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# GIS-based spatial nitrogen management model for maize: short- and long-term marginal net return maximising nitrogen application rates

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## Abstract

Crop growth models including CERES-Maize and CROPGRO-Soybean have been used in the past to evaluate causes of spatial yield variability and to evaluate economic consequences of variable rate prescriptions. In this work, a nitrogen prescription program has been developed that simulates the consequences of different nitrogen prescriptions using the DSSAT crop growth models. The objective of this paper is to describe a site-specific nitrogen prescription and economic optimizer program developed for computing spatially optimum N rates over long periods of weather and plant population for maize (*Zea mays* L.) using the CERES-Maize model. The application of the model was demonstrated on a field in Germany and another one in the USA to evaluate the concept across different environmental conditions. The user can determine the short- and the long-term optimal spatial nitrogen prescription based on crop price and nitrogen cost. The program simulated short-term optimum N applications that averaged 9% (McGarvey field, USA) and 48% (Riech field, Germany) lower than the uniform rates actually applied in the fields. The program indicated different site-specific N management options for low and high yielding fields under the assumed prices for maize and N. The implementation of a site-specific plant population management was investigated. A site-specific-optimization of plant population showed a higher profitability in the heterogeneous field in Germany. Hard pan depth, hard pan factor, root distribution factor and the percentage of available soil water across the heterogeneous field were useful indicators in predicting the magnitude of site-specific plant population benefits over uniform rates.

**Keywords** CERES-Maize · Nitrogen management · Plant population · Nitrogen balance · Marginal net return

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## Introduction

Precision agriculture is a revolutionary technology for crop production around the world. The importance of decision support tools complimenting available sensor technologies for economic and environmental risk assessment of farming practices is increasing. The DSSAT crop growth models are designed to simulate the crop growth and development processes from sowing to harvest by incorporating all information of farming practices, soil properties, crop genetics and weather (Jones et al. 2003). The DSSAT models can be used to evaluate farming practices at different locations by incorporating site-specific information on soil properties, management and weather.

Today, producers can measure spatial yields, obtain aerial images of crop biomass, gather information such as soil water content and spatial N levels, and use this information to manage their crops precisely at a small spatial scale. However, producers have difficulties in interpreting the vast amount of data available and turning that data into production decisions.

Nitrogen (N) is critical for crop production, but over-application of N can reduce profits and cause environmental degradation. In 2014, nearly 2 Mt of N was used for agricultural production in Germany, while 12.5 Mt were used in the USA (FAO 2014). Over-application of N is common in these countries and around the world and there is a great need to reduce $NO_3$–N amounts left in the soil after harvest to prevent leaching into the ground water. Optimizing N timing and spatial application rate to better match crop needs can lead to a reduction in N losses to the environment.

Crop growth models have been used in the past to estimate long term optimum spatial N rates for maize (*Zea mays* L.). Paz et al. (1999) developed a technique to calibrate spatial soil properties for the CERES-Maize v3.7 model for individual grids within a field to minimize the error between simulated and measured yields over multiple years. In this approach, they divided fields into smaller grids and collected spatial yield data over several seasons for each grid. They developed crop model input files and weather files for each year and grid. Then they coupled the CERES-Maize model to an optimizer that used a simulated annealing algorithm to estimate optimum soil parameters for each grid that minimized the error between simulated and measured yield, over multiple seasons for each grid. Using this technique, they were able to explain over 80% of spatial yield variability in maize and soybean fields in Iowa based on variable soil properties. This technique was integrated into a software system called Apollo (**A**pplication of **P**recisi**O**n Agricu**L**ture for Fie**L**d Management **O**ptimization) which was developed in Visual Basic for implementation on a personal computer (Batchelor et al. 2004). The Apollo software was extended to evaluate optimum N rates and plant population for each grid. The software was designed to use calibrated soil properties for each grid to simulate different combinations of N application timing and rate, and plant populations over many seasons of historical weather data in order to determine the N rate and population that maximized the long term marginal net return (MNR) for assumed values of N and seed cost and yield price (Batchelor et al. 2004). The software was written in Visual Basic for Windows XP and is no longer operational on recent Microsoft Windows platforms due to substantial changes made to Visual Basic to integrate it with the Microsoft.NET platform supported in recent releases of Windows.

Other researchers have implemented these techniques for soybean (Paz et al. 2001), wheat (Link et al. 2008) and maize (Miao et al. 2006), but required extensive training from the Apollo model developers. Using process-oriented crop growth models to evaluate spatial yields and prescriptions at small spatial scales is complex, because the crop models require numerous inputs and specialized software such as Apollo to assist with spatial model calibration and prescription development. Thus, these techniques have not been widely adopted, and a comprehensive software package does not exist to use crop growth models for precision agriculture decisions (Link et al. 2006).

Thorp and Bronson (2013) developed an open source model optimization software package called GeoSim, which is distributed as a plug-into the open source QGIS geographic information software (QGIS Development Team 2009). The purpose of GeoSim is to allow users to calibrate parameters for any environmental or crop model using an optimizer based on the simulated annealing optimization technique. This software offers a modern open source replacement to the calibration procedures developed in the Apollo software. Using QGIS and GeoSim, users can develop a map of a field, divide the field into management units, set up crop modelling input files for each grid, and calibrate soil properties to minimize the error between simulated and measured spatial yields over multiple seasons of weather and yields. GeoSim was written in Python, which is an open source language and is available as a plug-in for QGIS. It can be downloaded at http://www.qgis.org/. While GeoSim provides an excellent platform for model calibration, it does not contain software to develop and evaluate N management prescriptions.

