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Agricultural Systems 85 (2005) 59–81
AGRICULTURAL SYSTEMS
www.elsevier.com/locate/agsy

Comparison of adaptive techniques to predict crop yield response under varying soil and land management conditions

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Received 8 May 2003; received in revised form 1 June 2004; accepted 22 June 2004

Abstract

Decision-making processes in agriculture often require reliable crop response models to assess the impact of specific land management. While process-based models are often preferred over empirical ones in current modelling communities, empirical crop growth models can play an important role in identifying the hidden structure of crop growth processes relating to a wide range of land management options. This study investigates the potential of predicting crop yield responses under varying soil and land management conditions by applying three different adaptive techniques: general linear models (GLMs), artificial neural networks (ANNs), and regression trees (RTs). The crop yield data used in this research consist of 720 maize yield indices from 11 different land management trials in southern Uganda. GLM showed the poorest results in terms of modelling accuracy, prediction accuracy, and model uncertainty, which might suggest its inability to model the non-linear causal relationships present in complex soil–land and crop-management interactions. The other two non-parametric adaptive models show significantly higher prediction accuracy than GLM. RT is the most robust technique for predicting crop yield at the study site. ANN is also a promising tool for predicting crop yield and offers insight into the causal relationships through the use of sensitivity analyses, but the complex parameterization and optimum model structure require

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0308-521X/$ - see front matter
doi:10.1016/j.agsy.2004.06.021

further attention. The three adaptive techniques compared in this research showed different advantages and disadvantages. When these methods are used together, valuable information can be provided on crop responses, and more reliable crop growth models may result.

Keywords: Artificial neural networks; Regression tree; General linear model; Crop simulation model; Decision-support system

1. Introduction

In recent years, crop growth models have become increasingly important as major components of agriculture-related decision-support systems (Jones, 1993; Jame and Cutforth, 1996; Stephens and Middleton, 2002). Crop growth is an extremely complex process in both time and space. Changes in weather conditions influence soil moisture, plant root uptake and water- and temperature-related stress on plants. The depletion and replenishment of soil nutrients over time and the occurrence of pests and diseases lead to significant changes in crop yields. At the same time, different parts of the landscape experience different water availability and soil nutrient status because of pedological heterogeneity and lateral water-nutrient flows related to the shape of the terrain. With the increasing awareness of such spatial and temporal heterogeneity, site-specific land management has gained importance for maximizing crop yield potential, and at the same time for minimizing soil degradation (Burrough, 1993; Van Ranst and Vanmechelen, 1995). The success of such site-specific land management decisions relies heavily on the understanding of the complex relationships between environmental conditions, management practices, and resulting crop yield variability (Matthews, 2002a,b).

There are two distinct modelling approaches, empirical and process models, for identifying crop yield responses to given environmental conditions and management options, even though they are not mutually exclusive (Jame and Cutforth, 1996). Empirical models attempt to determine functional relationships between crop yield and soil–land management factors using either an existing or a specially designed agronomic experiment. Regression or correlation analyses are generally used to characterize the statistical relationship between controlled variables and crop yield. Technologically, empirical crop growth models are relatively simple to build or develop, but these models cannot take account of temporal changes in crop yields without long-term field experiments (Jame and Cutforth, 1996). Furthermore, the derived functional equation is locally specific, and it is thus difficult to extrapolate to other areas unless environmental conditions are similar.

Process-based crop growth models are built using mathematical equations to model quantitatively plant–soil–atmospheric interactions (Godwin and Vlek, 1985; Sinclair and Seligman, 1996; Matthews, 2002a,b). Because process models explicitly include plant physiology, agro-climatic conditions, and biochemical processes, these models are supposed to be able to simulate both temporal and spatial dynamics of crop yields. Consequently, the ability to include temporal changes of crop yields

and extrapolation potentials is much greater than in the case of empirical models (Jame and Cutforth, 1996). While process-based modelling approaches are often preferred to empirical ones, the high demands of technological sophistication and demanding calibration–verification procedures are the main limiting factors for wider application (Sinclair and Seligman, 1996; Stephens and Middleton, 2002). The main process components for the major crops have already been developed, but they require careful calibration and verification for local crop varieties and different environmental conditions. Especially when crop growth models are used for agricultural decision-making processes, it is essential to include a wide range of input options that are relevant to policy and agricultural questions (Stephens and Middleton, 2002). Such calibration and verification issues are especially problematic for developing countries, where the necessary technological and financial resources are not readily available (Bouman et al., 1996; Stephens and Middleton, 2002). Consequently, parameterization often comes from previous research conducted in different environmental conditions or from expert opinion. The uncertainty associated with such parameterization may greatly decrease the validity of model outputs and the reliability of model application (Penning de Vries et al., 1989; Aggarwal, 1995; Bouman et al., 1996; Stephens and Middleton, 2002).

In view of the fact that even the most deterministic models still rely heavily on empirical functional relationships to varying degrees (Jame and Cutforth, 1996), empirical crop growth models may play an important role as explanatory tools for identifying the hidden structure of crop growth processes. They may even offer a more reliable method of investigating crop response than poorly calibrated process models when the necessary data are available. The main limitation of traditional regression-based empirical models is the lack of non-linear modelling ability, which is apparent in crop responses to agro-ecological conditions. This may be the case particularly when various land management practices are applied under different scenarios.

Some adaptive and non-parametric models have been recently introduced in environmental science for predictive purposes. Artificial neural networks and regression trees are the most widely used numerical techniques. An important characteristic of those two techniques is their adaptive nature with regard to learning by examples to solve problems. They also allow an illustration of complex and non-linear relationships without rigorous assumptions regarding the distribution of samples (Bishop, 1995; Breiman et al., 1984). These methods are gaining popularity for research areas where there is little or incomplete understanding of the problem to be solved, but where training data are available.

This study investigates the possibility of predicting crop response under varying soil and land management conditions by applying three different adaptive techniques: general linear models (GLMs), artificial neural networks (ANNs), and regression trees (RTs). GLM is related to traditional linear regression models that have been widely used in empirical crop modelling. GLM allows the use of categorical variables together with continuous-ratio variables and interactions among input variables. Unlike its popularity in earth sciences such as hydrology and soil science (e.g., Schultz et al., 2000; Dawson and Wilby, 2001; Park and Vlek, 2002), the

application of ANN to crop growth modelling has been rather limited. Drummond et al. (2000) compare ANN with linear and non-linear regression methods (multiple stepwise regression and progression pursuit regression) to predict crop yield based on soil, topography, and climatic variables in central Missouri, USA. They conclude that the generalization ability of ANN is higher than that of other linear and non-linear regression methods (multiple stepwise regression and progression pursuit regression). They emphasize that extensive seasonal data are required to model the temporal variation of crop yield. No previous application of RT for the purpose of crop growth modelling is known to the authors.

We obtained farm trial data for two cropping seasons in southern Uganda. The experiment was designed to identify the best technological method for increasing agricultural productivity in smallholder farming communities. Eleven land management inputs were applied with basic soil attributes. In this research the farm trial data set was analyzed with regard to the following technical aspects of the methods used: (1) the overall performance of GLM, ANN, and RT as empirical modelling tools for predicting crop yield; (2) data efficiency of these three empirical models; (3) cross-seasonal predictability, and (4) ability to identify causal relationships for crop response to given soil and land management conditions.

