

# NON-PARAMETRIC CROP YIELD FORECASTING<sup>1</sup>

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## 1. Introduction

Operational crop yield forecasting is often assumed to be done with crop simulation models. In fact, crop simulation models are usually not the most appropriate tools. This note critically assesses the potential of various crop-forecasting approaches, mainly based on a case study with Zimbabwean data.

For the purpose of this paper, *crop forecasting* and *crop yield forecasting* refer to operational within-season regional yield forecasts, i.e. forecasting of crop yield (tons of agricultural product per ha) over large areas. The areas are usually administrative units, as this is the scale at which most socio-economic data and crop statistics are available to decision makers.

It is stressed that crop forecasts are eventually calibrated against crop statistics, so that, strictly speaking, crop forecasts are actually forecasts of agricultural statistics; they incorporate all the errors and biases that affect statistics.

Crop forecasts are typically issued between the time of planting and the time of harvest. They use past data (data between planting or before and the time of the forecast) and “future” data. Future data can be implicit or explicit. In the first case, the future is assumed to be “normal” whereas the second requires that numerical values be actually specified<sup>2</sup>.

There are a variety of generic forecasting methods, of which most can somehow be applied to crop forecasting as well (Petr, 1991). According to Armstrong (2001b), “judgement pervades all aspects of forecasting”, which is close to a definition which the author 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” (Gommès, 2003). 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”.

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<sup>1</sup> Paper presented at the *Curso de alto Nivel sobre Agroclimatología Tropical*, Corporación Colombiana de Investigación Agropecuaria, Bogotá, Colombia, 9-12 June 2003.

<sup>2</sup> A number of methods can be used, including historical data or synthetic data, or data which themselves derive from a model.

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 roughly grouped as

- Judgemental, based on stakeholders' intentions or on the forecaster's or other experts' *Opinions* or *Intentions*
- Statistical, including univariate (or *Extrapolation*), *Multivariate* (statistical "models") and *Theory-based* methods.

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*.

For the purpose of this paper, 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<sup>3</sup>. They include essentially crop simulation models<sup>4</sup> and statistical<sup>5</sup> "models" which empirically relate crop yield with assumed impacting factors. Obviously, crop-yield-weather simulation belongs to Armstrong's *Theory-based Models*<sup>6</sup>. Non-parametric forecasting methods are those that rely more on the qualitative description of environmental conditions and do not involve any simulation as such (Armstrong's *Expert Systems* and *Analogies*).

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<sup>3</sup> The factors that affect crop yield variability include mainly technology trends and weather in varying proportions, plus extreme events, and agricultural policy.

<sup>4</sup> Also known as process-oriented models or mechanistic models.

<sup>5</sup> For an overview of regression methods, including their validation, refer to Palm and Dagnelie (1993) and to Palm (1997).

<sup>6</sup> Armstrong considers only econometric models.

## 2. Process-oriented models

### a. Process-oriented models as forecasting tools

Process-oriented crop simulation methods 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 thus 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 usually not suitable for operational regional crop forecasts, for a variety of reasons, in particular their complexity. A corollary of the complexity is the arbitrariness<sup>7</sup> of many parameters when models are run in regional forecasting mode.

To illustrate the complexity, note that the current versions of models like 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). The 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, Angot's value 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 scale of a field. 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:

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<sup>7</sup> In practice, many inputs and parameters have to be "guessed"

- operating models with regional input data that are regional (spatial) averages of point data. This is often meaningless because many required inputs are either meaningless at the regional scale (average regional rainfall, average soil water holding capacity, average regional fertilizer application rate, etc) or not available altogether (e.g. average number of grains per spike);
- 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);
- 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 spatialized (gridded, rasterised) so that a regional average can be computed. This is the approach usually followed by FAO (Gommes, Snijders and Rijks, 1998).

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.

#### **b. A word about model calibration and sources of errors**

Model calibration is the comparison of model output with some reference values. The term is used mainly for simulation models and it does not necessarily cover the same concept nor criteria for different authors (for a more detailed discussion, see Gommes, 1999). 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. it is not water uptake that is measured but rather soil moisture, which is the result of the interaction between a crop (model) and the environment. In addition, reference data are often from experimental field, 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 is obviously only one yardstick, regional yields as provided by National Statistical Services. This is why 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.

Actual regional yields are usually regressed against one or more variables and indicators to produce a “yield function” which is eventually used in forecasting. The regression is fitted using least squares. It is worth observing that, for crop forecasting, it would probably be more appropriate to minimize the relative error.

