PREDICTION OF CROP YIELDS ACROSS FOUR CLIMATE ZONES IN GERMANY: AN ARTIFICIAL NEURAL NETWORK APPROACH

Working Paper FNU-34

Thomas Heinzow[a,] and Richard S.J. Tol[a,b,c]*

[a] Centre for Marine and Climate Research, Hamburg University, Germany

[b] Institute for Environmental Studies, Vrije Universiteit, Amsterdam, The Netherlands

[c] Center for Integrated Study of the Human Dimensions of Global Change, Carnegie Mellon University, Pittsburgh, PA, USA

Contact for correspondence:

Thomas Heinzow

Research Unit Sustainability and Global Change

Centre for Marine and Climate Research

University of Hamburg

Troplowitzstr. 7

22529 Hamburg

Germany

Telephone: 0049 40 42838 5744

Fax: 0049 40 42838 7009

Email: heinzow@dkrz.

ABSTRACT: This paper shows the ability of artificial neural network technology to be used for the approximation and prediction of crop yields at rural district and federal state scales in different climate zones based on reported daily weather data. The method may later be used to construct *regional* time series of agricultural output under climate change, based on the highly resolved output of the global circulation models and regional models. Three 30-year combined historical data sets of rural district yields (oats, spring barley and silage maize), daily temperatures (mean, maximum, dewpoint) and precipitation were constructed. They were used with artificial neural network technology to investigate, simulate and predict historical time series of crop yields in four climate zones of Germany. Final neural networks, trained with data sets of three climate zones and tested against an independent northern zone, have high predictive power ($0.83 < R^2 < 0.9$). Hindcasts, based on a 25-year training period and independent weather data of a 5 (3)-year future have a relative root mean square error of less than 9%. The model approximates and predicts historical reported yields in an area with a wide range of climatic variance and heterogeneous soil conditions. Mean temperatures during growing seasons ranged from 8.7° C (10.4°) to 19.3° C (21.1°) for April - July (May – September) and precipitation from 73 mm (141) to 548 mm (1016). The output of general circulation models and dynamical crop growth models can easily be integrated to simulate impacts of climate change.

Keywords

global change, agriculture, artificial neural networks, yield prediction

JEL Classification

Q10, Q25

1. INTRODUCTION

Weather patterns in the short and climate in the long run are major components that influence crop production. Most climate change impact studies use expected changes of mean values of climate variables, but do not focus on interannual or intra-annual changes of climate variables and the consequences for agricultural production (Beniston & Tol 1998). Since earnings and losses will depend on the innerannual and intra-annual changes of climate variables and the CO_2 fertilizer effect (Mendelsohn et al. 1996), the current general circulation models (GCMs) and regional models (REMOs) now give researchers the possibility to use dynamical agronomic models at subnational scales (county or rural district level) instead of the common static approaches (Mendelsohn et al. 1999). There exists a gap, however. Consistent crop growth simulation models with the ability to calculate yields in heterogeneous and fragmented regions under realistic farming conditions, have not been fully developed or validated yet (e.g. Landau et al. 1998). Calculations of the regional and national adaptation costs depending on the changing inventories or stock losses by an increase of extreme regional weather events like droughts, heavy rainfall, hailstorms or floods were not possible. What is needed, however, are time series of regional agricultural output to measure the intra-annual and spatial changes of future agricultural output, their costs or benefits. This paper describes a possible way to close the gap with a self-learning nonlinear statistical regression tool.

This paper is empirical in nature. It is designed to demonstrate that artificial neural network (ANN) techniques can be a strong tool to transform the highly resolved weather output of the REMOs into realistic time series of intra-annual agricultural output and economic values at regional scales, so that the effects of climate change may be simulated at the same scale in the agricultural sector. This paper is organised as follows. Section 2 gives an overview of previous research, models and applications of ANNs in meteorological, agroecological and economical modelling. Section 3 describes our database and ANN scheme. Section 4 incorporates a description of the German agrarian characteristics, changes in the past 50 years and the development, training and validation of our ANN-application. Performances of the approximations and hindcasts are presented in section 5. Section 6 concludes and discusses.

2. PREVIOUS RESEARCH

2.1 Models and methods of crop yield-analysis and -prediction

In the early 1920s simple descriptive approaches of the relationship between weather and crop growth appeared (Monteith 1999, Landau et al. 2000). In the late 1960s and early 1970s more and more statistical crop-weather models emerged based on (multi-)linear regression methods concomitant with the increasing power of computer systems (Hanus 1978, Hanus & Aimiller 1978). Crop growth is a multifactorial nonlinear process and mechanistic integrated crop growth models and model families – e.g. the CERES-family for wheat, maize, soybeans etc. – have been developed for different purposes in agricultural management and economy (Guerif et al. 1985). With increasing knowledge about plant growing processes and how to express them by mathematical formulations these deterministic models have reached a high complexity. Simulations cover crop development stages or the duration between them and the plant reactions in different phenological stages to different environmental conditions by using empirical approximation functions. Sometimes the underlying assumptions are that the response of plant growth to temperature or other environmental parameters during approximated development stages is linear or constant (e.g. Porter 1985, Jame et al. 1999). In reality, the relations are curvilinear or unknown, factors act additively or interactively and the response function of plant growth to temperature and available soil moisture is nonlinear. A flawed implementation of nonlinear responses may be one possible explanation of the huge differences of simulated yields in diverse environments found by Otter and Ritchie (1985) and Landau et al. (1998) or reported by Goudriaan (1996). In tests with 10 (8) wheat models in

Minnesota (spring wheat) and in the Netherlands (winter wheat), the simulated yields ranged between 2.5 tons/ha to 8.0 t/ha or 5.4 t/ha to 10.3 t/ha, respectively (Goudriaan 1996).

Furthermore the need of a lot of meteorological, soil and management inputs for regional validation, which are not available everywhere, has to be emphasized. Finally most crop models - McMaster (1997) counted more than 70 wheat models – are mainly developed to simulate crop growth on small and optimally managed experimental fields. For other objectives they have to be calibrated by statistical methods for cultivar properties, regions, farmers behaviour, local management practices and environments (Schultz & Wieland 1997). These models adopt a number of simplifications, too. Bouman et al. (1996 S. 189) claim that "Major gaps still exist in our knowledge of the effects of nutrient limitation and it is not yet possible to use mechanistic models directly for farm level applications." Calibration of models with growth data of experimental fields and special cultivars - which often have yields higher than those currently typical under farming conditions – confines applicability with respect to the target region and environmental conditions. Mirschel et al. (2000) found that yields on experimental fields may be 10 to 30 % higher than those of commercial acreage due to greater soil and crop homogeneity under abnormal experimental conditions. These problems (e.g. more and severe pests or compacted soil by heavy machinery) cannot be addressed in single site experiments and hence cannot be considered in the models.
Most of the previous impact studies (IPCC 1990, 1995, 1998, 2001, Parry & Rosenzweig 1993 & 1998, Tubiello et al. 2002) were based on these models and in reality were mere single site studies using the output of different GCMs with low spatial resolution (distances of grid-points greater than two degrees latitude and longitude). Thorough validation of phenology models using empirical data sets of varieties grown across a wide range of environments is scarce (Stapper & Lilley 2001). There are only a few rigorous studies establishing the validity of the models (Monteith 1999). Studies on larger scales, for example

Otter & Ritchie (1985, World), Landau et al. (1998 UK), Singh et al. (1998, Quebec), Tubiello et al. (2002, US), Chipanshi (1999, Saskatchewan), Supit (1997, EU15), Priya & Shibasaki (2000, India), Tan & Shibasaki (2003, World) or Harrison & Butterfield (1996, Europe), showed predicting accuracy measured by the correlation coefficient in a range from 0.00 (Landau et al., 1998), 0.70 (Chipanshi 1999), 0.59 – 0.74 (Priya & Shibasaki 2000), 0.81 (Otter & Ritchie 1985) to more than 0.96 (Hammer, see Monteith 1999).

Consequently researchers tried to find other approaches to estimate impacts due to climate change, particularly (linear) regression techniques. We thus observe a retrograde tendency in crop growth modelling to the (multi-)linear statistical methods of the 70's (see e.g. Jagtap & Jones 2001, 2002). This may not be the best way as the crop growing process is highly nonlinear.

Mendelsohn et al. (1994) tried another statistical approach by estimating the impacts of climate change on US-agriculture with a "Ricardian" approach based on land prices at county resolution. They defined their Ricardian analysis, relying upon standard rent theory, as a regression of land values on climate, soil and socio-economic variables. The implementation was strongly criticised (Cline 1996, Darwin 1999, Quiggin & Horowitz 1999), as it is static, violating basic principles of agriculture or economics or have multicollinearity problems.

Lang (1999a, 1999b) tried a similar way for measuring impacts on agriculture in Western Germany, based on 41 agroecological regions and 75 weather stations. However, agricultural socio-economic systems have regional or sub-national scales in wide parts of the world, depending on soil qualities, climate barriers, regional farm practices, farmers` experiences and regional economic structures, e.g. growing of spring barley in Germany near to breweries or intensive silage maize production in the vicinity of industrial livestock production. In addition vulnerability and economical structures are determined by government policy (e.g. taxes, subsidies and discouraging agricultural production, Gitay et al., 2001). Therefore most of the vulnerability is given at regional or sub-national scale. The Ricardian approach does not capture regional changes of temperature, precipitation and the carbon fertilization effect (Mendelsohn et al. 1996), but includes farmers behaviour. Therefore the Ricardian approach is not an alternative of the principal need to have realistic predictions of crop yield potentials in any region of the world at any time to do a dynamic analysis based on calculations of future demand, supply and prices under climate change.

Crop growth models or other common statistical models have not reached the necessary maturity of development, as they do not achieve simulations of crop growth in a wide variety of climate regions and real management practices at economically relevant scales (Jame & Cutforth 1996). Hence most studies are only valid for homogeneous regions (Harrison & Butterfield 1996). Special adaptations or modifications are needed to enable models to simulate the regional or nationwide realized yields, because crop models simulate the current range of agricultural technology including high-yielding varieties and cultivars (Rosenzweig et al. 1993, Mirschel & Schultz 2000, Rosenzweig et al. 2002). The crop growth modellers are implementing more and more empiricism (e.g. linear detrending, time series analysis, spatial interpolation) into their models (Jagtap & Jones 2001, Zalud & Dubrovský 2002). This approach is, however, strongly limited by the necessary input data (Hansen & Jones 2000). Thus it is legitimate to ask how much confidence we should have in the state of the art models for economic purposes at different spatial and time scales. With this question we do not repudiate these models.