2. Study area and field methods

The on-farm experiment was carried out in three villages in the Imanyiro sub-county of Iganga District in Eastern Uganda (0°35′N, 32°29′E). The district lies at an altitude of 1070–1161 m above sea level and covers an area of about 11 km^2. The overall topography is a gently rolling landscape that has an average slope gradient of 3°, ranging from 0.5° on the summit to 12° slope on shoulder and back-slope positions. Geologically, the area belongs to the Buganda Surface, which covers the southern part of Uganda and consists of granites, gneisses and schists of the Precambrian age (Harrop, 1970). The Buganda surface is part of the Ugandan basement complex and a product of long-term weathering processes.

The soils of the study site can be classified as Oxisols (USDA Soil Taxonomy) or Ferralsols (FAO classification). The soils are highly weathered and have a sandy clay loam to sandy clay texture. Hydromorphic soils can be found in the valley. On erosion-affected parts of the hillslope where the A horizon has been completely removed, the plinthite-rich B horizon is exposed to the surface and hardens when exposed to air, which leads to the development of laterite crusts. Most soils have an organic matter (OM) content ranging from 1.1% to 3.1% and are deficient in N and P (Wortmann and Kaizzi, 1998).

The climate regime is characterized by erosive tropical rainfall that may cause various erosion problems. The rainfall seasonality is bimodal with rainy seasons from March until May and from September until November. The average annual precipitation totals to 1319 mm, with monthly values ranging from 61 mm during the dry season to 193 mm during the rainy seasons (Brunner et al., 2004).

Small-scale farmers cultivate a wide range of food crops, such as maize, beans, sweet potato, cassava, groundnuts and several vegetables and fruits at a subsistence level. The average size of a small-scale farmer's field is about 2.5 ha (African Highland Initiative, 1997). The farming systems are biologically and agronomically diverse with small but numerous parcels having varying cropping associations, planting dates, etc. Field preparation, such as seeding, weeding and harvesting, is performed by employing family labour (Esilaba et al., 2001).

2.1. Crop yield experiment

The crop yield data used for this research consist of 720 agronomic trials (see Tables 1 and 2). The on-farm experiments were conducted under the framework of a Participatory Learning and Action Research (PLAR) process in a collaboration between the Centro Internacional de Agricultura Tropical (CIAT) and the National Agricultural Research Organisation (NARO), Uganda (Defoer et al., 2000). Twenty farmers representing three soil fertility management classes were chosen as test farmers for intensive monitoring of the on-farm experimentation (Esilaba et al., 2001). Farmers designed 11 different experiments including no specific land management, and they designed procedures for monitoring and evaluation under the participatory approach. Even though the experiment was conducted under researchers' supervision, we expected that such participatory research might have had larger errors in the estimation of actual crop yields than experiments conducted in research plots by trained scientists (Wortmann and Kaizzi, 1998).

Table 1
The descriptive statistics of soil attributes and crop yield information used for this study ($n = 285$)

Variables used	Soil properties	Unit	Mean	Minimum	Maximum	SD	Skewness
pHl[a]	Soil pH		5.36	4.00	5.90	0.45	−1.59
OM	Organic matter content	%	2.72	1.30	3.60	0.53	−0.69
Ns	N-Total	g/kg	0.09	0.04	0.13	0.02	0.16
Ps	Bray P	g/kg	3.58	0.07	22.35	5.29	−0.70
KsL[a]	Available K	g/kg	22.24	0.47	34.43	7.63	2.43
Na	Available Na	g/kg	5.60	0.24	8.65	1.82	−0.74
Ca	Available Ca	g/kg	49.68	6.76	74.32	14.99	−0.89
Mg	Available Mg	g/kg	26.40	6.07	41.57	8.63	−0.38
SANDSQ[b]	Sand content	%	64.99	50.56	84.92	9.03	0.31
CLAY	Clay content	%	25.25	8.52	36.88	8.60	−0.33
SILT	Silt content	%	9.77	6.20	18.20	2.68	1.31
CY[a]	Cob yield after harvest	kg/ha	2216.67	42.06	10256.93	2171.20	1.21
GY[a]	Grain yield after harvest	kg/ha	3255.35	76.53	9395.40	1904.57	0.64
TB[a]	Total biomass after harvest	kg/ha	9050.13	240.45	31716.07	5178.74	0.86

[a] Log_{10} transformed variable was used for the analyses.
[b] Square root transformed data were used for the analyses.

Table 2
Land management factors used in this research and the occurrence of each land management for two cropping seasons (February–March 2000, season A) and (August–December 2000, season B)

Variables used	Treatment[a]	Season A (n = 378)		Season B (n = 352)	
		Occurrence	%	Occurrence	%
Control	No treatment	99	26.2	92	26.1
FYM	Farmyard manure (10 ton/ha)	9	2.4	9	2.5
MRP	Minjingu rock phosphate (100 kg/ha)	41	10.8	36	10.2
BRP	Busumbu rock phosphate (100 kg/ha)	21	5.5	18	5.1
TSP	Triple SuperPhosphate (100 kg/ha)	41	10.8	38	10.8
Blend	Busumbu blend (90% BRP and 10% TSP) (100 kg/ha)	21	5.5	18	5.1
Pre.Pac	N (urea at 40 kg N ha^{-1}) and P fertilisers (MRP at 100 kg P ha-1), rhizobium inoculant, seed adhesives and lime pellets	20	5.3	17	4.8
GM	Green Manure (10 ton/ha)	64	16.9	64	18.1
N	Inorganic N fertilizer (100 kg/ha)	20	5.3	20	5.7
NP	Inorganic N (100 kg/ha) and P fertilizer (100 kg/ha)	21	5.5	20	5.7
NPK	Inorganic N(100 kg/ha), P(100 kg/ha), K (100 kg/ha) fertilizer	21	5.5	20	5.7

[a] The dose of each treatment is given in the parenthesis.

Maize (*Zea mais*, *variety Longe 1*) yield indices under 11 different land management practices were used for model comparison (see Table 2 for details). Crop yield was measured by three indices (cob yield, grain yield, and total biomass). The experiments were first carried out in February–March 2000 (season A) and continued in August–December 2000 (season B). Land management varied from a minimum of two treatments to a maximum of five treatments in each farmer's field. In total, 378 and 352 trial results are available for seasons A and B, respectively. The frequency of each land management in each cropping season is given in Table 2. For some trials, the number of cases is small (e.g. 9 for farm manure application). In statistical modelling approaches, such a small number of cases may reduce the significance of established statistical procedures. However, we retained them in the modelling exercise, because the main objective of this research was to compare the performance of different models for the given research questions.

Prior to the farm trials, soil samples were collected from the test farmers' plots at 0–20 cm depth. A maximum of five samples from each plot were collected and combined together to measure soil pH, N, P, K, Ca, Mg, Na, and organic matter content. In total, 285 soils were collected and analyzed for different plots. All soil attributes except P were measured using the methods proposed by Foster (1971). Available Bray P was measured following the method of Okalebo et al. (1993). The Kjeldahl method was used to measure total N in soils. Table 1 contains the general descriptive summary of each soil parameter. Full details of the results of soil analyses may be found in Esilaba et al. (2001).

3. Statistical models

3.1. Adaptive crop prediction models

The three adaptive techniques, GLM, ANN and RT, have different theoretical assumptions and development pathways. Detailed reviews of these methods are beyond the scope of this paper, so this section gives only a brief summary for each technique. One common advantage of these techniques is their ability to include both categorical and continuous variables as predictors. Because the predictor variables in this research are a mixture of categorical (land management) and continuous variables (soil attributes), the multivariate normality assumption is not upheld.

