CERES-Maize model performance under mineral and organic fertilization in nemoral climate conditions

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Core ideas

CERES-Maize model was evaluated under different fertilizer types and climatic conditions

The model provided estimates of N losses via leaching and gaseous emissions

CERES-Maize model can be used for maize yield prediction under nemoral climate conditions

Abstract

Little information is available regarding the performance of the CERES-Maize model under nemoral climate conditions. Therefore, this study aims to estimate and compare major soil-plant nitrogen (N) cycle parameters in grain maize crop after application of synthetic and different organic fertilizers solely or in combination in nemoral zone maize production, using the DSSAT model. Field experiments carried out during 2015, 2016, and 2017 in Akademija (Lithuania) were considered for model calibration and validation. The model was successfully validated for total aboveground biomass (TAB, $R^2 = 0.89$), grain yield (GY, $R^2 = 0.85$), and acceptably for leaf area index (LAI, $R^2 = 0.57$), total plant N uptake ($R^2 = 0.61$), and residual soil mineral nitrogen ($R^2 = 0.64$). The lower plant N uptake and soil mineral nitrogen (SMN) observed for the pelletized cattle manure (PCM) and green

This article has been accepted for publication and undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process, which may lead to differences between this version and the Version of Record. Please cite this article as doi: 10.1002/agj2.20636.

waste compost (GWC) treatments compared to the fertilization with synthetic ammonium nitrate (AN) were successfully captured by the model. Finally, the model provided reasonable predictions of the temporal dynamics of measured soil water content (SWC) and soil temperature. The validated model was further used to provide N loss estimations during the maize growing seasons via leaching and gaseous emissions. The results showed that the CERES-Maize model can successfully be used to simulate maize growth under the extreme climatic conditions of the nemoral zone in combination with different N managements. Nevertheless, additional efforts are needed to verify and fine-tune the model to comprehensively simulate the N cycle, especially losses by drainage water and gaseous emissions.

Keywords. N uptake, soil mineral nitrogen, N losses, grain yield

1. Introduction

In agricultural systems, climate change is leading to alterations in yield potentials, crop suitability, and impacts agricultural practices such as sowing and fertilization dates but also fertilization rates. In Northern Europe, increased temperatures and a longer warm-season period encourages expansion of summer crops with higher yield potential, and fosters intensification of management including fertilization, increasing the risk of surface and groundwater pollution through nutrient leaching and surface runoff (Jeppesen et al., 2009; Supit et al., 2010). In 2002, grain maize has been cultivated in Lithuania on an area of 2,900 ha^{-1}, and during the last 2 decades, the cultivation area significantly increased to 12,770 ha^{-1}, during the same period total crop production increased from 8,300 t to 97,970 t (FAOSTAT 2019). The projected climate scenarios indicate grain maize expansion northwards. In fact, the maize cropping share by 2040 in southern Scandinavia and Baltic countries is expected to increase by 4 to 20% of the total agricultural area (Elsgaard et al., 2012). A recent model study has shown that in the nemoral climate zone, maize grain yield potential can reach about 11 t ha^{-1} (Žydelis et al., 2018). However, the high year-to-year variability, induced by abiotic factors, particularly drought stress, can significantly reduce yields (Webber et al., 2018). Employing the best crop management practices adapted to local climate and specific farming conditions is crucial to achieve optimum yields and to minimize impacts on air and water quality.

Nitrogen (N) is essential for crop production. However, currently only ~47% of the nitrogen added globally onto cropland is converted into harvested products (Lassaletta et al., 2014). Thus, more than half of the nitrogen used for crop fertilization is currently lost into the environment. Nitrogen loss through nitrate leaching into ground and surface waters is one of the major concerns in the EU, particularly in the Baltic Sea region (Povilaitis et al., 2014), because almost the entire Baltic Sea is surrounded by land and it is more sensitive to pollution than other marine ecosystems. It is also well known that part of the applied fertilizer N is lost as ammonia (NH_3), or, via nitrification and denitrification, as nitrous oxide (N_2O) and dinitrogen (N_2) (Coskun et al., 2017). Although, the emission through N_2O losses is quantitatively of minor importance in terms of soil N balance, losses are highly important because of its impact on the greenhouse effect due to its radiative properties (i.e. the global warming potential of 1 kg N_2O is equivalent to 265 kg of CO_2). The European Common Agricultural Policy has delivered the Nitrates (91/676/EEC) and the Air Quality (2016/2284/EU) Directives to reduce N leaching and N losses to the atmosphere, respectively. Both directives emphasize the need to improve nitrogen use efficiency through application of the best nutrient management practices (BNMP). These Directives have been translated to the different countries or regions according to their specific crops, climatic, and management conditions. However, the practical application of the BNMP is not straightforward because optimum N rates change according to several factors, especially with variability in annual and local conditions. Therefore, mid-season adjustments are recommended as was shown for maize fields in the U.S. (Dhital and Raun, 2016).

The use of synthetic fertilizers dominates current agricultural practices in industrialized countries. However, their partial substitution by organic fertilizers from nearby livestock or poultry farms can be a good solution to simultaneously improve nutrient cycling at regional scale and soil quality (Tripolskaja et al., 2010; Francis and Porter, 2011). Short- and long-term effects of different manures on crop yield, soil fertility, as well as impacts on water and, to a lesser extent, on air quality, have been comprehensively investigated and broadly described (Merbach and Schulz, 2013; Duan et al., 2014). Yet, redistribution of manure nutrients from intensive animal production areas to crop production land needs further agronomic, environmental, and socio-economic assessment. Nutrient content of pelletized manure can be similar to that of raw manure, although the organic matter decomposition and N mineralization can substantially differ from those of its raw material (Hadas et al., 1983; Jimenez et al., 2017). In addition, a wide range of wastes with diverse characteristics and quality parameters such as total N content, form of N, and C:N ratio, generated from municipal and agricultural activities, can be used as a nutrient source for agricultural crops (Mohanty et al., 2013). Thus, we can expect different crop yield response and potential N losses across years because different N sources can demonstrate source-specific behaviour. A recent meta-analysis by Abalos et al. (2016), including 200 U.S. maize field experiments, suggested that total or partial substitution of synthetic fertilizers by organic sources may contribute to the mitigation of N_2O emissions, but potentially at the cost of substantial yield reduction.

Traditional field experiments have been the common approach to evaluate the impact of changes in agricultural management practices on crop performance. However, major constraints of field experiments are that they are labour-intensive and time-consuming and data interpretation can become complicated when it is necessary to assess the interaction of multiple factors in the plant-soil-climate system and to estimate crop yield traits and environmental impacts. Alternatively, crop models are powerful tools facilitating the assessment of the interaction that occurs between crops and the environment. Crop models simulate plant growth and development and predict crop yields based on crop management, soil and weather conditions, and the choice of cultivar (Li et al., 2018) and provide insights into "What-if" questions about crop production. CERES-Maize is a well-known crop simulation model developed to predict maize growth (Hoogenboom et al., 2010). Since its launch in 1986 (Jones and Kiniry, 1986), it has been periodically updated and its latest version (v 4.7.5) was released in 2019 (Hoogenboom et al., 2019). CERES-Maize has been intensively tested worldwide in terms of irrigation management (Malik and Dechmi, 2019), N fertilizer management (Yakoub et al., 2017; Malik et al., 2019), predicting water and nitrogen requirements (Hammad et al., 2018), simulating the maize N cycle (Liu et al., 2011) and N leaching losses (Gerakis et al., 2006). However, less information is available about the performance of CERES-Maize in the nemoral climate zone, which is characterized as continental, cool with a rather short growing season (Metzger et al., 2012).

To implement the strategy of full or partial N substitution of synthetic fertilizers with those from organic sources requires a better understanding of the effects of different organic fertilizers on the soil-plant system. In particular, it is important to obtain reliable estimates of mineralization rates of organic N under local soil conditions, because this process is essential to predict the amounts and time of release of plant available soil N. Besides, it governs major N loss pathways such as nitrate leaching, ammonia volatilization, or nitrous oxide emissions. Responses of grain maize and N cycle to fertilizers, especially organic, have not yet been adequately addressed in the nemoral climate zone, and most of the crop growth models tested in the Baltic Sea region so far, have mainly focused on mineral fertilizers (Povilaitis and Lazauskas, 2010; Salo et al., 2016; Zhou et al., 2018).

