Potential for a Rye Cover Crop to Reduce Nitrate Loss in Southwestern Minnesota

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ABSTRACT

Cover cropping practices are being researched to reduce artificial subsurface drainage NO_3–N losses from agricultural lands in the Upper Mississippi watershed. This study was designed to investigate the influences of fall planting date and climate on cereal rye (*Secale cereale* L.) biomass and N uptake in the spring, and to assess subsurface drainage NO_3–N loss reductions. A soil–plant–atmosphere simulation model, RyeGro, was developed and used to predict rye cover crop establishment and growth, soil water balance, N cycling, and drainage NO_3–N losses from mid-September through May in southwestern Minnesota. An imbedded stochastic weather generator provided model climate inputs. Inclusion of a rye cover crop sown on 15 September reduced N losses by 11.1 kg N ha^{-1} or 45% for a corn (*Zea mays* L.)–soybean [*Glycine max* (L.) Merr.] crop rotation. Fall sowing dates of 1, 15, and 30 October resulted in reductions of 7.8, 5.8, and 4.6 kg N ha^{-1}, respectively, by the end of May. Desiccation of the rye on 1 May resulted in reductions of 4.5, 2.2, 1.2, and 0.7 kg N ha^{-1}, for the 15 September and 1, 15, and 30 October sowing dates, respectively. Cover cropping practice provides promising opportunities for reductions in N losses for cropping rotations wherein the primary crops are harvested before mid-September and planted after mid-May. We predict that a winter rye crop can reduce drainage NO_3–N losses on average 7.4 kg N ha^{-1} for southwestern Minnesota if planted on 15 September and desiccated on 15 May.

Hypoxic zones occur in several coastal estuaries around the world, and one of the largest zones can be seen in the northern Gulf of Mexico at the mouths of the Mississippi and Atchafalaya rivers (Rabalais et al., 2001). The low levels of O_2 in the Gulf waters can be traced to a cycle that is exacerbated by high levels of N entering the Gulf from these rivers (Rabalais et al., 1996). Nutrient loading in the Mississippi River has been increasing in quantity since the 1950s (Antweiler et al., 1995). Analysis of the sources of the N in the Mississippi River indicates that the Upper Mississippi watershed, including Minnesota and Iowa, is a significant contributor. Agricultural subsurface drainage systems can exacerbate N losses from agricultural lands to surface waters (Zucker and Brown, 1998). These systems are used to increase crop productivity and reduce the risk of lowered crop yields from root zone excess water stress during wet years (Fausey et al., 1995); however, agricultural drainage systems have created a pathway by which nutrients can escape from the fields they are intended to enhance (Skaggs et al., 1994).

One general strategy to mitigate the loss of NO_3–N through subsurface drainage systems is to minimize the amount of nutrients reaching the drains (Mitsch et al., 2001; Randall and Mulla, 2001; Dinnes et al., 2002). Examples of methods proposed to implement this strategy include managing nutrient application more effectively, changing cropping systems, and using appropriate tillage practices. One of the methods related to cropping system modification is the use of fall-planted cover crops to assimilate residual soil NO_3^- before establishment of the succeeding summer crop. Cover crops can affect the water balance, reduce the soil NO_3–N level, and provide residue cover on agricultural fields that are normally fallow between summer crops. A cover crop growing in fall and spring takes up soil NO_3–N, which is a leachable mineral form of N, and produces a nonleachable pool of organic N (ON) in the biomass of the plant (Hoyt and Mikkelsen, 1991). The ON in the plant residue is left on the surface of the ground, where it will be broken down and recycled during a period of months and years. Because of their ability to reduce NO_3–N leaching, cereal cover crops have become a major part of the proposed strategies to reduce nutrient loadings to the Chesapeake Bay (Boesch et al., 2001). In addition to N scavenging benefits, cover cropping can provide the advantages of surface cover, erosion protection, snow trapping, and weed suppression on fields from which silage corn or shorter season canning crops are harvested.

The majority of research to date on the use of winter cover crops to reduce NO_3–N leaching to groundwater or drainage effluent has been performed in warm, humid climates where the majority of nutrient loss occurs during the winter. In colder climates where the soil profile freezes during the winter, the majority of nutrient loss through subsurface drainage occurs during the spring, before significant biomass accumulation of the summer row crop. Moreover, the precipitation regimes are considerably different between the warm, humid climates and the drier, colder northern climates. For example, the percentages of average annual precipitation falling during the period of October through March for a Washington state experimental site (Kuo et al., 1997), a Maryland site (Ranells and Wagger, 1997), and Lamberton, MN (Strock et al., 2004), are 75, 45, and 26%, respectively.

The challenge of obtaining the benefits of winter cover crop use in the northern Corn Belt is the short and cold growing season between summer row crops (Dinnes et al., 2002). There is a lack of research quantifying how effective the technique of growing cover crops between

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Abbreviations: ON, organic nitrogen; RSN, residual soil nitrate; SMC, soil moisture content; SWROC, Southwest Research and Outreach Center.

summer crops is in reducing NO_3–N losses through agricultural drainage effluent in the northern Corn Belt, given variations in climate. Strock et al. (2004) conducted a 3-yr field study of rye as an N-scavenging cover crop in southwestern Minnesota. The expense and time required to continue such a field study long enough to gain insight into water quality changes across decadal and longer time frames is prohibitive. Computer modeling has become a common technique for investigating the long-term consequences of changes to agronomic systems based on knowledge gained from short-term field research.

The Stanford Watershed Model is one of the earliest examples of a computer routine developed to simulate the processes involved in the hydrologic cycle (Crawford and Linsley, 1966). During the ensuing decades, models were developed to simulate biochemical processes as well as the hydrologic ones. Examples of models that have been used to investigate agronomic and water quality impacts of agricultural practices at the field level include: DRAINMOD (Skaggs, 1978), CREAMS (Knisel, 1980), EPIC (Williams et al., 1984), CERES-Wheat (Ritchie and Otter, 1985), DSSAT (Jones et al., 2003), AGNPS (Young et al., 1987), GLEAMS (Leonard et al., 1987), ADAPT (Alexander, 1988; Ward et al., 1988), and RZWQM (Great Plains Systems Research Unit, 1999). These models vary in the complexity of the underlying algorithms and of the input variables required to use them.