3.1.1. Artificial neural networks

The ANN method was initiated in artificial intelligence research that attempted to mimic the capacity to learn through biological neural systems. Many different types of neural nets are available and their structure is described in Bishop (1995), Ripley (1996) and Principe et al. (2000). The ANN structure used in this paper is a multilayer perceptron (MLP) that is the most popular neural network structure in ecological modelling and soil science (Schultz et al., 2000; Dawson and Wilby, 2001; Park and Vlek, 2002). In order to introduce non-linearity during the ANN training, the hyperbolic tangent function, which is the most popular activation function among many others, was used. Also, momentum, as a learning rule, was used without further investigation of its influence on model performance. More detailed investigations on the influence of different network structures and internal variables on crop simulation are necessary.

ANN requires the determination of the number of hidden nodes (process elements) for each hidden layer. There is no theory to date for determining the optimum value for these internal variables of an ANN model to approximate any given function (Bishop, 1995; Maier and Dandy, 1998). In this research, the number of hidden nodes was determined using a genetic algorithm to optimize model performance (Principe et al., 2000). The genetic algorithm was applied to a set of data containing 450 training, 100 cross-validation, and 170 testing data after a randomization of data from both seasons (A + B). This procedure was repeated five times, and 26 and 17 hidden nodes were set for the first and second hidden layers, respectively. The same ANN structure was used throughout the analyses.

3.1.2. General linear model

The GLM may be considered as a special form of ANN that does not have any hidden layers generating non-linearity during the training (McCullagh and Nelder, 1989). GLM differs from the well-known multiple regression model in two main respects. First, the distribution of the dependent or response variable does not have to be continuous. GLM allows categorical or nominal variables as predictors by recoding them into a number of dichotomous variables. Second, unlike multiple regressions which are intrinsically uni-variate methods, GLM

allows linear combinations of multiple dependent variables. As one might easily anticipate that soil and land management variables are highly correlated, the addition of interaction terms may give insight into which aspects of the yield response vary. This is a great advantage for this study because it can take into account not only the relationships of the predictor variables with the dependent variables, but also the relationships among the multiple dependent variables related to the predictor variables. On the other hand, it may be a disadvantage because an identification of the 'best set' of independent variables may be less meaningful because of a possible increase in multicolinearity.

3.1.3. Regression trees

A RT is a non-parametric type of regression model that successively splits the response value using the predictor variables until the error reaches a predefined criterion. The continuous splitting of data is called the binary recursive-partitioning (RP) algorithm (Breiman et al., 1984). Tree-based models also require a selection of internal parameters, particularly for the number of terminal nodes. If a large overgrown tree model is used, the model is frequently overfitted to the training set data, thus providing a close approximation of the collected samples but a biased description of the sampled population. The trees grown with the RT algorithm are usually post-pruned to ensure a better compromise between comprehensibility and predictive accuracy. While there are some rules on the decision of the numbers of terminal nodes, the trial-and-error approach using a cross-validation procedure is widely used (Breiman et al., 1984). In this research, the optimum number of terminal nodes for each RT model was determined by a minimal deviance-complexity cross-validation pruning procedure (Chambers and Hastie, 1992). A 10-fold cross-validation procedure was used to decide the number of optimum terminal nodes using training set data.

3.2. Statistical procedures

The measured values of soil pH, available K, sand content, and three crop response indices deviate strongly from a normal distribution. They were transformed into either a base 10 logarithmic or square root scale (Table 1). All soil attributes investigated showed an approximately normal distribution, but the Kolmogorov–Smirnov test indicates that only N-total and sand content show a normal distribution at the given sample mean and standard deviation. Land management information was coded as presence (1)/absence (0). GLM and RT were conducted using S-PLUS (MathSoft Inc., 1999), while ANN analyses were conducted using NeuroDimension 4.0 (Principe et al., 2000).

The whole crop yield data set was split into training and testing data for both model comparisons and the assessment of cross-seasonal predictability. In order to distinguish the data-fitting ability of each model for the training set and the ability to predict unknown samples using a trained model, we make a clear distinction between 'modelling accuracy' and 'prediction accuracy'. The 'modelling accuracy' is the goodness-of-fit (Pearson's r) of the model for the data used to

train the model, whereas 'prediction accuracy' refers to the goodness-of-fit (Pearson's r) between a predicted value using a trained model and the observed value of a testing data set. In order to test the uncertainty of each model, all analyses were repeated five times using a randomized data set unless stated otherwise. The uncertainty of a model is presented as the standard deviation of r.

One of the major limitations of empirical model building exercises is that they require a large amount of data to obtain reliable training results and to validate trained models (Schultz et al., 2000). This is a particularly important issue in agronomic research considering the cost and time necessary for conducting farm trials. The influence of the number of training-trial results on the performance of each adaptive technique was assessed by varying the number of training sets (from 50 to 550) against fixed numbers of testing sets (170).

During the training of neural networks, a cross-validation (CV) procedure is highly recommended to avoid overfitting a model to training set data (Principe et al., 2000). Because certain portions of the data should be reserved for the cross-validation procedure, this may not be desirable. In order to assess the influence of cross-validation, we also compared the model performance between ANN with and without cross-validation. For ANN with cross-validation, one hundred samples were reserved as a cross-validation data set. Consequently, a maximum of 450 training data sets were used for ANN with cross-validation models.

In order to assess cross-seasonal predictability, we divided the data for each season into training and testing data, and compared their modelling and prediction accuracies for the other cropping season. As only two seasonal data sets were used in this study, further generalization regarding the temporal response of crops may not be possible. Our objective, however, is limited to comparing the relative merits of each model for future modelling exercises. In this analysis, we could not assess the uncertainty of the models except for ANN. Because every ANN model has a different weight value for the trained model, we repeated the whole procedure three times. Early stopping based on the cross-validation procedure was not used in the assessment of cross-seasonal crop yield prediction.

In the assessment of modelling accuracy, the causal relationship between soil–land management inputs and crop yield response was also included. Direct comparison of the constructed models for GLM, RT and ANN was difficult because each technique provides its own means to assess a possible causal relationship. In the case of GLM, we identified statistically significant input variables from the summary table of a trained regression model. RT produces a regression tree after the training, which visualizes the partitioning processes of the model. ANN is not able to identify directly the influence of individual predictors on the model results. However, the sensitivity analysis embedded in NeuroSolution is able to assess the relative importance of each input variable to the trained model. During the sensitivity analyses, the performance of a built model is appraised with regard to the standard deviation of each input variable. Repetition of this procedure for all input variables produces a relative influence of each variable on total model output. The sensitivity analysis was also repeated five times for each training data set. No cross-validation procedure was used in the sensitivity analysis.

4. Results

4.1. Comparison of different adaptive techniques

In Fig. 1, the modelling and prediction accuracies of the different models for three crop yield indices are compared. The differences between the modeling and prediction accuracies are presented in Fig. 2. Table 3 shows the standard deviation of each of the models compared in Figs. 1 and 2. ANN without cross-validation (ANN hereafter) shows very high modelling accuracy, with *r*-values mostly exceeding 0.95. This is followed by ANN with CV (ANN-CV hereafter), RT and GLM. On average, the difference in *r*-values between ANN and GLM is more than 0.2 across the different number of samples. Cob yield shows consistently higher *r*-values than grain yield and total biomass.

