Simulating the Long-Term Performance of Drainage Water Management Across the Midwestern United States

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Abstract. *Drainage water management (DWM) has been proposed as a solution to reduce losses of nitrate (NO_3) from subsurface drainage systems in the midwestern U.S.; however, tests of DWM efficacy have only been performed over short time periods and at a limited number of sites. To fill this gap, the RZWQM-DSSAT hybrid model, previously evaluated for a subsurface-drained agricultural system in Iowa, was used to simulate both conventional drainage (CVD) and DWM over 25 years of historical weather at 48 locations across the midwestern U.S. Model simulations were used to demonstrate how variability in both climate and management practices across the region affects the ability of DWM to reduce losses of NO_3 in subsurface drainage. The regional average simulated reduction in drain flow was 151 mm yr^{-1} when using DWM instead of CVD, and the regional percent reduction over the long term was 53%. Reductions in drain flow were offset mainly by increases in surface runoff and evapotranspiration. Similarly for nitrogen (N), the regional average simulated reduction in NO_3 losses through subsurface drains was 18.9 kg N ha^{-1} yr^{-1}, and the regional percent reduction over the long term was 51%. Subsurface drain NO_3 loss reductions were counterbalanced mainly by increases in stored soil N, denitrification, and plant N uptake. The simulations suggest that if DWM can be practically implemented throughout the region, particularly in the southern states, then substantial reductions in the amount of NO_3 entering surface waters from agricultural systems can be expected.*

Keywords. *Controlled drainage, Drainage, Drainage water management, DSSAT, Midwest, Nitrate, RZWQM, Simulation.*

In the mid-nineteenth century, agriculturalists began to use artificial subsurface drainage systems to remove excess water from the prairie wetlands and swamps in the midwestern U.S., an endeavor that would eventually help to transform the region into one of the most productive agricultural sectors in the world (Urban, 2005). Today, artificial subsurface drainage systems continue to play an integral role for agriculture across the region by serving as a short-circuit route for transport of excess soil water to nearby surface water bodies. However, in spite of the vast increases in productivity that agricultural drainage has allowed over the past 150 years, the practice has more recently been scrutinized for its contribution to surface water quality problems. Of particular concern is excessive transport of nitrate (NO_3), an essential plant nutrient, from the soil matrix of agricultural fields to surface water bodies through artificial subsurface drainage systems (Jackson et al., 1973; Baker and Johnson, 1981; Cambardella et al., 1999; Jaynes et al., 2001). Excessive levels of NO_3 in water bodies have had ecologic and economic impacts throughout the drainage basin of the Mississippi River. Eutrophication of surface waters caused by algae growth responses to increased concentrations of NO_3 has been noted (Randall and Mulla, 2001), and the city of Des Moines, Iowa, has spent millions of dollars to build a facility for removal of NO_3 from drinking water when the public health limit of 10 mg N L^{-1} is exceeded (Keeney and DeLuca, 1993). Excess NO_3 in water bodies has caused negative impacts as far south as the Gulf of Mexico, where hypoxia threatens commercial and recreational fisheries. This effect has been linked directly to NO_3 transport down the Mississippi River from regions associated with midwestern corn and soybean production (Burkart and James, 1999; Goolsby et al., 2001).

Input pathways of nitrogen (N) to the soil systems of the region typically include application of synthetic N fertilizers or animal manure for corn *(Zea mays* L.) crops, return of N with crop residues, N fixation by leguminous soybean (*Glycine max* (L.) Merr) crops, and N deposition from precipitation. Soils of the region also have relatively high organic matter contents, meaning a large supply of N is naturally stored within the organic components of the soil system. Through the microbial reactions of mineralization and immobilization, N is transferred between organic forms and the inorganic ammonium (NH_4) form of N. Under typical soil conditions, NH_4 is readily converted to NO_3 through the microbial reaction of nitrification. Of all the forms of N in the soil, NO_3 is the most troublesome due to the high solubility of the NO_3 molecule in water. As a result of this physical characteristic, NO_3 transport out of an agricultural system is related to the pathways of water flow out of the system, including surface runoff, lateral and deep seepage, and artificial subsurface drainage (Jackson et al., 1973; Schuman et al., 1973; Burwell et al., 1976; Baker and Johnson, 1981;

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Spalding and Exner, 1993; Cambardella et al., 1999; Jaynes et al., 2001).

Drainage water management (DWM), or controlled drainage, is one of many strategies that have been proposed to curtail the excessive losses of NO_3 from agricultural systems in the midwestern U.S. (Evans et al., 1995; Fausey et al., 1995; Dinnes et al., 2002; Frankenberger et al., 2006). The practice utilizes a control structure at the end of subsurface drainage lines to vary the depth of the drainage outlet. With proper seasonal head gate adjustments, DWM has been shown to greatly reduce the mass of NO_3 leaving agricultural systems through subsurface drainage systems, a result attributed mainly to the overall decrease in flow volume from the drains (Gilliam et al., 1979; Gilliam and Skaggs, 1986). In a DWM demonstration project in Illinois, Pitts et al. (2004) reported a 40% reduction in NO_3 losses through subsurface drainage lines as a result of using DWM. On a silty clay loam soil in Ohio, Fausey (2004) found that DWM reduced subsurface drain flow by 40% and NO_3 losses were reduced by more than 45%. Similar studies in North Carolina (Dukes et al., 2003) and in other countries around the world (Lalonde et al., 1996; Wahba et al., 2001; Wesstrom et al., 2001) have also determined that DWM can greatly reduce the amount of NO_3 lost though subsurface drainage lines.

The ability of DWM to reduce drain flow and NO_3 losses through subsurface drainage systems varies greatly depending on soil type, climate, drainage system design, and management depth and intensity (Evans et al., 1995), and information regarding the performance of DWM has only been collected on a short-term basis for a limited number of sites and conditions. Agricultural systems models offer the potential to rapidly test the performance of DWM for multiple locations and over many seasons of historical weather. Skaggs et al. (1995) and Breve et al. (1998) demonstrated the use of DRAINMOD to simulate the long-term effects of drainage system design and management on crop production and losses of NO_3 from subsurface drains in North Carolina cornfields. Similarly, Ma et al. (2007) demonstrated the use of the Root Zone Water Quality Model (RZWQM) for simulating long-term DWM at a research farm in Nashua, Iowa. Simulation results showed that DWM could reduce drain flow and NO_3 losses from subsurface drains by 30% at the Iowa site. Agricultural systems models are also useful for closing the mass balances of agricultural systems and providing estimates for water and N movement through pathways that are more difficult to measure. This type of assessment is especially important for DWM, because the practice can drastically alter the flow of water and N through the agricultural system. For example, Ale et al. (2006) used DRAINMOD to simulate the effects of DWM on the hydrologic balance of an agricultural system in Indiana. Although their simulations showed a 25% reduction in drain flow using DWM, the model estimated a 37% increase in water lost as runoff.