Therefore, the objectives of this study were: (i) to calibrate and validate the CERES-Maize model under the climatic conditions of the Nordic-Baltic region, (ii) to evaluate the prediction capacity of the validated model in simulating the soil water content and temperature dynamics over three maize growing seasons, and (iii) to assess the impact of different rates and types of fertilizers (synthetic, manure, green compost, and their combination) in N losses by leaching and gaseous emissions to the environment under different maize growing seasons.

2. Materials and methods

2.1. Experimental location

The input data required for the CERES-Maize model were collected from maize (*Zea mays* L.) field experiments carried out during the years 2015, 2016, and 2017 in Akademija (Central Lithuania; 55°39′ N, 23°86′ E, 65 m asl). The field is located within an intensive cash crop production region. However, the application rate of organic fertilizers is restricted because the area is a declared nitrate vulnerable zone, with high risk of agricultural nitrate pollution (EU, 2018). The historical average (1981–2010) annual air temperature and precipitation was 7ºC and 557 mm, respectively. According to the Köppen climate classification (Kottek et al., 2006), the climate is humid continental

(*Dfb*) with warm summers and rather severe winters. The soil is a Stagnic Hypocalcic Luvisol (Loamic, Drainic) with a depth of 155 cm (WRB, 2014), which is the prevailing soil type in Lithuania. For each experimental year, the soil nutrient status was assessed from composite soil samples taken from 12 different locations within the experiment field. The main soil agrochemical characteristics were determined in the top soil layer (0−20 cm). Additionally, nitrate and ammonium concentration was determined from 0−30 and 30−60 cm soil depths (Table 1).

2.2. *Crop management*

A maize cultivar RGT AGIRAXX (FAO number 190) was selected due to its short growing period and because it is widely used by local farmers. The maize was grown after conventional tillage and was sown on 8th of May in 2015 and 10th of May in 2016 and 2017, when the soil temperature had reached 8 to 10°C, with a density of 70,000 plants ha^{-1} (0.75 m row and 0.18 m plant spacing). Weeds were controlled by the herbicide MAISTER OD (oil dispersion containing 30 g l^{-1} foramsulfuron + 1 g l^{-1} Iodosulfuron, rate 1.7 l ha^{-1}). Maize harvest was performed manually after the first autumn frosts (12th of October 2015, 10th of October 2016 and 2017). The field experiments of the three years included 8 treatments (Table 2) in a randomized block design with four replicates. The total area of each experimental plot was 30 m^2, and the harvest plot area was 12 m^2. The treatments included different nitrogen fertilization sources (mineral, organic fertilizers, and a combination of both sources) and two additional mineral supply of two levels superphosphate (45 and 90 kg N ha^{-1}) and potassium chloride (85 and 170 kg N ha^{-1}) fertilizers to avoid P and K deficiencies. The mineral fertilizers were in the form of ammonium nitrate (34.4-0-0), superphosphate (0-20-0), and potassium chloride (0-0-60). Fertilizers were applied manually in single application before planting and incorporated into the soil before maize drilling. The pelletized cattle manure (PCM) and pelletized poultry manure (PPM) were manufactured by local producers.

The highest N fertilization rate was selected according to the requirements of the Nitrates Directive of the European Union (91/676/EEC), which limits annual manure application rates to 170 kg of N per year in nitrate-vulnerable areas (Schröder et al., 2013). The main characteristics of the organic fertilizers are shown in Table 3.

2.3. Field measurements and laboratory procedures

During the maize vegetative period, plant development stages were recorded on a weekly basis. Maize vegetative (V) and reproductive (R) development stages were identified on the basis of each treatment when 50% or more of the plants were at a particular development stage (Abendroth et al., 2011). The leaf-collar method was used to record the development of vegetation stages, whereas reproductive stages were based on established visual indicators of kernel development. Leaf area was measured five times per season at vegetative (growing stages V8 and V14), tasseling (VT), reproductive milking (R3), and physiological maturity (R6) stages. For this, 20 randomly selected plants from each treatment (five plants per replicate) were used and leaf area was measured using a portable and non-destructive leaf area meter model CI-203 (CID® Inc, WA, USA). Based on the resulting values, the leaf area index (LAI) was calculated by:

$$LAI = \frac{leaf\ area\ (m^2)}{ground\ area\ (m^2)}$$

(1)

At maize physiological maturity (growth stage R6), the two central rows of each plot (12 m^2) were cut to determine the total aboveground biomass (TAB) and grain yield (GY). The maize samples were weighed (fresh mass) and dried at 65°C until constant weight (dry weight) to estimate the TAB and GY on a dry matter basis. TAB and GY subsamples taken at the R6 growing stage were used to determine total plant N concentration using Kjeldahl method (Mažeika et al., 2020). For each plot, accumulated N uptake in GY and remaining parts of plant (based on dry matter) were calculated separately by multiplying the resulting nitrogen concentration (N%) by the corresponding yield by:

$$N\ uptake\ (kg\ ha^{-1}) = \frac{N\% \times dry\ matter\ (kg\ ha^{-1})}{100}$$

(2)

For the modelling, determined N uptake in the GY and the N remaining parts of the plants (leaves, stalk, husk, and cobs) were added together to obtain the total maize N uptake.

The volumetric soil water content (SWC) was measured in the AN170 treatment regularly (eleven measurements in 2015 and 2017, eight measurements in 2016) at 0−10 cm soil depth using a portable TRIME-FM2 TDR field measurement device (IMKO, GmbH, Ettlingen, Germany). Additionally, SWC was measured at 60 cm soil depth using site specific calibrated "Watermark" soil moisture sensors (Irrometer Company, Riverside, CA, USA) every 7 to 14 days. Soil temperature (T_{soil}) was measured periodically at 0−10 cm soil depth using a TESTO thermometer. In total, 15 T_{soil} measurements were carried out in 2015, 10 in 2016, and 9 in 2017.

Two days after harvest, composite soil samples were taken at 0−30 and 30−60 cm depth to determine nitrate and ammonium content. In each plot, soil samples (≈ 400 g) consisting of four to five sub-samples, were taken at randomly selected points. For soil, the modelling of the bulk soil mineral nitrogen (SMN), the different nitrate and ammonium nitrogen concentrations determined from the two considered depths, were merged into a cumulative value representing the depth of 0−60 cm. SMN was measured spectrometrically (ISO 14256-2:2005) using a spectrometric analyser (Fiastar 5000, Foss Tecator AB).

2.4. Statistical analyses

Analyses of variance *(ANOVA)* for a randomized complete block design was used to analyse TAB, GY, SMN, and N uptake data. Combined analyses of three-year data were conducted to analyse year × treatment interaction, according to the procedures described by Petersen (1994). Statistical analyses were performed using proc GLM, SAS v9.4 (SAS Institute Inc., 2016). Treatment was considered as a fixed effect and year as a random effect. Multiple comparisons between treatments were performed using the Tukey's test at the 0.05 probability level. The statistical significance levels considered were: "ns" to indicate no significance ($p > 0.05$); "*" to indicate $0.05 \geq p > 0.01$; "**" to indicate $0.01 \geq p > 0.001$ and "***" to indicate $p \leq 0.001$.

2.5. CERES-Maize model description and input data

The DSSAT (Decision Support System for Agrotechnology Transfer) software comprises dynamic crop growth simulation models for over 42 crops (Hoogenboom et al., 2019a; Hoogenboom et al., 2019b; Jones et al., 2003). For maize, DSSAT uses the CERES-Maize model (Jones and Kiniry, 1986). The CERES-Maize version used in this work is the one included in DSSAT-4.7.5 The growing stages simulated include germination, emergence, end of juvenile, floral induction, 75% silking, beginning of grain fill, maturity, and harvest. The N component of the model includes soil mineralization and immobilization associated with decomposition of organic matter, transformation processes, movement (leaching), and plant uptake. The effects of water and N deficits on crop growth and development are taken into account by computing water and N stress factors, with the more limiting of the two effects controlling a given process. The model requires daily weather input data (maximum and minimum air temperature, solar radiation, precipitation, relative humidity, and wind speed), soil characteristics (horizons depth, texture, bulk density, water saturation, field capacity, wilting point, saturated hydraulic conductivity, initial nitrogen, water, and organic carbon content), as well as crop management practices (mainly tillage operations, sowing date, plant density, dates and amounts of both mineral and organic N fertilization, and harvest). The DSSAT model uses the Penman–Monteith-FAO56 method (Allen et al., 1998) to compute daily potential evapotranspiration, the Ritchie model to calculate infiltration and the soil water balance (Ritchie, 1998), radiation efficiency for photosynthesis, and the Ritchie−Ceres approach for soil evapotranspiration (Ritchie, 1998). For the turnover of organic matter, the CENTURY (Parton et al., 1994) model is implemented.