In the comparison of the changes in modelling accuracy (Fig. 1(a), (c) and (e)) with the increase in sample size, ANN-CV and RT show a rather different trend compared with the modelling accuracy of ANN and GLM. There is a progressive decrease of goodness-of-fit for ANN and GLM with the increase in the number of trials, which indicates a lower number of trials ANN-CV and RT require smaller number of samples to train a model than ANN and GLM.

In contrast to modelling accuracy, RT shows a consistently higher prediction accuracy than the other three methods (Fig. 1(b), (d) and (f)). The standard two-sample *t* test shows that the mean value of *r* of RT is significantly higher than those of the others ($p < 0.001$). ANN and ANN-CV then follow RT in terms of prediction accuracy. GLM shows the lowest prediction accuracy among the compared models. The difference in modelling accuracy between RT and ANN is relatively large with small numbers of training data sets, but the difference decreases with an increase in the number of training data sets (Fig. 2). It seems that at the 550th training set, the prediction of accuracy of ANN surpasses that of RT. This indicates that RT requires a smaller number of training data sets than ANN to reach the same level of prediction accuracy. It is also informative that there is virtually no difference in prediction accuracy between ANN with and without cross-validation despite the great difference in modelling accuracy.

For cob yield, the total variance explained by the RT model (R^2) reaches 78%, even though the total variances of the grain yield and total biomass are both only 54%. Considering that (1) 11 different land management practices were included in the 720 yield data set, (2) data were combined from two different seasons, and (3) the management activities were variable as they were carried out by individual farmers and not researchers, we believe this is quite a satisfactory result. The reasons for the marked difference in prediction accuracy between cob yield and total biomass or grain yield are not clear.

The prediction error becomes progressively smaller when more samples are collected in the training phase of the model (Fig. 2). Consequently, the difference between modelling accuracy and prediction accuracy becomes smaller with an increasing number of training data sets. At the 550th training sample, the difference in the correlation coefficient between modelling accuracy and prediction accuracy is

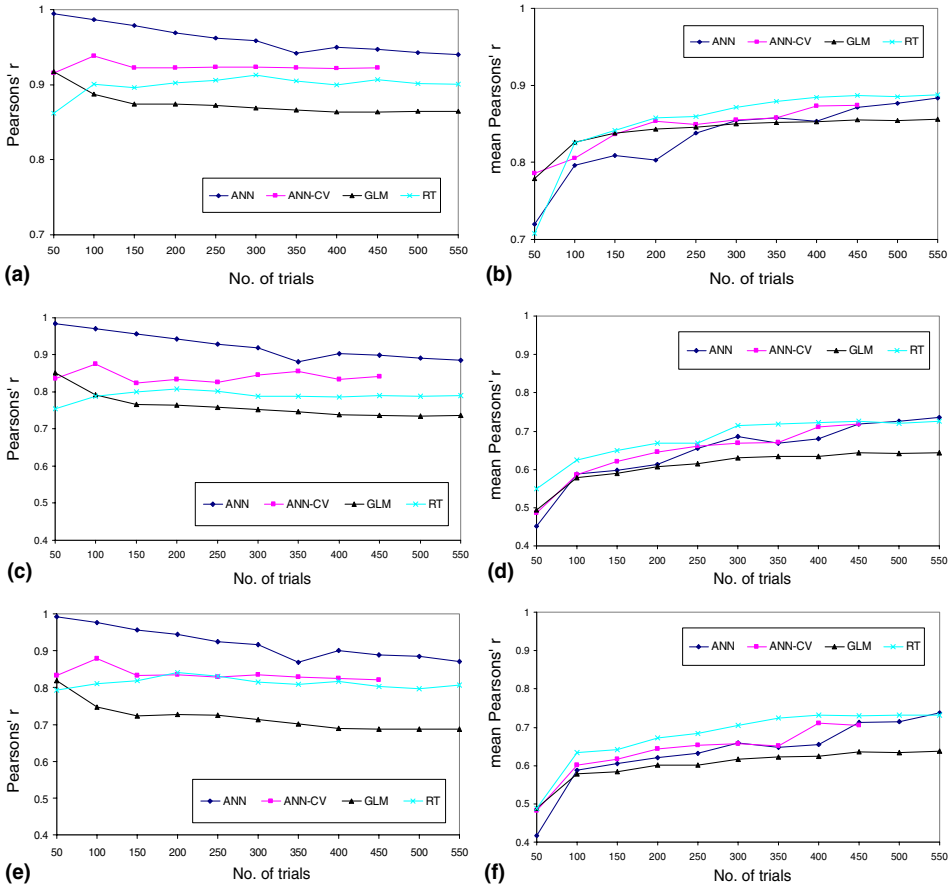

Fig. 1. Changes in modelling and prediction accuracy (Pearson's *r*) of four different adaptive techniques with the increasing number of trials brought into the model: (a) Modelling accuracy for cob yield for seasons A and B, (b) standard deviation of prediction accuracy for cob yield for seasons A and B, (c) Modelling accuracy for grain yield for seasons A and B, (d) standard deviation of prediction accuracy for grain yield for seasons A and B, (e) Modelling accuracy for total biomass yield for seasons A and B, and (F) standard deviation of prediction accuracy for cob yield for seasons A and B. ANN (artificial neural network), ANN-CV (artificial neural network with cross-validation), GLM (general linear model), and RT (regression tree).

less than 0.1. We expect that the difference will continue to decrease with a further increase in the number of training data sets.

The difference between modelling and prediction accuracy provides a clear insight into the generalization ability of the compared methods (Fig. 2). ANN without CV shows the greatest difference, indicating an overfitting of the trained model. Overfitting of the ANN model is a well-known disadvantage. Introducing CV clearly reduced the overfitting, but the difference between modelling and prediction accuracy is still higher than that of RT and GLM.

