THE USE OF ARTIFICIAL NEURONAL NETWORKS TO GENERATE DECISION RULES FOR SITE-SPECIFIC NITROGEN FERTILIZATION

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ABSTRACT

The use of adequate decision rules is the basis for successful and sustainable agriculture. When it comes to precision farming, these rules have to be applied to each sub-field, where they determine the actions to be taken.
This paper presents a method for site-specific nitrogen fertilization which automatically generates decision rules based on yield-predicting artificial neuronal networks. The database for the artificial neural net consists of information gained from sensors measuring apparent electrical conductivity, historical yield, historical fertilizer applications and in-season measurements such as the REIP (Red Edge Inflection Point, measuring the canopy-reflected sunlight) index.

One set of decision rules was generated for each of the three nitrogen applications that take place within a crop season; the rules are visualized by means of decision trees. Thus, the importance of the various heterogeneity indicators upon which the nitrogen recommendation is based can be analyzed.

The method was implemented on a winter wheat field on an Eastern German farm. The monetary result was compared with three other nitrogen fertilization strategies (uniform treatment, online-approach and unique injection fertilization).

From an economic point of view, the automatically-generated decision rules were by far the best of all the fertilization strategies.

Keywords: precision nitrogen fertilization, decision rules, artificial neural network, field trial, economical viability

INTRODUCTION

Decision Rules

The automatic generation of decision rules is still in its infancy, and as a result, almost no literature on the topic exists. On the other hand, the missing decision rules are recognized as being one of the main reasons for not using precision farming technologies (LOWENBERG-DeBOER, 1996): "One of the key factors limiting adoption of precision farming technology is the lack of decision support. There is too much data to sort and analyze manually or mentally, and little software to automate the process. Someone needs to estimate the surface-generating production function (…) someone needs to develop the optimization algorithm that will apply that information to generating next season's cropping strategy."

The lack of decision support obviously is still a key problem: GRIEPENTROG (2011) states that there is indeed much research on individual problems of precision farming, such as a certain sensor, but rarely research on the complexity of the every day decisions of a farmer with regard to precision farming, such as the decision on how much to fertilize.

To capture the real heterogeneity various variables will be necessary for deriving site-specific fertilization decision rules. In many studies only a few variables are taken into account when deriving fertilization recommendations.

For example, by linking electrical soil conductivity (EC) with the yield, LUND et al. (1999) develop decision rules for the seed sowing rate and nitrogen fertilization that are dependent on electrical conductivity. However, these rules are too vague for implementation. To develop the topic further, the same authors recommend combining EC data with other site-specific information for deriving decision rules.

For us, EC-data seem to serve as a good basic input for yield-predicting models: we found high, positive correlations between EC and yield data on our field trial areas north of the city of Halle (Saxony-Anhalt).

On the other hand, HUANG, KRAVCHENKO and THELEN (2005) write: "Generally, low EC values corresponded to high yield clusters in the studied fields". If both of the above statements are correct, conditions obviously vary from location to location.

Historical yield maps are often used for the application of precision farming technologies. In analyzing yield maps over several years, BLACKMOORE et al. (2003) found that: "Significant spatial variability is evident in most individual yield maps, which were expected to stabilize into areas of consistent trends after a few years. This can be seen as untrue as the maps become more homogenous over time." Contrary to BLACKMOORE we found a stable yield pattern over years on our experimental fields. LISSO (2003), who uses aerial image-corrected yield maps for planning site-specific sowing, fertilization, growth regulator and fungicide application, reports similar observations (stable yield patterns over time). Again: conditions obviously vary between locations if both statements are right.

PETERS et al., (1999) attempt to create site-specific nitrogen fertilization strategies. They recognize that: "… one of the perceived constraints on the adoption of precision farming techniques by farmers is the lack of readily available, definitive guidelines on variable rate nitrogen management." They describe an approach to divert decision rules for nitrogen fertilization with consideration of the yield potential of different soil types. The trial results are promising, but as yet there are no concrete decision rules.