The Agricultural Drainage Management Systems (ADMS) Task Force has recently been established to research, implement, and promote the use of improved agricultural drainage systems for decreasing NO_3 losses from agricultural fields and reducing hypoxia in the Gulf of Mexico (Jacobsen, 2005). Representatives from land grant universities, the USDA Agricultural Research Service (ARS), the USDA Natural Resources Conservation Service (NRCS), the Cooperative State Research, Education, and Extension Service (CSREES), and the drainage industry have united to solve these important problems. Initially, the Task Force has chosen to focus its efforts in eight states of the U.S. Midwest: Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri, Ohio, and Wisconsin. Variability in climatic conditions across these states is expected to affect the performance of DWM, and the use of DWM may be more effective in some areas of the region as compared to others. Characterizing the effectiveness of DWM across the region would help the ADMS Task Force target its efforts and resources to the most optimum locations. Thus, the main objective of this study was to apply the RZWQM-DSSAT hybrid model (Ma et al., 2005; Ma et al., 2006) to simulate both conventional drainage (CVD) and DWM in response to 25 years of historical climate information at 48 sites across the midwestern U.S. Comparisons of simulation output for the two drainage management strategies were used to characterize the effects of DWM on the hydrologic and N cycles at each site and to assess the relative performance of DWM in response to climate variability and management considerations across the region.

Materials and Methods

RZWQM-DSSAT Hybrid Model

RZWQM is a one-dimensional, field-scale agricultural systems model that can be used to simulate on a unit area basis the physical, chemical, and biological processes that govern movement of water, nutrients, and pesticides and growth of crops at a representative point in the field (Hanson et al., 1998; Ahuja et al., 2000a). A soil profile having up to ten distinct horizons can be simulated, and a modified Brooks and Corey (1964) approach is used to describe the soil water retention and hydraulic conductivity relationships in each horizon. Infiltration of water into the soil profile is computed using a modified Green and Ampt (1911) equation, and redistribution of water within the soil profile is simulated using a mass-conservative numerical solution of the Richards equation. Precipitation and irrigation water in excess of the infiltration rate enters macropores, if present. Any excess water remaining after macropore infiltration is considered runoff (Ahuja et al., 2000b). Routines for simulating subsurface drainage and fluctuating water tables (Johnsen et al., 1995; Singh et al., 1996) and for simulating drainage water management (Ma et al., 2007) are also incorporated in the model. Transfer of chemicals to runoff water is simulated using a non-uniform mixing approach. Transport of chemicals through the soil matrix during infiltration is achieved using sequential partial piston displacement and mixing, applied at 1 cm depth increments. Larger increments are used to compute chemical transport during redistribution (Ahuja et al., 2000b). During the chemical transport simulation, NO_3 moves through the soil profile as a non-adsorbing, conservative chemical, since reactive nutrient processes are simulated separately on a different time step. The concentration of NO_3 in subsurface drainage water is estimated as a function of its concentration in saturated soil layers (Kumar et al., 1998). Potential evapotranspiration (ET) is simulated in RZWQM using the Shuttleworth-Wallace double-layer form of the original Penman-Montieth ET model (Farahani and DeCoursey, 2000), incorporating the modifications of Farahani and Ahuja (1996). In addition to computing transpiration from the plant canopy, the model also partitions the soil surface into bare soil and residue-covered fractions and explicitly computes evaporation from each.

The comprehensive nutrient component in RZWQM includes two residue pools, three organic matter pools, and three microbial pools for simulating the dynamics of carbon and nitrogen within the soil system. Inorganic nitrogen is also simulated in NH_4 and NO_3 pools. Given initial conditions for each pool, the model simulates the processes of mineralization, immobilization, nitrification, denitrification, volatilization, urea hydrolysis, methane production, organic matter decay, and microbial growth and decay. Reaction rates are determined by microbial population, efficiency factors, and soil properties, including pH, O_2 content, temperature, water content, and ion strength (Shaffer et al., 2000). The model also simulates soil chemistry processes, pesticide processes, soil heat transport, snowpack dynamics, surface plant residue dynamics, and the effect of management practices on the agricultural system. Simulated management practices include tillage, applications of manure, fertilizer, and pesticide, planting and harvesting operations, and irrigation (Ahuja et al., 2000a).

Originally, a generic plant growth model was incorporated into RZWQM (Hanson, 2000); however, recent efforts have aimed to replace the RZWQM plant growth model with components from the Decision Support System for Agrotechnology Transfer (DSSAT) family of crop growth models (Jones et al., 2003), including CERES-Maize (Ma et al., 2006) and CROPGRO-Soybean (Ma et al., 2005). These models were used because they have the ability to simulate leaf number, phenological development, and other yield components that were not simulated with the original RZWQM plant growth model. RZWQM supplies the CERES or CROPGRO model with weather information, soil water and N contents, soil temperature, and potential ET. The crop growth model then returns simulated results for plant uptake of water and N and other plant growth variables, such as leaf area index and yield, to RZWQM.

Both RZWQM and DSSAT are well-known and widely used around the world. Specifically for agricultural systems in the midwestern U.S., RZWQM has undergone extensive evaluations as a part of the USDA-ARS Management Systems Evaluation Areas (MSEA) project (Watts et al., 1999). Under this project, model evaluations were performed throughout the midwestern U.S. for agricultural systems in Minnesota (Wu et al., 1999), Missouri (Ghidey et al., 1999), Iowa (Jaynes and Miller, 1999), Nebraska (Martin and Watts, 1999), and Ohio (Landa et al., 1999). RZWQM has also been widely applied to study how NO_3 is lost from subsurface drainage systems in the Midwest, particularly in Iowa (Kumar et al., 1998; Bakhsh et al., 2001; Bakhsh et al., 2004). The CERES-Maize crop model within DSSAT has been rigorously applied to study Midwest corn production in the work of Hodges et al. (1987), and more recently the model has been used to study site-specific crop development and to formulate N fertilizer prescriptions for corn (Paz et al., 1999; Thorp et al., 2006). CROPGRO-Soybean has also been developed (Pedersen et al., 2004) and evaluated (Sexton et al., 1998) for simulating soybean growth in the Midwest, and the model has been used to understand water stress effects on observed spatial yield variability (Paz et al., 1998) and to study site-specific soybean variety management (Paz et al., 2003). The RZWQM-DSSAT hybrid model has been previously evaluated and applied for agricultural systems in the Midwest in the work of Thorp et al. (2007) and Saseendran et al. (2007).