The section below discusses some sources of errors that commonly affect 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.
- space and time “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)
- 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 ( $s\ m^{-1}$ ) measured in the lab can be applied to a field let alone used for a whole district
- simulation model errors, i.e. programming errors in the computer implementation of models
- errors due to non-simulated factors (pests, weather at harvest). There exist models to assess 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. Assuming a linear or curvilinear trend will result in different forecasts
- statistical errors in the “future data”.
- “second order” errors occur when forecasts tend to be accurate, so that management decisions are made based on early forecasts<sup>8</sup>

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<sup>8</sup> This leads to the paradoxical situation where late forecasts (forecasts shortly before harvest) are less accurate than early forecasts. This situation occurs for instance when output volume markedly affects prices, so that producers can adjust their output while the crop is still growing.

- conflicts between results of different forecasting techniques: 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 of three agree, the third is discarded.

### 3. An overview of non-parametric or descriptive crop forecasting methods<sup>9</sup>?

Descriptive methods include the whole 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. A hypothetical example is given in Table 1.

Descriptive methods are non-parametric. It is sufficient to identify the environmental (agrometeorological) variables that are relevant for the crop 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 yield averages corresponding to different clusters significantly differ from each other.

**Table 1 : Hypothetical example of wheat yield (Tons/Ha) dependence on two climatological variables, with 95% confidence interval.**

		June average sunshine hours per day	
		6 hours and less	more than 6 hours
March total rainfall	75 mm and less	5 ±1	6±2
	More than 75 mm	8±1	10±2

One of the reasons why simple descriptive methods can be very powerful is that climate variables do not vary independently: they constitute a “complex”<sup>10</sup>. 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. An example is given in Table 2.

<sup>9</sup> This section is largely borrowed from Gomme, 1998a.

<sup>10</sup> This is not unrelated with the typical “weather types” described by meteorologists.

**Table 2: The table shows the links (expressed by the coefficient of correlation) between various climatological variables in March in Latin America (averages from 286 stations taken from the FAO FAOCLIM database).**

	<i>Tmin</i>	<i>Tmax</i>	<i>Rain</i>	<i>SunFrac</i>	<i>ETP</i>	<i>Cloud cover</i>	<i>Vapour Pressure</i>
<i>Tmin</i>	1.00						
<i>Tmax</i>	<b>0.84</b>	1.00					
<i>Rain</i>	0.36	<b>0.54</b>	1.00				
<i>SunFrac</i>	0.01	0.12	0.18	1.00			
<i>ETP</i>	<b>0.62</b>	<b>0.50</b>	-0.05	-0.03	1.00		
<i>Wind Speed</i>	<u>-0.27</u>	<u>-0.22</u>	<u>-0.28</u>	-0.02	0.05	1.00	
<i>Vapour Pressure</i>	<b>0.78</b>	<b>0.94</b>	<b>0.65</b>	0.14	0.35	<u>-0.25</u>	1.00

One of the first implicit uses of a descriptive method the author is aware of is the work of Krause (1992) where it appears that crop yields are associated with NDVI profiles over time. 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 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.

Many “El Niño” impacts on agriculture that are 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 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<sup>11</sup> based on a seasonal forecast issued by the South African weather service.

Descriptive methods have also been used successfully to estimate the quality of agricultural products such as wine. Given that the concept of “quality” is difficult to describe in quantitative terms<sup>12</sup>, the non-parametric approach is probably the most suitable.

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.).

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.

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<sup>11</sup> For instance, assume that the probability is 2/10 that the year will be dry, 3/10 that it will be normal and 5/10 that it will be wet. Two dry years, 3 normal years and 5 wet years will be selected from the historical series and used as “future” weather.

<sup>12</sup> Quality of wine is described by a combination of pH, sugar content and types, acid types, concentration of tannins, colour, etc.

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 (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. Case study: Zimbabwe**

##### **a. General setting and removal of yield trends**

To illustrate and compare some non-parametric methods, a didactic example was prepared to estimate yields in Zimbabwe (Southern Africa) covering 41 years from 1960-61 to 2001-2002.

Rainfall over the main maize growing area was extracted from NOAA<sup>13</sup> monthly rainfall grids using the WINDISP<sup>14</sup> software after the grids were converted to WINDISP format. All statistics given hereafter refer to the maize growing area illustrated in Figure 1. Average rainfall amounts to 812 mm per year, but the driest year (1991-92, an El Niño year) recorded only 462 mm, while the wettest experienced 1278 mm in 1973-74. Note, incidentally, that 1973-74 corresponds to a severe drought in the West African Sahel; this “correlation” derives directly from the movements of the inter-tropical Convergence Zone (ITCZ).