ISSENSEE et al. (2000) assume a theoretical model for decision finding by taking into account yield potential (soil, water conditions, relief, etc.), weather conditions (soil moisture, nitrogen delivery, etc.), plant type and other plant growing conditions (crop protection, trace elements, etc.). However, concrete decision rules have not yet been developed.

WELSH et al., (1999) indicate the necessity of identifying homogenous management zones where each zone has its own response function, but they offer no possibilities for accomplishing this.

WENKEL et al., (2001) work out decision rules for site-specific nitrogen fertilization and also show, with their modules for site-specific base fertilization, the application of uniform treatment recommendations in a site-specific context. The results of the field trials are positive. Unfortunately, the application of these decision rules assumes a prohibitively high site-specific information level.

Altogether, at the moment the situation is unsatisfactory concerning practical site-specific decision rules for nitrogen fertilization. With partly contradictory statements (considering conductivity or yield maps) we suspect that there will be no general decision rules for all locations. However, in regions with the same climatic conditions, there could be the possibility of transferring these rules from one location to another.

With this background, self-learning algorithms could possibly solve the problem; such an algorithm could be developed using "Data Mining" techniques. This paper shows the result of such a development, with a method that can be used independent of the location. Admittedly, it is based on a high information basis, but it can be transferred to other fields in an automatic manner and with low costs.

Data Mining Technologies

Apart from agricultural questions, a great deal of literature already exists on data mining applications. A survey by NAKHAEIZADEH et al., (1998) presents existing techniques, tools and applications in scientific research and industrial practice. Most of the applications are based on public financial questions (e.g. BAETGE and UTHOFF, 1998) with mainly classification problems being solved. These classification problems and analyses of dependencies (NAKHAEIZADEH et al., 1998) could be used for identifying homogenous sub-fields and the derivation of fertilization strategies. Very little literature can be found with regard to agricultural applications.

KOLLIG (1993) uses neuronal networks and rules-based systems to develop a decision support system for sugar beet cultivation; for the first time, this work showed neuronal networks quantifying parameters of influence on the sugar beet yield.

The attempt to generate decision rules for nitrogen fertilization strategies with data mining technologies is described by HOSKINSON et al. (1999), who obtained encouraging results. KITCHEN et al., (2003) predict the yield by using neuronal networks, electrical conductivity and topography. CHAUDHARY et al., (2005) are able to analyze yield-predicting influences by using data mining technologies. DIKER et al., (2005) forecast yields by training neuronal networks.

The authors have no knowledge of practical decision rules for site-specific nitrogen fertilization in the literature that are similar to the approach presented in this paper.

MATERIALS AND METHODS

Artificial Neuronal Network (ANN)

"An **artificial neural network (ANN) …** is a mathematical model or computational model that is inspired by the structure and/or functional aspects of biological neural networks. An ANN consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. Modern neural networks are non-linear statistical data modeling tools. They are usually used to model complex relationships between inputs and outputs or to find patterns in data. (WIKIPEDIA, keyword: "artificial neural networks", 2012-04-03).

The appendix "artificial" is given for the ANN to show the differences between it and biological neuronal networks. ANN can be used in approaches where almost no knowledge exists for solving a problem. They can also be used in cases where (for reasons of auto-correlation) statistical regression approaches cannot be used.

There is much literature dealing with ANN. For example CALLAN (2003) deals with fundamental drafts. For an agricultural application, KOLLIG (1993) describes how an ANN functions, as well as how to interpret ANN results.

In a strong relation to the presented paper WEIGERT (2006) describes how an ANN functions by focusing primarily on data preparation and ANN training.

Field Trial Designs

A neuronal network was trained for site-specific yield prediction, and the results were taken to recommend nitrogen application for winter wheat. For comparison, two other different site-specific fertilization strategies and a uniform field treatment were carried out.