DWM Simulation Strategy

Our simulation study focused only on DWM performance variability that was due to regional differences in climate, crop planting and harvest dates, and N fertilizer application rates across the midwestern U.S. Other factors that may contribute to variability in DWM performance across the region, such as soil type and topography, were not considered because a calibrated model for soils across the region is not yet available. Historical climate information for long-term simulations of DWM was obtained from the National Solar Radiation Data Base (NREL, 1995), also known as the Solar and Meteorological Observation Network (SAMSON) database. The database contains a complete 30-year, quality-controlled hourly solar radiation record along with many other meteorological variables for the period from 1961 to 1990. Data are available for 56 primary sites and 183 secondary sites across the U.S. For our study, all 30 years of SAMSON data from 48 sites across the Midwest (fig. 1) were manipulated to create RZWQM input files for daily meteorology and hourly breakpoint precipitation at each location. Daily meteorological information of interest included maximum temperature, minimum temperature, wind run, solar radiation, and relative humidity.

Independent calibrations and evaluations of the hydrologic and nutrient components of RZWQM-DSSAT for each of the 48 sites were not performed. Instead, RZWQM-DSSAT was evaluated for a subsurface-drained agricultural system in central Iowa (Thorp et al., 2007), and this evaluated model was applied to simulate DWM under the climatic conditions and management practices of 48 other locations around the Midwest. As reported by Thorp et al. (2007), evaluations of the hydrologic and nutrient components of RZWQM-DSSAT were completed using 10 years of measured data from an agricultural system near Story City, Iowa. The study site was divided into 12 plots, each uniquely drained by a separate drainage line. A corn/soybean rotation was used. During corn years, four N fertilizer application treatments (~200 kg N ha^{-1}, ~135 kg N ha^{-1}, ~70 kg N ha^{-1}, and ~60:60 kg N ha^{-1} split) were replicated three times over the 12 plots. No fertilizer was applied during soybean years. Under this management, the agricultural system was intensively monitored from 1996 to 2005. Daily subsurface drain flows, bi-weekly flow-weighted average NO_3 concentration (FWANC) in drain water, annual crop yield, and other measurements were collected to characterize the hydrology, N dynamics, and crop response at the site (Jaynes et al., 2001; Jaynes and Colvin, 2006). In the work of Thorp et al. (2007), the soil profile for this central Iowa site was simulated in RZWQM-DSSAT using ten soils layers to a depth of 298 cm (table 1). Model inputs for bulk density, saturated soil water content, and saturated hydraulic conductivity (K_{SAT}) were set equal to the values used by Bakhsh et al. (2001) based on the measurements of Bakhsh et al. (2000). To calibrate the hydrologic component of RZWQM-DSSAT for the site, Thorp et al. (2007) adjusted three parameters, the lateral hydraulic gradient, the lateral saturated hydraulic conductivity, and the bubbling pressure of the soil water retention curves, to reduce error between measured and simulated daily subsurface drain flows (tables 1 and 2). The calibrated model was able to simulate 10 years of annual subsurface drainage with a relative root mean squared error of 18% and a Nash and Sutcliffe (1970) model efficiency of 0.87, regardless of the N fertilizer treatment that was simulated.

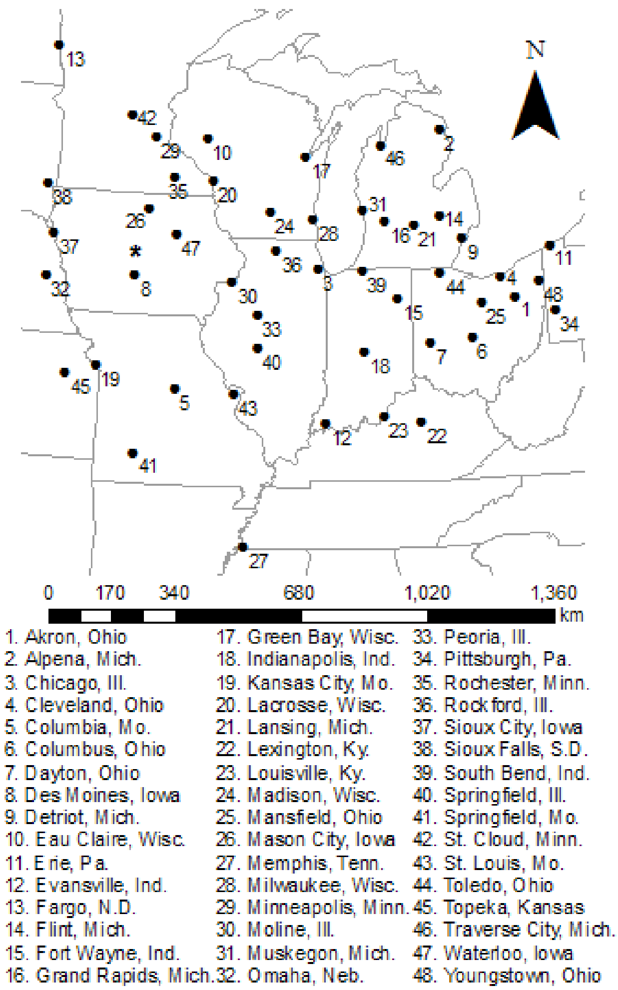

Figure 1. RZWQM-DSSAT simulations were run for 48 sites across the midwestern U.S. A separate site near Story City, Iowa, where data were collected for model calibration (Thorp et al., 2007), is denoted with an asterisk.

