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Crop Models as Decision Support Systems in Crop Production

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1. Introduction

The current challenges crop production faces in the context of required yield increases while reducing fertilizer, water and pesticide inputs have created an increasing demand for agronomic knowledge and enhanced decision support guidelines, which are difficult to obtain on spatial scales appropriate for use in a multitude of global cropping systems.
Nowadays crop models are increasingly being used to improve cropping techniques and cropping systems (Uehera and Tsuji, 1993; Penning de Vries and Teng, 1993; Boote et al., 1996). This trend results from a combination of mechanistic models designed by crop physiologists, soil scientists and meteorologists, and a growing awareness of the inadequacies of field experiments for responding to challenges like climate change. A general management decision to be made underlies the principle that a crop response to a certain input factor can only be expected if there is a physiological requirement and if other essential plant growth factors are in an optimum state. Hence, the challenge for a farmer is to determine how to use information with respect to the management decisions he has to make, in other words he has to find an efficient, relevant and accurate way how to evaluate data for specific management decisions. Crop models enable researchers to speculate on the long-term consequences of changes in agricultural practices and cropping systems on the level of an agro-ecosystem. Finally, models make it possible to identify very rapidly the adaptations required to enable cropping systems to respond to changes in the economic or regulatory context (Rossing et al., 1997).
The following chapter gives an overview on the current knowledge and use of crop models and addresses the problems associated with these methods. In a second part the use of crop growth models for decision support in terms of yield variability, fertilizer and irrigation strategies will be discussed in the context of two global case studies, one in China and the other one in Germany. The discussion focuses on the currently available modeling techniques and addresses the necessary future research areas in this context.

2. Decisions and uncertainty

Scientists have realized that farmers nowadays have multiple technologies like sensors, satellites etc. available to gather a myriad of data on weather, soil parameters, crop development and growth. The collected data is attributed to find the right management decision in the context of e.g. amount and timing of inputs, sowing and harvest date etc.

However, the collected data has opened a "Pandora's box" of uncertainty. The type of information gained, increases the level of uncertainty, because it emphasizes the apparent disorder, or in a physical sense the entropy, as is does not deliver the management decision itself, but rather provides information. The relationship between the three related attributes of uncertainty, information and entropy can be illustrated by different levels of uncertainty. In the first level of uncertainty, e.g. a single soil texture map represents minimal information but low entropy. In a second level representing e.g. multiple layers of information from a given field like yield, soil water and soil nitrogen (N), more information is presented, but it is of high entropy. The uncertainty of decision making is now realized and high. Finally, the third level reflects a decision support system, where the information content is high, so entropy is low leading to a reduced level of uncertainty in the taken management decision.

The current situation of cropping systems is represented in level two, where a lot of information is available, but it cannot be put in the right place yet. The challenge facing scientists now is to help farmers to understand this information. The farmer has to be enabled to use the information to manage his cropping system in a way that matches the underlying limitations. Thus, the optimum order will have minimum entropy and maximum information and a low level of uncertainty associated with the management decision. To capitalize on these features, however, the decision maker must have a more accurate assessment of the likely outcomes of action, thereby improving the likelihood of benefit to a degree, which justifies the additional effort required (Adams et al., 2000). Failure to do so has the consequence that uncertainty of outcomes remains to high, to provide reasonable benefit.

However, much of the uncertainty in management decisions cannot be removed in an easy way, because the outcome like crop yield is often timely separated from the decision like timing and amount of nitrogen fertilizer. Because of this, the outcome or consequence of a given action has to be predicted. Crop models can play a major role in trying to minimize the uncertainty associated with certain management actions as they integrate and consider multiple factors for the decision making process. The following section will focus on the different types of models available and their appropriateness for crop management.

3. Crop models

Model types are divided arbitrarily into the categories defined by Cook (1997) as 'conventional', 'intuitive', 'expert systems', 'deterministic' and 'stochastic'. The characteristics of the model types and their previous use in crop management have been discussed in Cook (1997) and Cook and Adams (1998).

Crop growth models have been used since the 1970s (Hoogenboom, 2003). The first crop growth models were based on approaches of simulating industrial processes (Forrester, 1961). Brouwer and De Wit (1968) and De Wit et al. (1970) developed some of the early crop growth models in a program called BACROS. The main aim of their modeling activities was to understand the underlying processes at the plant scale (Van Ittersum et al., 2003). While all models have achieved various degrees of success in application, they all have their weakness and fail under certain circumstances, wherefore authors of models should clarify the limitations of their models and ranges of applications (Ma and Schaffer, 2001).

In the past decade the dynamics of crop growth models has made substantial progress (Gerdes, 1993) and many crop models are available on the market. Many models exist for predicting how crops respond to climate, nutrients, water, light, and other conditions. One of the most widely used modeling systems across the world is the DSSAT model (Decision Support System for Agrotechnology Transfer). It was initially developed under the auspices of the International Benchmark Sites Network for Agrotechnology Transfer (Hoogenboom, 2003). Currently, the DSSAT shell is able to incorporate models of 27 different crops, including several cereal grains, grain legumes, and root crops (Hoogenboom, 2003). The models are process-oriented and are designed to work independent of location, season, crop cultivar, and management system. The models simulate the effects of weather, soil water, genotype, and soil and crop N dynamics on crop growth and yield (Jones et al., 2003). The models predict daily plant growth based on daily weather data and soil, management and genetic information. Growth is computed based on light interception and the daily photosynthesis, which can be reduced by temperature, water and N stress. Carbohydrate fixed by photosynthesis is then partitioned to plant components based on crop growth stage, and stress. Thus, the model is able to integrate daily effects of temporal stress on growth and yield. Information that is entered into the system, to be combined with yield potential, will include known variables such as soil types, soil depths, N leaching properties, soil nutrient status, information on pests, disease and weed populations, etc. Information on weather records is a further valuable source of information. Political factors can be taken into account, such as available subsidies or current legislation governing maximum rates of N application. Consideration can also be given to environmental issues, and the farmer's local knowledge and farm records may also be an essential input into the system. The farmer can test his preferred strategy, which could either be to increase the input (aiming at maximum yield) or to reduce inputs (aiming at reducing environmental pollution) to optimize gross margins.
With the aid of a crop model, a more detailed analysis of the management decisions and the possible effects on final yield can be undertaken. It also should be acknowledged that uncertainty exists in the final yield estimate as a result of uncertainty in the input data and errors in the models. Chen et al. (1997) used first order uncertainty analysis to examine the effect of uncertainty in input data on the model outcome of a mechanistic decision support system. They reported large uncertainty, which was contributed mostly to the given variability in specific model parameters. Therefore, the model output has to be critically assessed, which is mostly done based on regressions. The most commonly used criterion of model performance is the coefficient of determination (R^2), which is the ratio of the variance explained by the model to the total variance in the data. A number of authors have concluded that R^2 is not a good means of comparison between models representing yield response (Cerrato and Blackmer, 1990). A primary consideration for the unsuitability of R^2 is the fact that it gives no indication of how well a model performs when applied to data that were not used to create the model, as it does only provide information about the trend and does not provide information about the deviation of measured and simulated values. Over-fitting of calibrations leading to poor performance of the model on test data is often the result. Based on these considerations, another used measure of model accuracy is the root mean square error (RMSE). A major advantage of using RMSE over R^2 for model evaluation is that RMSE provides information about both on the calibration data and on new data not used in developing the model to estimate the true predictive ability of the model

(Drummond et al., 2003). Cross-validation is another more robust, reliable method of measuring prediction accuracy (Stone, 1973) of crop models.
Based upon the total information entered into the model, it will offer an agronomic recommendation on how to vary the inputs, change the management or optimize the overall gross margin. A crop growth model could therefore be used as a decision aid for determining different yields based on factors such as varying plant populations or nitrogen rates, which could help a farmer decide when to plant or replant areas within a field based on plant population data and risk factors for various soil types or how to manage nitrogen application rate and dates. It would give the farmer the analytical ability to identify relationships between different variables within the field and to find a best fit scenario on a high level of complexity.
Furthermore, crop models offer the possibility to aggregate knowledge on and over different scales. Linking the models with a GIS offers a mechanism to integrate many scales of data developed in and for agricultural research. Data access and final management decision can be expanded to a decision support system, which uses a mix of process-oriented models and biophysical data at different temporal and spatial scales (e.g. growing season, climate characteristics, soils). Thus, a need exists for an integrated GIS system which combines the different available information (e.g. soil map, yield, weather, management) to allow agricultural producers as well as policy makers to know the impact of differences between input and output spatially from one place or region to another to improve management, productivity and profitability.

3.1 Model applications

Crop yield and occurring yield gaps and are two important criteria for sustainable land management. Considering various agro-environments, several factors clearly account for crop yield and occurring yield gaps. Analysis of yield gaps in crop production is facilitated by using the concept of production ecology where different sets of eco-physiological variables affecting crop growth and development are distinguished (Penning de Vries et al., 1989). The approach recognizes three sets of factors affecting crop growth and development. Growth and yield determinants include mainly 1) crop genetics, 2) abiotic resources (water and nutrients, as well meteorological variables like temperature and solar radiation) which limit crop growth and development when their supply is suboptimal over different periods in the growing season, 3) biotic factors (pests, diseases, weeds). Hence, overall crop productivity is the result of growth and yield determining, limiting and reducing factors. Process-based crop models are increasingly being used in assessing these yield determining, limiting and reducing factors for a particular area or region with given agro-environmental conditions and are therefore a valuable tool to analyze occurring yield gaps.
Process-based crop growth models are a promising tool to help identify relationships between yield-limiting factors, management and environment. Crop models such as the DSSAT or the APOLLO (Batchelor et al., 2004b) model can be used to identify spatial yield-limiting factors (Batchelor et al., 2004b; Jones et al., 2003). Both models are based on the CROPGRO (Boote et al., 1998) and CERES (Ritchie et al., 1998) family of process-oriented crop models. Based on information about management (i.e. cultivar, planting, fertilization, plant protection, harvest) and environmental conditions (soil, weather), those process-oriented crop growth models compute the daily rate of plant growth, resulting in an

estimation of final yield and plant biomass. Therefore those models simulate the daily interaction of plant growth, water, nitrogen, and pest stress on plant growth processes.