The objectives of this work were to (1) develop a prototype open source software package to evaluate economic consequences of N management prescriptions for maize, (2) evaluate effects of different plant population rates on maize yield based on the site-specific concept, and (3) test the software for two maize datasets in Germany and the US. The long term goal is to distribute this software as an additional plug-into the QGIS software to be used in conjunction with GeoSim. This pair of plug-ins to QGIS will provide users with the tools needed to calibrate crop models to simulate historical spatial yield variability and to develop optimum N management prescriptions using long-term historical or future climate change weather records.

## Materials and methods

### Field experiments description

#### McGarvey field

The 20.25 ha McGarvey field is located near Perry, Iowa, USA (41.93080°N, 94.07254°W). Spatial maize yield data were collected every even-numbered year from 1994 to 2002, as maize was planted with soybean in a crop rotation. The field was divided into 100 grids 0.2025 ha in size. Weather data were measured at a weather station directly at the site. In 1994 and 1996, a uniform N rate of 207 kg N ha$^{-1}$ and 40.8 kg ha$^{-1}$ phosphorus (P) and potassium (K) was applied just before planting. In 1998, 2000 and 2002, 224 kg N ha$^{-1}$ and 121 kg ha$^{-1}$ of P and K were applied each season. A more detailed description of the soil information and the related crop management practices can be found in Thorp et al. (2006).

#### Riech field

The Riech field is 10 ha in size and located at Ihinger Hof, Agricultural Research Station, University of Hohenheim, Germany (48.666°N, 8.967°W). Maize was planted in 2006, 2007 and 2008 following standard farmer's management practices. Weather data were taken from a local weather station at the research station. The field was divided into 80 grids (0.125 ha) for this analysis. Yield was measured each season using a yield monitor implemented on a combine harvester. Soil information was available for crop model input file development based on the publication of Link et al. (2013). Model inputs were developed for each grid and year. Initial $NO_3$–N was measured for each grid (Fig. 5), prior to sowing. The farmer's practice was to apply 160 kg N $ha^{-1}$ as KAS (26% N) as a uniform rate.

## Model development methodology

In this project, the GeoSim Nitrogen Prescription Model (GeoSim NPM) was developed as a stand-alone Python program to simulate optimum N prescriptions for maize. The program uses optimum soil parameters calibrated using GeoSim (Thorp and Bronson 2013) to run different combinations of N rates and application dates using a user specified number of historical (or future) years of weather data. The program generates yield and N levels in the soil at harvest for user specified grids and weather years. The economic optimizer component of GeoSim NPM allows the user to enter the selling price for maize, the cost of N, and the cost of leaving N in the field to account for policies such as the current German compensation payment, which incentivises producers to limit N left in the field. It then computes the MNR for a range of N rates for user specified historical weather years. The seasonal MNRs are then used to compute the N prescription that maximizes the long-term MNR over the user selected seasons of weather data.

Figure 1 shows a block diagram of the system. Grey boxes represent computational parts of GeoSim and GeoSim NPM, while white boxes represent passed or computed (simulated) parameters or additional information necessary to compute final result. The modified version of CERES-Maize (v 3.7) used in Apollo allows the optimization of up to 10 soil-related input parameters for each grid in the field, including SCS (*Soil Conservation Service*) runoff curve number, drainage rate, effective tile drainage rate, saturated hydraulic conductivity of deep impermeable layer, hard pan factor, depth of hard pan, root distribution reduction factor, N mineralization factor, soil fertility factor and adjustment of soil water availability (Thorp et al. 2008). The setup of soil-related crop model input parameters was based on the given field-specific soil properties (Thorp et al. 2006; Link et al. 2013). The model uses a self-annealing algorithm to optimize the given soil-related input parameters for each grid to the obtained yield. Site-specific soil parameter optimization resulting in a small gap between observed and simulated yield can theoretically be achieved, when more soil-related input parameters are used, but overfitting of the soil profile is unlikely to give a good fit in the final validation process (Thorp et al. 2008). Combinations of these 10 parameters are optimized by GeoSim (Fig. 1a) and passed to GeoSim NPM using a text file (Fig. 1b).

In GeoSim NPM (Fig. 1c), the user specifies the historical weather seasons to be simulated, as well as the date of N applications, range and increments within the range of N levels to simulate yield and N left in the field at the end of each season in order to compute the optimum N rate for each grid or management zone over long term seasons of weather. The user can also define different plant population densities (population rate, Fig. 1c). Plant population density has an important role in maize growth due to the interplant competition (Tetio-Kagho and Gardner 1988). According to Duncan (1958), plant population density increase led to individual plant yield reduction while increasing maize yield per area unit. Plant population