The field trials were conducted between 2005 and 2011 on different winter wheat fields (e.g. field 350 (2005): 51°40'43''N 11°58'11''E) of the Domäne Görzig, an experimental farm owned by the University of Halle. The winter wheat was treated with four different nitrogen fertilization strategies (treatments): "Uniform Treatment" ("UT"), "Sensor", "Map" and "Neural Network" ("Net").

The location of the fields can be characterized as follows: with an average precipitation of 475 mm per year, there is a negative climatic water balance in the growing season, and the average annual temperature is 9 °C. The terrain lies

between 90 and 100 meters above sea level and is flat. The soil type is Chernozem, the texture class is silt loam. The field has an average soil number (german classification system) of 73 (0: poor soil, 100: best soil).
The four trial elements were laid as a strip trial design on the fields, with every trial element being repeated in two strips. The strips themselves were two or three tram lines wide (at a working width of 24 meters). An example, which is characteristic for all field trials, is shown in Figure 1.

Due to a lack of space in the field, the design was created without randomization of the strips. The average EC and historical yield from the previous year was determined for every strip. Distributing the fertilization strategies to the field strips was carried out with the aim of obtaining the same average heterogeneity indicators (EC and historical yield) with every fertilization strategy.

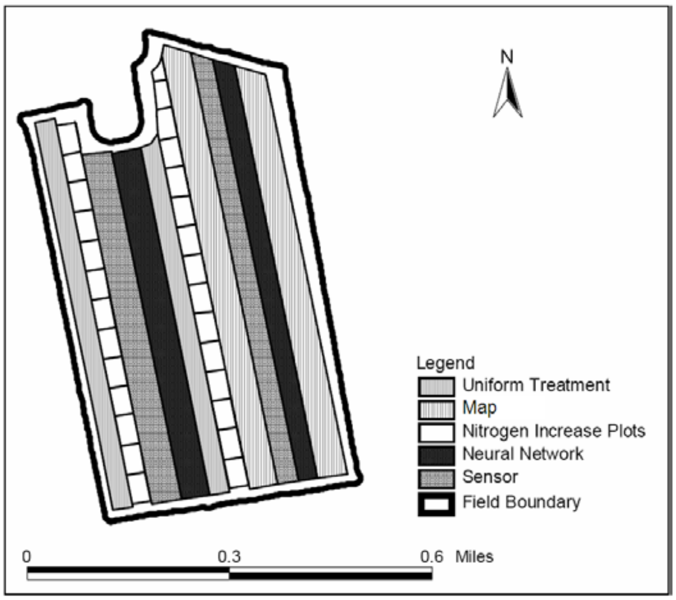

Figure 1: Example of a strip trial design (Field 350 in 2005, 63 ha.)

In addition, plots with varying nitrogen amounts were laid out in the field, with nitrogen application varying from 0 to 270 kg N/ha. These are needed to train the artificial neural network in the future.

All farming applications were carried out with normal farm techniques for a farm in this region. Apart from the amount and in-field distribution of nitrogen fertilizer, all farming decisions were made by a farmer and carried out uniformly.

Uniform Treatment (UT)

The amount of fertilizer was applied uniformly over the strips, with application decisions made by a farmer with long–standing experience in winter wheat production at this location. The fertilization was planned in consideration of nutrition deprivation. The average yield target for this field was planned to be 8 t/ha. Taking into account the nitrogen content in the harvested crop (winter wheat) and the mineralized nitrogen content of the soil, 175 kg N/ha of fertilizer had to be applied. This amount was divided into three partial applications.

For the first application, 55 kg N/ha was applied. The reasons for this decision were the usable nitrogen content in the soil and the crop rotation effect of the field's preceding crop. The second and third application amount was then given in accordance with the actual precipitation and visual crop situation.