In Zimbabwe, the growing season roughly covers the period from November to March-April (refer to Figure 2), and is also dependent on the different behaviours of the two main sectors of the Zimbabwean agriculture, i.e. large-scale commercial farms on the most suitable soils and smallholders in so-called “communal lands”. Part of the country being semi-arid with a marked dry season, water is the dominant factor driving the inter-annual variability of crop yield.

Since independence in 1980 but particularly after 1990, the country has been affected by a somewhat disorderly land reform aiming at redistributing part of the land under large-scale farms. This appears clearly in the maize yields curve in Figure 3 where a curvilinear trend had to be fitted to the data. Clearly, the trend is due to a combination of factors where weather plays only a minor part.

The trend must be removed before any agrometeorological analysis can be carried out. This was done for the lower curve in Figure 3, where yield is expressed as the difference between the observed values and the trend. The trend accounts for 13 % of the interannual yield variability, which is a low value considering that part of the country is semi-arid.

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<sup>13</sup> The data are available upon request from the website <ftp://ftpprd.ncep.noaa.gov/pub/precip/50yr/gauge/0.5deg/>

<sup>14</sup> WINDISP is a software developed by FAO and other agencies (USGS, USFS, FEWS, SADC) to process satellite imagery in food security projects. The latest version can be used for a number of gridded data, including rainfall. The software is available at <http://www.fao.org/>

Figure 1: Map of Southern Africa. The hatched area corresponds to the main maize growing areas. The background map shows vegetation densities as estimated from satellite indices (light, medium and heavy vegetation)

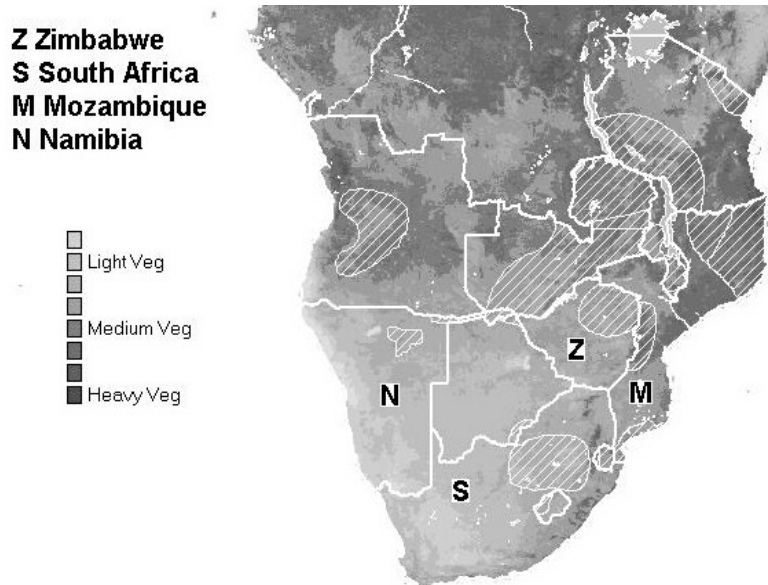
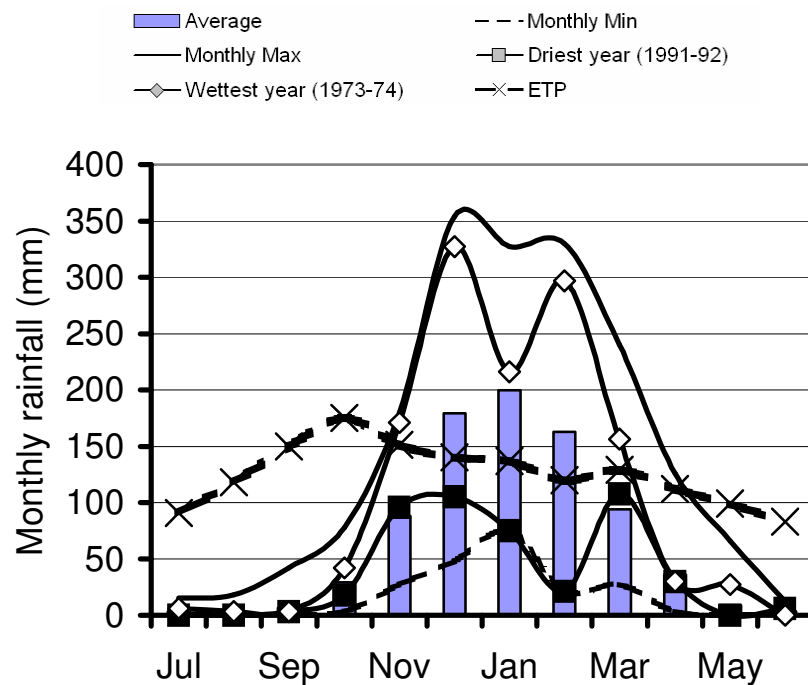
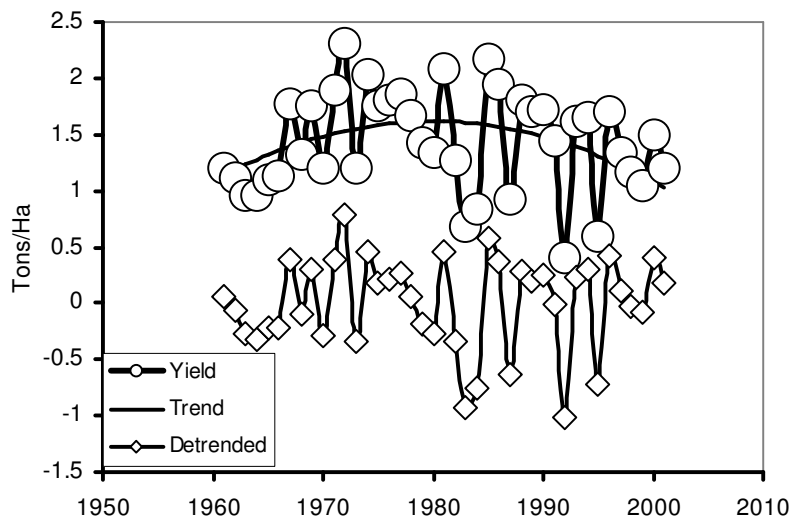