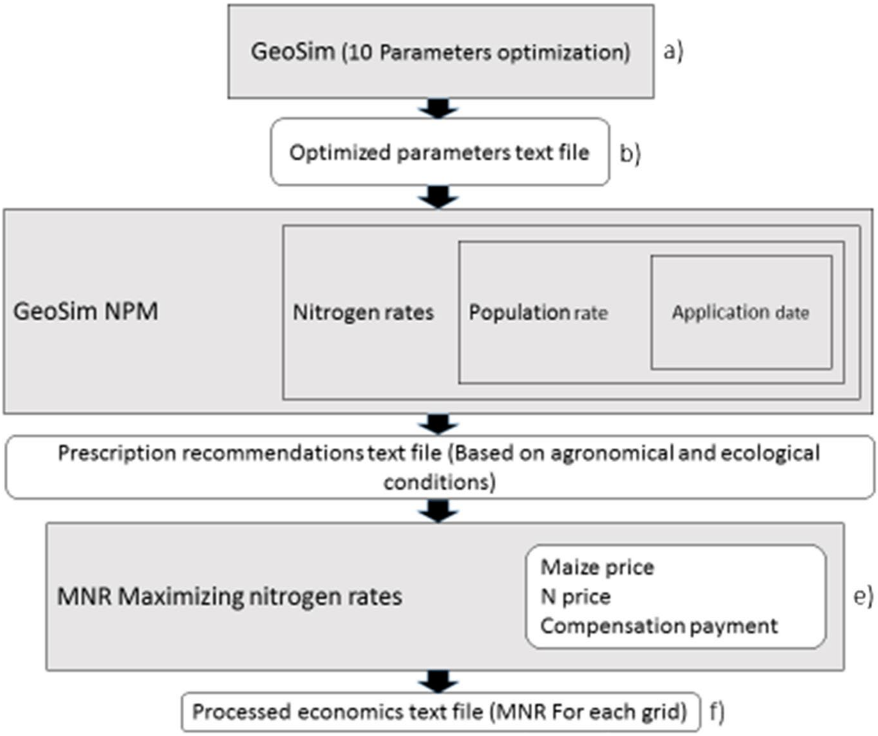


**Fig. 1** Flow diagram of the optimization and simulation process in GeoSim NPM

densities that maximise yield and economic return often vary from 3 to 9 plants $m^{-1}$, due to infield site-specific variabilities (Olson and Sanders 1988). The CERES-Maize model is then run for all combinations of N rates/plant population densities and seasons of weather data for each grid using the parameters calibrated for each grid by GeoSim and stores this information in a database for future analysis.

The GeoSim NPM software also requires the user to specify economic information including N price and value of yield in order to simulate MNR for different combinations of N rates. MNR is computed with Eq. 1.

$$MNR = Yield * Price - NRate * NCost + Compensation\ Payment, \tag{1}$$

where *MNR* is the marginal net return ($ $ha^{-1}$), *Yield* is simulated crop yield (kg $ha^{-1}$), *Price* is crop price ($ $kg^{-1}$), *NRate* is the N application rate (kg N $ha^{-1}$), *NCost* is nitrogen cost ($ $kg^{-1}$), and *Compensation Payment* is the value or penalty for leaving N in the field at harvest ($ kg $N^{-1}$ $ha^{-1}$). Once the database is computed for all combinations of N rates and seasons of weather, GeoSim NPM searches the database to determine the N rate that maximizes the average MNR computed over all seasons.

MNR for simulating different combinations of N rates and population densities simultaneously is computed with Eq. 3. Seed costs are calculated as plant population times cost per seed (Eq. 3).

$$SeedCost = Population\ rate\ (\mathrm{ha}) * Single\ Seed\ Price, \tag{2}$$

$$MNR = Yield * Price - NRate * NCost - SeedCost + Compensation\ Payment. \tag{3}$$

Equation 3 is used for MNR calculations only if the *Population Rate* option is activated in GeoSim NPM (Fig. 1c), in order to see the effect of different population densities on MNR. Once GeoSim NPM computes the MNR for combinations of N rate, population and years of weather, the optimum prescription can be determined for each grid by searching for the N rate and population that maximizes the average MNR over all seasons.

## Results

### McGarvey field

The process of site-specific soil parameters optimization based on GeoSim indicated that the three soil parameters, effective tile drain spacing, saturated hydraulic conductivity of the lower impermeable layer and the percentage of available soil water in each soil layer were the major soil factors that described spatial yield variability. The calibration of these three soil parameters minimized the error between simulated and observed maize yields in each of the 100 grids over five seasons, while the impact on yield of all other available soil parameters in the model could be neglected. Crop rotation effects of nitrogen fixing soybean as a previous crop where accounted for in the initial conditions of the model. The calibration results of the simulated and observed maize yields for the 100 grids and 5 years are shown in Fig. 2. The $R^2$ between simulated and observed yield over all grids and years was 0.94, which is consistent with results reported by Thorp et al. (2006), who used the Apollo model to conduct a similar calibration for this dataset. The calibrated soil properties explained 94% of given spatial yield variability over the 100 grids and 5 seasons.

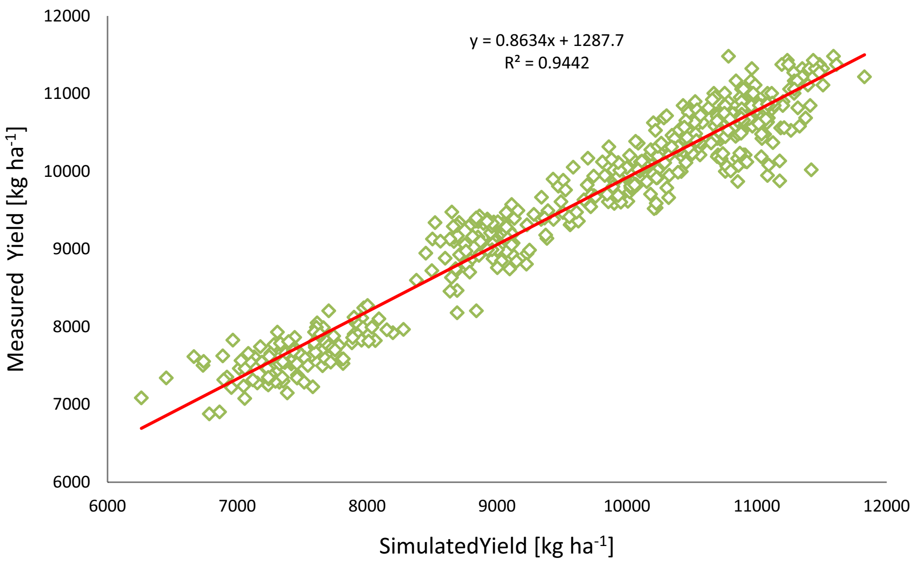


**Fig. 2** Relationship between simulated and measured maize yield (kg $ha^{-1}$) for the McGarvey field, Perry, Iowa using the following three soil parameters: the optimum effective tile drain spacing, the saturated hydraulic conductivity and the percentage of available soil water (n = 500)