Sensor

The Yara-N-Sensor® was used to determine nitrogen amounts in this fertilization strategy. With this system, fertilizer demand is determined based on the actual crop situation at the moment of fertilization by measuring the canopy-reflected sunlight. Thus, conclusions about the crops' nitrogen content can be drawn; for more information, see LINK et al., (2002).
The use of this sensor system requires an adequate crop covering of the ground's surface. Thus, the sensor was used only for the second and third nitrogen applications. The first treatment was made according to the uniform treatment.

Mapping approach (Map)

For this strategy, the total nitrogen demand was calculated according to a mapping approach using information from the 2004 yield map, and yields of three other years were used for the decision-making. The yield map was interpolated to a grid (20x20 meters) and clustered into three classes. Thus, three zones of different potential yields were determined. With the displacement of the middle potential yield zone to the higher and lower potential yield zones, the average yield of the three years in the different zones was determined. After this, the average yield over four years was calculated for the three different zones. The nitrogen application map was made by considering the nitrogen demand in the three different zones according to the average yield potential.

Neural Network (Net)

The decision rules for this fertilization strategy are based on the site-specific yield prediction of the artificial neural network. In order to train the Net, information about the soil (electrical conductivity), historical yields (2003 and 2004), historical in-season information in terms of the REIP (Red Edge Inflection Point) index of 2004 and the fertilization amount from 2004 were combined in a database. These data were collected from a field on the same farm where the field trials took place. The data available were interpolated with the spatial resolution of a 10x10 meter grid. For all three nitrogen applications, a neural network was trained based on this database.

Training for the first application took place by using historical yields, the first nitrogen application of 2004 and EC data. For training the neural networks for the second and third applications, the corresponding historical nitrogen applications and in-season attributes were used in addition to the information of the first application.

The REIP index is calculated based on information from an optical sensor system such as the Yara-N-Sensor® in field scan modus. The measuring takes place at the plant growing status of BBCH 32 (second application) and BBCH 49 (third application). This index contains the actual nitrogen status of the crops and is used to summarize past weather conditions. For all three neural networks, the historical yield from the year 2004 was used as the corresponding yield to the input data. The upper half of figure 2 shows the training procedure.

The software Clementine® (by SPSS, meanwhile called “modeler” (IBM)) was used. While training the neural net, the learned output value is compared each time with the actual aim value of the data set (here: yield 2004). The deviation between these two values is used as a control signal for the further development of net topology (backpropagation algorithm). For further information about this topic, see WEIGERT (2006, p. 27ff).

For the yield prediction, the according neural net was used with the real sub-field conditions of field 350 before every nitrogen application in 2005 (figure 2, lower part). The yield of each sub-field was forecasted for all possible nitrogen applications (0 to 100 kg N/ha in 10 kg N/ha steps). With the connections of revenue (yield multiplied by product price) and expense (nitrogen amount, multiplied by nitrogen price), according to the marginal principle, for every sub field (20x20 meters) the profit maximum nitrogen amount was determined. With a black box character, the connections of the neural net remain secret. However, with the knowledge of the optimum nitrogen amount, they can be visualized using decision tree algorithms (Figures 3 and 4).