Figure 2: : Rainfall and ETP (evapotranspiration potential) patterns in Zimbabwe between 1960-61 and 2001-2002: average monthly values, maximum and minimum recorded for each month, as well as rainfall profiles of driest and wettest years.



**Figure 3: Maize yields in Zimbabwe, together with their trend and the and detrended value (departure of actual values from the trend).**



#### **b. Yield-rainfall relation**

The simplest possible method to estimate crop yields is to regress them against rainfall, particularly in areas where water is a major limiting factor to agricultural production. Figure 4 shows the roughly linear relation between yield and rainfall, with a coefficient of determination amounting to 0.4563, i.e. about 46% of the variability of detrended yields can be assigned to rainfall.

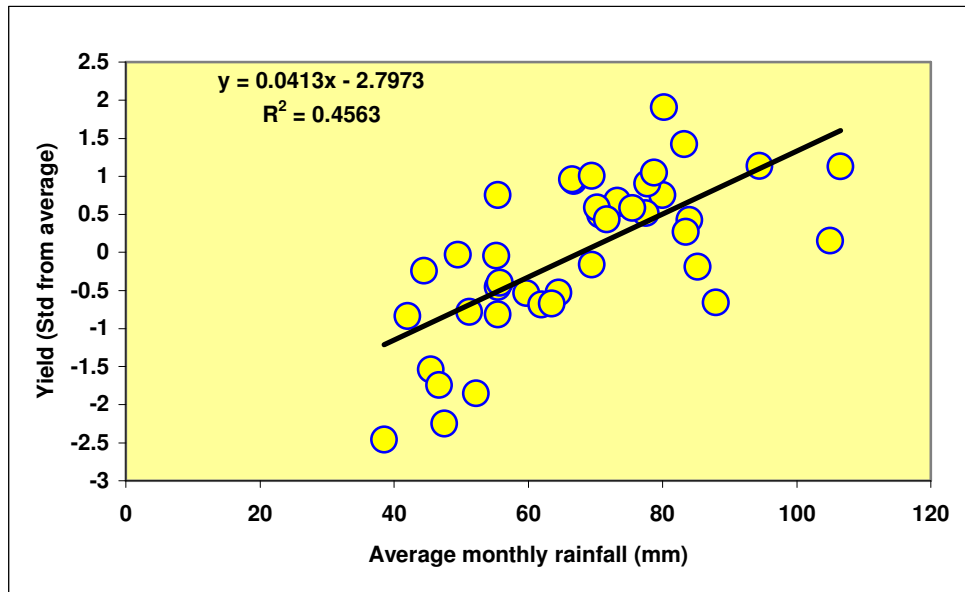
#### **c. A simple simulation of maize yields in Zimbabwe (1981-2002)**