GeoSim NPM was then used to compute MNR for different combinations of N rates for these five seasons (1994, 1996, 1998, 2000 and 2002) using measured weather data from the site. The price of maize and N fertiliser was assumed to be 0.13 and 0.5 \$ $kg^{-1}$, respectively. The N compensation payment was set to 0 \$ $kg^{-1}$ $ha^{-1}$ since there is no compensation payment for N management in the US. The GeoSim NPM simulation of N rates were defined in a range between 40 and 240 kg N $ha^{-1}$ with an increase in increments of 10 kg N $ha^{-1}$. The N rate associated with the highest MNR for each grid was selected as the optimum N rate for each season. Table 1 shows the field level computed MNR for the producer's practice. Different grids had different simulated optimum N rates that maximized MNR for each year. Table 1 shows the simulated optimum N rates and MNR averaged over all grids to compare to the producer's practices at the field level. Following the optimum N rates simulated by GeoSim NPM for each season, the producer would have obtained a 5% increase in MNR and 9% reduction in the applied amount of N compared to his current practice. Table 1 shows averaged values of $NO_3$–N and $NH_4$–N left after harvest each year over 100 grids based on the GeoSim NPM model.

Figure 3 shows the simulated optimum N rate for each grid. The years 1998 and 2002 had a low variability in simulated optimum N rate, with most grids having an optimum N rate of 201–230 kg N $ha^{-1}$. The year 2000 had lower optimum N levels, which corresponded with lower simulated yields (Table 1) due to unfavourable weather conditions. Lower simulated yield potential led to lower simulated optimum N rates due to the relative differences in yield value and cost of N. However, years 1994, 1998 and 2000 had higher simulated optimum N rates, ranging from 111 to 230 kg N $ha^{-1}$.

Table 2 shows the simulated N kg $ha^{-1}$ rates grouped in representative application ranges and number of corresponding covered grids. The geospatial spread of N groups across the field for every simulated year is shown in Fig. 3. Because of missing data in the years 1996, 1998 and 2002, no N application rates could be simulated for six grids out of 500. Grid maps were generated in QGIS and exported as images in QGIS Print Composer.

Additional simulations were conducted to simulate both optimum N rate and plant population densities that maximized simulated MNR for each of the five seasons. Two simulation scenarios were compared: N optimisation (*N Only*) and N with population densities optimisation (*N and Pop*). The N simulation scenarios were 40–240 kg N $ha^{-1}$ with an increase in increments of 10 kg N $ha^{-1}$. Population densities were simulated in a range between 3 and 9 plants $m^{-1}$ with one plant increments. Price of a single seed was assumed to be 0.0022 \$. Table 3 shows the results of the simulation scenarios, in which *N Only MNR* and *N and Pop MNR* included seed costs. According to the simulation results, a site-specific population density increase of 8% $m^{-2}$ resulting in a plant density of 7–9 plants $m^{-2}$ instead of 7–8 would require an additional 2% N kg $ha^{-1}$ increase to approximately maintain grain yields at the same level. In retrospect, site-specific plant population densities optimisation in combination with N optimisation would result in higher MNR.

Farmer's profit maximising N rates over 18 years of weather data (1966–1972, 1975–1982 and 1985–1987) were simulated with GeoSim NPM and are shown in Table 4. In these simulation scenarios, field-specific optimised soil parameters, farmer's practice (*Uniform N Rates*) and current prices were fixed. In GeoSim NPM, only daily temperature, precipitation and solar radiation varied on a daily basis over 18 years. The long-term N optimum showed 6% lower N application rates, averaged over 5 years.

The profit maximising simulated N rates in a long-term, especially over long periods of weather variability, did not convey optimum N rates for any specific grid or year. In a long-term with over 18 years of weather, simulated N rates would maximise the difference

**Table 1** Calculated marginal net return (MNR) for measured yields and simulated MNR, measured grain yield (kg $ha^{-1}$), simulated optimum N rate averaged over all grids for each growing season, N leached and left in the soil after harvest averaged over 100 grids for each season

| Years | **M** yield (kg $ha^{-1}$) | **S** yield (kg $ha^{-1}$) | **M** MNR ($ $ha^{-1}$) | **S** MNR ($ $ha^{-1}$) | Applied N (kg $ha^{-1}$) | Simulated N (kg $ha^{-1}$) | Avg. N leached (kg $ha^{-1}$) | Avg. $NO_3$–N left (kg $ha^{-1}$) | Avg. $NH_4$–N left (kg $ha^{-1}$) |
|---|---|---|---|---|---|---|---|---|---|
| 1994 | 10,788 | 11,021 | 1299 | 1331 | 207 | 202 | 0.2 | 4.1 | 6.3 |
| 1996 | 9076 | 8887 | 1076 | 1061 | 207 | 189 | 13.1 | 3.1 | 6.3 |
| 1998 | 9862 | 10,172 | 1170 | 1210 | 224 | 225 | 5.8 | 3.2 | 6.3 |
| 2000 | 7598 | 8768 | 876 | 1064 | 224 | 152 | 0.4 | 3.1 | 6.3 |
| 2002 | 10,431 | 10,661 | 1244 | 1274 | 224 | 225 | 8.4 | 3.2 | 6.3 |
| Change (%) | | 4 | | 5 | | − 9 | | | |

