Centre for Agrobiological Research
Wageningen Agricultural University

Crop growth simulation and statistical validation for regional yield forecasting across the European Community

Simulation Reports CABO-TT, no. 31

G.H.J. de Koning, M.J.W. Jansen, E.R. Boons-Prins,

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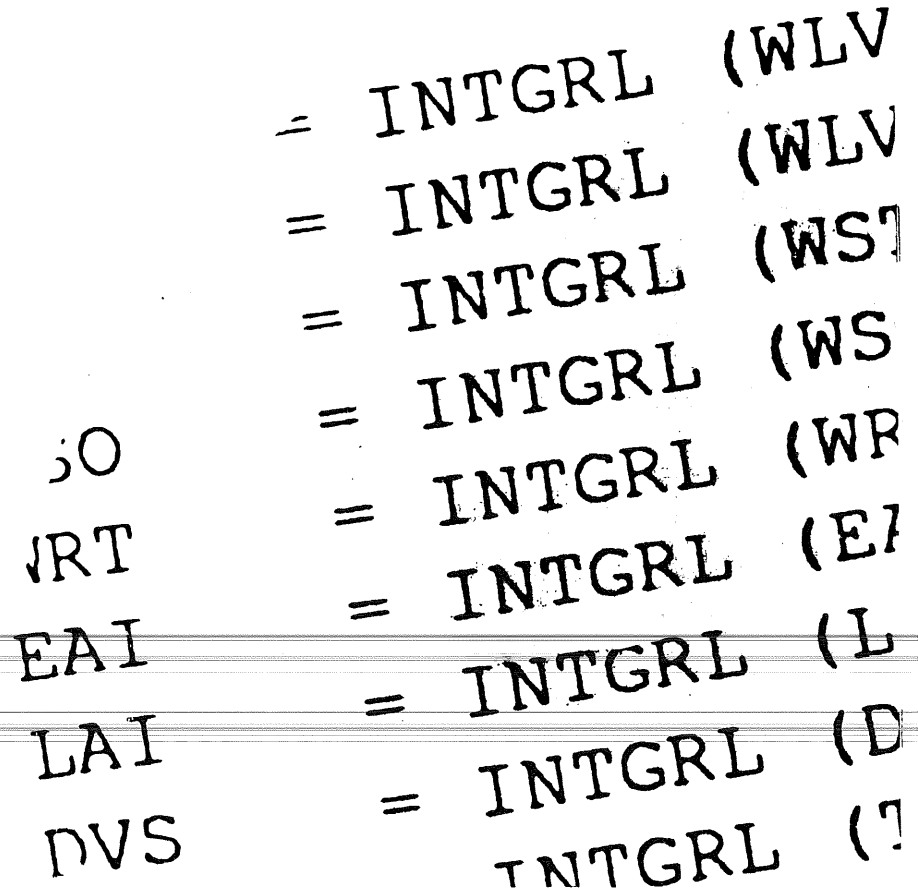

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Study carried out on behalf of:
Agricultural Information Systems,
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Simulation Reports CABO-TT

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The DLO Centre for Agrobiological Research (CABO-DLO) falls under the Agricultural Research Department (DLO) of the Dutch Ministry of Agriculture, Nature Management and Fisheries.

The aim of DLO is to generate knowledge and develop expertise for implementing the agricultural policies of the Dutch government, for strengthening the agricultural industry, for planning and management of rural areas and for the protection of the environment. At CABO-DLO experiments and computer models are used in fundamental and strategic research on plants. The results are used to:

- achieve optimal and sustainable plant production systems;
- find new agricultural products and improve product quality;
- enhance nature and environmental quality in the countryside.

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Contents

Preface

This report is prepared by the DLO Centre for Agrobiological Research in the framework of the development, validation and testing of crop-specific agrometeorological models for yield forecasting purposes. It describes the regional validation of the yield model of the Crop Growth Monitoring System, which in turn will form part of an Agricultural Information System on the European Community. This report describes the regional validation of the yield model of the Crop Growth Monitoring System (CGMS). The detailed description of the crop growth simulation model and its calibration for European crops are given in other reports. The Crop Growth Monitoring System was developed by the DLO Winand Staring Centre on behalf of the Institute for Remote Sensing Applications (IRSA) of the Joint Research Centre (JRC, Ispra-site) of the Commission of the European Community under contract 3965-90-04 ED ISP-NL "Yield Forecasting Models, Part II" (SC Project 7185), and further elaborated in cooperation with the DLO Centre for Agrobiological Research under contract 4436-91-08 ED ISP NL "Crop specific agrometeorological simulation models" (SC Project 7220, CABO Project 836).
This report is a contribution of the DLO Centre for Agrobiological Research (CABO-DLO) to the second contract. The overall objective of the second contract was to develop, validate and test new or existing crop-specific agro-meteorological simulation models for routine quantitative forecasting of national and NUTS-1 yields every 10 days, and for areawise qualitative monitoring, every 10 days, of the conditions of the agricultural season over the whole of the EC. The model should work for each of the following crops: wheat, barley, oats, maize, rice, potato, sugar beet, pulses, soybean, oilseed rape, sunflower, tobacco and cotton.

This report deals with the validation of regionally aggregated output of a crop growth simulation model against official regional agricultural statistics. Concerning the statistical validation of the yield model for its use for regional quantitative yield forecasting the following specifications were formulated :

- The official statistics include historical yield data available in the CRONOS (national yields, series of 15-35 years) and REGIO (regional yields, series of 14 years) data bases of the European Statistical Office (Eurostat, Luxembourg).
- The validations have to be carried out at the national and the regional NUTS-1 level.
- The regionally aggregated model output covers the same series of years.
- The timestep of the simulation model is one day.
- As the final goal is to forecast yields routinely every ten days, the yield series should be analysed as a function of intermediate 10-day model outputs, starting from the 5th ten-day period after planting.
- Technological time trends must be taken into account.
- An evaluation of the precision and stability of independent estimates should be included, as well as an analysis of the variability and stability of the regression coefficients.

Most of these requirements could be met, and are reported here. The CGMS system has the capability to generate time series over years of regionally aggregated model output (e.g. biomass) at any given 10 day but these results are not analyzed in this report, as already the validation of the model output at harvest time gave poor results. The possible reasons for this are discussed. A repetition of this discussion for all preceding ten day periods would not lead to a better understanding of the performance of the whole procedure.

Although a wealth of information is integrated through the succession of crop modelling, regional aggregation, and regression analysis, the available basic information on weather, crops, soils, land use and yield statistics was by no means complete. Because of limited availability of data, some procedures were simplified, or only a limited validation could be carried out. Information on the soil profile available water capacity was lacking, the interpolation for historic weather from stations to grid was not operational, statistical information was lacking completely for some crops and was not complete for others, and information on land use was insufficient (no maps, so no information on location of crops, and uncertain weighting of planted area over soils).
As the CGMS system is designed for the handling of this information, it is expected that more accurate crop yields can be simulated by the system once this currently lacking information can be taken into account. However, this does not necessarily improve the results of the statistical validation procedure because of the unknown inaccuracies in yield figures given by official statistics.

C.A. van Diepen, Project leader.

Summary

At the request of the Joint Research Centre of the European Communities, the DLO Winand Staring Centre (SC-DLO) in co-operation with the DLO Centre for Agrobiological Research (CABO-DLO) in Wageningen the Netherlands, has executed the project: "Development, validation and testing of crop specific agrometeorological simulation models". The objective of this project is to investigate the possibilities of agro-meteorological simulation models for quantitative forecasting of national and regional yields of the main agricultural crops of the EC.

The contribution of the DLO Centre for Agrobiological Research (CABO-DLO) consisted of the adaptation of an existing non-specific crop growth simulation model for specific European agricultural crops, and the development of a yield forecasting algorithm. For wheat, grain maize, barley, rice, sugar beet, potato, field bean, soybean, oilseed rape and sunflower, standard values were gathered of model parameters that represent specific crop characteristics. These crop parameter values were adapted to regional conditions throughout Europe. The effectiveness of using mathematical calibration procedures for optimizing parameter values was investigated. As result of this investigation for most crops a more simple approach for calibration was followed, namely the manual adaptation of crop parameters to limited regional data using general modelling knowledge.

Simulated regional and national yields were analysed and related to historical official statistical yields by means of regression methods. This resulted in the formulation of a forecasting algorithm using crop model output of current years for the forecasting of official yields. The accuracy of the yield forecasting algorithm was statistically determined and compared with the accuracy of forecasting without using a crop growth model.

In this report, the general methodology of the research at CABO-DLO will be discussed and results concerning the accuracy of yield predictions are presented. An extensive description of field data sets, cropping calendars and crop parameter values used in the simulation model is given in a separate report by Boons-Prins *et al.* (1993).

Over the whole of the EC the accuracy of predicting official NUTS-1 and NUTS-0 yields cannot yet be improved by using output of the crop growth model. This may be related to limitations in model concepts and to the quality and quantity of the input data available. However, also the reliability of the official yield statistics is an important factor. The accuracy of the official statistical yields is unknown, making it impossible to separate the effects of possibly unrealistic simulation results from errors in the official statistics.

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Furthermore we would like to thank W. Stol and J Withagen of CABO-DLO for their valuable contributions concerning modelling and statistical software, respectively.
Many thanks are also due to P. Vossen of JRC-Ispra for his kind support and counsel.

Wageningen, May 1993.

G.H.J. de Koning
M.J.W. Jansen
E.R. Boons-Prins
C.A. van Diepen
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1 General introduction

The Directorate General for Agriculture of the EC requires timely forecasting of agricultural production to support the Common Agricultural Policy (CAP). Integration of Community statistics has until now been performed by the Statistical Office of the European Community (O.S.C.E. or Eurostat) in Luxembourg. Prediction of yields by Eurostat is based on statistical methods, using historical data and taking into account time trends and weather indicators. The Institute for Remote Sensing Applications (IRSA) of the Joint Research Centre (JRC) of the EC, located in Ispra, Italy, is in charge of a program to improve agricultural yield forecasts. This program is known as the Agriculture Project or MARS project. Within the Agriculture Project of the EC, an Advanced System of Information on Agriculture is being developed. Three methods are investigated by JRC: conventional surveys, remote sensing, and agrometeorological modelling.
At the request of the JRC, the DLO Winand Staring Centre (SC-DLO) in co-operation with the DLO Centre for Agrobiological Research (CABO-DLO) in Wageningen the Netherlands, has executed the project: "Development, validation and testing of crop specific agrometeorological simulation models". The objective is in the contract described as "to develop, validate and test new or already existing agro-meteorological simulation models for 10 day routine quantitative forecasting of national and NUTS-1 yields and for 10-day areawise (regional), but qualitative monitoring of agricultural season conditions over the whole of the EC and for each of the following crops: wheat (spring and winter; hard and soft), barley (spring and winter), oats, maize (grain), rice, potato, sugar beet, pulses (human consumption), soybean, oilseed rape, sunflower, tobacco and cotton."
The project is a logical continuation of the project "Yield Forecasting Models, Part II", performed by the DLO Winand Staring Centre in 1991.

In "Yield Forecasting Models Part II", the DLO Winand Staring Centre has developed a Crop Growth Monitoring System (CGMS). This system includes a non-crop specific agrometeorological simulation model, linked with a weather system and a Geographical Information System (GIS). In the weather system, historic and current daily weather data are stored and interpolated to the grid points of a 50 x 50 kilometres mesh over the whole of the EC. The weather data are used in the crop growth model and the model results can be analysed and visualized with the GIS. In "Yield Forecasting Models, Part II", the crop growth simulation model was non-crop specific. In the current project, yields of all main agricultural crops of the EC were simulated individually. A yield forecasting algorithm was defined, based on comparison between simulation results and historical records of statistical data.

The contribution of the DLO Centre for Agrobiological Research (CABO-DLO) consisted of the adaptation of the crop growth model for crop specific calculations and development of the yield forecasting algorithm. For each of the crops, standard values were gathered of parameters that represent specific crop characteristics. Insufficient data were available for oats, tobacco and cotton and these crops had therefore to be omitted. For the other crops, crop parameter values were adapted to regional conditions throughout Europe. The effectiveness of using standard mathematical calibration procedures for optimizing parameter values was investigated. As result of this investigation for most crops a more simple approach for calibration was followed, namely the manual adaptation of crop parameters to limited regional data using general modelling knowledge. Crop simulation outputs of the calibrated model were compared with results from independent field trials. After CABO-DLO calibrated and validated the model at the point level, SC-DLO calculated grid yields for historical weather records with the CGMS and aggregated these yields to yearly regional averages. These historical records of simulated regional yields were analysed by CABO-DLO and related to historical official statistical yields by means of regression methods. This resulted in the formulation of a forecasting algorithm using crop model output of the current year for the forecasting of official yields in that year. The accuracy of the yield forecasting algorithm was statistically determined and compared with accuracy of forecasting without crop model output. This procedure has resulted in the integration of the yield forecasting algorithm in the CGMS, allowing yearly forecasts of official yields and updating of the forecasting algorithm to data of the most recent years.

In this report, the general methodology of the research at CABO-DLO will be discussed and yield forecasting results presented. A short description of the CGMS of SC-DLO is given in Chapter 2 because it is the basis of the calculations at CABO-DLO. The functions and parameters of the crop growth model, are shortly explained in Chapter 3, with references to more detailed descriptions in other documents. The procedures used for updating crop parameters and calibration of the model, being the core activities at CABO-DLO, are given in Chapter 4. An extensive description of these activities, together with field data sets and final crop parameter values are given in a separate report by Boons-Prins *et al.* (1993). The development of the yield forecasting algorithm in cooperation with the mathematical department of DLO (GLW-DLO) in Wageningen is described in Chapter 5. Some results are given in Chapter 6, focussing mainly on the accuracy of the yield predictions. This report ends with a discussion of the followed methodology, recommendations for further developments and final conclusions

CABO-DLO has executed the project in the period from 1-1-1992 until 31-12-1992. In addition to the authors, two more persons were involved in the project at CABO-DLO: W. Stol for support on model calibration software and J. Withagen for support on statistical software.

2 The Crop Growth Monitoring System (CGMS)

2.1 Introduction

Starting point for crop growth simulation work at CABO-DLO was the Crop Growth Monitoring System (CGMS), developed by SC-DLO in the project "Yield Forecasting Models, Part II" in 1991 (Bulens *et al.*, 1993; Hooijer *et al.*, 1993a, 1993b, 1993c). The CGMS includes a Geographical Information System (GIS) and combines components like interpolation algorithms, weather data handling procedures, geographic procedures and a crop growth simulation model. Within the CGMS a number of digitized maps are stored:
- the soil map of the EC (1 : 1 million)
- maps of administrative units within the EC (NUTS-0 and NUTS-1 level)
- a grid with 1350 cells of 50 x 50 kilometres, covering the whole of the EC (see Appendix 1)
- a map with weather stations.
- a terrain map

With the CGMS, basic data can be analysed and presented. An example of such output is shown in Appendix 2, were the precipitation during the period April-July 1992 is presented on grid basis as deviation from the long term mean precipitation over this period.
In this report, we deal with the use of a crop growth simulation model for the calculation of potential (with irrigation) and water-limited (without irrigation) crop yields. An explanation of the simulation model will be given in Chapter 3. The CGMS provides the basic input data for the model.

2.2. Weather data

The weather data base DBMETEO is described by Reinds (1991) and van der Drift & van Diepen (1992). The data base contains daily weather data of 360 weather stations for 15-30 **historic years**, up to 1989. For the **current years** (from 1990 onwards), daily weather data are available for 626 stations. Within one grid cell, weather is assumed to be homogeneous. In fact, each grid cell is considered as a unique climatic cell. For the historic years, daily weather data within a grid cell are considered equal to the weather data of the most similar nearby located weather station. Similarity is defined in terms of distance between station and grid centre, corrected for differences in altitude and in distance from the coast. For the current years an interpolation procedure is used to determine the daily weather within a grid cell (van der Voet *et al.,* 1993). With this interpolation procedure, for each grid cell an optimum number of surrounding weather stations is selected, taking into account distance from the station, altitude, distance from the coast, number of stations and climate divisions. From the selected weather stations, the daily weather data within the cell are calculated with variable-specific algorithms (van der Voet *et al.*, 1993; Beek, 1991a, 1991b).
Daily weather data needed for the model are:
- minimum air temperature (°C)
- maximum air temperature (°C)

- global radiation (MJ m^{-2} d^{-1})
- vapour pressure (mbar)
- wind speed m s^{-1}
- precipitation (mm)

For a number of stations, the raw data have to be converted, for example the conversion from wet bulb temperature to vapour pressure of the air, or the calculation of global radiation from sunshine duration (van der Drift & van Diepen, 1992). Furthermore, algorithms have been developed for handling of missing values.

2.3 Crop data

The type of crop parameters used in the model will be described in Section 3.4 of this report. Actual values of the model parameters were collected for individual crops within the European Communities and stored in separate files. The values of the crop parameters for region-specific varieties as used in this project have been documented by Boons-Prins *et al.* (1993) for each of the crops considered: wheat, grain maize, barley, rice, sugar beet, potato, field bean, soybean, oilseed rape and sunflower. Data on regional cropping calendars are also given by Boons-Prins *et al.* (1993).

2.4 Soil map

Also stored within the CGMS is the EC soil map. This map is used to derive soil parameters for the model and to estimate the area where a crop can be cultivated.

2.4.1 Soil data

In the crop growth model a number of soil physical soil parameters are needed to calculate water-limited yields. In this report it is assumed that all soils are freely draining. For such a soil, data are required on maximum rooting depth, total pore space, soil moisture content at field capacity and wilting point, subsoil permeability, maximum infiltration rate and the surface water storage capacity. In this stage of the project, differences in physical soil parameters between soil types are not taken into account. Only one standard soil parameter set is used, referring to an average soil (Appendix 4a). The water holding capacity of this soil amounts to 0.21 cm^3 cm^{-3} while the soil depth is set at 120 cm and the initial soil moisture content at field capacity. The actual depth of the layer from which the crop can take up water is determined by the rooting depth of the crop. The maximum depth is limited by either the maximum rootable depth of the soil or the maximum rooting depth of the crop under unrestricted root growth conditions. The crop specific maximum rooting depths used are given in Appendix 4b.

Because only one soil parameter set is used, for the time being within each grid cell yields will be calculated for only one weather-soil combination each year, because weather and soil data are considered homogeneous within the cell. In a next phase, soil specific physical parameters can be used to introduce soil heterogeneity within a grid cell, resulting in multiple runs within a cell for each year.

2.4.2 Estimation of suitable soils

A limitation in the present study is the lack of an accurate land use map. The only information available is the total area of land used for a specific crop within each NUTS-1 region. It is not known on which locations within the NUTS-1 region the crops are grown. For NUTS-1 regions where a specific crop is cultivated, calculation of crop yields should preferably be restricted to soil areas were the crop is actually grown. The soil area where a certain crop can be cultivated is estimated by applying land evaluation rules to the soil units of the soil map. These rules serve as a sieve to separate suitable and unsuitable soils. The crop growth simulation model is for a specific crop only applied to soils that are judged suitable for mechanized cultivation of the crop. All soil units that are judged unsuitable for this type of farming due to slope, stoniness, texture or drainage conditions (Reinds & van Lanen, 1992), are excluded from further crop yield calculations and are not used for the regional aggregation of simulated yields.

2.5 Aggregation of simulated yields to regional and national level

The simulated yields are calculated for each suitable land unit, represented by a unique combination of soil, grid and administrative region. For historic as well as current years, the simulated yields are aggregated over NUTS-1 regions and over countries. Simulated NUTS-1 yields are the weighted averages of the simulated yields on the land units within a NUTS-1 region, using the **estimated suitable crop area** within that region as the weighting factor. In a second step, the aggregated simulated yields at NUTS-1 level are further aggregated to the country level, using the **actual crop areas** within each NUTS-1 region according to official statistics as the weighting factor.
Names of NUTS-0 and NUTS-1 levels are given in Appendix 3.

2.6 Statistical data

Official statistical data are obtained from the regional data base "REGIO" of Eurostat, available in DBASE-4 format. In the Agricultural and Forestry Statistics of REGIO, fresh weight yields (tonnes ha^{-1}), areas (ha) and production volumes (tonnes) of agricultural crops are given at NUTS-0, NUTS-1 and, increasingly erratic, NUTS-2 level. Only NUTS-0 and NUTS-1 data are used in this report because NUTS-2 data are too incomplete. Maximally the years 1975-1990 are covered, the amount of missing data depending on crop type and region. Crops listed are wheat, grain maize, barley, rice, sugar beet, potato, oilseed rape and sunflower. Therefore, for three crops for which yields are simulated, no statistical data are yet available: oats, field bean and soybean. Wheat figures apply to the total of spring, winter, common and durum wheat. Barley includes spring as well as winter varieties and potato figures apply to the total of early and late varieties.
Data are exported from DBASE with a DBASE-procedure and written to crop specific files containing the yield and area data for series of years.

3 The crop growth model WOFOST

3.1 Introduction

The crop growth model WOFOST (WOrld FOod STudies) has been developed by the Centre for World Food Studies in Wageningen, the Netherlands, in cooperation with the Agricultural University and the DLO Centre for Agrobiological Research (van Diepen *et al.*, 1988, 1989). More recently the model has been further developed at the DLO Winand Staring Centre (Guiking, 1993). The basic principles of the processes underlying the model have been treated in detail by van Keulen and Wolf (1986). The model simulates phenological development and growth of a field crop from emergence to maturity as determined by the crop's response to environmental conditions.
WOFOST has been applied in a number of agro-ecological characterisation studies. Recently, the DLO Winand Staring Centre has investigated the physical crop production potentials for rural areas in the European Communities. In that study, quantitative estimates were provided of the yield potentials of grass and major arable crops when grown on land units suitable for agricultural use (van Lanen *et al.*, 1992; de Koning & van Diepen, 1992). Wolf & van Diepen (1991) have used WOFOST to investigate effects of possible changes in climate conditions on crop production and water use in the Rhine basin. Furthermore Wolf (1993) has investigated the effects of climate change on wheat and maize production in the EC using the WOFOST model.

3.2 Structure of the model

Within the model two production levels are distinguished: potential and water-limited. The potential yield is determined by crop genetic properties, solar radiation, temperature regime and sowing date, and indicates the production ceiling for crops growing under optimum soil moisture conditions throughout. For this production level it is therefore assumed that irrigation is applied if necessary to allow unrestricted plant growth. The water-limited yield depends on natural water supply and includes effects of water-shortage. Soil physical data and (in addition to radiation and temperature) weather data like rain, windspeed and humidity of the air are required for the description of the effects of drought stress on plant growth. For both potential and water-limited production, nutrient availability, pest, weed and disease control and farm management are taken to be optimal.
The main model can be broadly divided into 2 submodels: the crop growth submodel and the soil water submodel. These submodels are connected by means of a relation, describing the effect of the soil water status on the transpiration and photosynthesis rate of the crop.
The simulations are carried out in time steps of one day. WOFOST is integrated in a Fortran Simulation Environment (FSE) (van Kraalingen, 1991) and uses a Fortran utility library (TTUTIL) with simulation supporting subroutines and functions (Rappoldt & van Kraalingen, 1990). Both FSE and TTUTIL have been developed at CABO-DLO.

3.3 The crop growth submodel

Figure 1 illustrates the processes, as described in the crop growth submodel. The amount of intercepted light is determined by the level of incoming solar radiation and the leaf area of the crop. From the absorbed radiation and the photosynthetic characteristics of single leaves, the daily rate of potential gross photosynthesis is calculated. Detailed descriptions of the photosynthesis rate calculations in the model have been given in the literature. Spitters *et al.* (1986) have discussed the separation of diffuse and direct fluxes of global radiation while the calculation of assimilation rates from these fluxes is described by Spitters (1986). The integration of assimilation rates over the canopy and over the day is performed with the Gaussian integration method (Goudriaan, 1986).

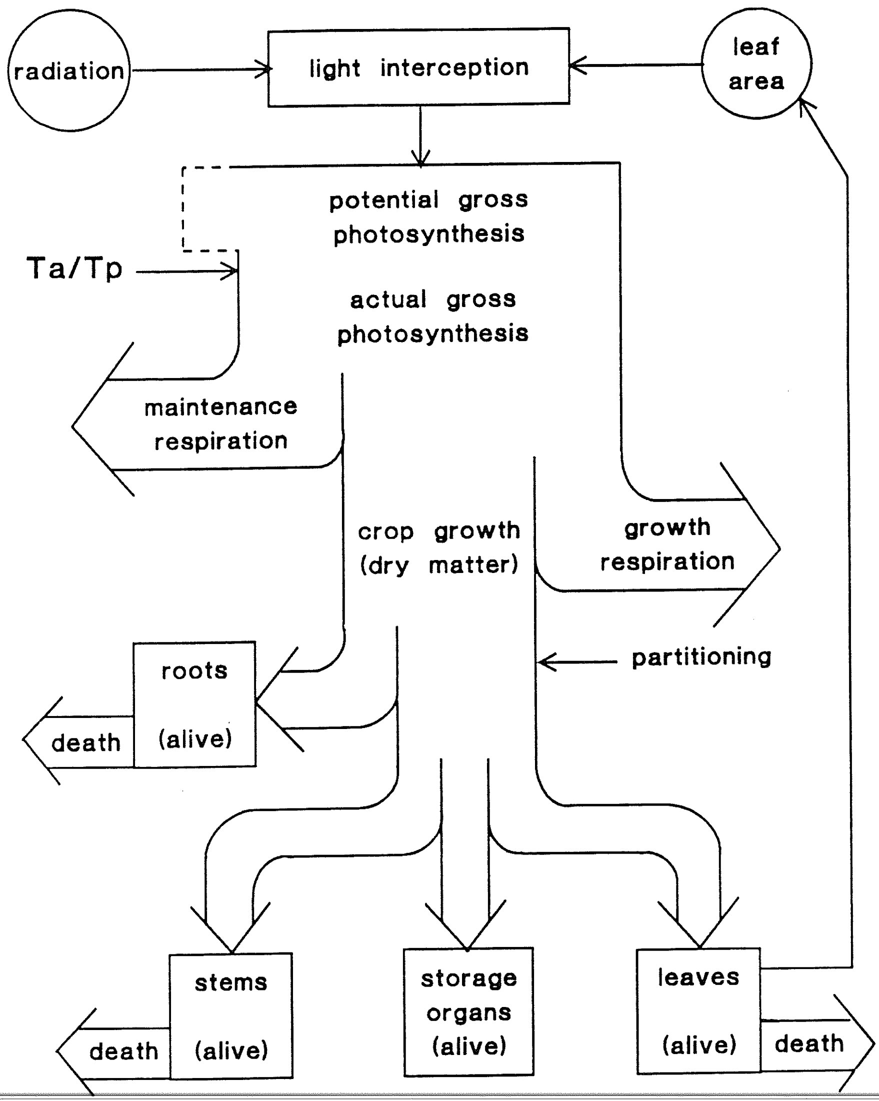

Figure 1. Crop growth processes. Ta and Tp are actual and potential crop transpiration rates, respectively.

Part of the daily production of assimilates is used to provide energy for the maintenance of the existing live biomass (maintenance respiration). The remaining carbohydrates are partitioned among the major plant organs: roots, leaves, stems and storage organs (van Heemst, 1986) and converted into structural plant material such as cellulose, proteins, lignin and lipids. In this conversion process some of the weight of carbohydrates is lost as growth respiration, in dependence of the composition of the various organs (Penning de Vries *et al.*, 1989). The leaf area index of the crop is calculated by multiplying the life leaf weight by the specific leaf area. During ageing of the crop, part of the life crop tissue dies due to senescence. Leaf mass is subdivided into age classes, and if the temperature sum of a class exceeds the crop-specific value during which leaves are functioning, they are assumed to die. The crop growth curve and resulting yield are found by integrating the daily dry matter increase, partitioned to the plant organs, over the total crop growth period (Figure 2.).