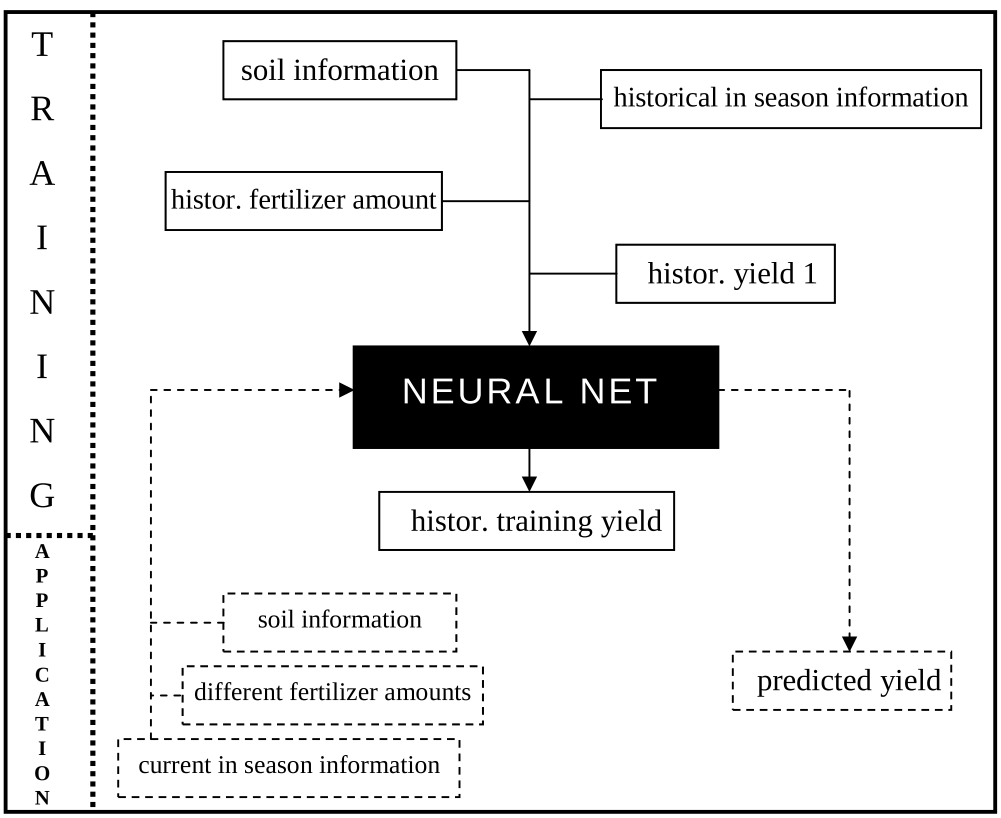

Figure 2: Schematic Presentation of Training and Application of the Neural Net

For sake of clarity, these decision trees are presented in a condensed manner. The full decision trees contain 9 and 13 ranks. Only a rough subdivision is shown with the 2 and 3 ranks presented.

The “inverse mapping approach” found by the neural net is conspicuous in the first application. This means that more nitrogen is applied on the patches on which only low yields were obtained in the past. Conversely, lower fertilizer amounts are applied where historical yields have been high. This feature is visualized in the decision tree of the first application (Figure 3).

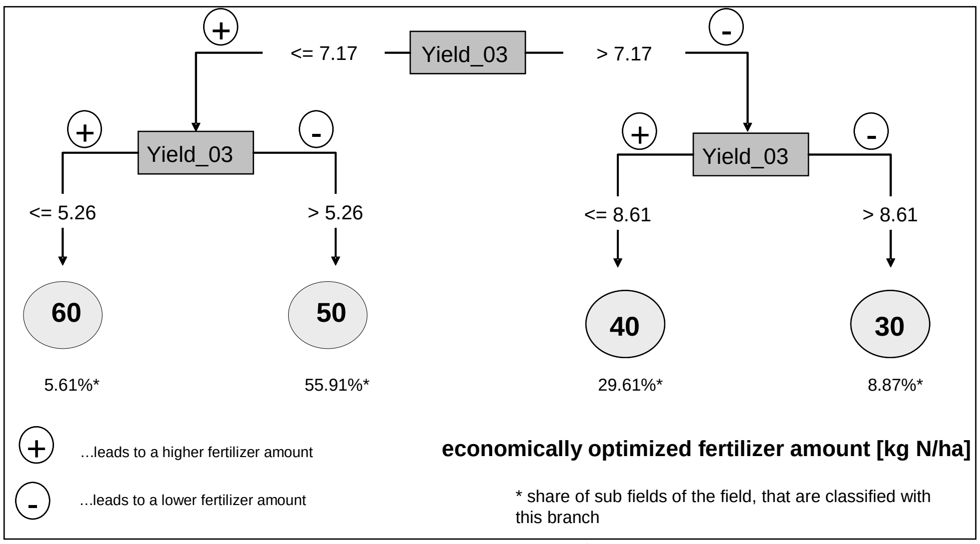

Figure 3: Reduced Decision Tree of the 1st Nitrogen Application

For the second nitrogen application, the decision structure shows a strong influence of the current nitrogen supply indicator REIP_32 (Figure 4). The general trend for sub-fields with a lower REIP_32 is a higher nitrogen recommendation. Also, other attributes such as the EC and historical yield influence decision-making; however, for the sake of a simplified presentation, they are not all contained in this illustration.