Thorp et al. (2007) initialized the nutrient component of RZWQM-DSSAT using 35 years of historical weather for the central Iowa site, and calibration of the nutrient component was performed by adjusting the denitrification rate and the decay rate of the slow organic matter pool to reduce error between measured and simulated annual FWANC in subsurface drain water. These nutrient parameters were adjusted further in the present work. Final readjusted values for the denitrification rate and the decay rate of the slow organic matter pool were 2.3e-14 and 3.0e-9, respectively (table 2). The recalibrated model was able to simulate 10 years of annual FWANC with a relative root mean squared errors of 34%, 28%, and 23% and model efficiencies of –1.7, –1.1, and –1.0 for plots receiving the low (~70 kg N ha^{-1}), medium (~135 kg N ha^{-1}), and high (~200 kg N ha^{-1}) fertilizer treatments, respectively, during corn years at the Story City, Iowa, site. Negative model efficiency indicated that the observed mean for FWANC in subsurface drainage was a better estimator than the model, but it occurred here as a result of having little variability in drainage FWANC among the 10 years. More representative model efficiencies of 0.38, 0.55, and 0.53 were computed for simulations of NO_3 mass lost in subsurface drainage when the low, medium, and high N rates were used, respectively. Simulations of corn yield with the recalibrated model were also shown to respond appropriately to the N fertilizer application rates used at the site. For the DWM simulation study presented herein, all hydrologic and nutrient parameters for all 48 sites across the Midwest, with the exception of the two readjusted parameters mentioned above, were set identical to those used by Thorp et al. (2007) in their application of the model to the site in Iowa (tables 1 and 2).

Simulations of both CVD and DWM across the Midwest were run using a corn/soybean rotation at each of the 48 sites: corn in even years and soybean in odd years. Model parameters for crop management, including crop cultivar coefficients, planting dates, and harvest dates, were defined with the aid of state- and county-level National Agricultural Statistics Service (NASS) data for crop development and management across the region (USDA, 2007). State-level information on the progress of planting and harvesting operations was obtained for growing seasons 2001 through 2006. This information was presented by NASS as the five-year average, state-level percent completion of planting and harvesting operations on a weekly basis throughout the growing season. For the 48 sites in our study, planting and harvest operations were simulated on the five-year average date at

Table 1. Parameterization of the soil profile (Thorp et al., 2007) used for all 48 sites.[a]

Layer	Depth (cm)	BD (Mg m^{-3})	Soil Water Retention[b] θ_s (cm^3 cm^{-3})	θ_r (cm^3 cm^{-3})	τ_b[d] (cm)	λ	Lateral K_{SAT}[c] (cm h^{-1})	Conductivity[c] K_{SAT} (cm h^{-1})	τ_{bK}[d] (cm)	SRGF
1	0-2	1.16	0.56	0.04	-15	0.1	5.0	3.50	-1	1.00
2	2-15	1.16	0.56	0.04	-15	0.1	5.0	3.50	-15	1.00
3	15-30	1.22	0.54	0.04	-15	0.1	5.0	3.50	-15	0.30
4	30-60	1.27	0.52	0.04	-15	0.1	5.0	3.50	-15	0.03
5	60-90	1.48	0.44	0.04	-15	0.1	5.0	2.00	-15	0.01
6	90-120	1.56	0.41	0.04	-15	0.1	5.0	1.00	-15	0.00
7	120-150	1.75	0.34	0.04	-15	0.1	5.0	0.10	-15	0.00
8	150-200	1.80	0.32	0.04	-15	0.1	1.0	0.01	-15	0.00
9	200-250	1.80	0.32	0.04	-15	0.1	0.8	0.01	-15	0.00
10	250-298	1.80	0.32	0.04	-15	0.1	0.6	0.01	-15	0.00

[a] BD = bulk density, θ_s = saturated soil water content, θ_r = residual soil water content, τ_b = bubbling pressure, λ = pore size distribution index, K_{SAT} = saturated hydraulic conductivity; τ_{bK} = conductivity curve bubbling pressure; SRGF = soil root growth factor.
[b] Other required parameters include A_1 (set to zero) and B (computed using the RZWQM default constraint) for all layers (Ahuja et al., 2000b).
[c] Other required parameters include N_1 (set to zero) and K_2 and N_2 (computed using the RZWQM default constraints) for all layers (Ahuja et al., 2000b).
[d] Calibrated parameters. Also, the lateral hydraulic gradient was adjusted to a value of 1E-5.

Table 2. Non-default RZWQM parameterization (Thorp et al., 2007) used for all 48 sites.[a]

Parameter	Value	Source
Hydrology Components		
Dry soil albedo	0.2	Bakhsh et al. (2001)
Wet soil albedo	0.1	Bakhsh et al. (2001)
Crop canopy albedo	0.25	Song (1999)
Residue albedo	0.8	Bakhsh et al. (2001)
Effective drain radius	1.1 cm	Youssef et al. (2006)
Bubbling pressure	-15 cm	Calibrated
Lateral K_{SAT}	5 cm h^{-1}	Calibrated
Lateral hydraulic gradient	1E-5	Calibrated
Nutrient Components		
Slow residue to IM-OM TC	0.3	Ma et al. (2007)
Fast residue to fast OM TC	0.6	Ma et al. (2007)
Fast OM to IM-OM TC	0.6	Ma et al. (2007)
IM-OM to slow OM TC	0.7	Ma et al. (2007)
Initial surface corn residue	0.5 t ha^{-1}	Assumed
Initial age of surface residue	87 d	Assumed
Initial height of surface residue	3 cm	Assumed
Initial residue C:N ratio	60	Assumed
Natural residue incorporation	80%	Assumed
Conc. of NO_3-N in rainwater	1 ppm	Assumed
Denitrification reaction RC	2.3E-14	Calibrated
Slow OM pool decay RC	3.0E-9	Calibrated
Management		
Corn row spacing	76 cm	Jaynes et al. (2001)
Soybean row spacing	18 cm	Jaynes et al. (2001)
Corn soil planting layer	2	Jaynes et al. (2001)
Soybean soil planting layer	1	Jaynes et al. (2001)
Harvest efficiency	97%	Assumed
Corn stubble height	15 cm	Assumed
Soybean stubble height	2 cm	Assumed
Corn minimum LSR	185 s m^{-1}	Assumed
Soybean minimum LSR	75 s m^{-1}	Assumed

[a] K_{SAT} = saturated hydraulic conductivity; IM-OM = intermediate organic matter pool; TC = transfer coefficient; OM = organic matter; C:N = carbon:nitrogen; NO_3-N = nitrate-nitrogen; RC = rate coefficient; LSR = leaf stomatal resistance.

which the operations were 50% complete in each site's respective state (table 3). When necessary, linear interpolation was used to find the true 50% completion date between weekly NASS estimates. For all sites, simulated corn crops were planted in the second soil layer with a planting density of 75,000 plants ha^{-1} and a row spacing of 76 cm. Simulated soybean crops were planted in the first soil layer with a planting density of 370,000 plant ha^{-1} and a row spacing of 18 cm. Harvest operations were simulated to remove grain only, and a harvest efficiency of 0.97 was used for all crops. Post-harvest stubble heights for corn and soybean were assumed to be 15 and 2 cm, respectively (table 2).