Future sustainable land management requires information on yield trends not only over time but also over space, to assess whether yields are stable or increasing, or whether they are decreasing and thereby signaling possible failure in the future. Spatial yield variability is a complex interaction of many factors including water stress, rooting depth, soil and drainage properties, weather, pests, fertility, and management. Spatial yield variability can also be related to spatial variability in soil fertility (Finke and Goense, 1993), soil organic matter content (Kravchenko and Bullock, 2000), and pest attacks (Plant et al., 1999). The challenge for farmers is to identify the factors that they can control and manage, and make appropriate management decisions to increase profits. Research advancements in data collection have given farmers the tools and capabilities to effectively map their fields, record yield histories and vary inputs and management strategies in response to variations in soil and environmental factors in the field. Recently, process-oriented crop growth models such as CROPGRO-Soybean (Hoogenboom et al., 1994), CERES-Maize (Jones and Kiniry, 1986) and CERES-Wheat (Godwin et al., 1989) have been used to study causes of spatial yield variability. The results have shown that the models can accurately simulate corn and soybean spatial yield variability, taking into account yield-limiting factors such as water stress in soybeans (Paz et al., 1998), soybean cyst nematodes (Paz et al., 2001), water stress in corn (Fraisse et al., 1998) and interaction of corn population and water stress (Paz et al., 1999). These studies also demonstrated that crop models can play an important role in understanding the causes of spatial yield variability. They can be used as a tool to explore hypotheses related to crop yield variability (Paz et al., 1998) and identify areas in the field, where problems due to varying growing conditions occur (Link et al., 2007). The spatial component of such a crop model is going to discretize a field studied in space and time into a finite number of regular cells and within those cells the model inputs are considered as uniform. With the appropriate computational hardware it is possible to discretize the modeled field into smaller and smaller grids in an effort to improve the quality of the model predictions. In theory, higher resolution modeling is expected to yield better predictions because of better resolved model inputs (e.g. soil texture, nutrients). The use of smaller grid sizes undeniably improves the appearance of simulation results, but the question raises how small can be to small to model as the potential benefits of higher resolution modeling have to be weighed against the increased demands on inputs. A separate issue might be the spatial coverage of data points and observations available to evaluate model performance. Observational data might not be sufficient to prove the benefits of higher resolution modeling and the model performance might get worse at smaller scales. It is therefore important to examine the relevant grid size for the model application on hand. The uncertainties in the underlying yield limiting parameters might not justify a high grid resolution. The aim of the following case study was to evaluate the reasons for spatial variability of corn yields using the APOLLO model to test its performance under German conditions, and to test it on various grid scales.

3.2 Case study Germany - Procedure to evaluate corn (*Zea mays* L.) yields in the upper Rhine valley using a crop growth model

Spatial yield variability is a result of complex interactions among different yield-limiting factors, such as soil properties, nutrient and water availability, rooting depth, pests and management. In order to manage spatial yield variability within a field, yield-limiting factors must be identified and understood. Initial efforts to study yield variability have focused on taking static measurements of soil, management, or plant properties and regressing these values against grid level yields (Sudduth et al., 1996). Classical statistics based on ordinary least squares have frequently been used to explore functional relationships between crop productivity and controlling factors (Long, 1998). Tomer and Anderson (1995) used linear regression to predict spatial patterns in yield based on soil fertility. However, it is difficult to represent the temporal effects of time dependent interactive stresses (i.e. water stress) on crop growth and yield using classical statistical techniques.

Characterization of yield variability requires the analysis of both spatial and temporal behavior of soil, weather, management and environmental factors. Thus, extending the use of crop models to examine within-field spatial yield variability is an intriguing challenge. In few studies, the APOLLO model was used to analyze causes of spatial yield variability in soybean (Batchelor et al., 2004b). The APOLLO model is a precision agriculture decision support system designed to use the CROPGRO-Soybean and CERES-Maize models to analyze causes of yield variability and to estimate the economic and environmental consequences of prescriptions (Batchelor et al., 2004a). Techniques in APOLLO have never been tested outside of the United States. To date, the APOLLO model has only been used in large fields with grid sizes ranging from 0.055 – 0.2 ha.

The overall goal of this work was to use the APOLLO model to study the spatial yield variability of three fields in the upper Rhine Valley (Germany) and to determine if crop model calibration techniques developed in the United States could be transferred to small fields in Germany. The specific objectives of this study were (i) to develop and test different calibration strategies to minimize the error between simulated and measured spatial corn yield, and (ii) to evaluate the impact of grid size on the error of simulated spatial yield variability.

3.2.1 Site, treatments and yield monitoring

The study was conducted as an on-farm study from 1998 through the 2002 growing season on three fields (I1, I2, I3) in the Upper Rhine Valley near Weisweil (48° 19′ N, 7° 67′ E), northwest of Freiburg, Germany. The mean annual precipitation in this area is 910 mm, the mean temperature is about 9.5° C and the sum of the yearly solar radiation averages about 11390 kJ m^{-2}. The major soil type is a silty loam. The aggregated size of the three fields was approximately 5.5 ha in total. Corn was grown each year from April – October during the years 1998 – 2002 in all three fields, with exception of field I1, where wheat was grown in 1999. The corn cultivars varied for each field and year (Table 1).

Each field was managed uniformly using the producer's current management practices. At sowing, a starter fertilizer of Ø 31 kg N ha^{-1} was applied uniformly as KAS (13 % NH_4-N, 13 % NO_3-N) to all fields in all 5 years. In the years 2000-2002 around the 4th leaf stage soil samples at a depth of 0 – 30, 30 – 60 and 60 – 90 cm were taken at 30 data collection points, which were set up at a distance of 40 x 40 m, and analyzed for soil available nitrogen. Table 2 shows the values of soil available nitrogen (kg N ha^{-1}) in the upper 90 cm of the soil layer around the 4th leaf stage. Urea (46 % N) was applied uniformly to each field based on the results of soil available nitrogen around the 4th leaf stage. Rates varied for each field and year, and ranged from 44 – 120 kg N ha^{-1}, to give an average of 250 kg N ha^{-1} in each field. In 2001 swine manure was applied in field I2, which provided an additional 40 kg N ha^{-1} in this field. No other field received swine manure. Herbicides and pesticides were applied as needed to control pests. After harvest in September or October, the corn residue was left on the surface of each field.

Field		1998	1999	2000	2001	2002
I1	Cultivars	Helix	*	Marista	Benicia	Marista
	Maturity	K220		K400	K250	K400
I2	Cultivars	Marista	Helix	Marista	Peso	Marista
	Maturity	K400	K220	K400	K290	K400
I3	Cultivars	Helix	Helix	Benicia	Benicia	DK514
	Maturity	K220	K220	K250	K250	K400

* in 1999 on field I1 wheat was grown

Table 1. Cultivars planted on field I1, I2, I3 during the 5-yr period (1998-2002). K indicates the maturity classification based on BSA (1998).

Geo-referenced corn grain yield data were collected over the 5-year period using a differentially corrected global positioning system and a yield monitor mounted on a combine harvester (Lexion, Claas, Harsewinkel, Germany). Corn grain yield and corn grain moisture content were measured every 5 seconds (10-m distance), resulting in about 200 yield monitor data points per hectare. Erroneous yield monitor data with missing values for yield or grain moisture content, or yield values greater than 15000 kg ha^{-1} were excluded from the yield monitoring dataset. In this paper, yield was calculated as corn grain yield at 0 % moisture content.

Yield monitor data were studied in four different scenarios (case A – D) to evaluate the impact of grid size on the accuracy of simulated spatial yield variability. A grid network was established using grid sizes defined for case A (grids of 10.5 x 10.5 m = 0.011 ha), case B (grids of 16.5 x 16.5 m = 0.027 ha) and case C (grids of 22.5 or 30.5 x 50.5 m = 0.114 or 0.154 ha). In case C two different grid sizes were used to better match the field boundaries. The smaller grids (22.5 x 50.5 m) were placed in the turning rows, and the larger grids (30.5 x 50.5 m) were placed in the middle of the field. The grids were overlaid onto yield maps and the average yield for each grid was computed using a software tool, developed and described by Thorp et al. (2004). Each grid contained at least three yield monitor points. Case D used the same grid configuration as in case C. In addition measured soil available nitrogen in the upper soil layers (0 – 30, 30 – 60 and 60 – 90 cm) around the 4th leaf stage in the years 2001 and 2002 (Table 2) was used to adjust model state variables on the measurement date during the simulation run.

Field		2000	2001	2002
I1	Mean	106	59	118
	Range		24-139	92-185
I2	Mean	45	98	176
	Range		25-359	119-230
I3	Mean	53	49	87
	Range		18-63	73-107

Table 2. Cumulative soil available nitrogen (kg N ha^{-1}) in the upper soil layer (0 – 90 cm) around 4th leaf stage; average for all data collection points in field I1, I2 and I3.