***M*** **m**easured, ***S*** **s**imulated, *MNR* marginal net return, *N* nitrogen, *Avg.* averaged

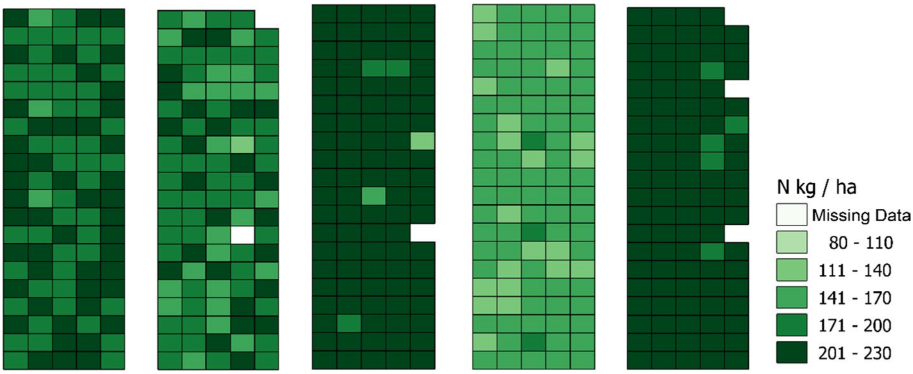


**Fig. 3** Maps of simulated N application rates that maximized MNR in each growing season (from left: 1994, 1996, 1998, 2000 and 2002) using GeoSim NPM

**Table 2** Number of the grids with simulated optimum N ranges over five growing seasons

| Years | N simulation ranges (kg ha$^{-1}$) | | | | Grids |
|---|---|---|---|---|---|
| | 111–140 | 141–170 | 171–200 | 201–230 | |
| 1994 | 0 | 3 | 50 | 47 | 100 |
| 1996 | 1 | 23 | 49 | 25 | 98 |
| 1998 | 1 | 1 | 3 | 94 | 99 |
| 2000 | 20 | 77 | 3 | 0 | 100 |
| 2002 | 0 | 0 | 5 | 92 | 97 |

between the farmer's income and the costs for N applications with current maize and N price.

## Riech field

In the simulation scenario for the Riech field, four soil parameters provided the best fit between observed and simulated yield values over three seasons and were chosen as the best soil-related input parameters combination of the field-specific soil properties. The soil-related crop model input parameters indicating a major impact on yield were: hard pan depth, hard pan factor, root distribution factor and percentage of available soil water. The results of the calibrations are shown in Fig. 4. The $R^2$ between simulated and measured yields across all grids and seasons was 0.75. Thus, 75% of the spatial yield variability in the field across all grids and seasons were explained by the four soil parameters.

GeoSim NPM was then used to compute MNR for different combinations of N rates for these three seasons (2006, 2007, and 2008). The price of maize and N fertiliser was assumed to be 0.13 and 0.5 \$ kg$^{-1}$, respectively. First, an N optimisation scenario was conducted without compensation payment (0 \$$^{-1}$ ha$^{-1}$). GeoSim NPM simulation N rates were set in a range between 40 and 180 kg N ha$^{-1}$ with an increase in increments of 10 kg N ha$^{-1}$. Simulation results suggested a 48% lower N rate, resulting in 11% higher MNR over three growing seasons compared to the farmer's actual practice (Table 5).

**Table 3** Simulation scenarios of N levels (*Only N*), and combination of N rates and plant population (*N and Pop*) as conducted for each simulation scenario with corresponding MNR, N-rates, and plant population (number of the plants $m^{-2}$) (seed costs are included in MNR calculations of N simulation scenarios (*N Only*) and plant population simulation scenarios (*N and Pop*))

| | Simulated (kg $ha^{-1}$) | | ($ $ha^{-1}$) | ($ $ha^{-1}$) | Simulated (kg $ha^{-1}$) | | Measured ($m^{-2}$) | Simulated ($m^{-2}$) |
|---|---|---|---|---|---|---|---|---|
| Simulation scenarios | N Only | N and Pop | N Only | N and Pop | N Only | N and Pop | N Only | N and Pop |
| Years | Yield | Yield | MNR | MNR | N | N | Plant Pop | Plant Pop |
| 1994 | 11,021 | 11,782 | 1148 | 1234 | 202 | 199 | 8.3 | 9 |
| 1996 | 8887 | 8881 | 878 | 887 | 189 | 193 | 8.3 | 7 |
| 1998 | 10,172 | 11,183 | 1025 | 1153 | 225 | 222 | 8.4 | 9 |
| 2000 | 8768 | 9630 | 901 | 967 | 152 | 173 | 7.4 | 9 |
| 2002 | 10,661 | 11,070 | 1111 | 1131 | 225 | 227 | 7.4 | 9 |
| Change (%) | | 6 | | 6 | | 2 | | 8 |

*N Only* nitrogen optimisation only, *N and Pop* nitrogen and plant population optimisation combined, *N* nitrogen, *Plant Pop* plant population