Long-term assessments require weather inputs from a weather record of sufficient length. Jin and Sands (2003) used an 85-yr historic weather record to perform a long-term hydrologic assessment of subsurface drainage systems for a southern Minnesota location. When access to such lengthy records has been limited, or when long-term weather patterns have been changing, the use of stochastically generated weather inputs to soil–plant–atmosphere models has been widely practiced. For example, the Climate Generator (CLIGEN; Nicks et al., 1995) has been used to generate climate input variables for several hydrologic and water quality simulation models, including EPIC, GLEAMS, SWRRB, and WEPP (Nicks and Gander, 1994). The advantages of employing a stochastic weather generator include the opportunity to create a wide range of possibilities for weather sequences and the ability to increase the certainty of the mean output values. The generator can be programmed to execute high numbers of simulation runs to the point that the sample mean of each model output has very low variance.

A soil–plant–atmosphere model, RyeGro, was developed, calibrated, and previously described by Feyereisen (2005) and Feyereisen et al. (2006a, 2006b). RyeGro was developed as a spreadsheet application, providing ease of use. Model inputs include basic soil and climate information; there are few parameters to be calibrated, which supports a straightforward calibration process. RyeGro was specifically developed to simulate cover crop growth during the fall through spring period and more closely estimated rye biomass accumulation for the calibration seasons than another widely used crop growth model.

We used RyeGro with the following objectives: (i) to develop a probabilistic assessment of the potential for using fall-planted cereal rye, also known as winter rye, to reduce NO_3–N leaching to field subsurface drainage effluent in southwestern Minnesota; (ii) to predict field losses of NO_3–N through artificial subsurface drainage for a corn–soybean crop rotation that includes, or does not include, a fall-planted cover crop of cereal rye after the corn harvest; and (iii) to investigate the influences of fall planting date and climate on rye biomass yield and N uptake in the spring.

METHODS

RyeGro Model

The soil–plant–atmosphere model RyeGro was developed to predict aboveground biomass production and N uptake of rye planted after the fall harvest of corn in the corn–soybean crop rotation common to southwestern Minnesota and to simulate subsequent artificial subsurface drainage NO_3–N losses at the field scale during the fall through spring period. The hydrology and N submodels of RyeGro were documented by Feyereisen et al. (2006a) and the plant growth submodel by Feyereisen et al. (2006b).

The available data set for the rye cover crop study in southwestern Minnesota contained only basic soil, weather, and crop growth information. In view of the nature of the input information, a decision was made to simulate physical processes in RyeGro only to a level of complexity necessary to meet the study's objectives. An example of the approach of sufficient complexity in model development is given by Hammer and Muchow (1994), who developed a simple, yet mechanistic crop simulation model for sorghum [*Sorghum bicolor* (L.) Moench]. They reported that their model was successful in accounting for 94% of the variability in biomass production on 38 data sets covering a broad range of environments.

In RyeGro, the soil profile was represented as a series of three soil layers: a surface layer, approximately the depth of the plow layer; Soil Layer 2, extending from the surface layer to the depth of the artificial subsurface drain tube; and Soil Layer 3, which extended below the drain tube to a calibrated depth. Percolation from one layer to the next lower layer was calculated when soil moisture content (SMC) in the higher layer exceeded field capacity. The infiltration scheme of Holtan (1961) was used to determine infiltration and surface runoff. The infiltration equation is:

$$f(t) = a\, S_{\mathrm{a}}^{1.4}(t) + f_{\mathrm{c}} \qquad [1]$$

where $f(t)$ is infiltration rate with time; f_c is the constant rate of infiltration after the storage capacity reaches zero and is typically given the value of the saturated hydraulic conductivity of the surface soil, k_{sat}; a is associated with surface-connected porosity; S_a, available storage capacity, is defined as:

$$S_{\mathrm{a}}(t) = [\theta_{\mathrm{sat}} - \theta(t)]D \qquad [2]$$

where θ_{sat} is saturation soil moisture content, $\theta(t)$ is soil moisture content during the current time step, and D is the depth of the surface soil layer. Percolation between layers, Perc, is governed by Eq. [3]:

$$\mathrm{Perc} = k_{\mathrm{sat}}\left[\frac{(\theta(t) - \theta_{\mathrm{fc}})}{(\theta_{\mathrm{sat}} - \theta_{\mathrm{fc}})}\right]^{e}, \text{ for } \theta(t) > \theta_{\mathrm{fc}}$$

$$\mathrm{Perc} = 0, \text{ for } \theta(t) \leq \theta_{\mathrm{fc}} \qquad [3]$$

where θ_{fc} is field capacity soil moisture content, k_{sat} is the saturated hydraulic conductivity of the soil in the layer through which soil moisture is percolating, and e is an exponent that can be calibrated. Subsurface drainage occurs from Soil Layer 2 when the soil moisture content in Soil Layer 3 becomes saturated and $\theta(t)$ in Soil Layer 2 is $>\theta_{fc}$. Depending on available climate inputs, evapotranspiration was determined by either the Priestley–Taylor method (Priestley and Taylor, 1972) or the Penman method (Penman, 1948). A simplified N cycle was used to estimate net mineralization, fresh ON mineralization, plant uptake, and mass flow of NO_3–N. Given that air and soil temperatures are near or below freezing in Minnesota during much of the season under study (fall–spring), mineralization of cellulose and lignin in the fresh stover, denitrification, and volatilization were ignored. Net mineralization is calculated on a daily basis by Eq. [4] (Arnold et al., 1998):

$$\mathrm{ONminN} = [\mathrm{ONact} - \mathrm{ONact}\exp(-\mathrm{MinRate})] \times (K_{\mathrm{wON}}\,K_{\mathrm{tON}})^{\mathrm{MinExp}} \quad [4]$$

where ONminN is daily net mineralized N, ONact is the active pool of readily mineralizable ON, MinRate is the daily net mineralization decay rate constant, K_{wON} and K_{tON} are soil water and temperature coefficients varying from 0 to 1, and MinExp is a calibrated parameter. A value for MinRate of 0.0077 d^{-1} is used in RyeGro, a value originating with Stanford and Smith (1972).

The plant growth submodel uses the solar radiation interception concept of Monteith (1977) and reiterated by Campbell and Norman (1998) to calculate assimilated biomass:

$$A_{\mathrm{nPOT}} = \varepsilon \int f_{\mathrm{PAR}} \mathrm{PAR}\, \mathrm{d}t \quad [5]$$

where A_{nPOT} is potential net assimilated biomass, ε is radiation use efficiency, f_{PAR} is the fraction of incident light intercepted by the rye canopy, and PAR is the photosynthetically active radiation portion of total solar radiation. A photosynthetic reduction factor, K_{p}, is used to reduce the quantity of daily potential biomass due to temperature stress or water stress. Each day the smaller of the stress reduction factors for temperature, K_{t}, or soil moisture, K_{w}, becomes the photosynthetic reduction factor. The photosynthetic reduction factor is multiplied by the daily potential biomass to calculate actual daily biomass production:

$$A_{\mathrm{nACT}} = A_{\mathrm{nPOT}} K_{\mathrm{p}} \quad [6]$$

where A_{nACT} is actual assimilated biomass. Using an empirical relationship between rye biomass accumulation and tissue N content derived from rye growth studies in Minnesota, the model calculates the amount of N accumulated in the growing rye crop and subtracts the assimilated N from the soil NO_3–N pool.