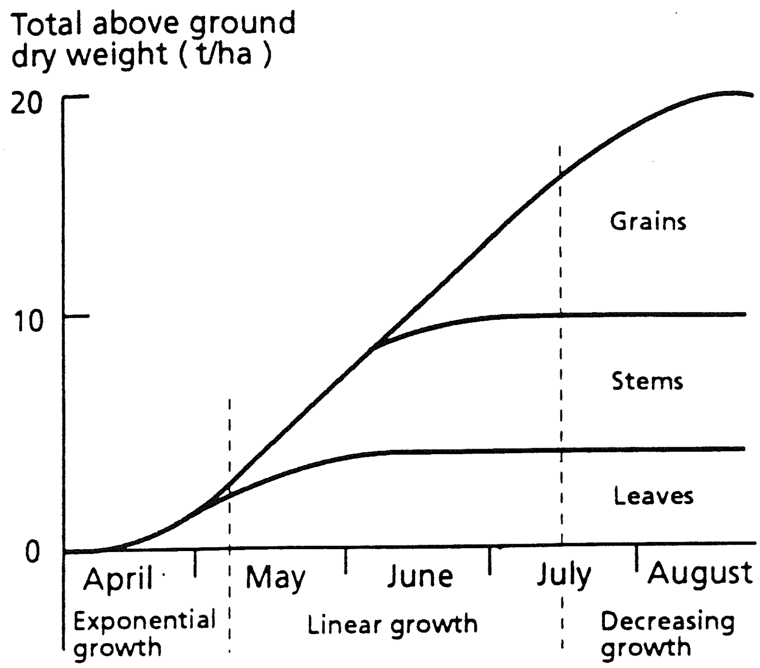

Figure 2. Simulated course of dry weights of the various plant parts for summer wheat growing in the Netherlands. (source: Wolf & Van Diepen, 1991).

Some simulated crop growth processes are influenced by temperature like the maximum rate of photosynthesis, and the maintenance respiration. Other processes are steered by the development stage: the partitioning of assimilates, the specific leaf area and the death rate of crop tissue. Phenological development of a crop can be characterized by the order and rate of appearance of vegetative and reproductive plant organs. In the model the development rate is a function of ambient temperature, possibly modified by the effect of daylength.

3.4 Crop parameters

A number of crop data are needed for the crop growth submodel. An example of a standard crop data file for barley is given in Appendix 5. After sowing of the crop, the time needed until emergence has taken place is determined by a temperature sum (TSUMEM) of daily

average temperatures above a threshold temperature (TBASEM) and with a maximum daily increase of the temperature sum of TEFFMX. In order to initiate crop growth, the dry weight (TDWI) and leaf area index (LAIEM) of the crop at emergence must be estimated. Growth after emergence depends on the photosynthesis rate, though the increase of leaf area during juvenile growth may be limited by the maximum relative daily increase of the leaf area index (LAI) in dependence of air temperature (RGRLAI). Phenological development is determined by temperature sums: TSUM1 from emergence to anthesis (development stage 1), TSUM2 from anthesis to maturity (development stage 2). The increases of temperature sum in dependence of the average air temperature is given by function DTSMTB. For some crops, phenological development is also influenced by daylength (IDSL), using an optimum (DLO) and critical (DLC) daylength. The assimilation parameters describe the response curve of single leaves to light: the maximum photosynthesis rate (AMAX) at light saturation and the light use efficiency (EFF) under light limiting conditions. AMAX depends on development stage (function AMAXTB) and average temperature (function TMPFTB). The gross photosynthesis of the canopy can also be limited due to low minimum temperatures (function TMNFTB). Light distribution within the canopy is influenced by the leaf angle distribution of the crop, in the model accounted for by the extinction coefficient for diffuse visible light (KDIF). The maintenance respiration rates (RML, RMO, RMR, RMS) and the growth respiration (CVL, CVO, CVR, CVS) of each organ are determined by the composition of the crop tissue. Q10 indicates the relation between the maintenance respiration rate and temperature. The partitioning functions FRTB, FLTB, FSTB and FOTB distribute the daily dry matter growth between different plant organs as function of the development stage. Also depending on development stage is the specific leaf area (function SLATB) which serves to calculate leaf area from leaf weight, while the life span (SPAN) of the leaves is used for the description of leaf death due to ageing. Leaf death due to drought stress is separately determined by the maximum relative death rate PERDL. Initial rooting depth (RDI), root growth rate (RRI), maximum rooting depth (RDMCR), transpiration characteristics (CFET) and drought sensitivity (DEPNR) of the crop are required to describe drought stress. RDRRTB and RDRSTB are the relative death rate of roots and stems, respectively, both depending on development stage
The crop growth submodel model is structured in a way that the growth of different annual crops can be simulated by adapting only the crop specific parameters.

3.5 Soil water status and crop growth

The potential rate of transpiration of the crop, i.e. the rate of water loss of a crop well supplied with water, depends on the leaf area and the evaporative demand of the atmosphere, characterized by level of radiation, vapour pressure deficit and wind speed. In the model potential transpiration is calculated with the Penman formula (Penman, 1948; Frère & Popov, 1979; Berkhout & van Keulen, 1986), for the present project adapted according to Choisnel *et al.* (1992).
Under optimal soil moisture conditions, the crop is able to replenish all transpiration losses by uptake of water by the root system. However, when the rooted soil is too dry, the transpiration rate of the crop is reduced, which leads to a proportional reduction in assimilation rate. The ratio between actual and potential transpiration, multiplied with the potential photosynthesis, yields the actual photosynthesis.
Figure 3 shows the relation between the soil moisture content and the ratio between actual and potential transpiration. Between a certain critical soil moisture content (SMcr) and field capacity (SMfc) this ratio is 1, allowing potential transpiration. Below the critical soil moisture

content actual transpiration is reduced due to drought stress. Under these conditions, actual transpiration is linearly related with the soil moisture content. At wilting point (SMwp), actual transpiration, and hence crop growth, come to a halt.
The value of the critical soil moisture content depends on the drought sensitivity of the crop and the atmospheric demand (Driessen, 1986). The higher the atmospheric demand, the higher the critical soil moisture content.

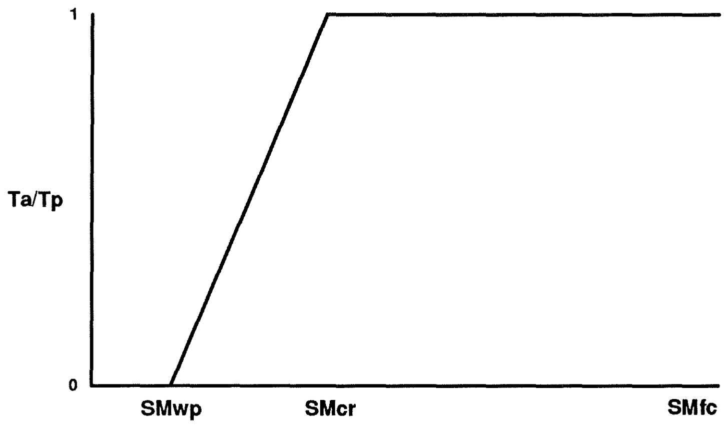

Figure 3. Relation between soil moisture content and transpiration ratio. Ta and Tp are actual and potential transpiration rates, respectively; SMwp, SMcr and SMfc are the soil moisture contents at wilting point, critical point and field capacity respectively.

3.6 The soil water submodel and soil parameters

The soil is schematized as a system consisting of 2 compartments: the rooted zone and the subsoil (Driessen, 1986). For the rooted zone the water balance equation is solved every daily timestep. At the upper boundary, processes comprise the infiltration of water from precipitation or infiltration, evaporation from the soil surface and uptake of water and transpiration by the crop. If rainfall intensity exceeds the infiltration and surface storage capacity of the soil, water runs off. Water can be stored in the rooted soil till field capacity is reached. Additional water percolates beyond the lower boundary of the rooting zone. Artificial drainage and, in case of groundwater influence, capillary rise can be simulated.
In order to simulate the soil water processes, a number of soil data are needed. For a freely draining soil these are maximum rooting depth, total pore space, soil moisture content at field capacity and wilting point, subsoil permeability which can be used to simulate a stagnating layer, maximum infiltration rate and finally the surface water storage capacity (Appendix 4a). If groundwater influence is simulated, a complete water retention curve and unsaturated hydraulic conductivity curve are needed. Furthermore the depth of the groundwater table must be known and, if drains are present, the depth and capacity of these drains. However, in the present study all soils were considered to be freely draining.

4 Calibration of the crop growth model

4.1 Introduction

In the project "Yield Forecasting Models Part II", WOFOST only calculated yields of a non-specific standard cereal. In the current project, crop parameters were defined that allow crop-specific calculations for 10 agricultural crops.
In Section 3.4 was explained which crop specific parameters are needed in WOFOST. Starting point in this project were the standard WOFOST crop parameter sets which have been given for 22 crops in the WOFOST 4.1 documentation (van Diepen *et al.*, 1988). The parameter values in these sets are based on data collected from the literature by van Heemst (1988). For a number of arable crops in the EC (wheat, maize, potato, sugar beet, oilseed rape), the parameter sets have been further updated within a study by van Lanen *et al.* (1992). For this update, data were used from the crop growth model SUCROS, (Spitters *et al.*, 1989) supplemented with results from field trials across Europe.
For the present project, extensive research was conducted to further adapt the crop parameters to regional conditions for a wider range of crops. This has been described in detail by Boons-Prins *et al.* (1993). A summary of the methodology followed will be given in this chapter. Crop parameters concerning crop phenology will be treated separately because of their special nature. Then an investigation in the possibilities of mathematical calibration will be discussed and finally a short summary of the calibration as eventually performed will be given.

4.2 Crop phenology

Initiated by the Joint Research Centre, an extensive inventory of agrometeorological aspects of all main agricultural crops in the European Communities has been made by a number of contractants (Bignon, 1990; Hough, 1990; Russell, 1990; Falisse, 1992; MacKerron, 1992; Narciso *et al.*, 1992). In these publications regional phenological calendars are given. These have been used to determine sowing/planting dates for all crops and to estimate development rates of the crop in dependence of ambient temperature (Boons-Prins *et al.*, 1993). For each crop, the regional long term average sowing/emergence, flowering and maturity/harvest dates have been combined with the regional long term average temperatures retrieved from the DBMETEO weather data base. This way the regional development rates of each crop were calculated, expressed as the temperature sum needed from sowing/emergence to flowering (TSUM1) and from flowering to maturity/harvest (TSUM2), using crop specific base temperatures for development (Boons-Prins *et al.*, 1993). The regional temperature sums were grouped, this way representing different precocity classes. To each NUTS-1 region, a precocity class was allocated, corresponding on average best to the local cropping calendar. These precocity classes, for each crop only differing in development rate, were the starting point for further crop parameter calibration.

4.3 Mathematical calibration

In Section 4.1 it was explained that the crop parameters needed in the model have been derived from the literature. When comparing sources, it becomes clear that different values are found for the same parameter, depending on the conditions of the experiment. In other words, there is a range of biologically plausible values to choose a parameter from. This introduces a source of uncertainty in explanatory agro-ecological models. Subsequent to initial choice of parameter values the final values used in a model are often selected on the basis of comparison between model output and one or more field datasets. Choosing the best parameter values is problematic because there is no way of knowing how good the final choice of parameters is relative to other possible choices. A solution to this problem would be to use a mathematical algorithm for finding the best combinations of model parameters for a given set of field data. There are a number of mathematical approaches to calibration of simulation models.
The calibration program used in this project consists of two calibration algorithms. The first one is developed by Price (1979). The second one is the Downhill-Simplex method from Nelder & Mead (1965) as implemented in Numerical Recipes (Press *et al.*, 1986). The Price algorithm was adapted to the calibration of simulation models by Klepper (1989) and has been used in a study by Klepper & Rouse (1991) to demonstrate its applicability to a potato crop growth simulation model. The Downhill Simplex method is a faster alternative to the Price-method which is a large consumer of computer time due to its thoroughness in (random) search. The structure of the two algorithms and the FORTRAN software to use the algorithms in combination with a crop growth simulation model, are described by Stol *et al.* (1992).
For application of the calibration program it is necessary to identify those model parameters that have a large range of uncertainty and to specify this range. The choice of a goodness of fit criterium to judge the degree of correspondence between model output and experimental data depends on the objectives of the researcher. These objectives dictate which state variables will be considered in the study and what goodness of fit function will be chosen. As an example, the objective may be to determine whether the model behaves similar to reality with respect to biomass production. In this case the dry weights of stems, leaves and storage organs might be chosen as state variables to be compared with experimental data.
The mathematical calibration procedure according to Stol *et al.* (1992) was in this project applied for wheat (Boons-Prins *et al.*, 1993). Eight detailed experimental data sets were available, five from the Netherlands, two from the United Kingdom and one from Belgium. The model parameters under consideration were RGRLAI, AMAXTB, SLATB, SPAN, and the partitioning of assimilates between leaves and stems. Goodness of fit was calculated for the combined state variables leaf area index, total biomass and grain weight. Eventually the best fitting parameter choices differed only slightly from the original data set, reflecting that the original set was already the result of a process of improvements through extensive comparison with experimental data. Furthermore it turned out that the calibration algorithms are more suited for application at the field level than at the regional level because calibration on just a few state variables of some experiments, does not necessarily result in a model that is robust at a regional level. However, the most important limitation to the mathematical calibration procedure at the level of the European Communities is the enormous amount of experimental data that is required to perform such a calibration for enough locations within the EC. The type of data needed are detailed sets of observations of leaf area and dry matter weights of different crop components at various times during the

growing season. Because the model describes potential and water-limited crop production as explained in Section 3.2, experiments should be conducted under very well controlled conditions. At the beginning of the project a questionnaire (see Appendix 6) has been sent to a number of researchers within the EC, asking for such data. A number of experimental data sets was obtained this way from the United Kingdom, Spain, Italy, Denmark, Belgium, Greece, France and the Netherlands (see also acknowledgements). Additionally the agricultural research centre ERSA-SMR in Bologna Italy was visited to collect data. Though all data proved to be useful, it turned out that within the time frame of this project not enough data would become available for a thorough calibration approach. It was therefore decided to use the limited amount of data that were available for a more conventional way of adjusting the model, described in the next section.

4.4 Calibration with limited data

As explained in the previous section a mathematical calibration procedure was only executed for wheat, mainly due to the limited amount of available experimental data for the other crops. Field data were therefore used in combination with modeling experience to find coherent crop parameter sets with regional validity for each crop. Crop precocity classes (Section 4.2) were the starting point for further refinement of the parameters. Simulation results were compared with regional field trial results in order to judge if adaptations were needed. Due to uncertainty in crop parameters for local varieties, it was tried to achieve satisfying agreement between simulation results and data by changing as few parameters as possible. This process of simulation and comparison has been extensively described by Boons-Prins *et al.* (1993). In that publication all experimental data are mentioned that have been used, together with the different crop precocity classes and crop parameter files. These aspects will therefore not be further treated here.

5 Yield prediction and statistical validation of predictions

5.1 Introduction

The goal of the present study, is to use crop growth simulation results as a basis to provide an algorithm allowing quantitative regional yield forecasting. The procedure followed for the development and validation of such an algorithm has taken advantage of the experience of earlier studies by Palm & Dagnelie (1993) made at the request of the Statistical Office of the European Communities to develop methods for yield prediction on the basis of official yield statistics and meteorological data. In statistical annual yield series, very often a time trend of rising yields can be found. This technological trend is the result of improved farming practices like the introduction of new varieties, higher application rates of fertilizers and more intensive control of weeds, pests and diseases. Within their prediction model, Palm & Dagnelie (1993) have separated the technological time trend from the effect of meteorological conditions:

$$Oy = f1(t) + g(m) + e$$

in which Oy is the official regional yield, f1(t) is the component representing the time trend, g(m) the component representing meteorological conditions of separate years and e the random component.
Palm & Dagnelie (1993) have investigated several ways to describe the time trend. After analysing the results they decided that a simple linear model is sufficient in most cases. A quadratic term gives hardly better results for time series from 20 to 30 years. According to Swanson & Nyankori (1979) linear time-trends for corn and soybean yields in the United States could not be significantly improved by various non-linear trends.
Assuming a linear trend, the regression model used by Palm & Dagnelie (1993) was:

$$Oy = a + b * t + \sum_{i=1}^{i=n}(c_i W_i) + e$$

in which Oy is the official regional yield, t is the year, W_i is the i^{th} weather variable of a total of n variables,
a, b and c are regression parameters and e is the random component. For a case study on maize yields in a number of French regions, weather variables used by Palm & Dagnelie (1993) were decadal values of evapotranspiration, precipitation, global radiation, and maximum, minimum and average temperature. Considering 24 decades from March until October, this amounts to a total of 144 variables that are potentially explicative (n=144). From these variables, secondary variables have been derived (mainly by accumulation of basic values) based on agronomic knowledge, for example the cumulative global radiation in July and August. From the basic and secondary weather variables a subset to be used for prediction was selected by significance testing followed by stepwise regression. This procedure has been followed to predict maize yields in France. After evaluation of the results

it was concluded that most of the yield variation is described by the trend and that the use of weather variables doesn't improve yield prediction, in fact it worsens yield prediction.

In the present project, yield forecasting with crop growth model output is explored. Within the CGMS, calculations with WOFOST are executed per single land unit and subsequently aggregated to obtain yields at regional (NUTS-1) and national (NUTS-0) level (see Chapter 2). After running the model for a series of historical years, the simulated regional yields and the official regional yields figures are used to construct yield prediction rules.
Using simulation techniques in yield forecasting has for example also been demonstrated by Horie *et al.* (1992) for rice. In a simulation approach, model output represents the integrated effect of weather conditions throughout a growing season on crop growth. It is expected that model output has more agronomic significance than individual weather variables.
The simulated yields can not directly be considered as the final yield forecasts, because official yields are in many regions considerably lower than the potential or water-limited yields due to sub-optimal cultivation practices. Furthermore, a trend of rising yields can be observed in official yields, as explained before. However, it was assumed that at farmers fields light, temperature and rainfall are still decisive factors in seasonal yield fluctuations and for this reason there should be a relation between simulated and official yields. With the simulation model it is tried to predict the deviation from the time trend due to weather conditions.
The development of the prediction rules using crop model indicators, and the accuracy of the predictions will be treated in this chapter. In this report, yield prediction for the current season is only performed on the basis of simulated final model outputs at the end of the season. The ultimate goal of the CGMS system is to enable the Agriculture Project to perform every 10 days and on a routine basis crop yield predictions during the course of the growing season, which are likely to become more and more reliable as the growing season progresses. The results of these predictions will be analyzed in the first operational year of the CGMS. A difference with the current approach, is that for preliminary 10-day predictions the model output choice is more limited, for example grain weight can not be used as model output when grains have not yet been formed (see Section 5.2.1). However, the same prediction methodology is being used as described in the next Chapter.
The Fortran software to execute the statistical analysis was designed and written by Jansen and Withagen. An explanation of the software and a listing of the source code are given in Appendix 7.

5.2 Prediction rules

5.2.1 Model indicators

Official statistics of regional mean yields in tonnes ha^{-1} fresh weight, are predicted using the following model indicators (all dry matter weights):

PG	:	simulated potential grain yield (tonnes ha^{-1})
WG	:	simulated water-limited grain yield (tonnes ha^{-1})
PB	:	simulated potential total biomass (tonnes ha^{-1})
WB	:	simulated water-limited total biomass (tonnes ha^{-1})

These model indicators have been obtained by simulation based on representative small scale soil and weather data at grid basis, followed by aggregation to regional level (see Chapter 2). For some crops, grain yield must be interpreted as storage organ yield, for example tuber yield for potatoes and yield of the main root for sugar beets.
The simulated yields represent production maxima, which can be reached under optimum conditions of nutrient supply, weed, pest and disease control, and farm management. The potential yield does not account for effects of water shortage and therefore applies to a situation with optimum irrigation. The water-limited yield represents maximum yields under rain-fed conditions.
Originally, it was intended to predict yields by solely using the water-limited grain yield (WG) as model indicator. Later on, the other three elementary predictors were added. Water limited yield, for instance, is inappropriate for a region with a lot of irrigation. For many regions it is not clear how large the area under irrigation is and where irrigation is applied within the region. Furthermore water-stress can be strongly reduced in case of groundwater influence, a factor which was not taken into account in the model. The total biomass model indicators were added because these are more robust, being less sensitive to modelling errors in the distribution of assimilates. Furthermore, biomass indicators allow 10-day yield predictions during the growing season, when grain filling has not yet started or grains are still very small. In this report, however, only final yields are considered (see Section 5.1).

5.2.2 Elementary predictors

Predictors of mean regional yield are formulated, which are based on official statistical yields of past seasons, model indicators of the same past seasons and model indicators of the season to predict. The predictor is chosen from the following elementary regional predictors, obtained by linear regression of the official regional yield (Oy_i) on the year (t_i) and on model indicators:

0-predictor: $\overline{Oy} + b * (t_i - \overline{t})$

PG-predictor: $\overline{Oy} + b * (t_i - \overline{t}) + c * (PG_i - \overline{PG})$

WG-predictor: $\overline{Oy} + b * (t_i - \overline{t}) + c * (WG_i - \overline{WG})$

PB-predictor: $\overline{Oy} + b * (t_i - \overline{t}) + c * (PB_i - \overline{PB})$

WB-predictor: $\overline{Oy} + b * (t_i - \overline{t}) + c * (WB_i - \overline{WB})$

Coefficient $\overline{Oy}$ represents the average official statistical yield (tonnes ha^{-1}) over the years on which the regression is based. The technological time trend is accounted for by the term $b * (t_i - \overline{t})$ in which coefficient b is the yearly increase of the official yield (tonnes ha^{-1}). The 0-predictor, only describing the trend, is already able to account for regional production level differences. The other predictors use model indicators PG, WG, PB or WB (see previous section) in order to account for seasonal effects due to weather and weather-soil interactions. Addition of a quadratic term $(t_i - \overline{t})^2$ to the time trend has been considered. Based on the results of Palm & Dagnelie (1993) (see Section 5.1) and additional testing on the REGIO database of Eurostat, it was concluded that a linear trend is sufficient to describe increasing official yields. A smooth trend of any type over a large number of years assumes a continuity which might be unrealistic. For that reason it has been decided to base the predictor only on data from the recent past, namely the 9 most recent years. Gradual shifts in the time trend are allowed for by the shortness of the time series of 9 years, used to derive the predictor. Suboptimal production circumstances are accounted for by the coefficient c, which should lie between 0 and 1.

5.2.3 Full prediction rules

Unfortunately there are no conclusive *a priori* arguments for selecting one particular elementary predictor for a particular region. Data to support such a choice are not available. Simultaneous regression of official statistics on technological trend and all four model indicators is unattractive: it is well known that, with limited data, predictions tend to get worse with increasing number of explanatory terms. The dilemma was partially resolved by selecting for each region separately as predictor the elementary predictor which appears to predict most accurately, from the elementary predictors mentioned above.
The full prediction rule for a region consists of a data-based selection of an elementary predictor. Each elementary predictor is fitted to the data currently available. Predictors with a negative estimate of c are rejected because this would make the use of the simulation model unrealistic. A negative value of c would mean that a better than average simulated yield would correspond with a worse than average official yield and the other way around.
In this report, two prediction rules (P0 and P5) are investigated and compared:

- P0 uses 0-predictor
- P5 chooses from: 0-predictor, PG-predictor, WG-predictor, PB-predictor and WB-predictor

P0 is just a regression on the technological trend for each region. P5 compares for each region separately which of the 5 predictors mentioned in Section 5.2.2 predicts the data of that region most accurately. The criterion of best prediction is described in the next section.

5.3 Characterization of prediction errors

In section 5.2.2, 5 yield predictors were introduced. For comparison of predictors, a measure for the accuracy of a prediction model must be formulated. The size of the prediction errors, is expressed by the Relative Root Mean Squared error (RRMS(e)) as percentage of the mean official yield:

$$\mathrm{RRMS}(e_1 \ldots e_k) = \frac{\sqrt{\frac{1}{k} * \sum_{i=1}^{i=k} e_i{}^2}}{\overline{Oy}} * 100$$

in which k is the number of predictions that is made, e_i is the error of the i^{th} prediction and $\overline{Oy}$ is the mean official yield of the predicted years. Use of the mean squared error of prediction has for example been described by Allen (1971) and Wallach & Goffinet (1989).
Two kinds of prediction are studied:

- one-year-ahead and two-years-ahead prediction
- leave-one-out (jackknife) prediction

These will be illustrated on the basis of 15 hypothetical historical years with official yields and simulated yields.

Jackknife error estimate of a predictor

The Jackknife method (also called the leave-one-out method or Allen's PRESS method) can be applied to any prediction rule (Allen, 1971). The yield observations of all years, except one, are used to construct a predictor which is applied to the year kept out of sight, in order to evaluate the prediction error. This is done for each year in turn. Subsequently, one calculates for instance the root mean squared prediction error. For a series of 15 years this is schematized in Table 5.1

Table 5.1. Calculation of the jackknife prediction error.

Years used to derive predictor (14 years out of 15)	Year for which yield is predicted and prediction error assessed
2 3 4 5 6 7 8 9 10 11 12 13 14 15	1
1 3 4 5 6 7 8 9 10 11 12 13 14 15	2
...	...
1 2 3 4 5 6 7 8 9 10 11 12 13 14	15
Jackknife errors are calculated by keeping data out of sight one after another during the construction of the predictor. In this example data of 15 seasons are available. Jackknife root mean squared prediction error: $\sqrt{((e_1{}^2 + ... + e_{15}{}^2)/15)}$	

In case the prediction rule consists solely of linear regression, jackknife errors can be very easily calculated (Montgomery & Peck, 1982). The jackknife error has also been used by Palm & Dagnelie (1993).

One-year-ahead and two-years-ahead error estimate of a prediction

In the present study the aim is to predict the future rather than to reconstruct the past. For direct application it is therefore important to investigate prediction accuracy for the current year. At the end of the growing season, weather data are available for simulation of crop yields, but official statistics are not yet available because of delayed data processing. When official statistics are not delayed more than one year, a one-year-ahead prediction (OYA) is performed. Because occasionally statistics are delayed for two years, two-years-ahead prediction (TYA) has also been studied .
For calculation of the OYA prediction errors, in a series of years the last year should be left out and be predicted on the basis of the previous years. In this study, a series of 9 years is used to predict the yield for the following year. For a series of 15 years, on the basis of the first 9 years the yield of the 10th year is predicted and the prediction error assessed. Then the yield of the 11th year is predicted on the basis of the second to the 10th year etcetera. Subsequently, the root mean squared prediction error can be calculated. For the TYA prediction an analogous procedure is followed: on the basis of the first 9 years the yield of the 11th year is predicted etcetera. For a series of 15 years the calculation of the OYA prediction error is schematized in Table 5.2.

Table 5.2. Calculation of one-year-ahead prediction error.

Years used to derive predictor (series of 9 years out of 15)	Year for which yield is predicted and prediction error assessed
1 2 3 4 5 6 7 8 9	10
2 3 4 5 6 7 8 9 10	11
...	...
6 7 8 9 10 11 12 13 14	15

One-year-ahead (OYA) prediction errors are calculated on the basis of nine preceding years. In this example data of 15 seasons are available.
OYA root mean squared prediction error: $\sqrt{((e_{10}^2 + ...+ e_{15}^2)/6)}$

5.4 Selection of elementary predictor

From the 5 elementary predictors, prediction rule P5 selects the one that predicts most accurately as far as can be seen from the years that are used for the construction of the P5 prediction. The jackknife prediction error measure of the elementary predictors was taken as a suitable selection criterion. In the present system the nine most recent years are used as a basis for OYA and TYA prediction, so the corresponding jackknife is obtained by comparing over these 9 years the realization in year 1 with the prediction based on year 2-9, etcetera. The elementary predictor with the lowest jackknife error over these 9 years is selected in the P5 prediction rule.

5.5 Assessment of the performance of P0 and P5

The accuracy of the rules P0 and P5 was investigated in two ways. First of all, we investigated how P0 and P5 perform in the OYA and TYA predictions, where the 9 most recent years are available to construct the predictor. If n years are available in the database we have n-9, respectively n-10, occasions to compare prediction with a realization lying one respectively two years ahead.