3.2.2 Apollo (application of precision agriculture for field management optimization)

APOLLO was developed to assist users in evaluating causes of spatial yield variability and to develop optimum prescriptions for nitrogen, water and seeding management (Batchelor et al., 2004a). It has modules to assist the user in 1) calibrating spatial soil inputs to minimize error between simulated and measured yield, 2) validating the calibrated model for independent seasons, and 3) developing management prescriptions. Management, soil, weather and cultivar information are required as input files to run the model. The management file (*.mzx) contains model inputs including weather file name, soil composition, initial soil water, nitrate, and ammonia content, planting date, row spacing, and residue amount. The soil profile characteristics for each grid are stored in the soil input file (*.sol). This file contains information such as bulk density, saturated hydraulic conductivity, upper and lower drained limit and root growth factor. Daily weather data, including daily maximum and minimum temperature, rainfall and solar radiation were stored in the weather file (*.wth). All weather data were obtained at the nearest German Weather Service station located at Emmendingen-Mundingen and Freiburg, which are about 16 and 25 km from the trial site, respectively. The cultivar file (*.cul) contains cultivar coefficient, which give information about the rate of development and the required growing degree days (GDDs) for each genotype. Yield data for each grid in the field were stored in a separate yield file over the 5 year period (*.mza).

Data about soil properties available are often mean values over the whole field (or even bigger areas) and thus do not take the existing variability into account. However, when trying to simulate spatial yield variability at small spatial scales, it is necessary to adjust soil properties over their expected range in order to more accurately reflect spatial soil properties within the field. APOLLO allows the user to adjust up to 10 soil parameters (Table 3) for each grid. The user can test if one or a combination of these soil parameters may help explain the spatial yield variability. When a user selects the parameters to adjust, APOLLO uses a simulated annealing optimization algorithm to estimate the parameter values that minimize the root mean square error (RMSE) between simulated and measured yield over selected years in each grid selected by the user. Calibration of the APOLLO model results in a unique set of soil properties for each grid.

		Parameters	Unit	Minimum	Maximum	Initial
1	CN	SCS curve number		40	90	70
2	DR	Drainage rate	fraction day^{-1}	0.1	0.5	0.4
3	ETDR	Effective tile drainage rate	1 day^{-1}	0.01	0.25	0.05
4	SHC	Saturated hydraulic conductivity of deep impermeable layer	cm day^{-1}	0.001	2	0.01
5	HPF	Hardpan factor	0.0 - 1.0	0.01	1.0	0.5
6	DHP	Depth to the hard pan	cm	5	150	30
7	RDRF	Root distribution reduction factor		-0.1	-0.001	-0.05
8	NMF	Nitrogen mineralization factor	0.0 - 1.0	0.1	1.0	0.8
9	SFF	Soil fertility factor	0.0 - 1.0	0.7	1.0	0.99
10	ASW	(adjust) Available soil water	%	-20	20	0

Table 3. Soil parameters available for calibration in the APOLLO model.

In this study several genetic coefficients were adjusted to set the maximum yield of different cultivars. In the next step APOLLO was used to compute soil inputs to minimize error between simulated and measured yield for each grid size scenario (case A, B and C) and for the scenario, where measured soil available nitrogen (kg N ha^{-1}) at 4th leaf stage was used to adjust simulated soil available nitrogen in the model database (case D).

Two calibration strategies were applied to the data set:

- soil parameters were calibrated one at a time to determine which parameter appeared to have the greatest power to explain spatial yield variability.
- combinations of soil parameters identified before were calibrated to determine if combinations of soil parameters improved the simulation of spatial yield variability.

These calibration strategies were applied to different scenarios, and the effects of grid resolution on model accuracy were examined. The accuracy of the model was evaluated by the correlation coefficient R between simulated and measured yields and RMSE.

3.2.3 Calibration strategies

The results of model calibration using single soil parameters showed that the adjustment of single soil parameters resulted in a good fit between simulated and measured yield. The calibration of the five soil properties (HPF + DHP, RDRF, NMF, SFF and ASW) reduced RMSE between simulated and measured yield compared to the default values, and thus, partially explained spatial yield variability (Table 4). However, the adjustment of soil parameters SCS CN, DR, ETDR + SHC (described in Table 3) did not significantly reduce

	Parameters									
	HPF + DHP		RDRF		NMF		SFF		ASW	
Scale	R	RMSE (kg ha^{-1})	R	RMSE (kg ha^{-1})	R	RMSE (kg ha^{-1})	R	RMSE (kg ha^{-1})	R	RMSE (kg ha^{-1})
Field I1										
Case A	0.47	1441	0.40	1852	0.42	1821	0.46	1483	0.43	1484
Case B	**0.83**	848	**0.75**	1328	**0.81**	1183	**0.90**	742	**0.81**	949
Case C	**0.88**	738	**0.76**	1304	**0.81**	1189	**0.92**	656	**0.82**	919
Case D	**0.96**	514	**0.96**	539	**0.96**	531	**0.95**	569	**0.96**	541
Field I2										
Case A	**0.55**	1308	0.30	1312	0.05	1514	0.21	1109	0.09	1275
Case B	**0.77**	1062	**0.52**	1177	0.14	1476	0.36	1062	0.21	1251
Case C	**0.80**	1020	**0.50**	1182	0.08	1516	0.34	1055	0.18	1258
Case D	**0.74**	993	**0.54**	930	-0.04	1009	0.33	1005	0.17	923
Field I3										
Case A	0.27	1058	0.18	963	-0.14	459	-0.05	1073	-0.22	781
Case B	**0.70**	884	**0.54**	823	-0.02	434	0.18	1070	-0.06	802
Case C	**0.81**	672	0.43	892	-0.33	421	-0.03	1056	-0.31	764
Case D	**0.83**	922	**0.66**	1198	0.51	841	0.31	1115	0.25	1033

Table 4. Correlation coefficient R and RMSE for simulated and measured yield after model calibration (2000 iterations) of field I1, I2 and I3 using multiple years of corn yield data and single soil parameters (5-10). Yield was calculated in dependency of the grids in case A (10.5 x 10.5 m grid size), case B (16.5 x 16.5 m grid size), case C (22.5 or 30.5 x 50.5 m grid size) and case D (22.5 or 30.5 x 50.5 m grid size). R >0.50 is written in bold letters.

error between simulated and measured yield and thus, did not explain spatial yield variability. Thus, not all soil parameters available for calibration by APOLLO contributed to explaining the given spatial yield variability. Table 4 shows the correlation coefficient R and RMSE for simulated and measured yields after model calibration using single soil parameters HPF + DHP, RDRF, NMF, SFF and ASW for the four scenarios (cases A – D). Based on these results HDF+DHP seem to have the greatest effect on within field variability in these fields.

In the next step combinations of parameters found in the previous calibration strategy that appeared to partially explain spatial yield variability. Based on the previous results of calibrating single soil parameters, the parameters HPF + DHP, RDRF, NMF, SFF and ASW were selected for further model calibration and applied to the different scenarios (case A – D). Table 5 shows the correlation coefficient R and RMSE for simulated and measured yield after model calibration of field I1, I2 and I3 using multiple soil parameters.

	Parameters							
	HPF + DHP + ASW		HPF + DHP + RDRF + NMF + SFF		HPF + DHP + RDRF + SFF + ASW		HPF + DHP + RDRF + NMF + SFF + ASW	
Scale	R	RMSE (kg ha^{-1})	R	RMSE (kg ha^{-1})	R	RMSE (kg ha^{-1})	R	RMSE (kg ha^{-1})
Field I1								
Case A	0.49	1318	0.59	1219	0.52	1330	0.62	1215
Case B	**0.86**	728	0.94	484	**0.93**	547	**0.95**	463
Case C	**0.88**	622	0.96	407	**0.95**	440	**0.96**	430
Case D	**0.97**	479	0.97	427	**0.97**	445	**0.97**	432
Field I2								
Case A	0.66	1154	0.60	1254	0.64	1142	0.66	1191
Case B	**0.80**	958	**0.84**	958	**0.84**	966	**0.86**	875
Case C	**0.81**	938	**0.83**	943	**0.87**	763	**0.88**	719
Case D	**0.80**	949	**0.82**	854	**0.84**	819	**0.86**	756
Field I3								
Case A	0.29	1035	0.32	978	0.34	951	0.35	957
Case B	**0.82**	672	**0.80**	704	**0.82**	674	**0.75**	718
Case C	**0.82**	667	**0.83**	667	**0.85**	590	**0.82**	657
Case D	**0.86**	859	**0.86**	757	**0.86**	809	**0.88**	696

Table 5. Correlation coefficient R and RMSE for simulated and measured yield after model calibration (2000 iterations) of field I1, I2 and I3 using multiple years of corn yield data and multiple soil parameters (5-10). Yield was calculated in dependency of the grids in case A (10.5 x 10.5 m grid size), case B (16.5 x 16.5 m grid size), case C (22.5 or 30.5 x 50.5 m grid size) and case D (22.5 or 30.5 x 50.5 m grid size). R >0.75 is written in bold letters.

Overall, the model explained the spatial yield variability in all grids over five years very well, when calibration was done using multiple soil parameters. In all three fields, slightly different combinations of soil parameters led to the best calibration of the model. The highest accuracy of the model was achieved in field I1 using yield values of case D and a combination of the soil parameters HPF + HPD + RDRF + NMF + SFF. These soil parameters explained about 94 % of the spatial yield variability in field I1 (Figure 1a). In field I2 a combination of the soil parameters HPF + HPD + RDRF + NMF + SFF + ASW explained about 77 % of the spatial yield variability (Figure 1b), when yield values of case C were used for the calibration process. However, in field I3 a combination of the soil parameters HPF + HPD + NMF + SFF + ASW explained about 77 % of the spatial yield variability, calculated by yield values of case D (Figure 1c). These results implied that the spatial yield variability was mostly influenced by six soil parameters. The soil parameters HPF + HPD + RDRF + NMF + SFF + ASW seem to count for at least 75 % of the spatial yield variability.