Experimental organic treatments (PCM, PPM, GWC) presented in Table 2 were entered into the model when updating the already existing organic amendments characteristics, while for mineral fertilizers' treatments we selected the required fertilizer material and fertilization rate. The soil lower limit of water holding capacity (LL), drained upper limit (DUL) and saturated soil water content (SAT) characteristics were measured in 2017 using the HYPROP® (UMS, München, Germany) method as described by Schindler et al. (2010) in combination with the WP4® Dewpoint Potentiometer (Decagon Devices, WA, USA). Saturated hydraulic conductivity, K_{sat}, was measured using a falling head by the KSAT system (UMS, München, Germany). For all measurements, 10 undisturbed soil samples of 250 cm^3 were extracted from the major soil horizons at depths of 15–20, 40–45, 70–75, 90–95, and 120–125 cm. Soil texture was analysed according to DIN ISO 11277 method (Müller et al., 2009) by wet sieving and the pipette method. To create the soil profile input file in the DSSAT model we used the SBuild program (Hoogenboom et al., 2019a). The model soil input data are presented in Table 4.

The daily meteorological input data for the study were obtained from a meteorological station of the Lithuanian Hydrometeorological Service (Ministry of Environment), located ~500 m from the maize experimental field. Daily groundwater levels were observed by the Lithuanian Geological Survey (Ministry of Environment). The groundwater monitor station was located at a distance of 5 m to the meteorological station.

2.6. Model calibration and validation

The calibration of CERES-Maize for a specific cultivar requires the estimation of six genetic coefficients: P1 (thermal time from emergence to end of juvenile phase), P2 (delay in development with photoperiod above 12.5 h), P5 (thermal time from silking to physiological maturity), G3 (potential kernel growth rate), G2 (potential kernel number per plant), and PHINT (phyllochron interval). In addition, the ecotype coefficient RUE (radiation use efficiency) and other nitrogen and root parameters should be adjusted. The nitrogen parameters are plant top minimum N concentration (TMNC=0.0045), nitrogen content in above-ground biomass at emergence (TANCE=0.044), root critical nitrogen concentration (RCNP=0.0107), root N content at emergence (RANCE=0.024), maximum value for critical tissue N concentration (CTCNP1=1.42), and coefficient for change in concentration with growth stage (CTCNP2=0.255). According to Liu et al. (2012) and Malik et al. (2019), the N concentration coefficient (CTCNP2) was also adjusted to improve the plant N estimation. Data from the 2015 and 2016 experimental plots and 8 treatments (Table 2) were considered for model calibration and information from the 2017 growing season was used for model validation. For both calibration and validation processes, the model was tested using the corresponding observed experimental data of maximum LAI, TAB, GY, total N uptake, and residual soil mineral nitrogen (SMN) after harvest. In addition, and due to the availability of measured SWC and T_{soil} within the AN170 treatment, the resulted simulated values of both variables using the calibrated parameters were compared to measured data for the three considered years for this treatment. The prediction capability of the model for both calibration and validation was tested by the coefficient of determination (R^2), BIAS, and RMSE computed as follows (Wallach, 2006):

$$R^2 = \left(\frac{\sum_{i=1}^{n}(y_i - \bar{y})(x_i - \bar{x})}{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2 \sum_{i=1}^{n}(x_i - \bar{x})^2}} \right)$$

(3)

$$BIAS = 1/n \sum_{i=0}^{n}(y_i - x_i)$$

(4)

(5) $$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2}$$

where n is the number of observed values, y_i and x_i are the simulated and observed values, and $\bar{y}$ and $\bar{x}$ are the average observed and simulated values for the i^{th} data pair. R^2 describes the proportion of the variance in measured data explained by the model and ranges from 0 to 1, with higher values indicating less error variance. The BIAS measures the average difference between measured and simulated values. A positive BIAS indicates model under-prediction and a negative BIAS indicates over-prediction. The RMSE is is the square root of the mean square error. The smaller BIAS and RMSE, the better the performance of the model. In this work, the DSSAT calibration objectives were to maximize R^2, and to minimize the BIAS, and RMSE values.

The calibration procedures were started with the default values of an available maize short season cultivar included in CERES-Maize. First, the genetic coefficients were manually adjusted and in a second step the ecotype parameters were optimized manually. The procedure was an iterative approach to obtain reasonable genetic coefficients through trial and error corrections until a maximum value of R^2 and a minimum value of RMSE among the observed and simulated TAB, GY, and maximum LAI data was reached. Afterwards, nitrogen parameters were adjusted because the model did not show acceptable results in terms of N uptake and SMN. Finally, the genotype coefficient calculator embedded in the DSSAT software was used to improve the manual calibration (Hoogenboom et al., 2019a).

2.7. Model application

The calibrated and validated CERES-Maize model was applied to assess the predicted N leaching below the root zone, and nitrous oxide (N_20) and Ammonia (NH_3) emissions for the different nitrogen fertilization trials during the three considered growing seasons.

3. Results

3.1. Maize growing conditions

The meteorological conditions during the three maize growing seasons (2015−2017) exhibited some differences in terms of air temperature and precipitation. From maize planting to harvest, the mean air temperature was 14.7°C in 2015, 15.9°C in 2016, and 14.9°C in 2017. Thus, the mean air temperature in 2016 was 0.8°C above the 1981-2010 historical average, while in 2015 and 2017 it was very close to the historical average. The minimum daily air temperature over the maize growing cycle ranged from −3.5°C to 18.7°C in 2015, from 2.2°C to 20.0°C in 2016, and from −1.3°C to 18.1°C in 2017, while the maximum daily temperature ranged from 6.1°C to 35.0°C in 2015, from 5.4°C to 31.9°C in 2016, and from 7.6°C to 32.8°C in 2017. Although time from planting to emergence was similar in the three years and varied within a narrow range of 11−14 days after planting (sum of growing degree days (GDD) 41−48°C), differences between growing seasons were apparent for the later development stages. In 2016, higher air temperatures resulted in a quicker maize development, particularly at the vegetative period (VE−VT), which was 11 and 6 days shorter than 2015 and 2017, respectively. It should be emphasized, that at the V5 growing stage some leaves turned purple on the majority of the maize plants in all three years. The colour change is likely be caused by changes in leaf pigments (anthocyanin) as a genetic response of short cultivars to chilly nights, as in this period the air temperature dropped below 8°C (Chalker-Scott, 1999). Roughly 14 to 18 days after this, the leaves fully recovered to their normal green colour without any apparent further consequences on growth.

The year 2015 was exceptionally dry with only 194.2 mm of precipitation over the entire maize growing season (66.5% of precipitation compared to the climate normal between 1981−2010). At the silking growing stage (R1), maize growth slowed down, mainly caused by insufficient soil moisture in the root zone. In consequence, a rapid senescence of basal leaves was observed. In contrast to 2015, rainfall was above climate normal with 378.4 mm (129.6%) in 2016 and 448.8 mm (153.7%) in 2017. The number of days with heavy precipitation (above 10 mm) was higher in the wetter years of 2016 and 2017 than 2015; 4 days in 2015, 12 days in 2016, and 15 days in 2017.

Groundwater levels corresponded well with precipitation sums and distribution. In 2015, groundwater levels were rather deep and varied between 203 and 289 cm below the soil surface during the growing season. In 2016, groundwater levels varied from 202 to 249 cm, while in 2017 groundwater was not so deep and varied from 109 to 231 cm.

Solar radiation over the maize growing season in all three years was above the climate normal with on average 15.2 MJ $m^{-2}d^{-1}$ in 2015 (107.9% compared to the climate normal), 14.90 MJ $m^{-2}d^{-1}$ (105.7%) in 2016, and 16.10 MJ $m^{-2}d^{-1}$ (114.2%) in 2017.

