DERIVING REGRESSION EQUATIONS (META-MODELS) FROM DETERMINISTIC SIMULATION MODELING FOR CROP FERTILIZATION

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ABSTRACT

Operating complex mathematical models, describing the plant-water-soil environment, is difficult and generally only done by experts. Complex data handling and parameterization of those models hamper the use by less skilled people and are a serious drawback on using information from deterministic simulation modeling in decision support systems for precision agriculture. In this study regression or meta-models for nitrogen fertilizer application in Winter Wheat on the Van Bergeijk farm in the Netherlands were derived from long-term simulation modeling. These meta-models only need simple, easily obtainable, weather data and basic soil information, such as soil organic matter content, to predict accurate timing and amount of spatial variable nitrogen applications. In a validation study, timing and amount of the various nitrogen applications in 1999 on a 15 ha field on the Van Bergeijk farm was always within 10 days and in almost all cases within 7 days compared to the recommendation of the decision support system. Predicted amounts of an individual application were accurate within 5-10 kg ha^{-1} compared to the decision support system. This study illustrates that results of complex deterministic simulation models can be used to derive simple regression based meta-models that can be used by farmers in simple straightforward calculators such as spreadsheets or pocket calculators.

INTRODUCTION

Fertilizer recommendations in the Netherlands are based on the total mineral nitrogen level (N-min), present in the rootable zone of a soil profile in early spring, to determine the application amount. The parameters for this fertilizer recommendation were derived from national field trials. These traditional nitrogen fertilizer recommendations do not account for soil spatial variability and are homogeneous for a farmer's field. Due to spatial variability within a field this

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approach results in over-fertilization, with corresponding leaching risks at some places and under-fertilization at others with the effect of sub optimal growing conditions for the crop (Verhagen and Bouma 1997, 1998).

Crop simulation models can play an important role in fine tuning fertilizer recommendations, spatially as well as temporal. Bouma (1997) made a distinction between the application of simulation models in a retrospective mode (backward looking) and using them in a predictive mode (forward-looking). Booltink *et al.* (1996) and Booltink and Verhagen (1997) applied the backward looking approach using weather data of a past growing season (1994) and comparing actual management with management options derived by the backward-looking modeling approach. Disadvantage of this method is that the season is already over when the simulations are done. Management decisions have already taken place and therefore adaptation of management strategies based on modeling results is no longer possible. However, a combination of simulation models with weather forecasts can also be used in a predictive way, providing information on which management in terms of fertilizer amount and timing can be adjusted. Using the real field and weather data, the simulation model can be continuously checked and adjusted throughout the growing season (Van Alphen and Stoorvogel, 2000a). In this mode we can use the simulation models to reduce the losses of nutrients to the environment and at the same time the nutrients are used more efficiently with respect to crop production. This type of modeling seems very promising and has high potential for the application within a decision support system for precision agriculture. A big disadvantage of this type of modeling is that the application of such simulation models requires a lot of experience and can usually only be carried out by well-trained specialists. Due to the more widely applied integration of simulation models into GIS (Hartkamp *et al.*, 1999) operation has become less complex. However, accurate parameterization and calibration of these models is still difficult and simulation results are more difficult to interpret as results are generally presented as nice maps obtained through generalizations of primary modeling results.

In this study a method to generate more user-friendly forecast models that avoid the use of unknown future weather data will be discussed. These meta-models will be derived from results of the complex and deterministic WAVE-model by means of regression analysis. It is expected that weather parameters are of direct influence on the timing and amount of fertilizer applications. The purpose of this study is to study the relation between timing and amount of fertilizer applications for winter wheat on the Van Bergeijk farm in the Netherlands and some important weather parameters.

STUDY AREA

The van Bergeijk farm, located in the southwest of the Netherlands, is a commercial farm of approximately one hundred hectares. Winter wheat, consumption potatoes and sugar beets dominate the intensive 4-year crop rotation. The soils consist of marine deposits, which are generally calcareous and have textures ranging from sandy loam to heavy clay-loam. Peat residues are incidentally found resulting in relatively high organic matter contents. With the excellent drainage system, controlled by a dense system of tile drains, these soils are considered to be prime agricultural land. (Booltink *et al.*, 1999).

