijders and Rijks, 1998).

28 Air moisture and air humidity are equivalent wording.

Without entering into the merits of the three approaches above, it is sufficient to observe that they tend to be very error prone where many pre-processed inputs are used (e.g. weather grids). In addition, they all have to be calibrated against agricultural statistics, thereby somehow losing the advantages associated with the “scientific” approach. Ideally, models should be calibrated against crop cuttings, i.e. the elementary plot yield sampled in statistical surveys, as mentioned above in a footnote.

Each of these approaches to the issue of spatial scale has its own advantages and disadvantages (see Hansen and Jones, 2000; Challinor et al., 2003). An important consideration is the complexity of the crop model and how this relates to the spatial scale and complexity of model inputs (Sinclair and Seligman, 2000; Challinor et al., 2006).

One of the main advantages associated with simulation models is very practical: if weather forecast information is available, then the models can be run of to the time of harvest, and the variable to be forecast (yield, pest development rate, etc.) can be calibrated against data corresponding to the time of their cycle (which corresponds with the time of harvest for crops). In other words, it is necessary to compute only one yield function, contrary to “statistical” models which often require a different equation or set of equations for each forecasting time: one at planting, one for flowering, one for each phenological phase.

When crop models are used with seasonal forecasts (Challinor et al., 2005a) or stochastic weather generators (Lawless and Semenov, 2005), probabilistic statements about the state of the crop at the end of the season can be made. As the season progresses forecast information can be replaced with observations (Hansen et al., 2004), and the skill of the forecast should then increase.

4.3 Non-parametric forecasts

For the purpose of this chapter of GAMP, we consider non-parametric forecasts to be methods that do not, at least explicitly, use any model nor statistical relations. Non-parametric methods are also known as descriptive methods, and they cover the spectrum from simple descriptive thresholds to expert systems to analogies. We suggest that they are particularly useful in assessing qualitative and indirect effects of weather on crops. The simplest descriptive methods are those that involve one or two thresholds.

For the simplest descriptive methods, it is sufficient to identify the environmental (agrometeorological) variables that are relevant to the organism under consideration. This is normally done with statistical clustering analysis on a combination of time-series and cross-sectional data. Once the groups have been identified, it must be verified that the response of the system being forecast corresponds to different clusters that significantly differ from each other.

One of the reasons why simple descriptive methods can be very powerful is that climate variables do not vary independently: they constitute a “complex”. For instance, low cloudiness is associated with high solar radiation, low rainfall, high maximum temperatures and low minimum temperatures. Each of the variables affects crops in a specific way, but since they are correlated, there is also a typical combined effect, which the non-analytical descriptive methods can capture. The same observations are at the root of the Crop Environment Matrix (CEM) proposed in 1990 by Hackett. This simple tabular method used to summarize crop ecophysiological relationships for land evaluation projects can serve as a rapid means of recording site characteristics and coarsely predicting crop performance.

The CEM approach was implemented for bananas, cashew, cassava, coconut, arabica coffee, robusta coffee, karuka (*Pandanus sp*.), mango, oil palm, pineapple and sweet potato.

Many non-parametric methods have been designed for forecasting outbreaks of pest and diseases. A famous example is the “Irish rules” that spell out the criteria that may trigger an outbreak of Potato Late Blight: more than 11 consecutive hours with relative moisture above 90% and temperature above 10°C (Keane, 1998). One of the first implicit uses of a descriptive method for crop yield forecasting the authors is aware of is the work of Krause (1992) where it appears that crop yields are associated with NDVI profiles over time, i.e. specifically not the NDVI values, but their behaviour over time between planting and harvest.

The descriptive methods have a number of advantages: (i) no assumption is made as to the type of functional relationship between the variables and the resulting yield; (ii) the clustering[29] takes into account the fact that many climatological variables tend to be inter-correlated, which often creates methodological problems, at least with the regression methods described above; (iii) confidence intervals are easy to derive and (iv), once developed, the descriptive methods require no data processing at all; their actual implementation is extremely straightforward. See Illustrations 9 and 10 for examples

Criteria 1 January rainfall (mm)	Yield (average and 95% confidence interval)	Criteria 2	Threshold	
75 to 155	-1.07	February rainfall	< 120 mm	>120 mm
	-1.64 to –0.50		-1.74	-0.52
			-2.35 to -1.13	-1.16 to 0.12
156 to 249	0.25	February rainfall	< 170 mm	> 170 mm
	-0.05 to 0.55		0.07	0.57
			-0.50 to 0.35	0.25 to 0.89
250 to 327	0.78	December rainfall	< 190 mm	> 190 mm
	0.35 to 1.08		0.92	0.66
			0.23 to 1.63	0.08 to 1.25

Illustration 9: Example of a threshold-based crop forecasting table for maize in Zimbabwe based on yields recorded during the period 1961-62 to 2000-2001. Yields are expressed in standard deviations about the average for the period. Gommes, unpublished.

Many “El Niño” impacts on agriculture being currently debated, can be treated by descriptive methods: El Niño effects on agriculture result from a long series of effects (El Niño -> Global atmospheric circulation -> Local weather -> Local crop yield) where each step introduces new uncertainties. As mentioned above, this chain of interactions can also be seen as a “complex” starting with the El Niño - Southern Oscillation (ENSO) index. In southern Africa, for instance, warm El Niño events are associated with a premature start to the rainy season, followed by a drought at the time of flowering of maize, the main crop

29 Clustering is the statistical method used to identify patterns of one or more variables. Clusters are purely qualitative, even if they can be characterised by the descriptive statistics of the variables.

grown in the area.

This pattern usually results in good vegetative growth, followed by drought induced crop losses. Cane et al., (1994) have found good relations between El Niño parameters (i.e. the very beginning of the causal chain) and maize yields in Zimbabwe, which constitutes a good illustration of the concepts described in the later sections of the paper. In Australia, Maia and Meinke (1999) have shown how groundnut yields can be associated with different phases of the Southern Oscillation Indices (SOI).

The literature also has some examples of combinations of non-parametric with parametric methods. Everingham et al. (2002) run a sugarcane model in which “future weather” is given by a set of analogue years based on a seasonal forecast issued by the South African weather service.

Expert systems are more complex (Russell et al. 1998a and 1998b). They use the techniques of artificial intelligence to infer the impact of environmental conditions on crop yield. To do so, they require a base of data, a knowledge base and an “inference engine” which is the software that constitutes the interface between the data and the users.

A knowledge base includes all the normal database functions, but has additional functionality in terms of the way questions can be asked. For instance, a knowledge base “knows” synonyms; it knows orders of magnitude (“low yield”), understands contexts (general information, e.g. properties of a group of plants, for instance grasses) and is normally able to perceive implicit information. Implicit information is the information generally associated with a category, like humic gleysol (pH, drainage properties, depth, texture, etc.).