A promising alternative may be a nonlinear statistical approach with the ANN technique, which ideally should be combined later with the dynamical models. ANN models are able to solve highly nonlinear problems and can approximate virtually any smooth, measurable function (Hornik et al. 1989, cited by Gardner & Dorling 1998). In comparison to the state of the art crop models the requirements concerning the number of input parameters are low. Furthermore, we can use standard meteorological and yield data sets and later GCM-outputs with the same spatial resolution (district scale and 50*50 km) as used by Mendelsohn et al. (1994) or Jagtap & Jones (2001).

2.2 ANNs in meteorological, agroecological and economical modelling

In the mid 1980s the ANN technology was rediscovered and neural network (NN) research became very popular in many fields and many applications of it have been done. For a description of what ANNs are and how they work we refer the reader to the substantial literature (e.g. Hertz et al.1993, Fu 1994, Gardner & Dorling 1997). NN techniques were found to outperform the Box-Jenkins models and other methods in forecasting time series (Hsieh & Tang 1998). NN techniques have been successful in text recognition, remote sensing, forecasting stock market prices (Knöpfel 2003) or the risk of insolvency of companies (Baetge1996). ANNs can represent nonlinear systems, are very data-driven and flexible and robust. All these are noteworthy assets in the domain of agroecology. However, ANNs are not a particularly favourite technique in agroecology (Schultz & Wieland, 1997) or in meteorology and oceanography (Hsieh & Tang 1998). Only few applications could be found. NN techniques were successfully used in forecasting Equatorial Pacific sea surface temperatures (Tang et al., 1999), monsoon rainfall (Navone & Ceccatto 1994, Sahai et al. 2000), long-range precipitation (Silverman & Dracup 2000), short-term precipitation (Kuglikowski & Barros 1998) and wind stress fields (Tang et al. 2001). NN-techniques have been also successfully used for downscaling the output of GCM of simulated daily temperature (Trigo & Palutikof 1999), predicting corn (Uhrig et al. 1992) and maize yields (O`Neal et al. 2002), seeding dates (Major et al. 1996) and maturity of spring wheat (Hill et al. 2002).

3. DATA AND METHODS

3.1 Crop yield and weather database

We established a 30-year (1972 –2001) yield database of three spring seed cereals: oats, spring barley and silage maize. Official yield data from the state statistical offices of four different climate regions in Western Germany at rural district level were taken (see table 1and fig. 1). District level is the highest available spatial solution supported by all statistical offices of German federal states and comparable to the 0.5 degree (~50 km) GCM-resolution

Table 1. Starting year of time series and number of used districts per federal state

Federal State	No. of districts	Year 1	No. of districts	Year 1	No. of districts	Year 1
	Oats		Barley		Maize	
Schleswig-Holstein	9	1972	7	1972	11	1976
Lower Saxony	14	1979	15	1979	12	1979
Baden-Württemberg	7	1972	9	1972	8	1976
Bavaria	12	1976	16	1976	14	1976
Total	**42**		**47**		**45**	

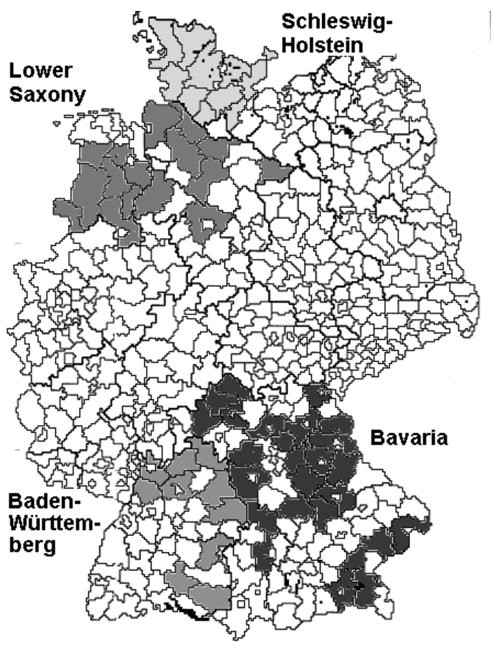

Fig. 1. Chosen districts. Source: Wendland (1993)

We selected districts with sufficient cultivated area of spring sown crops – oats, barley and silage maize – and representative soil characteristics omitting the low and high mountain regions and irrigated areas (e.g. the Luneburg Heath). Thereby uncertain influences on crop yield due to local effects like orographic rain, irrigation by slope water and inhomogeneous soil conditions were minimized. The chosen districts of the federal states of Schleswig-Holstein, Lower Saxony, Baden-Württemberg and Bavaria represent the whole climate variation from north (maritime) to south (continental) in Western Germany. The resolution is high enough, so that regional influences on crop growth like coastal effects below state level can be detected and simulated. The quality of reported yield data (oats and barley) is acceptable with a mean absolute deviation (MAD) of less than 3% and a maximum year to year fluctuation up to 40% (mean 12%). The reported yields of maize have higher deviations of approximately ± 5%, because they are only estimated by yield appraisers and not validated by random sampling (Grunwald 2002). Comparable data sets for the federal states in Eastern Germany (former German Democratic Republic) are shorter, starting in the mid-nineties and were therefore not used.

Our weather pattern database includes effective daily mean (TM) and maximum temperature (T_X), daily mean dewpoint temperature (T_D) and precipitation (RR) of 131 official climate stations, provided by the German Weather Service (DWD). Hours of sunshine or solar radiation were not available for all districts and could not be used as model input. Where there were several stations within a district, we preferred stations located away from the big cities to avoid city-influence. Daily mean temperature is defined by $\overline{T} = \frac{1}{24}\sum_{t=1}^{24} T_t$ or $\overline{T} = \frac{1}{4}\sum T_1 + T_2 + 2 * T_3$ (1 = 06 am, 2 = 01, 3 = 08 pm GMT - since 1987 + 30 min). The mean dewpoint is calculated by $\overline{T_D} = \frac{1}{24}\sum_{t=1}^{24} T_{D_t}$ or $\overline{T_D} = \frac{1}{3}\sum T_1 + T_2 + T_3$. Dewpoint Difference (TD) is defined as T_X - T_D. TM was formed by subtracting the vegetation threshold of 5° C (8° maize) from $\overline{T}$. Missing data in the time series were substituted by data of the nearest available or comparable station. Altogether we used time series from 113 climate stations.

3.2 The artificial neural network scheme

The most widely used types of ANNs in economic and ecological applications are fully connected feedforward networks with one or two hidden layers. We chose a four-layer backpropagation network with two hidden layers without subnets and the ability to emulate the radial-basis crop response function (Mendelsohn et al. 1996). The network runs with the Stuttgart Neural Network Simulator (SNNS). Other researchers (e.g. Uhrig et al. 1992, Liu et al. 2001) have modelled crop yield or other crop growth parameters with three-layer ANN. Our network's activation functions of the neurons are "identity" or "logistic" (see tab. 2). Network training is done with the resilient propagation algorithm (rprop). The adaptation of the weights of the connections between the neurons is determined for each training cycle by this offline-training method (Zell et al. 1995) after the last pattern has been presented to the network. Its learning process follows the weight-decay technique. Rprop is a very fast process and superior to other well tested and robust backpropagation learning algorithms based on the gradient descent method, not only by speed but also by generalisation (Fu 1994, Zell 1994). Our general connection scheme is shown by fig. 2:

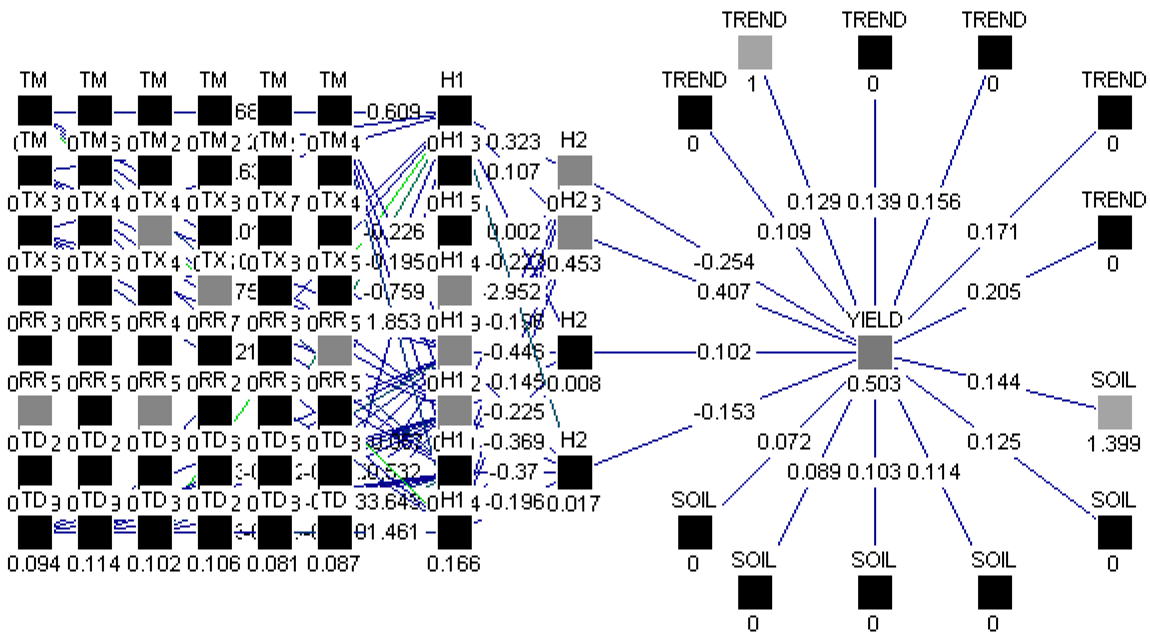

Fig. 2. Principal construction of our networks (not all connections and neurons shown).

Numbers below neurons are output, numbers between neurons are weights

Table 2. Parameters of the ANN

Layer	Parameter	Activation Function	Connection	Max. No. of Neurons	Min. No. of Neurons
Input	TM,TX,TD,RR	Identity	1.Hidden	60	24
Input	Soil	Identity	Output	47	6
Input	Trend	Identity	Output	47	6
1. Hidden	-	Logistic	2. Hidden	18	6
2. Hidden	-	Logistic	Output	18	6
Output	Yield	Identity	-	1	1

Empirical patterns presented to the network included combinations of ten day sums of TM, TX,TD, RR, the yield and in one case an empirical trend function. The sums are normalized to values between 0 and 1.9 (requisite by the SNNS). Based on this scheme we developed and tested different network types to find the combination and number of meteorological input paramaters and hidden neurons that gave reasonable approximations to the reported yields, and length of growing season was then set to 120 (150 for maize) days, starting with April 1st (May 1st).