The decision structure for the third nitrogen application follows a similar model. The feature characteristic of the REIP_49 measurement has a strong influence. With the concentration of most sub-fields to two branches of the first application decision tree (40 and 50 kg N/ha), an apparent homogeneity of the location is simulated. During the second application, the nitrogen recommendation varies more strongly (0 to 70 kg N/ha).

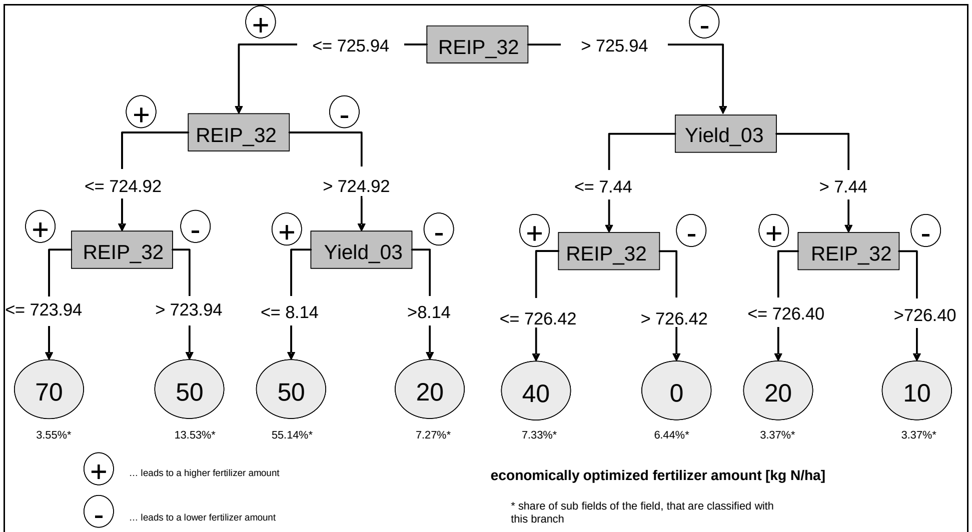

Figure 4: Reduced Decision Tree of the 2nd Nitrogen Application

RESULTS AND DISCUSSION

To get an impression of how differently the strategies act with regard to the N-amounts applied, Table 1 shows the N-amounts to each of the applications. In addition the minimum and maximum (scatter) for the precision strategies are indicated. The table summarizes the nitrogen applications at the example of field 350 in 2005. The low total fertilization level of the "Net" strategy is typically for all site-years. On average, almost 30 kg N/ha were saved in comparison to the uniform treatment strategy.

Table 1: Example of the nitrogen fertilization amounts of the different strategies (Field 350 in 2005)

fertilization strategy	**are a**	**1st application**		**2nd application**		**3rd application**		**Sum**
	ha	*kg N/ha*	*scatter (kg/ha)*	*kg N/ha*	*scatter (kg/ha)*	*kg N/ha*	*scatter (kg /ha)*	*kg N/ha*
"UT"	8.4	55	0	60	0	60	0	175
"Sensor"	11.1	55	0	61	44 – 80	66	53 – 80	182
"Injector"	14.3	190	165 – 220					190
"Net"	10.6	44	30 - 60	47	0 – 70	57	30 – 70	148

Table 2 summarizes the results of all of the 15 field trials. The yields and the amount of N-fertilizer were analyzed by comparing the means of the respective treatments. The total amount of nitrogen applied according to uniform field treatment varied in each year over all fields between 170 and almost 200 kg N/ha, except for field trial 211_2007 (see Table 2), where the second nitrogen application was saved due to there being no fertilizer requirements: In the past, this field received intensive manure applications, which came from a biogas plant located nearby.