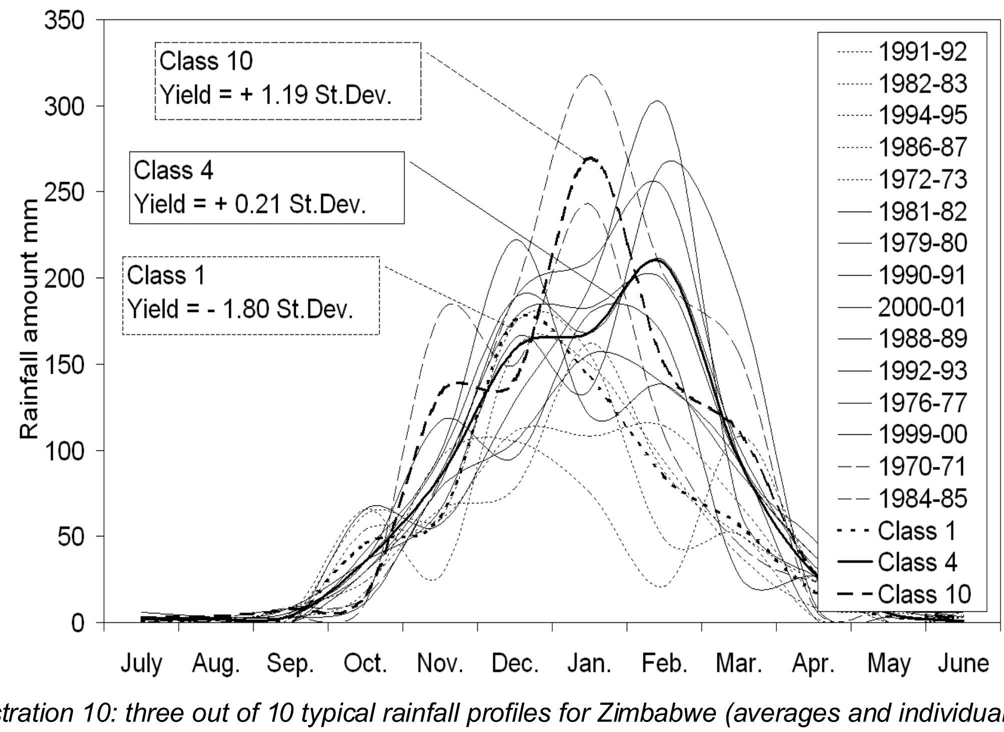

Illustration 10: three out of 10 typical rainfall profiles for Zimbabwe (averages and individual years). Rainfall is expressed in mm. From Gommes, unpublished.

The inference engine controls the reasoning used to answer queries. Knowledge bases can use the outcome of one rule as an input for another. Below we quote an example adapted from Russell (Russell and Muetzelfeldt, 1998), the author of a very detailed wheat knowledge base for Europe, which at the same time illustrates the concept and shows the usefulness of knowledge bases in crop-weather modelling:

What are the consequences of high temperatures in March on wheat yield in Spain?

The expert system must first “understand” what is meant by high temperatures, next it must “know” at what phenological stage wheat will be in Spain at the said time. Finally, the programme must “understand” the concept of Mediterranean region: if no specific data are available for Spain, the system will “know” that Italy, Greece and Southern France are part of the same region and that some data can be borrowed from there.

The European wheat knowledge base puts special emphasis on the identification of alarm situations, based on research and expert knowledge. As such, a knowledge base constitutes a unique monitoring tool as it is unlikely that any of the other types of models will be able to perceive the more complex environmental interactions and sequences, such as a succession of very warm days at the beginning of flowering of orchard crops, followed by a week of heavy rain, which will have several indirect effects, like poor pollination.

Expert systems can be combined with the traditional process-oriented models (Edwards-Jones, 1993). Kamel et al. (1995) have developed a tool to support the regional management of irrigated wheat in Egypt, which captures local expertise through the integration of expert system technology and a crop simulation model (CERES). The system can improve the selection of sowing date and variety, pest monitoring, identification and remediation and harvest management, and may allow better utilisation of resources, especially water.

4.4 Combination of methods

The section focuses on yield forecasts using different methods in combination[30]. In fact, most actual agrometeorological forecasting systems result from the combination of several approaches. Multiple linear regression models are quite adapted to integrate several yield forecasting methods. Their precursors include “biometric forecasts” where some biometric measure is related with yield, for instance, the correlation between the diameter of the stem base and clean coffee yield can be used for predictions (Bustamante et al., 2004.)

When a main limiting factor affects crop production, for instance rainfall in the semi-arid tropics, or solar radiation for lowland rice, models can be shown to be unnecessarily complex. For instance, Rivero (1999) has run CERES-rice with 30 years of data and found that, eventually, the yields simulated by the model are a simple linear function (R^2=0.845) of radiation during the grain filling stage: the inter-comparison between the outcome of different methods provides useful insight into the quality of the results achieved by different techniques.

Starting in the 1990s, the MARS project put together information from technological trend, agrometeorological models and remote sensing thanks to a multiple regression analysis (Genovese, 1998; Boogaard et al., 2002; Rojas et al., 2005). Due to the availability of new statistical techniques, simple climatic variables are currently used again

30This is not to be confused with situations such as a forecast of yields in mixed cropping systems. A specific example (Somarriba, 1990) is a model to estimate the stable timber output, basically a by-product, from shade stands of *Cordia alliodora* in coffee farms in Costa Rica.

by some practitioners as they can explain yields as well and sometimes even better than more sophisticated variables obtained through models. The explanatory variables of the multiple regressions were either selected by experts or derived from statistical selection.

Until recently, the selection of variables was limited by the number of variables and by the statistical tools available. For instance, Gibramu (1997) uses partial regression coefficients to manually identify main variables for his coffee yield forecasts. Recently, statistical tools were proposed to help agrometeorological experts select the best explanatory variables, according to a first statistical selection confirmed or not in a second step by their own expertise. STATCAT (Curnel et al., 2004) is one of them but the ASEMARS project, which has been launched for the extension and the update of the MARS project, is also producing its own statistical tool for extracting the best explanatory variables which explain the best yield estimates and predictions.

The procedure follows two steps: in a first “calibration” step, a subset of explanatory variables (containing sometimes several hundreds of candidate explanatory variables) which best explains crop yields is defined using an automatic stepwise selection method.

Traditionally, stepwise regression has been widely used since it requires little computing power, and is easy to understand and implement. The probability significance thresholds for entry and retention of candidate predictors in the model are both set to $\alpha=5\%$. However, models with high R^2 in this calibration step do not necessarily have high predictive power. Therefore, in a second “validation” step, the selected regression equations are tested in more depth using leave-one-out (LOO) cross-validation.

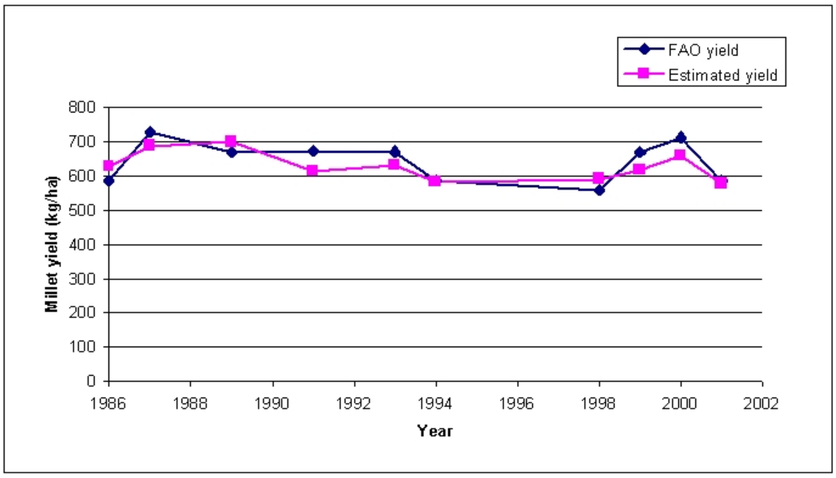

Illustration 11: Comparison between millet estimated yield and FAOSTAT data in Senegal (GMFS project, Rosillon and Tychon, 2006).