Stochastic Weather Generator

Daily weather input variables required by RyeGro include maximum and minimum air temperature, precipitation, and solar radiation. Additionally, maximum and minimum relative humidity and average wind speed were necessary for use of the Penman method to calculate reference evapotranspiration. Weather input variables to RyeGro were either read from an input file or generated stochastically by an imbedded weather generator.

Weather inputs for the RyeGro calibration and validation simulations were available from the 43-yr record (1961–2003) at the Southwest Research and Outreach Center (SWROC) at Lamberton, MN (44°15′00″ N, 95°18′36″ W). The record of shortwave solar radiation readings during the same period was less complete: 24 yr of solar radiation values, with a minimum of 330 d of daily values recorded during the year, existed.

Since the objective of the research was to assess probabilistically the long-term effects of using a fall-planted rye cover crop, stochastic generation of weather variables was used to extend the number of years of investigation beyond the available historic record by creating synthetic weather sequences with the same statistical properties as the measured variables. Because the SWROC record was quite short for solar radiation, wind speed, and relative humidity, an approach developed by Wilson and Hayes (2004) was used to estimate the variance, skewness coefficient, and serial coefficients of all the weather variables based on a 72-yr record from Sioux Falls, SD (43°33′36″ N, 96°43′48″ W), which is located 122 km from Lamberton and has similar geography and climate. The basic assumption was made that the variability of the weather variables and serial correlations was similar for Lamberton and Sioux Falls. A comparison of average monthly precipitation for Lamberton and Sioux Falls for the October through May time period is shown in Fig. 1.

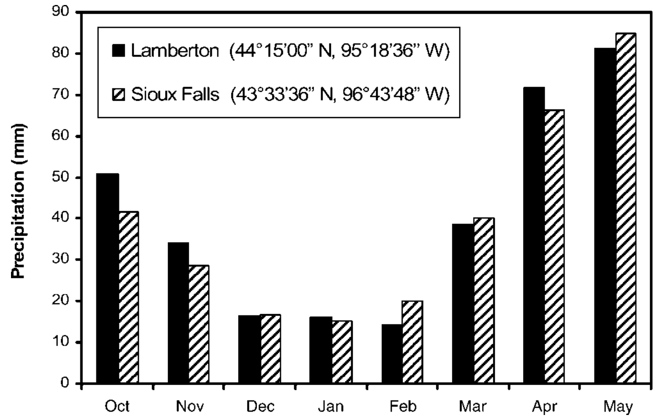

Fig. 1. Average monthly precipitation at Lamberton, MN, and Sioux Falls, IA.

The weather generator calculates precipitation occurrence and depth, maximum and minimum air temperature, shortwave solar radiation at the earth's surface, average wind speed, and maximum and minimum relative humidity on a daily basis. Weather variable estimates are generated independently of one another. See Feyereisen (2005) for additional details of the weather generator.

Model Inputs for Long-Term Stochastic Investigation

The calibration and validation of the plant growth submodel were performed using data from a rye growth trial at St. Paul, MN (44°58′48″ N, 93°10′48″ W) and a 3-yr field study involving fall sowing of rye after corn and before soybean, conducted from fall 1998 to spring 2001 at the SWROC. The calibration and validation of the hydrologic and drainage submodels were performed using data from the 3-yr study and from field measurements recorded on the same set of plots during a previous 6-yr study, conducted from 1988 to1993 by Randall

Table 1. Soil input values used for simulations.

Property	Surface layer	Layer 2	Layer 3
Depth, cm†	30	90	45
Saturated soil moisture content, $cm^3\ cm^{-3}$	0.526	0.400	0.400
Field capacity, $cm^3\ cm^{-3}$	0.320	0.308	0.300
Wilting point, $cm^3\ cm^{-3}$	0.195	0.191	0.200
Saturated conductivity, cm h^{-1}	0.91	0.30	0.0006
Percolation exponent†	0.5	0.5	1
Surface depressional storage, cm†	0.95	n/a‡	n/a
Holtan's surface parameter a, $in.^{-0.4}$ h†	0.3	n/a	n/a
Holtan's infiltration parameter f_c, cm h^{-1}	0.91	n/a	n/a
Soil transmissivity, mm d^{-1}	3.5	n/a	n/a

† Calibrated parameter.
‡ Not applicable.

Table 2. Plant growth, soil N cycle, and soil temperature input values used for simulations.

Input parameter	Value
Plant growth	
Radiation use efficiency, kg dry matter MJ^{-1} photosynthetically active radiation	2.8
Initial shoot biomass†, kg dry matter ha^{-1}	30
Base temperature†, °C	1
Optimum temperature†, °C	18
Heat units to emergence†, °C d	50
Maximum days to emergence†, d	14
Heat units to maturity†, °C d	2050
Maximum leaf area index	7
Maximum canopy height, m	1.14
Maximum root depth, m	0.6
Soil N cycle	
Soil organic matter, surface layer, %	6.03
Soil organic matter, Layer 2, %	2.76
Soil organic matter, Layer 3, %	1.55
Soil organic C/organic N ratio	10.5
Soil mineralization potential†, % of soil organic N	20
Net mineralization rate constant, wk^{-1}	0.54
Mineralization temperature and soil moisture exponent†	2.5
Corn stover carbohydrate N, kg ha^{-1}	9.6
Soil temperature	
Soil thermal conductivity, W m^{-1} °C^{-1}	1.042
Soil thermal diffusivity, cm^2 s^{-1}	0.004
Snow thermal conductivity, W m^{-1} °C^{-1}	0.625
Rain–snow dividing temperature, °C	0
Snowmelt base temperature, °C	2
Snowmelt coefficient, mm °C^{-1} d^{-1}	5

† Calibrated parameter.

et al. (1997). Details of the field trials are available in Strock et al. (2004) and Randall et al. (1997).

Soil and Crop Inputs

Tables 1 and 2 contain model inputs used for the simulations. The soil moisture contents, saturated hydraulic conductivity, and organic matter contents were obtained from the SSURGO (Soil Survey Geographic) database. The crop parameters were values for rye obtained from the literature, or, if values for rye were unavailable, crop parameter values for oat (*Avena sativa* L.) or wheat (*Triticum aestivum* L.) were used. The settings used for soil, crop, N, and soil and snow thermal inputs remained unchanged from the calibration and validation of the plant growth, hydrologic, and N submodels (Feyereisen et al., 2006a, 2006b).