Using the standard FAO methodology (Gommes et al., 1998) and the AMS<sup>15</sup> software, a crop specific soil water balance was computed for the years 1981-82 to 2001-02 using 10-daily data from 25 stations in Zimbabwe and 245 in the surrounding countries. Actual maize crop evapotranspiration (ETA, mm) was computed for all the stations, gridded over the region and averaged for the maize growing areas. Water balance parameters<sup>16</sup>, in particular ETA, are ideal “value-added” variables to be used in crop forecasting, and they are at the heart of the FAO crop forecasting approach (Gommes, 2003). The relation between ETA and maize yield is shown in Figure 5. Altogether, ETA and trend account for about 70 % of the interannual variability of maize yields.

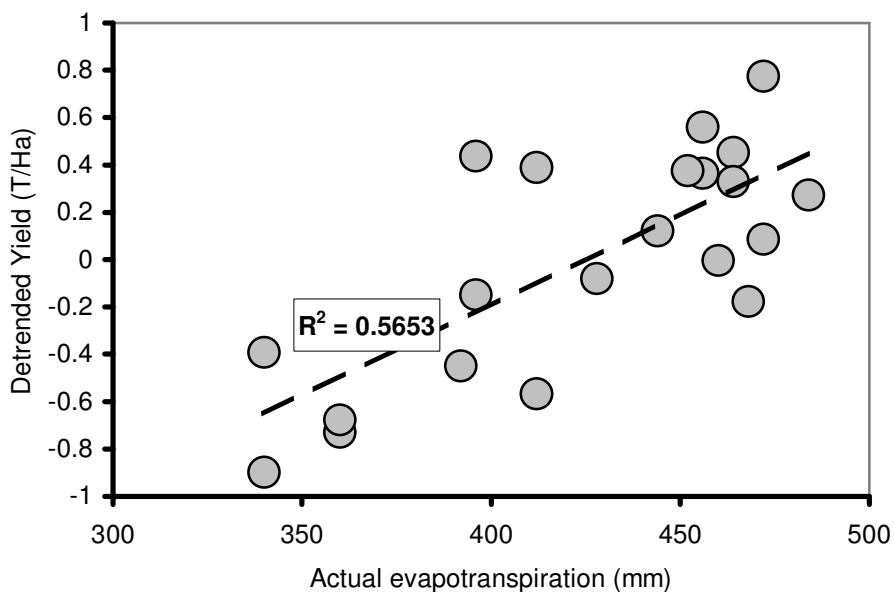
<sup>15</sup> AMS, the AgroMet Shell is a collection of tools used for agrometeorological crop forecasting. The final version should be released shortly (mid 2003).

<sup>16</sup> Water balance parameters include actual crop evapotranspiration, water surplus and water deficit over main crop stages (e.g. emergence, vegetative phase, flowering). The basic idea

**Figure 4: Relation between detrended maize yield (expressed as standard deviations from average) and average July-June rainfall in maize growing areas of Zimbabwe between 1982 and 2002**



**Figure 5: Relation between detrended yield and actual maize evapotranspiration in maize growing areas of Zimbabwe between 1982 and 2002**



behind the methodology adopted by FAO is that, as de Wit was among the first to recognise in the mid fifties, there is a direct link between plant transpiration and productivity (van Keulen and van Laar, 1986). For “not too severe” water stresses, actual evapotranspiration is rather linearly correlated with yield. Interestingly, this relation holds over various scales, from plant to region.

**d. Threshold based yield forecasting (1961-2001)**

As explained above (e.g. Table 1), it is often possible to derive a simple threshold-based crop-forecasting table.

In Zimbabwe, like in most of southern-central Africa, there is a tendency for rainfall distribution to be bimodal, with a dry period in January or February, as can be seen in Figure 2. In fact, when correlating yields with monthly rainfall, the coefficient turns out to be highest in February ( $r=0.656$ ) and January ( $0.500$ ). The next highest value corresponds to March ( $r=0.367$ )

It was found that a good separation of yield categories could be achieved when grouping years by February rainfall totals as shown in Table 3.