This technique ensures that results are replicable; it checks the prediction performance of a model for “new” years, which were not considered in the calibration step. In practice, for the validation of a given model (with fixed X-predictors, selected by the stepwise regression), the LOO is implemented as follows: remove one year from the database, fit the regression with the same X-predictors and the data of the remaining years, use the found equation to estimate the yield of the withdrawn year, and define that year’s error (estimated minus true yield Y).

When this procedure is repeated for all the years (i=1 to n), an independent error estimate can be obtained in absolute or relative terms:

Absolute error= $\frac{\sum_{i=1}^{n} |\hat{Y}_i - Y_i|}{n}$ (kg.ha^{-1}) Relative error= $\frac{\sum_{i=1}^{n} \frac{|\hat{Y}_i - Y_i|}{Y_i}}{n}$

where $\hat{Y}_i$ is the estimate of Y_i.

These LOO-derived criteria provide independent estimates of the predictive power of the selected models. In the same way, one can also derive an independent R_p^2-value. The p-suffix is added to distinguish R_p^2 from the less stringent R^2-value, found in the calibration.

In addition, three more diagnostic tools are used for model evaluation: multicollinearity between explanatory variables is detected with the Variance Inflation Factor (Kutner et al., 2005); preference is given to regression models with low "shrinkage" (difference between R^2 and R_p^2); and all models are rejected if the regression line between predicted and observed yields differed significantly from the diagonal (intercept=0, slope=1).

Each province, department or other sub-national level of a country has its own regression model calculated with the above approach. Outputs are then aggregated and are used for the yield prediction at country level. This approach has been successfully applied in Senegal and Morocco (Illustrations 11 and 12) and is presently being tested in Turkey.

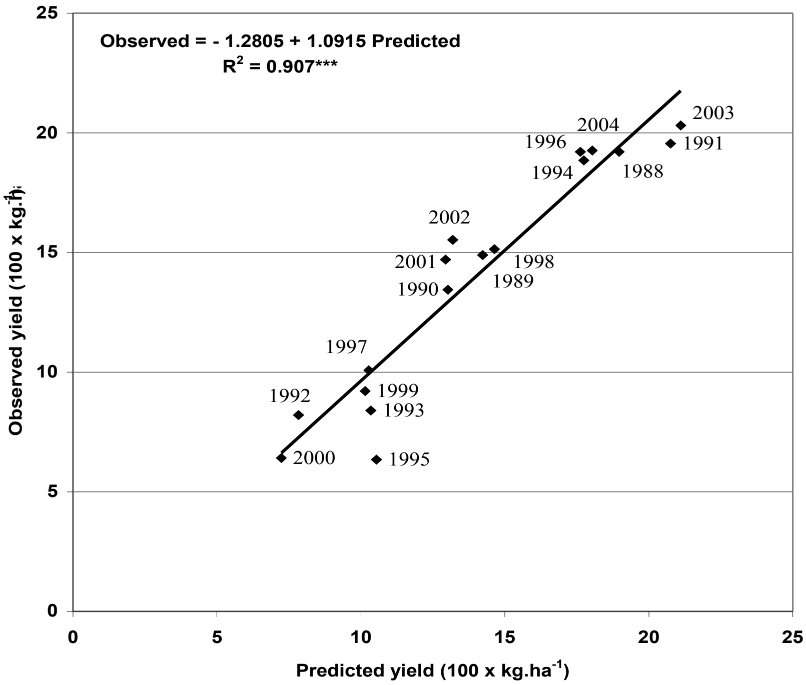

Illustration 12: Regression at country level between mean observed and predicted wheat grain yield using all Ordinary Least Squares models of 23 provinces of Morocco (Balaghi, 2006).

The combination of methods could be used to predict yields from different points of view, when all the factors affecting crops cannot be combined in a unique model. It should be based on local experience and judgement, choosing pragmatically the best methods according to the type of the limiting factors (rainfall, temperature, diseases, pests, irrigation, technical progress, etc.) and available databases.

The combination of methods is a way of estimating the uncertainty in the prediction. Let us assume one can assess yield with seven different models as in the example for Belgium here below (Illustration 13).

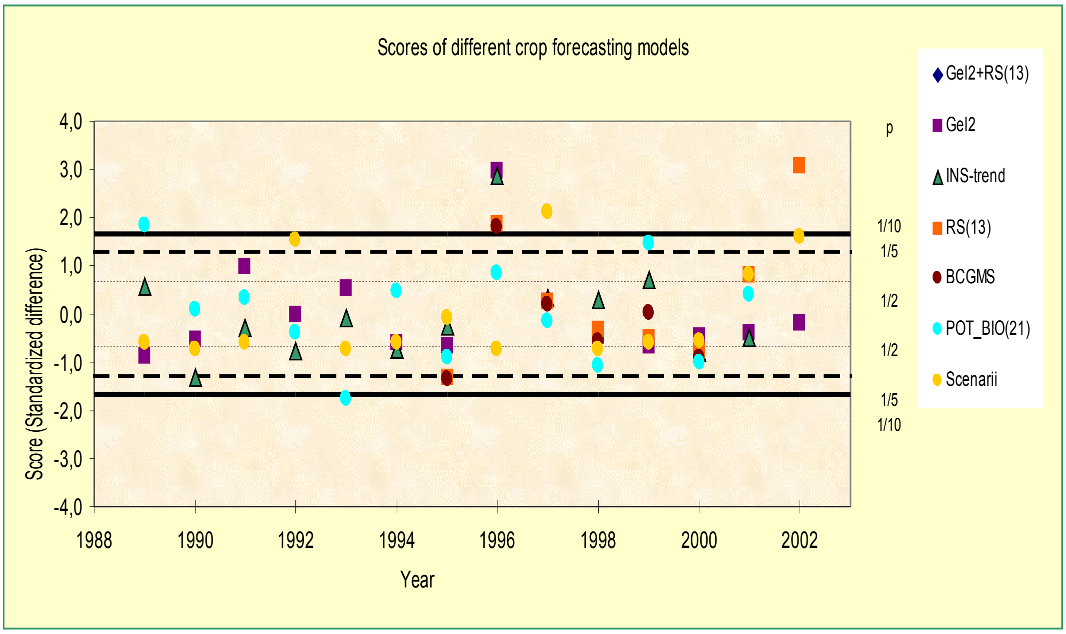

Illustration 13: uncertainty analysis of yield forecasting models (Oger et al., 2004)

The different models used by agrometeorologists for their prediction in the Belgian Agrometeorological Bulletin are:

- the technology trend: INS-Trend;
- the potential biomass calculated by an agrometeorological conceptual model: POT_BIO21;
- a remote sensing biomass status indicator: RS(13);
- a model derived from the number of days of frost during winter: Gel2;
- a linear model combining a RS indicator with a climatic indicator (number of frozen days in winter): Gel2 + RS(13);
- a scenario analysis: Scenarii;
- a complete model containing trend, climatic data, remote sensing and agrometeorological data: BCGMS.