Initial Soil Moisture Content

The initial SMC in each of the three soil layers is estimated at the time of rye sowing. Initial SMC of each of the soil layers is calculated as a function of the cumulative precipitation and average air temperature from 1 July until the fall sowing date. The relationships were obtained by regression analysis from the 1998 to 2001 rye field study at the SWROC (Strock et al., 2004). The equations for the surface soil layer (0–30 cm deep), Soil Layer 2 (30–120 cm deep), and Soil Layer 3 (120–165 cm deep) are as follows:

$$\theta_{Surf_{init}} = 0.315 - 0.0221\text{J1T}_{ave} + 0.0019\text{J1cumPrecip} \quad [7]$$

$$\theta_{Layer2_{init}} = 0.23 - 0.00201\text{J1T}_{ave} + 0.000173\text{J1cumPrecip} \quad [8]$$

$$\theta_{Layer3_{init}} = 0.29 - 0.00602\text{J1T}_{ave} + 0.000518\text{J1cumPrecip} \quad [9]$$

where $\theta_{Surf_{init}}$, $\theta_{Layer2_{init}}$, and $\theta_{Layer3_{init}}$ are initial SMCs of the surface layer, Soil Layer 2, and Soil Layer 3, respectively, J1T_{ave} is average air temperature from 1 July, and J1cumPrecip is cumulative precipitation from 1 July. The minimum value permitted for the initial SMC is the wilting point. The maximum value permitted for the initial SMC is field capacity, except for the case of Soil Layer 3, which has a maximum value of 0.95 times field capacity.

Initial Residual Soil Nitrate

The initial residual soil NO_3^- (RSN_{init}) in each of the three soil layers is also determined at the time of rye sowing. The equations for RSN_{init} are based on regression analysis of field data collected on the experimental plots at the SWROC for the 9-yr period from 1988 to 1996 and reported by Randall et al. (1997) and Huggins et al. (2001). The RSN_{init} values were measured, in the above studies, in the autumn following corn harvest in a corn–soybean rotation. Several regression models were tested with combinations of parameters including current, previous, and second-previous season precipitation as measured during the growing season, hydrologic year, or calendar year. The relationships that produced the best correlations were those that calculated RSN_{init} as a function of the previous year's annual precipitation and the second-previous growing season precipitation. The equations used in the model are as follows:

$$RSN_{SurfaceLayer\ init} = 84.2 - 0.05886\text{PrevAnPrecip} - 0.03546\text{Prev2GSPrecip} \quad [10]$$

$$RSN_{Layer2\ init} = 222 - 0.1623\text{PrevAnPrecip} - 0.1081\text{Prev2GSPrecip} \quad [11]$$

$$RSN_{Layer3\ init} = 57.0 - 0.0342\text{PrevAnPrecip} - 0.0317\text{Prev2GSPrecip} \quad [12]$$

where PrevAnPrecip is the cumulative annual precipitation, and Prev2GSPrecip is the cumulative precipitation during the growing season of the second-previous year, measured from 15 April to 1 October. The multiple coefficients of determination, R^2, for the three relationships are 0.49, 0.69, and 0.66, respectively.

Climate Inputs

The RyeGro model was prepared to be executed for hundreds of simulation years by stochastically generating weather inputs having the same statistical characteristics as the much shorter actual climate record. An initial simulation with one planting date was run for 5500 yr to evaluate the stability of the statistics of the meteorological variables. From the initial run, it was determined that the statistics were stable after 2500 yr and therefore the simulation runs with the various planting dates were conducted for 2500 yr.

Sensitivity Analysis

The purpose of a sensitivity analysis is to identify model parameters that have the greatest influence on model results (Hamby, 1994). Sensitivity is determined by identifying calibrated base values for a set of input parameters, then perturbing the inputs and comparing the change in the model output of interest to the change in model input parameter. An initial local sensitivity analysis was performed for 24 RyeGro input parameters on the cumulative subsurface drainage NO_3–N loss output for the 1998 to 1999 calibration year. Relative sensitivity coefficients, S_r, were calculated using the technique documented by Haan (2002):

$$S_r \cong \frac{(O_{P+\Delta P} - O_{P-\Delta P})}{O} \Big/ (2\Delta P/P) \qquad [13]$$

where O is the model output (cumulative subsurface drainage NO_3–N loss, in this case) with input parameters set at base values, $O_{P+\Delta P}$ and $O_{P-\Delta P}$ are model outputs with the input parameter being studied set at a value equal to the base value plus or minus a specified percentage (often taken to be in the range of 10–25%), P is the initial value of the input parameter, and ΔP represents the prescribed absolute change in the value of the input parameter. Relative sensitivity coefficients are unitless and therefore can be used to compare sensitivities among parameters (Haan, 2002). Negative values indicate that a change to an input parameter results in a change of opposite direction to the output value. The division of parameters into various degrees of sensitivity is subjective. For example, Haan and Skaggs (2003a) considered hydrologic parameters with absolute values for S_r of >0.15 and N cycle parameters with absolute values for S_r of >0.20 (Haan and Skaggs, 2003b) to be sensitive and warranting additional uncertainty analysis. We chose to perform additional analysis on 14 RyeGro input parameters for which $|S_r| > 0.20$ for the 1998 to 1999 calibration year. Simulations were performed on these 14 parameters for the 2000 to 2001 calibration year. The S_r values presented below represent the average values for the 2 yr.

Simulation Modeling Methodology

Two field treatments were simulated: the first was corn–fallow–soybean and the second was corn–winter rye–soybean. Four fall sowing dates were selected for study to analyze the influence of sowing date on rye biomass accumulation and subsurface drainage N losses in the spring: 15 September and 1, 15, and 30 October. Each simulation run was executed until 30 May, at which time the rye crop growth was assumed to be stopped either by chemical desiccation or by mechanical means. The end date of the simulation was set at the end of May for two reasons. First, the rye treatment is not intended to interfere with the yield of the subsequent summer crop. Extending the period of rye growth into June would interfere with timely planting of the subsequent soybean crop. Second, there is an increasing probability that certain assumptions made in the development of RyeGro would be violated, such as the assumption of no soil moisture upward flux. Estimates of rye biomass accumulation and subsurface drainage losses were recorded at several dates during the simulation runs: 1 December, 1 January, 1 February, 1 March, 1 and 15 April, and 1, 15, and 30 May.

Two simulations were performed with each of the 2500-yr simulation input variables: one with and one without the rye crop grown between the corn and soybean crops. Thus, the stochastic inputs were identical for each year's dual simulation.