**Table 4** Calculated MNR for simulated yield, and simulated N kg $ha^{-1}$ compared to the applied uniform N kg $ha^{-1}$ against 18 years of weather data (seed costs are not included in the calculations of simulated MNR in a long-term simulation scenario)

| Years | Simulated yield (kg $ha^{-1}$) | MNR ($ $ha^{-1}$) | Uniform N (kg $ha^{-1}$) | Simulated N (kg $ha^{-1}$) |
|---|---|---|---|---|
| 1994 | 9590 | 1150 | 207 | 192 |
| 1996 | 9892 | 1187 | 207 | 198 |
| 1998 | 10,053 | 1202 | 224 | 209 |
| 2000 | 10,111 | 1209 | 224 | 210 |
| 2002 | 10,168 | 1217 | 224 | 210 |
| Change (%) | | | | – 6 |

*MNR* marginal net return, *N* nitrogen Riech field

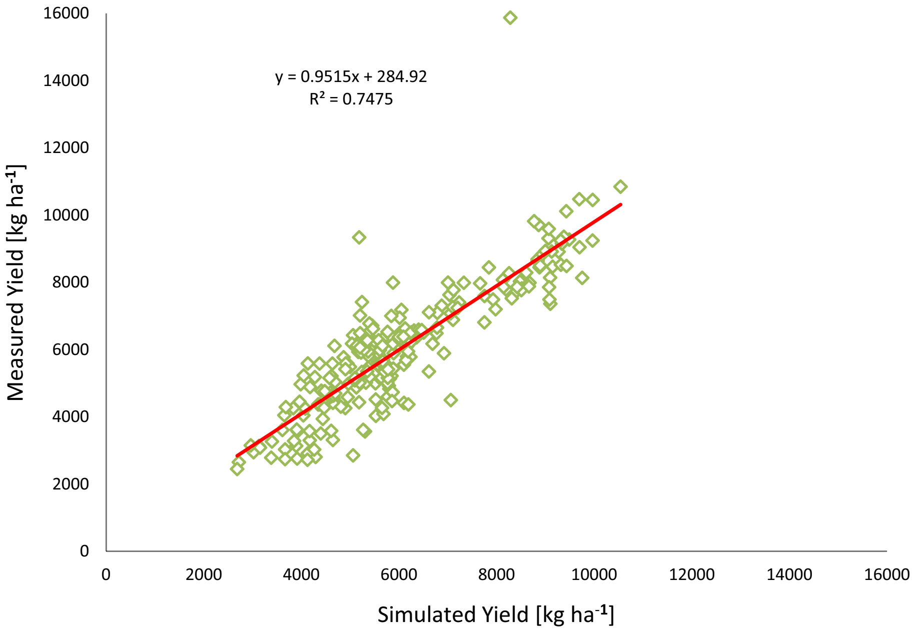


**Fig. 4** Relationship between simulated and measured maize grain yield (kg $ha^{-1}$) calibrated using four soil parameters for the Riech field, Ihinger Hof, Germany (n = 240)

Riech field had substantially lower yields kg $ha^{-1}$ when compared to the McGarvey field. Due to this, costs of N have a higher impact on MNR levels. Lower N rates in the simulations are also a result of the already existing high $NO_3$–N levels in the soil (Fig. 5), which were considered during the soil parameter optimisation in the GeoSim.

Additional simulations including the compensation payment (165 $ $ha^{-1}$) were conducted for the Riech field. GeoSim NPM compensation payment option is based on the $NO_3$–N and $NH_4$–N left in the upper soil layer at harvest (0–0.90 m). The N compensation threshold was set to less than 45 kg of $NO_3$–N plus $NH_4$–N kg $ha^{-1}$ left in the soil after harvest. Due to the simulated low amounts of $NO_3$–N and $NH_4$–N kg $ha^{-1}$ left in the field at harvest, the compensation payment did not affect N rate optimisation. All

**Table 5** Simulated MNR, grain yield (kg ha$^{-1}$) and simulated N kg ha$^{-1}$ compared with calculated MNR for measured yields, measured yield grain (kg ha$^{-1}$) and applied N kg ha$^{-1}$, over three growing seasons (seed costs are not included in calculations of M or S MNR) and compensation payment was not activated, N leached and left in the soil after harvest averaged over 80 grids for each season

| Years | **M** yield (kg ha$^{-1}$) | **S** yield (kg ha$^{-1}$) | **M** MNR ($ ha$^{-1}$) | **S** MNR ($ ha$^{-1}$) | Applied N (kg ha$^{-1}$) | Simulated N (kg ha$^{-1}$) | Avg. N leached (kg ha$^{-1}$) | Avg. $NO_3$–N left (kg ha$^{-1}$) | Avg. $NH_4$–N left (kg ha$^{-1}$) |
|---|---|---|---|---|---|---|---|---|---|
| 2006 | 5369 | 6167 | 617 | 766 | 160 | 71 | 0.0 | 3.9 | 7.2 |
| 2007 | 7016 | 7294 | 832 | 903 | 160 | 90 | 0.0 | 3.4 | 6.1 |
| 2008 | 5715 | 5459 | 662 | 664 | 160 | 91 | 0.0 | 3.7 | 6.4 |
| Change (%) | | 5 | | 11 | | − 48 | | | |