If the models' outputs are standardized and compared to a mean value, outputs can easily be interpreted as illustrated (illustration 13). For example, in 1995 and 2000, all the models propose a same yield estimate. It is probable that for these two years, the prediction uncertainty will be low and we can expect a good estimate while for year 1996, the expert will be confronted with large uncertainty in his forecast. At that time he/she will have to be very cautious in his/her comments and explain complexity of the situation.This uncertainty information is absolutely crucial in yield forecasting, as models could not take into account all the natural variability and all the environmental factors that affect yields (diseases, pests, soil types, etc.). Prediction without indication of its uncertainty remains a weak point of many present forecasting systems. Publications about models now regularly also provide information about uncertainty. See Chokmani et al. (2001) for an illustration from crop protection.

4.5 Extreme factors[31]

4.5.1 Introduction

The section begins with a word of caution about “extreme” factors. Strictly speaking, extreme factors are factors that are extreme in a statistical sense, i.e. their occurrence is infrequent. Common speech often uses the word “extreme” to describe violent factors such as strong winds. These two definitions of the word “extreme” do not always overlap. In the current section, we refer to “extreme” as “statistically rare and damaging to crops”

The effect of extreme factors on agricultural production systems is extremely difficult to forecast. This is because many extreme factors physically damage and hurt organisms: cattle may be exposed to drowning in the event of floods, cell walls are damaged by ice crystals during freeze events, sugar canes are broken during strong winds during hurricanes. Forecasting the response of biological systems under conditions that physically damage the organisms is usually extremely difficult. One of the reasons for the lack of any standard tools is the lack of good impact databases. Losses are often due to unexpected factors: one of the major causes of crop losses after hurricane "Juana" hit Nicaragua in 1988 was the germination of maize grains still on the cobs in the fields, i.e. before harvest (OSRO, 1989). This is not unlike the situation described below for the host-pest/pathogen-environment complex (5.3.2.B)

Finally, conditions can be extreme because of the combination of unusual conditions, resulting in rather complex interactions between factors. A typical complex interaction is the one observed during heavy rains and floods. Waters have during these events several combined destructive effects on crops, animals and the environment. Erosion and re-sedimentation are physical effects caused by running water, while water logging and root asphyxiation involve crop physiology. But floods may have positive effects as well like silt deposition, water reserves repletion and soil desalination. Of particular notice in this context are river-bed changes and major land-slides which may completely modify the agricultural landscape.

Another example of this is the combined effect of the tidal wave , strong winds and floods, and the "ocean spray" of sea water blown inland during storms or cyclones. Salt may take years to be washed out, thus reducing crop yields.

Agrometeorological disasters result from the interaction of a meteorological factor, or a combination of meteorological factors, with an agricultural system. The extent of the damage depends as much on the characteristics of the agricultural system as on the physical event which causes it. There are still few models that can handle processes

31 The section on extreme factors borrows mainly from Gommes, 1997, 1998c, 2003b.

(recovery and regrowth) after mechanical damage has occurred. A good early example is given by Moore and Osgood (1987) in their studies on yield forecasting after cyclones. Cyclones break a large proportion of the stalks in sugar cane fields. The model estimates the rate of recovery of the damaged plants in view of their age at the time of the cyclone, the extent of the damage, and the classical agrometeorological parameters. The mechanical damage has, however, to be estimated separately, and constitutes one of the inputs in Moore and Osgood's approach.

The section below presents a more systematic treatment of the factors to take into account when assessing vulnerability to, or the losses associated with extreme agrometeorological events.

4.5.2 Analysis of factors relevant for extreme factor impact assessments

4.5.2.A Weather factors

a. Mechanical versus non-mechanical. Mechanical factors are those which directly and physically damage plants. Continuous rains and drought fall into the category of non-mechanical disasters. The energies involved in non-mechanical disasters are usually of the same order of magnitude as the normal factors; non-mechanical disasters are more often due to abnormal duration, distribution or simultaneous occurrence rather than to unusual intensity.

b. As mentioned above, the energy or intensity of the weather factors linked with disasters may be vastly different from their normal range. High intensity is mostly linked with relatively short durations (hours or days). The wind speeds which accompany tornadoes/hurricanes are about one order of magnitude greater than the average. In addition, the kinetic energy (and destructive power) of winds vary with the square of wind velocity. Similar considerations apply to the size of hailstones and frost intensity.

c. Presence/absence characterizes factors such as hail, which occur with very low absolute frequencies ;

d. Cumulative/non cumulative effects. Trees uprooted by violent wind gusts are unlikely to suffer further damage from the same factor. However, heavy rains typically have a cumulative effect on soil erosion, where both the duration and the intensity play an important part (WMO 1983). A practical consequence is that for rainfall damage assessment a number of data is required, while for wind a single value (maximum wind speed) is usually sufficient.

e. Timing and succession of events: some extreme events build up gradually, quite independently of their intensity, as is the case with droughts or water logging. In many instances, it is not possible to assign a precise point in time for the beginning (or the end) of the extreme agrometeorological event. This is the main justification behind monitoring and warning systems. The rate of change also plays an important role for such factors as temperatures. Organisms can adapt more easily to slow changes.

4.5.2.B Crop factors

a. Thresholds and qualitative effects characterize a number of plants and animals with regard to their response to weather factors. Well known examples are the effect of high temperatures on the sterility of many annual crops (e.g. Wheeler et al., 2000) or the breaking of the stems and branches of certain rubber cultivars by wind. Another interesting example of this is given by Foong (1980, based on various authors) according to which abnormal sunshine duration leads to abnormal frequency of male inflorescence in oil palm.

The existence of thresholds are a major cause of non-linear response of crop yields to adverse weather factors.

b. Specific differences. There are numerous examples of certain crops suffering very different losses under comparable adverse conditions. According to OSRO (1988), hurricane "Juana" (21-23 Oct. 1988) almost completely destroyed coconut palms (more than 70% were broken or uprooted) in the worst-hit areas of the western coast of Nicaragua, while the most badly affected cocoa plantations lost less than half their trees. It is also a common observation that plantations suffer more direct and apparent damage than natural forest, to such that the latter constitute efficient protective barriers. However, it should be noted that the complex natural ecosystems may take a long time to rebuild their diversity, sometimes even centuries.

To quote an extreme example, it is also a common observation that root and tuber crops and creeping plants suffer very little from hurricanes while tree crops and cereals may be badly hit.

Similarly, floating rice varieties (like the B-Aman in Bangladesh) are characterized by very fast stem elongations which can keep pace with rapidly rising waters during floods.

c. Phenology and size. Crop development stages are a very important qualitative factor. While still in their early stages grasses and cereals suffer little wind damage (Sturrock, 1975); rice appears to be very sensitive to hail at the time of transplanting and harvest. Wind will affect rice most at the time of heading and reaping (Daigo, 1957) and the damage to adult trees may vary from defoliation to uprooting.

One of the major causes of crop losses after hurricane "Juana" hit Nicaragua in 1988 was the germination of maize still drying on the cobs in the fields (OSRO, 1989).

Flowering appears to be the most sensitive stage, as any factors preventing fertilization or flower-set will result in very poor yield, independently of the crop's standing biomass.