4. GERMAN AGRICULTURE

4.1. Agrarian characteristics of the research Area

The agrarian countryside of Germany is heterogeneous with fertile marshlands, swamps and sandy heathlands in the north, low mountains in the central, southeast, southwest regions and high mountains in the south with interspersed rolling hills and plains. Thirty percent of the acreage is forest area and about 50% agricultural area. Soil characteristics like fertility and usable field capacity are varying greatly in some regions at a scale that is smaller than the rural district scale. Soils range from heavy clay over loess to sand and gravel. In the high and low mountain regions, in particular, temperature variance, humidity, precipitation, drainage and natural irrigation via ground and slope water is strongly influenced by regional and local orographic effects, which are mostly unknown or cannot be extrapolated to larger scales.

Main growing seasons for oats and barley start at end of march and for maize at the end of April and come to a close at the ends of the months of July (cereals) and September (maize). Our main validation area is the small federal state of Schleswig-Holstein. We chose this state, because it is sited in the north of Germany, so that the influence of a northward shift of the climate due to climate change can be simulated. Furthermore it has 4 main soil characteristics and 22 specified ecoregions, determined by climate and soil characteristics (Fig. 3a), 11 rural districts and 4 independent cities (Fig. 3b).

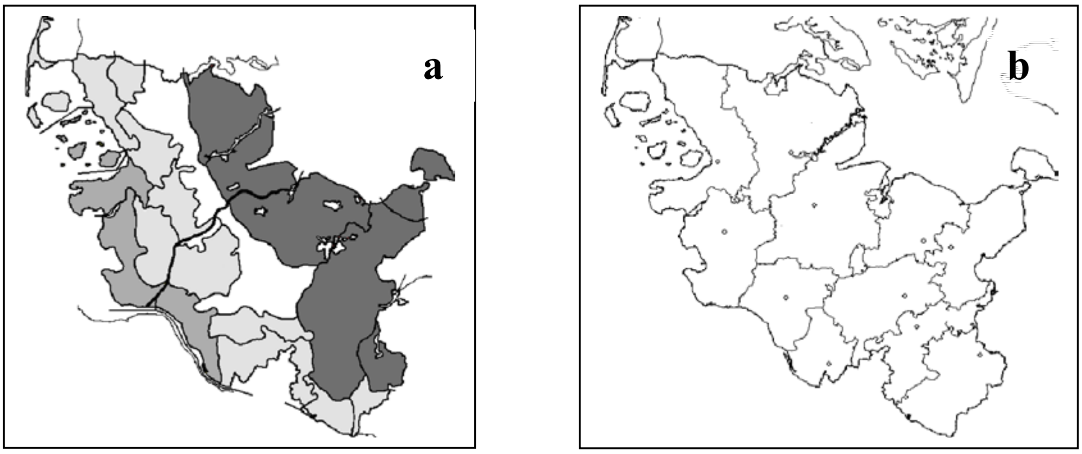

Fig. 3. Ecoregions (a) and Rural Districts (b) of the Federal State of Schleswig-Holstein

Source: Statistical Office of Schleswig-Holstein (2000)

Fertile marshland (heavy clay) is found along the west coast and the Elbe-River, two types of sandy heathland (sand and gravel) in the central regions and rolling hills with sandy loams in the southeast and along the coast of the Baltic Sea. The distribution of temperature, precipitation and solar radiation in Schleswig-Holstein is mostly influenced by the advection of air masses from above the North and Baltic Seas. The maximum spatial gradient of monthly mean temperature during growing season points southeastwards and reaches 1.6 °C in May. Mean precipitation values from April to July are in the range from 200 to 280 mm (standard deviation of about 60 mm) with a minimum in the coastal zones.

4.2. Changes of crop production and prices in Germany

Since the 1950`s agricultural production and grown crops changed dramatically in Western Germany and Europe, driven by economical constraints of agrarian politics and the “Green Revolution”. While in the fifties the main grown crops by area were rye, oats, potatoes, wheat and barley (see fig. 4a), in the nineties most grown crops were barley, wheat, (silage) maize and sugar beets. Based on estimated dry matter the most important crop nowadays is silage maize + corn with 27.5% of the yield (see fig. 4b).

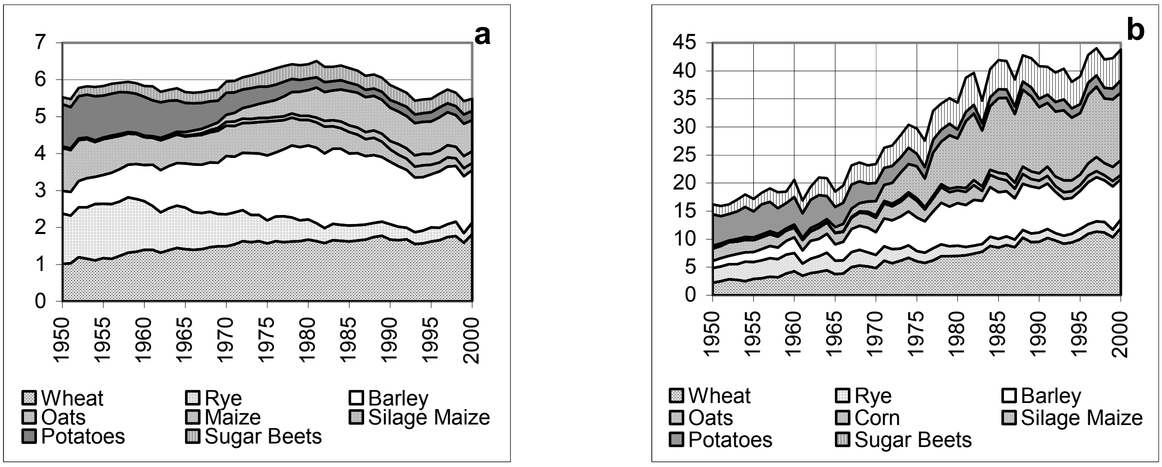

Fig. 4. Harvested area (a) [mln ha] and dry matter (b) [mln t] of 7 important crops

Source: Federal Statistical Office of Germany, Mitchell (1992), our calculations

The harvested dry matter of the 7 main crops increased from 16 mill. to 44 mill. tons. The real producer prices in Western Germany decreased since the mid eighties, due to the agrarian policy of the European Union (see fig. 5b). While the yield per hectare of all other crops increased nearly with a linear trend due to progress in breeding, technical and management processes, harvested silage maize shows about four different major trends during research period (see fig. 5a). The reasons for these trends are complex. Influencing factors are the evaluation method of federal statistics, changing management practices, use of less fertilizers since the eighties and breeding progress. Due to farmers` increasing use of hybrid cultivars with higher fractions of starch and bigger corn cobs (Kising 1962, Richter 2003), the better improved

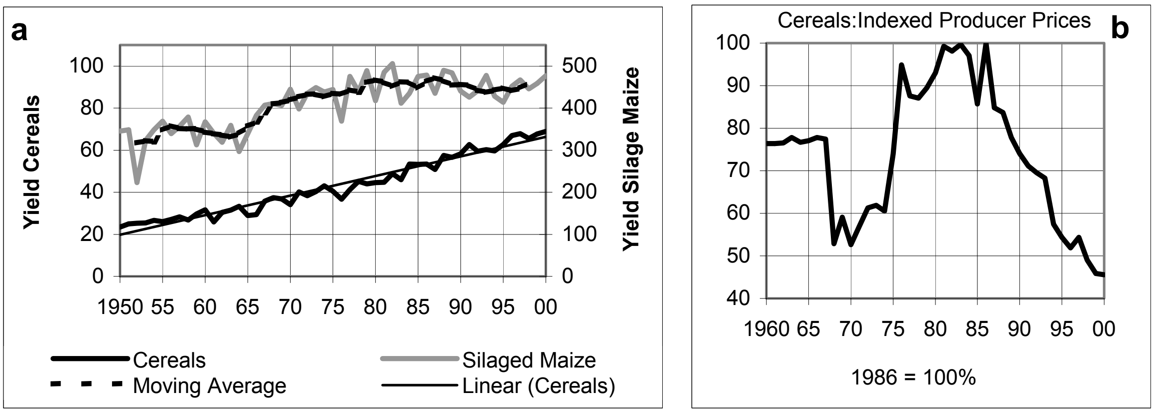

Fig. 5. Yield (a) [dt/ha] of cereals and silage maize; Indexed producer prices (b)

Source: Federal Statistical Office of Germany, Mitchell (1992), our calculations

management of their fields, optimized harvesting dates (Zscheisler 1979, Richter 2003) and growth of early maturing maize, the fraction of dry matter in total plant mass increased (Richter 2003) from roughly 20 to 25% up to 30 or 35%. During this period the reported total yield stagnated or decreased. A slight increase of total plant mass can be observed since 1995. As we found similar trends in other European countries with rainfed agriculture, the nonlinear trends and their explanations seem to be realistic. The regional reasons and consequences of these trends for the construction of our ANN-model are described below.

5. RESULTS

5. 1 Running the ANN-crop-yield-model

Since crop growth meteorologically is mostly determined by temperature, humidity and precipitation patterns, we used four parameters (TM, TX, TD and RR) to do a sensitivity analysis of different combinations and the performance of the approximation. We built reasonable combinations of the four available meteorological parameters and the reported yields in the districts from 1972 until 2001 (see table1). Four combinations of the parameters make sense (TMRR; TMTXTDRR; TMTXRR; TMTDRR) to capture the influence on crop growth by temperature, humidity, heat stress and precipitation.

Accounting for the unknown but also important influences of soil fertility and potential field capacity (relative soil quality), behaviour of farmers and breeding progress on crop growth (technical progress) is done by the network itself using a dummy construction. Every district is represented by two neurons, one for the soil quality and one for the yield trend. The corresponding values in the training patterns are set to one (relative soil quality) or to a linearly ascending value between 0 and 1.5 (technical trend), all others to zero (see fig. 2). As these neurons are directly and linearly connected to the yield neuron (see fig. 2 and table 2), the weight of the connections represents the relative base fertility of the district or the parameters of the linear yield trend due to technical progress and farmers' behaviour.