As a response to the differences in the three contrasting years observed, maize growth also varied. In the 2015−2017 growing seasons, the measured LAI reached the maximum values at the tasseling growing stage (VT) with lower values in the dry year of 2015 (LAI 2.76−3.21) and higher values in the wetter years of 2016 (LAI 3.03−3.47) and 2017 (LAI 2.79−3.27). The relatively low values of maximum LAI can be explained by the observed low number of leaves (14 leaves) produced under Nordic climatic conditions compared to other regions with warmer growing seasons where maize develops up to 20 leaves (Abendroth et al., 2011). Differences in observed maize TAB and GY between years were also directly linked to the total amount of precipitation and air temperature during the growing season. On average across all experimental treatments, TAB was 13.58, 17.43, and 15.31 t ha^{-1} in 2015, 2016, and 2017, respectively. Multi-year ANOVA analysis indicated the significant (p<0.01) effect of year, fertilizer treatment, and the interaction year x fertilizer treatment on TAB. Despite some exceptions the treatments effects on TAB showed the following order: AN170 ≈ AN + PCM ≈ AN + PPM ≈ AN + GWC > PPM ≈ AN90 > PCM ≈ GWC. On average, GY was 6.54, 8.68, and 7.54 t ha^{-1} in 2015, 2016, and 2017, respectively. The observed maize grain yields are in good agreement with independently reported data for the same region. For example, in the variety trials of the Lithuanian State Plant Service performed in 2015−2017, the same AGIRAXX variety as used in our study showed GY of 7.69−9.46 t ha^{-1} for a vegetation period of 126−135 days after maize emergence. Combined analyses of the three-year GY data showed highly significant differences between years and among treatments, but the year *x* treatment interaction was non-significant. The effects of treatments on maize GY were similar to those on TAB. Total maize N uptake at physiological maturity was significantly lower in dry season of 2015 than wet seasons of 2016 and 2017. On average, total N uptake was 117.1, 173.3, and 173.1 kg N ha^{-1} in 2015, 2016, and 2017, respectively. A multi-year ANOVA indicated the significant (p<0.01) effect of year, fertilizer treatment, and the interaction year *x* fertilizer treatment on N uptake. Additionally, substantial differences in residual SMN after harvest in the 0−60 cm soil layer between treatments were found. On average, SMN in the 0−60 cm soil layer was 71.6, 65.3, and 60.1 kg N ha^{-1} in 2015, 2016, and 2017. Combined analyses of the three-year SMN data indicated highly significant differences between years and among treatments, but the year *x* treatment interaction was not significant.

3.2. Model calibration

The resulting best genotype, ecotype, nitrogen, and root parameters obtained after calibration are shown in Table 5. The calibration results are presented for each considered year separately for comparison purposes (Fig. 1) as both years differ greatly in climate, even if the calibration was performed for both years simultaneously.

3.2.1. Total above-ground biomass, grain yield, and leaf area index

The total above-ground biomass (TAB) measured at physiological maturity (R6) varied between the fertilization trials from 11.62 to 14.81 t ha^{-1} in 2015 and from 15.27 to 19.04 t ha^{-1} in 2016, while the simulated ones varied from 12.45 to 13.92 t ha^{-1} in 2015 and from 15.38 to 18.34 t ha^{-1} in 2016. The statistical parameters of the calibration period (2015−2016) indicate in general a good agreement between observed and simulated TAB with RMSE, R^2, and BIAS of 0.74 t ha^{-1}, 0.94 ($p < 0.01$) and -0.39, respectively. These statistical metrics were quite similar for both calibration years (2015 and 2016) except for the BIAS, which showed better agreement for the year 2015 (-0.15 vs. -0.62). Interestingly, in the dry year of 2015, TAB values in the treatments with organic fertilizers (PCM, PPM, and GWC) were overestimated by the model by 0.4 to 8%, while in the wetter year of 2016, TAB was underestimated by 4 to 7% (except for PCM). Additionally, TAB was underestimated for both calibration periods for the ammonium nitrate treatment as well as for its combination with organic fertilizers.

The same trend as for TAB was found for the GY for the years 2015−2016, where the simulated values matched those observed in the trials, with small RMSE (0.39 t ha^{-1}), high R^2 0.90 ($p < 0.01$), and BIAS close to zero (-0.064), confirming a reasonable calibration of GY. When comparing fertilizer treatments and year, the simulated GY in many treatments of the year 2015 were slightly higher than the measured ones, whereas no noticeable trend could be detected in the year 2016. This is also reflected in the statistical parameters for the year 2016, where the RMSE obtained for 2015 is better than that for 2016. On the other hand, the contrary was observed for the BIAS.

The agreement between simulated and observed maximum LAI for the calibration period is presented in Figure 1. The statistical measures were reasonably good with a R^2 of 0.73 ($p < 0.05$) (0.47 in 2015; 0.62 in 2016), RMSE of 0.22 (0.21 in 2015; 0.23 in 2016) and BIAS 0.008 (-0.185 in 2015; 0.201 in 2016). In 2015, the model underestimated LAI by 6.2% due to higher water stress in comparison to the other growing periods, while in the wet year of 2016, maximum LAI was overestimated by 6.3%. Additionally, more spreading of the data from the 1:1 line between measured /simulated LAI was observed in comparison to TAB and GY (see Fig.1).

3.2.2. Maize N uptake and soil mineral nitrogen

The ability of the CERES-Maize model to simulate total maize N uptake and residual SMN is shown in Figure 1. The maize N uptake pattern differed significantly among years ($p < 0.01$), most probably associated to differences simulated in TAB and GY between the years. As can be seen, simulated total maize N uptake substantially varied between the years similar to the measured N uptake; and in 2015, N uptake was significantly lower compared to the warm-wet season in 2016.

Irrespective of the considerable N uptake variability, the calculated statistics for the entire calibration periods reflect a good agreement between model and observation with R^2 of 0.81 ($p < 0.01$), RMSE of 15.82 kg N ha^{-1}, and a BIAS of 2.538. During the drier 2015 season, the model simulated well N uptake for the mineral fertilizer treatments (AN90 and AN170), but overestimated the N uptake for the treatments with application of organic fertilizers (e.g., 33.2% in PCM) or the combination of both types of fertilizers (22.7% in AN+GWC and 22.2% in AN+PCM). In the most favourable season for maize growth in 2016, the model mostly underestimated N uptake, except treatments AN170, PCM, and AN+GWC.

Substantial differences in residual SMN in the 0–60 cm soil layer between treatments were found for both calibration seasons used (2015 and 2016). Here, it has to be noted that nitrate comprised a larger share of SMN, accounting for 80.4% in 2015 and 75.2% in 2016. The measured SMN content at harvest along with the predicted values obtained from CERES-Maize are presented in Figure 1. The calculated statistics indicate that SMN calibration is acceptable with R^2, RMSE, and BIAS of 0.63 ($p < 0.05$), 16.1 kg N ha^{-1}, and -11.87. In 2015–2016, the model underestimated SMN by 19.5 and 13.1%, whereby the highest discrepancies between measured and simulated SMN were observed in PCM and PPM treatments, while the calibration was more satisfactory for the mineral fertilizer treatments.

3.3. Model validation

The validation results for the year 2017 showed that the simulated TAB varied from 12.06 to 16.85 t ha^{-1} between the treatments, while the measured TAB varied from 13.31 to 16.49 t ha^{-1} (Figure

1). The calculated statistics R^2, RMSE, and BIAS were 0.89 (p < 0.01), 0.83 kg ha^{-1}, and -0.55, respectively, indicating similar results compared to statistics of the calibration process (Table 6).

Despite the fact that CERES-Maize slightly underestimated final GY, the model showed good agreement between simulated and measured GY during the validation season with R^2 of 0.85 (p <0.01), RMSE of 0.20 t ha^{-1}, and BIAS of -0.097. The model explained significantly more than 85% of the TAB and GY variability. However, for the rest of the evaluated parameters, the predictive capacity of the calibrated model for the validation period was less satisfactory compared to TAB and GY. For example, modelled maize maximum LAI for the validation year 2017 showed R^2 of 0.57 (p < 0.05), RMSE of 0.128, and BIAS of -0.070. Averaging over all plots, simulated maximum LAI values were lower than measured by 3.8%. Regarding the N uptake during the wettest year of the study (2017), the simulated N uptake values were lower than measured (underestimation up to 15.6%), especially in the treatments with mineral fertilizers (AN90 and AN170). CERES-Maize prediction capacity in simulating N uptake during the validation season was reflected by R^2 of 0.61 (p < 0.05), RMSE of 18.12 kg N ha^{-1}, and BIAS of -14.2, while for SMN the statistical measures were R^2 of 0.64 (p < 0.05), RMSE of 16.5 kg N ha^{-1}, and BIAS of -11.588.