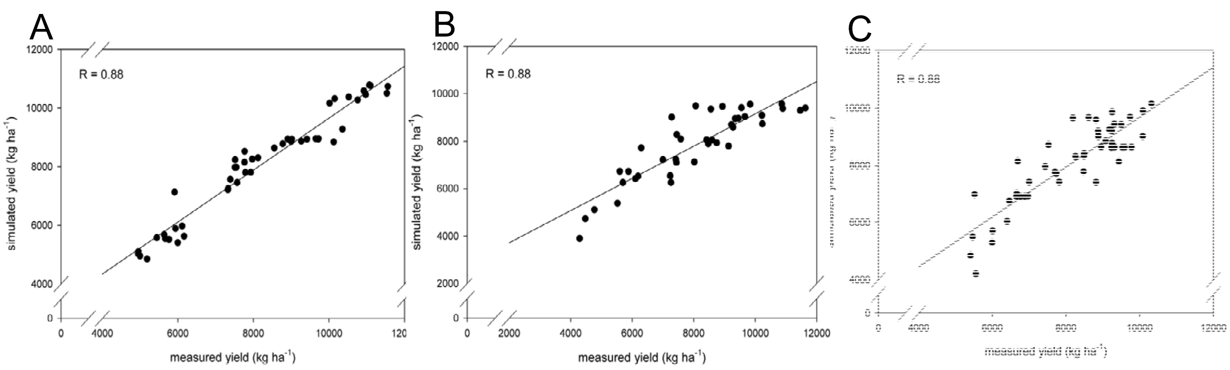

Fig. 1.a-c. Simulated vs. measured corn yields (kg ha-1) in field I1 (A), I2 (B), I3 (C) in the years 1998 – 2002. The simulation is based on the calibration of multiple soil parameters leading to yield variability.

Although a strong influence of available soil parameters could be determined, the best simulation of yield was achieved for the soil parameters HPF + DHP. In all three fields good correlations between simulated and measured yields were determined, when these parameters were used for model calibration. These results implied that HPF + DHP were the parameters with the biggest impact in explaining spatial yield variability. Hardpan is described as a factor that is mainly induced by management practices. The effect of soil compaction after tillage is described in the literature (Lindstrom and Voorhees, 1994; Lipiec and Simonta, 1994). Due to continuous cultivation of corn at all three fields over the 5-year period, it is highly possible that the hardpan was strongly manifested in all fields. As a result of a hardpan in the field, root distribution could be affected and led to spatial yield variability, as also assumed in studies of Arvidsson and Håkansson (1996). RDRF explained much of the spatial yield variability especially in field I2 and I3. In model simulations where RDRF was considered, high correlation coefficients were achieved in all three fields, indicating a strong influence of RDRF factor on yield. In addition, soil fertility seemed to have an influence on the spatial yield variability, especially in field I1. ASW might be spatially different due to a probably inhomogeneous flint layers in the deeper soil, which affects the water supply in the field.

3.2.4 Effect of grid size

In this study grid size had a strong influence on the results of the model calibration. In general, smaller grids (case A) resulted in weak correlations between simulated and measured yields (Table 4 and 5). In general, the model gave more accurate simulated yields for larger grids, suggesting that the applied calibration process may be more effective under large grid sizes. A slight improvement of the model accuracy was found when additional information on soil available nitrogen around the 4th leaf stage was imposed on the calibration process.

The larger grid sizes contained more yield monitor data points and thus, averaged over some of the spatial yield variation that occurred between two sequential yield monitor data points. Thus, the larger grid sizes averaged yield variability within the grid and thus were less acceptable for outlier, which was similar to results of Ping and Dobermann (2003). To work with spatial data sets in crop models, there appears to be a trade-off between maintaining spatial precision by selecting a small grid size and reducing noise in yield monitor data by selecting a larger grid size (Wong, 1995; Long, 1998). Combining area units into successively larger units, an agronomist will need to consider the scale at which the spatial variability of site-specific yield data has to be analyzed (Long, 1998). Considering the underlying soil factors, which had either a high range of variability or continuity, the model accuracy was improved by choosing larger grid sizes that captured the spatial variability and stability within different sites.

3.2.5 Evaluation of model performance

In general the APOLLO model preformed well in simulating yield of the three fields in the Upper Rhine Valley over the 5-year period. Among the yield limiting factors that were examined in this study, hardpan seemed to have a big impact on yield variability. However, one cannot discount the effect of other factors or interactions such as rooting depth, water availability etc. Nevertheless, the technique presented in this study demonstrates the value of using a crop growth model in quantifying individual as well as combined effects of factors leading to spatial yield variability. However, there is a need to further test and validate the model outputs by verifying the yield limiting factors through direct field measurements.

The case study has shown that yield variability may be explained by a combination of varying soil factors. The implemented crop models have proven to be useful tools to evaluate these complex interactions and to provide insight into causes of yield variability. However, the results of model calibration were affected by the grid size used for calibration. The model gave more accurate simulated yields for larger grids, suggesting that the applied calibration process may be more effective under large grid sizes.

Overall the ideal grid size for the calibration process seems to be determined by the underlying factors leading to spatial yield variability. Further research is needed to determine a suitable approach for the assessment of ideal grid sizes in model calibration and resulting grid resolution that captures enough information to represent spatial yield variability and temporal stability at a scale appropriate to finally optimize crop management and reduce yield gaps.

3.3 Case study China - model based analysis of a winter wheat - summer maize double cropping system in the North China Plain

Besides the prediction of crop yields and the analysis of yield gaps, there has been a substantial amount of crop model applications to improve crop management strategies like nitrogen (N) fertilization and irrigation. Especially in those crop production systems, where water resources are limited and risk of groundwater contamination with nitrate is high, it is important to optimize irrigation and fertilization use efficiencies via use of sound water and nitrogen management practices. However, development and validation of guidelines for optimal timing and water and nitrogen requirements requires extensive and expensive field experiments. Since it is impossible to test all the interactions between the amount of water and nitrogen during the seasons, use of simulation models can greatly facilitate the evaluation of different production practices and/or environments and thereby streamline the decision-making process.

This case study outlines the use of the CERES-Wheat and CERES-Maize models, both implemented in DSSAT V.4.0 (Jones et al., 2003), to evaluate a double cropping system of winter wheat and summer maize under different fertilizer and irrigation input scenarios regarding water consumption, grain yield and gross margin. The models were calibrated and validated using data derived from a field experiment conducted in Dongbeiwang, near Beijing, China.

One of the most important regions of agricultural production in China is the North China Plain (NCP) (Kendy et al., 2003). Considering China´s total grain yield, the NCP contributes approximately 41% of wheat and 25% of maize grain yield (Länderbericht China, 2000). The NCP, also known as the Huang-Huai-Hai Plain, is located in the north of the eastern part of China between 32° and 40° N latitude and 100° and 120° E longitude (Liu et al., 2001). Winter wheat (*Triticum aestivum* L.) and summer maize (*Zea mays* L.) are currently the two main crops combined in a single-year rotation also referred to as a double cropping system (Zhao et al., 2006). Winter wheat is sown at the beginning of October and harvested in mid June. Summer maize is sown immediately following winter wheat harvest and is harvested at beginning of October.

The climate in the NCP is warm-temperate with cold winter and hot summer. Precipitation shows a high spatial and temporal variability (Wu et al., 2006) and ranges from about 500 mm in the north to 800 mm in the south (Liu et al., 2001). About 50 to 75% of the total precipitation occurs from July to September during the summer monsoon. Depending on the seasonal precipitation situation, farmers usually irrigate winter wheat four to five times (Hu et al., 2006). In consequence, the irrigation water for wheat production comprises about 80% of the whole agricultural water consumption (Li, 1993).

Extensive use of fertilizer is also very common in the winter wheat-summer maize double cropping system. In Beijing area, for example, the average N application rates ranged around 309 kg N ha^{-1} for winter wheat and 256 kg N ha^{-1} for maize (Zhao et al., 1997). Besides the positive effects on yield, an increasing input of water and fertilizer is connected with increasing costs for the farmers and leads to environmental problems such as leaching or water scarcity. Therefore better management practices balancing both economic and environmental interests are required.

Numerous agricultural experiments were carried out to test the effects of different management strategies on grain yield and overall sustainability. However field experiments have their limitations as they are conducted at particular points in time and space. Besides, field experiments are time consuming, laborious and expensive (Jones et al., 2003) and therefore limited in extent and size. A viable alternative to these problems is to use crop models. Models can be applied as a valuable tool to propose better adapted crop management strategies and to test the hypothetical consequences of varying management practices (e.g. Saseendran et al., 2005). Furthermore, models can be used to optimize

economic efficiency by finding best management strategies under given and future environmental conditions (Link et al., 2006). However, studies which use crop models to evaluate crop production systems in the NCP are rare (Yu et al., 2006). Hu et al. (2006) used the RZWQM model to assess N-management in a double cropping system (winter wheat and summer maize) at Luancheng in the NCP. Results of the study indicated, that both, N and water could be reduced by about half of the typical application rates without a strong reduction in yield. Yang et al. (2006) used the CERES-Wheat and CERES-Maize models to estimate agricultural water use and its impact on ground water depletion in the piedmont region of the NCP. The results showed a strong correlation between the agricultural water use and the ground water depletion. The authors concluded that there is still a sustainable water reduction possible if water-saving technologies are applied.
The aim of this study was to evaluate the double cropping of winter wheat and summer maize in the NCP under water shortage conditions. For this purpose the models CERES-Wheat and CERES-Maize were calibrated and validated. Based on a gross margin analysis, different irrigation and N-fertilizer treatments were evaluated. Originated from the most profitable treatment, four different irrigation scenarios for the dry growing season 2000/2001 and their effect on water consumption, grain yield and gross margin were simulated.