The networks has, depending on the length of the crop growth period, in the maximum version 60 (maize) or 48 (oats, barley) weather neurons, 36 neurons in two hidden layers, 94 soil and trend neurons and one yield neuron. Different ANN constructions were trained with the regional and the overall pattern sets. That gave us a deeper insight into the influence of (1) the number of hidden neurons (2) the number of patterns (3) the combinations of meteorological parameters on the ability of the ANNs to approximate the reported yields. The performance was measured by the regional and overall correlation coefficients (R), their standard deviation (SD), the regional and overall root mean square error (RMSE), the mean average deviation (MAD) and the ability to approximate extreme yield deviations. A sensitivity analysis with other network constructions, for instance a third hidden layer or a subnet construction or other training algorithms showed us, that the 4-layer-feedforward-backpropagation-network trained within 100 cycles by the rprop algorithm gave best results without overtraining.

As the SNNS allows us to extract the automatically determined weights (including bias) of the connections between the neurons, we could use ANN technique to identify districts with equal relative soil quality and similar trends of technical progress and farmers behaviour. So we were able to reduce the number of soil and trend neurons from 42 to 7 (oats) and 47 to 6 (barley) by building soil and trend classes of the districts after training networks in the maximum size. This reduction was necessary to verify the suitability of the ANN for predictions across and outside the training area as independent average measures of soil quality at district level are not available. Then we found a huge difference (up to100 dt less yield per ha) between the maize yields Lower Saxony and Schleswig-Holstein (see fig. 6) within 150 km distance. This gradient cannot be explained by climate only even though maize cultivation in Schleswig-Holstein is at its temperature limits to reach maturity (Beinhauer & Günter). Class building across the four climate zones for maize was not possible, especially as farmers in Schleswig-Holstein now grow cultivars with very early maturity (based on temperature sums) and a corresponding lower yield potential but a higher content of starch and energy in the dry biomass. The mean yield/ha of total plant mass decreased between 1980 and 1994 by 22 % and after that increased until 2001 by 15%. A slightly less pronounced tendency was observed in Lower Saxony, but not in Bavaria or Baden-Württemberg (see fig. 6), where farmers have more experience in growing maize, because in the seventies more than 60 % of maize acreage of Western Germany was located in these states until the mid of the 1980s.

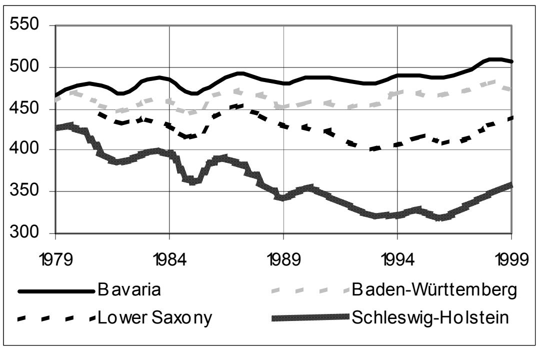

Fig. 6. Trends of Green Maize Yields: 5-Year Running Means [dt/ha]

Source: Federal Statistical Office of Germany; our calculations

Therefore these trends in Schleswig-Holstein and lower Saxony and the high yield gradient are not only induced by lower temperatures. Some other reasons could be identified. A consulted expert (Jäger 2003) indicated, that in the northern parts of Germany up to 40% of the farmers are harvesting too late, so that the silage is dryer and has less total mass. Due to a slow change from the improper use of cultivars with late (Kising 1962) to those with earlier maturity, the estimated dry mass has changed from approximately 20% up to 35% or more while the total plant mass decreased. The standard linear trend adaptation by our model will not be correct in the northern parts of Germany. On that account we replaced the standard linear trend adaptation by three empirical determined linear functions. This corrected model gave better approximations over the whole research area and not only for districts in northern Germany. Since the mean yields and technical progress at district level are not comparable across the four regions, we were not able to build classes of districts across the regions and could not run a hindcast outside the training area.

Special pattern sets were needed for training and validating the applicability of our model for predictions outside the training area and for future yields. The pattern sets were split into five pairs, one training and one validation set respectively. We cut out the patterns of the years 1997 – 2001 (oats and barley) and 1999 – 2001 (maize) and the patterns of Schleswig-Holstein (oats and barley). The reduced pattern sets were used for training and the cutout for validation. In all series of runs we pruned the network manually by reducing the number of hidden neurons to find a network with a high over all R, a low SD of the regional correlation coefficients, a low MAD and RMSE in the training sets. It was not our objective to find the best network, as a the optimization has to be done manually. Therefore we did not prune on the input side single neurons or connections with low weights. A sensitivity analysis at the end of our final training cycles showed some potential to find networks with better generalization attributes if we would prune the input side, too.

5.2. Performance of approximations

The performance of approximation of the reported yields was almost sufficient by the finally chosen and tested network configurations with mean variance higher than 0.85. Even only with two aggregated meteorological parameters (TM and RR) we achieved regional correlation coefficients between 0.68 and 0.97 for all crops by pruning. Performance of approximations differed slightly in our test series. Best meteorological input combinations seem to be for oats TMTDRR, spring-barley TMTXRR and silage maize TMRR (see table 3), but differences are marginal and may depend on the manual pruning technique and the

Table 3. Performance of approximation over all districts and years

Crop	Input Variables	Hidden Neurons	RI mean	R² mean	R max	R min	Sdev R	Mean Yield dt/ha	MAD dt/ha	Rel. MAD %	RMSE dt/ha	Rel. RMSE [%]
Oats	TMTXTDRR	10 08	0,920	0,847	0,974	0,798	0,044	44,3	2,4	5,4	3,1	7,0
Oats	TMTXRR	12 08	0,909	0,827	0,972	0,776	0,047	44,3	2,6	5,9	3,3	7,4
Oats	TMTDRR	12 08	0,922	0,850	0,972	0,796	0,033	44,3	2,4	5,4	3,1	7,0
Oats	TMRR	12 08	0,917	0,840	0,970	0,806	0,043	44,3	2,4	5,4	3,2	7,2
Barley	TMTXTDRR	10 08	0,913	0,833	0,967	0,775	0,047	41,6	2,2	5,3	2,8	6,7
Barley	TMTXRR	12 06	0,919	0,845	0,971	0,804	0,049	41,6	2,1	5,1	2,7	6,5
Barley	TMTDRR	10 06	0,918	0,843	0,967	0,795	0,042	41,6	2,1	5,1	2,7	6,5
Barley	TMRR	12 10	0,912	0,832	0,972	0,781	0,049	41,6	2,0	4,9	2,8	6,7
Maize	TMTXTDRR	12 08	0,921	0,848	0,943	0,628	0,074	436,6	19,4	4,4	24,5	5,6
Maize	TMTXRR	12 06	0,915	0,838	0,956	0,630	0,069	436,6	18,6	4,3	24,2	5,5
Maize	TMTDRR	12 08	0,922	0,850	0,937	0,626	0,076	436,6	19,5	4,5	24,3	5,6
Maize	TMTDRR	15 10	0,927	0,859	0,952	0,613	0,072	436,6	18,3	4,2	23,2	5,3
Maize	TMRR	12 10	0,925	0,856	0,958	0,683	0,057	436,6	17,4	4,0	22,6	5,2

random initial condition. Consistent, reproduceable and stable results for all crops through test series were achieved with three meteorological parameters (TMTDRR) and 12 neurons in the first and 8 in the second hidden layer, with the exception of maize. We found a second maximum with a 15 to 10 TMTDRR-network. Since the difference of maximum temperature and dewpoint temperature is highly correlated with the potential evapotranspiration, we ran the final hindcast tests for all crops in the TMTDRR1208 configuration. A sensitivity analysis, starting with 18 neurons in each hidden layer and ending with 6 to 4, did not show significantly better results. We take it as a sign of robustness, that it was impossible to force the network to learn wrong data sets (e.g. districts with damages by hailstorms or heavy rainfall) producing regional correlation coefficients less or equal than 0.97 (average over all districts > 0.93). Furthermore the assumed length of the growing period of 150 days for maize to be representative for the reported lengths by DWD (1955 – 1993) from 140 to 170 days, seemed to have little influence as the optimum harvest time of today's cultivars with a flexibility of 14 to 21 days (Spiekers, 2000). Districts with a flat topography or homogeneous soil characteristics had higher correlation coefficients and lower MAD and RMSE than those with heterogeneous soil conditions or rougher topography. Highest regional correlation coefficients were achieved for most districts of Schleswig-Holstein and Lower Saxony.

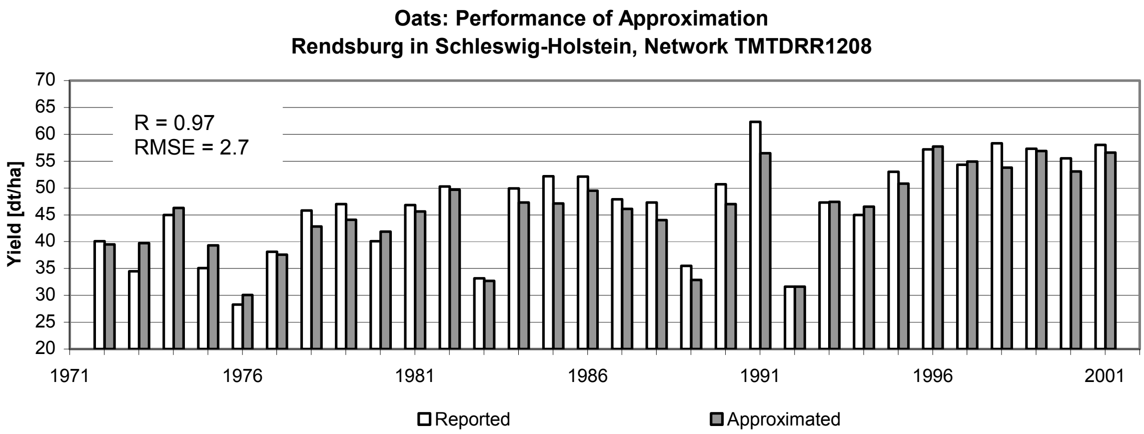

Fig. 7. Comparison of reported and approximated yields: the Rendsburg district with high

correlation. Source: Statistical Office of Schleswig-Holstein, our calculations

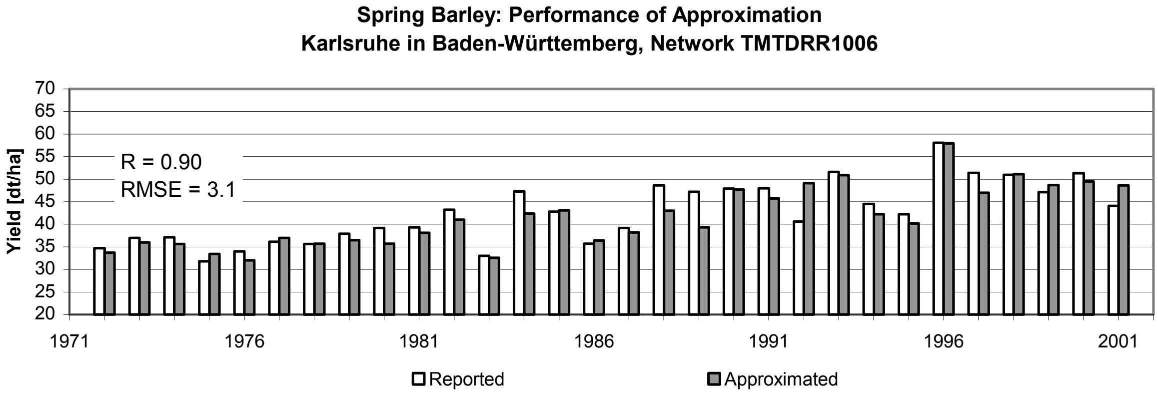

Fig. 8. Comparison of reported and approximated yields: the Karlsruhe district with average correlation. Source: Statistical Office of Baden-Württemberg, our calculations