Additionally, the jackknife prediction error of rule P5 was calculated, based on all data present for the region. This provides about twice as many, namely n, occasions to compare prediction and realization. Therefore it is expected that this latter measure of prediction error has better accuracy. Although the jackknife error measure of P5 is not directly relevant for one and two years ahead prediction, its greater accuracy makes it useful, particularly since the jackknife error measure is fully relevant for the investigation of the effect of the use of model indicators on prediction precision. In fact the only advantage of the one and two years ahead method is that the uncertainty about the time trend, which has its strongest effect at the end of the time interval, is duly taken into account.
The jackknife method used to assess the quality of prediction rule P5 works as follows. Each of the n years is predicted on basis of the remaining n-1 years: P5 is derived from these n-1 years, and used to predict the year left out. The jackknife error measure of P5 should not be confused with jackknife error measures of the particular elementary predictors from which P5 chooses one. By the definition of P5, the jackknife error of the elementary predictor selected

by P5 is never worse than that of P0 on the same n-1 years, but when it comes to assessment of the quality of P0 and P5, the predictions and realizations in the remaining year are compared, and there is no *a priori* reason why P5 should do better in that point. On the one hand, P5 has the advantage that weather effects are accounted for, by which the systematic error in the prediction will become smaller. But on the other hand, P5 has the disadvantage that the selection of the elementary predictor and the coefficient of the model indicator are based entirely on the small number of data available for the determination of the predictor. Thus P5 is influenced more by measurement errors. It is not clear in advance which of these two effects will be the strongest. In fact, it will appear later on that P0 predicts about just as well as P5.

6 Results

6.1 Introduction

In this chapter results will be given of the statistical analysis. In the CGMS that will be installed at JRC, software is applied in such a way that actual yield predictions for a current year are given. This deals with the accuracy of yield predictions at different aggregation levels and for different crops. This way it can be evaluated if the use of crop growth simulation contributes to improved yield predictions.
In Section 6.2 the type of output of the current statistical analysis will be explained on the basis of an example. In the next section summarized output will discussed, focussing on a comparison of prediction errors when using predictors with or without crop growth model indicators. Wheat will be treated as an example crop. Other crops are discussed more briefly.

6.2 Type of output

A detailed output of the statistical software is shown in Appendix 8. In this example the output for NUTS-1 region R22, the Bassin Parisien, is given. The results are based on 15 years of available official yields and simulation yields. In Appendix 8a, results are given for prediction rule P0, in other words prediction excluding model indicators and solely based on the time trend. Over the total period of 15 years, the average official yield is 5.644 tonnes ha^{-1} and the yearly increase of the yield is 0.186 tonnes ha^{-1} in this region. The t-value of 6.16, based on all years, indicates that the time trend is clearly significant. The critical value of t (5%, one-sided) is about 1.8 (for 15 years). Furthermore, the unadjusted and adjusted R^2 of the regression are given. More important, however, are the estimates of the root mean squared prediction errors which are all expressed as percentage of the 15-year mean. The jackknife error is based on all 15 years and is estimated at 9.5%. The OYA and TYA errors are based on 6 and 5 predictions, respectively, using 9 preceding seasons for each prediction as explained in Section 5.3. The OYA and TYA errors amount to 12.0% and 14.3%, respectively. The mean official yield and yield increase of the 9 most recent years available (up to 1990) is given, allowing to formulate a predictor based on the last 9 years, which is in this case:
$6.190 + 0.151 * (\text{year} - 1985)$
Thus, for the year 1991 (i.e. OYA) and 1992 (i.e. TYA), the predicted yields for this region using this predictor are 7.096 tonnes ha^{-1} and 7.247 tonnes ha^{-1}, respectively.
In Appendix 8b, results are for the same region given for prediction rule P5, choosing the best of 5 possible predictors. The mean official yield of the series `of years is the same of course. However, based on all years, the predictor using model indicator 1 (potential grain yield) has been selected. The jackknife error of 9.2% listed in the output, is the jackknife of P5 (see Section 5.5). This error measure will be used to compare the accuracy of the predictions of P0 and P5. The t-value of 3.1 (based on all years) indicates that the effect of using a model indicator in the prediction is significant. The OYA and TYA errors have also been calculated for the full prediction rule and amount to 12.0% and 14.3%, respectively, given as percentage of the 15-year mean. According to the output, the predictor based on the last 9 most recent years available (up to 1990), is for this region:
$4.528 + 0.125 * (\text{year} - 1985) + 0.480 * (\text{ind}[1] - 5.187)$

Like for the prediction based on all 15 years, indicator 1 (potential grain yield) has been selected in the predictor based on the 9 most recent years available. Suppose that the simulated potential grain yield is 9 tonnes ha^{-1} in 1991 and 8 tonnes ha^{-1} in 1992, then the predicted yield for this region for 1991 (OYA) and 1992 (TYA) would be 7.108 tonnes ha^{-1} and 6.753 tonnes ha^{-1}, respectively.

6.3 Crop specific results

In this section some selected results will be given for specific crops. For three crops, yields were simulated but no official statistics were available: oats, field bean and soybean. For these crops no predictions could be made. For the other crops, results are available at NUTS-1 and NUTS-0 level, but with varying completeness, depending on availability of simulation results (weather years) or official yields. Results for Germany only apply to former West Germany.
The type of results presented in Section 6.2 are summarized for the P0 and P5 prediction rules. These are listed in Appendix 9 and Appendix 10 for NUTS-1 and NUTS-0 level, respectively. For each region or country the number of available years and the mean official yield over this period is indicated. For the P5 predictor the model indicator of the selected predictor based on all years (having the smallest jackknife error) is listed. Indicator 1, 2, 3 and 4 represent the PG-predictor, WG-predictor, PB-predictor and WB-predictor, respectively (see Section 5.2.2). When no indicator is listed, the 0-predictor (only time trend) is selected. When a model indicator is listed, also the coefficient and the t-value of the model indicator term based on all years is given. Then follow the R^2 based on all years, and the relative residual error of the regression based on the last nine seasons. The last three columns in Appendix 9 and 10 give the jackknife, OYA and TYA root mean squared errors as percentage of the mean over all years. An asterisk indicates that not enough years are available to allow the calculation of a prediction error. For OYA, at least 10 years are needed, and for TYA 11 years. The minimum amount of years needed for calculation of the jackknife error was set at 8. When less than 8 years are available for a region or a country, no analysis is made and it is left out of Appendix 9 and 10. No results can also indicate that the crop is not growing at all in that region or country.

6.3.1 Wheat

In Table 6.1, an indication is given of the NUTS-1 wheat yield prediction errors with the P0 prediction rule, in other words, prediction on the basis of only the time trend. A regional frequency distribution is given of the jackknife and one-year-ahead root mean squared prediction errors. The jackknife error varies for the majority of regions between 5 and 15 %. The one-year-ahead errors are based on less predictions and are therefore more variable.
In Appendix 9 it can be seen that in case of the P5 prediction rule, for 26 NUTS-1 regions a predictor using a model indicator is selected. All four indicators occur, in 6 regions potential grain yield is selected, in 5 regions water-limited grain yield, in 8 regions potential biomass and in 3 regions water-limited biomass. In 31 regions the 0-predictor is chosen, using no model indicator at all. The t-values in Appendix 9 indicate if the relation between model indicator and official yield is significant. For a series of 15 years, the critical value of t (5%, one-sided) is about 1.8. In most of the cases the model indicator has a significant effect. Most

important, however, are the prediction errors. A frequency distribution of the prediction errors of the full P5 prediction rule is given in Table 6.2.

Table 6.1. Wheat yield prediction for NUTS-1 regions. Frequency distribution of jackknife and one-year-ahead (OYA) root mean squared prediction errors for the P0 prediction rule.

Jackknife errors of P0 prediction rule		OYA errors of P0 prediction rule	
prediction error range (%)	number of NUTS-1 regions	prediction error range (%)	number of NUTS-1 regions
0 - 5	0	0 - 5	1
5 - 10	23	5 - 10	12
10 - 15	25	10 - 15	18
15 - 20	2	15 - 20	16
20 - 25	4	20 - 25	3
> 25	3	> 25	7

Table 6.2 Wheat yield prediction for NUTS-1 regions. Frequency distribution of jackknife and one-year-ahead (OYA) root mean squared prediction errors for the P5 prediction rule.

Jackknife errors of P5 prediction rule		OYA errors of P5 prediction rule	
prediction error range (%)	number of NUTS-1 regions	prediction error range (%)	number of NUTS-1 regions
0 - 5	0	0 - 5	0
5 - 10	20	5 - 10	8
10 - 15	26	10 - 15	21
15 - 20	4	15 - 20	16
20 - 25	4	20 - 25	6
> 25	3	> 25	5

In order to compare the performance of P0 and P5, the differences between the RRMS errors were calculated for each region. A frequency distribution of these differences is shown in Table 6.3. A negative value in Table 6.3 means that the prediction error of the P5 prediction rule is larger than that of the P0 prediction rule. For 35 NUTS-1 regions, the difference between jackknife error varies from minus one to one percent, which can be interpreted as P0 and P5 being equal. In 16 regions P5 predictions are worse than P0 predictions, and in 6 regions P5 predictions are better. The one-year-ahead errors show the same pattern. This indicates that the use of model indicators does not improve accuracy of NUTS-1 wheat yield predictions in comparison with a trend analysis.
After aggregation to NUTS-0 (country) level, the same analysis can be made. These results are shown in Appendix 10. In 7 countries a model indicator is selected in the P5 prediction. Each of the 4 indicators occurs. In almost all cases the t-value indicates a significant effect of the model indicator.
The differences between the P0 and P5 prediction errors is for each country given in Table 6.4. Again a negative value of prediction error means that the prediction error of the P5 prediction rule is larger than that of the P0 prediction rule. For most countries P5 predictions are worse than the P0 predictions, though the differences are small. Only in Greece, the P5 predictor seems to be notably successful.

Table 6.3. Wheat yield prediction for NUTS-1 regions. Frequency distribution of the differences in prediction errors between the P0 and P5 prediction rule. Differences given for both jackknife and one-year-ahead (OYA) root mean squared prediction error.

jackknife difference between P0 and P5		OYA difference between P0 and P5	
prediction error range (%)	number of NUTS-1 regions	prediction error range (%)	number of NUTS-1 regions
< -10	0	< -10	2
-10 - -5	2	-10 - -5	1
-5 - -1	14	-5 - -1	15
-1 - 1	35	-1 - 1	31
1 - 5	6	1 - 5	5
5 - 10	0	5 - 10	3
> 10	0	> 10	0

Table 6.4. Wheat yield prediction for countries. Differences in prediction errors between the P0 and P5 prediction rule. Differences given for both jackknife and one-year-ahead (OYA) root mean squared prediction error.

jackknife difference between P0 and P5		OYA difference between P0 and P5	
country	difference (%)	country	difference (%)
Germany	-0.2	Germany	-0.5
France	+1.1	France	-0.2
Italy	-0.9	Italy	-0.7
Netherlands	-0.6	Netherlands	-0.1
Belgium	0	Belgium	-1.0
Luxembourg	-0.4	Luxembourg	-1.1
United Kingdom	-1.3	United Kingdom	-1.2
Ireland	-1.3	Ireland	-1.7
Denmark	+0.8	Denmark	+0.3
Greece	+3.8	Greece	+4.5
Spain	-2.4	Spain	-6.8

6.3.2 Other crops

Results for wheat have been treated in detail in the previous section. In this section a summarized analysis of the results for the other crops is given, focussing on a comparison between the P0 and P5 prediction rule. Basic data are given in Appendix 9 and 10 as explained in Section 6.3. At the NUTS-1 level the differences in jackknife and one-year-ahead prediction errors of the P0 and P5 prediction errors are given in Tables 6.5 to 6.11 for the crops grain maize, spring barley, rice, sugar beet, potato, oilseed rape and sunflower.

Table 6.5. Grain maize yield prediction for NUTS-1 regions. Frequency distribution of the differences in prediction errors between the P0 and P5 prediction rule. Differences given for both jackknife and one-year-ahead (OYA) root mean squared prediction error.

jackknife difference between P0 and P5		OYA difference between P0 and P5	
prediction error range (%)	number of NUTS-1 regions	prediction error range (%)	number of NUTS-1 regions
< -10	0	< -10	1
-10 - -5	0	-10 - -5	1
-5 - -1	12	-5 - -1	13
-1 - 1	16	-1 - 1	12
1 - 5	9	1 - 5	8
5 - 10	0	5 - 10	2
> 10	0	> 10	0

Table 6.6. Spring barley yield prediction for NUTS-1 regions. Frequency distribution of the differences in prediction errors between the P0 and P5 prediction rule. Differences given for both jackknife and one-year-ahead (OYA) root mean squared prediction error.

jackknife difference between P0 and P5		OYA difference between P0 and P5	
prediction error range (%)	number of NUTS-1 regions	prediction error range (%)	number of NUTS-1 regions
< -10	0	< -10	0
-10 - -5	1	-10 - -5	0
-5 - -1	9	-5 - -1	16
-1 - 1	34	-1 - 1	32
1 - 5	8	1 - 5	5
5 - 10	5	5 - 10	2
> 10	0	> 10	2

Table 6.7. Rice yield prediction for NUTS-1 regions. Frequency distribution of the differences in prediction errors between the P0 and P5 prediction rule. Differences given for both jackknife and one-year-ahead (OYA) root mean squared prediction error.

jackknife difference between P0 and P5		OYA difference between P0 and P5	
prediction error range (%)	number of NUTS-1 regions	prediction error range (%)	number of NUTS-1 regions
< -10	0	< -10	0
-10 - -5	0	-10 - -5	0
-5 - -1	5	-5 - -1	1
-1 - 1	7	-1 - 1	9
1 - 5	1	1 - 5	2
5 - 10	0	5 - 10	0
> 10	0	> 10	0

Table 6.8. Sugar beet yield prediction for NUTS-1 regions. Frequency distribution of the differences in prediction errors between the P0 and P5 prediction rule. Differences given for both jackknife and one-year-ahead (OYA) root mean squared prediction error.

jackknife difference between P0 and P5		OYA difference between P0 and P5	
prediction error range (%)	number of NUTS-1 regions	prediction error range (%)	number of NUTS-1 regions
< -10	0	< -10	0
-10 - -5	0	-10 - -5	3
-5 - -1	7	-5 - -1	6
-1 - 1	23	-1 - 1	21
1 - 5	5	1 - 5	1
5 - 10	1	5 - 10	1
> 10	0	> 10	1

Table 6.9. Potato yield prediction for NUTS-1 regions. Frequency distribution of the differences in prediction errors between the P0 and P5 prediction rule. Differences given for both jackknife and one-year-ahead (OYA) root mean squared prediction error.

jackknife difference between P0 and P5		OYA difference between P0 and P5	
prediction error range (%)	number of NUTS-1 regions	prediction error range (%)	number of NUTS-1 regions
< -10	0	< -10	1
-10 - -5	1	-10 - -5	0
-5 - -1	8	-5 - -1	6
-1 - 1	20	-1 - 1	26
1 - 5	14	1 - 5	5
5 - 10	3	5 - 10	6
> 10	0	> 10	1

Table 6.10. Oilseed rape yield prediction for NUTS-1 regions. Frequency distribution of the differences in prediction errors between the P0 and P5 prediction rule. Differences given for both jackknife and one-year-ahead (OYA) root mean squared prediction error.

jackknife difference between P0 and P5		OYA difference between P0 and P5	
prediction error range (%)	number of NUTS-1 regions	prediction error range (%)	number of NUTS-1 regions
< -10	0	< -10	0
-10 - -5	0	-10 - -5	1
-5 - -1	7	-5 - -1	0
-1 - 1	18	-1 - 1	22
1 - 5	1	1 - 5	1
5 - 10	0	5 - 10	0
> 10	0	> 10	0

Table 6.11. Sunflower yield prediction for NUTS-1 regions. Frequency distribution of the differences in prediction errors between the P0 and P5 prediction rule. Differences given for both jackknife and one-year-ahead (OYA) root mean squared prediction error.

jackknife difference between P0 and P5		OYA difference between P0 and P5	
prediction error range (%)	number of NUTS-1 regions	prediction error range (%)	number of NUTS-1 regions
< -10	1	< -10	3
-10 - -5	1	-10 - -5	0
-5 - -1	8	-5 - -1	0
-1 - 1	5	-1 - 1	6
1 - 5	1	1 - 5	3
5 - 10	3	5 - 10	0
> 10	0	> 10	3

It can be seen in Tables 6.5 to 6.11 that for most crops in most regions the difference between the P0 and P5 prediction errors varies from minus one to one percent, indicating that the two prediction rules are about equal in accuracy. For some crops (potato, sunflower) the P5 prediction rule seems to relatively perform slightly better than for other crops (oilseed rape), but over the whole it may be concluded that the P5 predictions are equal to the P0 predictions. As for wheat, this indicates that over the whole of the EC the use of crop growth model indicators does on average not improve the accuracy of NUTS-1 yield prediction in comparison with just a simple trend analysis.

In Tables 6.12 to 6.18 the difference between the P0 and P5 prediction errors is given at country level for each crop separately. In some cases, jackknife errors are available but one-year-ahead errors are missing because the series of years is to short (see Section 6.3). Again, one-year-ahead errors are more variable because these are based on less predictions.

Table 6.12. Maize yield prediction for countries. Differences in prediction errors between the P0 and P5 prediction rule. Differences given for both jackknife and one-year-ahead (OYA) root mean squared prediction error.

jackknife difference between P0 and P5		OYA difference between P0 and P5	
country	difference (%)	country	difference (%)
Germany	+1.8	Germany	+3.3
France	+1.5	France	+3.2
Italy	+0.1	Italy	-1.4
Netherlands	+4.3	Netherlands	-10.9
Belgium	-3.4	Belgium	-3.3
Greece	-1.2	Greece	-6.3
Spain	-1.0	Spain	-1.7

Table 6.13. Spring barley yield prediction for countries. Differences in prediction errors between the P0 and P5 prediction rule. Differences given for both jackknife and one-year-ahead (OYA) root mean squared prediction error.

jackknife difference between P0 and P5		OYA difference between P0 and P5	
country	difference (%)	country	difference (%)
Germany	-0.2	Germany	+0.1
France	+1.8	France	+1.3
Italy	-2.2	Italy	-4.7
Netherlands	+1.0	Netherlands	-0.6
Belgium	-1.0	Belgium	-1.7
Luxembourg	+4.4	Luxembourg	+0.6
United Kingdom	-0.8	United Kingdom	-1.0
Ireland	+0.1	Ireland	-3.1
Denmark	-0.4	Denmark	0
Greece	-4.4	Greece	-17.5
Spain	+8.8	Spain	+9.9

Table 6.14. Rice yield prediction for countries. Differences in prediction errors between the P0 and P5 prediction rule. Differences given for both jackknife and one-year-ahead (OYA) root mean squared prediction error.

jackknife difference between P0 and P5		OYA difference between P0 and P5	
country	difference (%)	country	difference (%)
France	+1.8	France	+2.0
Italy	0	Italy	-0.1
Greece	+0.6	Greece	*
Spain	-1.7	Spain	0

Table 6.15. Sugar beet yield prediction for countries. Differences in prediction errors between the P0 and P5 prediction rule. Differences given for both jackknife and one-year-ahead (OYA) root mean squared prediction error.

jackknife difference between P0 and P5		OYA difference between P0 and P5	
country	difference (%)	country	difference (%)
Germany	0.0	Germany	0
France	+1.6	France	-2.4
Italy	+3.1	Italy	-4.9
Netherlands	-0.7	Netherlands	*
Belgium	-0.3	Belgium	-7.7
Luxembourg	0	Luxembourg	0
United Kingdom	0	United Kingdom	0
Ireland	+0.1	Ireland	-5.5
Denmark	+1.3	Denmark	-1.7
Greece	+0.2	Greece	*
Spain	-0.8	Spain	0

Table 6.16. Potato yield prediction for countries. Differences in prediction errors between the P0 and P5 prediction rule. Differences given for both jackknife and one-year-ahead (OYA) root mean squared prediction error.

jackknife difference between P0 and P5		OYA difference between P0 and P5	
country	difference (%)	country	difference (%)
Germany	+1.1	Germany	-1.4
France	+1.5	France	+9.2
Italy	+0.3	Italy	0
Netherlands	+2.7	Netherlands	+0.9
Belgium	+5.3	Belgium	+8.1
Luxembourg	+10.0	Luxembourg	-10.3
United Kingdom	+2.0	United Kingdom	+3.6
Ireland	+1.5	Ireland	+3.6
Denmark	-1.9	Denmark	+2.3
Greece	+1.8	Greece	*
Spain	0	Spain	0

Table 6.17. Oilseed rape yield prediction for countries. Differences in prediction errors between the P0 and P5 prediction rule. Differences given for both jackknife and one-year-ahead (OYA) root mean squared prediction error.

jackknife difference between P0 and P5		OYA difference between P0 and P5	
country	difference (%)	country	difference (%)
Germany	0	Germany	0
France	0	France	0
Italy	- 0.1	Italy	0
Netherlands	0	Netherlands	0
Belgium	0	Belgium	0
United Kingdom	0	United Kingdom	0

Table 6.18. Sunflower yield prediction for countries. Differences in prediction errors between the P0 and P5 prediction rule. Differences given for both jackknife and one-year-ahead (OYA) root mean squared prediction error.

jackknife difference between P0 and P5		OYA difference between P0 and P5	
country	difference (%)	country	difference (%)
France	+0.7	France	-17.0
Italy	+2.4	Italy	-5.2
Spain	-4.0	Spain	0

When looking at the jackknife errors at country level, the P5 prediction rule does not convincingly perform better than the P0 prediction rule. Potato is a crop for which P5 seems to be better than P0 but over the whole range of crops and countries one may conclude that the use of crop model indicators does not really contribute to significant improvement of yield prediction at country level. The same conclusion can be drawn from the one-year-ahead prediction errors.

Furthermore, there seems to be no geographical pattern. Over the range of crops, there is no clear distinction between countries in the possibilities for accurate prediction of their yields. It should be realized that yields to be predicted are the official yields according to statistics and these are not to be considered "real" yields. Official yields are estimates of which the accuracy is unknown. This problem will be further elaborated in the next chapter.

7 Discussion

7.1 Introduction

The potential value for yield prediction with the agro-meteorological simulation model WOFOST according to the methodology presented in this report, is the speed and consistency of the approach across all countries and crops.
However, from the results presented in Chapter 6, it could be concluded that over the whole of the EC the accuracy of predicting official NUTS-1 and NUTS-0 yields can not yet be improved by using crop growth model output. In this report only yield prediction based on final model outputs at the end of the growing season is considered. The Crop growth Monitoring System is also capable of generating 10 day predictions during the growing season, on the basis of simulated biomass. However, considering the results given in this report it is not likely that these predictions will be more accurate.
The inaccuracy in predicting official yields using crop growth model indicators may be related to limitations in the concepts of the model or the quality and quantity of the available input data, but also to the reliability of the yields to be predicted. These are not the real yields harvested by the farmers, but the official statistical yields. The accuracy of these official yields is unknown and therefore unrealistic simulation results can not be separated from errors in official statistics. Aspects concerning the crop growth model and statistical analysis will be discussed in this chapter.

7.2 Crop growth model and data

The Joint Research Centre has published agrometeorological aspects of a number of important agricultural crops of the EC in a series of reports called: Agricultural Information System for the European Community (Bignon, 1990; Hough, 1990; Russell, 1990; Falisse, 1992; MacKerron, 1992; Narciso *et al.*, 1992). These reports turned out to be useful in determining regional cropping calendars. By combining sowing, emergence, flowering and maturity dates with data from the meteo database of SC-DLO, regional crop specific development rates were calculated. However, a main cause of variation in crop phenology is altitude. In mountainous areas the effect of altitude on cropping calendar will probably be larger than the effect of latitude. This has not been taken into account in the reports and can therefore have influenced the determination of the right regional development rates within the crop growth model.
Furthermore, in order to be able to calibrate the model to regional conditions, a large number of detailed data from field experiments was needed. Preferably, these experiments should have been performed for a number of years, and under well controlled conditions because the model describes growth under conditions with optimal nutrition and absence of pests, weeds and diseases. For the calibration of potential yields, irrigated fields are necessary. Beside phenological development, the most useful plant data from experiments are weights of plant organs at various times throughout the growing season, composition of final yield, and leaf area development. These data are not given in the JRC reports. CABO-DLO has tried to obtain data through an inquiry to a number of colleagues in the EC, but this resulted in too few data to allow optimal calibration. This will probably remain a problem. It

is worthwhile to further invest whether better results can be obtained in predicting yields at the field level.
Test of the model for yield variability for several crops at a plot level, where experimental data for validation were available, confirmed that WOFOST performs better for some crops (e.g. field bean and sugar beet) than for others (e.g. wheat and potatoes). It appears that our approach, of one model structure (WOFOST) for all crops, and only crop specific data, was probably too simplistic. In season calibration of the model with data collected from a number of closely monitored fields across Europe might also be necessary.
Due to the large uncertainty on physical properties of European soils, so far calculations have only been performed using a standard soil with the same water holding capacity and without groundwater influence for the whole of the EC. This may have influenced the results for regions with a relative high proportion of worse than average or better than average soils. Furthermore, only one sowing date has been used for each crop in each region. Wetness of the soil and temperature conditions, however, influence sowing dates in specific years.
Because no land use map was available, a qualitative estimation was made of soils suitable for crop production within a grid. For more accurate calculations, simulation should only be performed for soil/climate combinations where the crop is actually grown. Having better land use information, for example by means of remote sensing techniques, would therefore be very useful.
It should be taken in mind that sub-optimal growing conditions as result of nutrient supply, weeds, pests and diseases are not described by the model, assuming that these conditions mainly determine the average yield level within a region and not so much seasonal yield fluctuations. However, these growth factors may still be important causes in seasonal fluctuations in official yields as well. More information has therefore to be gathered on the separate contributions of weather conditions and other growth factors in the explanation of the actual yield level. Furthermore, some effects of weather may influence the crop yield indirectly, for example through disease level, nutrient availability or workability of the soil.

7.3 Statistical analysis

No official indication of the accuracy of the Eurostat official yields is available. For some crops (soybean, field bean and oats) no statistical regional data were available at all.
National yield forecast in the Netherlands are aggregates of estimates by experts of hectare yields of all crops, during and after the growing season in about 60 regions in the country. There is no direct measurement of actual yields involved, neither during the season nor afterwards. This system of estimating yields was developed early in this century, and still satisfies the needs of the central statistical bureau (CBS) quite well at a reasonable cost. The average values of yields reported are probably reliable, as several cross checks are performed, such as with trade in crop products and their use in industry. However, the cross checks in any year cannot be very accurate. Differences of a few percent per year may remain unnoticed for the bulk crops and even more so for smaller crops. Such differences lead to adjustments in administrative 'national stocks' (source: CBS, pers. comm.). The implication of this method of yield estimation in the Netherlands is we that do not have data to accurately test the model at the regional level. The average values of official national yields are probably quite accurate but for prediction purposes it is necessary that the year to year fluctuations are correct.
Because no information is available about the measurement error of the official yield figures in the Netherlands as well as in the rest of the EC, a conclusive interpretation of the quality

of the model based predictions is impossible. The prediction error of official yield figures is the sum of the measurement error in the official yields and the error in predicting the true yield. The information required to disentangle these two errors is lacking. Possibly, the disappointing improvement of prediction accuracy obtained by modelling is partly caused by small variation due to weather fluctuations in combination with large variation due to measurement errors. In other words by a low signal-to-noise ratio.

In Appendix 9 and 10 the t-values of the model indicators are given, as explained in Chapter 6. The variance ratio of the model term is equal to $F=t^2$ were t is the Student statistic. The signal-to-noise ratio is estimated by F-1. Often, model terms are included in a predictor depending on whether or not F-1 is greater than 1 (see for instance Linhart & Zucchini, 1986). This selection procedure provides an alternative to the jackknife which we used to select an elementary predictor.

The following example illustrates the adverse effect of a low signal-to- noise ratio. It shows that a model term which is actually present may be quite useless for predictions.