5 Special applications

5.1 Crop-specific methods

Most simulation models are currently packaged as multi-crop modular tools made crop specific through crop specific parameters. A well known example is WOFOST, a family of models[32] known as the "Wageningen family" (van Diepen et al. 1989; Supit et al. 1994; Hijmans et al. 1994; van Kraalingen et al. 1991). The crop growth model is generic but parameters are provided for wheat, grain maize, barley, rice, sugar beet, potato, field bean, soy bean, oilseed rape and sunflower. The original version simulated crop behaviour under European conditions. Other versions exist for tropical regions.

Another well known family of models (CERES[33]) has variants that can simulate wheat, maize, rice, sorghum, millet, barley, sunflower, sugarcane, chickpea, tomato, pasture, groundnut and potatoes. There are models for Bambara nuts and tulips, onions and tobacco, garden crops, field crops and greenhouses, mushrooms, silkworms etc.

Yet, amid this plethora of tools, agrometeorological forecasting remains a difficult task whenever yields are to be forecast for decision making at the provincial or regional level. The specific reasons for this situation have been outlined above.

It is also stressed that yield is not the only variable for which there is demand in the private and public sectors. An example is pest, disease and crop phenology, especially outbreak or maturity dates. Many fruits are still harvested by hand, and the logistics of hiring the labour, storing and transporting the produce, and marketing are is best planned as long as possible in advance. Some applications are costly to implement, and they are usually confined to high-value fragile crops such as grapes (Riou, 1994), vegetables[34] (Bazlen et al. 1996) and flowers (when they are grown outdoors).

5.2 Quality of produce

A new category of forecasting has been gaining importance over the recent years, i.e. forecasting the quality of products. This concerns not only the very impressionistic wine market[35] (Desclée, 1991; Ashenfelter et al. 1995; Jayet and Mathurin, 1997, Jones et al., 2005), but also some processed cereals where, for instance, starch/protein ratios should ideally remain within a relatively narrow range. Descriptive methods have also been used successfully to estimate the quality of agricultural products such as wine. Given that the concept of "quality" is sometimes difficult to describe in quantitative terms, the non-parametric approach is probably the most suitable, i.e. any index that describes the

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32 Other major model families include EPIC, the Environmental Policy Integrated Climate (formerly Erosion Productivity Impact Calculator), and SWAT , the Soil and Water Assessment Tools, both TAMUS (Texas A&M University System). Still another is CropSyst developed since starting in the early nineties by Stöckle (1994).

33 CERES (cereals), CROPGRO (mainly legumes), CANEGRO (sugar cane) are now grouped under CSM (Cropping System Model); Jones et al., 2003.

34 The paper by Bazlen also includes an example of a "biometric" forecast combined with a more classical agrometeorological approach. In biometric forecasts, some characteristic size is measured on a plant at a typical time (e.g. cob length in maize) and used as a forecasting variable, alone or in combination with other factors.

35 "Impressionistic" because next to quality proper (defined by pH, tannin content, sugar, colour, etc.) the manipulation of demand plays a prominent role, particularly during average and mediocre years (see Ashenfelfter et al. 1995).

similarity between the current year and historical “good” years would, de facto, constitute a useful forecasting variable..

The definition of quality varies from produce to produce, and is often determined by an industrial process. For instance, the quality of milk can be defined by the concentrations in fat and casein (Bettati and Cavuto, 1994), for wheat, grain protein content, gluten content and grain hardness are used. Other variables that are often considered include concentrations of starch and water in grain crops or the water content of hay. They are part of the German agrometeorological advisory system AMBER (Löpmeyer, 1995; Löpmeyer & Friesland, 1998). For forecasting grain quality, it is feasible to establishing correlation equations between biochemical constituents and canopy-reflected spectrum (Huang WenJiang et al., 2004).

5.3 Pests and diseases

5.3.1 Introduction

This item covers several different forecasting related issues. The first is the forecasting of the presence[36] of pest and disease agents (pathogens) as a function of environmental variables. This was given some attention above.

“Presence” can result from the development of the pathogen *in loco*, or from its transport by vectors that may or not be related to weather. The “presence” measures the exposure of vulnerable organisms to pest and disease attack risk (warning system). Whether or not there will be resulting economic loss depends on the vulnerability[37] of the system exposed to the pathogen. Assessing vulnerability is the second issue to be covered to forecast potential impact. According to the context, “vulnerability” can take different forms. For white fir in California, Ferrel et al. (1994), use the term “vigour”.

It should also be noted that the emphasis is now often on the role of agrometeorological forecasting as a tool to reduce the cost of pest and disease control operations by reducing their frequency and spraying only when the risk and vulnerability are high.

Some situations may involve several pathogens and a chain of intermediate hosts, which make forecasting particularly difficult (Malone et al. 1998) because several types of organisms and different models are concerned. This clearly affects data requirements compared with simpler situations. In addition, due to the complexity of population dynamics, it is often necessary to resort to data covering several years in order to model pest attacks, for instance for the East African Army worm (Haggis, 1996).

Refer to Strand for recent assessment (Strand, 2000), and to Shtienberg (2000) for a note about the increasing relevance of models in disease forecasting. A good review for a developing country is given by Bains et al. 1995.

5.3.2 Plant pests and biotic diseases

5.3.2.A Overview

The number of different pests and diseases affecting crops and forest trees is so

36 Even if conditions are favourable, the pathogen is not necessarily present. The incidence (i.e. the impact) of the pathogen is relevant only if a pathogen is present.

37 This is a variable which has to be defined operationally.

large that a general treatment of the agrometeorological approach to these organisms is almost impossible.

According to the population development, pests and diseases can be subdivided in mono or polycyclic, respectively if they accomplish a single cycle (e.g.: smuts and buns of cereals, one-generation insects) or multiple cycles (e.g.: cereal aphids, leaf blight, leaf spot diseases, rusts and mildews) during the growing period of crop. The expected damage for monocyclic pests and diseases depends mainly on the initial level of attack (e.g.: seed and seedling removal); on the other hand, the damage level for polycyclic pests and diseases depends not only on the initial level of infection but also on the ability of the causal agent to develop through repetitive life cycles to a level that affects crop production (Rijsdijk, 1986).

Another criterion of classification of pests and diseases is the mode of interaction with the host: certain pests and diseases remove green tissues or whole plants without affecting remaining part of plants or plants (e.g.: leaf beetles and various soil pests that remove whole seedlings). Many other pests and diseases not only affect tissues but influence the physiology of plant parts not yet infected (e.g. effects on photosynthesis and leaf ageing by cereal aphids and many plant diseases).

5.3.2.B The host-pest/pathogen-environment complex

The knowledge of meteorological variables is crucial to define the of pests and diseases. This fact was qualitatively well known from long time but a quantitative evidence of it was attained after the implementation of mathematical models simulating the host-pathogen-environment complex for plant diseases and host-pest-predator/parasite-environment complex for pests (France & Thornley, 1984; Magarey, Sutton and Thayer, 2006).

The beginning and of a pest/disease attack is determined by (i) abundance of disease inoculum or pest population (ii) condition of host (iii) environmental relations affecting the complex plant – pest/disease and acting for example on the susceptibility of plants and virulence of diseases.