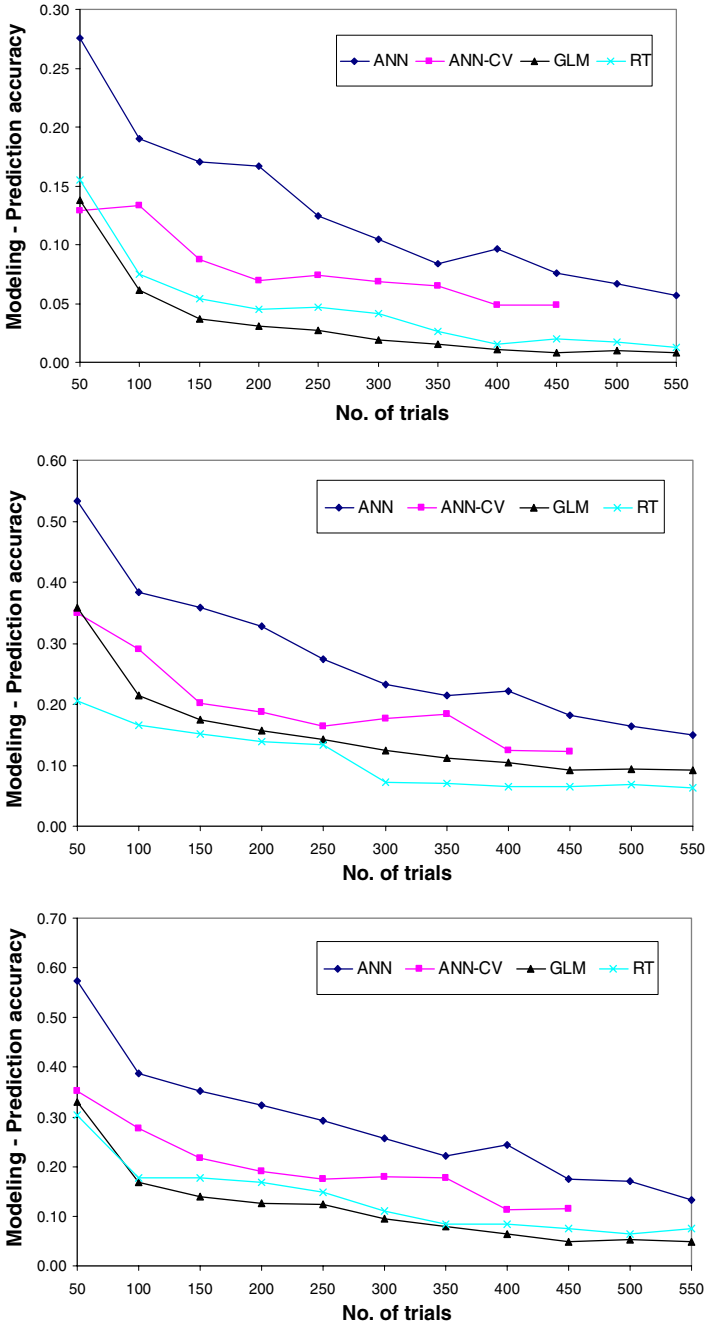

Fig. 2. A comparison of the difference between modelling accuracy and prediction accuracy of four different adaptive models for the total farm trials data set: (a) cob yield, (b) grain yield, and (c) total biomass.

Table 3
Model uncertainty as presented as the standard deviation of Pearson's r for different adaptive models for the total data set used in this research

Models[a]	No. of trial	50	100	150	200	250	300	350	400	450	500	550
Cob yield												
ANN	Modelling (A)	0.0056	0.0059	0.0058	0.0056	0.0059	0.0036	0.0041	0.0049	0.0034	0.0046	0.0055
ANN-CV		0.0399	0.0397	0.0336	0.0264	0.0163	0.0222	0.0204	0.0180	0.0128		
GLM		0.0353	0.0335	0.0415	0.0445	0.0448	0.0465	0.0482	0.0446	0.0446	0.0435	0.0447
RT		0.0520	0.0246	0.0206	0.0122	0.0102	0.0075	0.0150	0.0210	0.0181	0.0179	0.0195
ANN	Prediction (B)	0.0344	0.0289	0.0108	0.0395	0.0151	0.0128	0.0139	0.0079	0.0165	0.0139	0.0128
ANN-CV		0.0485	0.0384	0.0224	0.0139	0.0226	0.0151	0.0159	0.0148	0.0158		
GLM		0.0462	0.0359	0.0304	0.0258	0.0195	0.0203	0.0197	0.0180	0.0172	0.0163	0.0161
RT		0.0405	0.0242	0.0169	0.0147	0.0175	0.0173	0.0129	0.0196	0.0203	0.0180	0.0192
ANN	A–B	−0.0288	−0.0230	−0.0051	−0.0339	−0.0092	−0.0092	0.0102	−0.0030	−0.0132	−0.0093	−0.0073
ANN-CV		−0.0086	0.0013	0.0112	0.0125	−0.0063	0.0071	0.0045	0.0032	−0.0030		
GLM		−0.0109	−0.0024	0.0112	0.0187	0.0252	0.0262	0.0284	0.0265	0.0274	0.0272	0.0286
RT		0.0116	0.0003	0.0038	−0.0025	−0.0073	−0.0099	0.0020	0.0014	−0.0022	−0.0001	0.0003
Grain yield												
ANN	Modelling (A)	0.0195	0.0184	0.0114	0.0099	0.0072	0.0095	0.0031	0.0120	0.0093	0.0073	0.0098
ANN-CV		0.0739	0.0843	0.0754	0.0741	0.0521	0.0628	0.0466	0.0569	0.0444		
GLM		0.0417	0.0283	0.0451	0.0623	0.0447	0.0507	0.0524	0.0409	0.0424	0.0399	0.0439
RT		0.0492	0.0213	0.0525	0.0426	0.0252	0.0404	0.0402	0.0421	0.0475	0.0379	0.0308
ANN	Prediction (B)	0.1178	0.0566	0.0680	0.0857	0.0624	0.0386	0.0193	0.0324	0.0489	0.0308	0.0260
ANN-CV		0.0948	0.0256	0.0350	0.0595	0.0407	0.0523	0.0499	0.0294	0.0368		
GLM		0.1568	0.0939	0.0855	0.0805	0.1056	0.1015	0.1094	0.1046	0.0842	0.0913	0.0920
RT		0.0685	0.0479	0.0483	0.0464	0.0599	0.0426	0.0332	0.0315	0.0205	0.0175	0.0288
ANN	A–B	−0.0984	−0.0382	−0.0566	−0.0757	−0.0551	−0.0291	0.0438	−0.0203	−0.0396	−0.0235	−0.0163
ANN-CV		−0.0209	0.0587	0.0404	0.0145	0.0114	0.0105	−0.0033	0.0275	0.0076		
GLM		−0.1151	−0.0656	−0.0404	−0.0182	−0.0610	−0.0508	−0.0570	−0.0636	−0.0418	−0.0514	−0.0481
RT		−0.0193	−0.0266	0.0041	−0.0038	−0.0347	−0.0023	0.0069	0.0106	0.0270	0.0204	0.0019

(*continued on next page*)

Table 3 (*continued*)

Models[a]	No. of trial	50	100	150	200	250	300	350	400	450	500	550
Total biomass												
ANN	Modelling (A)	0.0093	0.0102	0.0074	0.0127	0.0060	0.0096	0.0094	0.0105	0.0125	0.0074	0.0081
ANN-CV		0.0576	0.0800	0.0676	0.0384	0.0321	0.0467	0.0520	0.0467	0.0410		
GLM		0.0484	0.0613	0.0495	0.0483	0.0530	0.0562	0.0668	0.0610	0.0543	0.0542	0.0545
RT		0.0504	0.0638	0.0891	0.0508	0.0447	0.0572	0.0423	0.0327	0.0324	0.0264	0.0350
ANN	Prediction (B)	0.0601	0.0746	0.0537	0.0700	0.0556	0.0331	0.0432	0.0506	0.0403	0.0386	0.0146
ANN-CV		0.1083	0.0475	0.0323	0.0588	0.0334	0.0529	0.0305	0.0274	0.0411		
GLM		0.0592	0.0681	0.0684	0.0579	0.0432	0.0453	0.0448	0.0405	0.0354	0.0377	0.0374
RT		0.2251	0.0473	0.0698	0.0652	0.0479	0.0485	0.0209	0.0239	0.0168	0.0209	0.0110
ANN	A–B	−0.0508	−0.0644	−0.0463	−0.0573	−0.0496	−0.0235	0.0262	−0.0401	−0.0279	−0.0311	−0.0065
ANN-CV		−0.0507	0.0326	0.0353	−0.0205	−0.0013	−0.0063	0.0215	0.0193	−0.0001		
GLM		−0.0108	−0.0068	−0.0188	−0.0096	0.0098	0.0109	0.0220	0.0205	0.0189	0.0165	0.0171
RT		−0.1746	0.0164	0.0193	−0.0144	−0.0032	0.0087	0.0214	0.0088	0.0157	0.0055	0.0240

[a] ANN, artificial neural network without cross-validation; ANN-CV, artificial neural network with cross-validation; GLM, general linear model; RT, regression tree.