RESULTS

Meteorological Variable Outputs

Statistics for the meteorological variables generated for the long-term simulations—precipitation, maximum and minimum air temperatures, and solar radiation—are shown in Table 3. Some differences between the generated variables and the values measured at Lamberton were expected because the wet–dry transitional probabilities, standard deviations, and skewness coefficients for the generated variables were based on the weather record at Sioux Falls. The generated annual precipitation values were 1.9% higher than the 43-yr mean measured at Lamberton, although the number of wet days estimated was slightly less than measured, 87.2 vs. 88.0. The transitional probabilities used to predict days with or without precipitation were those from the long-term record at Sioux Falls. Since Sioux Falls is slightly drier and has fewer wet days than Lamberton, it is reasonable to expect underprediction of wet days.

Table 3. Comparison of 43 yr of measured weather variables from Lamberton, MN, and 5500 yr of generated weather outputs used in model simulations.

Weather variable	Measured mean (SD)	Simulation mean (SD)
Annual precipitation, mm	668.4	681.1
Mean daily precipitation, mm	1.83 (6.15)	1.87 (6.46)
Skewness coefficient daily precipitation	6.39	6.81
Annual wet days	88.0	87.2
Air temperature max., °C	13.18 (13.8)	13.23 (12.9)
Air temperature min., °C	0.81 (12.5)	0.82 (7.8)
Solar radiation, MJ m^{-2} d^{-1}	13.94	14.47 (7.74)

The shortwave solar radiation prediction was 14.47 MJ m^{-2} d^{-1}, or 3.8% higher than the mean solar radiation from the 24-yr record at Lamberton. Sioux Falls has more clear sky throughout the year than does Lamberton, thus the slightly higher value of predicted vs. measured solar radiation seems reasonable.

Sensitivity Analysis

Table 4 contains a list of the 14 input parameters that were tested for sensitivity to cumulative subsurface drainage output, along with the base values of the parameters and their S_r values. The S_r values are ranked by absolute value; the greatest is for the field capacity SMC of Soil Layer 2, at −1.55, and the smallest is for the RSN of the surface soil layer, at −0.12. Five of the six most sensitive parameters are related to soil water content. Three of the

Table 4. Relative sensitivity coefficients, S_r, for 14 RyeGro input parameters.

Parameter	Parameter base value, P	S_r
Field capacity soil moisture content, Soil Layer 2, cm^3 cm^{-3}	0.308	−1.55
Saturation soil moisture content, Soil Layer 3, cm^3 cm^{-3}	0.400	−1.39
Initial soil moisture content, Soil Layer 3, cm^3 cm^{-3}	0.29	0.92
Initial soil moisture content, Soil Layer 2, cm^3 cm^{-3}	0.23	0.88
Residual soil N, Soil Layer 2, kg N ha^{-1}	50.9	0.70
Field capacity soil moisture content, surface layer, cm^3 cm^{-3}	0.320	−0.53
Radiation use efficiency, kg dry matter ha^{-1} MJ^{-1} m^{-2}	2.8	−0.48
Maximum leaf area index, m^2 m^{-2}	7	−0.47
Initial soil moisture content, surface layer, cm^3 cm^{-3}	0.32	0.39
Saturation soil moisture content, surface layer, cm^3 cm^{-3}	0.526	0.36
Initial aboveground shoot biomass, kg dry matter ha^{-1}	30	0.23
Saturated hydraulic conductivity, Soil Layer 3, cm h^{-1}	0.0006	0.20
Mineralization potential, %	20	−0.16
Residual soil N, surface layer, kg N ha^{-1}	15.0	−0.12

five include parameters that affect the available water capacity of the three soil layers. The other two parameters are the initial SMCs of Soil Layer 3 and Soil Layer 2. Since RyeGro's hydrology model is based on the simple representation of the soil as three layers, it can be expected that the subsurface drainage response, which is simulated from Soil Layer 2 when the SMC exceeds the field capacity SMC, will be sensitive to both the available water content and the initial values for the moisture content in these layers. Three N cycling parameters were tested: the RSN of Soil Layer 2, the mineralization potential of the soil organic matter content, and the RSN of the surface soil layer. These parameters were ranked 5th, 13th, and 14th in sensitivity. The three plant-related parameters included in the analysis: radiation use efficiency, maximum leaf area index, and initial aboveground shoot biomass, were ranked 7th, 8th, and 11th in sensitivity. Thus, the hydrologic parameters are more influential in the prediction of cumulative subsurface drainage NO_3–N losses than are either the N cycling or plant growth parameters. Knowing which parameters are most sensitive provides the model user guidance as to which parameters require careful selection when setting up a simulation scenario.

Initial Residual Soil Nitrate and Soil Moisture Content

The mean value of the initial residual soil NO_3^- in the three soil layers on the fall rye sowing date was calculated as 108 kg N ha^{-1} (SD of 36 kg N ha^{-1}), which is slightly lower than an estimate of 123 kg N ha^{-1} expected in the ground to a depth of 1.5 m after the corn portion of a corn–soybean crop rotation in southwestern Minnesota (G. Randall, personal communication, 2004).

The mean values of the predicted SMC in the three soil layers were 9.2, 11.2, 12.5, and 13.7 cm for the 15 September and 1, 15, and 30 October sowing dates, respectively. The long-term, observed mean values at the SWROC under continuous corn to a depth of 1.5 m for the same sowing dates were 10.9, 10.9, 11.4, and 12.2 cm, respectively. The predicted values are comparable to the measured values for the 1 October and 15 October sowing dates. Soil moisture was underestimated on average by 1.7 cm for the 15 September sowing date and overpredicted by 1.7 cm for the 30 October sowing date. The predicted initial soil moisture contents follow the expected trend of a wetter soil profile toward the end of autumn.

Rye Aboveground Biomass Accumulation

The mean estimate of aboveground biomass production on a dry matter basis as a function of fall sowing date is shown in Fig. 2. In terms of growth relative to sowing date, the model predicts that, until the first week of May, rye planted in mid-September will produce twice as much aboveground biomass as rye planted in October. In May, the late-planted rye eventually develops a complete canopy and is able to convert intercepted solar energy to biomass at the same rate as the earliest planted rye; however, the difference in cumulative biomass due to planting date is not overcome. The consequences of lower cumulative biomass production are lower NO_3–N uptake and hence less reduction in NO_3–N subsurface drainage loss due to the scavenging effect of the growing rye crop.