Let yield figures (y) be randomly generated using the following equation, so that there is no doubt that the model indicator influences the yield:

$$y = 5000 + 130 * (T - \overline{T}) + 0.25 * (m - \overline{m}) + e$$

in which e denotes a random measurement error consisting of independent identically distributed elements with a mean of zero and a standard deviation of 600 (12% of the mean of y, 5000). The times T range from 1975 to 1989. The values of model indicator m are drawn from a normal distribution with a mean of 9000 and a standard deviation of 1000. The parameter values chosen are typical values extracted from the regression of wheat grain yields. Analysis of this model shows that it happens frequently (roughly in half of the cases) that according to the signal-to-noise criterion, predictions only get worse by the inclusion of the model indicator in the predictor, although we know for sure in this case that the model indicator influences the yield.

If the cause of bad predictions is really a low signal-to-noise ratio, it may well happen that longer series with more accurate measurements will lead to better results within this project. Apart from that, better datasets, containing sufficient information about measurement accuracy (e.g. duplicate measurements) should be necessary for a better interpretation of the current results.

The problem of the low signal-to-noise ratio may be expected to manifest itself in strongly enhanced form in the approach of Palm & Dagnelie (1993), where y is regressed on 10-day means of weather data such as temperature, radiation and rainfall during the growing season. A large number of candidate regressors is available (see Section 5.1) and by some selection procedure a subset is constructed. However, it is to be expected that each individual term in the regression is very small, i.e. that each individual signal is very weak. When the predictor is entirely based on official statistics, it might well happen that each signal is much too weak to be useful for prediction, and that the predictor selected conveys more about the particularities of the dataset than about the underlying process. This phenomenon is sometimes called 'overfitting' (Linhart and Zucchini, 1986).

Whatever may be the true cause, Palm & Dagnelie (1993) show quite convincingly that each of a large number of predictors based on raw weather data is worse than the predictor ignoring weather. A major methodological conclusion of Palm & Dagnelie (1993) is that the jackknife method provides no adequate criterion of validation. This conclusion sounds quite alarming since jackknife methods are frequently used in validation. However, the jackknife used by Palm & Dagnelie (1993) was not the jackknife of the prediction rule (including intensive selection) that has been actually applied, but merely the jackknife of the selected regression expression. For a conclusive validation of a prediction rule, the jackknife method must also be applied to the full prediction rule and it is then a valuable instrument.

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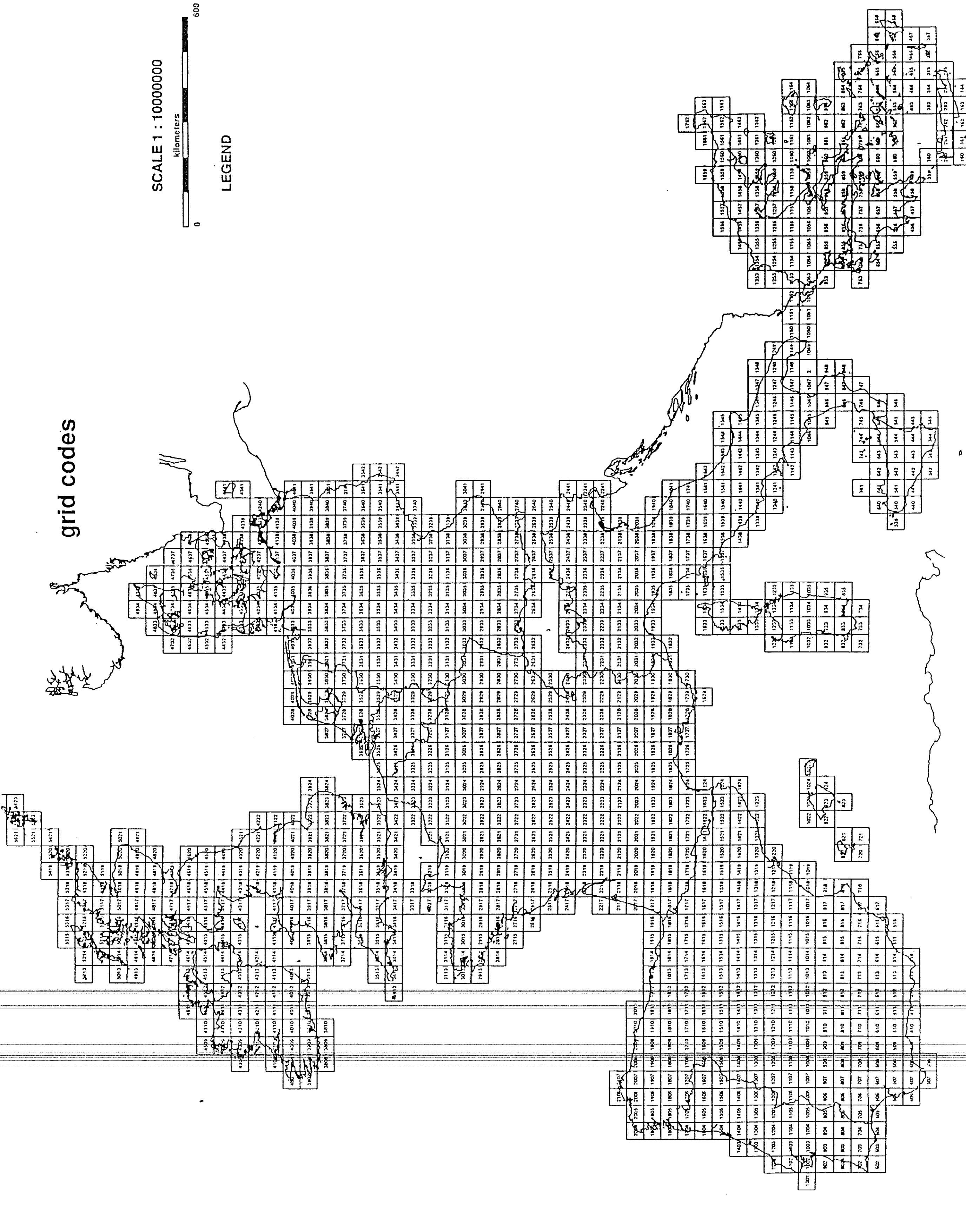
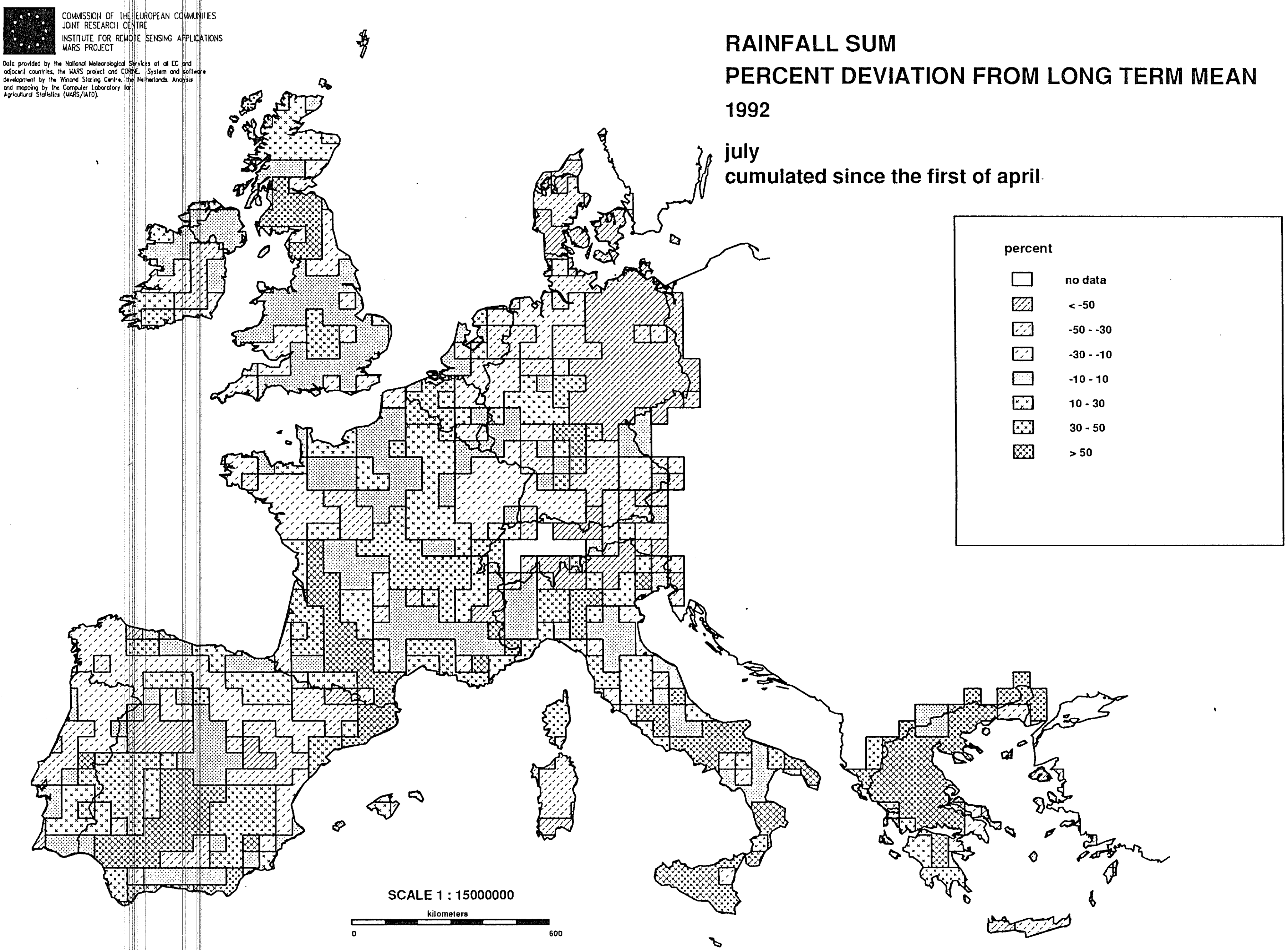
Appendix 1. EC-grid. (50 x 50 kilometres)





Appendix 2. Deviation of 1992 rainfall sum.
(period 1 April- 31 July)

Appendix 3. Nomenclature of Statistical Territorial Units (NUTS).

NUTS0		NUTS1	
R1	Deutschland		
		R11	Schleswig-Holstein
		R12	Hamburg
		R13	Niedersachen
		R14	Bremen
		R15	Nordrhein-Westfalen
		R16	Hessen
		R17	Rheinland-Pfalz
		R18	Baden-Württemberg
		R19	Bayern
		R1A	Saarland
		R1B	Berlin
R2	France		
		R21	Ile de France
		R22	Bassin Parisien
		R23	Nord-Pas-de-Calais
		R24	Est
		R25	Ouest
		R26	Sud-Ouest
		R27	Centre-Est
		R28	Mediterranée
R3	Italia		
		R31	Nord Ovest
		R32	Lombardia
		R33	Nord Est
		R34	Emilia-Romagna
		R35	Centro
		R36	Lazio
		R37	Campania
		R38	Abruzzi-Molise
		R39	Sud
		R3A	Sicilia
		R3B	Sardegna
R4	Nederland		
		R41	Noord-Nederland
		R42	Oost-Nederland
		R45	Zuid-Nederland
		R47	West-Nederland
R5	Belgique-België		
		R51	Vlaams Gewest
		R52	Region Wallone
		R53	Brussel

R6	Luxembourg	
R7	United Kingdom	
	R71	North
	R72	Yorkshire and Humberside
	R73	East Midlands
	R74	East Anglia
	R75	South East
	R76	South West
	R77	West Midlands
	R78	North West
	R79	Wales
	R7A	Scotland
	R7B	Northern Ireland
R8	Ireland	
R9	Danmark	
RA	Ellada	
	RA1	Voreia Ellada
	RA2	Kentriki Ellada
	RA3	Attiki
	RA4	Nisia
RB	Espana	
	RB1	Noroeste
	RB2	Noreste
	RB3	Madrid
	RB4	Centro
	RB5	Este
	RB6	Sur
RC	Portugal	
	RC1	Continente
	RC2	Açores
	RC3	Madeira

Appendix 4a. WOFOST soil data file for a medium textured soil.

** Moisture data set 2 for texture class 2 (medium) of EC soil map.
** Minimum data set on soil physics for use in subroutine WATFD,
** water balance for freely draining soils.

** soil water retention

SMW	=	0.100	! soil moisture content at wilting point [cm^3 cm^{-3}]
SMFCF	=	0.320	! soil moisture content at field capacity [cm^3 cm^{-3}]
SM0	=	0.430	! soil moisture content at saturation [cm^3 cm^{-3}]
CRAIRC	=	0.075	! critical soil air content for aeration [cm^3 cm^{-3}]

** percolation parameters

K0	=	10.0	! hydraulic conductivity of saturated soil [cm day^{-1}]
SOPE	=	10.0	! maximum percolation rate root zone[cm day^{-1}]
KSUB	=	10.0	! maximum percolation rate subsoil [cm day^{-1}]

** soil workability parameters

SPADS	=	0.800	! 1st topsoil seepage parameter deep seedbed
SPODS	=	0.040	! 2nd topsoil seepage parameter deep seedbed
SPASS	=	0.900	! 1st topsoil seepage parameter shallow seedbed
SPOSS	=	0.070	! 2nd topsoil seepage parameter shallow seedbed
DEFLIM	=	0.000	! required moisture deficit deep seedbed

Appendix 4b. Crop specific maximum rooting depths.

wheat:	125 cm
grain maize:	100 cm
barley:	125 cm
rice:	80 cm
sugar beet:	120 cm
potato:	50 cm
field bean:	100 cm
soybean:	120 cm
oilseed rape:	120 cm
sunflower:	150 cm

Appendix 5. WOFOST crop data file for spring barley

** emergence

TBASEM	=	0.0		! lower threshold temperature for emergence [C°]
TEFFMX	=	30.0		! maximum efficient temperature for emergence [C°]
TSUMEM	=	110.		! temperature sum from sowing to emergence [C° d]

** initial

TDWI	=	60.00		! initial total crop dry weight [kg ha^{-1}]
LAIEM	=	0.274		! leaf area index at emergence [ha ha^{-1}]
RGRLAI	=	0.0075		! maximum relative increase in LAI [ha ha^{-1} d^{-1}]

** phenology

IDSL	=	0		! indicates whether pre-anthesis development depends
				! on temperature (=0), daylength (=1) , or both (=2)
DLO	=	-99.0		! optimum daylength for development [hr]
DLC	=	-99.0		! critical daylength (lower threshold) [hr]
TSUM1	=	800.		! temperature sum from emergence to anthesis [C° d]
TSUM2	=	750.		! temperature sum from anthesis to maturity [C° d]
DTSMTB	=	0.00,	0.00,	! daily increase in temperature sum
		35.00,	35.00,	! as function of average temperature [C°; C° d]
		45.00,	35.00	
DVSEND	=	2.00		! development stage at harvest (= 2.0 at maturity [-])

** green area

SLATB	=	0.00,	0.0020,	! specific leaf area
		0.30,	0.0035,	! as a function of DVS [-; ha kg^{-1}]
		0.90,	0.0250,	
		1.45,	0.0220,	
		2.00,	0.0220	
SPA	=	0.000		! specific pod area [ha kg^{-1}]
SSA	=	0.000		! specific stem area [ha kg^{-1}]
SPAN	=	25.		! life span of leaves growing at 35 C° [d]
TBASE	=	0.0		! lower threshold temperature for ageing of leaves [C°]

** assimilation

KDIF	=	0.440		! extinction coefficient for diffuse visible light [-]
EFF	=	0.40		! light-use efficiency single leaf [kg ha^{-1} hr^{-1} J^{-1} m^2 s]
AMAXTB	=	0.00,	35.00,	! maximum leaf CO2 assimilation rate
		1.20,	35.00,	! as function of development stage [-; kg ha^{-1} hr^{-1}]
		2.00,	5.00	
TMPFTB	=	0.00,	0.00,	! reduction factor of AMAX
		10.00,	1.00,	! as function of av. temp. [C°; -]
		30.00,	1.00,	
		35.00,	0.00	
TMNFTB	=	0.00,	0.00,	! reduction factor of gross assimilation rate
		3.00,	1.00	! as function of low minimum temperature [C°; -]

** conversion of assimilates into biomass

CVL	=	0.720		! efficiency of conversion into leaves [kg kg^{-1}]
CVO	=	0.740		! efficiency of conversion into storage org. [kg kg^{-1}]
CVR	=	0.720		! efficiency of conversion into roots [kg kg^{-1}]
CVS	=	0.690		! efficiency of conversion into stems [kg kg^{-1}]

```
** maintenance respiration
Q10      = 2.0             ! relative increase in respiration rate per 10 C°temp. incr. [-]
RML      = 0.030           ! rel. maintenance resp. rate leaves [kg CH2O kg-1 d-1]
RMO      = 0.010           ! rel. maintenance resp. rate stor. org. [kg CH2O kg-1 d-1]
RMR      = 0.010           ! rel. maintenance resp. rate roots [kg CH2O kg-1 d-1]
RMS      = 0.015           ! rel. maintenance resp. rate stems [kg CH2O kg-1 d-1]
RFSETB   = 0.00,    1.00,  ! reduction factor for senescence
           2.00,    1.00   ! as function of DVS [-; -]

** partitioning
FRTB     = 0.00,    0.60,  ! fraction of total dry matter to roots
           0.40,    0.55,  ! as a function of development stage [-; kg kg-1]
           1.00,    0.00,
           2.00,    0.00
FLTB     = 0.00,    1.00,  ! fraction of above-ground dry matter to leaves
           0.33,    1.00,  ! as a function of development stage [-; kg kg-1]
           0.80,    0.40,
           1.00,    0.10,
           1.01,    0.00,
           2.00,    0.00
FSTB     = 0.00,    0.00,  ! fraction of above-ground dry matter to stems
           0.33,    0.00,  ! as a function of development stage [-; kg kg-1]
           0.80,    0.60,
           1.00,    0.90,
           1.01,    0.15,
           2.00,    0.00
FOTB     = 0.00,    0.00,  ! fraction of above-ground dry matter to storage organs
           0.80,    0.00,  ! as a function of development stage [-; kg kg-1]
           1.00,    0.00,
           1.01,    0.85,
           2.00,    1.00

** death rates
PERDL    = 0.030           ! maximum relative death rate of leaves due to water stress
RDRRTB   = 0.00,    0.000, ! relative death rate of stems
           1.50,    0.000, ! as a function of development stage [-; kg kg-1 d-1]
           1.5001,  0.020,
           2.00,    0.020
RDRSTB   = 0.00,    0.000, ! relative death rate of roots
           1.50,    0.000, ! as a function of development stage [-; kg kg-1 d-1]
           1.5001,  0.020,
           2.00,    0.020

** water use
CFET     = 1.00            ! correction factor transpiration rate [-]
DEPNR    = 4.5             ! crop group number for soil water depletion [-]
IAIRDU   = 0               ! air ducts in roots present (=1) or not (=0)

** rooting
RDI      = 10.             ! initial rooting depth [cm]
RRI      = 1.2             ! maximum daily increase in rooting depth [cm d-1]
RDMCR    = 125.            ! maximum rooting depth [cm]
```

Appendix 6. Request for data.

Dear ..

Our institute is involved in a project entitled: "Crop state monitoring on a regional scale in the European Communities". This project is executed in the framework of the "Agriculture Project" of the Joint Research Centre of the EC in Ispra, Italy. The purpose of the study is forecasting of regional yields of the major crops in the European Communities, using crop growth simulation models in combination with real time weather data.
In order to calibrate our crop growth simulation models to regional conditions throughout the EC, we have an urgent need for crop yields from field experiments that are performed under well defined and well controlled conditions, preferably under optimal fertilization and proper weed, pest and disease control. Experiments that are performed at one location for a series of years are especially valuable, because these allow us to evaluate seasonal effects which are of major importance to our study. Relevant data are given in an appendix to this letter. Crops under consideration are some of the main field crops that are grown in your region. We simulate the following crops: wheat, barley, oats, maize, rice, potato, sugar beet, field bean, soybean, oilseed rape and sunflower. We would be very pleased if you could provide us with information. If you don't have access to such data, but know a colleague in your country who does, we would appreciate it when you forward this letter to him/her. References to literature or internal reports are also very helpful for us. We will be able to use your information when it reaches us before April. The results of our study will be reported to the Joint Research Centre of the EC by the end of 1992 and will be freely available. We will not forsake to mention your contributions in the final report.
At your request we will send you some results of recent research at our institute. With this letter some general information and a list of publications is included.

Thank you very much in advance for your cooperation, sincerely yours, ..

APPENDIX WITH REQUESTED DATA:

EXPERIMENT DESCRIPTION
location name, latitude, longitude, altitude:
year(s) :
crop/variety :
soil type (name, clay content) :
groundwater availability for crop growth :

AGRICULTURAL PRACTICES
sowing rate/plant density :
nutrient/fertilizer supply :
level of crop protection:
occurrence of crop damage or yield limiting factors :
irrigation rate :

PHENOLOGY
dates of sowing, emergence, flowering/heading and maturity/harvest:

CROP MEASUREMENTS
yield composition (kg dry matter per hectare) :
harvest index :
light interception during growth (% groundcover or leaf area index)

Appendix 7a. Program XCL. User guide, input/output

Prediction of regional yields based on exclusive regression. Fortran program XCL written by:
Michiel Jansen, DLO Agricultural Mathematics Group (GLW-DLO).
Jacques Withagen, DLO Centre for Agrobiological Research (CABO-DLO).

Input file.
The first record of the file is expected to be a general title for that file. This record is skipped. The next record should contain a title for the following dataset (region). This title is read from the inputfile and printed in the outputfile with the results. The maximum length of this title is 30 characters. If a summary output file is requested, only the first six characters of the title will be printed in the summary output file.
The next record contains the number of datarecords of the set. This value is not used by the program since the program counts the records until the end-of-data symbol is found. After this record the data-records are expected. On each record 6 values should occur separated by spaces or a comma. The values are:

year,
official yield,
potential grain yield,
water-limited grain yield,
potential biomass,
water-limited biomass

(in this order).
Within each set the same unit must be used (e.g. tons/ha) and years must be given in ascending order. Records containing 'missing values' are skipped (missing values are denoted by an asterix or the value -99). The end of a dataset must be given by a colon ":" (with no values on that record). When this end-of-data symbol is found, the program starts calculations and prints the results in the outputfile(s). Then the program will search for a next dataset (starting with a title for that new set) until the end of file is reached.

Running the program.
The program starts by asking the names of the input file and detailed output file (don't use extension ".SUM" as this is used for an eventual summary file). If the output file already exists the program gives a warning and asks whether or not you want to overwrite this file. Next the program asks how many years you want to use for 'one year ahead' and 'two year ahead' predictions (default = 9).
Then the program asks if you want a summary output file. The name of this file will be the same as that of the detailed output file but with extension ".SUM". The last question is which model indicators you want to be used in the regression calculations. You can choose any combination out of the four given model indicators (1= potential grain yield, 2= water-limited grain yield, 3= potential biomass, 4= water-limited biomass) by giving the numbers 1 to 4 separated by comma's (default = all), or give the value 0 if you want no indicators to be used. Now the program starts calculating and prints the results in the output file(s). Messages are also printed on the screen. If the number of observations is less than 8, the dataset will be skipped and the program will continue with the next dataset.

Output file(s)
A detailed output file will be generated and, when asked for it, a summary output file. An example of a detailed output file is given in Appendix 8 and explained in Section 6.2. Summary output files are give in Appendices 9 and 10 and explained in Section 6.3

Appendix 7b. Program XCL. Brief description

INTRODUCTION

The program XCL calculates yield predictors for a number of crops in a number of regions. The accuracy of the predictors is assessed per crop per region.

For each crop and each region a dataset is read containing the following columns:
- an ascending series of years, e.g. 1975...1989
- the corresponding official yield statistics
- a number of optional columns containing the corresponding model indicators

Various elementary predictors are obtained by linear regression of the official yield figures on
- the vector (1,1...1)
- a zero-mean linear increase with the year
- at most one zero-mean model indicator

(from the latter two vectors the mean has been subtracted).

By assigning weight 1 or 0 to each year, only part of the data can be made available for the construction of the predictor. The full predictor is constructed by selecting an elementary predictor: from the elementary predictors having a non-negative coefficient for the model indicator the one with the smallest jackknife sum of squares on the available data is selected. The selected predictor may be the one without model indicator.

Linear regression producing the elementary predictors is executed by the subroutine LINREG. The best elementary predictor is selected by the subroutine XCLUR. Calling LINREG for all possible optional regressors, and selecting the one that performs best on the data made available, XCLUR produces the predictor actually used. The performance of this predictor is assessed by comparing prediction and official figures in years that were unavailable for the construction of the predictor.

The next description contain descriptions of the main program XCL, of XCLUR and of LINREG.

1. DESCRIPTION OF THE MAIN PROGRAM XCL

The following integers determine the sizes of the data structures used in the program

```
NX1     number of obligatory regressors
MX1     maximum number of obligatory regressors
NX2     number of optional regressors
MX2     maximum number of optional regressors
NOBS    number of seasons in database for current region
MOBS    maximum number of seasons in database for current region
MTERM   maximum number of terms in regression
```

The major data structures used in the program are:

```
YEAR(MOBS)         series of years (increasing)
OFFIC(MOBS)        official statistics
```

```
W(MOBS)            weights(0 or 1)
FIT(MOBS)          regression fit
LEV(MOBS)          regression leverages
EST(MTERM)         estimates of regression coefficients
SE(MTERM)          standard errors of these estimates
VCOV(MTERM,MTERM   variance covariance matrix of these estimates
IND(MOBS, MX2)     has its columns filled with optional regressors (model
                   indicators)
X1(MOBS, MX1)      has its columns filled with obligatory regressors (constant
                   and zero-mean annual trend)
X2(MOBS, MX2)      has its columns filled with zero-mean optional regressors
                   (model indicators)
```

Prediction based on all data.
The calculations start with some initializations:

```
MEAN               = mean of OFFIC
TOTSS              = sum of squares of OFFIC-MEAN
YRMEAN             = mean of YEAR
INDMEAN(J)         = mean of j-th column of IND
X1(I,1)            = 1.
X1(I,2)            = YEAR(I) - YRMEAN
X2(I,J)            = IND(I,J) - INDMEAN(J)
W(I)               = 1.
```

Subsequently the predictor is determined as follows:

```
        CALL XCLUR(NOBS, NX1, NX2, OFFIC, W, X1, X2,
     -             FIT, LEV, EST, SE, VCOV, RSS, RDF, OUTPUT)
```

The jackknife prediction error sum of squares of XCLUR based on all data is estimated in the following fragment:

```
      JSS=0.0
      DO 61 I=1,NOBS
         DO 60 J=1,NOBS
            IF(J.EQ.I) W(J)=0.0
            IF(J.NE.I) W(J)=1.0
 60      CONTINUE
         CALL XCLUR(NOBS, NX1, NX2, OFFIC, W, X1, X2,
     -             FIT, LEV, EST, SE, VCOV, RSS, RDF, OUTPUT)
         JR=OFFIC(I)-FIT(I)
         JSS    = JSS+JR**2
 61   CONTINUE
      JACKKN = 100 * SQRT(JSS/REAL(NOBS)) / MEAN
```

Prediction based on last NUSED seasons.
The calculations start with some initializations:

```
NUSED              = number of seasons used to construct predictor (<=NOBS)
MEAN               = mean of OFFIC over seasons used
TOTSS              = sum of squares of OFFIC-MEAN over seasons used
YRMEAN             = mean of YEAR over seasons used
INDMEAN(J)         = mean of J-th column of IND over seasons used
W(I)               = weight: 1. if I in last NUSED seasons, else 0
```

```
X1(I,1)          = 1.
X1(I,2)          = YEAR(I) - YRMEAN
X2(I,J)          = IND(I,J) - INDMEAN(J)
```

Subsequently the predictor is determined:

```
      CALL XCLUR(NOBS, NX1, NX2, OFFIC, W, X1, X2,
     -           FIT, LEV, EST, SE, VCOV, RSS, RDF, OUTPUT)
```

The one and two years ahead prediction error sum of squares are estimated as follows. By weighting, a moving window of NUSED consecutive seasons is made available for construction of a predictor FIT. The value of FIT one and two years ahead of the window is compared with OFFIC at those years. The integers FUSED (First USED) and LUSED (Last USED) indicate the first
and last year available for construction of the predictor.

```
      OYASS=0.
      TYASS=0.
      IF (NOBS.GT.NUSED) THEN
         DO 81 LUSED=NUSED,NOBS-1
            FUSED=LUSED-NUSED+1
            NEXT1=LUSED+1
            NEXT2=LUSED+2
            DO 80 I=1,NOBS
               IF (I.GE.FUSED .AND. I.LE.LUSED) THEN
                  W(I) = 1.0
               ELSE
                  W(I) = 0.0
               ENDIF
 80         CONTINUE

            CALL XCLUR(NOBS, NX1, NX2, OFFIC, W, X1, X2,
     -                 FIT, LEV, EST, SE, VCOV, RSS, RDF, OUTPUT)

            OYASS = OYASS + (OFFIC(NEXT1)- FIT(NEXT1))**2
            IF (NEXT2.LE.NOBS)
     -         TYASS = TYASS + (OFFIC(NEXT2)- FIT(NEXT2))**2
 81      CONTINUE
      ENDIF
```

2. DESCRIPTION OF XCLUR

The subroutine XCLUR has the following arguments:

```
INTEGER NOBS              in; number of observations
INTEGER NX1               in; number of obligatory regressors
INTEGER NX2               in; number of optional regressors
REAL    Y(MOBS)           in; dependent variable
REAL    W(MOBS)           in; weights
REAL    X1(MOBS,MX1)      in; obligatory regressors in columns
REAL    X2(MOBS,MX2)      in; optional regressors in columns
REAL    FIT(MOBS)         out; fitted values
REAL    LEV(MOBS)         out; leverages
REAL    EST(MTERM)        out; estimates of regression coefficients
```

```
REAL    SE(MTERM)          out; standard deviations of estimates
REAL    VCOV(MTERM,MTERM) out; variance covariance matrix of estimates
REAL    SS                 out; residual sum of squares
REAL    DF                 out; residual degrees of freedom
INTEGER MES                in; file receiving error messages and warnings
```

Years are made available or unavailable for the construction of the predictor by assigning weight 1 or 0. The subroutine performs weighted least squares linear regressions calling

```
LINREG (NOBS, NTERM, Y, W, X, FIT, LEV, EST, SE, VCOV, SS, DF, OUT).
```

The matrix X is varied: X = X1, and X = (X1, u) with the additional column u assuming the values of the various columns of X2. Each X matrix gives a predictor. The best predictor is initialized at the value given by regression with X = X1. For the consecutive values of u a 'current' predictor is constructed. The current predictor will replace the best predictor if the coefficient of current regressor u is positive and if the jackknife sum of squares of the current predictor is smaller than that of the best predictor on the available years. The jackknife sum of squares is calculated in the following way .

```
          CJACSS = 0
          DO 31 J=1,NOBS
             IF (W(J).NE.0.) THEN
                JR = (OFFIC(J)-CFIT(J))/(1-CLEV(J))
                CJACSS = CJACSS + JR*JR
             ENDIF
 31       CONTINUE
```

(The prefix 'C' stands for 'current', the jackknife residual JR is calculated by means of the current leverage, see for instance Montgomery & Peck, 1992.)
XCLUR has been tested by comparing its results with those of Genstat for a number of representative datasets.