For the soil water content and soil temperature, model comparison between observed and simulated data are presented in Figure 2 for all period (2015, 2016 and 2017) and AN170 treatment. As expected, the predicted SWC content fluctuations in the upper Ap soil layer (-10 cm) were larger than at greater depth such as the E soil layer (-60 cm), which can be related to the effect of precipitation-evapotranspiration processes that affect topsoil soil water dynamics most . The agreement between simulated and observed SWC during the wet years of 2016 and 2017 was satisfactory, with RMSE 0.023 cm^3 cm^{-3} (R^2=0.77, (p < 0.01)) in 2016 and 0.025 cm^3 cm^{-3} (R^2=0.81, (p < 0.01)) in 2017. However, during the drier 2015 season, some peaks of SWC were not properly captured at the 10 cm depth with RMSE 0.036 cm^3 cm^{-3} (R^2=0.48). During 2015 and 2016, the observed SWC at the 60 cm soil-depth was very stable, while in 2017 observed SWC presented more variation and was closer to saturation (Fig. 2). The statistical indicators, RMSE and R^2, showed that in

2015 and 2017 the model captured moderately well the pattern of SWC dynamics at 60 cm, while in 2016 simulation of SWC (-60 cm) was less well represented.

In general, CERES-Maize smoothly simulated the temporal dynamics of soil temperature at the upper Ap soil layer (-10 cm) during the maize growing seasons (Fig. 2). The statistical measures indicated a good agreement between observed and simulated soil temperature values with R^2 ranging from 0.80 to 0.88 ($p < 0.01$) and RMSE ranging from 1.5 to 1.8ºC.

3.4. Model application to assess the environmental impact of different fertilizers

3.4.1. N leaching

Differences in the mass of nitrate leached below 155 cm soil depth were mostly associated to year-to-year climatic variability rather than to differences associated to fertilizer treatments (Fig. 3). During the cold and dry growing season in 2015, simulated N leached was low, ranging from 0.19 to 0.38 kg NO_3-N ha^{-1} only. Slightly larger N leaching losses were simulated for the warm and rainy growing season in 2016, with 1.25 to 1.79 kg $N0_3$-N ha^{-1}. A major part of these losses occurred during a short time period between the growing stages maize blister (R2) to milking (R3). In 2017, $N0_3$-N leaching of N started earlier (at the tasseling−silking (VT/R1) growing stage) and was more intensive than in 2016. The greater leaching rates are likely caused by the higher amount of precipitation, especially during the maize reproductive period. In 2017, cumulative N leaching over the maize growing season was the highest among all years and for all treatments (Fig 3). The cumulative N leached value varied from 4.38 $N0_3$-N ha^{-1} (AN90 treatment) to 4.97 kg $N0_3$-N ha^{-1} (PPM treatment).

3.4.2. N_2O and NH_3 emissions

Considering all the simulations (3 year *x* 8 fertilizer treatments), the simulated cumulative N_2O emissions ranged from 0.02 to 0.17 kg N ha^{-1}. Plots receiving AN presented similar simulated N_2O emissions across seasons, with somewhat higher values in N170 (0.10−0.11 kg N ha^{-1}) than in N90 (0.06−0.07 kg N ha^{-1}) treatments (Fig. 4). The lowest simulated N_2O emissions in all years were found in plots under GWC treatment, while emissions from plots with PPM treatment in all years tended to be the highest. Additionally, the PCM treatment showed the highest variability in N_2O emissions among seasons.

Simulated NH_3 emissions from organic fertilizers were similar to those obtained for the mineral fertilizer treatments (ammonium nitrate), and in general lower than expected. In 2015, NH_3 emissions were 29.9% on average and 34.3% lower than in 2016 and 2017, respectively.

4. Discussion

The CERES-Maize model was first calibrated and validated in the nemoral climate using the locally measured grain maize yield under different fertilizer types and contrasting meteorological growing seasons. Experimental results showed a relatively wide range of yield levels, resulting both from year-to-year weather variability and contrasting fertilization rates and types. This study refers to the region which represents a current northern frontier of grain maize expansion where the best management practices are still to be defined, thus simulation of maize growth is indispensable for exploring promising options to achieve economically and environmentally sustainable production. The results of this study indicate that a substantial yield gap exists in the region as the maize GY in the experiment were higher by 34.5, 22.2, and 29.3% than the actual yields reported by Lithuanian farmers for 2015, 2016, and 2017, respectively (FAOSTAT, 2019). The calibration and validation results indicated lower simulated grain yield errors than reported by Malik et al., (2019) under Mediterranean conditions (RMSE from 0.533 to 0.811 t ha^{-1}) and Yang et al. (2009) in North Carolina environments (average RMSE of 0.701 t ha^{-1}). Regarding the maximum LAI the results of our study are in agreement with results found by Dechmi et al. (2010), where the model results showed less accuracy than yield prediction. The maximum LAI results also agree in part with Soler et al. (2007).

A specific aspect of this study was the involvement of organic fertilizers from different sources with contrasting characteristics and mineralization rates of organic N. As a result, in the experiment a wide range of N uptake was obtained notwithstanding that the same amount of total N (170 kg ha^{-1}) was applied. This explains the GY variability between treatments within each considered year. Unfavourable weather conditions (mainly low temperature and water shortage) in 2015 resulted in rather low TAB (simulated values ranged from 12.45 to 13.92 t ha^{-1}) and N uptake (range from

116.2 to 145.6 kg ha^{-1}). The calibration and validation results of N uptake; (RMSE from 15.40 to 18.11 kg N ha^{-1}) and SMN (RMSE from 14.75 to 17.39 kg N ha^{-1}) using CERES-Maize under the application of different mineral and organic fertilizers are better than others studies performed under different experimental conditions (Malik and Dechmi, 2019; Yakoub et al., 2017). In fact, working with data of an irrigated area in Spain, Malik and Dechmi (2019) reported the worst statistics values in simulating N uptake (RMSE= 43 kg N ha^{-1} in grain and 59 kg N ha^{-1} in vegetative biomass) and SMN (RMSE= 53 kg N ha^{-1}). Yakoub et al. (2017) also obtained lower adjustment in predicting N uptake in Spain (RMSE= 41 kg N ha^{-1}).

Under the experimental conditions, our results suggest that significant N leaching beyond the rooting zone is unlikely to occur in late spring or early summer, in particular during the period of intensive vegetative growth of the maize, due to the high evapotranspiration and a the soil depth associated with deep rooting. According to the model estimation in all three considered seasons, nitrate leaching losses during the period from May to July were low irrespective of N fertilizer type. This behaviour is in agreement with the outcomes of Øygarden et al. (2014) who showed that N runoff and leaching losses in the Nordic–Baltic region during the summer season are low even after high precipitation events. Yet, high rainfall events in spring after sowing and fertilization can result in substantial N losses with water percolation below the root zone and also surface runoff might occur. However, during the maize reproductive period from August to October (R1−R6 growth stages) leaching losses of $N0_3$-N can be noticeable if rainfall during this period exceeds ≈ 170 mm. During the reproductive period, N uptake from the soil is reduced, even if the temperature regime is favourable, because a larger part of N for grain yield formation is remobilized from vegetative organs. In general, the results of simulated nitrate leaching during the maize growth cycle are in line with findings reported by other authors claiming that nitrate leaching into deeper soil horizons depends on water flux densities during the growing period (Godwin and Jones, 1991). Relatively low differences in N leaching among treatments with AN and organic fertilizers as found in our study are somewhat unexpected, because AN is a very soluble fertilizer and N leaching can reach substantial levels within a short period of time (Wang et al., 2019).

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Simulation of soil mineral N remaining at harvest after application of 170 kg ha^{-1} as for the AN170 treatment produced similar or slightly higher values than experimentally measured. However, the model in most cases underestimated SMN content when organic fertilizers were applied. SMN is a relevant indicator for both crop N nutrition status and water pollution risk assessment. The majority of treatments the residual SMN content at harvest in the dry conditions of 2015 was higher than in corresponding treatments of the wetter years in 2016 and 2017. This indicates that after a droughty season, the risk of N leaching during the non-growing period can be higher because a substantial part of SMN is inevitably lost during the autumn-winter period.