Cultivar parameters for the CERES-Maize and CROPGRO-Soybean components of RZWQM-DSSAT were obtained from the cultivar files packaged with the DSSAT software. Considerable variation in cultivar parameters was expected across the region due to differences in day length and growing degree day accumulation rates. To find the appropriate cultivar for each site, the generic DSSAT cultivar parameter sets were systematically tested until simulated dates for crop phenological development closely matched state-level crop development estimates provided by NASS. Specifically for corn, emphasis was placed on determining, for each site, the set of generic cultivar parameters that gave

Table 3. Estimates for the five-year average (2001 to 2006) day of year (DOY) that state-wide planting and harvesting operations for corn and soybean were 50% complete (USDA, 2007)[a] and five-year average (2001 to 2006) state-wide nitrogen (N) fertilizer application rate for corn (USDA, 2008).

	Corn			Soybean	
State	Plant DOY	Harvest DOY	N Rate (kg ha^{-1})	Plant DOY	Harvest DOY
Illinois	117	282	174	138	280
Indiana	123	293	165	138	283
Iowa	122	295	144	138	279
Kansas	118	271	158	143	287
Kentucky	112	267	181	152	294
Michigan	130	301	138	144	287
Minnesota	124	297	138	140	280
Missouri	111	268	175	145	292
Nebraska	124	295	152	140	281
North Dakota	130	299	125	143	278
Ohio	124	302	181	137	283
Pennsylvania	130	290	91	141	304
South Dakota	130	299	118	145	282
Tennessee	108	260	175	149	299
Wisconsin	132	304	112	145	288

[a] Planting and harvest DOY was incremented by one for leap years.

simulated silking dates closest to the NASS five-year average date (2001 to 2006) of 50% silking completion in each site's respective state. For soybean, the generic sets of DSSAT cultivar coefficients were systematically tested until the simulated dates for soybean harvest maturity were close to, but did not exceed, the soybean harvest date used for each site. After finding the set of generic cultivar parameters that appropriately simulated crop phenological development at each site, slight adjustments were made to the cultivar parameters that control biomass growth and grain yield. Historical crop yield estimates at each site were obtained from county-level NASS data, computed as the average, county-level yield for each crop over the 2001 through 2006 growing seasons. If a site was located in a county without significant agricultural production due to urban development (i.e., Chicago, Ill.), yield estimates were obtained from the nearest county with substantial agricultural production. Cultivar coefficients that affect yield were then adjusted within a reasonable range to reduce error between simulated yield and county-level NASS yield estimates at each site and for each crop. Simultaneously, cultivar coefficients that affect biomass growth were adjusted within a reasonable range to achieve harvest indices around 0.5 for corn (Tollenaar et al., 2006) and 0.38 for soybean (Sadras and Calvino, 2001). Essentially, we adjusted the cultivar coefficients in this way to ensure that the crop models were simulating typical crop growth, development, and yield at each of the 48 sites.

Other management practices were performed in relation to the planting and harvest dates at each site. During corn years, N fertilizer was applied as an injection of anhydrous ammonia seven days prior to the planting date. Nitrogen fertilizer application rates (table 3) were assigned to each site as the five-year average, state-level N rate from 2001 to 2006, as reported by an Economic Research Service website (USDA, 2008). Simulated tillage operations for both crops included a field cultivator one day prior to planting and a moldboard plow five days after harvest. RZWQM default values for the average effective depth and the tillage intensity of these operations were used (Rojas and Ahuja, 2000). Artificial subsurface drains were simulated at a depth of 145 cm with a spacing of 2740 cm. For simulations of DWM, the head gate was lowered to the drain depth of 145 cm three weeks prior to planting. Four weeks after planting, the gate was raised to a depth of 60 cm for the duration of the growing season. This schedule was chosen hypothetically to allow adequate time for pre- and post-emergence management activities. In preparation for harvest, the gates were again lowered to the 145 cm drain depth two weeks before the harvest date. One week after harvest and two days after the fall tillage operation, the gates were raised to 30 cm for the duration of the fall and winter seasons. To simulate CVD, the head gate was set at the drain depth of 145 cm for the entire simulation period.

Simulations were run for both CVD and DWM at each site using the 30-year record of SAMSON weather data from 1961 to 1990. However, because of a limitation in the RZWQM-DSSAT user interface, analysis of the simulation results was performed only on the final 25 years of simulations from 1966 to 1990. Currently, each DWM head gate change in RZWQM-DSSAT must be uniquely specified, and only 100 total head gate changes are possible. Since we are simulating four head gate changes per year, RZWQM-DSSAT currently allowed only 25 years of DWM to be simulated. As a result, we chose to simulate the first five years of the weather record without DWM and to begin using DWM in 1966. This strategy also allowed a small initialization period for further stabilization of the nutrient pools. The results of a 35-year initialization, performed previously for conditions in Iowa (Thorp et al., 2007), were used as the initial conditions for each site in this study; therefore, an additional period of initialization was found useful for further stabilization of the nutrient component for weather conditions elsewhere in the region.

Analysis of Simulation Results

To assess the performance of DWM across the region, the absolute and percent differences between CVD and DWM simulation results for all components of the hydrologic and N cycles were computed at each site. The data were then brought into ArcGIS (Version 9.2, ESRI, Inc., Redlands, Cal.) to examine the results spatially. Universal kriging (Cressie, 1993) with linear trend removal was used to summarize the reductions in drain flow and NO_3 losses in response to DWM across the region. Results were classified into five groups for display purposes using the "natural breaks" classification algorithm in ArcGIS. In addition, by examining the absolute differences between CVD and DWM simulation results for each component of the hydrologic and N cycle, we ranked the pathways and/or processes most affected by adoption of DWM and characterized the degree to which DWM altered the flow of water and N through each pathway of agricultural system.