The concept of environmental relations adopted in the above-mentioned scheme is very large and includes (i) micrometeorological variables (ii) soil physical properties (temperature, air, water and so on) (iii) soil microbiological conditions (including effects on cycles of macro and microelements) and (iv) agro-ecosystemic interactions among different leaving organisms, including interactions between parasite and predators or interactions between diseases and pests.

An example of environmental relations is given by the enhancement of the effect of diseases/pests produced by previous attacks of other disease/pest (e.g.: the wounds produced by chewing insects leave openings in foliage and stems for bacteria and fungi to enter the plant; some insects (e.g.: aphids) act as vectors for viruses. Furthermore, it is well known that plants subjected to water shortage, lack of nutrients or other stress conditions are more susceptible to pests (insects, mites, nematodes and so on) or diseases (fungi, bacteria or viruses).

5.3.2.C Mathematical models for pests/diseases

The approach to plant disease epidemics and their control based on mathematical models has a relatively long history (Kranz, 1974; Pietravalle et al., 2003) and at present is an integral part of current research in plant disease epidemiology; plant pest modelling has been largely the preserve of entomologists and applied ecologists.

In this context it is possible to identify two main kinds of models:

- field models working at microscale (canopy layer);
- territorial models working at mesoscale.

If an empirical approach is often a specific characteristic of territorial models, field models show frequently the presence of a semi-empirical or mechanistic approach.

Pests/disease models may represent modules of crop production models because a quantitative evaluation of losses of production due to pests and diseases is needed in order to estimate the final production of crop.

Principal end users of pests/disease models are:

- farmers, which main task is the raising of crops and the production of food and which only interest is to apply control measures where they are effective, economically warranted and environmentally sustainable;
- extension agents responsible for advice for pest and disease control;
- agricultural authorities responsible of rural policy, food markets and food security;
- environmental authorities responsible for environment protection.

For each type of end user a reference model can be defined, as described in Illustration 14.

End user	***Reference models***	
	Field models (microscale)	Territorial models (mesoscale)
Farmers	X	
Extension agents	X	X
Agricultural authorities		X
Environmental authorities		X

Illustration 14: Simulation models of pests/diseases for different kinds of end users.

In this context, agrometeorology plays some specific roles and in particular:

- support to the implementation, calibration and validation of models;
- production of meteorological data (past, present and forecast) for models;
- production of biological observations (e.g.: outputs of phenological networks);

- Support to integration of data coming from different sources (physical and biological data, remote sensing, weather stations and NWP models).

5.3.2.D Agrometeorological data for pests and disease models

For the end users of pests/disease models, the final questions are (i) when will an epidemic develop (ii) how will the epidemic develop and (iii) what will the final disease/pest severity be. An answer to these questions can be obtained by means of specific simulation models producing forecasts of starting and development of pests/diseases.

It is important to know that the term “forecast” adopted by experts in pests and diseases represents a description of the real time development of an infection on the base of real time monitoring of meteorological variables (Magarey, Sutton and Thayer, 2005). This is quite different from the concept of forecast used in agrometeorology (forecast of the of an infection on the base of forecast meteorological variables); this difference of terms reflects a lack of dialogue and can be overcome with a better knowledge of reliability and limits that characterise the present day technologies referred to analysis and forecast of meteorological variables. This knowledge is crucial in order to adopt a modelling chain useful for the production of continuous and reliable information about pests and diseases.

The adoption of forecast meteorological data for pests/disease simulation models is significantly limited by two kind of problems: (i) the insufficient level of quality of deterministic forecasts and (ii) the existing gap between the scale of development of pests and diseases (micrometeorological scale, canopy layer) and the reference scales of NWP models.

The problem of quality of deterministic forecasts can be approached with probabilistic methods. They are useful to define scenarios of development of pests and diseases with an associated level of probability.

The existing gap between the scale of development of pests and diseases and NWP scales can be overcome by improved on-site measurements (station density) and by means of two principal techniques of downscaling:

- physical techniques founded on micrometeorological models
- statistical techniques based on the analysis of relations between NWP data and microscale data, techniques that in meteorology are known as MOS (Model Output Statistics).

Micrometeorological models may represent mechanistically the space and time behaviour of meteorological variables in the canopy layer based on data produced by NWP models or meteorological stations outside the canopy.

MOS techniques are based on algorithms that can be adapted to specific weather types , topography aspects and characters of canopy (e.g.: in mid latitudes, anticyclonic conditions in mountain territories produce phenomena like thermal belts or cold lakes and the dynamics of cold air masses is influenced by shape, dimension and orientation of canopies).

5.3.2.E Long distance transport of pests and diseases

Meteorological forecasts and, in particular, the study of trajectories of air masses can be useful in order to evaluate the risk of long distance transport of pests and diseases.

A most remarkable case of migration in a noctuid *lepidopteron* is that of *Agrotis ipsilon*, which travels from tropical areas towards mid latitudes. A forecast of arrival of adults of *Agrotis* in North Italy can be based on:

- the presence of seedlings of crops (e.g.: maize, soybean);
- a wet surface of soils;
- circulation pattern with advection of air masses from North Africa. Normally these conditions are represented by a trough on western Mediterranean with North-South axis.

After their arrival, adults deposit eggs and a new generation of caterpillars will eventually damage seedlings. In reality the mechanism of migration of these insects is sometimes more complicated because adults coming from Africa can deposit eggs in South Italy, producing new populations that migrate towards North in the next year.

Another example is represented by bacteria cells of plant pathogen Ervinia amilovora which are sometimes aerosolised from ocean water, transported within clouds systems and successively deposited in precipitation at inland sites. This transport process may be implicated in the transfer of plant pathogenic bacteria from aquatic environments to susceptible plant hosts, which ultimately results in greater risk of crop loss due to disease development (Franc and DeMott, 1998).

5.4. Fire forecasting

5.4.1 Overview

Wildfires, also known as forest fires, vegetation fires, grass fires, brush fires, or bushfires, are uncontrolled fires often occurring in wildland areas, but which can also consume houses or agricultural resources (FAO, 1986). After a triggering event (sometimes represented by a lightning without rainfall, in other cases by a voluntary – arson - or involuntary human action) the wildfire ignites, followed by a phase of propagation and a phase of senescence that preludes the extinction.

5.4.2 Wildfire modelling

Mathematical models adopted in this field are useful in quantifying the risk of fire, and describing or forecasting the propagation of wildfires.

A necessary condition for the starting and the successive propagation of wildfires is the presence of a sufficient quantity of fuel: dry plant material and litter such as leaves, needles and small twigs lying on the ground in a freshly fallen or decomposing state. In living green plants the water content is usually too high for ignition. Only if the water uptake via the roots ceases during drought, can the water content decline to a level favourable for ignition. Dead material, however, can more rapidly take up and lose moisture because there is no water-transfer control by the stomata and no water repellence on the leaves whose waxy surface decays with time. The meteorological factors which control the moisture content and therefore enhance or damp the wildfire risk are: wind, temperature, solar radiation, precipitation (rainfall, dew, snow), drought (as a prolonged water-deficiency period) (Bovio et al. 2002).

All the listed factors are pure physical meteorological factors; the only exception is drought that is a physical and biological phenomenon that can be quantified, for example, by water balance models.