**Table 3: 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.**

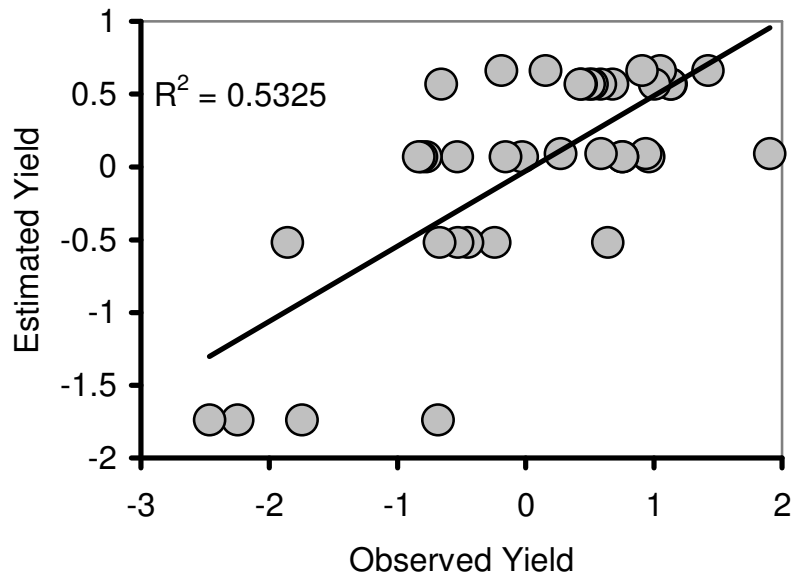
Criteria 1 January rainfall (mm)	Yield (average and 95% confidence interval)	Criteria 2	Threshold	
75 to 155	-1.07 -1.64 to -0.50	February rainfall	< 120 mm -1.74 -2.35 to -1.13	>120 mm -0.52 -1.16 to 0.12
156 to 249	0.25 -0.05 to 0.55	February rainfall	< 170 mm 0.07 -0.50 to 0.35	> 170 mm 0.57 0.25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

For instance, yields fall in the range of  $-0.05$  to  $0.55$  standard deviations from average when rainfall is between 156 and 249 mm: they are about average ( $0.25$  standard deviations higher than the average). When we now separately examine the group of years characterized by January rainfall from 75 to 155 mm (Group 1, Table 3), 156 to 249 mm (Group 2) and 250 to 327 (Group 3) rather contrasting correlations are found between yields and monthly rainfall. For instance, in Groups 1 and 2, the highest correlation is between yield and February rainfall (see the example of Group 1 in Table 4), while in Group 3, we find a negative highest correlation between yield and December rainfall. This results from the fact that high January rain will not have a detrimental effect on yield only if December is relatively dry.

**Table 4: Correlations between maize yield and monthly rainfall for the 11 years between 1961-62 and 2000-2001 in which January rainfall was between 75 and 155**

	July	Aug.	Sep.	Oct.	Nov.	Dec.	Jan.	Feb.	Mar.	Apr.	May	June
July	1.00											
Aug.	0.33	1.00										
Sep.	-0.38	-0.10	1.00									
Oct.	-0.34	-0.11	-0.31	1.00								
Nov.	0.03	-0.27	0.32	-0.67	1.00							
Dec.	-0.03	-0.16	-0.33	0.68	-0.27	1.00						
Jan.	-0.26	-0.33	0.13	0.23	-0.24	-0.05	1.00					
Feb.	0.02	-0.05	0.75	-0.40	0.33	-0.30	0.27	1.00				
Mar.	0.21	-0.30	-0.08	-0.48	0.27	-0.17	0.01	0.37	1.00			
Apr.	0.00	0.48	0.26	-0.07	0.29	0.24	-0.65	0.05	-0.35	1.00		
May	0.33	0.13	0.46	-0.35	0.20	-0.57	-0.05	0.49	-0.14	0.12	1.00	
June	-0.27	-0.13	0.67	-0.07	0.25	-0.08	-0.40	0.20	-0.40	0.50	0.48	1.00
<b>Y obs</b>	-0.11	0.20	0.40	-0.03	0.11	0.24	0.19	<u>0.66</u>	0.23	0.24	-0.19	-0.15

**Figure 6: Comparison of estimated and observed yields in Zimbabwe between 1961 and 2001 using the threshold method described in Table 3. Yields are expressed in standard deviations from the average.**



The described method will of course forecast only the six yield values that appear in Table 3, together with their confidence interval. Yet, the strength of the correlation remains comparable with the one obtained with the less empirical simulation approach (Figure 6).

**e. Rainfall profile clustering method (1961-2001)**

The method assumes that similar rainfall profiles (July to June) will on average result in similar yield categories.