***M*** **m**easured yield, ***S*** **s**imulated yield, *MNR* marginal net return, *N* nitrogen, *Avg.* averaged

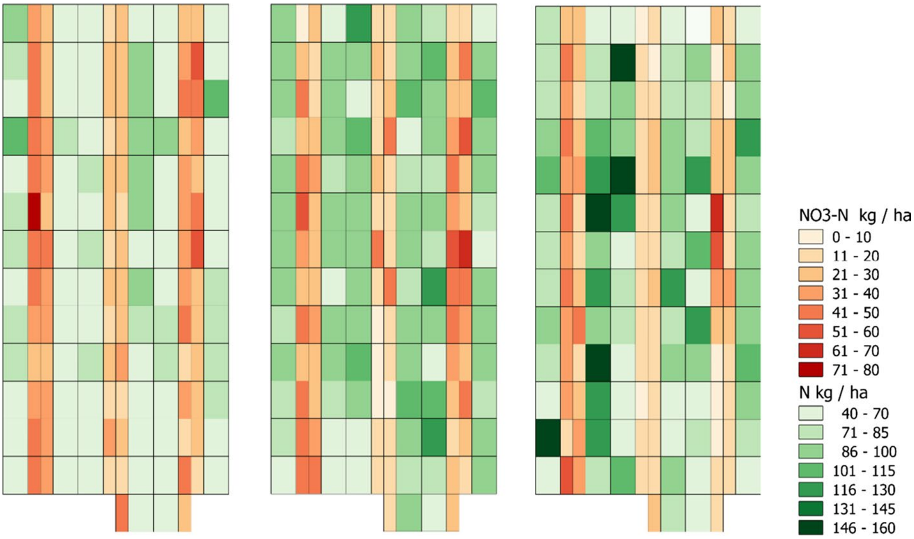


**Fig. 5** Maps of simulated N application rates that maximized MNR in each growing season (2006, 2007 and 2008) for the Riech field (green squares) using GeoSim NPM. Orange boxes indicate the $NO_3$–N kg $ha^{-1}$ levels before sowing in the soil as mean of the corresponding grids. Amount of $NO_3$–N kg $ha^{-1}$ for each grid was considered in the computation of necessary N application rates and thus in the overall N balance of the vegetation period of maize (Color figure online)

simulation output values were the same as in the basic N rate optimisation scenario, as shown in Table 5.

Over three growing seasons, the applied N rates are grouped in representative application amounts kg $ha^{-1}$ (Table 6). They are graphically shown in Fig. 5. Orange boxes in Fig. 5 indicate the amount of $NO_3$–N in the soil for each grid prior to sowing, based on the soil samplings. Grid maps were generated in QGIS and exported as images in QGIS Print Composer.

Additional simulations were conducted to test the influence of population densities on MNR levels and optimum N rates. GeoSim NPM simulation N rates were set in a range between 40 and 180 kg N $ha^{-1}$ with increments of 10 kg N $ha^{-1}$. Plant population densities were set in a range between 5 and 10 plants $m^{-1}$ with one plant increase for each run. GeoSim NPM nitrogen and plant population optimisation included seed costs. Price of one single seed was assumed to be 0.0022 $. Over three growing seasons, simulated MNR was 3% higher when plant population (*N and Pop*) was considered, and both nitrogen and population densities were optimised simultaneously (Table 7). With relatively low yield

**Table 6** Number of the field grids with specific N amount ranges over three growing seasons

| Years | N simulation ranges (kg $ha^{-1}$) | | | | | | | Grids |
|---|---|---|---|---|---|---|---|---|
| | 40–70 | 71–85 | 86–100 | 101–115 | 116–130 | 131–145 | 146–160 | |
| 2006 | 54 | 16 | 8 | 2 | 0 | 0 | 0 | 80 |
| 2007 | 13 | 15 | 42 | 7 | 3 | 0 | 0 | 80 |
| 2008 | 19 | 22 | 20 | 5 | 9 | 0 | 5 | 80 |

**Table 7** Simulation scenarios of N levels (*Only N*), and the combination of N rates and plant population (*N and Pop*) as conducted for each simulation scenario with corresponding MNR, N-rates, plant population (number of the plants $m^{-2}$) [seed costs are included in MNR calculations of N simulation scenarios (N Only) and plant population simulation scenarios (N and Pop)]

| | Simulated (kg $ha^{-1}$) | | | | Simulated (kg $ha^{-1}$) | | Measured ($m^{-2}$) | Simulated ($m^{-2}$) |
|---|---|---|---|---|---|---|---|---|
| Simulation scenarios | N Only | N and Pop | N Only ($ $ha^{-1}$) | N and Pop ($ $ha^{-1}$) | N Only | N and Pop | N Only | N and Pop |
| Years | Yield | Yield | MNR | MNR | N | N | Plant Pop | Plant Pop |
| 2006 | 6167 | 6194 | 586 | 600 | 71 | 71 | 8.2 | 7 |
| 2007 | 7294 | 7348 | 701 | 712 | 90 | 86 | 9.2 | 9 |
| 2008 | 5459 | 5186 | 479 | 503 | 91 | 74 | 8.4 | 6 |
| Change (%) | | − 1 | | 3 | | − 8 | | − 15 |

*N Only* nitrogen optimisation only, *N and Pop* nitrogen and plant population optimisation combined, *Plant Pop* plant population kg ha$^{-1}$ as is the case of Riech field, profit maximisation would be achieved by reducing the amount of seeds by 15% and N by 8% (Table 7).

Farmer's profit maximising N rates over 11 years of weather data (1992–2002) were simulated with GeoSim NPM and are shown in Table 8. In these simulation scenarios, field specific optimised soil parameters, farmer's practice (*Uniform N rates*), current prices and observed soil values were fixed. Long-term optimum N showed 45% lower N rates, averaged over 3 years.

The profit maximising simulated N rates in a long-term did not convey optimum N rates for any specific grid or year. In a long-term with over 11 years of weather, simulated N rates would maximise the difference between the farmer's income and the costs for N applications with current maize and N price.