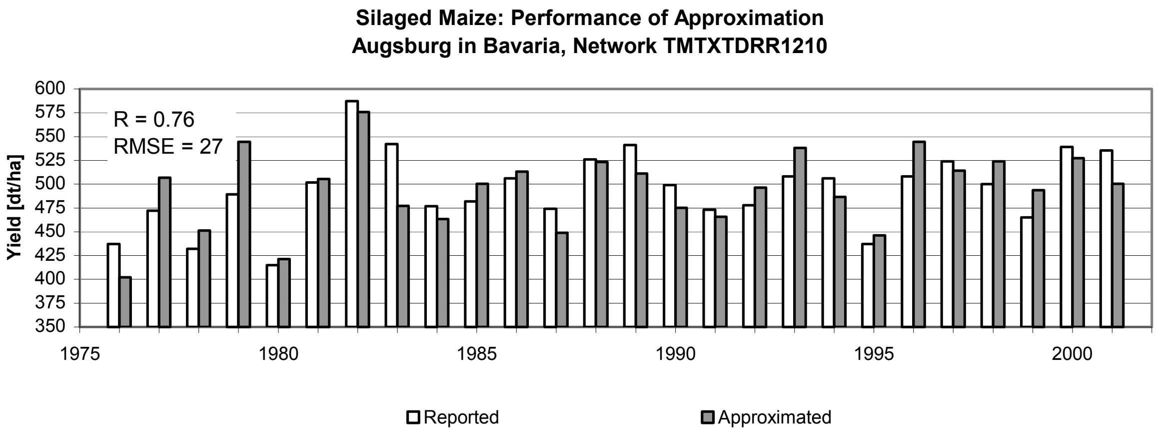

Fig. 9. Comparison of reported and approximated yields: the Augsburg district with low correlation. Source: Statistical Office of Bavaria, our calculations

In some years our model showed for districts of Bavaria and Baden-Württemberg systematical overestimations for maize. We identified regional hailstorms as the cause of it, because maize is much more vulnerable to hailstorms than other cereals (Richter 2003).

5.3. Performance of hindcasts

The results of our realistic thirty year forecast simulation for a region with subnational scale outside the training sample are shown in fig. 10 and 11.

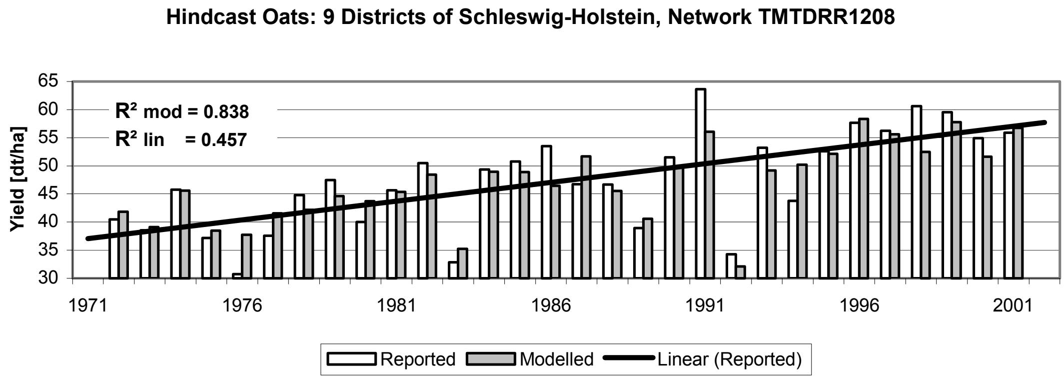

Fig. 10. Performance of hindcasted yields for oats in Schleswig-Holstein. Source: Statistical Office of Schleswig-Holstein, our calculations

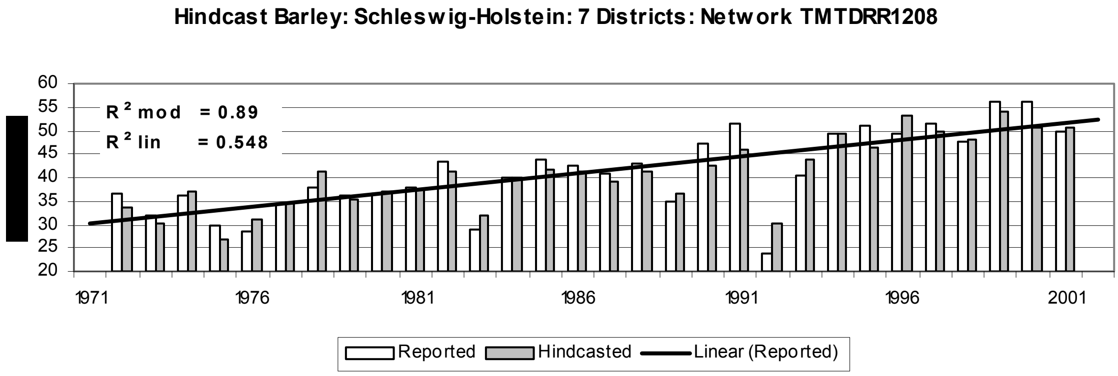

Fig. 11. Performance of hindcasted yields for barley in Schleswig-Holstein. Statistical Office of Schleswig-Holstein, our calculations

The reported and hindcasted mean yields are calculated by interpolation of the cereal-grown area of the districts, reported every four years. The achieved R^2 higher than 0.8 are more than sufficient for economical purposes. They do not differ from other statements of the crop yield variability due to weather (Petr 1991, Fageria 1992, cited by Hoogenboom 2000). The ability of the model to give nearly perfect predictions of the yields in most of the arid years (1975, 76, 83, 89 and 92) within our research period is remarkable. The model predicted for instance, compared to the linear trend of the 30 years, for the 1992 severe drought in Schleswig-Holstein a 37% (33) loss for oats (barley) while a 33% (46) loss was reported. With the global economic conditions today, without subsidies by the EU, farmers would have a negative marginal return, which is correctly predicted by the model. The yields for oats (barley) in years with more or less normal growth conditions are hindcasted by the model with a MAD of 2.7 (2.3) dt/ha and a relative of 5.5 (5.6)%. The relative RMSE of all hindcasts is about 7.6 (7.0) %, a value sufficiently small to allow us to calculate the marginal costs of such extreme events due to possible climate change and increasing number of droughts. The other realistic simulation, predicting future yields across all 4 climate regions, based on the pattern until 1996 (1998), gave nearly identical results and are shown in figs. 12, 13 and 14.

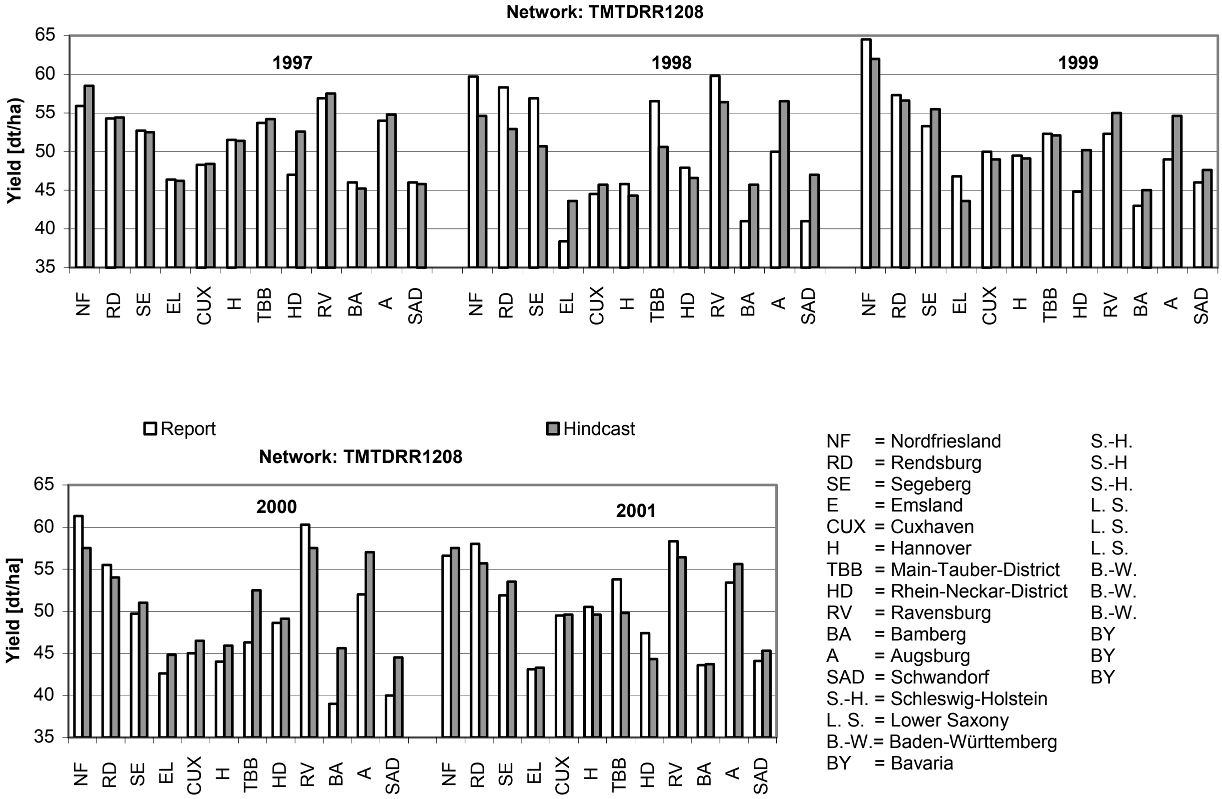

Fig. 12. Oats: Performance of hindcasted yields of 12 districts in 4 federal states. Source: Statistical Offices of Schleswig-Holstein, Lower Saxony, Baden-Württemberg and Bavaria, our calculations