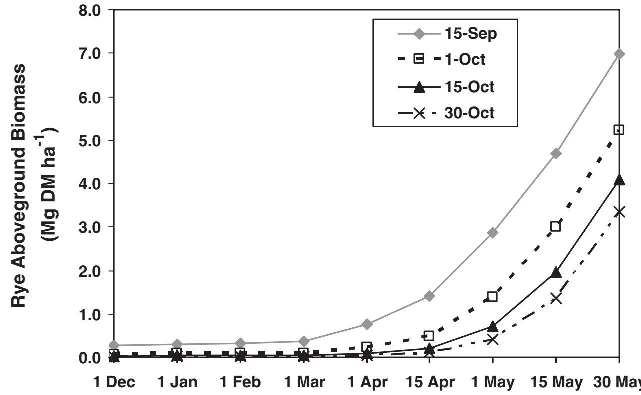

Fig. 2. Cumulative rye aboveground biomass (DM, dry matter) for four fall sowing dates; the data represent mean values after 2500 simulation years.

Rye growth is highly variable, depending on soil and climate conditions in the fall, winter, and spring. The weather generator provided a means by which rye growth could be predicted given numerous patterns of weather. The estimated variability of biomass production is shown in Table 5.

Artificial Subsurface Drainage Nitrate-Nitrogen Losses

The long-term simulation results quantify the mean reduction in NO_3–N losses at the field scale through artificial subsurface drainage systems due to N uptake and reduction in drainage volume due to a growing rye cover crop. The model predicted a mean value of 25 kg N ha^{-1} for drainage NO_3–N losses for the mid-September through May time frame without a growing rye crop. Figure 3 illustrates the mean drainage NO_3–N losses of treatments with and without a rye cover crop for four fall planting dates. The mid-September sowing effects a mean reduction in NO_3–N losses of 11 kg N ha^{-1} by the end of May, more than twice that predicted when the rye was planted at the end of October. The simulation outcomes for the four sowing dates are presented as a percentage reduction in NO_3–N losses in Fig. 4.

Average subsurface drainage NO_3–N losses from 15 September to 30 May were predicted to be 24.9 kg N ha^{-1} for a standard corn–soybean rotation (Fig. 3). Inclusion of a rye cover crop sown on 15 September reduced the

Table 5. Means and standard deviations of aboveground biomass production for 2500 simulation years for four fall planting dates.

Sowing date	Biomass production			
	15 Apr.	1 May	15 May	30 May
	Mg dry matter ha^{-1}			
15 Sept.	1.4 (0.7)	2.9 (0.9)	4.7 (1.1)	7.0 (1.2)
1 Oct.	0.5 (0.3)	1.4 (0.7)	3.0 (0.9)	5.2 (1.0)
15 Oct.	0.2 (0.1)	0.7 (0.4)	2.0 (0.7)	4.1 (0.9)
30 Oct.	0.1 (0.1)	0.4 (0.3)	1.4 (0.6)	3.3 (0.9)

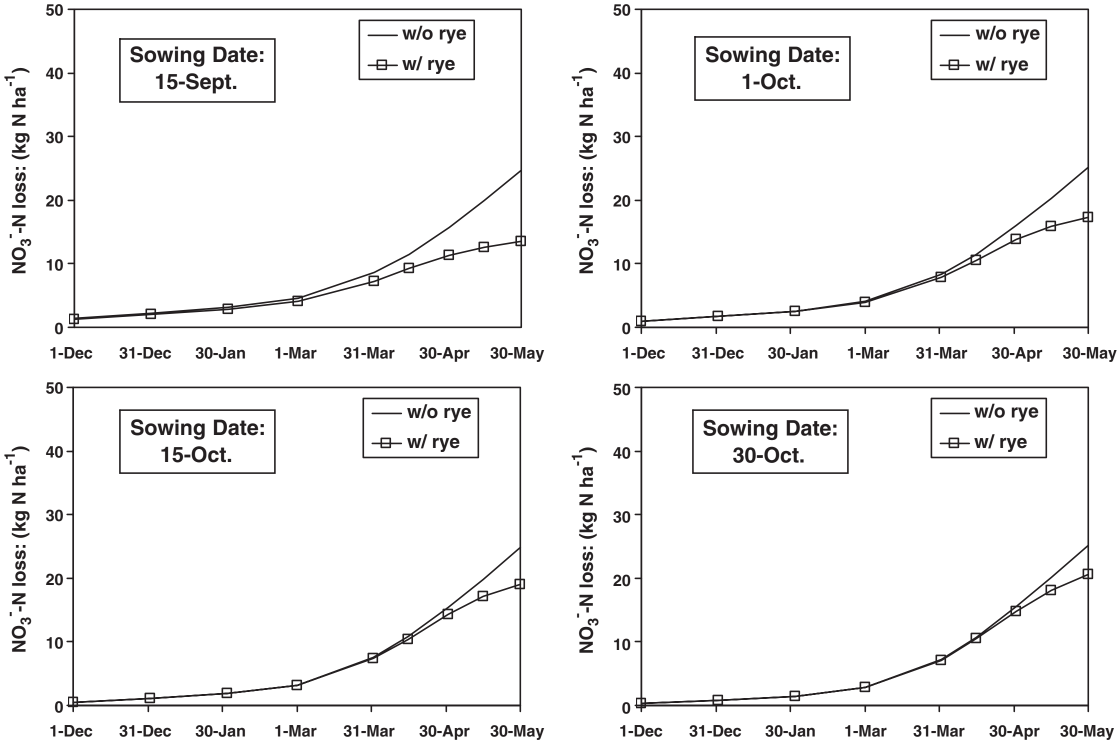

Fig. 3. Predicted cumulative subsurface NO_3–N losses for corn–soybean and corn–rye–soybean treatments for four fall rye sowing dates.

losses by 11.1 kg N ha^{-1} or 45%. Fall sowing dates of 1, 15, and 30 October resulted in reductions of 7.8, 5.8, and 4.6 kg N ha^{-1}, respectively, by the end of May. Desiccation of the rye on 1 May resulted in reductions of 4.5, 2.2, 1.2 and 0.7 kg N ha^{-1}, for the 15 September, and 1, 15, and 30 October sowing dates, respectively (Fig. 3).

The calculation of drainage N losses terminated each year at the end of May. No attempt was made to analyze the effects of the rye cover crop on drainage volume after desiccation of the rye. Conceivably the rye would reduce available soil water and thus reduce drainage volume and subsequent N losses both while growing and for some period of time after having been killed.