3. DESCRIPTION OF LINREG

The subroutine LINREG has the following arguments:

```
INTEGER NOBS               in; number of observations
INTEGER NTERM              in; number of model terms
REAL    Y(MOBS)            in; dependent variable
REAL    W(MOBS)            in; weights
REAL    X(MOBS,MTERM)      in; regressors in columns
REAL    FIT(MOBS)          out; fitted values
REAL    LEV(MOBS)          out; leverages
REAL    EST(MTERM)         out; estimates of regression coefficients
REAL    SE(MTERM)          out; standard deviations of estimates
REAL    VCOV(MTERM,MTERM) out; variance covariance matrix of estimates
REAL    SS                 out; residual sum of squares
REAL    DF                 out; residual degrees of freedom
INTEGER OUT                in; file receiving error messages and warnings
```

LINREG performs weighted least squares regression. With respect to its inputs and outputs, LINREG is similar to the Genstat command FIT (Payne & Lane, 1987). The subroutine has been tested by comparing its results with those of Genstat for a number of representative datasets. Inputs are the dependent nobs-vector Y, a weight nobs-vector W, and a design-matrix X the nterm columns of which are filled with the regressors of length nobs. Output are the nobs-vector of fitted values, FIT; the nobs-vector of leverages, LEV; the nterm-vectors EST and SE containing the estimated regression coefficients and their standard deviations; the nterm-by-nterm variance covariance matrix VCOC of the estimates; the residual sum of squares and degrees of freedom SS and DF. OUT points to a file for error messages or warnings. The inputs and outputs of LINREG are in single precision; internally double precision is used.

The generalized inverse of the symmetric non-negative definite matrix Xt W X is calculated in a way similar to SVDREG in Press et al. (1986). By means of a procedure DJCOBI the matrix is brought on the form Xt W X = V D Vt, with V orthogonal and D diagonal. DJCOBI is based on JACOBI of Press et al. (1986); the major modification is that DJCOBI works in double precision. The generalized inverse is calculated as XTWXINV = (Xt W X)-1 = V DINV Vt, with diagonal matrix DINV defined by: if D(I) is above some small tolerance DINV(I) = 1 / D(I) , else DINV(I) = 0. For each instance of DINV(I) = 0, indicating aliased model terms, a warning is issued.
The subsequent calculations are simple matrix operations (see for instance Montgomery & Peck, 1991).

```
EST  = XTWXINV Xt W Y
FIT  = X EST
LEV  = diag(X XTWXINV Xt W)
SS   = SUM(W(I)*(Y(I)-FIT(I))**2)
VCOV = XTWXINV SS / DF
SE   = SQRT(diag(VCOV))
```

REFERENCES FOR XCL

Montgomery, D.C. & Peck, E.A., 1991, Introduction to linear regression analysis, second edition, Wiley.

Payne, R.W. & Lane, P.W. (eds.), 1987, Genstat 5 Reference Manual, Clarendon Press, Oxford.

Press, W.H. & Flannery, B.P. & Teukolsky, S.A. & Vettering, W.T., 1986, Numerical recipes: the art of scientific computing, Cambridge University Press.

Appendix 7c. Program XCL. Full listing.

```
************************************************************************
* Program: XCL
* Date:    10 May, 1993
* Version: 1.0
*
* Authors:
*    M.J.W. Jansen, DLO Agricultural Mathematics Group (GLW-DLO)
*    J.C.M. Withagen, DLO Centre for Agrobiological Research (CABO-DLO)
* Address:
*    c/o DLO Centre for Agrobiological Research (CABO-DLO)
*    P.O. Box 14
*    6700 AA Wageningen
*    The Netherlands
* Reference:
*    Koning, G.H.J. de, M.J.W. Jansen, E.R. Boons-Prins, C.A. van
*    Diepen & F.W.T. de Penning de Vries, 1993. Crop growth simulation
*    and statistical validation for regional yield forecasting across
*    the European Communities. Simulation Reports CABO-TT, N0.31, DLO Centre for
*    Agrobiological Research (CABO-DLO), Wageningen, The Netherlands. 105 pp.
* Purpose:
*    Construction of a regional crop yield predictor by means of
*    exclusive regression.
*    Assessment of prediction errors (jackknife error, one-year-ahead
*    prediction error, two-years-ahead prediction error).
* Library used:
*    TTUTIL (Rappoldt, C., D.W.G. van Kraalingen, 1990. Reference
*    manual of the Fortran utility library TTUTIL with applications.
*    Simulation Reports CABO-TT nr. 20, CABO-DLO Wageningen. 122 pp.)
* Other subroutines used:
*    DJCOBI: subroutine JACOBI from W. H. Press, B. P. Flannery, S. A.
*    Teukolsky, W. T. Vetterling, Numerical recipes (1st edition) 1986,
*    with some minor modifications (e.g. changing to double precision).
* Disclaimer:
*    Publication of any work or study based on this software and/or
*    database should include reference to the suppliers.
*    The suppliers disclaim all warranties for fitness, performance
*    or simulation accuracy for any purpose of the supplied software
*    and/or database. The suppliers assume no liability or
*    responsibility to the user or anyone, for loss or damage caused
*    by errors in, or inadequate use of the supplied software and/or
*    database.
************************************************************************

      PROGRAM XCL

* dimensions ------------------------------------------------------- *

      INTEGER    MOBS,    MTERM,   MX1,   MX2
      PARAMETER (MOBS=30, MTERM=8, MX1=2, MX2=4)

* variables and arrays used --------------------------------------- *

      INTEGER NOBS, NX1, NX2, DATSET
      INTEGER INPUT, OUTPUT, OUTSUM
      INTEGER I, J, IX2, ILEN, INDIC(MX2)
```

```
      INTEGER FUSED, LUSED, NUSED, NEXT1, NEXT2, ISTART

      REAL    YEAR(MOBS), OFFIC(MOBS), W(MOBS), IND(MOBS,MX2)
      REAL    X1(MOBS,MX1), X2(MOBS,MX2)
      REAL    MEAN, YRMEAN, MNUSED, INDMN(MX2)

      REAL    FIT(MOBS), LEV(MOBS)
      REAL    EST(MTERM), SE(MTERM)
      REAL    VCOV(MTERM,MTERM)
      REAL    RSS, RDF, JSS, OYASS, TYASS
      REAL    RESIDL, JACKKN, OYA, TYA
      REAL    TOTSS, JR
      REAL    ESTIM, STUD, RSQ

      CHARACTER*30 TMP,TITLE,INFIL,OUTFIL,SUMFIL
      CHARACTER*1  CRSUM,DUM
      CHARACTER*8  SELECT
      CHARACTER*7  ONEYRA, TWOYRA
C      CHARACTER*21 SELTXT

      LOGICAL EOF

      DATA INPUT,OUTPUT /10,20/
      DATA NUSED /9/
      DATA NX1   /2/
      DATA NX2   /4/
      CRSUM='Y'

* ask name inputfile and open this file --------------------------- *

      CALL ENTCHA ('input-file',INFIL)
      CALL FOPEN  (INPUT,INFIL,'OLD',' ')

* ask name outputfile and open this file -------------------------- *

      CALL ENTCHA ('output-file',OUTFIL)
      CALL FOPEN  (OUTPUT,OUTFIL,'NEW','UNK')

* ask number of years to be used for predictor -------------------- *

      CALL ENTDIN ('number of seasons to be used for predictor'
     -            ,NUSED,NUSED)

* ask wether or not to open summary-file -------------------------- *

      CALL ENTDCH ('open summary-file (Y/N)',CRSUM,CRSUM)

      IF (INDEX('Yy',CRSUM).GT.0) THEN
         CALL EXTENS (OUTFIL,'SUM',1,SUMFIL)
         OUTSUM=30
         CALL FOPEN  (OUTSUM,SUMFIL,'NEW','UNK')
         WRITE (OUTSUM,'(1X,2A)')
     -         'NUTS    NOBS   MEAN SELECTED  COEFF       t    RSQ',
     -         '     RES. JACKKN     OYA     TYA'
      ELSE
         OUTSUM=0
      ENDIF
```

```
* read first record (not used) ------------------------------------- *

      READ (INPUT,'(A)',END=9) TITLE

* initialize dataset counter --------------------------------------- *

      DATSET=0

* read title and dummy line ---------------------------------------- *

 1    TITLE(1:30)=' '
      READ (INPUT,'(A)',END=9) TITLE
      READ (INPUT,'(A)',END=9) DUM

* place title at beginning of string ------------------------------ *

      I=ISTART(TITLE)
      J=ILEN(TITLE)
      TMP=TITLE(I:J)
      TITLE=TMP

* read dataset ----------------------------------------------------- *

      NX2 = MX2
      CALL VDATIN(INPUT,YEAR,OFFIC,IND,MOBS,NOBS,NX2,INDIC,EOF)
      DATSET=DATSET+1

* test setting 'exclude indicator'-option and presence of indicators *

C       IF (NX2.GT.0) THEN
C          SELTXT='(including selection)'
C       ELSE
C          SELTXT='(excluding selection)'
C       ENDIF

* and check number of observations ---------------------------------*

      IF (EOF) GOTO 9
      IF (NOBS.LT.8) THEN
         WRITE (OUTPUT,'(1X,A,I3,A,/,1X,A,35X,A)')
     -         '*** Error at dataset',DATSET,
     -                  ': number of observations less than 8 ***',
     -         '*** Going to next dataset','***'
         WRITE (OUTPUT,'(1X,70A1)') ('-',I=1,70)
         WRITE (*,'(1X,A,I3,A,/,1X,A,35X,A)')
     -         '*** Error at dataset',DATSET,
     -                  ': number of observations less than 8 ***',
     -         '*** Going to next dataset','***'
         GOTO 1
      ENDIF

* write title to outputfile and to screen ------------------------- *

      WRITE (OUTPUT,'(/,/,1X,A,A)')  'name              = ',TITLE
      WRITE (*,'(A,I4,A,A)') '  dataset ',DATSET,' : ',TITLE

* check years (must be increasing) -------------------------------- *
```

```
      DO 10 I=2,NOBS
         IF (YEAR(I-1).GE.YEAR(I)) THEN
            WRITE (OUTPUT,'(1X,A)')
     -            '*** Error: seasons not increasing ***'
            WRITE (*,'(1X,A)')
     -            '*** Error: seasons not increasing ***'
            STOP
         ENDIF
 10   CONTINUE

* calculate means of 'offic', 'year' and 'model' ------------------- *

      MEAN  = 0.
      YRMEAN= 0.
      DO 20 I=1,NOBS
         MEAN   = MEAN   + OFFIC(I)
         YRMEAN = YRMEAN + YEAR(I)
 20   CONTINUE
      MEAN   = MEAN   / REAL(NOBS)
      YRMEAN = YRMEAN / REAL(NOBS)

      IF (NX2.GT.0) THEN
         DO 21 I=1,MX2
            INDMN(I)=0.
 21      CONTINUE
         DO 23 I=1,NOBS
            DO 22 J=1,NX2
               INDMN(J) = INDMN(J) + IND(I,J)
 22         CONTINUE
 23      CONTINUE
         DO 24 J=1,NX2
            INDMN(J) = INDMN(J) / REAL(NOBS)
 24      CONTINUE
      ENDIF

* calculate totss of 'offic' --------------------------------------- *
      TOTSS=0.
      DO 30 I=1,NOBS
         TOTSS=TOTSS+ (OFFIC(I)-MEAN)**2
 30   CONTINUE

* write number of observations and mean(offic) to output ----------- *

      IF (NX2.EQ.0) WRITE (OUTPUT,'(5X,A)')
     -  '----- no model indicators were included for selection -----'
      WRITE (OUTPUT,'(1X,A,I8)')   'number of seasons =', NOBS
      WRITE (OUTPUT,'(1X,A,F8.3)') 'mean              =', MEAN

* copy values to y-variate and design-matrixces -------------------- *
* and substract means --------------------------------------------- *

      DO 41 I=1,NOBS
         X1(I,1) = 1.
         X1(I,2) = YEAR(I) - YRMEAN
         IF (NX2.GT.0) THEN
            DO 40 J=1,NX2
               X2(I,J) = IND(I,J) - INDMN(J)
 40         CONTINUE
```

```
        ENDIF
        W(I)=1.
 41   CONTINUE

      CALL XCLUR(NOBS, NX1, NX2, OFFIC, W, X1, X2,
     -           FIT, LEV, EST, SE, VCOV, RSS, RDF, OUTPUT)


* write parameter-estimates to output ------------------------------ *

      WRITE (OUTPUT,'(/,A,/,A)') ' Prediction based on all data',
     -                           ' ============================'
      WRITE (OUTPUT,'(1X,A)')
     -      'term                      est         se         t'
      WRITE (OUTPUT,'(1X,A,2F10.3,F10.2)')
     -      'constant       ', EST(1), SE(1), EST(1)/SE(1)

      WRITE (OUTPUT,'(1X,A,F6.1,A,2F10.3,F10.2)')
     -      '(year-',YRMEAN,')  ',EST(2), SE(2), EST(2)/SE(2)


      SELECT = ' '
      ESTIM  = 0.
      STUD   = 0.
      IX2    = 0
      IF(NX2.GT.0) THEN
         DO 50 I = 3,NX1+NX2
            IF (SE(I).GT.0) THEN
               IX2=I-2
               ESTIM  = EST(I)
               STUD   = EST(I)/SE(I)
               WRITE (SELECT,'(A,I1,A)') ' ind[',INDIC(IX2),'] '
               WRITE (OUTPUT,'(1X,A,I1,A,F6.3,A,2F10.3,F10.2)')
     -               '(ind[',INDIC(IX2),']-',INDMN(IX2),')',
     -                EST(I), SE(I), STUD
            ENDIF
 50      CONTINUE
      ENDIF
      IF(IX2.EQ.0) WRITE (OUTPUT,'(1X,A)')
     -               '(IND[*]-     *)         *         *         *'

* CALCULATE MEAN SQUARE ERRORS ------------------------------------- *

      RSQ=1.0 - RSS/TOTSS
      WRITE (OUTPUT,'(/,1X,A,F10.2)')
     -       'R-squared          :',RSQ

      RESIDL = 100.0 * SQRT(RSS/RDF) / MEAN

      JSS=0.0
      DO 61 I=1,NOBS
         DO 60 J=1,NOBS
            IF(J.EQ.I) W(J)=0.0
            IF(J.NE.I) W(J)=1.0
 60      CONTINUE
         CALL XCLUR(NOBS, NX1, NX2, OFFIC, W, X1, X2,
     -              FIT, LEV, EST, SE, VCOV, RSS, RDF, OUTPUT)
         JR=OFFIC(I)-FIT(I)
```

```
         JSS     = JSS+JR**2
   61    CONTINUE
         JACKKN = 100 * SQRT(JSS/REAL(NOBS)) / MEAN


         WRITE (OUTPUT,'(/,1X,A,F8.3,A)')
     -   'Estimated relative root mean squared errors (% of',mean,')'

         WRITE (OUTPUT,'(1X,A,F10.1)') 'residual          ',RESIDL
         WRITE (OUTPUT,'(1X,A,F10.1)') 'jackknife         ',JACKKN

* one and two year ahead estimations ------------------------------ *

         WRITE (OUTPUT,'(/,A,I3,A,/,A)')
     -         ' Prediction based on last',NUSED,' seasons',
     -         ' =================================='


         LUSED=NOBS
         FUSED= LUSED-NUSED+1
         DO 70 I=1,NOBS
            IF (I.GE.FUSED .AND. I.LE.LUSED) THEN
               W(I) = 1.
            ELSE
               W(I) = 0.
            ENDIF
   70    CONTINUE

         MNUSED  = 0.
         YRMEAN    = 0.
         TOTSS     = 0.
         DO 71 I=FUSED,LUSED
            MNUSED   = MNUSED + OFFIC(I)
            YRMEAN = YRMEAN + YEAR(I)
   71    CONTINUE
         MNUSED   = MNUSED   / REAL(NUSED)
         YRMEAN     = YRMEAN / REAL(NUSED)
         DO 72 I=FUSED,LUSED
            TOTSS = TOTSS + (OFFIC(I)-MNUSED)**2
   72    CONTINUE

         IF (NX2.GT.0) THEN
            DO 73 I=1,MX2
               INDMN(I)=0.
   73       CONTINUE
            DO 75 I=FUSED,LUSED
               DO 74 J=1,NX2
                  INDMN(J) = INDMN(J) + IND(I,J)
   74          CONTINUE
   75       CONTINUE
            DO 76 J=1,NX2
               INDMN(J) = INDMN(J) / REAL(NOBS)
   76       CONTINUE
         ENDIF

         DO 78 I=1,NOBS
            X1(I,1) = 1.0
            X1(I,2) = YEAR(I) - YRMEAN
```

```
         IF (NX2.GT.0) THEN
            DO 77 J=1,NX2
               X2(I,J) = IND(I,J) - INDMN(J)
77          CONTINUE
         ENDIF
78    CONTINUE

      CALL XCLUR(NOBS, NX1, NX2, OFFIC, W, X1, X2,
     -           FIT, LEV, EST, SE, VCOV, RSS, RDF, OUTPUT)


      WRITE (OUTPUT,'(1X,A)')
     -      'term                       est        se         t'
      WRITE (OUTPUT,'(1X,A,2F10.3,F10.2)')
     -      'constant       ', EST(1), SE(1), EST(1)/SE(1)

      WRITE (OUTPUT,'(1X,A,F6.1,A,2F10.3,F10.2)')
     -      '(year-',YRMEAN,')  ',EST(2), SE(2), EST(2)/SE(2)


      IX2=0
      IF(NX2.GT.0) THEN
         DO 79 I=3,NX1+NX2
            IF (SE(I).GT.0) THEN
               IX2=I-2
               WRITE (OUTPUT,'(1X,A,I1,A,F6.3,A,2F10.3,F10.2)')
     -               '(ind[',INDIC(IX2),']-',INDMN(IX2),')',
     -                EST(I), SE(I), EST(I)/SE(I)
            ENDIF
79       CONTINUE
      ENDIF
      IF(IX2.EQ.0) WRITE (OUTPUT,'(1X,A)')
     -             '(ind[*]-     *)          *          *          *'

      WRITE (OUTPUT,'(/,1X,A,F10.2)')
     -     'R-squared           :',1.0-RSS/TOTSS

      RESIDL = 100.0 * SQRT(RSS/RDF) / MEAN

      WRITE (OUTPUT,'(/,1X,A,F8.3,A)')
     - 'Estimated relative root mean squared errors (% of ',MEAN,')'
      WRITE (OUTPUT,'(1X,A,F10.1)') 'residual           ',RESIDL

      OYASS=0.
      TYASS=0.
      IF (NOBS.GT.NUSED) THEN
         DO 81 LUSED=NUSED,NOBS-1
            FUSED=LUSED-NUSED+1
            NEXT1=LUSED+1
            NEXT2=LUSED+2
            DO 80 I=1,NOBS
               IF (I.GE.FUSED .AND. I.LE.LUSED) THEN
                  W(I) = 1.0
               ELSE
                  W(I) = 0.0
               ENDIF
80          CONTINUE
```

```
            CALL XCLUR(NOBS, NX1, NX2, OFFIC, W, X1, X2,
     -                 FIT, LEV, EST, SE, VCOV, RSS, RDF, OUTPUT)

            OYASS = OYASS + (OFFIC(NEXT1)- FIT(NEXT1))**2
            IF (NEXT2.LE.NOBS)
     -         TYASS = TYASS + (OFFIC(NEXT2)- FIT(NEXT2))**2
 81      CONTINUE
      ENDIF

      IF (NOBS.GT.NUSED) THEN
         OYA= SQRT(OYASS/REAL(NOBS-NUSED)) / MEAN
         WRITE (OUTPUT,'(1X,A,F10.1,3X,A,I3,A)')
     -         'one season ahead   ',OYA*100.,
     -         '(based on',NOBS-NUSED,' comparisons)'
         WRITE (ONEYRA,'(F7.1)') OYA*100.
      ELSE
         WRITE (OUTPUT,'(1X,A)') 'one season ahead            *'
         WRITE (ONEYRA,'(A)') '    ***'
      endif

      IF (NOBS.GT.NUSED+1) THEN
         TYA= SQRT(TYASS/REAL(NOBS-NUSED-1)) / MEAN
         WRITE (OUTPUT,'(1X,A,F10.1,3X,A,I3,A)')
     -         'two seasons ahead  ',TYA*100.,
     -         '(based on',NOBS-NUSED-1,' comparisons)'
         WRITE (TWOYRA,'(F7.1)') TYA*100.
      ELSE
         WRITE (OUTPUT,'(1X,A)') 'two seasons ahead           *'
         WRITE (TWOYRA,'(A)') '    ***'
      ENDIF

      IF (OUTSUM.GT.0)
     -   WRITE (OUTSUM,
     -    '(1X,A,I5,F7.2,1X,A,1X,F6.3,F6.2,F6.3,1X,2F7.1,2A)')
     -         TITLE(1:6), NOBS, MEAN, SELECT, ESTIM, STUD,
     -         RSQ, RESIDL, JACKKN, ONEYRA, TWOYRA

**********************************************************************
* end of dataset --------------------------------------------------- *
      WRITE (*,'(A,I4,A,A,A)') '+ dataset ',DATSET,' : ',TITLE,
     -                         '    done'
      WRITE (OUTPUT,'(1X,70A1)') ('-',I=1,70)
      IF (.NOT.EOF) GOTO 1

 9    WRITE (OUTPUT,'(1X,A)') '*** end of file ***'
      STOP '*** end of datafile ***'
      END

*--------------------------------------------------------- data input *
* records with missing values  ('*' or '-99') are skipped
* end-of-data sign ':' (no values on that record)
* all data-records must have the same number of values.

      SUBROUTINE VDATIN(INPUT,YEAR,OFFIC,MODEL,
     -                  MOBS,NOBS,NX2,INDIC,EOF)

*---------------------------------------------------------- arguments *
      INTEGER   INPUT, MOBS, NOBS, NX2, INDIC(4)
```

```
      REAL      YEAR(MOBS), OFFIC(MOBS), MODEL(MOBS,NX2)
      LOGICAL   EOF

*---------------------------------------------------- local variables *
      INTEGER MWORD
      PARAMETER (MWORD=10)

      INTEGER      NWORD, NWSET, IWB(MWORD), IWE(MWORD)
      INTEGER      I, J, NINDIC,  FIRST
      REAL         VMAG(MWORD)
      CHARACTER*80 RECORD
      CHARACTER*8  CINDIC

      DATA FIRST /1/

      EOF    = .FALSE.
      CINDIC = '1,2,3,4 '
      NWSET  = 0

* ask which model indicators to be used (at first call only) ------- *

      IF (FIRST.EQ.1) THEN
         WRITE (*,'(1X,A,5(/,10X,A),/)')
     -         'Modelindicators:',
     -         '1  potential grain yield',
     -         '2  water-limited grain yield',
     -         '3  potential biomass',
     -         '4  water-limited biomass',
     -         '0  no indicators'
5        CALL ENTDCH ('combination of indicators to be used'
     -               ,CINDIC,CINDIC)
         CALL WORDS  (CINDIC,MWORD,' ,',IWB,IWE,NINDIC)
         CALL DECREC (CINDIC,NINDIC,VMAG)
         IF (NINDIC.GT.0 .AND. VMAG(1).GT.0.) THEN
            DO 10 I=1,NINDIC
               INDIC(I)=INT(VMAG(I)+.1)
               IF (INDIC(I).GT.4.OR.INDIC(I).LT.0) THEN
                  WRITE (*,'(1X,A,/)') '*** choise out of range ***'
                  GOTO 5
               ENDIF
10          CONTINUE
         ELSE
            NINDIC=0
         ENDIF
         FIRST=0
      ENDIF

      NOBS=0
      DO 21 I=1,MOBS
         CALL GETREC (INPUT,RECORD,EOF)
         IF (EOF) RETURN
         IF (INDEX(RECORD,':').GT.0) GOTO 9
         IF (INDEX(RECORD,'*').EQ.0.AND.INDEX(RECORD,'-99').EQ.0) THEN
            CALL WORDS  (RECORD,MWORD,' ,',IWB,IWE,NWORD)
            IF (NWORD.GT.0) THEN
               IF (NWSET.EQ.0) NWSET=NWORD
               IF (NWORD.NE.NWSET) THEN
                  CALL ERROR('reading',
```

```
     -                         'inconsistent number of values')
               ELSE
                  NOBS=NOBS+1
                  CALL DECREC(RECORD,NWORD,VMAG)
                  YEAR(NOBS)   = VMAG(1)
                  OFFIC(NOBS) = VMAG(2)
                  IF (NWORD.GT.2 .AND. NINDIC.GT.0) THEN
                     DO 20 J=1,NINDIC
                        MODEL(NOBS,J) = VMAG(INDIC(J)+2)
 20                  CONTINUE
                  ENDIF
               ENDIF
            ENDIF
         ENDIF
 21   CONTINUE

 9    IF (NWSET.GT.2) THEN
         NX2=NINDIC
      ELSE
         NX2=0
      ENDIF
      RETURN
      END

* ---------------------------------------------------------- linreg *
      SUBROUTINE LINREG (NOBS, NTERM,
     -                   Y, W, X, FIT, LEV,
     -                   EST, SE, VCOV, SS, DF, OUT)

* dimensions ------------------------------------------------------ *
      INTEGER MOBS,MTERM
      PARAMETER (MOBS=30, MTERM=5)

* arguments ------------------------------------------------------- *
      INTEGER NOBS,NTERM, OUT
      REAL    Y(MOBS), W(MOBS), X(MOBS,MTERM)
      REAL    FIT(MOBS), LEV(MOBS)
      REAL    EST(MTERM), SE(MTERM)
      REAL    VCOV(MTERM,MTERM)
      REAL    SS, DF

* local variables and arrays ------------------------------------- *
      INTEGER          I,J,K, NROT
      DOUBLE PRECISION TOL, DMAX, DMIN, S
      DOUBLE PRECISION XTWX(MTERM,MTERM), XTWXIN(MTERM,MTERM)
      DOUBLE PRECISION V(MTERM,MTERM)
      DOUBLE PRECISION D(MTERM), DINV(MTERM)
      REAL             R, Z

      TOL = 1.0E-7
      DF  = REAL(NOBS-NTERM)
      SS  = 0.0

* fill matrix xtwx ----------------------------------------------- *

      DO 32 I=1,NTERM
         DO 31 J=1,NTERM
            S=0.
```

```
            DO 30 K=1,NOBS
               S=S+ DBLE( X(K,I) * W(K) * X(K,J) )
 30         CONTINUE
            XTWX(I,J)=S
 31      CONTINUE
 32   CONTINUE

* call subroutine jacobi (DJCOBI) from Numerical Recipes ----------- *

      CALL DJCOBI (XTWX,NTERM,MTERM,D,V,NROT)

* check inverse matrix ------------------------------------------- *

      DMAX = 0.
      DO 40 I=1,NTERM
         IF (D(I).GT.DMAX) DMAX=D(I)
 40   CONTINUE
      DMIN = TOL*DMAX

      DO 41 I=1,NTERM
         IF (D(I).GT.DMIN) THEN
            DINV(I) = 1.0/D(I)
         ELSE
            DINV(I) = 0.0
            DF      = DF + 1.0
            WRITE (OUT,'(/,2(/,1X,A))') '*** Alias ***', 'combination'
            WRITE (OUT,'(1X,10F10.3)') (V(I,J),J=1,NTERM)
            WRITE (OUT,'(1X,A)') 'constrained to 0.'
         ENDIF
 41   CONTINUE

      DO 52 I=1,NTERM
         DO 51 J=1,NTERM
            S = 0.0
            DO 50 K=1,NTERM
               S=S+ V(I,K) * DINV(K) * V(J,K)
 50         CONTINUE
            XTWXIN(I,J)=S
 51      CONTINUE
 52   CONTINUE

      DO 62 I=1,NOBS
         S = 0.0
         DO 61 J=1,NTERM
            DO 60 K=1,NTERM
               S=S+ XTWXIN(J,K) * DBLE(X(I,J)*X(I,K)*W(I))
 60         CONTINUE
 61      CONTINUE
         LEV(I)=S
 62   CONTINUE

      DO 72 I=1,NTERM
         S = 0.0
         DO 71 J=1,NOBS
            DO 70 K=1,NTERM
               S=S+ XTWXIN(I,K) * DBLE(X(J,K) * W(J) * Y(J))
 70         CONTINUE
            EST(I)=S
```

```
 71       CONTINUE
 72    CONTINUE

       DO 81 I=1,NOBS
          Z = 0.0
          DO 80 J=1,NTERM
             Z = Z+ EST(J) * X(I,J)
 80       CONTINUE
          FIT(I) = Z
          R      = Y(I)-Z
          SS     = SS+ DBLE(R* W(I) * R)
          IF (W(I).EQ.0.) DF=DF-1.
 81    CONTINUE

       DO 91 I=1,NTERM
          DO 90 J=1,NTERM
             VCOV(I,J)= XTWXIN(I,J) * DBLE(SS / DF)
 90       CONTINUE
          SE(I)= REAL(SQRT(VCOV(I,I)))
 91    CONTINUE

       RETURN
       END

* ----------------------------------------------------------- Jacobi *
      SUBROUTINE DJCOBI(A,N,NP,D,V,NROT)

      INTEGER          N,NP,NROT,NMAX
      PARAMETER        (NMAX=20)
      INTEGER          IP,IQ,I,J
      DOUBLE PRECISION A(NP,NP),D(NP),V(NP,NP),B(NMAX),Z(NMAX)
      DOUBLE PRECISION SM,TRESH,G,H,THETA,C,S,T,TAU

      DO 12 IP=1,N
         DO 11 IQ=1,N
            V(IP,IQ)=0.00
11       CONTINUE
         V(IP,IP)=1.00
12    CONTINUE
      DO 13 IP=1,N
         B(IP)=A(IP,IP)
         D(IP)=B(IP)
         Z(IP)=0.00
13    CONTINUE
      NROT=0
      DO 24 I=1,50
         SM=0.
         DO 15 IP=1,N-1
            DO 14 IQ=IP+1,N
               SM=SM+ABS(A(IP,IQ))
14          CONTINUE
15       CONTINUE
         IF(SM.EQ.0.)RETURN
         IF(I.LT.4)THEN
           TRESH=0.2*SM/N**2
         ELSE
           TRESH=0.
         ENDIF
```

```
      DO 22 IP=1,N-1
        DO 21 IQ=IP+1,N
          G=100.*ABS(A(IP,IQ))
          IF((I.GT.4).AND.(ABS(D(IP))+G.EQ.ABS(D(IP)))
     *       .AND.(ABS(D(IQ))+G.EQ.ABS(D(IQ))))THEN
            A(IP,IQ)=0.
          ELSE IF(ABS(A(IP,IQ)).GT.TRESH)THEN
            H=D(IQ)-D(IP)
            IF(ABS(H)+G.EQ.ABS(H))THEN
            T=A(IP,IQ)/H
          ELSE
            THETA=0.5*H/A(IP,IQ)
            T=1./(ABS(THETA)+SQRT(1.+THETA**2))
            IF(THETA.LT.0.)T=-T
          ENDIF
          C=1./SQRT(1.00+T**2)
          S=T*C
          TAU=S/(1.+C)
          H=T*A(IP,IQ)
          Z(IP)=Z(IP)-H
          Z(IQ)=Z(IQ)+H
          D(IP)=D(IP)-H
          D(IQ)=D(IQ)+H
          A(IP,IQ)=0.
          DO 16 J=1,IP-1
            G=A(J,IP)
            H=A(J,IQ)
            A(J,IP)=G-S*(H+G*TAU)
            A(J,IQ)=H+S*(G-H*TAU)
16        CONTINUE
          DO 17 J=IP+1,IQ-1
            G=A(IP,J)
            H=A(J,IQ)
            A(IP,J)=G-S*(H+G*TAU)
            A(J,IQ)=H+S*(G-H*TAU)
17        CONTINUE
          DO 18 J=IQ+1,N
            G=A(IP,J)
            H=A(IQ,J)
            A(IP,J)=G-S*(H+G*TAU)
            A(IQ,J)=H+S*(G-H*TAU)
18        CONTINUE
          DO 19 J=1,N
            G=V(J,IP)
            H=V(J,IQ)
            V(J,IP)=G-S*(H+G*TAU)
            V(J,IQ)=H+S*(G-H*TAU)
19        CONTINUE
          NROT=NROT+1
        ENDIF
21      CONTINUE
22    CONTINUE
      DO 23 IP=1,N
        B(IP)=B(IP)+Z(IP)
        D(IP)=B(IP)
        Z(IP)=0.
23    CONTINUE
24  CONTINUE
```

```
      PAUSE '50 iterations should never happen'
      RETURN
      END

      SUBROUTINE XCLUR (NOBS,NX1,NX2,Y,W,X1,X2,
     -                  FIT,LEV,EST,SE,VCOV,SS,DF,MES)

* ------------------------------------------------------------------ *
*   best linear regression of y
*   on X1 and at most one of the columns of X2
*   the best is the minimal-jackknife-ss one over the w!=0
*   observations from those with nonnegative coefficient for the
*   X2-term

* dimensions ------------------------------------------------------- *
      INTEGER    MOBS,   MTERM,  MX1,  MX2
      PARAMETER (MOBS=30,MTERM=8,MX1=3,MX2=5)

* arguments -------------------------------------------------------- *
      INTEGER NOBS, NX1, NX2, MES
      REAL    Y(MOBS), W(MOBS), X1(MOBS,MX1), X2(MOBS,MX2)
      REAL    FIT(MOBS), LEV(MOBS), EST(MTERM), SE(MTERM)
      REAL    VCOV(MTERM,MTERM), SS, DF

* local variables and arrays --------------------------------------- *
      INTEGER BSTFIT, I, J
      REAL    X(MOBS,MTERM),CVCOV(MTERM,MTERM),BVCOV(MTERM,MTERM)
      REAL    CSS,CJACSS,CFIT(MOBS),CLEV(MOBS),CEST(MTERM),CSE(MTERM)
      REAL    BSS,BJACSS,BFIT(MOBS),BLEV(MOBS),BEST(MTERM),BSE(MTERM)
      REAL    JR, CDF, BDF

      DO 11 I=1,NOBS
         DO 10 J=1,NX1
            X(I,J) = X1(i,J)
 10      CONTINUE
 11   CONTINUE

      CALL LINREG(NOBS, NX1, Y, W, X, BFIT, BLEV, BEST,
     -            BSE, BVCOV, BSS, BDF, MES)

      BSTFIT = 0
      BJACSS = 0
      DO 20 J=1,NOBS
         IF (W(J).NE.0) THEN
            JR = (Y(J)-BFIT(J))/(1-BLEV(J))
            BJACSS = BJACSS + JR*JR
         ENDIF
 20   CONTINUE

* from X2 take the variate giving the best jackknife ss ------------ *
      IF (NX2.GT.0) THEN
         DO 32 I=1,NX2
            DO 30 J=1,NOBS
               X(J,NX1+1) = X2(J,I)
 30         CONTINUE
            CALL LINREG(NOBS, NX1+1, Y, W, X, CFIT, CLEV, CEST,
     -                  CSE, CVCOV, CSS, CDF, MES)
            CJACSS = 0
```

```
            DO 31 J=1,NOBS
               IF (W(J).NE.0.) THEN
                  JR = (Y(J)-CFIT(J))/(1-CLEV(J))
                  CJACSS = CJACSS + JR*JR
               ENDIF
 31         CONTINUE
            IF (CJACSS.LT.BJACSS .AND. CEST(NX1+1).GT.0.) THEN
               BSTFIT = I
               CALL EXCRS(BJACSS,CJACSS)
               CALL EXCRS(BSS,CSS)
               CALL EXCRS(BDF,CDF)
               CALL EXCR1(MOBS,BFIT,CFIT)
               CALL EXCR1(MOBS,BLEV,CLEV)
               CALL EXCR1(MTERM,BEST,CEST)
               CALL EXCR1(MTERM,BSE,CSE)
               CALL EXCR2(MTERM,MTERM,BVCOV,CVCOV)
            ENDIF
 32      CONTINUE
      ENDIF

* copy results to outputparameters --------------------------------- *
      SS = BSS
      DF  = BDF

      DO 40 I=1,NOBS
         FIT(I) = BFIT(I)
         LEV(I) = BLEV(I)
 40   CONTINUE

      DO 41 I=1,NX1
         EST(I) = BEST(I)
         SE(I)  = BSE(I)
 41   CONTINUE

      IF (NX2.GT.0) THEN
         DO 42 I=NX1+1,NX1+NX2
            EST(I) = 0.0
            SE(I)  = 0.0
 42      CONTINUE
      ENDIF

      IF (BSTFIT.NE.0) THEN
         EST(NX1+BSTFIT) = BEST(NX1+1)
         SE(NX1+BSTFIT)  = BSE(NX1+1)
      ENDIF

      IF (NX2.GT.0) THEN
         DO 44 I=1,NX1+NX2
            DO 43 J=1,NX1+NX2
               VCOV(I,J) = 0.0
 43         CONTINUE
 44      CONTINUE
      ENDIF

      DO 46 I=1,NX1
         DO 45 J=1,NX1
            VCOV(I,J) = BVCOV(I,J)
 45      CONTINUE
```

```
 46    CONTINUE

       IF (BSTFIT.NE.0) THEN
          DO 47 I=1,NX1
             VCOV(NX1+BSTFIT,I) = BVCOV(NX1+1,I)
 47       CONTINUE
          DO 48 I=1,NX1
             VCOV(I,NX1+BSTFIT) = BVCOV(I,NX1+1)
 48       CONTINUE
          VCOV(NX1+BSTFIT,NX1+BSTFIT) = BVCOV(NX1+1,NX1+1)
       ENDIF

       RETURN
       END

       SUBROUTINE EXCRS(V1,V2)
       REAL V1,V2,P
       P  = V1
       V1 = V2
       V2 = P
       RETURN
       END

       SUBROUTINE EXCR1(N,V1,V2)
       INTEGER N,I
       REAL V1(N),V2(N),P

       DO 10 I=1,N
          P     = V1(I)
          V1(I) = V2(I)
          V2(I) = P
 10    CONTINUE
       RETURN
       END

       SUBROUTINE EXCR2(N1,N2,V1,V2)
       INTEGER N1,N2,I,J
       REAL V1(N1,N2),V2(N1,N2),P

       DO 11 I=1,N1
          DO 10 J=1,N2
             P       = V1(I,J)
             V1(I,J) = V2(I,J)
             V2(I,J) = P
 10       CONTINUE
 11    CONTINUE
       RETURN
       END
```