Table 2: Results of the field trials

Field Trial	Strategy	avg. N-amount (kg/ha)	Yield (t/ha)	N-eff. (kg N / t Y)	NCfR[a] (€/ha)	Δ to UT[c] (€/ha)
350_2005 (63 ha)	UT	175	7,19	24,3	583,80	
	“Sensor”	182	7,45 [b]	24,4	579,90	-3,90
	“Net”	148	7,56 [b]	19,6	598,80	15,00
432_2005 (93 ha)	UT	180	7,63	23,6	664,00	
	“Sensor”	117	7,71 [b]	15,2	698,00	34,00
	“Map”	148	7.81 [b]	19,0	681,00	17,00
411_2006 (35 ha)	UT	180	6,11	29,5	620,50	
	“Sensor”	164	5,75 [b]	28,5	621,80	1,30
	“Map”	200	5,69	35,1	562,00	-58,50
330_2006 (72 ha)	UT	170	5,83	29,2	567,60	
	“Sensor”	187	5,67	33,0	529,10	-38,50
	“Net”	142	5.99	23,7	592,80	25,20
131_2006 (34 ha)	UT	170	5,08	33,5	518,20	
	“Net”	142	5.02 [b]	28,3	533,40	15,20
432_2007 (93 ha)	UT	180	5,68	31,7	767,90	
	“Sensor”	158	5,71	27,7	778,20	10,30
	“Map”	162	5,39	30,1	732,80	-35,10
631_2007 (113 ha)	UT	180	4,60	39,1	605,90	
	“Sensor”	144	4,62 [b]	31,2	622,70	16,80
	“Map”	160	4,65 [b]	34,4	615,20	9,30
	“Net”	136	4,70	28,9	651,90	46,00
611_2007 (51 ha)	UT	169	5,33	31,7	708,50	
	“Sensor”	164	5,20 [b]	31,5	711,40	2,90
	“Net”	146	5,26 [b]	27,8	720,50	12,00
211_2007 (64 ha)	UT	120	6,41	18,7	899,20	
	“Net”	83	6,50	12,8	932,80	33,60
610_2008 * (110 ha)	UT	175	9,69	18,1	1425,98	
	“Sensor”	147	9,46	15,5	1416,21	-9,76
	“Net”	135	9,70	13,9	1468,03	42,05
631_2008 * (58 ha)	UT	176	8,90	19,8	1290,74	
	"Net"	148	8,84	16,7	1309,12	18,38
430_2009 * (76 ha)	UT	170	9,89	17,2	840,16	
	“Sensor”	182	10,17	17,9	854,41	14,25
	“Net”	130	9,52	13,7	849,61	9,45
540_2009 * (28 ha)	UT	170	8,32	20,4	672,95	
	“Sensor”	170	8,09	21,0	648,55	-24,40
	“Net”	154	8,34	18,5	694,30	21,35
211_2010 * (64 ha)	UT	194	9,31	20,8	1598,53	
	“Sensor”	160	9,06	17,7	1577,59	-20,94
	“Net”	135	9,06	14,9	1599,13	0,60
440_2011 * (41 ha)	UT	197	6,02	32,7	945,57	
	“Net”	156	5,93	26,3	973,87	28,30

[a] NCfR: Nitrogen Cost-free Revenue

[b] No significant yield differences between site-specific management and uniform field treatment were observed. For further calculations of the NCT, the yield according to the UT strategy was used.

[c] positve result better than UT; negative result worse than UT

* no statistical correction so far

For the different site-specific strategies, except the “Net” strategy, the total nitrogen amount applied is very similar to the uniform field treatment range. It is obvious that the applied nitrogen amounts of the “Net” strategy were much lower than that of the other strategies, whereas the yields are mostly higher or at least not considerably lower! This results in a far better N-use-efficiency than the uniform field treatment shows and should not be underestimated with regard to ecological aspects, especially groundwater contamination.