Estimating forest fire risk (that, according to FAO terminology, is the chance of a fire starting) involves identifying the potentially contributing variables and integrating them into a mathematical expression, i.e. an index. This index, therefore, quantifies and indicates the level of risk. A literature review of wildfires risk methods shows how different approaches are used for the evaluation of fire risk and, traditionally, forest fire risk has been computed at national or local scales using different data sources and methodologies (San-Miguel-Ayanz et al., 2003).

For example the following national models can be listed:

- the US National Fire Danger Rating System;
- the Canadian Forest Fire Danger Rating System;
- the Australian and the New Zealand systems;
- the European integrated forest fire risk index.

The behaviour of fire (in particular direction and speed of propagation) is determined by factors like fuel availability and type, topography, temperature and humidity of air masses and wind speed and direction. In particular, hot, dry and gusty winds (e.g. foehn winds) represents a crucial factor for the propagation of wildfires. These elements are considered in deterministic or probabilistic models that analyse or forecast the of fires and can give an important support to wildfire suppression. The effect of receiving information at the fire front that was correct and timely, enabled fire teams to move to safe locations without being caught by a change in meteorological conditions (e.g. wind).

Wildfire models (of risk or propagation) must be calibrated and validated locally on time series of wildfires and meteorological data of sufficient length; calibrated models can be run with past or real time meteorological data or with forecast ones. A review of Information systems for wildland fire management was presented by Albright and Meisner (1999).

After the end of fire it is important to carry out a rational damage assessment and fire damage mitigation in order to prevent negative effects like soil erosion or enhanced flooding. Specific models can be useful in order to produce:

- a post-fire quantitative evaluation of fire severity (Scanlon and Valachovic, 2006);
- a prediction of post-fire mortality of trees (Fowler et al., 2006);
- a prediction of the colonisation of burned area by new vegetation.

Meteorological and remote sensed data can be important inputs for these models and GIS techniques are useful in order to obtain final products useful for management activities.

		Reference forecasts			
Activity	Reference models	NC and VSRF	SRF	MRF	LRF
Planning of monitoring activities	Risk indices		X	X	X
Decision processes for wildfire suppression	Propagation models	X	X	X	
Decision processes for prescribed fire	Propagation models	X	X	X	X
Planning of Ecosystem recovery after wildfire	"After wildfire" models			X	X

Illustration 15: Usefulness of different kinds of forecasts for different activities. NC: nowcasting, VSRF: very short range forecast, SRF: short range forecast, MRF: medium range forecast, LRF: long range forecast. Also refer to chapter 4.2 where additional information can be found on the time horizon of forecast models.

5.4.3 Forecasts for wildfire planning

Weather forecasts, directly used or used as inputs for wildfire models (Illustration 15), can significantly improve decision processes for:

- planning of monitoring activities with the choice of the right level of attention;
- planning of wildfire suppression activities;
- planning of prescribed fire (controlled application of fire to existing naturally occurring fuels under specified environmental conditions, following appropriate precautionary measures, which allows the fire to be confined to a predetermined area and accomplishes the planned land management objectives).

Wildfire suppression planning is usually focused on short-term high-resolution predictions, but prescribed fire planning can require a long-range forecast horizon. Because the research to date indicates that forecast accuracy is limited beyond one-two weeks, specific measures of uncertainty are needed that are germane to fire management planning. For long-range planning, ensemble forecasts are needed to identify a range of possible scenarios with associated probability measures.

5.4.4 Examples of existing models

The Canadian Forest Fire Behaviour Prediction (FBP) System (Forestry Canada Fire Danger Group 1992) is used to estimate the rate of spread. The FBP system is an empirical model that predicts fire behaviour conditions for 17 fuel types found in Canada. Using daily and hourly weather values and indices from the Canadian Forest Fire Weather Index (FWI) System as inputs, the FBP system predicts measurable physical parameters, including the forward rate of spread (ROS) in metres per minute (Anderson et al., 2005).

The BEHAVE Fire Behaviour Prediction and Fuel Modelling System (Andrews 1986) incorporates Rothermel's model, based on the principle of conservation of energy. Rothermel (1983) represents the rate of fire spread as a function of fuel density, particle size, bulk density, and rate of fuel consumption. Because an analytical solution to the problem of fire behaviour is not possible on this basis, Rothermel approximates a solution from laboratory experiments.

The European integrated forest fire risk index (Sebastian-Lopez et al., 2000) is based on the one developed for the computation of the Fire Potential Index (Burgan et al. 1998). The model requires as inputs Normalized Difference Vegetation Index (NDVI) values, to calculate the Relative Greenness, meteorological data to estimate the Dead Fuels Moisture Content, and a Fuel Map to estimate the fuel loads.

The Experimental Climate Prediction Centre (ECPC) has been exploring an experimental research forecast capability of fire severity and danger. The current experimental fireweather forecasts are being updated to include the National Fire Danger Rating System (NFDRS) that has been used over the continental United States since 1978. In addition to fire danger indices, a drought index is also produced as part of the fire danger rating. There are three basic inputs to computing fire danger rating: weather, topography and fuels. Because fire danger is a cumulative phenomenon, weather is the driver in terms of producing seasonal changes in fire danger estimates.

Topography is used to reflect the fact that fire burns faster upslope than on flat ground. Vegetation is deemed to be fuel for fire danger rating purposes. Twenty NFDRS fuel models represent the vegetation types across the U.S., defining fuel characteristics such as depth, load by live and dead classes, heat content, fuel particle size, etc. These basic inputs are converted into various fire danger indices by processing them through a modified version of the firespread model. The fuels data for the FDRS is defined at 25km spatial resolution, while the weather data is at 25, 50, 200 km resolution. The higher resolution fuels data permits display of more fire danger variability through the assumption that the actual weather parameter values are reasonably constant over this area.

There are still a number of research questions that need to be answered including persistence characteristics, cross correlations among the indices, predictability characteristics, and relation of these indices to fire occurrence and size as well as the accuracy of the fire danger predictions. The National Fire Danger Rating System (NFDRS) module created for the severity forecasting research project by the US Forest Service is being used to convert weather forecasts into experimental fire danger rating forecasts. NFDRS indices include forecasts of energy release component, burning index, spread component and ignition component, derived directly from the model output and these forecasts cover daily, weekly, monthly and seasonal time periods (Roads et al. 2005)

5.5 Phenology[38]

Phenology, the description of the development stages of wild plants, agricultural fruit and crop and other organisms (for instance, insects) has several well defined applications, next to its use in simulation models. Certain agricultural activities often require advanced information on the dates of specific stages of crops development.

Most European countries maintain networks that collect phenological data. For instance, the German Weather Service (Deutscher Wetterdienst, DWD) currently runs a phenological network comprising approximately 1550 stations. The phenological observation programme of DWD 167 stages of development. On selected trees, bushes and shrubs the unfolding of leaves, flowering, fruit ripeness and colouring of the leaves, for example, are observed; in the case of agricultural crops, tillage and harvest data are also collected in addition to selected phases.

The observed data from the basic phenological network have been collected and archived at the end of every vegetation period since 1951.

An early forecast of the ripening dates of many crops has considerable economic advantage. It provides a lead time for organizing such operation as the harvesting, packaging and transporting of produce as well as for planning the time of harvest to coincide with market requirements (Lomas,1970; Edey 1977). In experimental and plant breeding work it is necessary to have a good understanding of the effect of environmental factors on behaviour of crop development (Goyne et al. 1977; Brown 1978; Clarkson & Russel, 1979). Information on the rate of development and the date of various phenological stages is useful as input into models used for crop-weather surveillance systems and for agricultural economics analyses. Because of it's importance in a number of agricultural areas of activity, it is necessary to understand the physiological process of development and how the rate of development is affected by certain environmental factors.