3.3.1 Study site and field experiment

The CERES-Maize and CERES-Wheat models were used with field study information of Böning-Zilkens (2004) for testing different irrigation scenarios in a double cropping system of winter wheat and summer maize in the NCP. The chosen field experiment was conducted from 1999-2002 (three vegetation periods, six harvests). The experimental site was Dongbeiwang located in the northwest of Beijing (40.0° N and 116.3° E). Soil type was a Calcaric Cambisol (FAO taxonomy) formed of silty loam. The winter wheat cultivar Jindong 8 was sown at the beginning of October with a row spacing of 15 cm and an aspired plant density of 480 plants m^{-2}. Wheat was harvested at the beginning of June each year. After winter wheat summer maize was sown directly without time lag and harvested at the beginning of October. The maize cultivar Jingkeng 114 was sown with a density of 6 plants m^{-2} and a row spacing of 70 cm. The experiment was designed as a three factorial split-split-plot design with four replications and included three different irrigation regimes, three N-fertilization rates as well as a treatment with and without straw. No major diseases were reported during the growing period. For the purpose of this study only the treatments without straw removal were used because this is the usual practice in the NCP.
Fertilization treatments varied between 0 and 600 kg N ha^{-1} a^{-1} (Table 6). In the traditional treatment N-fertilization was carried out according to farmers practice. The treatment reflects the standard production system in the NCP with the fertilizer inputs being very high. The fertilization of the optimized treatment was based on measured soil available nitrogen (Nmin-content) and target yield. No nitrogen fertilizer was applied in the control treatment.
Irrigation treatments varied between 195 and 354 mm (Table 6). The traditional irrigation was carried out according to farmers practice using border irrigation. The optimized irrigation was based on measurements of the volumetric soil water content aiming to keep the available field capacity between 45 and 80 % following Steiner et al. (1995). Available field capacity was defined as field capacity minus the amount of water which is retained through high soil water

tension (pF < 4.2) and therefore not available to the plant. The volumetric soil water content was measured with time domain reflectometry probes (0-15, 15-30, 30-45, 45-60, 60-90, 90-120 cm depth) every four days. The suboptimal irrigation exemplified the control. Irrigation in this treatment was based on the amount of approximately two third of the optimized strategy. In the optimized and suboptimal irrigation treatments irrigation was carried out using sprinkler irrigation. Plot size for the factor irrigation was 50 x 70 m. Two-jet complete circle sprinkler with a height of 1 m were used, adjusted in a grid of 12 x 18 m. Summer maize was not irrigated in any of the experimental years (Böning-Zilkens, 2004), as precipitation is usually sufficient (Lohmar et al., 2003).

Treatment	Management		N-fertilization (kg N ha^{-1} a^{-1})			Irrigation (mm)	
	irrigation	fertilization	wheat	maize	total	wheat	maize
1	suboptimal	suboptimal	0	0	0	195	0
2	suboptimal	traditional	300	300	600	195	0
3	suboptimal	optimized	50	53	103	195	0
4	traditional	suboptimal	0	0	0	354	0
5	traditional	traditional	300	300	600	354	0
6	traditional	optimized	87	59	146	354	0
7	optimized	suboptimal	0	0	0	293	0
8	optimized	traditional	300	300	600	293	0
9	optimized	optimized	72	65	137	293	0

Table 6. Average amounts of nitrogen fertilizer (kg ha^{-1} a^{-1}) and irrigation amounts (mm) for winter wheat and summer maize over the three vegetation periods (1999/2000-2001/2002) of field experiments.

Different growth stages of winter wheat (emergence, hibernation, jointing, full flowering, medium milk, ripening) and maize (emergence, beginning of stem elongation, heading, end of flowering, medium milk) were recorded according to Zadoks et al. (1974). Four time harvests were done by hand in the growth stages mentioned before. Final harvest was done manually by cutting three times 3 m² of winter wheat and one time 39.2 m² of summer maize. Winter wheat ears and maize plants were counted. After harvest, plants were separated and grains and kernels were threshed and dried to constant weight at 105 °C to obtain total dry matter. Thousand kernel mass, grains per ear, kernels per row, kernels per cob and rows per cob were determined.

Weather data were collected from a local weather station at Dongbeiwang and including daily solar radiation, maximum and minimum air temperatures and precipitation. Mean annual temperature for 2000-2002 ranged between 11.5-11.7 °C and did not differ from the long-term average of 11.5 °C. The annual precipitation amounted 448, 366 and 520 mm. In comparison to the long-term average (556 mm), all three years were drier.

Statistical analyses of the data were performed with Sigma Stat 3.5 (Jandel Scientific Corp, San Rafae, CA). Differences between experimental groups were tested by using one factor analysis of variance (ANOVA). Tukey tests were carried out for comparison of means.

3.3.2 Model description

The CERES-Maize and CERES-Wheat models were calibrated and validated using data from Böning-Zilkens (2004). The growing seasons 1999/2000 and 2001/2002 were used for model calibration. Phenology and growth data such as biomass at different growth stages and the dates of phenological events were used to determine the cultivar coefficients for wheat and maize (Table 7). The calibration of these parameters followed a sequence of variables suggested by the DSSAT manual (Boote, 1999). As irrigation was carried out by border irrigation, irrigation efficiency was set to 0.45, according to Xinhua News (2001). For sprinkler irrigation the irrigation efficiency was set to 0.55 as strong winds during the experiment diminished the water distribution.

Winter wheat cv. Jindong 8		
Parameter	Description	Value
P1V	Sensitivity to vernalisation	35
P1D	Sensitivity to photoperiod	50
P5	Grain filling duration	500
G1	Kernel number per unit weight at anthesis	20
G2	Kernel weight under optimum conditions	36
G3	stem + spike dry weight at maturity	1.8
PHINT	Phyllochron interval	95
Summer maize cv. Jingkeng 114		
P1	Growing degree days from emergence to end of juvenile phase	180
P2	Photoperiod sensitivity	0.3
P5	Cumulative growing degree days from silking to maturity	685
G2	Potential kernel number	730
G3	Potential kernel growth rate	8.0
PHINT	Phyllochron interval	44

Table 7. Cultivar coefficients of winter wheat cv. Jindong 8 and summer maize cv. Jingkeng 114 used for model calibration and validation.

Model validation was carried out with an independent dataset from the dry growing season 2000/20001 using the cultivar coefficients obtained by calibration. The model validation involved the use of the model with the calibrated values without making any further adjustments of the constants (Gungula et al., 2003). The Root Mean Square Error (RMSE), between simulated and measured values was used to evaluate simulation results. For graphical representations the 1:1 line of measured vs. simulated values was used. Correlation coefficients were also reported to express the scatter of the simulated values compared with the measured data.

3.3.3 Economic analysis

Gross margins in Chinese Yuan (¥) (RMB, 1 ¥ ~ 0.12 US$) have been developed with information provided from literature to compare the different treatments form the field experiments used for model calibration and validation as well as to compare the simulated scenarios. The analysis was carried out according to the following equation:

$$\text{gross margin} = \text{revenue} - \text{variable costs} \tag{1}$$

where gross margin is ¥ ha^{-1} a^{-1}.
The revenue parameter is the result of equation 2:

$$\text{revenue} = YWt \times PW + YMt \times PM \quad (2)$$

where YWt is the grain yield (kg ha^{-1}) of winter wheat W per year t, PW is the price of winter wheat W (¥ kg^{-1}), YMt is the grain yield (kg ha^{-1}) of summer maize M per year t, and PM is the price of summer maize M (¥ kg^{-1}).
The variable cost parameter is the result of equation 3:

$$\text{variable costs} = (NWt + NMt) \times PN + WWt \times PW \quad (3)$$

where NWt is the N-fertilizer rate (kg ha^{-1}) applied to winter wheat W in year t, NMt is the N-fertilizer rate (kg ha^{-1}) applied to summer maize M in year t, PN is the price of N fertilizer (¥ kg^{-1} N), WWt is the amount of irrigation water (m^3 ha^{-1}) used for winter wheat W in year t, and PW is the price for the irrigation water (¥ m^{-3}).
The prices for nitrogen fertilizer (4.0 ¥ kg N^{-1}), winter wheat (1.10 ¥ kg^{-1}) and summer maize (1.00 ¥ kg^{-1}) were obtained from Chen et al. (2004). In the study of Chen et al. (2004) prices for wheat and maize were based on grain moisture of 15 %. As the model input requires a grain moisture of 0% the price for maize was set to 1.18 ¥ kg^{-1} dry matter (DM) and to 1.29 ¥ kg^{-1} DM for winter wheat. The price for irrigation water was set to 0.60 ¥ m^{-3} based on information from Li et al. (2005). Note, that all the prices represent average prices for the NCP and will vary from region to region and year to year.

3.3.4 Simulated irrigation scenarios

To achieve high yields farmers in the NCP tend to overirrigate winter wheat (Zhang et al., 2004). The simulations show the potential saving of irrigation water and its effect on grain yield and gross margin under the conditions at the Dongbeiwang site. Based on the treatment with the highest gross margin of the field experiment, five different irrigation scenarios for the dry growing season 2000-2001 were simulated.