As a result of our simulation strategy, variation in the simulation results across the region was dependent only on differences in meteorology and management practices. A regression analysis was used to identify which of these inputs contributed most greatly to the reductions in subsurface drain flow and NO_3 losses when using DWM instead of CVD. Dependent variables of interest were the total precipitation, the average daily minimum and maximum temperatures, and the average daily incoming solar radiation, wind run, and relative humidity over the 25-year simulation period at each site. Since the management decisions for fertilization date, tillage, and head gate changes were simulated in relation to the planting and harvest dates, the dependent variables used to characterize these management differences were the average day of year for planting and the average day of year for harvest. Computations of the average planting and harvest dates were made without regard to the different crop species grown in rotation. The N fertilizer application rate for each site was also included in the analysis. Initially, all of the dependent variables were included in the regression analysis, and variables were systematically removed until all estimated regression coefficients were significantly different from zero. During model development, several spatial statistical tests, including Moran's I test and Lagrange multiplier tests for error dependence or a missing spatially lagged dependent variable (Cressie, 1993), were conducted to assess the level of spatial autocorrelation in the regression models. Since this analysis sometimes showed that spatial autocorrelation was significant, efforts were taken to develop a simultaneous autoregressive spatial model to describe our data. The semiparametric spatial filtering method of Tiefelsdorf and Griffith (2007) was used to develop the spatial model. The basic form of the model is:

$$\mathbf{Y} = \mathbf{X}\hat{\boldsymbol{\beta}} + \mathbf{E}\hat{\gamma} + \hat{\boldsymbol{\varepsilon}} \tag{1}$$

where $\mathbf{Y}$ is an $(n \times 1)$ vector of georeferenced observations for the independent variable, $\mathbf{X}$ is an $(n \times k)$ vector of dependent variables including an $(n \times 1)$ unity vector, $\hat{\boldsymbol{\beta}}$ is the $(k \times 1)$ vector of regression coefficients for the dependent variables, $\mathbf{E}$ is an $(n \times m)$ vector of eigenvectors computed from $\mathbf{X}$ and a spatial weights matrix, $\hat{\gamma}$ is the $(m \times 1)$ vector of regression coefficients for the eigenvectors, and $\hat{\boldsymbol{\varepsilon}}$ is the $(n \times 1)$ vector of random error. The purpose of the $\mathbf{E}\hat{\gamma}$ term is to capture the spatial autocorrelation of the variables in $\mathbf{X}$ and to include it as a separate component in the model. The eigenvectors included in $\mathbf{E}$ are obtained from the complete set of eigenvectors of $\mathbf{M}_{(\mathbf{X})}\frac{1}{2}(\mathbf{V} + \mathbf{V}^{\mathbf{T}})\mathbf{M}_{(\mathbf{X})}$, where $\mathbf{M}_{(\mathbf{X})}$ is $\mathbf{I} - \mathbf{X}(\mathbf{X}^{\mathbf{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathbf{T}}$ and $\mathbf{V}$ is a spatial weights matrix for the data. A stepwise procedure is used to select the eigenvectors for $\mathbf{E}$, where Moran's I test is the evaluation criterion. Eigenvectors are successively added to the model until the p-value for Moran's I test reaches a given threshold, 0.25 in our case. One advantage of the spatial filtering method is that the model in equation 1 can be solved using classical ordinary least squares estimation of the regression coefficients. Algorithms for the spatial filtering method are currently available in the "spdep" package of the R statistical software.

To assess the performance of the model, simulation results for select sites and growing seasons were compared with data from several literature-reported drainage studies across the region (Gast et al., 1978; Baker and Johnson, 1981; Kladivko et al., 2004; David et al., 1997; Fausey, 2004). Because of differences in site location, soil type, and management between the literature-reported studies and our simulations, these comparisons were loose at best; however, we wanted to provide an indication that the model could reasonably simulate long-term average responses in spite of these differences.

Results and Discussion

DWM Effects on Hydrology

Simulations of the hydrologic balance demonstrated that DWM had the greatest effect on subsurface drainage, followed by surface runoff and ET. Drainage water management reduced subsurface drainage by an average of 151 mm yr^{-1} across the region, which corresponded to a 53% reduction over 25 years (table 4). The maximum effect of DWM occurred at the southernmost simulated site (Memphis, Tenn.), which had a 364 mm yr^{-1} average reduction in subsurface drainage. The minimum effect of DWM on subsurface drainage occurred at sites in the northwest. Minimum average reduction in drain flow was 22 mm yr^{-1} at Fargo, North Dakota. Drainage reduction percentages in response to DWM ranged from a 35% reduction (Omaha, Neb.) to a 68% reduction (Memphis, Tenn.). Under CVD and DWM, subsurface drainage was 32% and 15% of precipitation plus storage losses, respectively (table 5). Both the volume of the drain flow reduction (fig. 2a) and the percent reduction of drain flow (fig. 2b) tended to decrease when moving from the southeast to the northwest across the region. This result indicates that, when considering only variability in climate and certain management practices across the region, DWM is most effective at reducing drain flow across the southern portions of Missouri, Illinois, Indiana, and Ohio. It is moderately effective in southern Michigan and across the northern portions of Missouri, Illinois, Indiana, and Ohio. Of the eight states in the Midwest, DWM is least effective in Iowa, Minnesota, and Wisconsin.

Decreases in subsurface drainage were offset mainly by increases in surface runoff and ET. The average regional increase in surface runoff was 85 mm yr^{-1}, which corresponded to a 327% increase over 25 years (table 4). The minimum effect of DWM on surface runoff occurred at Fargo, North Dakota, which had an average runoff increase of only 2 mm yr^{-1}. With an average increase of 260 mm yr^{-1}, Memphis, Tennessee, experienced the greatest response of surface runoff to DWM. The percent differences in surface runoff across the region when using DWM instead of CVD ranged from a 22% increase (Fargo, N.D.) to an 860% increase (Youngstown, Ohio). Percent increases in runoff were sometimes large, but the volume of the runoff increase was not excessive due to low simulated runoff values. Under CVD and DWM, runoff was 3% and 12% of precipitation plus storage losses, respectively (table 5). In addition, runoff simulations in RZWQM-DSSAT do not account for depressional storage or potholes, which may mean that runoff is overestimated by the model. The average regional increase in ET was 52 mm yr^{-1}, which corresponded to an 11% increase over 25 years (table 4). The minimum effect of DWM on ET occurred at Fargo, North Dakota, with an average increase of 16 mm yr^{-1}. Drainage water management had the greatest effect on ET in Memphis, Tennessee, with an average increase of 98 mm yr^{-1}. Percent increases in ET ranged from a 4% increase (Fargo, N.D.) to a 19% increase (Erie, Pa.). Under CVD and DWM, ET was 52% and 58% of precipitation plus storage losses, respectively (table 5). Use of DWM did not increase average deep seepage by more than 22 mm yr^{-1} at any site. In addition, long-term changes in soil water storage were similar between CVD and DWM simulations. The average regional increase in stored soil water was 1 mm yr^{-1}. These results demonstrate how DWM changes the hydrologic balance when considering regional differences in climate and management practices; however, considerable variation in the reported values would be expected if differences in soil types and drainage system designs were also considered.