Based on the overall prediction accuracy (Fig. 1), uncertainty of models (Table 3), and its generalization potential (Fig. 2), we can confidently conclude that RT outperforms the other three models as a crop response model followed by ANN-CV. GLM shows the poorest results.

4.2. Cross-seasonal prediction

Table 4 compares the model and prediction accuracies of the three models cross-seasonally. As observed in Section 4.1, modelling accuracy ($0.64 < r < 0.91$) is consistently higher than prediction accuracy ($0.52 < r < 0.68$) for all models. The total variance of one set of seasonal data, explained by the model trained for another season's data, ranges from 27% to 46%, which is much lower than that of the mixed seasonal data ($0.54 < R^2 < 0.78$). This demonstrates the limitation of a cross-seasonal extrapolation of empirical models. In a previous discussion on the general cross-seasonal prediction of crop yield, Jame and Cutforth (1996) argue that more than 10 years of continuous data are often required to confidently predict crop growth in any empirical modelling.

The modelling accuracy for each season shows the same results as observed in Section 4.1; high r-values for ANN followed by RT and GLM. RT and GLM show similar r-values for prediction accuracy. Fig. 3 illustrates the scatter plots of modelling accuracy in season B and prediction accuracy in season A, predicted by a model trained using the data set from season B. In this figure, the residuals from ANN and

Table 4
Comparison of prediction accuracy of different adaptive models for within- and cross-seasonal prediction

Models[a]	A[b] → A	B[b] → B	A → B	B → A
Grain yield				
GLM	0.695	0.689	0.522	0.529
RT	0.757	0.818	0.649	0.582
ANN	0.862	0.908	0.655	0.560
ANN-STDEV	0.003	0.004	0.026	0.018
Cob yield				
GLM	0.693	0.687	0.547	0.557
RT	0.785	0.813	0.666	0.579
ANN	0.840	0.905	0.670	0.576
ANN-STDEV	0.004	0.004	0.020	0.017
Total biomass				
GLM	0.641	0.695	0.577	0.535
RT	0.761	0.815	0.680	0.641
ANN	0.863	0.894	0.668	0.591
ANN-STDEV	0.007	0.005	0.021	0.013

[a] GLM, general linear model; RT, regression tree; ANN, artificial neural network without cross-validation; ANN-STDEV, the standard deviation of ANN model prediction based on three replicated runs.

[b] A, B indicates season A (February–March 2000) and season B (August–December 2000) farm trial, respectively.

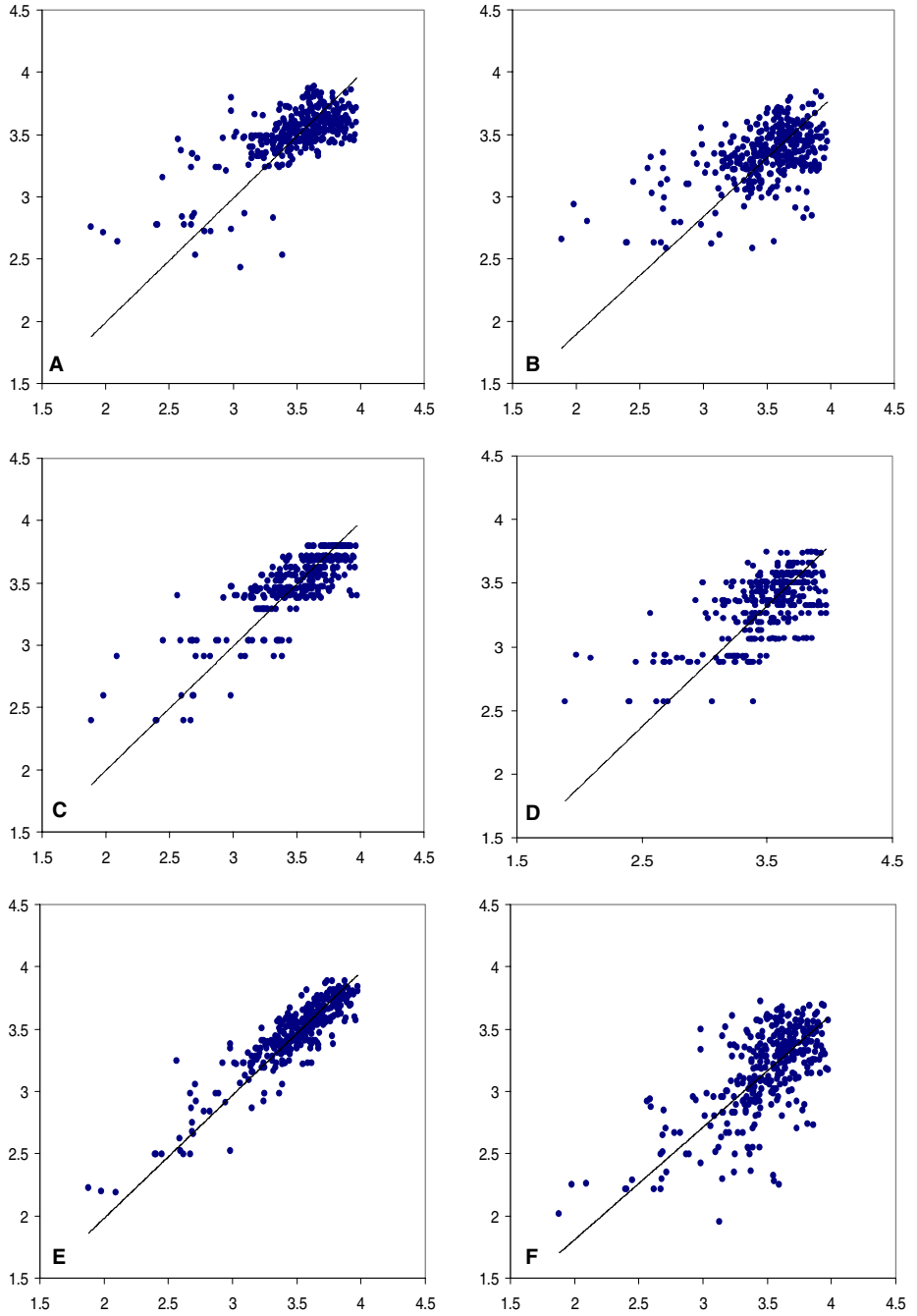

Fig. 3. The comparison of goodness-of-fit of three adaptive techniques to assess cross-seasonal predictability. (A) GLM modelling accuracy of season B, (B) GLM prediction for season A using season B, (C) RT modelling accuracy of season B, (D) RT prediction for season A using season B, (E) ANN modelling accuracy of season B, (F) ANN prediction for season A using season B.