Appendix 8a. Example of detailed statistical output. Prediction rule P0

crop = wheat
region name = R22 (Bassin Parisien)
number of seasons = 15
mean = 5.644

<u>Predictions based on all data:</u>

term	est	se	t
constant	5.644	0.130	43.28
(year-1982.0)	0.186	0.030	6.16
(ind[*]- *)	*	*	*

R-squared : 0.74

Estimated relative root mean square errors (% of 5.644):
residual : 8.9
jackknife : 9.5

<u>Predictions based on last 9 seasons:</u>

term	est	se	t
constant	6.190	0.193	32.12
(year-1985.0)	0.151	0.075	2.02
(ind[*]- *)	*	*	*

R-squared : 0.37

Estimated relative root mean square errors (% of 5.644):
residual : 10.2
one year ahead : 12.0 (based on 6 comparisons)
two years ahead : 14.3 (based on 5 comparisons)

Appendix 8b. Example of detailed statistical output. Prediction rule P5.

crop = wheat
region name = R22 (Bassin Parisien)
number of seasons = 15
mean = 5.644

Predictions based on all data:

term	est	se	t
constant	5.644	0.101	55.80
(year-1982.0)	0.168	0.024	6.97
(ind[1]- 8.538)	0.331	0.107	3.10

R-squared: 0.86

Estimated relative root mean square errors (% of 5.644):
residual: 6.9
jackknife: 9.2

Predictions based on last 9 seasons:

term	est	se	t
constant	4.528	0.700	6.47
(year-1985.0)	0.125	0.058	2.15
(ind[1]- 5.187)	0.481	0.198	2.43

R-squared : 0.68

Estimated relative root mean square errors (% of 5.644)
residual: 7.9
one year ahead: 10.2 (based on 6 comparisons)
two years ahead: 13.5 (based on 5 comparisons)

Appendix 9 and 10. Summarized results, explanation of abbreviations.

Two prediction rules are investigated:

P0: no model indicators used

P5: chooses between no model indicator, potential grain yield, water limited grain yield, potential biomass and water-limited biomass.

Each region or country corresponds to a line in a dataset. The columns contain:

nuts : region or country NUTS-code (see Appendix 3)
nobs : number of years
mean : mean yield over years
sel : indicator selected: [1]= potential grain yield, [2]= water-limited grain yield, [3]= potential biomass, [4]= water-limited biomass
coef : coefficient of the selected indicator
t : t-value of indicator
rsq : R^2 of selected regression based on all years
res : relative root mean squared residual error of selected regression based on last 9 years
jack : relative root mean squared jackknife error of complete prediction rule based on all years
oya : relative root mean squared one year ahead error of complete prediction rule
tya : relative root mean squared two years ahead error of complete prediction rule

*** : no data available

Appendix 9. Summary output Nuts-1.

Explanation abbreviations: page 85.

Wheat P0

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R11	15	6.639		0.000	0.00	0.781	6.3	7.5	7.7	8.1
R12	15	6.095		0.000	0.00	0.745	8.2	8.3	11.9	13.1
R13	15	5.617		0.000	0.00	0.594	12.2	10.6	17.5	19.7
R14	10	5.250		0.000	0.00	0.786	4.9	5.1	2.6	***
R15	15	5.6 79		0.000	0.00	0.821	6.7	7.8	9.0	9.0
R16	15	5.374		0.000	0.00	0.690	7.8	8.7	8.5	7.7
R17	15	4.919		0.000	0.00	0.708	7.9	9.6	9.3	8.7
R18	15	4.918		0.000	0.00	0.765	9.7	7.9	12.4	14.3
R19	15	5.261		0.000	0.00	0.813	10.3	8.8	13.5	12.6
R1A	15	4.580		0.000	0.00	0.491	21.4	21.6	27.8	32.7
R21	15	6.119		0.000	0.00	0.705	11.1	10.4	12.7	13.3
R22	15	5.644		0.000	0.00	0.745	10.2	9.5	12.0	14.3
R23	15	6.178		0.000	0.00	0.776	11.6	9.5	15.1	14.1
R24	15	4.850		0.000	0.00	0.602	14.5	12.3	18.0	18.4
R25	15	4.731		0.000	0.00	0.731	7.3	8.3	8.6	7.1
R26	15	3.989		0.000	0.00	0.541	14.1	13.1	19.4	20.9
R27	15	4.299		0.000	0.00	0.553	13.4	12.9	17.3	15.7
R28	15	2.959		0.000	0.00	0.274	13.8	12.5	16.4	16.3
R31	15	3.652		0.000	0.00	0.625	11.5	11.9	15.5	13.1
R32	15	4.771		0.000	0.00	0.653	7.3	7.5	10.2	7.1
R33	15	4.747		0.000	0.00	0.815	4.2	7.2	7.2	7.8
R34	15	4.696		0.000	0.00	0.294	7.6	10.3	12.1	15.5
R35	15	2.971		0.000	0.00	0.658	5.6	6.6	7.6	8.0
R36	15	2.634		0.000	0.00	0.339	11.7	12.3	15.3	13.9
R37	14	2.329		0.000	0.00	0.788	3.9	8.1	5.8	7.3
R38	14	2.446		0.000	0.00	0.440	8.4	10.6	12.3	13.4
R39	14	1.919		0.000	0.00	0.001	24.3	22.2	28.5	17.5
R3A	14	1.685		0.000	0.00	0.003	18.2	19.7	23.9	25.1
R3B	15	1.475		0.000	0.00	0.032	41.7	35.0	47.9	36.6
R41	15	6.129		0.000	0.00	0.552	9.3	9.3	12.1	12.0
R42	15	6.815		0.000	0.00	0.634	8.6	9.8	12.7	14.4
R45	15	6.443		0.000	0.00	0. 795	8.2	9.3	11.6	13.2
R47	14	6.939		0.000	0.00	0.696	8.4	9.6	12.1	14.1
R51	15	5.536		0.000	0.00	0.643	15.2	13.1	19.6	19.3
R52	15	5.543		0.000	0.00	0.773	10.0	9.8	12.4	13.6
R53	14	4.981		0.000	0.00	0.755	8.2	9.1	10.0	6.4
R60	15	3.548		0.000	0.00	0.595	12.3	15.1	10.0	10.4
R71	14	5.944		0.000	0.00	0.594	11.8	11.4	15.6	20.6
R72	14	6.203		0.000	0.00	0.680	11.6	10.6	14.8	20.8
R73	14	5.995		0.000	0.00	0.607	12.9	11.7	16.9	21.7
R74	14	6.122		0.000	0.00	0.502	11.2	11.8	18.8	23.6
R75	14	5.909		0.000	0.00	0.493	10.5	11.8	15.5	20.7
R76	14	5.801		0.000	0.00	0.571	8.0	10.1	11.0	13.9
R77	14	5.704		0.000	0.00	0.601	9.2	9.9	12.1	16.5
R78	14	5.516		0.000	0.00	0.223	11.1	12.6	14.3	13.4
R 79	14	5.678		0.000	0.00	0.307	13.9	13.6	8.1	11.0
R7A	14	6.537		0.000	0.00	0.534	11.4	11.6	17.1	11.4
R7B	14	5.252		0.000	0.00	0.125	27.8	24.0	34.4	20.9
R80	15	6.018		0.000	0.00	0.740	13.2	11.6	17.7	21.6
R90	16	5.954		0.000	0.00	0.650	10.9	9.9	14.4	14.7
RA1	10	2.664		0.000	0.00	0.197	13.5	13.5	6.3	***
RB1	15	1.641		0.000	0.00	0.576	11.9	10.8	16.2	18.2
RB2	15	2.404		0.000	0.00	0.732	13.6	13.9	21.2	23.1
RB3	15	1.717		0.000	0.00	0.257	21.4	25.7	30.0	26.8
RB4	15	1.663		0.000	0.00	0.493	21.7	22.7	28.6	29.4
RB5	15	2.595		0.000	0.00	0.712	15.5	14.8	22.1	23.6
RB6	15	2.440		0.000	0.00	0.246	30.0	25.6	30.2	22.7

Appendix 9 (continued). Summary output Nuts-1. Explanation abbreviations: page 85.

Wheat P5

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R11	15	6.639		0.000	0.00	0.781	6.3	8.3	11.6	11.9
R12	15	6.095		0.000	0.00	0.745	8.2	9.7	16.8	17.2
R13	15	5.617		0.000	0.00	0.594	12.2	10.6	17.6	19.7
R14	10	5.250		0.000	0.00	0.786	4.9	5.1	2.6	***
R15	15	5.6 79		0.000	0.00	0.821	6.7	8.2	9.1	9.0
R16	15	5.374	ind[2]	0.173	1.68	0.749	7.8	9.0	9.2	7.8
R17	15	4.919	ind[2]	0.271	3.55	0.858	7.9	6.5	10.6	4.6
R18	15	4.918	ind[3]	0.108	1.07	0.785	9.0	8.0	11.8	14.5
R19	15	5.261	ind[4]	0.129	1.00	0.828	10.3	9.1	14.1	12.3
R1A	15	4.580	ind[3]	0.342	1.62	0.582	21.1	21.2	29.9	29.2
R21	15	6.119	ind[1]	0.391	3.38	0.849	6.4	10.8	10.5	9.6
R22	15	5.644	ind[1]	0.331	3.10	0.858	7.9	9.2	10.2	13.5
R23	15	6.178		0.000	0.00	0.776	11.6	9.5	15.1	14.1
R24	15	4.850	ind[1]	0.336	2.44	0.734	11.7	13.3	15.4	16.6
R25	15	4.731	ind[3]	0.344	3.48	0.866	5.7	6.3	9.5	10.0
R26	15	3.989		0.000	0.00	0.541	11.9	14.1	22.3	26.2
R27	15	4.299	ind[4]	0.106	1.31	0.610	13.4	14.8	17.4	15.6
R28	15	2.959	ind[3]	0.354	4.15	0.702	8.0	8.7	8.5	17.3
R31	15	3.652		0.000	0.00	0.625	11.5	11.9	15.5	13.1
R32	15	4.771		0.000	0.00	0.653	7.3	7.5	10.2	7.1
R33	15	4.747		0.000	0.00	0.815	4.2	7.2	7.2	7.8
R34	15	4.696		0.000	0.00	0.294	7.6	10.3	12.1	15.5
R35	15	2.971		0.000	0.00	0.658	5.6	6.6	7.6	8.0
R36	15	2.634		0.000	0.00	0.339	11.7	12.3	15.3	13.9
R37	14	2.329		0.000	0.00	0.788	3.9	8.9	5.8	7.3
R38	14	2.446		0.000	0.00	0.440	8.4	11.4	12.3	13.4
R39	14	1.919	ind[2]	0.445	3.30	0.498	15.9	19.2	21.6	16.6
R3A	14	1.685	ind[2]	0.196	1.94	0.257	15.3	20.4	23.1	27.1
R3B	15	1.475		0.000	0.00	0.032	41.7	41.4	55.5	52.7
R41	15	6.129	ind[1]	0.351	1.71	0.640	9.3	10.0	12.1	12.0
R42	15	6.815	ind[1]	0.372	1.67	0.703	8.0	9.9	12.7	14.4
R45	15	6.443	ind[3]	0.132	1.30	0.820	8.2	9.5	11.8	12.4
R47	14	6.939	ind[1]	0.654	2.75	0.820	7.1	12.1	12.1	14.1
R51	15	5.536		0.000	0.00	0.643	15.2	15.4	22.5	14.5
R52	15	5.543		0.000	0.00	0.773	8.3	16.2	12.8	12.1
R53	14	4.981		0.000	0.00	0.755	8.2	10.3	13.5	2.7
R60	15	3.548	ind[2]	0.257	2.95	0.765	12.3	15.5	11.1	15.3
R71	14	5.944		0.000	0.00	0.594	11.8	11.4	15.6	20.6
R72	14	6.203		0.000	0.00	0.680	11.6	10.9	14.8	20.8
R73	14	5.995		0.000	0.00	0.607	12.9	12.3	16.9	21.7
R74	14	6.122	ind[2]	0.376	1.33	0.571	11.2	12.6	17.7	22.7
R75	14	5.909		0.000	0.00	0.493	10.5	11.8	16.1	19.7
R76	14	5.801	ind[3]	0.193	1.68	0.659	7.1	10.2	12.1	12.9
R77	14	5.704		0.000	0.00	0.601	8.1	10.6	13.3	19.7
R78	14	5.516		0.000	0.00	0.223	11.1	13.7	15.6	15.0
R 79	14	5.678		0.000	0.00	0.307	13.9	15.0	11.5	13.1
R7A	14	6.537		0.000	0.00	0.534	11.4	11.6	17.1	11.4
R7B	14	5.252		0.000	0.00	0.125	27.8	24.0	34.4	20.9
R80	15	6.018		0.000	0.00	0.740	13.2	12.9	19.4	23.6
R90	16	5.954	ind[2]	0.467	2.38	0.756	7.9	9.1	14.1	17.1
RA1	10	2.664	ind[4]	0.107	1.94	0.477	11.6	14.6	10.0	***
RB1	15	1.641		0.000	0.00	0.576	9.9	11.9	19.1	22.7
RB2	15	2.404	ind[3]	0.214	3.00	0.847	11.6	11.6	21.7	28.2
RB3	15	1.717	ind[2]	0.094	1.91	0.431	21.4	27.8	47.4	29.0
RB4	15	1.663	ind[2]	0.172	2.56	0.672	12.2	23.1	22.4	25.0
RB5	15	2.595	ind[3]	0.528	3.93	0.874	10.5	13.6	18.6	19.6
RB6	15	2.440		0.000	0.00	0.246	30.0	28.1	43.9	38.0

Appendix 9 (continued). Summary output Nuts-1. Explanation abbreviations: page 85.