Treatment	Grain yield (kg DM ha^{-1} a^{-1})						Gross margin (¥ ha^{-1} a^{-1})*					
	wheat		maize		total		wheat		maize		total	
1	3280	c	5435	a	8715	d	3061	ab	6413	a	9475	abc
2	3493	c	5786	a	9279	cd	2136	b	5327	a	7763	d
3	3647	c	5834	a	9480	bcd	3334	a	6672	a	10006	ab
4	4077	abc	5397	a	9473	bcd	3135	ab	6368	a	9503	abc
5	4940	a	5590	a	10530	ab	3049	ab	5397	a	8445	cd
6	4947	a	5707	a	10653	a	3909	a	6498	a	10407	a
7	3730	bc	5364	a	9094	d	3054	ab	6330	a	9384	bc
8	4657	ab	5600	a	10257	abc	3049	ab	5408	a	8457	cd
9	4780	a	5780	a	10560	a	4120	a	6560	a	10680	a

*Currency Chinese Yuan (¥) (RMB, 1 ~ 0.12 US$)

Table 8. Average grain yield (kg DM ha^{-1}) and gross margin (¥ ha^{-1}) over the three vegetation periods (1999/2001-2001/2002) for winter wheat, summer maize and the double cropping of both cultivars regarding different irrigation and nitrogen fertilizer treatments in the field experiment. Different letters indicate significant differences at α=0.05.

From the calibration and validation results, the CERES-Maize and CERES-Wheat models were found to simulate yields well. The average RMSE between simulated and measured yield for winter wheat was 432 kg ha^{-1} (calibration) and 342 kg ha^{-1} (validation). Similar results were obtained for summer maize with an average RMSE of 253 kg ha^{-1} (calibration) and 414 kg ha^{-1} (validation). The results of the study showed that the differences between simulated and measured grain yields were within the range of differences reported in the literature.

Maximizing yield and gross margin as a function of inputs and production costs is one of the main goals when making management decisions such as fertilizer and irrigation applications (Bannayan et al., 2003). The effects of different management strategies on grain yield and gross margin are represented in Table 8.

The average winter wheat grain yields over the three vegetation periods indicated that, independent of irrigation regimes, the highest grain yields were reached by the treatments "optimized fertilization" (3, 6, 9), followed by the treatments "traditional" (2, 5, 8) and "suboptimal fertilization" (1, 4, 7). However between the treatments "optimized" and "traditional fertilization" no significant difference existed, whereas grain yields in the "suboptimal" treatments decreased significantly. Considering the different irrigation treatments the highest winter wheat grain yields were reached by the "traditional treatments" (4-6), followed by the "optimized" (7-9) and "suboptimal treatments"(1-3). The differences between the "traditional" and "optimized irrigation" treatments were not significant whereas grain yield of the "suboptimal irrigation" treatments was significantly reduced. Summer maize was not irrigated and the different irrigation treatments applied to winter wheat showed only small, or no significant effects on the grain yield of succeeding maize. The same was true for the fertilization treatments. The highest grain yield was reached by the treatments "optimized fertilization" followed by the treatments "traditional" and "suboptimal fertilization".

Overall, the results showed, that the differences in grain yield between "traditional" and "optimized fertilization" were not significant. One possible reason could be that crop N demand of wheat and summer maize is much lower than the applied rates of N in the NCP (Gao et al., 1999). This corresponds with results of Jia et al. (2001) and Chen et al. (2004) who showed that without any risk of yield decrease N fertilizer rates for winter wheat in the NCP could be reduced to <180 kg N ha^{-1} when soil NO_3 testing or a yield response curve method was used. Similar results were found for irrigation management. According to Zhang et al. (2005) winter wheat could attain its maximum yield with less than full application of the current irrigation practice.

Beside the effects on grain yield, Table 8 indicates also the effects of different irrigation and N-fertilizer amounts on gross margin. The highest gross margin regarding the different fertilizer amounts was reached within the "optimized" treatments (3, 6, 9) followed by the "suboptimal" (1, 4, 7) and "traditional fertilizer" (2, 5, 8) treatments. Even if grain yields of the "suboptimal" treatments were significantly lower than grain yields of the "traditional" treatments they reached the same level of gross margin because the "suboptimal fertilizer" treatments went along without any costs for nitrogen fertilization. The gross margin of the different irrigation treatments increased by the order "suboptimal", "optimized" and "traditional irrigation". However, the differences between the "traditional" and "optimized" treatments were small. The highest total gross margin in the double cropping of winter wheat and summer maize was observed with treatment number 9 ("optimized irrigation" and "optimized N-fertilization"). The analysis of the different irrigation and N-fertilizer treatments of the field experiment showed that with a higher input of nitrogen fertilizer and irrigation water grain yields did not equally rise as the costs for the input factors. Therefore, the highest gross margin was not reached with the highest input of nitrogen and irrigation. This result corresponds with the report of Zhu and Chen (2002) who had reviewed the nitrogen fertilizer use in China. They found that the maximum yield, demonstrated by yield versus N application rate curves, is usually higher than the yield of the maximum economic efficiency.

In a next step, five different irrigation scenarios for winter wheat and their effects on grain yield, water consumption and gross margin were simulated for the dry season 2000/2001. As a starting point (= scenario 1) for the simulation of different irrigation scenarios treatment 9 ("optimized irrigation" and "optimized fertilization") was used because this treatment reached the highest gross margin (Table 8). The nitrogen fertilization amount for winter wheat in treatment 9 was 65 kg N ha^{-1}. The costs for the N-fertilizer amounted to 260 ¥ ha^{-1} (4.00 ¥ kg N^{-1}) and were considered in all succeeding scenarios. Table 9 gives an overview on the changes in irrigation amount, total water supply, grain yield and gross margin.

One of the most important aspects of water-saving in irrigated agriculture is the irrigation scheduling because the water sensitivity varies among different growth stages (Zhang et al., 1999). The irrigation in scenario one took place at six different growth stages. However the results of scenario three, four and five demonstrated that a reduction in irrigation frequency may not always lead to a decrease in grain yield. Commonly grain crops are more sensitive to water stress during flowering and early seed formation than during vegetative or grain filling phases (Doorenbos and Kassam, 1979). Results of Zhang et al. (2003) showed that irrigation before the over-wintering period could be omitted due to its loss to soil evaporation and its effects on increasing the non-effective tillers in spring. According to Zhang et al. (1999) wheat is particularly sensitive to water stress in the growth stages from jointing to heading and from heading to milk stage. Similar results were found in our study. The results showed that irrigation during seedling development (before winter) and at milk stage was not essential for the formation of grain yield. However, an additional irrigation during the regreening stage (scenario five) might lead to a further increase in grain yield.

	Irrigation		**Total water supply****		**Grain yield**		**Gross margin**		
Scenario	mm	%	mm	%	kg ha^{-1} a^{-1}	%	wheat ¥* ha^{-1} a^{-1}	maize ¥ ha^{-1} a^{-1}	total ¥ ha^{-1} a^{-1}
1	310	100	452	100	4436	100	3602	7051	10654
2	0	-100	262	-42	1089	-75.5	1144	7244	8388
3	155	-50	370	-18.1	3721	-16.1	3610	6982	10592
4	200	-35.5	394	-12.8	4445	0.2	4274	6994	11268
5	290	-6.5	442	-2.2	5243	18.2	4763	7134	11897

*Currency Chinese Yuan (¥) (RMB, 1 ~ 0.12 US$)
** Total water supply = effective irrigation+ precipitation + depletion of the initial soil water content

Table 9. Irrigation amount (mm), total water supply (mm), grain yield (kg ha^{-1} a^{-1}) and gross margin (¥ ha^{-1} a^{-1}) of winter wheat.

Besides the irrigation frequency also the irrigation amount affected grain yield. With a complete renouncement of irrigation like in scenario 2 grain yield dropped to 1089 kg per ha^{-1} leading to a decrease of 68.2 % in gross margin, as the yield reduction could not be compensated by the saved irrigation costs (Table 9). Hence, a supplemental irrigation is required in wheat to maintain high yields and to ensure an adequate gross margin for the farmers. Besides the necessity of irrigation for wheat, scenario 3 demonstrates the enormous potential for water saving without a financial deterioration for the farmers. The simulation indicated that a reduction in the irrigation frequency from six to four times and a reduction in the irrigation amount of up to 50 % are possible without any decrease in gross margin. As the Chinese government aims to achieve the goal of self-sufficiency (Huang 1998), scenario 4 tested the considerable potential for reducing the irrigation amount without any decrease in actual yield level. The simulation indicated that a reduction of the amount of irrigation water of up to one third is possible without any yield losses. The saved irrigation costs would lead to an increase in gross margin of up to 672 ¥ ha^{-1} (18.6 %). A maximum gross margin of 4763 ¥ ha^{-1} was reached in scenario 5. The maximum gross margin was connected with the highest grain yield of 5243 kg ha^{-1}. Changes in the irrigation amounts and frequencies to winter wheat showed only small effect on yields of the following crop summer maize because there was enough precipitation. The total gross margin for the different scenarios of double cropping winter wheat and summer maize is given in Table 9 and indicated that scenario 4 and 5 would lead to the highest gross margin in the double cropping system while saving up to 35 % of irrigation water and having no yield loss.

The results of the simulated scenarios showed that there is a considerable potential for saving irrigation water even under dry conditions like in the growing season 2000/2001. For the purpose of improvement of gross margin, models can help to determine an optimum value for total water consumption where grain yield and gross margin were all relatively high. However this value largely depends on the cost of irrigation water. Crop models such as DSSAT offer the possibility to estimate crop water use and can help to develop appropriate irrigation strategies. It can be concluded that in areas with similar conditions as in the simulations, the common irrigation amount to wheat could be reduced by about one third without any yield losses. Furthermore, a reduction of about 50 % may be possible without a decrease in the initial gross margin. However, without irrigation gross margin would be very low, because the saved water costs could not balance the losses in grain yield. Therefore, a supplemental irrigation at critical growth stages seems to be essential to maintain high yields and to ensure an adequate gross margin for the farmers.