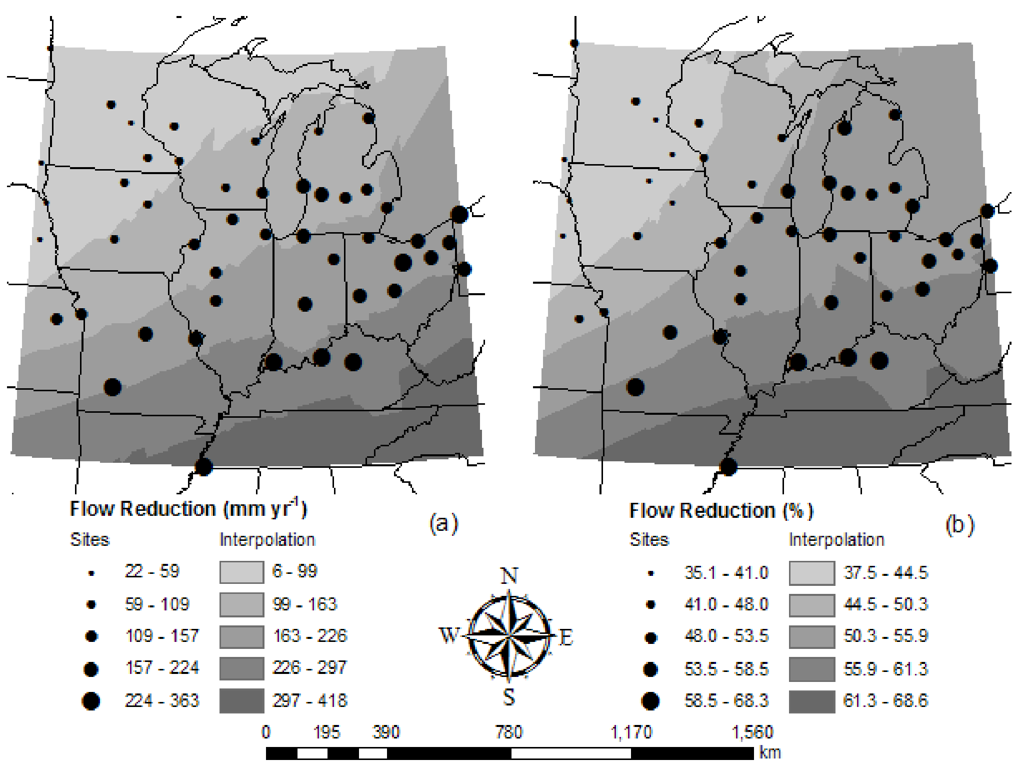

Figure 2. (a) Average annual subsurface drain flow reduction, and (b) long-term percent reduction of subsurface drain flow when using drainage water management instead of conventional drainage across the midwestern U.S.

Table 4. Comparison of average annual simulation results for water and nitrogen movement under conventional drainage (CVD) and drainage water management (DWM) in the pathways most greatly affected by adoption of DWM practices.