Maize P0

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R11	13	5.518		0.000	0.00	0.720	9.6	15.8	9.8	11.5
R12	15	5.572		0.000	0.00	0.658	12.7	11.4	13.7	12.1
R13	15	5.787		0.000	0.00	0.585	11.5	9.8	14.2	14.6
R15	15	6.320		0.000	0.00	0.729	7.7	7.2	10.5	8.8
R16	15	6.530		0.000	0.00	0.727	5.8	8.8	5.4	6.5
R17	15	5.759		0.000	0.00	0.410	6.6	11.1	8.7	10.9
R18	15	6.319		0.000	0.00	0.284	17.2	16.1	19.0	21.4
R19	15	6.265		0.000	0.00	0.676	9.8	9.7	9.8	9.3
R1A	15	4.589		0.000	0.00	0.438	25.5	23.4	24.5	22.8
R21	15	6.541		0.000	0.00	0.588	9.0	13.4	11.4	12.2
R22	15	5.736		0.000	0.00	0.780	6.8	9.6	7.5	7.4
R23	15	5.898		0.000	0.00	0.667	8.9	8.7	10.8	11.1
R24	15	6.874		0.000	0.00	0.804	9.5	8.3	8.2	10.1
R25	15	5.673		0.000	0.00	0.640	8.8	12.8	10.6	11.5
R26	15	5.945		0.000	0.00	0.873	5.9	6.5	9.1	9.8
R27	15	5.661		0.000	0.00	0.524	13.6	11.5	13.5	17.4
R28	15	5.423		0.000	0.00	0.839	6.3	6.1	8.8	10.0
R31	15	6.407		0.000	0.00	0.517	5.7	5.4	7.7	7.1
R32	15	7.698		0.000	0.00	0.759	4.9	4.9	5.2	7.4
R33	15	7.664		0.000	0.00	0.551	6.9	6.2	8.3	9.3
R34	15	7.772		0.000	0.00	0.704	6.2	5.5	7.2	7.0
R35	15	6.561		0.000	0.00	0.749	5.5	6.0	8.0	8.5
R36	15	5.805		0.000	0.00	0.891	7.8	6.4	10.8	10.8
R37	14	4.227		0.000	0.00	0.801	13.0	16.0	24.3	29.3
R38	14	4.625		0.000	0.00	0.657	8.7	9.7	13.0	16.4
R39	14	2.410		0.000	0.00	0.855	8.1	7.3	10.1	12.0
R3A	14	5.001		0.000	0.00	0.859	8.1	15.2	9.9	13.3
R3B	15	6.563		0.000	0.00	0.001	18.2	14.9	21.5	25.3
R51	15	6. 797		0.000	0.00	0.705	8.1	8.9	11.3	13.0
R52	15	6.531		0.000	0.00	0.242	19.6	16.4	24.7	17.6
RA1	10	8.574		0.000	0.00	0.438	11.3	16.0	3.7	***
RB1	15	2.765		0.000	0.00	0.496	6.7	10.3	6.5	7.9
RB2	15	6.621		0.000	0.00	0.397	11.2	12.9	16.2	21.5
RB3	15	7.452		0.000	0.00	0.642	10.2	8.5	11.1	11.5
RB4	15	6.570		0.000	0.00	0.378	19.0	17.9	26.4	27.8
RB5	15	5.435		0.000	0.00	0.380	9.3	8.7	12.0	11.6
RB6	15	6.981		0.000	0.00	0.817	9.4	11.7	9.2	11.5

Appendix 9 (continued). Summary output Nuts-1. Explanation abbreviations: page 85.

Maize P5

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R11	13	5.518		0.000	0.00	0.720	6.1	15.8	10.0	10.1
R12	15	5.572	ind[2]	0.155	1.93	0.739	5.4	13.3	8.3	6.7
R13	15	5.787	ind[4]	0.168	2.65	0.738	6.3	9.7	11.4	10.2
R15	15	6.320	ind[2]	0.241	2.85	0.838	4.0	6.6	8.3	7.9
R16	15	6.530	ind[2]	0.331	3.64	0.870	3.9	6.7	7.8	7.0
R17	15	5.759	ind[2]	0.231	1.74	0.529	5.5	13.9	12.7	19.2
R18	15	6.319	ind[4]	0.406	3.02	0.593	10.4	13.0	15.2	19.9
R19	15	6.265	ind[4]	0.191	2.40	0.781	7.4	9.2	8.5	10.5
R1A	15	4.589	ind[4]	0.311	4.29	0.778	12.4	18.8	17.6	17.5
R21	15	6.541	ind[2]	0.253	4.09	0.828	6.9	8.5	17.2	11.8
R22	15	5.736	ind[4]	0.135	3.48	0.891	6.7	6.9	8.3	10.3
R23	15	5.898		0.000	0.00	0.667	6.9	13.3	8.7	7.9
R24	15	6.874	ind[4]	0.187	4.69	0.931	4.8	6.3	5.8	8.3
R25	15	5.673	ind[4]	0.163	5.46	0.897	5.3	7.9	8.1	9.5
R26	15	5.945	ind[2]	0.069	1.54	0.894	4.2	7.3	8.3	9.8
R27	15	5.661	ind[2]	0.195	2.76	0.709	9.1	12.9	17.9	19.5
R28	15	5.423		0.000	0.00	0.839	3.7	7.4	6.5	9.1
R31	15	6.407	ind[4]	0.094	1.76	0.616	5.7	6.0	9.7	12.9
R32	15	7.698	ind[4]	0.082	1.90	0.815	4.9	4.8	7.2	10.0
R33	15	7.664	ind[4]	0.166	1.86	0.651	6.9	7.8	11.4	11.5
R34	15	7.772	ind[3]	0.162	2.33	0. 796	4.5	5.8	10.0	9.4
R35	15	6.561		0.000	0.00	0.749	5.5	6.4	8.0	8.5
R36	15	5.805		0.000	0.00	0.891	7.8	6.4	11.3	11.4
R37	14	4.227	ind[4]	0.121	1.63	0.840	13.0	17.0	28.5	29.3
R38	14	4.625	ind[4]	0.089	2.98	0.810	8.7	7.9	13.0	16.1
R39	14	2.410	ind[3]	0.067	1. 79	0.888	7.0	10.9	11.3	12.1
R3A	14	5.001		0.000	0.00	0.859	8.1	15.2	9.9	13.3
R3B	15	6.563	ind[1]	0.404	1.34	0.131	18.2	16.4	21.5	25.3
R51	15	6. 797	ind[4]	0.106	1.71	0.762	6.2	11.4	13.6	14.1
R52	15	6.531	ind[3]	0.471	3.14	0.585	12.2	13.8	46.6	47.6
RA1	10	8.574		0.000	0.00	0.438	11.3	17.1	3.7	***
RB1	15	2.765		0.000	0.00	0.496	6.1	10.3	7.1	9.1
RB2	15	6.621		0.000	0.00	0.397	11.2	12.9	16.2	21.5
RB3	15	7.452		0.000	0.00	0.642	10.2	9.3	13.3	12.7
RB4	15	6.570		0.000	0.00	0.378	19.0	20.7	28.1	28.8
RB5	15	5.435	ind[3]	0.094	1.08	0.435	9.3	9.2	13.3	13.6
RB6	15	6.981		0.000	0.00	0.817	9.4	11.7	9.2	11.5

Appendix 9 (continued). Summary output Nuts-1. Explanation abbreviations: page 85.

Barley P0

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R11	15	5.531		0.000	0.00	0.750	8.9	8.6	10.2	10.1
R12	15	4.987		0.000	0.00	0.801	5.5	7.0	6.4	6.3
R13	15	4.539		0.000	0.00	0.744	3.7	4.5	5.4	5.4
R14	10	4.297		0.000	0.00	0.761	4.5	4.5	5.4	***
R15	15	4.967		0.000	0.00	0.767	6.1	6.1	7.7	6.0
R16	15	4.740		0.000	0.00	0.628	8.5	8.7	8.7	10.4
R17	15	4.096		0.000	0.00	0.433	9.0	11.2	7.4	6.3
R18	15	4.235		0.000	0.00	0.681	9.2	7.4	11.9	14.3
R19	15	4.287		0.000	0.00	0.670	11.8	10.0	15.7	18.0
R1A	15	3.945		0.000	0.00	0.352	10.0	11.6	7.4	7.2
R21	15	5.276		0.000	0.00	0.752	10.1	9.7	10.1	8.5
R22	15	4.849		0.000	0.00	0.861	8.5	7.5	9.5	6.2
R23	15	5.764		0.000	0.00	0.738	9.8	9.2	10.9	8.2
R24	15	4.063		0.000	0.00	0.484	16.2	13.0	16.4	15.9
R25	15	3.925		0.000	0.00	0.652	13.4	13.3	15.2	14.4
R26	15	3.449		0.000	0.00	0.650	13.6	10.9	16.0	13.4
R27	15	3.534		0.000	0.00	0.504	15.1	14.6	19.1	18.1
R28	15	3.101		0.000	0.00	0.249	10.5	10.4	11.2	12.6
R31	15	3.667		0.000	0.00	0.617	16.4	15.0	22.6	17.4
R32	15	4.735		0.000	0.00	0.601	10.8	10.3	15.6	14.0
R33	15	4.284		0.000	0.00	0.725	10.8	10.9	16.2	20.3
R34	15	4.239		0.000	0.00	0.780	6.9	8.2	11.2	13.6
R35	15	2.749		0.000	0.00	0.722	5.6	8.2	9.0	8.2
R36	15	2.833		0.000	0.00	0.541	9.1	13.1	14.4	15.8
R37	14	2.326		0.000	0.00	0.731	6.6	8.7	9.8	10.8
R38	14	2.313		0.000	0.00	0.726	7.7	8.7	13.5	16.9
R39	14	1.971		0.000	0.00	0.129	20.2	18.5	21.4	20.9
R3A	14	1.514		0.000	0.00	0.019	18.6	17.6	25.2	27.8
R3B	15	1.533		0.000	0.00	0.008	37.9	32.0	47.2	34.3
R41	15	4.977		0.000	0.00	0.175	12.9	11.5	15.0	18.3
R42	15	4.883		0.000	0.00	0.451	11.1	9.5	13.4	13.6
R45	15	4.718		0.000	0.00	0.492	9.9	11.5	12.1	14.7
R47	14	5.178		0.000	0.00	0.356	14.5	13.1	17.8	18.5
R51	15	5.041		0.000	0.00	0.604	10.1	10.1	10.8	9.9
R52	15	5.429		0.000	0.00	0.762	9.4	8.7	8.2	6.7
R53	14	4.843		0.000	0.00	0.5 79	9.2	11.5	10.0	6.4
R60	15	3.333		0.000	0.00	0.225	15.9	17.2	6.4	5.5
R71	14	4.557		0.000	0.00	0.398	10.4	10.1	12.5	16.7
R72	14	4.851		0.000	0.00	0.677	9.5	8.4	12.5	16.8
R73	14	4.656		0.000	0.00	0.537	12.1	12.2	15.9	21.7
R74	14	4.657		0.000	0.00	0.543	8.7	9.8	14.0	17.1
R75	14	4.731		0.000	0.00	0.599	8.9	10.8	12.0	17.7
R76	14	4.587		0.000	0.00	0.559	9.4	10.4	11.4	16.4
R77	14	4.626		0.000	0.00	0.515	12.1	11.8	15.7	20.6
R78	14	4.206		0.000	0.00	0.211	11.0	11.4	12.2	16.4
R 79	14	4.300		0.000	0.00	0.149	11.7	12.5	15.1	19.9
R7A	14	4.735		0.000	0.00	0.075	6.8	8.2	7.5	5.0
R7B	14	4.031		0.000	0.00	0.214	12.1	10.9	12.2	10.1
R80	15	4.955		0.000	0.00	0.657	7.7	8.7	9.7	9.5
R90	16	4.298		0.000	0.00	0.650	11.9	9.8	12.0	9.4
RA1	11	2.575		0.000	0.00	0.028	14.8	14.2	16.1	23.3
RB1	15	1.663		0.000	0.00	0.128	9.4	8.6	10.5	8.9
RB2	15	2.326		0.000	0.00	0.009	19.7	20.4	28.1	26.7
RB3	15	2.049		0.000	0.00	0.062	24.1	26.9	34.4	33.5
RB4	15	2.068		0.000	0.00	0.112	23.7	24.9	29.2	29.0
RB5	15	2.253		0.000	0.00	0.267	25.4	23.4	32.6	29.0
RB6	15	1.527		0.000	0.00	0.117	25.5	26.2	31.5	28.7

Appendix 9 (continued). Summary output Nuts-1. Explanation abbreviations: page 85.

Barley P5

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R11	15	5.531		0.000	0.00	0.750	8.9	8.6	10.2	10.1
R12	15	4.987		0.000	0.00	0.801	5.5	7.0	6.4	6.3
R13	15	4.539	ind[4]	0.080	1.42	0.781	3.7	4.7	5.4	5.4
R14	10	4.297		0.000	0.00	0.761	4.5	4.5	5.4	***
R15	15	4.967	ind[4]	0.263	2.87	0.862	5.4	5.0	9.2	6.4
R16	15	4.740	ind[4]	0.475	3.14	0. 796	7.2	8.5	11.2	9.8
R17	15	4.096	ind[2]	0.464	2.64	0.642	9.0	11.9	8.7	8.1
R18	15	4.235	ind[1]	0.443	2.53	0. 792	7.0	7.3	11.3	13.3
R19	15	4.287	ind[4]	0.408	3.25	0.825	7.3	8.2	16.2	13.6
R1A	15	3.945	ind[2]	0.472	4.24	0.741	8.3	9.9	9.2	9.8
R21	15	5.276	ind[2]	0.425	3.43	0.875	6.9	8.8	7.5	4.9
R22	15	4.849	ind[4]	0.311	3.36	0.928	8.5	6.6	8.8	6.1
R23	15	5.764		0.000	0.00	0.738	9.8	9.2	12.2	8.4
R24	15	4.063	ind[2]	0.407	2.03	0.616	14.6	12.3	15.2	12.4
R25	15	3.925	ind[4]	0.568	5.61	0.904	6.6	7.6	13.5	14.2
R26	15	3.449	ind[3]	0.337	3.80	0.841	6.3	8.5	17.0	13.4
R27	15	3.534	ind[2]	0.329	1.57	0.588	15.1	18.2	19.2	15.2
R28	15	3.101	ind[4]	0.333	7.14	0.857	3.2	5.0	6.5	14.6
R31	15	3.667	ind[3]	0.197	1.65	0.688	14.6	16.1	22.6	17.4
R32	15	4.735		0.000	0.00	0.601	10.8	10.3	15.6	14.0
R33	15	4.284		0.000	0.00	0.725	10.8	10.9	16.2	20.3
R34	15	4.239		0.000	0.00	0.780	6.9	8.2	11.2	13.6
R35	15	2.749	ind[4]	0.098	1.08	0.747	5.6	8.0	9.0	8.2
R36	15	2.833		0.000	0.00	0.541	9.1	13.1	14.4	15.8
R37	14	2.326		0.000	0.00	0.731	6.6	8.7	9.8	10.8
R38	14	2.313		0.000	0.00	0.726	6.8	9.5	13.5	17.6
R39	14	1.971	ind[4]	0.237	1.50	0.278	18.8	19.3	23.2	28.6
R3A	14	1.514	ind[4]	0.268	2.70	0.410	14.6	17.5	26.1	27.8
R3B	15	1.533		0.000	0.00	0.008	33.6	35.5	50.2	36.3
R41	15	4.977	ind[2]	0.695	2.35	0.436	12.9	12.7	15.8	18.3
R42	15	4.883		0.000	0.00	0.451	11.1	9.9	13.9	15.3
R45	15	4.718	ind[2]	0.461	2.64	0.6 79	8.6	9.9	10.2	14.1
R47	14	5.178	ind[1]	0.756	2.00	0.528	12.9	13.9	17.8	18.5
R51	15	5.041	ind[1]	0.392	1.60	0.673	8.8	10.9	11.2	7.5
R52	15	5.429		0.000	0.00	0.762	6.0	10.7	10.3	7.1
R53	14	4.843		0.000	0.00	0.5 79	9.2	12.5	11.2	5.7
R60	15	3.333	ind[2]	0.572	3.72	0.640	15.9	12.8	5.8	8.2
R71	14	4.557		0.000	0.00	0.398	10.4	10.1	12.9	17.0
R72	14	4.851		0.000	0.00	0.677	9.5	8.9	11.9	17.4
R73	14	4.656		0.000	0.00	0.537	12.1	12.2	15.9	21.7
R74	14	4.657		0.000	0.00	0.543	8.7	10.4	14.0	17.1
R75	14	4.731		0.000	0.00	0.599	8.9	10.8	12.0	17.7
R76	14	4.587		0.000	0.00	0.559	9.4	10.4	11.4	16.4
R77	14	4.626		0.000	0.00	0.515	12.1	12.2	17.2	20.4
R78	14	4.206	ind[1]	0.407	1.76	0.385	11.0	12.8	13.4	17.4
R 79	14	4.300		0.000	0.00	0.149	11.7	12.5	15.1	19.9
R7A	14	4.735		0.000	0.00	0.075	6.1	9.7	7.8	6.4
R7B	14	4.031		0.000	0.00	0.214	12.1	11.5	16.0	9.8
R80	15	4.955	ind[1]	0.486	2.03	0.744	7.7	8.6	12.8	10.5
R90	16	4.298		0.000	0.00	0.650	11.9	10.2	12.0	9.4
RA1	11	2.575		0.000	0.00	0.028	14.8	21.7	16.1	23.3
RB1	15	1.663		0.000	0.00	0.128	9.4	9.6	11.5	11.7
RB2	15	2.326	ind[4]	0.312	3.81	0.552	11.3	17.0	22.9	22.9
RB3	15	2.049	ind[4]	0.243	3.07	0.475	16.7	22.9	26.7	30.5
RB4	15	2.068	ind[3]	0.407	4.67	0.685	8.7	17.5	17.7	23.2
RB5	15	2.253	ind[4]	0.720	4.27	0.709	14.5	17.3	21.7	25.4
RB6	15	1.527	ind[2]	0.352	3.09	0.508	20.0	20.9	34.4	33.5

Appendix 9 (continued). Summary output Nuts-1. Explanation abbreviations: page 85.

Rice P0

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R28	15	4.421		0.000	0.00	0.609	11.9	15.8	13.7	12.2
R31	15	5.612		0.000	0.00	0.238	2.8	12.1	3.9	7.6
R32	15	5.287		0.000	0.00	0.264	8.2	11.6	8.2	11.5
R33	15	5.477		0.000	0.00	0.412	16.5	14.6	21.0	25.9
R34	15	5.271		0.000	0.00	0.413	6.7	7.9	6.8	3.9
R35	13	5.048		0.000	0.00	0.591	9.2	12.4	6.3	5.9
R39	12	4.545		0.000	0.00	0.478	22.8	27.3	55.4	36.5
R3B	15	5.583		0.000	0.00	0.668	9.4	8.5	10.8	7.6
RA1	9	6.024		0.000	0.00	0.589	8.1	10.7	***	***
RB2	15	4.146		0.000	0.00	0.157	19.4	17.2	26.7	26.2
RB4	15	5.657		0.000	0.00	0.229	11.3	13.2	10.0	12.3
RB5	15	6.141		0.000	0.00	0.011	5.6	5.9	5.2	5.4
RB6	15	6.236		0.000	0.00	0.002	14.1	11.9	12.9	15.8

Rice P5

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R28	15	4.421	ind[1]	0.554	2.35	0.732	9.6	14.0	11.6	7.7
R31	15	5.612		0.000	0.00	0.238	2.8	12.1	4.5	8.3
R32	15	5.287		0.000	0.00	0.264	8.2	11.6	8.0	15.6
R33	15	5.477		0.000	0.00	0.412	12.5	17.1	20.8	25.8
R34	15	5.271		0.000	0.00	0.413	6.7	7.9	6.8	3.9
R35	13	5.048		0.000	0.00	0.591	9.2	14.2	6.7	5.9
R39	12	4.545	ind[4]	0.463	2.01	0.640	22.8	29.5	51.3	32.4
R3B	15	5.583		0.000	0.00	0.668	9.4	9.1	13.8	11.5
RA1	9	6.024	ind[1]	0.695	2.03	0.756	6.8	10.9	***	***
RB2	15	4.146	ind[1]	0.163	0.74	0.194	17.4	18.5	26.7	26.2
RB4	15	5.657	ind[1]	0.409	1.64	0.371	11.3	14.2	10.0	12.3
RB5	15	6.141		0.000	0.00	0.011	5.6	5.9	5.4	5.5
RB6	15	6.236		0.000	0.00	0.002	14.1	11.9	12.9	15.8

Appendix 9 (continued). Summary output Nuts-1. Explanation abbreviations: page 85.

Sugar beet P0

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R11	12	40.737		0.000	0.00	0.195	14.9	14.0	22.6	10.2
R12	8	40.835		0.000	0.00	0.290	7.7	8.2	***	***
R13	12	43.346		0.000	0.00	0.286	9.9	9.5	7.1	8.8
R15	12	48.891		0.000	0.00	0.375	9.4	9.4	4.3	3.9
R16	12	47.098		0.000	0.00	0.332	6.4	7.7	3.1	1.2
R17	12	51.933		0.000	0.00	0.209	7.7	8.2	4.4	1.5
R18	12	51.558		0.000	0.00	0.275	7.8	6.9	1.6	1.0
R19	12	54.396		0.000	0.00	0.248	7.1	8.4	5.2	4.7
R1A	9	36.418		0.000	0.00	0.005	19.3	21.9	***	***
R21	11	55.251		0.000	0.00	0.735	6.5	11.8	7.8	2.2
R22	11	54.726		0.000	0.00	0.877	5.7	7.3	4.5	0.3
R23	11	50.774		0.000	0.00	0.697	9.2	9.3	6.4	7.3
R24	11	50.159		0.000	0.00	0.633	6.8	6.8	6.5	10.6
R25	11	47.768		0.000	0.00	0.718	7.7	9.5	14.9	15.1
R27	11	54.214		0.000	0.00	0.913	5.7	5.9	0.8	1.2
R31	10	52.345		0.000	0.00	0.134	11.2	11.8	10.3	***
R32	10	53.078		0.000	0.00	0.359	8.4	8.9	3.1	***
R33	10	53.771		0.000	0.00	0.385	11.7	11.9	20.3	***
R34	10	51.520		0.000	0.00	0.007	8.5	8.3	0.2	***
R35	10	40.800		0.000	0.00	0.209	16.8	16.9	2.3	***
R36	10	47.801		0.000	0.00	0.063	10.0	10.5	17.4	***
R37	10	30.270		0.000	0.00	0.001	25.4	26.7	36.3	***
R38	10	45.999		0.000	0.00	0.024	17.1	17.8	10.3	***
R39	10	38.531		0.000	0.00	0.048	16.7	17.2	14.2	***
R3B	10	41.200		0.000	0.00	0.157	19.4	20.5	12.1	***
R51	12	51.424		0.000	0.00	0.273	6.9	8.4	6.7	4.7
R52	12	51.694		0.000	0.00	0.367	9.7	10.2	11.0	13.0
R53	11	49.368		0.000	0.00	0.042	3.9	11.2	4.9	3.6
R60	11	45.628		0.000	0.00	0.320	26.3	31.0	30.7	36.9
R80	11	42.507		0.000	0.00	0.004	12.3	11.3	6.9	5.3
R90	13	44.082		0.000	0.00	0.548	11.5	10.0	12.4	9.0
RB2	11	39.146		0.000	0.00	0.772	9.1	9.3	18.3	18.7
RB3	11	35.516		0.000	0.00	0.1 79	7.0	10.0	11.6	8.0
RB4	11	41.587		0.000	0.00	0.374	10.8	10.8	14.1	16.1
RB5	9	28.908		0.000	0.00	0.235	31.0	32.6	***	***
RB6	10	31.697		0.000	0.00	0.573	14.8	15.5	25.8	***

Appendix 9 (continued). Summary output Nuts-1. Explanation abbreviations: page 85.

Sugar beet P5

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R11	12	40.737	ind[2]	4.058	4. 79	0.773	7.1	8.8	10.7	6.2
R12	8	40.835		0.000	0.00	0.290	6.7	10.3	***	***
R13	12	43.346		0.000	0.00	0.286	8.4	10.4	10.9	8.9
R15	12	48.891	ind[2]	2.033	1.98	0.564	7.2	10.2	2.7	2.5
R16	12	47.098	ind[2]	1.214	2.04	0.544	5.7	8.3	3.5	2.3
R17	12	51.933	ind[4]	1.508	2.88	0.589	7.7	9.0	3.9	1.3
R18	12	51.558		0.000	0.00	0.275	7.8	6.9	1.6	1.0
R19	12	54.396		0.000	0.00	0.248	7.3	8.5	6.0	4.7
R1A	9	36.418	ind[4]	1.876	2.36	0.484	15.0	23.2	***	***
R21	11	55.251	ind[4]	1.606	5.18	0.939	6.5	7.1	8.4	11.0
R22	11	54.726	ind[2]	1.110	2.58	0.933	5.7	5.7	5.6	7.0
R23	11	50.774		0.000	0.00	0.697	9.2	9.3	6.4	7.3
R24	11	50.159		0.000	0.00	0.633	6.8	6.9	5.9	10.2
R25	11	47.768	ind[4]	0.943	4.78	0.927	4.3	5.1	7.4	2.8
R27	11	54.214		0.000	0.00	0.913	5.7	5.9	0.8	1.2
R31	10	52.345		0.000	0.00	0.134	8.8	13.5	10.3	***
R32	10	53.078		0.000	0.00	0.359	8.4	8.9	3.1	***
R33	10	53.771	ind[3]	3.089	2.44	0.667	9.3	10.1	24.2	***
R34	10	51.520	ind[3]	1.959	5.28	0.801	4.1	4.4	6.5	***
R35	10	40.800	ind[3]	2.607	2.22	0.535	12.7	16.3	10.1	***
R36	10	47.801		0.000	0.00	0.063	10.0	10.9	17.4	***
R37	10	30.270	ind[4]	1.377	1.66	0.283	20.0	30.8	36.3	***
R38	10	45.999		0.000	0.00	0.024	16.5	21.1	10.3	***
R39	10	38.531	ind[4]	1.967	2.80	0.550	11.7	17.2	15.6	***
R3B	10	41.200		0.000	0.00	0.157	19.4	20.5	12.1	***
R51	12	51.424		0.000	0.00	0.273	6.8	8.4	11.3	12.2
R52	12	51.694		0.000	0.00	0.367	9.8	10.9	13.7	17.4
R53	11	49.368		0.000	0.00	0.042	3.9	11.2	4.9	3.6
R60	11	45.628		0.000	0.00	0.320	26.3	31.0	30.7	36.9
R80	11	42.507	ind[3]	3.098	2.80	0.498	6.3	11.2	12.4	6.1
R90	13	44.082	ind[2]	2.130	3.37	0.788	7.0	10.9	11.8	14.4
RB2	11	39.146	ind[2]	1.053	1.42	0.818	8.5	10.7	19.0	10.7
RB3	11	35.516	ind[2]	0.847	1.50	0.359	7.0	10.9	11.6	8.0
RB4	11	41.587	ind[2]	1.428	1.53	0.516	10.8	12.2	14.1	16.1
RB5	9	28.908		0.000	0.00	0.235	31.0	32.6	***	***
RB6	10	31.697	ind[4]	2.858	2.36	0.762	12.2	15.5	25.8	***

Appendix 9 (continued). Summary output Nuts-1. Explanation abbreviations: page 85.