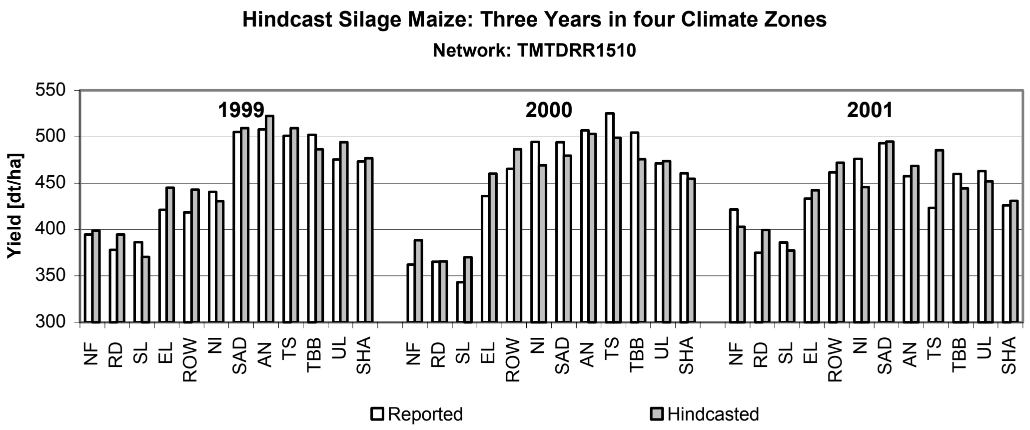

Fig. 13. Silage maize: Performance of hindcasted yields of 12 districts in 4 federal states.

Source: Statistical Offices of Schleswig-Holstein, Lower Saxony, Baden-Württemberg and Bavaria, our calculations

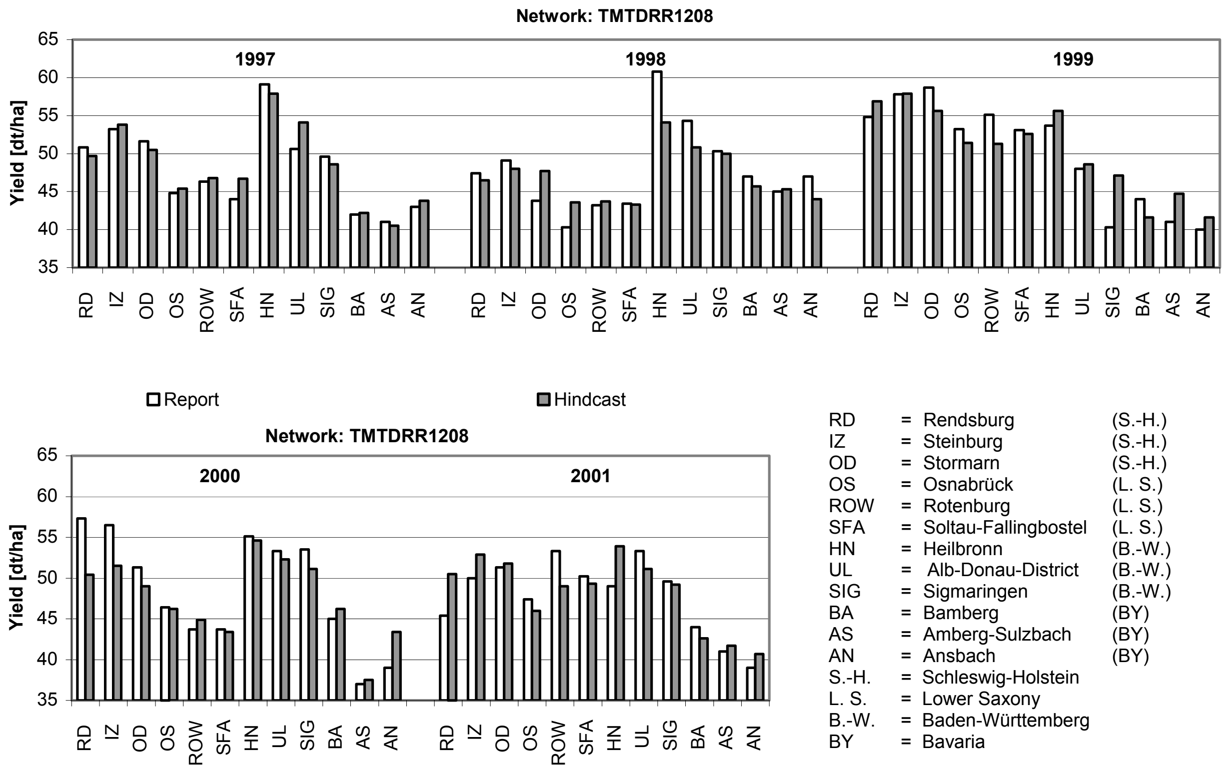

Fig. 14. Spring-Barley: Performance of hindcasted yields of 12 districts in 4 federal states.

Source: Statistical Offices of Schleswig-Holstein, Lower Saxony, Baden-Württemberg and Bavaria, our calculations

All runs showed the ability of the model to give good predictions for a presented weather pattern outside the training area and period and across a wide monthly mean temperature and precipitation variability, which is shown in table 4 and 5. The model predicted yields under the maritime climate of Schleswig-Holstein as well as under the continental of Bavaria or Baden-Württemberg. The district with the highest growing season mean temperature during research period was Heidelberg (Baden-Württemberg) with 15.9 °C (19.2 for maize), the coldest was Nordfriesland (Schleswig-Holstein) with 10.8 °C (13.0 for maize). Related to the monthly and seasonal mean temperatures and precipitation in other European Cities and in the northern US-states, the model would principally run after extra training to catch the extremes in these regions too. Precipitation during growing season ranged between 73 mm (141 for maize) and 548 mm (1016).

Table 4. Monthly Mean Temperatures [C°] during Research Period
Source: DWD, our calculations

Research Area	April	May	June	July	Aug.	Sep.	Apr. - Jul.	May - Sep.
Min Mean Temp.	3,8	6,5	11,5	13,0	12,2	8,6	-	-
Max Mean Temp.	13,5	17,7	21,6	24,4	22,4	19,6	-	-
Mean Temp.	7,7	12,9	15,6	17,7	17,3	13,5	13,5	15,4
Warmest Season	11,5	13,2	19,6	24,4	22,0	16,7	17,2	19,2
Coldest Season	5,2	10,4	13,9	13,6	14,6	12,4	10,8	13,0
Heidelberg Mean	9,9	14,6	17,1	19,7	19,5	16	15,3	17,4

Table 5. Monthly Mean Precipitation [mm] during Research Period
Source: DWD, our calculations

Research Area	April	May	June	July	Aug.	Sep.	Apr. - Jul.	May - Sep.
Min. Prec.	2	2	2	4	3	9	2	2
Max. Prec.	195	257	231	226	342	306	257	342
Mean Prec.	50	59	78	76	77	75	263	365
Driest (Oats)	13	14	28	18	-	-	73	-
Driest (Maize)	-	44	15	19	28	35	-	141
Wettest (Oats)	146	50	126	226	-	-	548	-
Wettest (Maize)	-	120	370	130	240	157	-	1016
Heidelberg (Mean)	52	73	77	80	49	70	282	349

6. CONCLUSIONS

The objective of this paper was to show that the use of ANN technology is a possible way to close an existing gap between climate models and common site specific crop growth models to construct regional time series of agricultural output under climate change. The applicability of ANNs for regional crop yield simulation and prediction of grain was evaluated in this study by developing a four-layer rprop-ANN and testing it in four different climate zones of Germany. The main advantage of this nonlinear empirical statistical modelling technique is, that no deep and particular knowledge about relationships between the variability of weather patterns, soil characteristics, farmers management practices and plant growth is necessary, as a proper design of the input-output pattern implicitly incorporates them. The requirements for the number of input parameters are low in comparison to other dynamical and sophisticated crop growth models. These parameters are in principle available worldwide. The model can be used in all regions where time series of temperature, precipitation and crop yields are reported at sufficient spatial scales. The benefits of this robust modelling system for the assessment of the impact of global warming on agricultural production are huge. On the one hand, the ANN technology has been shown to be a useful tool to investigate, approximate and predict spring crop yields in a heterogeneous climate region with wide ranges of temperature and precipitation. On the other hand, the ANN approach can be used for systems analysis in order to determine key variables without knowing the exact dependencies. Unknown base yields and technical trends due to changing soil fertility or farmer´s management practices can automatically be determined by the model or separately by traditional regression or estimation methods. The same can be done with the CO2 fertilizer effect or improvement of plant breeding. With modern ANN software packages it is easy to construct different networks for these special purposes. Output of REMOs or GCMs can directly be used to simulate crop yields or yield potentials under climate change. A direct coupling with other dynamical crop growth models is possible.

There are limiting factors, however. To avoid the known overtraining effect ANNs need long and numerous time series of regional weather and yield pattern of heterogeneous regions. The ability to generalize and the accuracy of predictions outside the training area are limited by the ranges and the variability of input parameters of the training and prediction area and by the continuity and comparability of soil characteristics and management practices. Consequently special ANNs have to be developed for non comparable climate regions. For example our trained ANNs may give with some adaptations predictions for Denmark, Poland, France or Great Britain but would not work in Finland, as the length of growing season is up to 50 days shorter there than in Germany and the usable solar radiation is different. Another limiting factor are the unsufficient validation techniques (Schultz et al. 2000) and the black-box character of the ANN. Nevertheless the presented examples show that the accuracy of ANN technology compared to other estimation methods for this are equal or better, so that traditional approaches can be substituted where needed.

Acknowledgements

Thanks to David Maddison and Uwe Schneider for constructive discussions. The EU DG Research through the GreenSense project (EVG1-CT-2000-00022), the US National Science Foundation through the Center for Integrated Study of the Human Dimensions of Global Change (SBR-9521914) and the Michael Otto Foundation provided welcome financial support. All errors and opinions are ours.