A detailed soil survey was conducted at the Van Bergeijk farm in the spring of 1997. Approximately 600 augurings were done, 300 sampling points were located according to a regular grid and the other 300 on places where highest variability was expected, based on information obtained from aerial photography.

Most soil properties, needed as input for a simulation modeling, were determined directly. Others could be derived indirectly using pedotransfer functions (Wösten and Van Genuchten, 1988). Soil layers were classified into a total of 16 taxonomic classes defined by the Dutch 'Staring series' (Wösten, 1987). This classification distinguishes between topsoil and subsoil layers, which are further differentiated towards texture and SOM-content. Each taxonomic class was sampled in the field to determine average soil physical characteristics using the crust infiltrometer (Booltink, 1991) and multi-step outflow methods (Van Dam *et al.*, 1990). Van Alphen and Booltink (2000) showed that hydraulic characteristics derived through a combination of pedotransfer estimates and simple on-site physical measurements (*i.e.* saturated moisture content and bulk density) gave best results when simulating soil moisture regimes in the study area.

Soil variability was described in terms of selected soil functional properties. These were derived for individual soil profiles (point data). In a simulation study Van Alphen and Stoorvogel (2000) determined management units by means of fuzzy clustering techniques. These management units are areas within a farmer's field that respond more or less homogeneous in terms of crop growth and nitrate leaching. For the study area of 15 ha all spatial variability could be included in 4 significantly different management units.

SIMULATION MODELING

Model Description

Dynamic simulations of soil-water-plant interaction were conducted with the mechanistic-deterministic simulation model 'WAVE' (Water and Agrochemicals in soil and Vadose Environment) (Vanclooster *et al.*, 1994). WAVE integrates four existing models describing:

1. One-dimensional soil water flow: SWATRER (Dierckx *et al.*, 1986),
2. Heat and solute transport: LEACHN (Hutson and Wagenet, 1992),
3. Nitrogen cycling: SOILN (Bergström *et al.*, 1991) and,
4. Crop growth: SUCROS (Spitters *et al.*, 1988).

Differential equations governing water movement (Richards' equation) and solute transport (convection-dispersion equation) are solved with a finite difference calculation scheme. For this purpose soil profiles were divided into five-centimeter compartments.

Water stress is calculated according to Feddes *et al.* (1978). Maximum uptake rates are defined by a sink term, which is considered constant with depth. Water uptake is reduced at high and low pressure head values, according to crop-specific thresholds. Stress resulting from N-deficiency occurs when required N-concentrations in the plant cannot be sustained by actual uptake rates. Crop production is then reduced proportionally to the ratio of actual over required uptake. Van Alphen and Stoorvogel (2000) presented a detailed description of modeling procedures. Model calibration and validation was described by Van Alphen and Booltink (2000)

Simulation Based Fertilizer Recommendations

WAVE was used to generate the necessary fertilizer application dates and amounts for a single winter wheat field. Weather data for the Van Bergeijk farm were available for a period of 15 subsequent years ranging from 1981 to 1996. For each of the distinguished management units a representative soil profile was selected from the soils database. In Table 1, main soil characteristics and Van Genuchten parameters for these representative profiles are presented. In the Netherlands generally three fertilizer applications are given in winter wheat. Timing and amount in conventional agriculture is determined by expert judgement of the farmer. In this study we used this expert judgement and defined the following fertilization procedure:

1. The first nitrogen application is fixed: at 80 kg ha^{-1} of nitrogen at the beginning of March.
2. The timing of the second application is calculated with the help of the method, described by van Alphen (2000a). This method uses the WAVE-model to quantify soil nitrogen levels and nitrogen uptake rates on a real-time basis. Once the soil nitrogen concentration drops below a threshold level, warning signals are generated by the model as an indication that fertilizer should be applied. The threshold value is defined as:

   Eq. 1 $$SN_{min} < 2\phi_w$$

   Where SN_{min} is the soil mineral N content over the first 30 cm of the soil profile (kg ha^{-1}) and ϕ_w is the weekly N uptake rate of the crop (kg $week^{-1}$ ha^{-1}). If this threshold is exceeded a second application of 60 kg N ha^{-1} is given.
3. As soon as the nitrogen concentration in the soil drops again below the threshold level, the third application will be given. The amount of this application will be determined separately for every individual simulation.
   A WAVE simulation is done with an assumed third nitrogen application of 80 kg ha^{-1}. The total amount of nitrogen in the soil can then be determined at the end of the growing season. In view of an average precipitation surplus of approximately 300-mm during the winter season in the Netherlands, the amount of mineral N present directly after harvest (leaching potential) should not exceed 35 kg N ha^{-1}. Higher amounts than this will lead to high probabilities of exceeding the 50 g m^{-3} NO_3 level (Verhagen and Bouma, 1998). When assuming that nitrogen leaching of 35 kg N ha^{-1} is acceptable, the surplus of nitrogen in the soil can be calculated when comparing the simulated nitrate level at harvest with the 35 kg N ha^{-1} threshold value. Subtracting this nitrogen surplus from the hypothetical 80 kg N ha^{-1} scenario, the amount of the third fertilizer application can easily be calculated for every individual simulation.

This simulation procedure was carried out for each of the 4 management units within field 6 for 15 years in which weather data were available. This generated data set was used for the derivation of the meta-models.

Table 1. **Main soil characteristics of field 6. S.O.M. refers to the soil organic matter content θ_r refers to the residual water content, θ_s to the saturated water content, α, n and γ are shape parameters in the Van Genuchten equation (Van Genuchten, 1980), and K_{sat} is the saturated hydraulic conductivity.**

Site Number	Layer number	Thickness (cm)	Horizon code	Clay (%)	Silt (%)	Sand (%)	S.O.M. (%)	Bulkdensity kg dm-3	θ_r $m^3 m^{-3}$	θ_s $m^3 m^{-3}$	α cm^{-1}	n (-)	K_{sat} (cm day^{-1})	γ (-)
A	1	30	Ap	41.5	51.0	7.5	3.0	1.229	0.00	0.0924	1.0884	0.0812	105.29	-1.248
	2	30	Cg1	45.6	46.6	7.9	1.0	1.486	0.00	0.0550	1.0971	0.0885	38.65	-1.338
	3	95	Cg2	12.5	25.7	61.8	0.4	1.467	0.00	0.0178	1.2909	0.2253	15.53	-0.587
	4	70	Cr	12.5	25.7	61.8	0.8	1.467	0.00	0.0329	1.2463	0.1976	29.70	-0.554
B	1	25	Apg	41.5	50.0	8.5	3.0	1.229	0.00	0.4700	0.0924	1.0884	105.29	-1.248
	2	35	Cg1	43.3	46.6	10.1	0.1	1.486	0.00	0.4600	0.0246	1.1842	5.42	-1.383
	3	40	Cgj	51.3	42.8	6.0	0.1	1.261	0.00	0.4700	0.0236	1.1673	4.03	-1.433
	4	60	Cg1	34.2	47.5	18.3	5.0	1.434	0.00	0.4600	0.0625	1.1039	106.08	-1.085
	5	65	Cr	27.4	41.8	30.8	3.0	1.434	0.00	0.4600	0.0753	1.1170	101.36	-1.044
C	1	25	Ap	41.5	51.0	7.5	5.0	1.229	0.00	0.4700	0.0714	1.0911	107.82	-1.176
	2	65	Cg1	51.3	46.6	2.2	1.0	1.261	0.00	0.4700	0.0533	1.0907	30.64	-1.375
	3	35	Cg2	37.6	48.5	13.9	5.0	1.486	0.00	0.4600	0.0669	1.0974	108.39	-1.132
	4	40	Cg3	22.8	38.0	39.2	1.0	1.504	0.00	0.4500	0.0490	1.1524	51.68	-1.004
	5	60	Cr	17.1	32.3	50.6	1.0	1.467	0.00	0.4500	0.0441	1.1869	44.12	-0.802
D	1	35	Ap	29.0	43.0	28.0	6.0	1.400	0.00	0.4500	0.0460	1.1215	89.63	-0.941
	2	20	Cg1	34.2	47.5	18.3	0.1	1.434	0.00	0.4600	0.0242	1.2126	6.44	-1.294
	3	40	Cg2	27.4	41.8	30.8	0.1	1.434	0.00	0.4600	0.0228	1.2455	6.28	-1.190
	4	65	Cg3	37.6	47.5	14.9	3.0	1.486	0.00	0.4600	0.0888	1.0943	109.03	-1.206
	5	65	Cr3	37.6	47.5	14.9	3.0	1.486	0.00	0.4600	0.0888	1.0943	109.03	-1.206