4. Conclusion

Crop models represent a means for agricultural scientists to provide farmers with information like possible crop yields for different levels of input factors and procedures for decision making by integrating the most relevant parameters affecting crop yield. The evolving area of crop model research represents an attempt of scientists to intervene and improve farmers' management and to fill this existing knowledge gap. However, the attempts to intervene and influence management decisions by delivering appropriate decision support tools have been harder than first thought. But crop models are considered to be an important tool for gaining a theoretical understanding of a crop production system. Finally, it has to be constituted and recalled that crop models do not offer a panacea for problem solving. They are limited in their ability to simulate various parts of a biological system and address complex systems in an often simplified manner. In summary, it can be adhered that crop models are a first step into the direction of decision making process. Besides all existing constrains to date, due to their highly innovative nature and potential for improved quality of production and crop management, models have the credentials to be a key candidate for a well-focused future research area.

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6. References

Adams, M.L., Cook, S.E., Corner, R. 2000. Managing Uncertainty in Site-Specific Management: What is the Best Model? Precision Agriculture 2: 39-54.

Arvidsson, J., Håkansson, I. 1996. Do effects of soil compaction persist after ploughing? Results from 21 long-term field experiments in Sweden. Soil Tillage Res. 39, 175-197.

Bannayan, M., Crout, N.M.J., Hoogenboom, G., 2003. Application of the CERES-Wheat model for within-season prediction of winter wheat yield in the United Kingdom. Agron. J. 95, 114-125.

Batchelor, W.D., Link, E.J., Thorp, K.R., Graeff, S., Paz, J.O. 2004b. The role of crop growth models in precision farming. Workshop Precision Farming, May 13, Renningen, Germany. pp 11-16.

Batchelor, W.D., Paz, J.O., Thorp, K.R. 2004a. Development and evaluation of a decision support system for precision farming. Proceedings of the 7th International Conference on Precision Agriculture. July 25-26, 2004, Minneapolis, MN. ASA, CSSA, SSSA Inc., Madison, WI, USA.

Böning-Zilkens, M.I., 2004. Comparative appraisal of different agronomic strategies in a winter wheat - summer maize double cropping system in the North China Plain with regard to their contribution to sustainability. Diss., Institute of Crop Production and Grassland Research, University of Hohenheim.

Boote K.J., Jones J.W., Pickering N.B. 1996. Potential uses and limitations of crop models, Agronomy Journal 88: 704–716.

Boote, K.J., 1999. Concepts of calibrating crop growth models. In: Hoogenboom, G., Wilkens, P.W., Tsuji, G.Y. (Eds.), DSSAT Version 3. A decision support system for agrotechnology transfer, pp. 179-200, Vol. 4, Univ. of Hawaii, Honolulu.

Boote, K.J., Jones, J.W., Hoogenboom, G.J, Pickering, N.B. 1998. The GROPGRO for grain legumes. In: Tsuji, G.Y., Hoogenboom, G.J., Thornton, P.K. (Eds.), Understanding Options for Agricultural Production. Kluwer Academic Publishers, Dordrecht, The Netherlands. pp 99-128.

Brouwer, R., De Wit, C. 1968. A simulation model of plant growth. In: Proc. Easter School in Agricultural Science, University of Nottingham, UK. Butterworths, Londres, RU.

Cerrato, M.E., Blackmer, A.M. 1990. Comparison of models for describing corn yield response to nitrogen fertilizer. Agronomy Journal 82(1): 138-143.

Chen, G., Yost, R.S., Li, Z.C., Wang, X., Cox, F.R. 1997. Uncertainty analysis for knowledgebased decision aids: application to phosphorus decision support system (PDSS). Agricultural Systems 55: 461-472.

Chen, X., Zhou, J., Wang, X., Blackmer, A.M., Zhang, F., 2004. Optimal rates of nitrogen fertilization for a winter wheat-corn cropping system in Northern China. Communications in Soil Sci. Plant Anal. 35, 583-597.

Cook, S.E. 1997. Data interpretation and risk analysis for precision agriculture. In: Precision agriculture: What can it offer the Australian Sugar Industry? Bramley, R.G.V., Cook, S.E., McMahon, G.G., (eds.) CSIRO Land and Water, Proceedings of a Workshop held in Townsville, pp. 77-85.

Cook, S.E., Adams, M.L. 1998. In: Precision Weed Management in Crop and Pastures. Medd, R.W., Tratley, J.E. (eds.) Richarson, Melbourne, Australia, p.101.

De Wit, C.T., Brouwer, R., Penning de Vries, F.W.T. 1970. The simulation of photosynthetic systems. In:, Prediction and measurement of photosynthetic productivity. Setlik, I. (ed.) Proceeding IBP/PP Technical Meeting Trebon 1969. Pudoc, Wageningen, The Netherlands, pp. 47-70.

Doorenbos, J., Kassam, A.H., 1979. Yield response to water. Irrig. and Drain. Pap. 33. FAO, Rome.

Drummond, S.T., Sudduth, K.A., Joshi, A., Birrell, S.J., Kitchen, N.R. 2003. Statistical and neural methods for site-specific yield prediction. Transactions of the ASAE 46(1): 5-14.

Finke, P.A., Goense, D. 1993. Differences in barley grain yields as a result of soil variability. Journal of Agricultural Science 120: 171–180.

Forrester, J.W. 1961. Industrial dynamics. Cambridge, Mass. U.S.A., Massachusetts Institute of Technology Press.

Fraisse, C.W., Sudduth, K.A., Kitchen, N.R. 1998. Evaluation of crop models to simulate site-specific crop development and yield. In: Robert, P.C, Rust, R.H., Larson, W.E. (Eds.),, Proceedings of the 4th International Conference on Precision Agriculture. ASA, CSSA, SSSA, Inc., Madison, WI, USA. pp 1297-1308.

Gao, W., Huang, J., Wu, D., Li, X., 1999. Investigation on nitrate pollution in ground water at intensive agricultural region in Huanghe-huaihe-haihe Plain. Eco-agric. Res. 7, 41-43 (in Chinese).

Gerdes, G. 1993. Calibration of the soybean growth simulation model SOYGRO for Central Portugal. Verlag Ulrich E. Grauer, Wendlingen.

Godwin, D.C., Ritchie, J.T., Singh, U., Hunt, L., 1989. A user´s guide to CERES Wheat-V2.10. International Fertilizer Development Center, Muscle Shoals, AL.

Gungula, D.T., Kling, J.G., Togun, A.O., 2003. CERES-Maize predictions of maize phenology under nitrogen-stressed conditions in Nigeria. Agron. J. 95, 892-899.

Hoogenboom, G. 2003. Crop growth and development. In: Handbook of Processes and Modeling in the Soil-Plant System. Bendi D.K., Nieder R. (eds.) The Haworth Press, Binghamton, New York, pp. 655-691.

Hoogenboom, G., Jones, J.W., Wilkens, P.W., Batchelor, W.D., Bowen, W.T., Hunt, L.A., Pickering, N.B., Singh, U., Godwin, D.C., Baer, B., Boote, K.J., Ritchie, J.T., White, J.W. 1994. Crop models. In: DSSAT Version 3, vol. 2. Tsuji, G.Y., Uehara, G., Balas, S. (eds.), University of Hawaii, Honolulu, HI, pp. 95-244.

Hu, C., Saseendran, A., Green, T.R., Ma, L., Li, X., Ahuja, L.R., 2006. Evaluation nitrogen and water management in a double-cropping system using RZWQM. Vadose Zone J. 5, 493-505.

Huang, J.K., 1998. Agricultural policy, development and food security in China. In: Tso, T.C., Tuan, F., Faust, M. (Eds.), Agriculture in China 1949-2030, pp. 209-257, IDEALS, Inc., Beltsville, Maryland.

Jia, L., Chen, X., Zhang, F., Liu, B., Wu, J., 2001. The study of optimum N supplying rate for winter wheat in Beijing area. J. Chinese Agric. Univ. 6, 67-73 (in Chinese).

Jones, C.A., Kiniry, N., 1986. CERES-Maize, a simulation model of maize growth and development. Texas A&M University Press, College Station, TX.

Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U., Gijsman, A.J., Ritchie, J.T. 2003. DSSAT Cropping System Model. European Journal of Agronomy 18: 235-265.

Jones, J.W., Ritchie, J.T. 1990. Crop growth models. In: Management of farm irrigation systems, Hoffman, G.J., Howell, T.A., Solomon, K.H. (eds.) ASAE:St. Joseph, Michigan, pp. 63-89.

Kendy, E., Gerhard-Marchant, P., Walter, M.T., Zhang, Y.Q., Liu, C.M., Steenhuis, T.S., 2003. A soil-water-balance approach to quantify groundwater recharge from irrigated cropland in the North China Plain. Hydrol. Proces. 17, 2011-2031.

Kravchenko, A.N., Bullock, D.G. 2000. Correlation of grain yield with topography and soil properties. Agronomy Journal 92: 75–83.

Länderbericht China, 2000. Politik, Wirtschaft und Gesellschaft im chinesischen Kulturraum. Herrmann-Pillath, C., Lackner, M. (Eds.), Bundeszentrale für politische Bildung, Schriftreihe Bd. 351, Bonn.

Li, J., Eneji, A.E., Duan, L., Inanaga, S., Li, Z., 2005. Saving irrigation water for winter wheat with phosphorus application in the North China Plain. J. Plant Nutrition 28, 2001-2010.

Li, P.C., 1993. The development of water-saving type agriculture. Agri. Res. Arid Areas 11, 57-63.