References

Baetge J, Kruse A, Utthoff C (1996) Bonitätsklassifikation von Unternehmen mit Neuronalen Netzen. Wirtschaftsinformatik 38:273-281

Beinhauer R, Günther J (1990) Agrarmeteorologische Arbeitsunterlagen und Planungshilfen für Norddeutschland. Agrarmeteorologische Beratungs- und Forschungsstelle Quickborn, Deutscher Wetterdienst (ed), Wissenschaftsverlag Vauk, Kiel

Beniston M, Tol RSJ, Delecolle R, Hoermann G, Iglesias A, Innes J, McMicheal AJ, Martens WJM, Nemesova I, Nicholls RJ, Toth FL (1998) Europe. In: Watson RT, Zinyowera MC, Moss RH, Dokken DJ (eds) The Regional Impacts of Climate Change - An Assessment of Vulnerability - A Special Report of IPCC Working Group II. Cambridge University Press, Cambridge, p 149-185

Bouman BAM, van Keulen H, van Laar HH, Rabbinge R (1996) The 'School of de Wit' Crop Growth Simulation Models: A Pedigree and Historical Overview. Agric Syst 52:171-198

Chipanshi AC, Ripley EA, Lawford RG (1999) Large-Scale simulation of wheat yields in a semi-arid environment using a crop-growth model. Agric Syst 59:57-66

Cline WR (1996) The Impact of Global Warming on Agriculture: Comment. Am Econ Rev 86:1309-1311

Darwin R (1999) The Impact of Global Warming on Agriculture: A Ricardian Analysis: Comment. Am Econ Rev 89:1049-1052

Deutscher Wetterdienst(ed) (1972 - 2000) Deutsches Meteorologisches Jahrbuch. Deutscher Wetterdienst, Offenbach am Main

Fu L (1994) Neural Networks in Computer Intelligence. McGraw-Hill, New York

Fageria NK (1992) Maximizing Crop Yields. Dekker M, New York

Gardner MW, Dorling SR (1998) Artificial neural networks (the multilayer perceptron)-a review of applications in the atmospheric sciences. Atmos Environ 32:2627-2636

Gitay H, Brown S, Easterling W, Jallow B, Antle J, Apps M, Beamish R, Chapin T, Cramer W, Frangi J, Laine J, Erda L, Magnuson J, Noble I, Price J, Prowse T, Root T, Schulze E, Sirotenko O, Sohngen B, Soussana J (2001) Ecosystems and Their Goods and Services. In: McCarthy JJ, Canziani OF, Leary NA, Dokken DJ, White KS (eds) Climate Change 2001. Cambridge University Press, Cambridge, p 235-342

Goudriaan J (1996) Predicting crop yields under global change. In: Walker B, Steffen W (eds) Global Change and Terrestrial Ecosystems. Cambridge University Press, Cambridge, p 260-274

Grunwald (2002) Personal Communication 8-11-2002. Statistisches Landesamt, Schleswig-Holstein, Kiel

Guerif M, Philipe O, Delécolle R (1985) Statistical Modelling of Winter Yield at Regional Scale. In: Day W, Atkin RK (eds) Wheat Growth and Modelling. Plenum Press, New York, London, p 371-379

Hansen JW, Jones JW (2000) Scaling-up crop models for climate variability applications. Agric Syst 65:43-72

Hanus, H (1978) Vorhersage von Ernteerträgen aus Witterungsdaten in den Ländern der EG. Agricultural Statistical Studies(21). Statistical Office of the European Communities, Kiel

Hanus H, Aimiller O (1978) Ertragsvorhersage aus Witterungsdaten (Unter besonderer Berücksichtigung methodischer Probleme). Verlag Paul Parey, Berlin,Hamburg

Harrison PA, Butterfield RE (1996) Effects of climate change on Europe-wide winter wheat and sunflower productivity. Clim Res 7:225-241

Hertz J, Krogh A, Palmer RG (1993) Introduction to the theory of neural computation. Addison-Wesley, Reading, Massachusetts

Hill BD, McGinn SM, Korchinski A, Burnett B (2002) Neural network models to predict the maturity of spring wheat in western Canada. Can J Plant Sci 82:7-13

Hoogenboom G (2000) Contribution of agrometeorology to the simulation of crop production and its applications. Agric For Meteorol 103:137-157

Hornik K, Stinchcombe M, White H (1989) Multilayer feedforward networks are universal approximators. Neural Networks 2:359-366

Hsieh W, Tang B (1998) Applying Neural Network Models to Prediction and Data Analysis in Meteorology and Oceanography. Bull. Am. Meteorol. Soc. 79:1855-1870

Isermeier F, Riedel J, Möller C (1999) Analyse der internationalen Wettbewerbsfähigkeit mit Hilfe des IFCN, dargestellt am Beispiel der Weizen- und Zuckerproduktion. Kiel; available at http://www.uni-kiel.de/agrarmarketing/Gewisola99/B1isermeyer.pdf

IPCC (2001) Climate Change 2001: Impacts, Adaptation & Vulnerability: Contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change (IPCC). McCarthy JM, Canziani OF, Zinyowera MC, Leary NA, Dokken DJ, White SK (eds). Cambridge University Press, Cambridge

IPCC (1998) The Regional Impacts of Climate Change: An Assessment of Vulnerability. Watson RT, Zinyowera MC, Moss RH, Dokken DJ (eds). Cambridge University Press, Cambridge

IPCC (1995) Climate Change 1995: Impacts, Adaptations and Mitigation of Climate Change: Scientific-Technical Analyses: Contribution of Working Group II to the Second Assessment of the Intergovernmental Panel on Climate Change. Watson RT, Zinyowera MC, Moss RH, Dokken DJ (eds). Cambridge University Press, Cambridge

IPCC (1990) Impacts Assessment of Climate Change – Report of Working Group II. Tegart WJM, Sheldon GW, Griffiths DC (eds). Australian Govt. Pub. Service, Canberra

Jäger F (2003) Personal Communication 9-7-2003. KWS MAIS GmbH, Fachberatung Mais, Einbeck

Jagtap SS, Jones JW (2002) Adaptation and evaluation of the CROPGRO-soybean model to predict regional yield and production. Agriculture Ecosystems & Environment 93:73-85

Jagtap SS, Jones JW (2001) Predicting Regional Soybean Yield And Production - Scaling Up Crop Simulations; available at http://www.agen.ufl.edu/~sjagtap/ssj/AgEco2.pdf

Jame YW, Cutforth HW, Ritchie J (1999) Temperature response function for leaf appearance rate in wheat and corn. Can J Plant Sci 79:1-10

Jame YW, Cutforth HW (1996) Crop growth models for decision support systems. Can J Plant Sci 76:9-19

Kising W (1962) Maisanbau auf neuen Wegen. Kniebühler, Endingen a.K.

Knöpfel A (2003). Investox - die Börsensoftware; available at http://www.investox.de

Kuligowski RJ, Barros AP (1998) Experiments in Short-Term Precipitation Forecasting Using Artificial Neural Networks. Mon Weather Rev 126:470-482

Landau S, Mitchell RAC, Barnett V, Colls JJ, Craigon J, Moore KL, Payne RW (1998) Testing winter wheat simulation models` predictions against observed UK grain yields. Agric For Meteorol 89:85-99

Landau S, Mitchell RAC, Barnett V, Colls JJ, Craigon J, Payne RW (2000) A parsimonious, multiple-regression model of wheat yield response to environment. Agric For Meteorol 101:151-166

Lang G (1999a) Globaler Klimawandel und Agrarsektor. Mohr Siebeck, Tübingen

Lang, G (1999b) Global Warming and German Agriculture: Impact Estimations Using a Restricted Profit Function. In: Blum R, Hanusch H, Pfaff M (eds) Volkswirtschaftliche Diskussionsreihe, Beitrag 185, Universität Augsburg, Augsburg

Liu J, Goering CE, Tian L (2001) A neural network for setting target corn yields. Transactions of the ASAE 44:705-713

Major DJ, Hill BD, Touré A (1996) Prediction of seeding date in southern Alberta. Can J Plant Sci 76:59-65

McMaster, GS (1997) Phenology, development, and growth of the wheat (Triticum aestivum L) shoot apex: A review. Sparks, DL. (ed) Advances in Agronomy 59. Academic Press, San Diego; London; Boston; New York; Sydney; Tokyo; Toronto, p 63-118

Mendelsohn R, Nordhaus W, Shaw D (1996) Climate impacts on aggregated farm value: accounting for adaptation. Agric For Meteorol 80:55-66

Mendelsohn R, Smith JB, Neumann JE (1999) Introduction. In: Mendelsohn R, Neumann JE (eds) The Impact of Climate Change on the United States Economy. Cambridge University Press, Cambridge, p 1-17

Mirschel W, Schultz A, Wenkel K-O (2000) Ertragsabschätzungen bei Wintergetreide auf den Skalen zwischen Schlag und Region. In: Wittmann J, Gnauck A, Page B, Wohlgemuth V (eds) Simulation in Umwelt- und Geowissenschaften: Workshop Hamburg 2000, Workshop Kölpinsee 1999. Berichte aus der Umweltinformatik. Wohlgemuth, Aachen, p 227-238

Mitchell BR (1992) International Historical Statistics, Europe. Stockton Pr., New York

Monteith JL (2003) Agricultural Meteorology: evolution and application. Agric For Meteorol 103:5-9

Navone HD, Ceccatto HA (1994) Predicting Indian monsoon rainfall: a neural network approach. Clim Dyn 10:305-312

O'Neal MR, Engel BA, Ess DR, Frankenberger JR (2002) Neural Network Prediction of Maize Yield using Alternative Data Coding Algorithms. Biosystems Engineering 83:31-45

Otter S, Ritchie JT (1985) Validation of the CERES Wheat model in diverse environments. In: Day W, Atkin RK (eds) Wheat Growth and Modelling. Plenum Press, New York; London, p 307-310

Porter JR (1985) Approaches to Modelling Canopy Development in Wheat. In: Day W, Atkin RK (eds) Wheat Growth and Modelling. Plenum Press, New York; London, p 69-82

Priya S, Shibasaki R (2000) National Spatial Crop Yield Simulation Using GIS-Based Crop Production Model. Center for Spatial Information Science, University of Tokyo; available at http://www.csis.u-tokyo.ac.jp/japanese_2002/research_activities/publica-tions/dp/dp.html

Quiggin J, Horowitz JK (1999) The Impact of Global Warming on Agriculture: Comment. Am Econ Rev 89:1044-1045

Richter K (2003) Personal Communication 8-9-2003. Humboldt-Universität zu Berlin, Institut für Pflanzenbauwissenschaften, Grünlandsysteme

Rosenzweig C, Parry ML, Fischer G, Frohberg K (1993) Climate change and world food supply, Research Report 3. Environmental Change Unit, University of Oxford; available at http://www.ciesin.columbia.edu/docs/004-046/004-046.html

Rosenzweig C, Hillel D (1998) Climate Change and the Global Harvest. Oxford University Press, New York, Oxford