DERIVING META-MODELS

Statistical Analysis

Multiple regression on simulated fertilizer amount and timing was performed to define meta-models for predicting timing and amount of fertilizer applications. Simulation results were converted into data-files and imported into S-plus 2000 (Mathsoft, 1997). In the statistical analyses, all possible parameters were included. Linear regression models, based on all parameters, were derived and statistical properties of the models were determined. The R^2 of the output is an estimate of how well the regression model fits the population. The R^2 varies between 0 and 1. When R^2 equals 1, the model fits perfectly. When R^2 is close to 0, there is no significant relationship. The Pr ($> |t|$) is illustrating the participation of the regression parameter to the model. A Pr of 0 indicates that the parameter has a highly significant contribution to the outcome of the regression model indicating that the parameter has to be taken into account. When the Pr-value of the parameter is larger than 0.10, the parameter is explaining too little to the model outcome. Consequently this parameter is rejected from the model. Parameters are rejected until the Pr-value of all parameters is less than 0.10 (starting with the highest Pr-value). This procedure results in a stripped regression model with only statistical significant parameters.

Location Dependent Meta-Models

Two approaches were followed. First place dependent regression models were determined for the representative profiles of every of the 4 distinguished management units in. Since the regression models were derived for one specific site within the field, soil physical and chemical parameters can be considered as constants. Therefore, these parameters do not have to be taken into account. As mentioned already the timing and amount of the first fertilizer application in winter wheat is generally fixed in this part of the Netherlands at the beginning of March at 80 N kg ha^{-1}. The amount of the second application is also fixed at approximately 60 kg N kg ha^{-1}. The cumulative amount of 140-kg N kg ha^{-1} can easily be taken up by the crop. The timing of the second application can differ considerably and is therefore included in the regression analysis. For the third application the timing and the amount is included in the regression analysis. The 15 year database derived with WAVE was used to generate these fertilizer dates and amounts.

To be useful as a management tool the derived regression equations should have predictive capabilities. So rather predicting an exact fertilizer date, *"the number of days till fertilization"* (D_D) was predicted. This approach allows a flexible day tot day or week to week estimation of the next fertilization.

Growing stages of a crop can be described by the development stages (DVS). A DVS of 0.01 indicates emergence of the crop. A DVS of 1 and 2 indicate flowering and maturity respectively. It is expected that weather parameters, both from the beginning of the year and from DVS = 0.01 (start of crop growth), will affect timing and amount of the fertilizer applications.

Table 2. Regression parameters used in the analysis for the timing and amount of the place dependent and the place independent regression models. DOF2 and DOF3 refer to the day of forecasting the second (D2) and the third (D3) fertilizer application respectively.