The exceedance probabilities for the difference in NO_3–N drainage losses given the four fall sowing dates

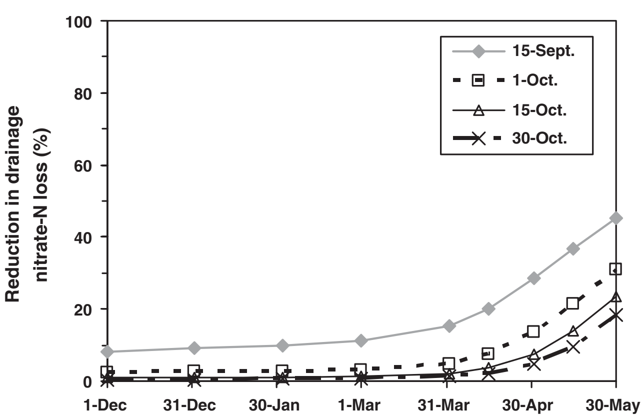

Fig. 4. Reduction in subsurface drainage NO_3–N losses for the corn–rye–soybean treatment compared with the corn–soybean treatment for four different planting dates.

and four spring kill dates under investigation are depicted in Fig. 5. The values for the reductions or changes in NO_3–N losses at 50% exceedance probability correspond to the differences between average values for the NO_3–N losses with and without rye shown in Fig. 3. The set of graphs clearly shows the influence of early sowing dates and later kill dates on NO_3–N reductions due to a rye cover crop. As the rye is sown later, the curve for the 30 May kill date shows increased separation from the curves for the other kill dates, indicating that to effect more than modest reductions in NO_3–N losses, the rye must be permitted to grow until late May.

Figure 6 combines on one graph the exceedance probabilities for one spring kill date, 30 May, given the four sowing dates. Just as the plots of cumulative aboveground biomass and exceedance probabilities of changes in NO_3–N loss indicated separation between values for the 15 September sowing date and the 1, 15, and 30 October sowing dates, the graphs of exceedance probability evidence the marked reduction in NO_3–N losses when the rye was sown in mid-September.

In 3 yr out of 4 (exceedance probability = 75%), rye effected reductions in drainage NO_3–N loss from 2.6 to 7.0 kg N ha^{-1} through 30 May for fall rye sowing dates from 15 September through 30 October. In 1 yr in 4, drainage N loss reductions ranged from 6.2 to 14.8 kg N ha^{-1} for the same sowing dates, and for 1 yr in 10, from 8.3 to 19.1 kg N ha^{-1}.

Under favorable climatic conditions for cover crop growth, growing fall-sown rye after corn in the corn–soybean crop rotation can make a substantial difference in the amount of NO_3–N leaving the field via subsurface drainage systems. On the other hand, there are years

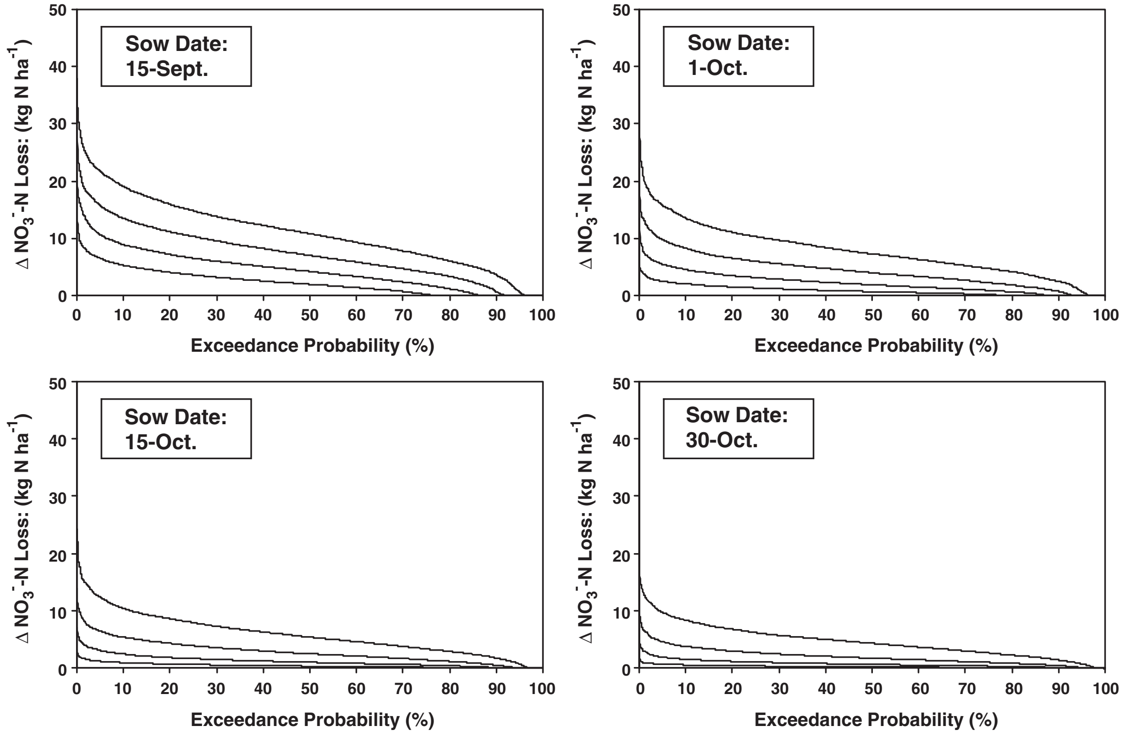

Fig. 5. Exceedance probability of the difference in subsurface drainage NO_3–N losses between the corn–soybean and corn–rye–soybean treatments for four spring dates and four different fall sowing dates. The four curves in each graph display results for the four spring kill dates: 30 May, 15 May, 1 May, and 15 April (top to bottom).

during which the use of fall-sown rye makes no difference in drainage system effluent losses (Fig. 7). During years when the drainage volume was estimated to be zero, growing rye made no difference in NO_3–N losses. Figure 7 shows the percentage of years during which there were no drainage N losses for treatments with and without rye, given a planting date of 1 October.

DISCUSSION

Seasonal crop production constraints in Minnesota make the use of winter cover crops challenging. A winter rye crop can be expected to reduce subsurface drainage losses of NO_3–N an average of 2.8 kg N ha^{-1}, or 11%, if planted on 15 October and desiccated on 15 May. Over the long term, farm operations now using the current standard field corn–soybean crop rotation, with a typical October corn harvest and mid-May soybean planting date, will realize a minimal benefit in reduction of off-field transport of N through subsurface drainage systems by the conventional use of a fall-planted cover crop; however, creative planting solutions of rye before summer crop harvest, for example aerial seeding when soil moisture conditions are conducive to germination, and of soybean into standing rye before chemical desiccation or shredding of the rye in spring, have the potential to

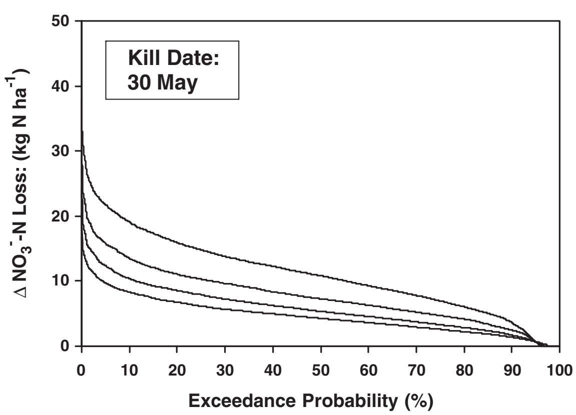

Fig. 6. Exceedance probability of the difference in subsurface drainage NO_3–N losses between the corn–soybean and corn–rye–soybean treatments on 30 May given four different sowing dates. The four curves display results for the four sowing dates: 15 September and 1, 15, and 30 October (top to bottom).