Simulated N_2O emissions, if compared to the IPPC Tier 1 default value of 1% of the N input from fertilizer, can be rated as rather low. However, similar results to ours were reported in studies investigating organic fertilizers (e.g., Bell et al., 2016). Unfortunately, there are no measured N_2O emission data available from arable soils in Lithuania to rank or justify our results. In any case, simulated N_2O emissions should be carefully interpreted because of multiple sources of uncertainty (Zimmermann et al., 2018), and therefore, calibration of modelled N_2O fluxes against measured data would be advantageous. Finally, our modelling study indicated rather low NH_3 emissions, which can be a result of the method of fertilizer application as the organic fertilizers were incorporated into soil immediately after application. It is a well-known fact that immediate incorporation of manure into the soil is a highly effective measure for reducing NH_3 emissions (Webb et al., 2010). Although, there is a lack of experimental evidence of NH_3 emissions from fertilizer application in Lithuania, globally a large number of experimental data on NH_3 emissions from livestock manure applied to fields have been collected, and there is a consensus that manure is the largest source of NH_3 emissions to the atmosphere (Hafner et al., 2018). Yet accurate estimations of these emissions under specific local conditions and comparisons, for example between locations or application of manure from different sources, can be challenging because of a lack of supporting data and standard protocols for their use.

Estimates of relevant N transformation pathways obtained by modelling have provided important insight into the soil N cycle and potential losses after application of synthetic and organic fertilizers, solely or in combination. Application of PCM and GWC resulted in much lower N uptake and SMN than that of AN application, while treatments with application of PPM or AN combined with organic fertilizers provided intermediate results. However, the differences in estimates of N losses among treatments during the growing season are not so contrasting. Thus, lower crop N uptake was not associated with proportionately reduced N losses as expected. Estimates of N budget are a good starting point for a discussion on replacing synthetic fertilizers with N from organic sources. In general, quantification of N losses via leaching and emission is a complicated task in field experiments and state-of-the-art modelling seems to be a powerful tool to estimate these losses. However, even if subject to quite large uncertainties, the estimations are quite important in order to draw stakeholders' attention to best N management practices.

Estimates from our study can serve as a partial basis for policy makers and assist farmers in optimizing maize N fertilization in the nemoral zone, where no information about the best management practices yet available. The segregation of livestock and crop production intensified in the recent years and hindered the potential benefits of a circular nutrient management, thus return to crop-livestock integration can be beneficial, although more comprehensive assessment is needed (Noordwijk and Brussaard, 2014) due to the heterogeneity of organic fertilizers. According to McCrackin et al. (2018), even partial redistribution of manure from intensive animal farming areas to arable land, together with improved agronomic practices, can reduce nitrogen and phosphorus losses, and will have ameliorating effects on eutrophication conditions of the sensitive environment of the Baltic Sea. In this context, the outcomes of our study can provide relevant information in searching for alternative ways to mitigate environment pollution from agroecosystems.

Although, our study demonstrated that the CERES-Maize model can successfully capture weather and N management effects on crop development variations relevant for maize yield formation under the nemoral climate zone, additional efforts are needed to verify and to fine-tune the model to comprehensively simulate the N cycle, losses to the surface and groundwater and air in particular.

5. Conclusions

This study is a first attempt to estimate and compare via modelling major N cycle parameters in a grain maize crop under synthetic and different organic fertilizers solely or in combination, in the nemoral zone, which is north of the traditional maize growing areas. Very good agreement between simulated and measured maize total aboveground biomass and grain yields indicate that the CERES-Maize model can successfully capture effects of weather and N management factors relevant for maize yield formation under the favourable and sub-optimal (drier) weather conditions. Additionally, reasonable fits between simulated and experimental values of N uptake and soil mineral nitrogen were found and the model identified well the differences among treatments, with lower N uptake and soil mineral nitrogen in pelletized cattle manure and green waste compost than those for ammonium nitrate, with intermediate results in pelletized poultry manure and ammonium nitrate combined with organic fertilizers. The model provided reasonable simulation of the soil water content and temperature dynamics over the course of the maize growing seasons, which is an essential precondition for reliable prediction of the N cycling pattern. The relevant estimates of N losses over the course of the maize growing seasons via leaching depends on water flux intensity during the growing period. However, lower crop N uptake was not ultimately associated with proportionately reduced N losses as expected. In general, the results of this study indicate that the calibrated CERES-Maize model can be used for maize yield prediction under nemoral climate conditions. Regarding N losses via leaching and gaseous emission, even if their estimation in this study is subject to quite large uncertainties, the resulting values are quite important in order to draw stakeholders' attention to best N management practices. However, future research should experimentally verify the capacity of this model to provide a comprehensive simulation of the N cycle and N losses under various fertilization, in particular organic.

Acknowledgements

The Agency for Science, Innovation and Technology (MITA) funded the internship (27/01/2019−16/03/2019) at the Agrifood Research and Technology Centre of Aragon, Spain.

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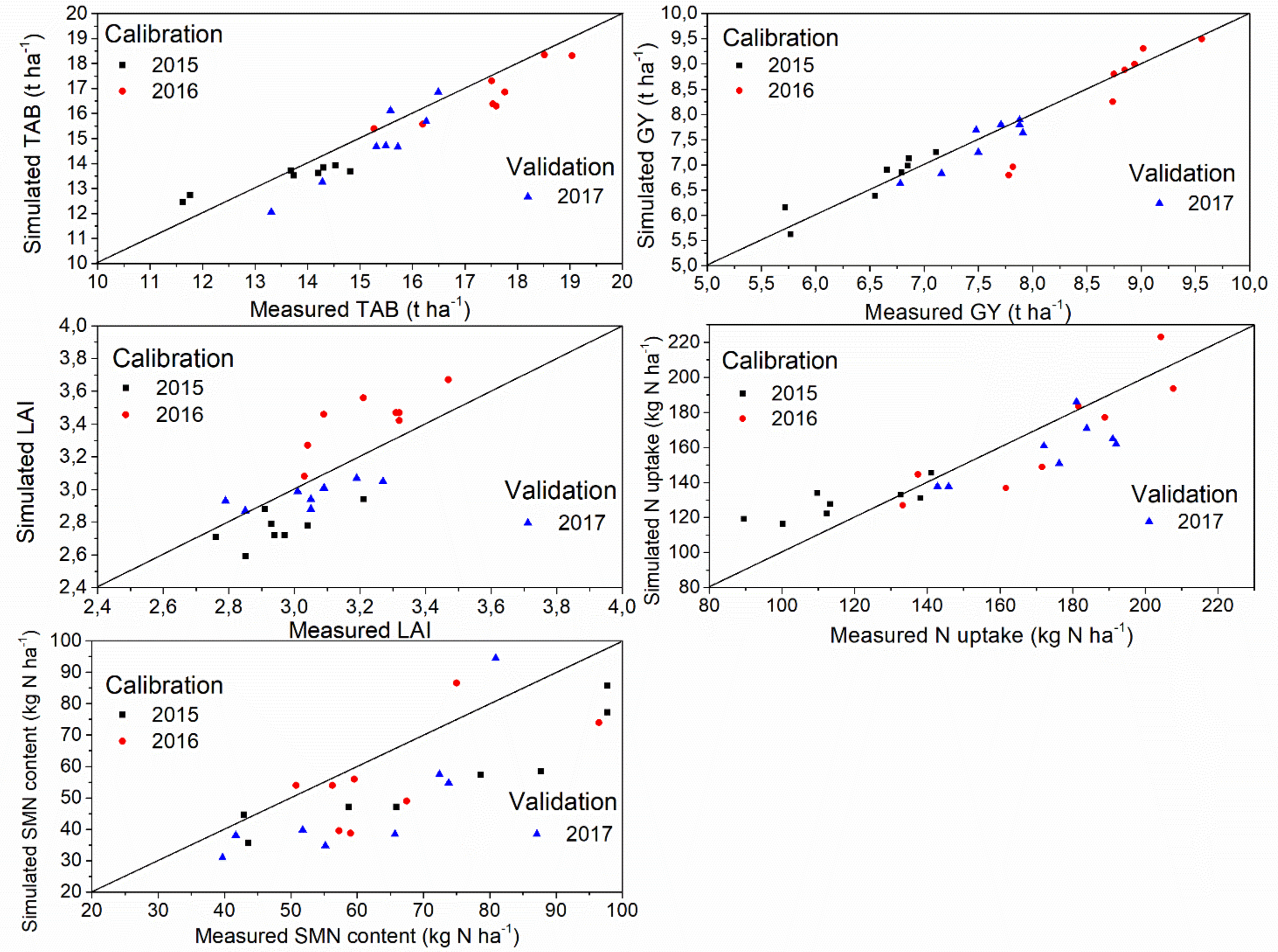

Figure 1. Observed and simulated total above ground biomass (TAB), grain yield (GY), maximum leaf area index (LAI), total N uptake and soil mineral nitrogen (SMN) 0−60 cm at harvest of 8 experimental treatments in three years. The black line represents the 1:1 relationship.