Parameter	*Description*	*Time interval of the parameter*					
		1 Jan	*DVS=0.01*	*DOF2*	*D2*	*DOF3*	*D3*
D_{D2}	Total number of days until D2						
$Rain_{DOF2}$	Total rainfall (mm) at DOF2						
Rad_{DOF2}	Total global radiation (J cm^{2} day^{-1}) at DOF2						
$Rain_{DOF2-0.01}$	Total rainfall (mm) between DVS = 0.01 and DOF2						
$Rad_{DOF2-0.01}$	Total global radiation (J cm^{2} day^{-1}) between DVS = 0.01 and DOF2						
DVS_{DOF2}	Development stage on DOF2						
$DN_{DVS\,0.01}$	Day number at DVS =0.01						
D_{D3}	Total number of days until D3						
$Rain_{DOF3}$	Total rainfall (mm) at DOF3						
Rad_{DOF3}	Total global radiation (J cm^{2} day^{-1}) at DOF3						
$Rain_{DOF3-0.01}$	Total rainfall (mm) between DVS = 0.01 and DOF3						
$Rad_{DOF3-0.01}$	Total global radiation (J cm^{2} day^{-1}) between DVS = 0.01 and DOF3						
DVS_{DOF3}	Development stage on DOF3						
$Rain_{DOF3-D2}$	Total rainfall (mm) between D2 and DOF3						
$Rad_{DOF3-D2}$	Total global radiation (J cm^{2} day^{-1}) between D2 and DOF3						
$Rain_{D3}$	Total rainfall (mm) at D3						
Rad_{D3}	Total global radiation (J cm^{2} day^{-1}) at D3						
$Rain_{D3-D2}$	Total rainfall (mm) between D2 and D3						
Rad_{D3-D2}	Total global radiation (J cm^{2} day^{-1}) between D2 and D3						
$Rain_{D3-0.01}$	Total rainfall (mm) between DVS = 0.01 and D3						
$Rad_{D3-0.01}$	Total global radiation (J cm^{2} day^{-1}) between DVS = 0.01 and D3						
$D3_{am}$	Amount of the third nitrogen application (kg ha^{-1})						
DVS_{D3}	Development stage on D3						
BD_{prof}	Profile-weighted bulk density (kg dm^{-3})						
SOM_{prof}	Profile-weighted SOM (%)						

Consequently, daily values of rainfall and radiation are cumulated, both from the beginning of the year and from the start of the crop growth (DVS = 0.01) until the days of second (D2) and third (D3) fertilizer application. In addition, the DVS at the time of fertilizer applications is determined. In this way a second data set of crop and weather parameters was created for every of then 15 simulation years. Both data sets were combined for statistical analysis. In Table 2 an overview of all examined parameters is presented. Since the variables DOF2 and DOF3 represent the day at which a forecast is made they are not fixed dates but can be any date between DVS=0.01 and D2 (for DOF2) and any date between D2 and D3 for DOF3. In practice, however, management decisions with respect to fertilization are taken on a weekly base, which is the time span we used in this study.

Location Independent Meta-Models

After deriving place dependent regression models for all four sites within the study area, another set of meta-models was derived. Place independent models have the advantage that only one single meta-model for a field or farm is necessary, in contrast with place dependent models that need to be developed for every distinguished management unit. Place independent models should therefor include parameters determining soil spatial variability. The database was therefore expanded with site-specific soil data to explain the spatial variation as it was determined in the soil survey. In Table 2 an overview of the parameters used for the derivation of the regression models is presented. The additional site-specific data are bulk density and soil organic matter content (SOM). Texture is not taken into account in this study. The texture of the study area shows little variability and is therefore of minor importance in the explaining spatial variation. However, when applied on a wider range of textures, the clay content of the plough layer may become an important parameter as well.

Since SOM and bulk density are variable within one soil-profile, the profile-weighted average of these properties was derived. Roots are more concentrated near the surface and also mineralization of nitrogen is higher in the top of the soil profile. Deeper in the profile root concentration is decreasing, just like the mineralization. A triangular pattern was used, reflecting the distribution of the roots and the mineralization. The root zone of 0.90 m was split into 9 layers of 0.10 m. The value of the highest layer got a weight of 9, the second a weight of 8 etc.

RESULTS

Location Dependent Meta-Models

For every of 4 management units place depended regression models were derived. Three properties were predicted: (i) the number of days of the current day to the second fertilizer application (D_{D2}), (ii) the number of days to the third fertilizer (D_{D3}) after the second application has been given, and (iii) the amount of the third application ($D3_{am}$). For a full description of the parameters and their characteristics see Table 2.

Regression equations for determining the timing of the second application Eq.2 contained the following parameters:

Eq.2 $D_{D2} = \varepsilon_1 - \alpha_1 Rain_{DOF2} - \beta_1 Rad_{DOF2} - \chi_1 Rain_{DOF2-0.01} - \delta_1 Rad_{DOF2-0.01} - \varphi_1 DVS_{DOF2}$

Table 3. Regression parameters for the place depended meta-models to predict timing of the second and third fertilizer application and the amount of fertilizer for the third application.