The nitrogen cost-free turnover is the difference between the proceeds and the costs of N-fertilizer. The proceeds are calculated by multiplying the yields with the market prices of winter wheat after harvesting in August of the respective years. The N-costs are calculated by multiplying the amount of N-fertilizer applied with the market prices in March of the respective years.

Table 3: N-efficiency and NCfR of the tree site specific strategies in comparison to UT (Δ: “+” benefit; “-“ loss).

	N-efficency (kg N / t Y)				NCfR (€/ha △ to UT)		
field trail	UT	"Map"	"Sensor"	"Net"	"Map"	"Sensor"	"Net"
350_2005	24,3		24,4	19,6		-3,90	15,00
432_2005	23,6	19,0	15,2		17,00	34,00	
411_2006	29,5	35,1	28,5		-58,50	1,30	
330_2006	29,2		33,0	23,7		-38,50	25,20
131_2006	33,5			28,3			15,20
432_2007	31,7	30,1	27,7		-35,10	10,30	
631_2007	39,1	34,4	31,2	28,9	9,30	16,80	46,00
611_2007	31,7		31,5	27,8		2,90	12,00
211_2007	18,7			12,8			33,60
610_2008	18,1		15,5	13,9		-9,76	42,05
631_2008	19,8			16,7			18,38
430_2009	17,2		17,9	13,7		14,25	9,45
540_2009	20,4		21,0	18,5		-24,40	21,35
211_2010	20,8		17,7	14,9		-20,94	0,60
440_2011	32,7			26,3			28,30
average	**26,0**	**29,6**	**24,0**	**20,4**	**-16,83**	**-1,63**	**22,26**

Within the seven year timeframe, only the “Net” strategy can offer advantages in comparison to UT throughout (Table 3). Both of the other strategies show positive as well as negative results. Based on these field trial results, a ranking of the three strategies can be made: the best strategy is “Net” with positive NCfR differences in comparison to UT in the range of one and 46 €/ha (out of twelve field trials); next comes the “Sensor” strategy, with five negative, two comparable and four positive field trial results. On average, the “Net” strategy tops UT with 22 €/ha. The “Map” strategy, with two positive and two negative results, was worse than UT on average, whereas the “Sensor” was comparable. The more expensive the fertilizer becomes and the more the prices for grain increase, the more the “Net” strategy will gain advantage because this strategy is the only one which shows a much better nitrogen efficiency than all of the other strategies: for producing one ton of wheat the “Net” strategy needs 20.4 kg of N-fertilizer compared to 26 kg in the UT. That means that the UT needs 27.4 % more N than the “Net”. Thus, the “Net” strategy shows a positive environmental aspect and a payoff for the farmer!

At this point, the results’ limited validity has to be mentioned: they are only valid for the examined locations. Furthermore, no additional costs of site-specific management have yet been taken into account. However, it becomes obvious that precision farming must not be profitable in every case and in every year. The success of precision farming depends largely on the quality of the approach and its underlying decision rules.

CONCLUSIONS

All four fertilization strategies were based on decision rules, but due to the subjective nature of the uniform treatment strategy, its rules are not completely reproducible. However, the decision rules of the strategies “Sensor”, “Map” and “Net” are reproducible. The aim of the “Sensor” and “Mapping” strategies is the maximization of yield, not the maximization of profit. A methodically conclusive method of maximizing the benefit of sub-fields in connection with reproducible and well-documented decision rules is represented by the “Net” strategy.

The best result of this field trial came from the fertilization strategy that was based on the largest amount of information. Artificial neural networks seem to offer the possibility of finding connections between input and output data in big databases. Due to the large amount of information, it is possible to automatically generate complex decision rules with the help of decision tree algorithms.

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