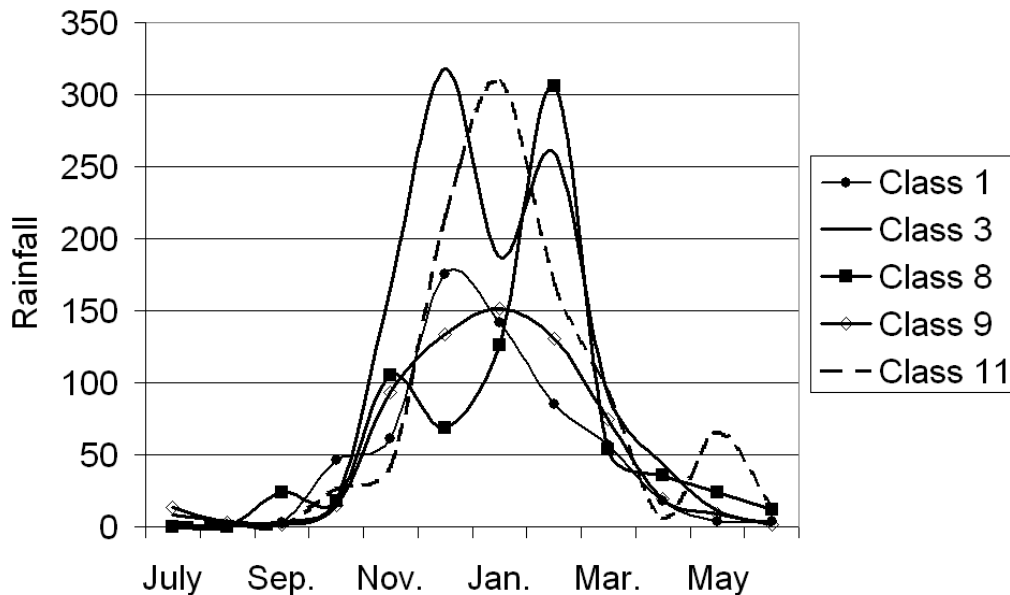
The profiles were obtained using the ADDATI<sup>17</sup> multivariate statistical package developed by Griguolo. The number of classes to adopt is somewhat arbitrary. In this case, 12 were found to be a good compromise. Some typical rainfall profiles are shown in Figure 7.

With the classification method, the number of different yields is obviously the same as the number of classes.

To use the approach for crop forecasting in operational mode, a given season is compared with the 12 classes and assigned to one of them. The yield for the year is then taken as the average yield (with confidence interval) of the class. Some contrasting examples are shown in Figure 8.

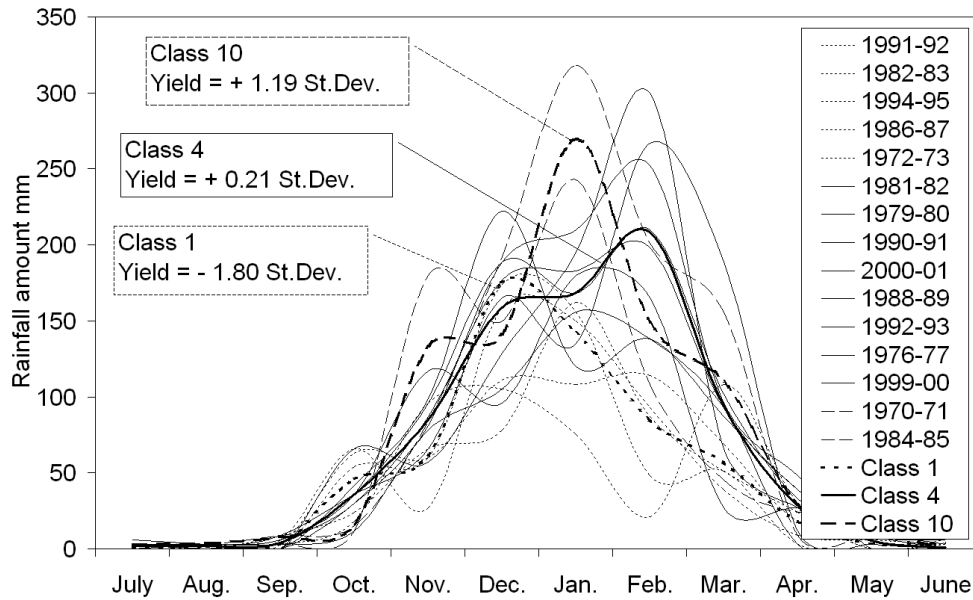
Regarding the potential value of the method as a crop-forecasting tool, the  $r^2$  of 0.5665 is amazingly close to the one obtained with the crop specific soil water balance (0.5653, Figure 9).