	Site	ε_1	α_1	β_1	χ_1	δ_1	φ_1			R^2
D_{D2}	A	83.17	0.06	$0.26*10^{-3}$	0.01	$0.12*10^{-3}$	64.57			0.95
	B	82.42	0.07	$0.25*10^{-3}$	-*	$0.14*10^{-3}$	64.22			0.95
	C	86.12	0.05	$0.30*10^{-3}$	0.02	$0.06*10^{-3}$	65.99			0.96
	D	90.42	0.06	$0.29*10^{-3}$	0.02	$0.05*10^{-3}$	61.17			0.96
		ε_2	α_2	β_2	χ_2	δ_2	φ_2	τ_2	λ_2	
D_{D3}	A	54.72	-	$0.09*10^{-3}$	0.09	-	-	0.14	$0.50*10^{-3}$	0.85
	B	67.46	0.04	$0.06*10^{-3}$	0.05	-	29.00	0.15	$0.30*10^{-3}$	0.83
	C	34.44	-	$0.07*10^{-3}$	0.10	$0.11*10^{-3}$	33.29	0.16	$0.77*10^{-3}$	0.80
	D	-6.94	0.05	$0.04*10^{-3}$	0.13	$0.25*10^{-3}$	47.03	0.25	$-1.30*10^{-3}$	0.78
		ε_3	α_3	β_3	χ_3	δ_3	φ_3	η_3		
$D_{D3\text{-}AM}$	A	137.40	-	$2.22*10^{-3}$	-	$2.15*10^{-3}$	57.72	1.87		0.86
	B	150.58	-	$1.84*10^{-3}$	-	$1.85*10^{-3}$	54.23	1.62		0.94
	C	237.26	0.10	$3.81*10^{-3}$	0.32	$4.08*10^{-3}$	66.44	3.33		0.93
	D	57.14	-	-	-	-	53.09	-		0.70

-* These parameters were included in the regression analysis but did not have a significant contribution.

Where ε_1 represents the error term of the regression equation Eq.2, $\alpha_1, \beta_1, \chi_1, \delta_1, \varphi_1$ are the regression coefficients. In a full overview of all the regression coefficients for every of the 4 management units is presented.

The regression model or meta-models to predict the timing of the third fertilizer application were similar to Eq.2, except that weather information after the date of the second application (D2) has been included:

Eq. 3
$$D_{D3} = \varepsilon_2 - \alpha_2 Rain_{DOF3} - \beta_2 Rad_{DOF3} - \chi_2 Rain_{DOF3-0.01} - \delta_2 Rad_{DOF3-0.01} - \varphi_2 DVS_{DOF3} + \tau_2 Rain_{DOF3-D2} - \lambda_2 Rad_{DOF3-D2}$$

Regression parameters for this model were: ε_2 α_2, β_2, χ_2, δ_2, φ_2, τ_2, and λ_2 respectively. In Table 2 the values are presented.

The meta-models that predicted the amount of fertilizer for every individual management unit were:

Eq. 4
$$D3_{AM} = \varepsilon_3 - \varphi_3 DVS_{D3} - \eta_3 DN_{DVS0.01} - \alpha_3 Rain_{D3} + \beta_3 Rad_{D3} + \chi_3 Rain_{D3-D2} - \delta_3 Rad_{DF3-0.01}$$

Values for the regression parameters (: ε_3 α_3, β_3, χ_3, δ_3, φ_3, η_3) are presented in Table 3.

The set of regression equations clearly shows a good linear correlation between climatic characteristics and fertilizer dates and amounts. Although the R_ of the models to predict the third fertilizer date are somewhat lower they still are highly significant.