Table 5
The standardized coefficient of the general linear models (GLMs) and their significance level for the grain yield prediction of total samples, season A (February–March 2000) and season B (August–December 2000)

	Total (n = 550)[a]				Season A (n = 378)[a]		Season B (n = 352)[a]	
	Mean		STDEV					
	Standardized coefficients	Sig.	Standardized coefficients	Sig.	Standardized coefficients	Sig.	Standardized coefficients	Sig.
Constant	−1.13	0.655	4.112	0.244	52.67	**0.000**	43.97	**0.000**
PHL	−0.015	0.663	0.047	0.134	0.431	**0.000**	0.320	**0.001**
OM	−0.066	0.586	0.047	0.253	0.373	**0.000**	0.212	0.068
NS	0.003	0.764	0.032	0.187	0.256	**0.000**	0.094	0.187
PS	−0.016	0.681	0.044	0.307	−0.275	**0.000**	−0.246	**0.000**
KSL	0.027	0.665	0.074	0.278	0.349	**0.002**	0.729	**0.000**
NA	−0.196	0.545	0.151	0.225	−0.037	0.904	−1.183	**0.000**
CA	0.186	0.598	0.144	0.274	−0.354	0.230	0.615	0.051
MG	−0.006	0.752	0.042	0.144	0.081	0.405	0.045	0.664
SANDSQ	0.346	0.655	1.011	0.260	−8.638	**0.000**	−7.257	**0.000**
CLAY	0.382	0.660	0.996	0.280	−8.599	**0.000**	−6.906	**0.000**
SILT	0.130	0.636	0.350	0.292	−2.747	**0.000**	−2.175	**0.000**
FYM					−0.190	**0.000**	0.078	0.062
MRP	−0.004	0.576	0.030	0.199	0.029	0.497	0.064	0.151
BRP	−0.101	**0.019**	0.005	0.005	0.083	**0.042**	0.094	**0.028**
TSP	−0.200	**0.000**	0.008	0.000	0.122	**0.005**	0.101	**0.025**
BLEND	−0.149	**0.001**	0.007	0.000	0.052	0.202	0.096	**0.025**
PRE.PAC	−0.205	**0.000**	0.009	0.000	0.009	0.819	−0.055	0.194
GM	−0.151	**0.000**	0.004	0.000	−0.038	0.401	0.021	0.667
N	−0.145	**0.001**	0.011	0.001	0.108	**0.008**	−0.018	0.673
NP	0.247	**0.000**	0.004	0.000	0.177	**0.000**	0.073	0.087
NPK	0.149	**0.001**	0.010	0.001	0.153	**0.000**	0.093	**0.029**
R[b]	0.326	0.221[b]			0.695	0.243[b]	0.689	0.246[b]

[a] Based on five time randomized data sets.
[b] Standard error of the estimate of the GLM models.

RT are more evenly spread around the regression line. RT, however, shows a 'step' shape distribution among measured and predicted values, which may be explained by the consecutive partitioning algorithm of RT. On the other hand, GLM shows a rather 'clustered' residual at the higher values of grain yield.

4.3. Interpretation of causal relationships

Table 5 shows the standardized regression coefficients (β) and their statistical significance of GLM models for seasons A and B, season A, and season B. There is a marked difference in the combination of variables that are significant ($p < 0.05$) for each GLM model. One noticeable pattern is the shift of significant variables from individual season data to the total (A and B) data set. When the model was applied to seasons A and B, some soil parameters (e.g., pH, P.K, and soil texture) explained a large portion of the significant input variables in the GLM models. Once these soil variables were excluded in the total data, land management factors became dominant. We could not identify the reason behind this change. The interpretation of causal relationships demands a cautious approach, because many soil variables are highly correlated with each other.

The results of the sensitivity analyses in ANN provide a more straightforward interpretation of the relative influence of different soil attributes and land management factors (see Fig. 4). The total grain yield is sensitive to soil attributes, including pH (phL), N content (Ns), and organic matter (OM). As land management factors, NP and NPK show the third and fourth most sensitive indicators for predicting crop

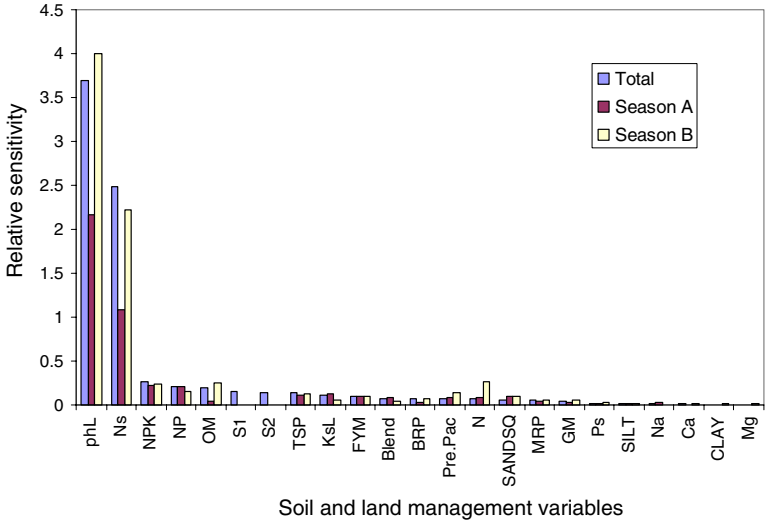

Fig. 4. The results of sensitivity analyses of the ANN model for the season B trial. The relative sensitivity was calculated from three replications sorted in descending order.

yield. Unlike the regression coefficient in GLM, both mixed-seasonal and individual seasonal data sets perform similarly with only minor differences. Considering the multicolinearity of the input variables, the sensitivity analyses provide the most directly interpretable results. However, it should be noted that only one variable was included in each step of the sensitivity analysis; possible interaction between different land management types and soil attributes could not be analyzed.

Regression trees grown from the RT model for seasons A and B are depicted in Figs. 5 and 6, respectively. The trees for total samples are not given. The trees are different for each training set, as clearly shown when comparing Figs. 5 and 6. It is well known that the recursive partitioning procedure of RT is sensitive to small changes in the data structure (Park and Vlek, 2002). The interpretation of the regression trees is also too complex to identify any significant agronomic causal relationships. Despite the high prediction accuracy and model uncertainty, the lack of means for characterizing causal relationships may be the main limitation of RT.

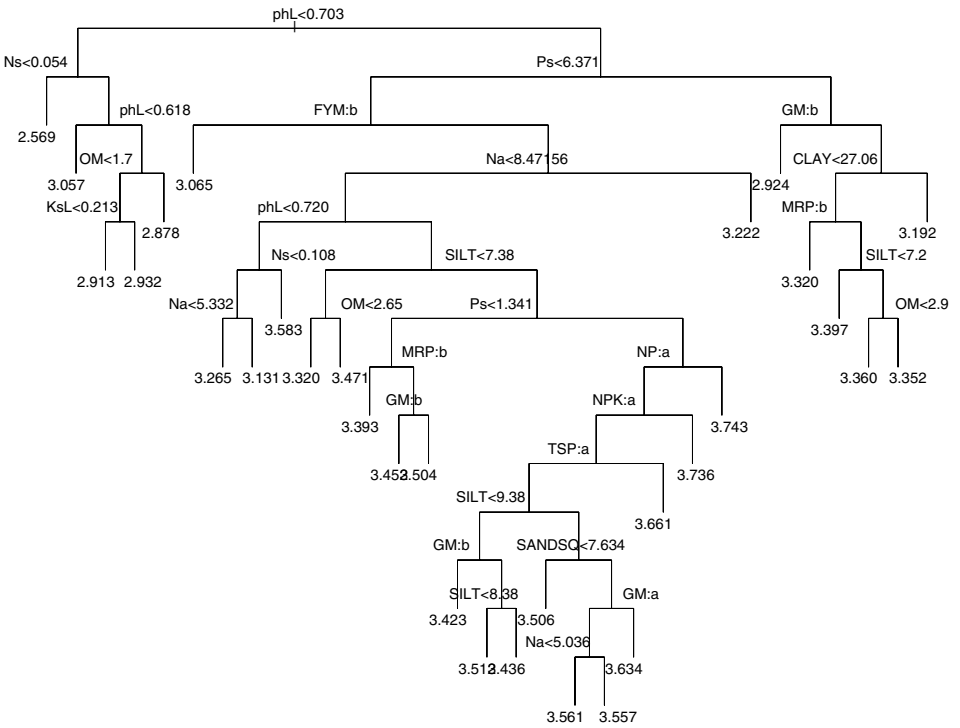

Fig. 5. The regression tree grown from the season A data set. Terminal nodes for total data set used for this model totalled 31 after the 10-fold optimum recursive shrinking procedure. Compare season B in Fig. 6.