Lindstrom, M.J., Voorhees, W.B. 1994. Response of temperates crops in North America to soil compaction. In: Soane, B.D., van Ouverkerk, C. (Eds.), Soil Compaction in Crop Production, Elsevier, Amsterdam. pp. 265-286.

Link, J., Graeff, S., Batchelor, W.D., Claupein, W., 2006. Evaluating the economic and environmental impact of environmental compensation payment policy under uniform and variable-rate nitrogen management. Agri. Syst. 91, 135-153.

Link, J., Graeff, S., Batchelor, W.D., Claupein, W., 2007. Identification of problem grids within a wheat and corn field by the implementation of a process-oriented precision farming crop growth model. Proceedings of GIL, 27th annual conference, p. 131-134.

Lipiec, J., Simota, C. 1994. Role of soil and climated factors in Influencing crop response to soil compaction in Central and Eastern Europe. In: Soane, B.D., van Ouverkerk, C. (Eds.), Soil Compaction in Crop Production, Elsevier, Amsterdam. pp. 365-390.

Liu, C., Yu, J., Kendy, E., 2001. Groundwater exploitation and its impact on the environment in the North China Plain. Water Intern. 26, 265-272.

Lohmar, B., Wang, J., Rozelle, S., Huang, J., Dawe, D., 2003. China´s agricultural water policy reforms: increasing investment, resolving conflicts, and revising incentives. USDA Economic Res. Service, AIB 782.

Long, D.S. 1998. Spatial autoregression modeling of site-specific wheat yield. Geoderma. 85, 181-197.

Ma. L., Schaffer, M.J. 2001. A Review for carbon and nitrogen processes in nine U.S. soil nitrogen dynamics models. In: Modeling Carbon and Nitrogen Dynamics for Soil Management. Schaffer, M.J., Ma, L., Hansen, S. (eds.) Lewis Publishers, pp. 651.

Paz, J.O., Batchelor, W.D., Babcock, B.A., Colvin, T.S., Logsdon, S.D. Kaspar, T.C., Karlen, D.L., 1999. Model-based technique to determine variable-rate nitrogen for corn. Agric. Syst. 61, 69-75.

Paz, J.O., Batchelor, W.D., Colvin, T.S., Logsdon, S.D., Kaspar, T.C., Karlen, D.L. 1998. Analysis of water stress effects causing spatial yield variability in soybeans. Agric. Systems 61, 69-75.

Paz, J.O., Batchelor, W.D., Tylka, G.L. 2001. Method to use crop growth models to estimated potential return for variable-rate management in soybeans. Trans. ASAE. 44, 1335-1341.

Penning de Vries, F.W.T. & Teng, P.S. 1993. Systems approach to agricultural development. Kluwer Academic Publishers, the Netherlands.

Penning de Vries, F.W.T., D.M. Jansen, H.F.M. ten Berge and A. Bakema, 1989. Simulation of Ecological Processes of Growth in Several Annual Crops, Pudoc, Wageningen and IRRI, Los Baños, 271 pp.

Ping, J.L., Dobermann, A. 2003. Creating spatially continuous yield classes for site-specific management. Agron. J. 95, 1121-1131.

Plant, R.E., Mermer, A., Pettygrove, G.S., Vayssieres, M.P., Young, J.A., Miller, R.O., Jackson, L.F., Denison, R.F., Phelps, K. 1999. Factors underlying grain yield spatial variability in three irrigated wheat fields. Transactions of the ASAE 42: 1187–1202.

Ritchie, J.T., Singh, U., Godwin, D.C., Bowen, W.T. 1998. Cereal growth, development and yield. In: Tsuji, G.Y., Hoogenboom, G.J., Thornton, P.K. (Eds.), Understanding Options for Agricultural Production. Kluwer Academic Publishers, Dordrecht, The Netherlands. pp 79-88.

Rossing W.A.H., Meynard J.M., van Ittersum M.K. 1997. Model-based explorations to support development of sustainable farming systems: case studies from France and the Netherlands. European Journal of Agronomy 7:271–283.

Saseendran, S.A., Ma, L., Nielsen, D.C., Vigil, M.F., Ahuja, L.R., 2005. Simulating planting date effects on corn production using RZWQM and CERES-Maize models. Agron. J. 97, 58-71.

Steiner, J.L., Smith, R.C.G., Meyer, W.S., Adeney, J.A., 1985. Water use, foliage temperature and yield of irrigated wheat in south eastern Australia. Australia J. Agric. Res. 36, 1-11.

Stone, M. 1973. Cross-validatory choice and assessment of statistical predictions. Journal of the Royal Statistical Society B 36: 111-147.

Sudduth, K.A., Drummond, S.T., Birrell, S.J., Kitchen, N.R. 1996. Analysis of spatial factors influencing crop yield. In:. Robert, P.C, Rust, R.H., Larson, W.E. (Eds.), Proceedings of the 3rd International Conference on Precision Agriculture. ASA, CSSA, SSSA, Inc., Madison, WI, USA. pp 129-140.

Thorp, K.R., Batchelor, W.D., Paz, J.O. and Steward, B.L. 2004. Estimating Yield and Environmental Risks Associated With Variable Rate Nitrogen Management for Corn Using Apollo. Proceedings of the 7th International Conference on Precision Agriculture. July 25-26, 2004, Minneapolis, MN. ASA, CSSA, SSSA Inc., Madison, WI, USA.

Tomer, M.D., Anderson, J.L. 1995. Field evaluation of a soil water-capacitance probe in a fine sand. Soil Sci. 159, 90-98.

Tsuji, G.Y., Hoogenboom, G., Thorton, P.K. (Eds.), 1998. Understanding options for agricultural production. Kluwer Academic Publishers, Dordrecht, The Netherlands.

Uehera, G., Tsuji, G.Y. 1993. The IBSNAT project. In: Systems approach to agricultural development. Penning de Vries, F.W.T., Teng, P.S. (eds.) Kluwer Academic Publishers, The Netherlands. p. 505-514.

Van Ittersum, M.K., Leffelaar, P.A., van Keulen, H., Kropff, M.J., Bastiaans, L., Goudriaan, J. 2003. On approaches and applications of the Wageningen crop models. European Journal of Agronomy 18: 201-234.

Wong, D.W.S. 1995. Aggregation effects in geo-referenced data. In: Arlinghaus, S.L., Griffith, D.A. (Eds.), Practical Handbook of Spatial Statistics. CRC Press, Boca Raton, FL. pp 83-106.

Wu, D., Yu, Q., Hengsdijk, H., 2006. Quantification of production potentials of winter wheat in the North China Plain. Eur. J. Agron. 24, 226-235.

Xinhua News Agency, 2001. China Plans to Promote Efficient Irrigation. http://service.china.org.cn/link/wcm/Show_Text?info_id=16509&pqry=efficient%20and%20irrigation.

Yang, Y., Watanabe, M., Zhang, X., Hao, X., Zhang, J., 2006. Estimation of groundwater use by crop production simulated by DSSAT-wheat and DSSAT-maize models in the piedmont region of the North China Plain. Hydrol. Process. 20, 2787-2802.

Yu, Q., Saseendran, S.A., Ma, L., Flerchinger, G.N., Green, T.R., Ahuja, L.R., 2006. Modeling a winter wheat-corn double cropping system using RZWQM and the RZWQM-CERES Hybrid. Agric. Syst. 89, 457-477.

Zadoks, J.C., Chang, T.T. Konzak, C.F., 1974. A decimal code for the growth stages of cereals. Weed Res. 14, 415-421.

Zhang, H., Wang, X., You, M., Liu, C., 1999. Water-yield relations and water-use efficiency of winter wheat in the North China Plain. Irrig. Sci. 19, 37-45.

Zhang, X., Chen, S., Liu, M., Pei, D., Sun, H., 2005. Improved water use efficiency associated with cultivars and agronomic management in the North China Plain. Agron. J. 97, 783-790.

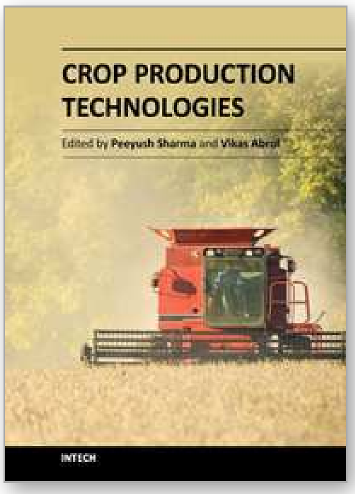
Zhang, X.Y., Pei, D., Hu, C.S., 2003. Conserving groundwater for irrigation in the North China Plain. Irrig. Sci. 21, 159-166.

Zhang, Y., Kendy, E., Qiang, Y., Changming, L., Yanjun, S., Hongyong, S., 2004. Effect of soil water deficit on evapotranspiration, crop yield, and water use efficiency in the North China Plain. Agric. Water Manage. 64, 107-122.

Zhao, J.R., Guo, Q., Guo, J.R., Wie, D.M., Wang, C.W., Liu, Y., Lin, K., 1997. Investigation and analysis on current status of chemical fertilizer inputs and crop yields in agricultural field of Beijing Subburb. J. Beijing Agric. Sci. 15, 36-38 (in Chinese).

Zhao, R., Chen, X., Zhang, F., Schroder, H., Römheld, V., 2006. Fertilization and Nitrogen Balance in a Wheat-Maize Rotation System in North China. Agron. J. 98, 938-945.

Zhu, Z.L., Chen, D.L., 2002. Nitrogen fertilizer use in China - Contributions to food production, impacts on the environment and best management strategies. Nutr. Cycling Agroecosyst. 63, 117-127.



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