Rosenzweig C, Tubiello FN, Goldberg R, Mills E, Bloomfield J (2002) Increased crop damage in the US from excess precipitation under climate change. Global Environ Change 12:197-202

Sahai AK, Soman MK, Satyan V (2000) All India summer monsoon rainfall prediction using an artificial neural network. Clim Dyn 16:291-302

Schultz A, Wieland R (1997) The use of neural networks in agroecological modelling. Computers and Electronics in Agriculture 18:73-90

Schultz A, Wieland R, Lutze G (2000) Neural networks in agroecological modelling – stylish application or helpful tool? Computers and Electronics in Agriculture 29:73-97

Silverman D, Dracup JA (2000) Artificial Neural Networks and Long-Range Precipitation in California. J Appl Meteorol 39:57-66

Singh B, El Maayar M, André P, Bryant CR, Thouez J-P (1998) Impacts of a GHG-Induced Climate Change on Crop Yields: Effects of Acceleration in Maturation, Moisture Stress, and Optimal Temperature. Clim Chang 38:51-86

Spiekers, H (2000) Silomais: Intuition ist gut - Reifemanagement ist besser! Land & Forst; available at http://www.saaten-union.de/index.cfm?cfid=1939758&cftoken=48313132&doc=1463&startid=292

Statistisches Bundesamt (ed) (1972 – 2001) Bodennutzung und pflanzliche Erzeugung. In: Statistisches Bundesamt (ed), Land- und Forstwirtschaft, Fischerei, Fachserie 3, Reihe 3. Verlag W. Kohlhammer GmbH, Stuttgart, Mainz

Statistisches Landesamt Schleswig-Holstein (ed) (1972 – 2001) Bodennutzung und Ernte in Schleswig-Holstein. In: Statistische Berichte CI/CII, Statistisches Landesamt Schleswig-Holstein (ed). Statistisches Landesamt Schleswig-Holstein, Kiel

Stapper M, Lilley JM (2001) Evaluation of simtag and nwheat in Simulating Wheat Phenology in Southeastern Australia. Proceedings of the 10th Australian Agronomy Conference. Hobart; available at http://www.regional.org.au/au/asa/2001/1/d/stapper.htm

Supit I (1997) Predicting national wheat yields using a crop simulation and trend models. Agric For Meteorol 88:199-214

Tan G, Shibasaki R (2003) Global estimation of crop productivity and the impacts of global warming by GIS and EPIC integration. Ecol. Model. 168:357-370

Tang B, Hsieh WW, Monahan AH, Tangang FT (2000) Skill Comparisons between Neural Networks and Canonical Correlation Analysis in Predicting the Equatorial Pacific Sea Surface Temperatures. J Clim 13:287-293

Tang Y, Hsieh WW, Tang B, Haines K (2001) A neural network atmospheric model for hybrid coupled modelling. Clim Dyn 17:445-455

Trigo RM, Palutikof JP (1999) Simulation of daily temperatures for climate change scenarios over Portugal: a neural network model approach. Clim Res 13:45-59

Tubiello FN, Rosenzweig C, Goldberg RA, Jagtap S, Jones JW (2002) Effects of climate change on US crop production: simulation results using two different GCM scenarios. Part I: Wheat, potato, maize, and citrus. Clim Res 20:259-270

Uhrig JW, Engel BA, Baker WL (1992) An Application of Neural Networks: Predicting Corn Yields. In: Watson DG (ed) Computers in agricultural extension programs: proceedings of the 4th International Conference 28-31 January 1992, Orlando, Florida. American Society of Agricultural Engineer, St. Joseph, Michigan, p 348-353

Zalud Z, Dubrovský M (2002) Modelling climate change impacts on maize growth and development in the Czech Republic. Theor Appl Climatol 72:85-102

Zell A (1994) Simulation Neuronaler Netze. Addison-Wesley (Deutschland) GmbH, Bonn

Zell A, Mamier G, Vogt M, Mache N, Hübner R, Döring S, Herrmann K-U, Soyez T, Schmalzl M, Sommer T, Hatzigeorgiou A, Posselt D, Schreiner T, Kett B, Clemente G (1995) Stuttgart Neural Network Simulator. University of Stuttgart, Stuttgart

Zscheisler J, Estler MC, Groß F, Neuman H, Geißler B (1979) Mais, Anbau und Verwertung. DLG-Verlags-GmbH, Frankfurt am Main

Working Papers

Research Unit Sustainability and Global Change

Centre for Marine and Climate Research, Hamburg University, Hamburg

Heinzow, T. and Tol, R.S.J. (2003), *Prediction of Crop Yields across four Climate Zones in Germany: An Artificial Neural Network Approach,* **FNU-34** (submitted)

Tol, R.S.J. (2003), *Adaptation and Mitigation: Trade-offs in Substance and Methods,* **FNU-33** (submitted)

Tol, R.S.J. and T. Heinzow (2003), *Estimates of the External and Sustainability Costs of Climate Change*, **FNU-32** (submitted)

Hamilton, J.M., Maddison, D.J. and Tol, R.S.J. (2003), *Climate change and international tourism: a simulation study,* **FNU-31 (**submitted**)**

Link, P.M. and R.S.J. Tol (2003), *Economic impacts of changes in population dynamics of fish on the fisheries in the Barents Sea*, **FNU-30** (submitted)

Link, P.M. (2003), *Auswirkungen populationsdynamischer Veränderungen in Fischbeständen auf die Fischereiwirtschaft in der Barentssee*, **FNU-29** (submitted to *Essener Geographische Arbeiten*)

Lau, M. (2003), *Coastal Zone Management in the People's Republic of China – An Assessment of Structural Impacts on Decision-making Processes*, **FNU-28** (submitted)

Lau, M. (2003), *Coastal Zone Management in the People's Republic of China – A Unique Approach?*, **FNU-27** (*China Environment Series,* Issue 6, pp. 120-124; http://www.wilsoncenter.org/topics/pubs/7-commentaries.pdf)

Roson, R. and R.S.J. Tol (2003), *An Integrated Assessment Model of Economy-Energy-Climate – The Model Wiagem: A Comment*, FNU-26 **(submitted to *Integrated Assessment*)**

Yetkiner, I.H. (2003), *Is There An Indispensable Role For Government During Recovery From An Earthquake? A Theoretical Elaboration*, **FNU-25**

Yetkiner, I.H. (2003), *A Short Note On The Solution Procedure Of Barro And Sala-i-Martin for Restoring Constancy Conditions*, **FNU-24**

Schneider, U.A. and B.A. McCarl (2003), *Measuring Abatement Potentials When Multiple Change is Present: The Case of Greenhouse Gas Mitigation in U.S. Agriculture and Forestry*, **FNU-23** (submitted)

Zhou, Y. and Tol, R.S.J. (2003), *The Implications of Desalination to Water Resources in China - an Economic Perspective*, FNU-22 (forthcoming in *Desalination*)

Yetkiner, I.H., de Vaal, A., and van Zon, A. (2003), *The Cyclical Advancement of Drastic Technologies*, FNU-21

Rehdanz, K. and Maddison, D. (2003) *Climate and Happiness*, **FNU 20** (submitted)

Tol, R.S.J., (2003), *The Marginal Costs of Carbon Dioxide Emissions: An Assessment of the Uncertainties*, **FNU-19** (submitted).

Lee, H.C., B.A. McCarl, U.A. Schneider, and C.C. Chen (2003), *Leakage and Comparative Advantage Implications of Agricultural Participation in Greenhouse Gas Emission Mitigation*, **FNU-18** (submitted).

Schneider, U.A. and B.A. McCarl (2003), *Implications of a Carbon Based Energy Tax for U.S. Agriculture*, **FNU-17** (submitted).

Tol, R.S.J. (2002), *Climate, Development, and Malaria: An Application of* FUND, **FNU-16** (submitted).

Hamilton, J.M. (2003), *Climate and the Destination Choice of German Tourists,* **FNU-15** (revised and submitted).

Tol, R.S.J. (2002), *Technology Protocols for Climate Change: An Application of* FUND, **FNU-14** (submitted to *Climate Policy*).

Rehdanz, K (2002), *Hedonic Pricing of Climate Change Impacts to Households in Great Britain*, **FNU-13** (submitted to *Climatic Change*).

Tol, R.S.J. (2002), *Emission Abatement Versus Development As Strategies To Reduce Vulnerability To Climate Change: An Application Of* FUND, **FNU-12** (submitted).

Rehdanz, K. and Tol, R.S.J. (2002), *On National and International Trade in Greenhouse Gas Emission Permits*, **FNU-11** (submitted).

Fankhauser, S. and Tol, R.S.J. (2001), *On Climate Change and Growth*, **FNU-10** (submitted to *Resource and Energy Economics*).

Tol, R.S.J.and Verheyen, R. (2001), *Liability and Compensation for Climate Change Damages – A Legal and Economic Assessment*, **FNU-9** (forthcoming in *Energy Policy*).

Yohe, G. and R.S.J. Tol (2001), *Indicators for Social and Economic Coping Capacity – Moving Toward a Working Definition of Adaptive Capacity*, **FNU-8** (*Global Environmental Change*, **12** (1), 25-40).

Kemfert, C., W. Lise and R.S.J. Tol (2001), *Games of Climate Change with International Trade*, **FNU-7** (forthcoming in *Environmental and Resource Economics*).

Tol, R.S.J., W. Lise, B. Morel and B.C.C. van der Zwaan (2001), *Technology Development and Diffusion and Incentives to Abate Greenhouse Gas Emissions*, **FNU-6** (submitted to *International Environmental Agreements*).

Kemfert, C. and R.S.J. Tol (2001), *Equity, International Trade and Climate Policy*, **FNU-5** (*International Environmental Agreements*, **2**, 23-48).

Tol, R.S.J., Downing T.E., Fankhauser S., Richels R.G. and Smith J.B. (2001), *Progress in Estimating the Marginal Costs of Greenhouse Gas Emissions*, **FNU-4**. (*Pollution Atmosphérique – Numéro Spécial: Combien Vaut l'Air Propre?*, 155-179).

Tol, R.S.J. (2000), *How Large is the Uncertainty about Climate Change?*, **FNU-3** (*Climatic Change*, **56** (3), 265-289).

Tol, R.S.J., S. Fankhauser, R.G. Richels and J.B. Smith (2000), *How Much Damage Will Climate Change Do? Recent Estimates*, **FNU-2 (***World Economics,* **1** (4), 179-206)

Lise, W. and R.S.J. Tol (2000), *Impact of Climate on Tourism Demand*, **FNU-1** (*Climatic Change*, **55** (4), 429-449).