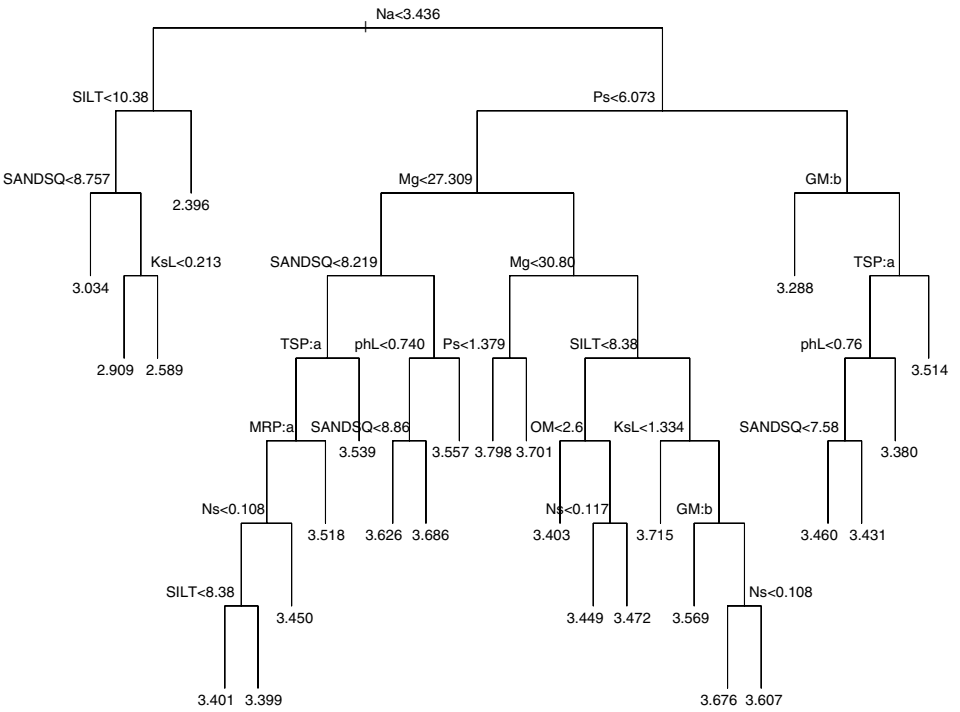

Fig. 6. The regression tree grown from the season B data set. Terminal nodes for total data set used for this model totalled 26 after the 10-fold optimum recursive shrinking procedure. Compare season B in Fig. 5.

5. Summary and conclusion

As an empirical crop yield model under varying soil and land management conditions, the three different adaptive techniques showed different advantages and disadvantages. Traditional Euclidian distance-based GLM produced the poorest results for the data sets compared in this research in terms of modelling accuracy, prediction accuracy, and also model uncertainty. Such poor performance might be due to its inability to model non-linear causal relationships present in complex soil–land and crop-management interactions. The other two non-parametric adaptive models, ANN and RT, show significantly higher prediction accuracy than GLM. RT is an especially robust technique for predicting crop yield, considering its low model uncertainty and prediction error. The difficulty in interpreting causal relationships, especially when a large number of input variables are used, is a clear drawback for the application of RT. With regard to prediction accuracy, ANN is intermediate between GLM and RT. The complex initial parameterization procedures of ANN networks need further attention. Furthermore, it is necessary to reserve certain portions of the data for cross-validation procedures to avoid overfitting, which is not a desirable characteristic for an empirical model-building tool. However, the sensitiv-

ity procedure for identifying causal relationships for crop yield offers the most robust interpretability regarding important input factors for crop response.

It is interesting to compare this result with the authors' previous comparison regarding the prediction of three-dimensional soil spatial variability (Park and Vlek, 2002). In that research, the authors selected six soil attributes representing different pedogeomorphological processes on a three-dimensional hillslope. Then they applied ANN, GLM, and RT to predict the spatial distribution of individual soil attributes using terrain parameters, the occurrence of vegetation, different soil types, and depth. They found that GLM with interaction terms outperforms the other two non-linear adaptive models, ANN and RT, with respect to both simplicity of model structure and performance of derived empirical functions. Because of the stronger dependency of ANN and RT on the training data set, the generalizations of the former two techniques become less successful than those of GLM. The expected non-linearity modelling of vertical soil functions by ANN and RT was not clearly seen in that study. Those conclusions are clearly different to the findings in this present study.

Many factors related to both data structure and quality may contribute to the difference between the two studies. However, mostly likely these contrasting results are the result of the intrinsic characteristics of the spatial distribution of individual soil attributes and crop response to soil attributes and land management factors. Park and Vlek (2002) found the shape of topography to be a predominant predictor for spatial distribution with marginal contributions from vegetation patterns. The distribution of soil properties shows a clear linear response to the water-energy-mass flow processes governed by surface topography, even though this generalization strongly depends on measured soil attributes (Odeh et al., 1994; Park and Vlek, 2002). On the other hand, crop yield in our study sites shows more complex, non-linear dynamics among yield responses and soil-management inputs. Many previous regression models have already shown that the response of crops to a single given soil nutrient is already complex enough, and should be modelled as cubic or quadratic functions (e.g., Tejeda et al., 1980; Campbell et al., 1988). The combination of these soil nutrient factors in addition to climatic conditions, water variability, and land management practices results in complex causal responses (Bouman et al., 1996).

Despite the high demands of a reliable crop simulation model for decision-support models, our knowledge and methodological framework for predicting crop yield are still being developed (Bouman et al., 1996). This is especially the case when multiple land management options are required in resource poor conditions. Small-holder farming systems are the main economic backbone for many developing countries. A tool to assess various land management options to ensure the sustainability of agricultural resources is thus critical, given the uncertainty of future natural, economic, and environmental conditions. The land management options proposed by policy makers are often locally specific with large heterogeneity in local environmental and land-crop management conditions. We have found that the rigid structure of existing models is not able to take account of such complexity and diversity in a cost-effective way. Even though we strongly believe that a more deterministic and physically sound crop simulation modelling approach must be a future research

priority, the non-parametric adaptive techniques used in this research provide valuable tools for identifying crop responses in many situations. Process-based and empirical modelling should be considered as complementary tools. Among the techniques compared, the two non-parametric adaptive techniques (RT and ANN) outperform the traditional regression approach (GLM). These methods, however, also have some apparent disadvantages. When these methods are used together, valuable information can be provided on crop responses, that can be used to help build more reliable crop growth models.

Acknowledgment

The farm trial data used in this research were provided by Dr. A.O. Esilaba (CIAT, Uganda). We are grateful for his generosity in allowing us to use there data for this research.

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