Models do show some differences in reliability. Especially the models forecasting the amount of the third fertilizer application have a very variable reliability. While the model belonging to site B has a R_ of 0.94, the model belonging to site D only has a R_ of 0.70. The data sets used to derive the regression models for forecasting the fertilizer timing are much more extensive than the data sets used to derive the regression models for forecasting the fertilizer amount. The data sets used to derive timing regression models Eq.2 and Eq. 3 exist of a few thousand records. However, the data sets, used to derive regression models for the fertilizer amounts Eq. 4 only counted 15 records. Consequently the amount of degrees of freedom is much larger in the models forecasting fertilizer timing than in the models forecasting fertilizer amounts.

In Eq.2 and Eq. 3 rainfall, DVS, and radiation all have a negative contribution to the fertilizer timing, which can be expected since high temperatures and radiation values increase photosynthesis and associated biomass production. High precipitation amounts either cause leaching or are supplying the crop with the necessary water. All processes are shortening the fertilizer application time.

When this type of regression models are derived for all spatial units within a farmers field, they can be used to forecast the optimal timing and amount of nitrogen fertilizer applications. A disadvantage however is that the models have to be derived for every individual unit, which is time-consuming.

Location Independent Meta-Models

To create place independent forecasting models data of the four sites within the experimental field were joined and expanded with site-specific soil parameters (weighted averages of the organic matter content (SOM_{prof}) and bulkdensity (BD_{prof})). The following regression model could were derived to predict the timing of the second application:

Eq. 5
$$D_{D2} = 75.20 - 0.061 Rain_{DOF2} - 0.28 * 10^{-3} Rad_{DOF2} - 0.02\ Rain_{DOF2-0.01} - 0.09 * 10^{-3} Rad_{DOF2-0.01} - 63.31 DVS_{DOF2} + 4.15 SOM_{prof}$$

To predict the timing of the third fertilizer application:

Eq. 6
$$D_{D3} = 6.65 - 0.03 Rain_{DOF3} + 0.15 Rain_{D3-D2} - 0.89 * 10^{-3} Rad_{D3-d2} - 0.12 Rain_{DOF3-0.01} + 0.05 * 10^{-3} Rad_{DOF3-0.01} + 38.74 DVS_{DOF3} + 5.02 SOM_{prof}$$

and finally to predict the amount of the third fertilizer application:

Eq. 7
$$D3_{AM} = 215.10 - 53.81 DVS_{D3} - 2.25 DN_{DVS0.01} + 2.70 * 10^{-3} Rad_{D3} - 0.057 Rain_{D3} + 0.11 Rain_{D3-D2} - 18.59 SOM_{prof}$$

The $R^2$of the models in Eq. 5, Eq. 6, and Eq. 7 were 0.95, 0.77, and 0.94 respectively. This indicates that the models are describing the variation very well. Although the $R^2$of the model describing the number of days until the third fertilizer application D_{D3} is clearly lower, the correlation is still highly significant.

The amount of organic matter in the soil (SOM_{prof}) appears to be an important parameter in explaining the variation in the field. It can be seen that high SOM values lead to late fertilizer applications and decrease the amount applied, which is a result of mineralization of organic nitrogen. When removing SOM_{prof} from the regression models, the R_ decreases considerably Eq. 5: R_ = 0.93, Eq. 6: R_ = 0.74, and Eq. 7: R_ = 0.84). Bulkdensity (BD_{prof}) is not part of the regression models. The Pr (> |t|) was in all cases more than 0.1 and therefore, bulkdensity was rejected from the models. This effect is probably caused by the variation of bulkdensity in the top soil caused by tillage activities, which was not spatially correlated.

High amounts of rainfall lead to early application dates and higher amounts, which is an indication that leaching processes in this part of the growing season for Dutch circumstances is a more important process than water supply to the crop.

The regression models in Eq. 5, Eq. 6, and Eq. 7 were derived with data of only four different sites in one field. It is likely that good regression models for predicting the timing and amount of fertilizer applications can be derived. However, expanding the models to more sites with wider ranges of organic matter and textures is necessary before they can be widely applied.