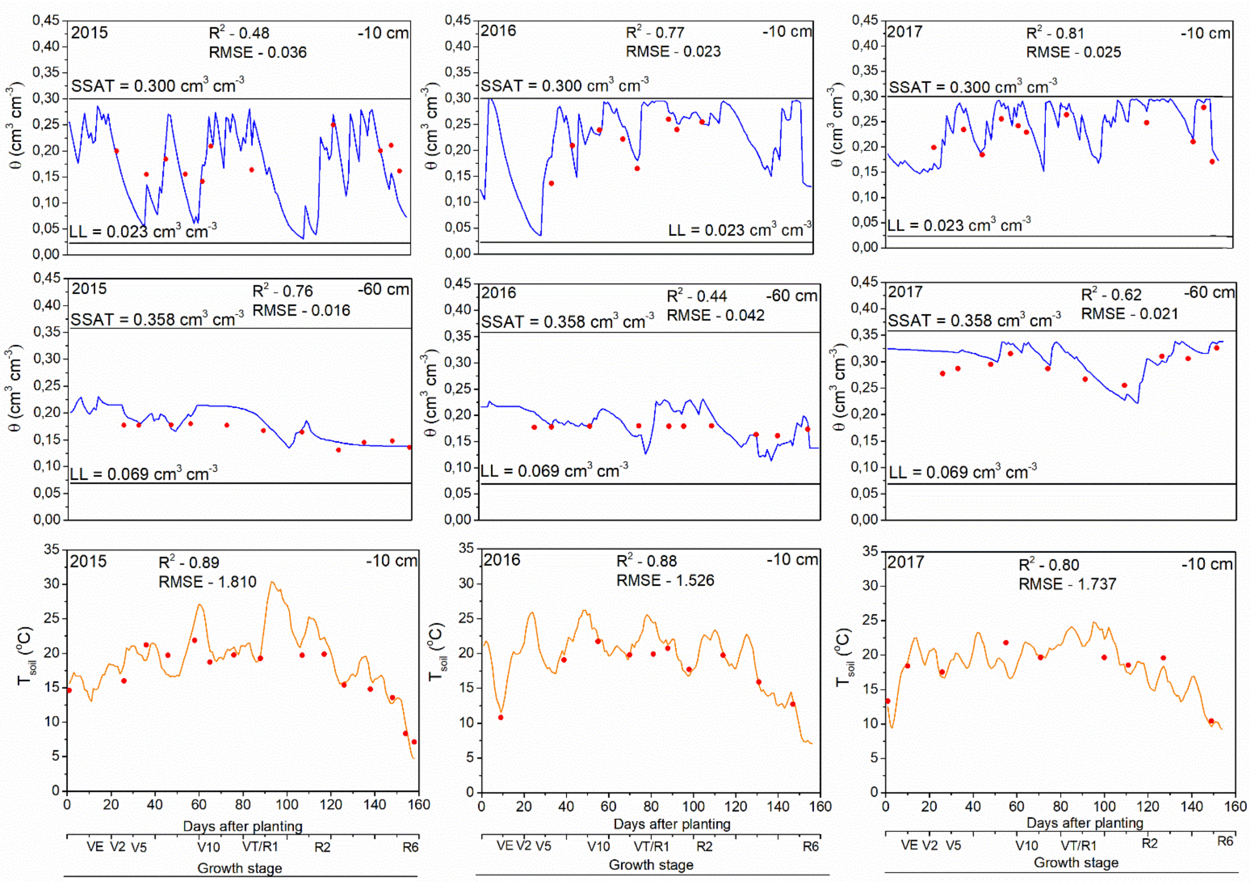

Figure 2. Observed (dots) and simulated (lines) soil water content (θ, cm^3 cm^{-3}) at 10 and 60 cm depths and soil temperature at 10 cm depth in AN170 plots for the 2015−2017 years. *SSAT* is the saturated soil water content, *LL* is the soil water lower limit.

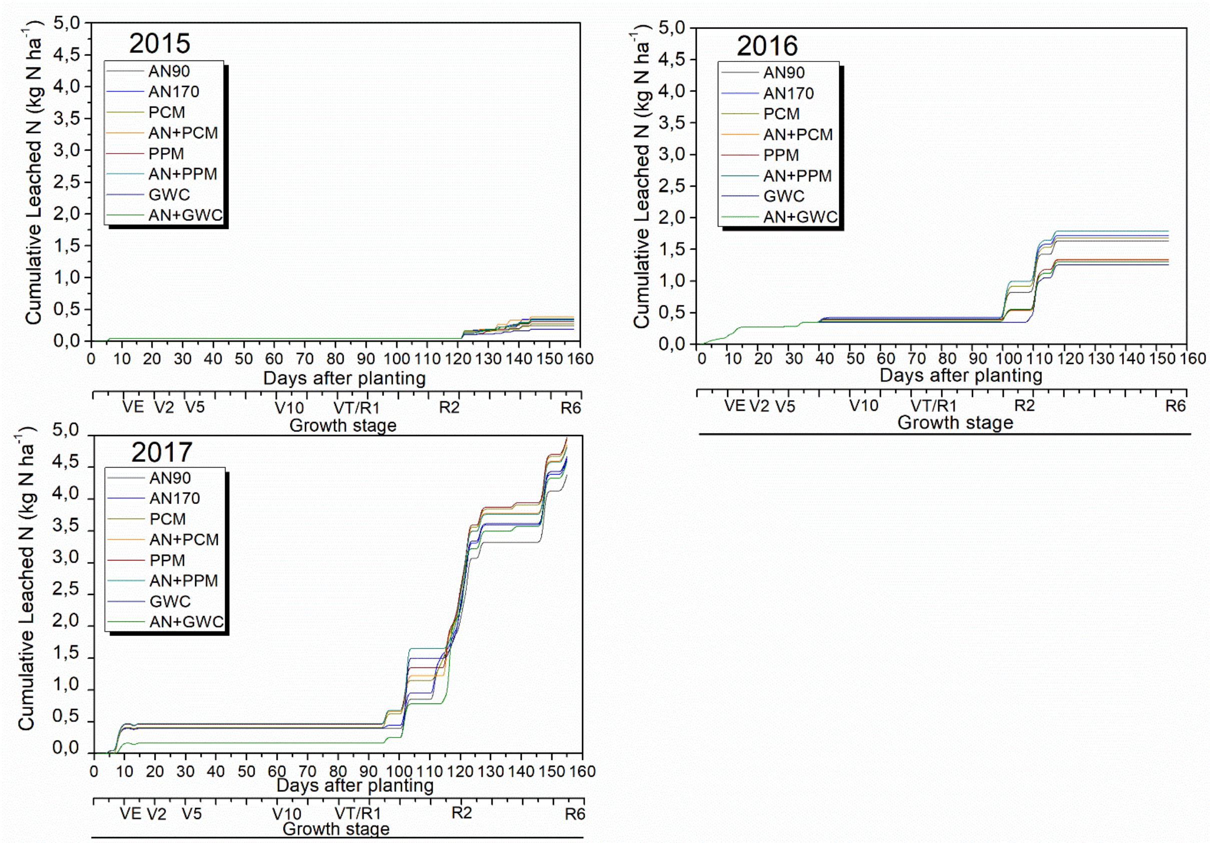

Figure 3. Simulated cumulative N leaching (kg N ha^{-1}) out of the soil profile at 155 cm depth for the different fertilizer treatments and years.