Phenology can be modelled based on vernalisation, photoperiod, thermal response and intrinsic earliness (Cao and Moss,1997), most of which are plant specific. Intrinsic earliness is conditioned by the genetic features of the plant and it has constituted a main target for breeders. It is one of the mechanisms to avoid (evade) several difficulties linked with adverse factors like drought or early fall frost. Photoperiod and vernalisation are qualitative responses of seeds or young plants that require exposure to a cold period of a certain length and intensity before they can develop properly (Gommes, 1998a).

Temperature plays a directly observable effect on the rate of development of plants and cold blooded organisms. Regarding crops, the effects are significant not only in temperate countries, but in tropical countries as well (examples for rice are given by Dingkuhn, 1995, and Mahmood, 1997).

The most common method to determine the effect of temperature is the often criticised method of temperature sums, also known as SDD, Sum of Degree-Days (Chang, 1974), or thermal time. The method assumes that the amount of heat (measured by temperature) required for a plant to develop from planting to stage S is a constant.

38 For a more detailed treatment of this subject, including the "Q_{10}" and other approaches to the simulation of development rates, the reader is referred to Gommes, 1998a.

Starting from planting[39], the following sum is computed

$$SDD_S = \sum_{\text{Planting } day}^{\text{Day on which stage } S \text{ is } reached} (T - T_b) \quad where \quad \begin{matrix} T - T_b \text{ is taken as } 0 \text{ when } T < T_b \\ T \text{ is taken as } T_u \text{ when } T > T_u \end{matrix}$$

T is average daily temperature, T_b is the base temperature below which no development takes place, and T_u is an upper threshold temperature above which it is assumed that temperatures ceases to have an effect on development. For instance, the sum of temperatures from sowing to emergence could be 100, meaning that, with a base temperature of 10, the plant would emerge after 10 days at 20.

The concept of growing degree days has been rightly criticised as an oversimplification. It remains nevertheless in wide use, and a number of modifications have been suggested to adapt it to specific crops, regions and other circumstances. For instance, Dawod (1996) used the equation below to compute daytime temperatures T_{DD} (average temperature from sunrise to sunset) as an input to phenological estimations for potatoes in Egypt:

$$T_{DD} = T_A + (T_X - T_N) / 6.1$$

where T_A is the mean 24 hour temperature, T_X maximum temperature and T_N stands for minimum temperature.

5.6 Climate change

5.6.1 Introduction

This section provides a short overview of some issues related to agrometeorological forecasting and climate change impacts.

Increasing recognition of the importance of anthropogenic climate change and its impacts has lead to the birth of very long-range agrometeorological forecasting. Forecasting the yield of crops for the coming decades - even to the end of the century - is useful for both adaptation and mitigation. Hence long-range forecasts can enable long-term planning of resources such as germplasm that can be used to adapt to climate change. Where negative impacts are predicted, these can be used to highlight the importance of reducing emissions of greenhouse gases. Climate scientists are becoming increasingly interested in working with crop scientists in order to understand and evaluate the impacts of climate change on agriculture (e.g. Huntingford et al., 2005). Climate change is likely to have a significant impact on the prevalence of pests and diseases, the availability of water, the growth and development of crops, and many other agricultural processes. This section focuses on crops.

Climate change has both direct and indirect impacts on crop growth and development. Higher ambient levels of carbon dioxide have an impact on C3 crops by increasing photosynthesis and decreasing water use. Indirect effects result from changes in weather and climate that result from higher levels of greenhouse gases. These changes may be within, or beyond, the current observed range of climate variability. This distinction is significant because agricultural systems will be particularly at risk when the changes in

39 The calculations can also start from some conventional date before planting if the planting date is to be determined in temperate and cold climates.

climate are unprecedented. Hence the projected increase in extremes of rainfall and temperature are critical for agriculture. Many crops are sensitive to high temperatures during flowering, for instance, and to further complicate matters this sensitivity may only occur during a particular part of the day (Challinor et al., 2005b; Wheeler et al., 2000).

5.6.2 Methods

The long-range nature of climate change projections, coupled with the potential for unprecedented conditions, has three major implications. Firstly, it is difficult to justify the use of empirical crop models, since these are calibrated under current conditions. For example, we have some information about the response to increased carbon dioxide from experimental studies (e.g. Ainsworth and Long, 2005); however, this information is incomplete and we are forced to rely upon the dialogue between crop experiments and modelling to extrapolate the future impacts more precisely. Hence most climate change studies use process-based models of the kind described in section 1.4.

A related concern exists for process-based models. If models are over-tuned for the current climate then the credibility of the model when it is run with climate change data will be in question. There is a risk of over-tuning increases with the number of unconstrained parameters in the model, since observations may be correctly simulated without representing the processes involved (i.e. the right answer for the wrong reason). Hence a crop model should be sufficiently complex to capture the response of the crop to the environment whilst minimising the number of parameters that cannot be estimated directly from data (see Sinclair and Seligman, 2000). Whilst this issue is particularly important for climate change (where new conditions and interactions are likely) it can be applied more generally, for example where a model is calibrated for one site and then used at another.

Some studies (e.g. Parry et al., 2004) use predictive equations based on the statistical relationships between climate and crop model output. Even for a simple model this can produce very different results to the direct use of the model (Challinor et al., 2006). Here again there is the risk of relying on observed relationships that may change as climate changes.

The third implication of the characteristics of climate change is the importance of quantifying uncertainty. There is a cascade of uncertainty from levels of emissions of greenhouse gases, to the response of the atmosphere and the subsequent response of the agricultural system. This make the deterministic forecasting of climate change impacts impossible; any predictions must be made probabilistically. Uncertainty can be quantified by sampling a range of crops, locations, models, or scenarios. Using a range of (crop and/or climate) models can account for structural model error (see section 1.2.4). Uncertainty associated with parameter values can be quantified by varying model parameters within known uncertainty ranges (Challinor et al., 2005c).

The approaches used to quantify the impacts of climate change on food production are subject to the same issues with spatial scale as are shorter-range forecasts (section 1.4). Assessments can be made at the field scale, and then scaled up, or simulations can be carried out at the regional scale using large-scale inputs. Each of these has its own advantages and disadvantages (Challinor et al., 2006, 2003; Baron et al., 2005; Hansen and Jones, 2000).

Field-scale assessment has the advantage of potentially capturing important local-scale management and bio-physical processes and their interactions. However, such assessments require weather data at a much higher resolution than is provided by climate models. Techniques for downscaling weather information are often empirical, and hence necessarily produce location-specific results whose accuracy is contingent on the stationarity of the relationships used. Another option is crop modelling at or near the scale of the climate model. Whilst this ‘large-area’ method leaves the crop simulations prone to both aggregation error and the propagation of errors from the climate model, which can be significant, this method has shown promising results (e.g. Challinor et al., 2006). It also permits full integration of the crop and climate model, which can account more fully for changes in land use and their potential feedbacks, such as methane emissions from rice, on the climate system (Osborne et al., 2006).

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