Meta-Model Validation

Although all models in the previous sections are highly significant, their validity needs to be tested independently. The meta-models were tested on a data set for site B in 1999, which was not used for the derivation of the models. Validation is performed, using both the place dependant models and the place independent models. Timing and amount of the fertilizer application were also determined with the WAVE-model. In Figure 1 the results are presented. The power of the place dependent and place independent models to predict the second application strongly increases if the fertilizer date is less then 30 days away. Close to the actual fertilizer date the predicted days of fertilization only deviates a few days from the calculations done by WAVE (22 of April). The deviation is rather small, 1 and 3 days for the place independent and place dependent models respectively. When considering a time window of approximately 7 days on which the farmer is taking this type of management decisions this difference becomes insignificant. The predictions for the third application show a clear deviation for the place independent models. The prediction made with the WAVE-model deviates about ten days from the predictions made with the place independent model. Since there was only one year of data available to validate the model it is unclear whether or not this is an incidental deviation or not. It is however obvious that the role of organic matter plays an important role here. Further extension of the meta-model with wider ranges of organic matter contents and texture is very likely going to stabilize the regression results and increase the R^2 of 0.77 of the model in Eq. 6 to the level of the other equations.

The amount of the third fertilizer application was also predicted, using the meta-models. While the WAVE-model calculated a third fertilizer application of 73 kg ha^{-1} nitrogen, the meta-models predicted 65 and 63 kg ha^{-1} for the place dependent and place independent models respectively, an underestimation of 8-10 kg ha^{-1}. For management decisions, these differences are acceptable.

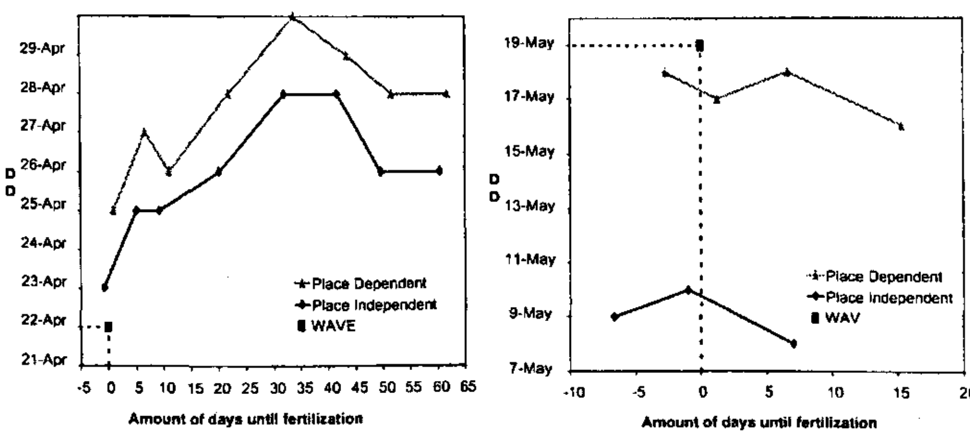

Figure 1. Validation of the meta-models to predict the fertilizer date in 1999 compared to the model prediction. (A) To predict the timing of the second application and (B) to predict the timing of the third application.

CONCLUSIONS

This study demonstrates that meta-modeling can be a reliable tool to replace complex simulation modeling for management decisions on nitrogen application dates and amounts. These meta-models can be included in simple calculation schemes and do not require expert knowledge on mathematical modeling of crop-soil-water processes. The meta-models contain basic climatic and soil characteristics as input parameters and once derived by experts they can be used by any farmer and easily integrated in (GIS-based) decision support systems.

Place dependent (only valid for one management unit) and place independent (valid for a whole field or farm) forecasting models were derived in this study. The R_ for all models varies between 0.70 and 0.96 which is highly significant. Validation of these meta-models has been done on an independent data set for 1999. The fertilizer timing deviated only a few days for the place dependent models and the predicted amount deviated only between 8-10 kg/ha compared to the results obtained by WAVE. The derived place dependent meta-models can make predictions, falling within the time window of a week on which a farmer makes management decisions on fertilization. After validation of these models for other soil types, they can be easily incorporated within a decision support system. The place independent models for forecasting the timing of the second application performed well (within 2-3 days); also the amount of the third fertilizer application was predicted satisfactory. However, the timing of the third fertilizer application showed a deviation of about ten days, which is not acceptable when regarding a time window of 7 days. Further extension of this model with a wider range of organic matter contents and textures will very likely increase the quality of this model.

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