**Figure 7: Some typical rainfall profiles for Zimbabwe. Rainfall is expressed in mm.**

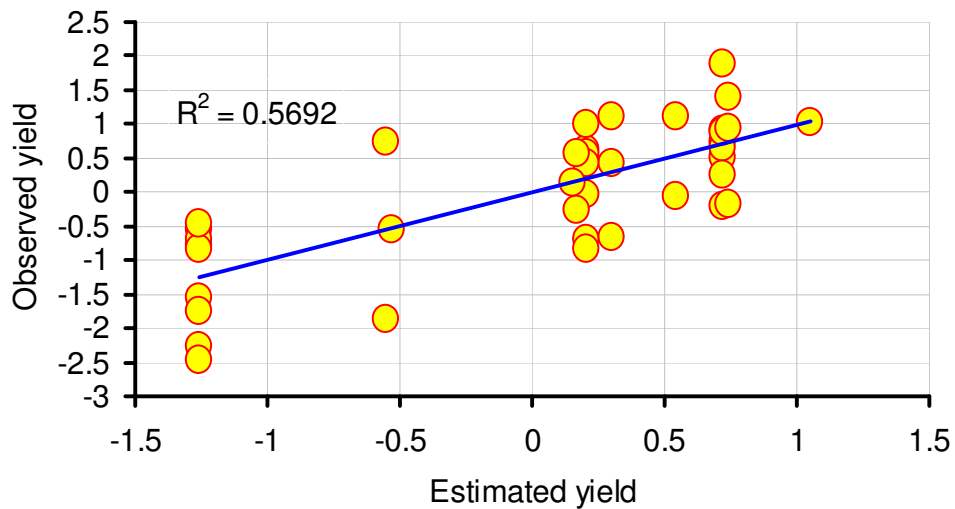


<sup>17</sup> The latest update (November 2002) can be downloaded from [http://cidoc.iuav.it/~silvio/addati\\_en.html](http://cidoc.iuav.it/~silvio/addati_en.html)

**Figure 8: Some typical rainfall profiles for Zimbabwe. Rainfall is expressed in mm**



**Figure 9: Comparison of estimated and observed yields in Zimbabwe between 1961 and 2001 using the rainfall profile method. Yields are expressed in standard deviations from the average.**



**f. Conclusions**

The inter-comparison of several crop-forecasting tools is given in table 5. It appears that, with the exception of the simple use of rainfall totals, the methods tested yield similar results. In view of the ease of implementation of the non-parametric methods, it is certainly worth exploring their potential further.

**Table 5: Comparison of several maize yield forecasting approaches in Zimbabwe (fraction of variance accounted for by the different methods).**

<b>Method</b>	<b>R<sup>2</sup></b>		
	<b>Trend</b>	<b>Method</b>	<b>Total</b>
<b>Average Rainfall</b>	0.1702 +	0.4563	0.6265
<b>Water Balance</b>		0.5653	0.7355
<b>Threshold</b>		0.5311	0.7013
<b>Clustering</b>		0.5692	0.7394

**5. Summary**

The spectrum of available crop yield forecasting methodologies covers a number of deterministic and empirical approaches.

The deterministic tools attempt to quantify the mechanisms behind the environment-crop interactions; they include mainly crop models and, to some extent, multiple regression equations. The empirical approaches, also known as non-parametric or descriptive methods, attempt to describe the general environmental conditions (especially weather) under which the crops are grown, and assume that similar conditions will determine similar yields.

Various forms of non-parametric approaches have been used with success, in particular those that relate El Niño indices and crop yield, or those that relate temporal profiles of satellite-based vegetation indices with yields.

Timeliness, cost, spatial scale and accuracy are some of the criteria that are adopted when selecting crop-forecasting methods. It appears that non-parametric methods are as accurate as the deterministic ones, and that they are comparable in terms of timeliness. Non-parametric approaches, however, are much less demanding in terms of inputs and “technology” (processing power), so that some of them can even be applied at village level (the “threshold-based” approach).

The various families of crop models (CERES, WOFOST, EPIC...) are all very much based on the same principles. They need a number of inputs that are difficult to obtain for operational crop forecasting work. It is, indeed, the definition of parameters that is a main bottleneck (Gabrielle et al. 1999).

The simulation models have also reached a degree of sophistication where only marginal improvements can be expected. Non-parametric methods, on the other hand, are still young. Significant progress for crop yield forecasting can be expected if they receive wider attention, particularly in view of their application in developing countries.

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