Potato P0

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R11	11	28.262		0.000	0.00	0.476	16.9	20.6	16.0	19.5
R12	11	29.635		0.000	0.00	0.662	12.5	14.3	13.5	16.6
R13	11	32.588		0.000	0.00	0.763	9.9	10.0	6.3	3.1
R15	11	33.550		0.000	0.00	0. 798	8.2	10.2	13.2	5.9
R16	11	27.204		0.000	0.00	0.385	15.3	15.6	10.8	1.8
R17	11	26.781		0.000	0.00	0.566	11.0	12.5	2.9	5.7
R18	11	27.995		0.000	0.00	0.105	15.2	15.0	13.8	13.3
R19	11	30.495		0.000	0.00	0.440	13.0	12.9	22.2	19.0
R1A	11	24.535		0.000	0.00	0.345	24.8	26.6	22.7	32.5
R21	10	32.671		0.000	0.00	0.630	17.4	21.4	7.1	***
R22	10	33.869		0.000	0.00	0.720	15.3	16.8	3.6	***
R23	10	38.454		0.000	0.00	0.612	13.1	15.3	3.2	***
R24	10	29.962		0.000	0.00	0.609	29.4	33.0	72.9	***
R25	10	24.685		0.000	0.00	0.784	11.3	13.3	10.0	***
R26	10	25.389		0.000	0.00	0.763	15.6	18.6	20.8	***
R27	10	20.756		0.000	0.00	0.523	15.9	20.2	22.0	***
R28	10	20.208		0.000	0.00	0.827	6.5	7.4	10.0	***
R31	11	20.090		0.000	0.00	0.341	14.9	14.5	21.0	18.6
R32	11	23.390		0.000	0.00	0.378	11.3	11.6	20.2	26.5
R33	11	26.296		0.000	0.00	0.718	5.8	5.9	7.7	6.5
R34	11	27.054		0.000	0.00	0.819	7.5	7.6	8.9	13.9
R35	11	13.672		0.000	0.00	0.377	8.1	8.7	15.2	20.6
R36	11	17.986		0.000	0.00	0.820	7.9	9.5	5.9	0.1
R37	10	20.328		0.000	0.00	0.042	14.3	15.0	6.3	***
R38	10	15.375		0.000	0.00	0.689	9.5	10.5	0.3	***
R39	10	11.601		0.000	0.00	0.718	9.7	10.0	12.2	***
R3A	11	17.751		0.000	0.00	0.062	28.3	27.6	43.6	35.5
R3B	12	15.323		0.000	0.00	0.129	9.0	11.8	19.2	24.0
R41	12	34.7 79		0.000	0.00	0.495	9.5	9.4	7.8	4.3
R42	12	42.473		0.000	0.00	0. 798	7.9	7.2	8.2	10.3
R45	12	43.502		0.000	0.00	0.697	6.6	10.2	7.6	12.7
R47	11	39.676		0.000	0.00	0.812	6.5	6.4	6.3	6.0
R51	11	33.128		0.000	0.00	0.512	10.0	16.0	14.5	17.6
R52	11	33.427		0.000	0.00	0.267	13.4	17.2	14.0	1.9
R53	10	29.065		0.000	0.00	0.302	20.5	21.7	9.5	***
R60	12	27.788		0.000	0.00	0.217	19.1	26.3	16.1	18.4
R7A	9	34.492		0.000	0.00	0.381	6.0	6.4	***	***
R7B	10	25.783		0.000	0.00	0.073	6.8	6.4	2.9	***
R80	11	23.223		0.000	0.00	0.174	13.1	12.4	13.4	10.4
R90	12	30.993		0.000	0.00	0.789	9.8	12.0	5.3	9.7
RB1	10	12.426		0.000	0.00	0.333	17.4	31.6	50.4	***
RB2	10	17.859		0.000	0.00	0.597	6.0	21.2	3.2	***
RB3	10	20.385		0.000	0.00	0.372	1.5	19.9	8.6	***
RB4	10	16.868		0.000	0.00	0.686	6.9	14.5	6.7	***
RB5	10	15.020		0.000	0.00	0.518	4.6	29.3	15.3	***
RB6	10	17.034		0.000	0.00	0.590	9.0	28.8	5.8	***

Appendix 9 (continued). Summary output Nuts-1. Explanation abbreviations: page 85.

Potato P5

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R11	11	28.262	ind[4]	1.158	3.34	0.781	16.9	14.5	15.9	8.3
R12	11	29.635	ind[4]	0.856	3.52	0.867	9.3	12.3	14.0	10.4
R13	11	32.588	ind[3]	3.347	2.50	0.867	6.7	11.3	10.8	11.1
R15	11	33.550	ind[4]	0.701	2.73	0.896	4.6	10.0	10.2	1.3
R16	11	27.204	ind[1]	2.196	1.90	0.576	15.3	16.9	9.9	7.4
R17	11	26.781	ind[1]	2.098	3.91	0.851	7.1	8.7	7.3	11.1
R18	11	27.995		0.000	0.00	0.105	15.2	15.9	13.8	13.3
R19	11	30.495	ind[1]	2.169	1.46	0.558	12.2	13.3	22.0	19.7
R1A	11	24.535	ind[1]	3.102	2.78	0.667	18.6	22.1	27.6	42.8
R21	10	32.671	ind[1]	3.408	3.95	0.886	10.4	20.2	0.7	***
R22	10	33.869	ind[1]	3.057	4.04	0.916	9.1	13.5	6.8	***
R23	10	38.454	ind[4]	1.047	3.23	0.844	8.6	14.2	1.3	***
R24	10	29.962	ind[1]	4.407	2.47	0. 791	25.7	30.8	67.0	***
R25	10	24.685	ind[1]	1.558	3.50	0.921	3.5	11.1	2.2	***
R26	10	25.389	ind[3]	1.254	1.52	0.822	13.0	18.8	14.9	***
R27	10	20.756	ind[4]	0.552	2.10	0.707	13.8	24.0	13.6	***
R28	10	20.208		0.000	0.00	0.827	6.5	8.4	10.0	***
R31	11	20.090		0.000	0.00	0.341	14.9	14.5	21.0	18.6
R32	11	23.390		0.000	0.00	0.378	11.3	11.6	20.2	26.5
R33	11	26.296		0.000	0.00	0.718	5.8	6.4	7.7	6.5
R34	11	27.054	ind[2]	0.369	2.48	0.898	6.3	6.0	8.9	13.9
R35	11	13.672	ind[3]	0.437	2.04	0.590	7.1	9.3	15.2	20.6
R36	11	17.986		0.000	0.00	0.820	7.9	10.5	5.9	0.1
R37	10	20.328		0.000	0.00	0.042	14.3	15.7	6.3	***
R38	10	15.375	ind[4]	0.277	1.53	0.767	8.7	10.9	0.0	***
R39	10	11.601	ind[3]	0.556	1.42	0.781	9.3	10.6	10.7	***
R3A	11	17.751		0.000	0.00	0.062	28.3	32.4	43.6	35.5
R3B	12	15.323		0.000	0.00	0.129	9.0	12.7	19.2	24.0
R41	12	34.7 79	ind[4]	0.809	4.62	0.850	5.1	6.1	7.9	6.4
R42	12	42.473	ind[3]	1.831	2.45	0.8 79	5.0	6.8	7.4	10.3
R45	12	43.502	ind[1]	2.654	3.44	0.869	4.8	8.4	8.2	4.2
R47	11	39.676		0.000	0.00	0.812	6.5	8.1	6.3	6.0
R51	11	33.128	ind[1]	4.021	6.24	0.917	4.8	9.1	0.9	2.2
R52	11	33.427	ind[2]	1.063	3.26	0.685	11.3	16.1	15.1	22.5
R53	10	29.065	ind[1]	3.986	3.95	0.783	11.5	19.4	3.6	***
R60	12	27.788	ind[1]	3.630	3.66	0.685	19.1	16.9	20.1	22.6
R7A	9	34.492	ind[3]	1.862	1.96	0.623	5.1	6.5	***	***
R7B	10	25.783	ind[1]	0.749	1.00	0.189	6.7	6.7	2.8	***
R80	11	23.223	ind[3]	2.075	2.47	0.531	10.3	10.9	9.8	11.7
R90	12	30.993	ind[2]	0.363	1.24	0.819	9.8	13.9	3.0	7.2
RB1	10	12.426		0.000	0.00	0.333	17.4	31.6	50.4	***
RB2	10	17.859		0.000	0.00	0.597	6.0	21.2	3.2	***
RB3	10	20.385		0.000	0.00	0.372	1.3	19.7	8.6	***
RB4	10	16.868		0.000	0.00	0.686	6.9	23.7	56.1	***
RB5	10	15.020		0.000	0.00	0.518	4.6	29.3	15.3	***
RB6	10	17.034		0.000	0.00	0.590	9.0	28.8	5.8	***

Appendix 9 (continued). Summary output Nuts-1. Explanation abbreviations: page 85.

Oilseed rape P0

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R11	11	2.921		0.000	0.00	0.357	16.6	16.1	17.1	22.2
R12	11	2.674		0.000	0.00	0.3 79	11.6	11.6	13.7	18.7
R13	11	2.603		0.000	0.00	0.902	5.5	6.1	7.2	3.1
R15	11	2.648		0.000	0.00	0.834	8.9	8.5	3.1	5.5
R16	11	2.500		0.000	0.00	0.876	6.8	8.8	3.2	1.8
R17	11	2.452		0.000	0.00	0.753	6.7	9.9	3.9	4.4
R18	11	2.586		0.000	0.00	0.899	5.5	5.9	10.2	5.2
R19	11	2.742		0.000	0.00	0.850	6.6	7.2	11.3	12.2
R1A	11	2.357		0.000	0.00	0.636	10.8	13.0	21.0	25.2
R21	11	2.805		0.000	0.00	0.628	19.6	18.9	20.6	24.0
R22	11	2.475		0.000	0.00	0.674	19.0	18.8	18.7	23.0
R23	11	2.629		0.000	0.00	0.749	15.0	15.5	7.6	10.9
R24	11	2.565		0.000	0.00	0.597	16.7	17.2	13.4	17.5
R25	11	2.417		0.000	0.00	0.596	19.4	20.3	24.3	28.0
R26	11	2.205		0.000	0.00	0.336	19.0	21.0	19.3	30.3
R27	11	2.243		0.000	0.00	0.225	28.2	27.5	27.4	27.1
R28	11	2.066		0.000	0.00	0.390	13.5	14.0	12.7	19.4
R32	8	2.146		0.000	0.00	0.082	36.4	42.4	***	***
R33	10	2.432		0.000	0.00	0.405	12.5	14.5	13.8	***
R35	9	2.360		0.000	0.00	0.104	36.5	38.6	***	***
R41	11	3.026		0.000	0.00	0.421	10.5	10.8	9.3	1.8
R42	11	3.190		0.000	0.00	0.591	10.2	10.6	15.9	22.5
R45	11	2.611		0.000	0.00	0.001	20.8	21.3	22.1	9.4
R47	10	2. 790		0.000	0.00	0.100	13.4	13.7	10.6	***
R51	11	2.448		0.000	0.00	0.245	13.6	30.9	24.9	17.3
R52	11	2.836		0.000	0.00	0.150	14.1	14.9	7.4	8.7

Appendix 9 (continued). Summary output Nuts-1. Explanation abbreviations: page 85.

Oilseed rape P5

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R11	11	2.921		0.000	0.00	0.357	13.4	19.7	17.1	22.2
R12	11	2.674		0.000	0.00	0.3 79	9.4	14.5	13.7	18.7
R13	11	2.603		0.000	0.00	0.902	4.7	6.1	7.2	3.1
R15	11	2.648		0.000	0.00	0.834	8.9	8.5	3.1	5.5
R16	11	2.500		0.000	0.00	0.876	6.8	8.8	3.2	1.8
R17	11	2.452		0.000	0.00	0.753	6.7	9.9	3.9	4.4
R18	11	2.586	ind[1]	0.110	0.86	0.908	5.5	6.2	10.2	5.2
R19	11	2.742	ind[1]	0.230	1.55	0.884	6.6	6.8	11.3	12.2
R1A	11	2.357	ind[4]	0.078	1.95	0.754	10.3	12.8	21.0	25.2
R21	11	2.805		0.000	0.00	0.628	19.6	18.9	26.4	21.9
R22	11	2.475		0.000	0.00	0.674	19.0	18.8	18.7	23.0
R23	11	2.629	ind[1]	0.655	1.38	0. 797	14.9	16.8	7.6	10.9
R24	11	2.565		0.000	0.00	0.597	16.7	17.2	13.4	17.5
R25	11	2.417		0.000	0.00	0.596	19.4	21.7	24.1	13.3
R26	11	2.205		0.000	0.00	0.336	14.6	23.9	19.3	30.3
R27	11	2.243		0.000	0.00	0.225	28.2	27.5	27.4	27.1
R28	11	2.066	ind[1]	0.555	2.40	0.646	9.3	12.2	10.4	14.8
R32	8	2.146		0.000	0.00	0.082	36.4	42.4	***	***
R33	10	2.432		0.000	0.00	0.405	12.5	17.1	13.8	***
R35	9	2.360		0.000	0.00	0.104	36.5	38.6	***	***
R41	11	3.026		0.000	0.00	0.421	10.5	10.8	9.3	1.8
R42	11	3.190	ind[3]	0.065	1.65	0.695	9.6	12.1	15.9	22.5
R45	11	2.611		0.000	0.00	0.001	20.8	21.3	22.1	9.4
R47	10	2. 790		0.000	0.00	0.100	13.4	13.7	10.6	***
R51	11	2.448		0.000	0.00	0.245	13.6	30.9	24.9	17.3
R52	11	2.836		0.000	0.00	0.150	14.1	14.9	7.4	8.7

Appendix 9 (continued). Summary output Nuts-1. Explanation abbreviations: page 85.

Sunflower P0

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R21	10	2.407		0.000	0.00	0.236	16.6	22.5	18.9	***
R22	10	2.174		0.000	0.00	0.774	10.5	11.7	9.3	***
R24	10	2.310		0.000	0.00	0.833	13.5	18.3	14.3	***
R25	10	2.103		0.000	0.00	0.485	18.5	19.5	21.9	***
R26	10	1.961		0.000	0.00	0.359	21.8	22.9	35.1	***
R27	10	2.230		0.000	0.00	0.801	10.6	11.5	13.9	***
R28	10	2.070		0.000	0.00	0.185	11.6	15.6	25.2	***
R33	10	2.818		0.000	0.00	0.208	22.7	23.0	28.2	***
R35	10	2.125		0.000	0.00	0.290	15.7	16.1	8.2	***
R36	10	2.217		0.000	0.00	0.073	18.0	21.2	16.6	***
R37	8	2.464		0.000	0.00	0.689	22.2	18.9	***	***
R38	9	1.924		0.000	0.00	0.101	20.6	22.4	***	***
R39	9	1.846		0.000	0.00	0.000	40.0	43.7	***	***
R3A	9	0.998		0.000	0.00	0.087	24.3	25.7	***	***
RB2	10	1.141		0.000	0.00	0.757	12.9	13.4	6.5	***
RB3	10	0.630		0.000	0.00	0.000	30.9	30.1	16.3	***
RB4	10	0.669		0.000	0.00	0.508	16.8	17.6	13.9	***
RB5	10	1.092		0.000	0.00	0.710	22.6	22.2	18.9	***
RB6	10	0.955		0.000	0.00	0.592	29.4	29.1	27.6	***

Sunflower P5

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R21	10	2.407		0.000	0.00	0.236	16.6	22.5	18.9	***
R22	10	2.174		0.000	0.00	0.774	10.5	16.5	37.1	***
R24	10	2.310		0.000	0.00	0.833	13.5	20.6	14.3	***
R25	10	2.103	ind[4]	0.214	3. 79	0.831	11.5	17.5	41.6	***
R26	10	1.961	ind[4]	0.309	4.97	0.859	10.4	15.2	4.9	***
R27	10	2.230	ind[2]	0.259	5.93	0.967	4.1	6.0	1.1	***
R28	10	2.070	ind[2]	0.548	4.18	0.767	6.3	9.3	10.9	***
R33	10	2.818		0.000	0.00	0.208	22.3	24.8	28.2	***
R35	10	2.125	ind[4]	0.185	1.25	0.419	16.4	16.9	3.3	***
R36	10	2.217		0.000	0.00	0.073	18.0	22.2	16.6	***
R37	8	2.464		0.000	0.00	0.689	22.2	20.2	***	***
R38	9	1.924		0.000	0.00	0.101	20.6	26.4	***	***
R39	9	1.846	ind[3]	0.823	1.52	0.277	36.7	55.0	***	***
R3A	9	0.998		0.000	0.00	0.087	24.3	28.1	***	***
RB2	10	1.141	ind[2]	0.237	1.49	0.815	12.9	14.2	1.6	***
RB3	10	0.630		0.000	0.00	0.000	30.9	30.8	16.3	***
RB4	10	0.669	ind[4]	0.067	2.02	0.690	14.4	19.2	11.1	***
RB5	10	1.092		0.000	0.00	0.710	22.6	22.2	18.9	***
RB6	10	0.955		0.000	0.00	0.592	29.4	37.9	58.6	***

Appendix 10. Summary output Nuts-0.

Explanation abbreviations: page 85.

Wheat P0

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R1	15	5.440		0.000	0.00	0.884	6.1	5.8	8.3	6.5
R2	15	5.200		0.000	0.00	0.788	8.8	8.1	10.3	11.2
R3	15	2.689		0.000	0.00	0.227	6.9	7.3	9.8	8.6
R4	15	6.651		0.000	0.00	0.699	7.5	8.6	10.8	12.2
R5	15	5.535		0.000	0.00	0.761	10.6	10.0	12.8	12.3
R6	15	3.548		0.000	0.00	0.595	12.3	15.1	10.0	10.4
R7	15	5.849		0.000	0.00	0.654	10.4	11.4	15.6	18.7
R8	15	6.018		0.000	0.00	0.740	13.2	11.6	17.7	21.6
R9	16	5.954		0.000	0.00	0.650	10.9	9.9	14.4	14.7
RA	12	2.529		0.000	0.00	0.023	13.1	15.9	10.9	13.2
RB	15	1.998		0.000	0.00	0.558	18.6	17.8	25.5	23.5

Wheat P5

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R1	15	5.440		0.000	0.00	0.884	6.1	6.0	8.8	6.5
R2	15	5.200	ind[3]	0.293	2.63	0.866	7.7	7.0	10.5	12.4
R3	15	2.689		0.000	0.00	0.227	6.9	8.2	10.5	9.7
R4	15	6.651	ind[1]	0.383	1.71	0.758	7.5	9.2	10.9	11.3
R5	15	5.535		0.000	0.00	0.761	10.6	10.0	13.8	9.3
R6	15	3.548	ind[2]	0.257	2.95	0.765	12.3	15.5	11.1	15.3
R7	15	5.849	ind[4]	0.146	1.27	0.694	10.4	12.7	16.8	20.2
R8	15	6.018		0.000	0.00	0.740	13.2	12.9	19.4	23.6
R9	16	5.954	ind[2]	0.467	2.38	0.756	7.9	9.1	14.1	17.1
RA	12	2.529	ind[4]	0.121	2.84	0.486	9.1	12.1	6.4	10.7
RB	15	1.998	ind[2]	0.164	1.90	0.660	18.6	20.2	32.3	45.4

Appendix 10 (continued). Summary output Nuts-0. Explanation abbreviations: page 85.

Maize P0

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R1	15	6.197		0.000	0.00	0.600	10.0	9.5	11.7	11.6
R2	10	6.382		0.000	0.00	0.751	4.9	5.7	7.0	***
R3	15	6.897		0.000	0.00	0.837	4.1	3.9	4.7	5.5
R4	11	4.348		0.000	0.00	0.000	30.5	30.9	9.6	17.2
R5	15	6.743		0.000	0.00	0.687	8.5	8.4	10.3	10.5
RA	11	7.613		0.000	0.00	0.676	11.5	16.8	24.6	28.4
RB	15	5.305		0.000	0.00	0.916	7.0	6.4	7.4	9.5

Maize P5

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R1	15	6.197	ind[4]	0.239	3.08	0.776	5.6	7.7	8.4	10.8
R2	10	6.382	ind[2]	0.165	3.29	0.902	3.0	4.2	3.8	***
R3	15	6.897	ind[4]	0.118	2.57	0.895	2.7	3.8	6.1	6.4
R4	11	4.348	ind[1]	1.224	3.35	0.584	21.9	26.6	20.5	31.4
R5	15	6.743	ind[4]	0.095	1.59	0.741	5.9	11.8	13.6	10.6
RA	11	7.613	ind[4]	0.284	1.11	0.719	11.3	18.0	30.9	28.6
RB	15	5.305		0.000	0.00	0.916	7.0	7.4	9.1	12.1

Barley P0

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R1	15	4.567		0.000	0.00	0. 790	6.2	5.7	7.4	7.5
R2	15	4.396		0.000	0.00	0.842	8.5	7.6	9.9	6.7
R3	15	3.096		0.000	0.00	0.826	7.3	7.1	11.0	9.9
R4	15	4.952		0.000	0.00	0.387	11.2	10.3	13.0	15.1
R5	15	5.269		0.000	0.00	0.726	9.3	9.1	8.7	7.0
R6	15	3.333		0.000	0.00	0.225	15.9	17.2	6.4	5.5
R7	15	4.567		0.000	0.00	0.632	7.9	8.6	10.9	12.9
R8	15	4.955		0.000	0.00	0.657	7.7	8.7	9.7	9.5
R9	16	4.298		0.000	0.00	0.650	11.9	9.8	12.0	9.4
RA	12	2.304		0.000	0.00	0.011	12.8	14.4	12.2	15.9
RB	15	2.070		0.000	0.00	0.121	21.5	21.6	28.7	27.4

Barley P5

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R1	15	4.567	ind[4]	0.206	1.93	0.840	6.2	5.9	7.3	7.1
R2	15	4.396	ind[4]	0.356	4.31	0.938	8.5	5.8	8.6	5.6
R3	15	3.096		0.000	0.00	0.826	7.3	9.3	15.7	9.8
R4	15	4.952	ind[1]	0.634	2.24	0.568	11.2	9.3	13.6	11.6
R5	15	5.269		0.000	0.00	0.726	6.8	10.1	10.4	5.4
R6	15	3.333	ind[2]	0.572	3.72	0.640	15.9	12.8	5.8	8.2
R7	15	4.567		0.000	0.00	0.632	7.9	9.4	11.9	13.4
R8	15	4.955	ind[1]	0.486	2.03	0.744	7.7	8.6	12.8	10.5
R9	16	4.298		0.000	0.00	0.650	11.9	10.2	12.0	9.4
RA	12	2.304		0.000	0.00	0.011	12.8	18.8	29.7	15.4
RB	15	2.070	ind[4]	0.358	5.15	0.726	10.5	12.8	18.8	25.7

Appendix 10 (continued). Summary output Nuts-0. Explanation abbreviations: page 85.

Rice P0

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R2	15	4.422		0.000	0.00	0.609	11.9	15.8	13.7	12.3
R3	15	5.483		0.000	0.00	0.287	4.6	10.7	4.7	8.8
RA	9	5.889		0.000	0.00	0.681	7.6	9.9	***	***
RB	15	6.093		0.000	0.00	0.013	5.3	5.2	4.2	4.9

Rice P5

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R2	15	4.422	ind[1]	0.554	2.35	0.732	9.7	14.0	11.7	7.7
R3	15	5.483		0.000	0.00	0.287	4.6	10.7	4.8	9.4
RA	9	5.889	ind[1]	0.695	2.24	0.826	6.0	9.3	***	***
RB	15	6.093		0.000	0.00	0.013	3.4	6.9	4.2	4.9

Sugar beet P0

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R1	11	48.857		0.000	0.00	0.327	9.1	9.5	6.3	1.5
R2	11	54.088		0.000	0.00	0.866	5.6	7.3	3.9	1.1
R3	10	48.385		0.000	0.00	0.152	9.3	9.1	4.2	***
R4	8	54. 799		0.000	0.00	0.139	9.0	11.0	***	***
R5	11	51.466		0.000	0.00	0.353	8.3	9.4	5.8	5.8
R6	11	45.628		0.000	0.00	0.320	26.3	31.0	30.7	36.9
R7	11	38.095		0.000	0.00	0.505	12.5	14.4	10.5	15.7
R8	11	42.507		0.000	0.00	0.004	12.3	11.3	6.9	5.3
R9	12	43.730		0.000	0.00	0.546	11.3	10.4	10.4	11.2
RA	8	60.662		0.000	0.00	0.233	5.9	8.5	***	***
RB	10	37.778		0.000	0.00	0.801	6.6	7.1	12.8	***

Sugar beet P5

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R1	11	48.857		0.000	0.00	0.327	9.1	9.5	6.3	1.5
R2	11	54.088	ind[2]	1.173	2.60	0.927	5.6	5.7	6.3	8.0
R3	10	48.385	ind[3]	2.201	4.13	0.753	4.9	6.0	9.1	***
R4	8	54. 799	ind[2]	2.993	1.98	0.518	7.1	11.7	***	***
R5	11	51.466		0.000	0.00	0.353	8.3	9.7	13.5	5.8
R6	11	45.628		0.000	0.00	0.320	26.3	31.0	30.7	36.9
R7	11	38.095		0.000	0.00	0.505	10.3	14.4	10.5	15.7
R8	11	42.507	ind[3]	3.098	2.80	0.498	6.3	11.2	12.4	6.1
R9	12	43.730	ind[2]	2.285	3.84	0.828	7.4	9.1	12.1	13.0
RA	8	60.662	ind[3]	1.483	1.97	0.568	5.9	8.3	***	***
RB	10	37.778		0.000	0.00	0.801	5.9	7.9	12.8	***

Appendix 10 (continued). Summary output Nuts-0. Explanation abbreviations: page 85.

Potato P0

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R1	11	30.910		0.000	0.00	0.743	8.8	8.7	7.0	6.8
R2	10	29.998		0.000	0.00	0. 790	12.5	14.6	11.5	***
R3	11	18.415		0.000	0.00	0.450	10.7	10.1	8.8	2.9
R4	11	37.978		0.000	0.00	0.727	7.4	7.6	6.6	8.5
R5	11	32.953		0.000	0.00	0.462	8.8	15.4	11.3	12.2
R6	11	27.405		0.000	0.00	0.203	19.2	27.7	10.9	13.4
R7	11	32.302		0.000	0.00	0. 797	7.0	9.8	11.5	17.9
R8	11	23.223		0.000	0.00	0.174	13.1	12.4	13.4	10.4
R9	12	30.993		0.000	0.00	0.789	9.8	12.0	5.3	9.7
RA	8	17.170		0.000	0.00	0.724	5.9	5.3	***	***
RB	10	15.049		0.000	0.00	0.534	6.3	22.9	22.6	***

Potato P5

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R1	11	30.910	ind[1]	2.727	3.51	0.899	4.8	7.6	8.4	12.0
R2	10	29.998	ind[1]	2.322	3.51	0.924	6.2	13.1	2.3	***
R3	11	18.415	ind[1]	0.705	1.38	0.555	10.4	9.8	8.8	2.9
R4	11	37.978	ind[4]	0.696	4.20	0.915	4.3	4.9	5.7	0.3
R5	11	32.953	ind[1]	3.655	4.97	0.868	5.7	10.1	3.2	6.4
R6	11	27.405	ind[1]	3.871	3.54	0.690	19.2	17.7	21.2	0.8
R7	11	32.302	ind[4]	0.632	2.50	0.886	7.0	7.8	7.9	11.5
R8	11	23.223	ind[3]	2.075	2.47	0.531	10.3	10.9	9.8	11.7
R9	12	30.993	ind[2]	0.363	1.24	0.819	9.8	13.9	3.0	7.2
RA	8	17.170	ind[3]	0.677	3.35	0.915	5.9	3.5	***	***
RB	10	15.049		0.000	0.00	0.534	6.3	22.9	22.6	***

Appendix 10 (continued). Summary output Nuts-0. Explanation abbreviations: page 85.

Oilseed rape P0

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R1	11	2.748		0.000	0.00	0.745	8.4	8.0	8.3	11.6
R2	11	2.455		0.000	0.00	0.672	16.9	17.1	18.1	22.3
R3	11	2.305		0.000	0.00	0.266	14.7	15.2	9.7	11.4
R4	11	3.089		0.000	0.00	0.649	7.8	7.3	6.9	8.8
R5	11	2.6 79		0.000	0.00	0.374	13.7	21.3	5.8	0.6
R7	11	2.823		0.000	0.00	0.591	12.0	15.7	18.1	24.8

Oilseed rape P5

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R1	11	2.748		0.000	0.00	0.745	8.4	8.0	8.3	11.6
R2	11	2.455		0.000	0.00	0.672	16.9	17.1	18.1	22.3
R3	11	2.305	ind[1]	0.244	0.49	0.287	14.7	15.3	9.7	11.4
R4	11	3.089		0.000	0.00	0.649	7.8	7.3	6.9	8.8
R5	11	2.6 79		0.000	0.00	0.374	13.7	21.3	5.8	0.6
R7	11	2.823		0.000	0.00	0.591	12.0	15.7	18.1	24.8

Sunflower P0

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R2	10	2.088		0.000	0.00	0.622	14.6	14.9	12.8	***
R3	10	2.054		0.000	0.00	0.267	16.5	16.5	6.8	***
RB	10	0.809		0.000	0.00	0.643	21.3	20.9	23.1	***

Sunflower P5

nuts	nobs	mean	sel	coef	t	rsq	res	jack	oya	tya
R2	10	2.088	ind[4]	0.197	3.22	0.848	9.0	14.2	29.8	***
R3	10	2.054	ind[4]	0.206	1.68	0.478	15.1	14.1	12.0	***
RB	10	0.809	ind[4]	0.120	1.65	0.743	19.4	24.9	23.1	***