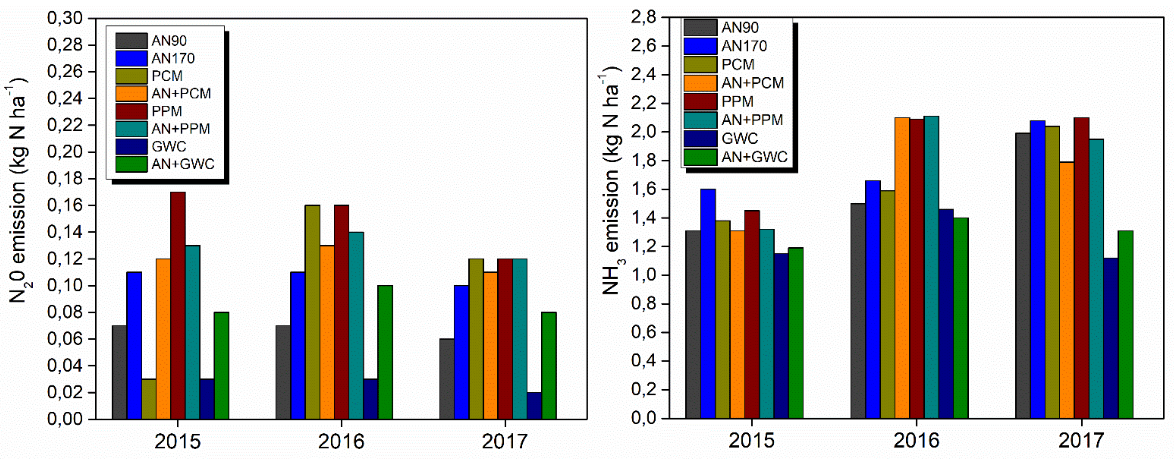

Figure 4. Simulated cumulative N_20 and NH_3 emissions in the different fertilizer treatments and years (2015–2017).

Table 1. Soil agrochemical characteristics determined before maize planting of each considered year: pH, soil organic carbon content, plant available phosphorus (P_2O_5), plant available potassium (K_2O), total nitrogen after Kjeldahl (total N), nitrate nitrogen (NO_3^--N), and ammonium nitrogen (NH_4^+-N).

Soil characteristic	**2015**	**2016**	**2017**
pH (1 N KCl extraction), 0−20 cm	6.85	6.70	6.20
P_2O_5 (mg kg^{-1};Egner-Riehm-Domingo (A–L)), 0−20 cm	154	129	85
K_2O (mg kg^{-1};Egner-Riehm-Domingo (A–L)), 0−20 cm	138	140	154
Soil organic carbon (%; Tjurin), 0−20 cm	1.08	1.04	0.99
Total N (%; Kjeldahl), 0−20 cm	0.109	0.110	0.103
NO_3^--N (mg kg^{-1}), 0−30 cm	8.4	9.4	4.2
NO_3^--N (mg kg^{-1}), 30−60 cm	4.3	4.9	2.2
NH_4^+-N (mg kg^{-1}), 0−30 cm	1.8	3.7	2.5
NH_4^+-N (mg kg^{-1}), 30−60 cm	1.2	2.7	1.8

Table 2. Fertilization rates of nitrogen, phosphorus, and potassium applied in the different treatments (average 2015−2017).

Treatments	**Codes**	**Nutrient rate (kg ha^{-1})**		
		N	**P**	**K**
Ammonium nitrate N90 + P + K	(AN90)	90	45	90
Ammonium nitrate N170 + P + K	(AN170)	170	85	170
Pelletized cattle manure N170	(PCM)	170	90	318.1
Ammonium nitrate N90 + pelletized cattle manure N80	(AN + PCM)	170	42.3	149.7
Pelletized poultry manure N170	(PPM)	170	78.3	250.6
Ammonium nitrate N90 + pelletized poultry manure N80	(AN+PPM)	170	36.8	118
Green waste compost N170	(GWC)	170	93.7	220.4
Ammonium nitrate N90 + Green waste compost N80	(AN + GWC)	170	44.1	103.7

Table 3. Chemical characteristics (dry matter basis) of pelletized cattle manure (PCM), pelletized poultry manure (PPM), and green waste compost (GWC) for the considered growing seasons 2015, 2016, and 2017.

	PCM			**PPM**			**GWC**		
	2015	**2016**	**2017**	**2015**	**2016**	**2017**	**2015**	**2016**	**2017**
pH	9.5	9.2	9.6	6.6	6.0	6.4	8.4	8.0	8.8
Dry matter (%)	82.30	81.05	85.37	81.10	78.13	83.29	70.30	84.49	59.74
Total nitrogen (N) (%)	2.80	3.04	2.49	4.70	5.14	4.39	0.60	0.59	0.60
Total phosphorus (P_2O_5) (%)	1.20	0.75	1.45	2.40	0.88	3.52	0.30	0.17	0.40

Total potassium ($K_2$0) (%)	7.10	4.63	7.17	3.60	2.78	3.22	0.80	0.68	0.48

Table 4. Clay content (*SLCL*), silt content (*SLSI*), lower limit of water holding capacity (*LL*), drained upper limit (*DUL*), soil saturation (*SSAT*), soil bulk density (*SBDM*), saturated hydraulic conductivity (*SSKS*), and soil root growth factor (*SRGF*) of each soil horizon.

Horizon description	SLCL (%)	SLSI (%)	LL (cm^3 cm^{-3})	DUL (cm^3 cm^{-3})	SSAT (cm^3 cm^{-3})	SBDM (g cm^{-3})	SSKS (cm day^{-1})	SRGF
Ap[1] (0−30 cm)	13.1	31.9	0.023	0.289	0.300	1.81	0.6	1
E[2] (30−60 cm)	6.2	23.4	0.069	0.354	0.358	1.70	2.2	0.407
Bt[3] (60−80 cm)	29.3	35.7	0.122	0.317	0.342	1.73	6.1	0.247
B[4] (80−110 cm)	19.9	22.6	0.083	0.343	0.351	1.68	62.0	0.15
Ck[5] (110−155 cm)	14	31.6	0.062	0.234	0.245	1.96	3.2	0

[1]: mineral surface horizon with an accumulation of humified organic matter.

[2]: mineral horizon in which the main feature is loss of silicate clay.

[3]: mineral illuvial horizon with accumulation of silicate clay.

[4]: mineral illuvial horizon.

[5]: initial horizon with accumulation of pedogenic carbonates.

Table 5. Best genetic coefficients, nitrogen, and root parameters values obtained for maize cv. RGT AGIRAXX after CERES-Maize calibration using both 2015 and 2016 experimental data.

Parameter	Definition	Value
Genotype parameters		
P1	Growing Degree Days (GDD) from seedling emergence to the end of the juvenile phase (°C)	128
P2	Photoperiod sensitivity (hr^{-1})	0.2924
P5	Growing Degree Days (GDD) from silking to physiological maturity (°C)	620
G2	Maximum possible number of kernels per plant	900
G3	Kernel filling rate (mg m^{-2} d^{-1})	7.5
PHINT	Phyllochron interval, the interval in thermal time between successive leaf tip appearances (°C)	36.75
Ecotype parameters		
TBASE	Base temperature below which no development occurs (°C)	8
RUE	Radiation use efficiency (g plant dry matter MJ^{-1})	3.7
Nitrogen parameters		
TMNC	Plant top minimum N concentration (g N g^{-1} dry matter)	0.0045
TANCE	Nitrogen content in above-ground biomass at emergence (g N g^{-1} dry matter)	0.044

RCNP	Root critical nitrogen concentration (g N g^{-1} root dry weight)	0.0107
RANCE	Root N content at emergence (g N g^{-1} root)	0.024
CTCNP1	Maximum value for critical tissue N concentration	1.42
CTCNP2	Coefficient for change in concentration with growth stage	0.255
Root parameters		
PORM	Minimum porosity required for supplying oxygen to roots for optimum growth	0.06
RLWR	Root length to weight ratio	0.96

Table 6. CERES-Maize model performance (R^2, RMSE, BIAS) of total aboveground biomass (TAB), grain yield (GY), leaf area index (LAI), total N uptake, and residual soil mineral N (SMN) for the calibration (2015−2016) and the validation (2017) periods.

	R^2			RMSE			BIAS		
	2015	**2016**	**2017**	**2015**	**2016**	**2017**	**2015**	**2016**	**2017**
TAB (t ha^{-1})	0.909**	0.829**	0.886**	0.697	0.779	0.830	-0.148	-0.624	-0.554
GY (t ha^{-1})	0.895**	0.938**	0.851**	0.203	0.506	0.203	0.109	-0.248	-0.097
LAI	0.468	0.617*	0.566*	0.207	0.227	0.128	-0.185	0.201	-0.070
N uptake (kg N ha^{-1})	0.653*	0.794**	0.607*	16.234	15.399	18.116	11.538	-6.463	-14.200
SMN (kg N ha^{-1})	0.839**	0.453	0.641*	17.395	14.750	16.454	-14.923	-8.804	-11.588

* - p <0.05; **- p<0.01