## Discussion

According to the results of the simulations, it can be concluded that low yielding fields (kg ha$^{-1}$) can maximize their profit with lower N amounts applied, depending on the N price. If the gap between price of maize kg$^{-1}$ and price of N kg$^{-1}$ is high, profit can be maximised with lower amounts of applied N, because yield increases in low yielding fields are not high enough to cover N costs. With GeoSim NPM, it would be possible to investigate which price gap (the grain yield price kg$^{-1}$ and N price kg$^{-1}$) and grain yield range (maximum and minimum yield kg$^{-1}$ ha out of all defined grids in the field) would be a good indicator for a farmer to adjust an already existing uniform rate, if not ready to switch to variable N application.

Results of the model soil properties calibration for fields in Germany and the USA explained 75 and 94% of historical spatial yield variability. This indicates that the adjustments of soil parameters accounted for a significant amount of the spatial and temporal yield variability across the field.

The lower $R^2$ between simulated and observed yield in the field in Germany can be explained by a higher variability within the field, wherefore a higher level of insecurity is associated with the simulated N prescriptions for the field in Germany.

For the McGarvey field, the simulated average yield across the field over 5 years was 9902 kg$^{-1}$ ha with a standard deviation of 524 kg$^{-1}$ ha. For the Riech field, the simulated average grain yield over 3 years and all grids was 6307 kg ha$^{-1}$ with a standard deviation of 1445 kg ha$^{-1}$. The higher standard deviation of the Riech field may be a result of the given higher spatial variably within the field in comparison to the McGarvey field as well as the availability of only 3 years of yield data in comparison to 5 years.

**Table 8** Calculated MNR for simulated yield, and simulated N kg ha$^{-1}$ compared to the applied uniform N kg ha$^{-1}$ against 11 years of weather data (seed costs are not included in the calculations of simulated MNR in a long-term simulation scenario)

| Years | Simulated yield (kg ha$^{-1}$) | MNR ($ ha$^{-1}$) | Uniform N (kg ha$^{-1}$) | Simulated N (kg ha$^{-1}$) |
|---|---|---|---|---|
| 2006 | 6107 | 750 | 160 | 89 |
| 2007 | 6251 | 769 | 160 | 89 |
| 2008 | 5487 | 671 | 160 | 85 |
| Change (%) | | | | – 45 |

*MNR* marginal net return, *N* nitrogen

The GeoSim NPM was used to compute the optimum N rates that maximized MNR. Results indicated that N rates could be reduced in both fields compared with current producer practices. In the McGarvey field, N rates could be 9% lower and in Riech field N rates could be 48% lower without profit loss.

As can be seen from the results of short (McGarvey 9% and Riech 48% lower N rates) and long-term (McGarvey 6% and Riech 45% lower N rates) N optimisation, site-specific N application has a short-term management potential, based on averaging N rates across longer periods (long-term). The profit maximising N rates over long periods of weather data could result in an over-application in low yielding years and N deficiencies in high yielding years. However, in the long-term, the farmer's profit would be maximised. In order to quantify a potential increase in uncertainty associated with predicted weather data for the rest of the growing season, a more detailed analysis of weather data is needed.

The impact of year due to changing weather conditions was obvious regarding the different grain yield amounts over a few seasons on the same field, assuming that all other inputs and practices were not changed. Additional analysis could be done to test GeoSim NPM N application timing (temporal variability) options and to see if different N application timings would have more influence on grain yield with more efficient use of N. According to the difference between short- and long-term differences lower site-specific variability in the field leads to more uniform N rate prescriptions.

It has to be noted that the results regarding plant population and N are all model-based and were not validated with field samplings or experiments. However they can serve as a good indicator of farm cost management strategies of N and plant population site-specifically in the context of fields indicating a high spatial heterogeneity (Riech) versus fields with a lower heterogeneity (McGarvey). If the causes of the spatial variability are soil-related, they cannot be changed easily or without substantial costs involved. In that case, the farmer can consider the option of reducing existing costs involved in the production, rather than trying to further increase the yield.

The objective of the site-specific N and plant population simulations was to highlight the impact of crop production related costs on decision making in precision farming. 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. However, the results of model calibration were affected by the soil parameters used for calibration. Overall the ideal combination of soil parameters used 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 soil parameters in model calibration 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. The aim of using the model is of course to find a fertilization and sowing strategy better than the one used so far by the farmer and, in this way, increase the profit of the farmer. But while the model results seem to generate good profit characteristics, it has to be taken into account that the model responses to N application and population changes, N leaching and N left in the soil after harvest need to be validated. Based on a qualitative analysis of the results, it can be concluded that the model is doing well and could be applied in practice as a management decision support tool to achieve good profit performance of the farm. Further validation experiments would be an asset as model predictions are highly dependent on calibrated soil and yield parameters.

## Conclusion

The potential of crop models as decision support for variety broad range of field scouting and sampling sensor technologies is evident. However, the collected data has to be linked with proper decision support tools to reach the full potential and gain further insights into existing complexity and interactions between different parameters influencing crop growth and thus final management.

In this project, an open source software package has been developed that can be used in conjunction with the GeoSim open source software and QGIS to allow users to calibrate the CERES-Maize model to simulate historical spatial yield variability (GeoSim) and evaluate the economic consequences of variable rate N and plant population prescriptions (GeoSim NPM). While GeoSim NPM is currently operated as a stand-alone program, future work will focus on making this an open source plug-in for QGIS, which can be installed with the GeoSim plug-in.

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