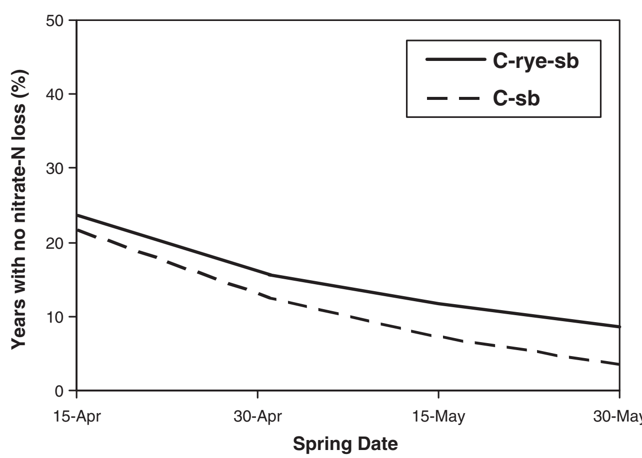

Fig. 7. Percentage of years having no NO_3–N drainage losses through the spring date shown on the *x* axis, given a rye sowing date of 1 October. C-rye-sb = corn–rye–soybean; C-sb = corn–soybean.

extend the N reduction benefits of cover crops within the confines of the current corn–soybean crop rotation.

Cover cropping practice offers promising opportunities for reductions in N losses for cropping rotations wherein the primary crops are harvested before mid-September and planted after mid-May. A winter rye crop can be expected to reduce drainage NO_3–N losses on average 7.4 kg N ha^{-1} if planted on 15 September and desiccated 15 May, and on average 11.1 kg N ha^{-1} if desiccated 30 May (Fig. 3). The obvious conclusion is that early autumn sowing of the cover crop substantially reduces drainage NO_3–N losses. Also, the longer the cover crop is allowed to grow in the spring, the greater the reduction in N losses.

Although the routine, conventional use of cover crops in the standard corn–soybean rotation appears to provide a small benefit in off-field export of N, strategic use of cover crops could provide important N scavenging services when climatic and soil conditions favor high spring drainage losses. Research in Minnesota has shown that RSN levels rise in dry years, setting the stage for large NO_3–N losses in wet years (Randall, 1998; Strock et al., 2004). Since crops are often harvested early during the drier years, cover crops could be planted early in an effort to scavenge N that is positioned for spring loss. In this case, the cover crop would need to be managed in the spring, given the climatic conditions at the time, to avoid loss of soil moisture needed by the subsequent summer crop.

In support of the research objectives, the soil–plant–atmosphere model RyeGro was developed as an analysis tool for investigation of the water quality effects of a winter rye cover cropping practice in the northern Corn Belt. RyeGro uses a relatively simple and approximate approach to represent key physical biogeochemical processes. The level of model complexity was appropriate for providing estimates of approximately ±20% for subsurface drainage N losses, given the existence of spatial variability in soil properties and real-world field variables such as snow accumulation, drifting, and thawing, soil freezing and thawing, and the extent and effects of soil macropores. The modeling approach suitably fit the field input data, which were limited in scope.

The use of a stochastic climate generator was an effective method for estimating the probabilities of subsurface N loss reduction by a winter rye cover crop. Weather variables generated through the summer months during each simulation year were used to reestablish fall initial soil moisture and residual soil NO_3^- values, key components to predicting rye establishment and spring drainage N losses, respectively. The continuous generation of weather variables maintained realistic probabilities for the values of the initial variables each year. The use of a centuries-long generated climate record provided the range of climate conditions possible for cover crop establishment and growth and reduced the variation about the model's mean predictions. Thus, the stochastic weather generator contributed to meeting the research objective of determining the influence of climate on the efficacy of the winter rye cover cropping practice.

The objective that the model be user friendly was achieved. Once the relationships were established in the various model components, calibration and operation of the model were performed with a modest investment of time and effort. The use of the model in another location will require basic soil property inputs, data from which fall initial soil moisture content–RSN–climate relationships can be determined, data from which drainage event flow decay rate can be obtained, and climate inputs.

Estimates of plant N uptake and determination of spring soil thaw and subsequent first drainage events were two model outcomes that require more detailed, mechanistic representation of relevant processes to improve their predicted accuracies. By design, the N uptake curve in RyeGro represents an average value derived from a scatter of field measurements. More accurate prediction of plant N uptake would require determination of the causes of seasonal variations in uptake and development of algorithms to better represent the processes involved. The processes of soil freezing and thawing have been represented in existing models to a higher level of detail than in RyeGro. Even with additional complexity, however, the modeling of spring thaw drainage events is challenging (Sands et al., 2003) and more detailed snow–freeze–thaw algorithms are still being sought for agronomic systems models (Malone et al., 2004).

SUMMARY AND CONCLUSIONS

The objectives of this research were to investigate the influences of fall planting date and climate on rye biomass yield and N uptake in the spring and to assess the probability that a fall-planted cereal rye reduces NO_3–N loss through artificial subsurface drainage systems in southern Minnesota. Computer simulation modeling was used to predict rye cover crop establishment and growth, soil water balance, N cycling, and drainage NO_3–N losses from mid-September through May. A soil–plant–atmosphere model, RyeGro, was developed for the analysis. A stochastic weather generator imbedded in RyeGro estimated the necessary climate variables to carry out the probabilistic analysis for 2500 simulation years (Feyereisen, 2005), thus providing an opportunity to investigate outcomes across the broad range of climatic conditions experienced in this geographic region.

We conclude that the simulation techniques used by this research provide reasonable insight into the effect of autumn planting date of a rye cover crop on subsurface drainage NO_3–N losses. To reduce average field NO_3–N losses by >11%, the cover crop will need to be planted before 15 October and permitted to grow until 15 May. Reduction in average field NO_3–N losses of 30% or more are possible if the cover crop is planted 15 September and permitted to grow until 30 April, or is planted 1 October and grown until 30 May. Used in an appropriate cropping system and managed properly, cover crops in southwestern Minnesota offer promise to reduce field losses of NO_3–N through artificial subsurface drainage systems.

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