	Significant Inputs[a]			Hydrology (mm yr^{-1})						Nitrogen (kg N ha^{-1} yr^{-1})							
				Drainage		Runoff		ET		Drainage		Δ Storage		Denitrif.		Uptake	
Location	Precip (mm)	T_{min} (°C)	N Rate (kg ha^{-1})	CVD	DWM	CVD	DWM	CVD	DWM	CVD	DWM	CVD	DWM	CVD	DWM	CVD	DWM
Akron, Ohio	951	5.3	181	342	162	16	126	463	521	42.0	20.3	-11.1	0.9	14.5	21.2	236.6	242.7
Alpena, Mich.	740	0.8	138	244	118	16	78	351	391	22.8	10.3	0.3	7.0	11.3	16.4	181.8	182.2
Chicago, Ill.	941	4.6	174	289	139	26	107	504	554	36.0	17.0	-16.4	-5.9	12.6	17.1	245.7	251.5
Cleveland, Ohio	965	5.3	181	332	147	16	119	487	555	40.6	19.7	-13.6	-2.0	13.9	20.4	206.0	210.9
Columbia, Mo.	1006	6.9	175	338	151	42	149	506	573	61.9	31.3	-37.0	-25.4	16.3	23.4	249.0	257.7
Columbus, Ohio	984	5.9	181	338	153	16	123	501	564	41.6	18.3	-12.7	-0.3	16.2	23.9	237.9	241.8
Dayton, Ohio	960	5.8	181	318	148	16	118	505	562	52.8	27.1	-25.1	-12.8	17.6	24.1	260.6	267.4
Des Moines, Iowa	846	4.9	144	202	111	17	55	533	573	33.0	18.8	-30.8	-23.0	14.4	17.7	283.0	289.0
Detroit, Mich.	837	4.4	138	246	112	11	76	463	518	34.7	17.0	-21.5	-12.4	11.4	15.6	207.9	213.6
Eau Claire, Wisc.	781	1.3	112	211	117	23	59	433	473	23.5	12.0	-15.4	-9.0	7.7	9.9	191.7	195.1
Erie, Pa.	1093	5.0	91	488	209	29	212	426	509	23.5	9.2	-3.7	6.4	8.2	14.4	179.7	181.7
Evansville, Ind.	1122	7.8	165	411	166	35	208	558	621	52.0	24.4	-37.1	-24.1	12.4	18.2	263.1	269.1
Fargo, N.D.	490	-0.4	125	52	30	9	11	373	389	15.6	8.5	-32.0	-29.8	9.2	10.1	218.7	223.4
Flint, Mich.	798	3.7	138	245	114	11	66	417	475	26.0	12.3	-13.4	-5.2	9.9	13.9	176.8	179.2
Fort Wayne, Ind.	904	4.9	165	283	137	17	105	482	527	37.5	18.9	-19.8	-9.1	12.9	17.9	245.7	252.2
Grand Rapids, Mich.	955	3.7	138	354	154	27	157	438	489	30.0	11.9	-8.2	2.7	10.4	16.3	214.6	215.7
Green Bay, Wisc.	737	1.7	112	209	116	15	53	395	430	17.1	8.5	-6.3	0.0	8.8	11.7	203.1	203.8
Indianapolis, Ind.	1005	6.2	165	339	151	19	144	526	577	44.7	21.9	-22.1	-8.3	14.5	21.0	279.5	280.3
Kansas City, Mo.	949	7.2	175	269	149	40	78	529	594	59.2	34.0	-38.9	-29.6	14.4	18.8	231.3	239.4
Lacrosse, Wisc.	796	2.8	112	192	103	65	104	442	477	20.1	10.1	-18.1	-13.0	9.2	11.6	216.3	220.7
Lansing, Mich.	800	3.2	138	244	116	16	80	416	462	24.7	10.8	-9.3	-0.4	11.5	15.5	227.3	231.6
Lexington, Ky.	1149	7.6	181	462	180	38	218	512	602	53.2	24.3	-20.5	-7.2	13.9	22.8	211.4	213.9
Louisville, Ky.	1135	8.5	181	434	172	42	205	535	625	58.6	26.6	-29.4	-15.5	15.4	23.9	225.2	229.5
Madison, Wisc.	799	2.0	112	230	121	16	68	435	474	19.3	9.7	-8.8	-2.2	9.6	12.8	218.9	218.9
Mansfield, Ohio	1052	5.1	181	439	202	30	199	441	493	34.5	15.8	-5.2	6.1	12.1	19.2	217.9	218.7
Mason City, Iowa	747	1.9	144	172	104	14	39	464	492	24.9	14.2	-21.2	-13.6	10.3	13.1	256.4	261.2
Memphis, Tenn.	1346	11.8	175	533	169	94	354	596	694	85.4	35.8	-59.5	-40.7	16.0	26.6	234.7	242.1
Milwaukee, Wisc.	862	3.8	112	279	128	20	109	442	488	26.2	12.2	-11.6	-3.7	8.3	11.6	191.0	194.2
Minneapolis, Minn.	722	2.4	138	147	89	19	37	478	510	30.6	18.2	-29.5	-24.5	11.2	13.1	224.9	233.4
Moline, Ill.	992	4.5	174	303	148	41	131	528	576	36.9	17.8	-17.1	-6.6	14.5	20.2	271.8	275.3
Muskegon, Mich.	842	4.1	138	298	126	22	131	392	436	30.3	12.9	-12.0	-2.7	10.1	15.0	192.1	194.6
Omaha, Neb.	719	4.8	152	139	90	11	26	495	521	33.6	22.4	-39.0	-35.2	17.5	19.9	280.7	285.7
Peoria, Ill.	935	5.1	174	282	140	25	101	513	560	41.3	19.7	-22.1	-10.9	14.6	19.2	285.3	290.0
Pittsburgh, Pa.	956	5.3	91	341	149	12	112	475	553	28.4	12.5	-13.0	-3.0	9.2	14.5	176.1	179.3
Rochester, Minn.	741	1.4	138	191	118	21	46	432	462	22.1	13.1	-12.6	-6.9	11.0	13.7	236.3	238.6
Rockford, Ill.	940	3.6	174	315	159	35	118	460	512	36.3	17.7	-12.3	-2.1	11.6	16.9	219.1	222.1
Sioux City, Iowa	643	3.5	144	108	65	7	14	464	492	31.5	18.9	-41.9	-37.6	15.3	17.6	266.5	273.1
Sioux Falls, S.D.	600	1.7	118	102	63	10	19	419	442	20.2	12.2	-30.8	-27.6	10.2	11.5	236.6	241.9
South Bend, Ind.	1084	5.2	165	389	166	82	237	476	529	40.1	16.9	-11.8	0.1	12.5	19.4	229.1	234.0
Springfield, Ill.	904	6.3	174	263	126	24	98	505	557	48.0	24.8	-34.8	-23.3	14.0	18.8	287.3	292.6
Springfield, Mo.	1130	7.5	175	411	160	57	210	533	618	59.4	27.0	-35.5	-22.1	13.9	21.3	221.3	228.7
St. Cloud, Minn.	680	-0.2	138	181	102	17	42	374	410	22.9	12.3	-12.9	-7.8	8.9	11.8	200.9	205.2
St. Louis, Mo.	971	8.0	175	317	131	26	135	512	578	74.2	33.9	-48.9	-36.0	17.9	24.3	268.3	284.0
Toledo, Ohio	862	4.1	181	269	129	15	91	456	504	33.8	16.9	-13.5	-2.4	13.1	18.4	252.7	255.8
Topeka, Kansas	904	6.4	158	254	132	35	76	507	571	53.1	30.1	-36.7	-28.8	15.0	19.7	225.8	234.5
Traverse City, Mich.	688	2.4	138	194	89	10	64	365	398	27.5	12.3	-12.7	-5.0	10.2	14.2	190.2	193.0
Waterloo, Iowa	825	2.6	144	213	126	22	59	488	523	25.9	14.4	-16.5	-9.2	12.5	16.1	251.3	254.1
Youngstown, Ohio	971	4.3	181	390	173	15	144	422	493	42.2	17.8	-2.9	8.4	14.2	25.0	208.0	212.1
Average	893	4.5	152	283	132	26	111	468	520	37.1	18.2	-20.9	-11.5	12.5	17.5	229.9	234.5

[a] Total 25-year precipitation, average minimum temperature (T_{min}), and corn-year nitrogen (N) application rate were the statistically significant model input variables governing reductions of drain flow and nitrate losses under DWM.

DWM Effects on Nitrogen Cycle

Simulations of the nitrogen balance demonstrated that DWM had the greatest effect on NO_3 in subsurface drainage, followed by soil N storage changes, denitrification, and plant N uptake. Drainage water management reduced NO_3 in subsurface drainage by an average of 18.9 kg N ha^{-1} yr^{-1} across the region, which corresponded to a 51% reduction over 25 years (table 4). Similar to the results for hydrology, the maximum effect of DWM occurred at Memphis, Tennessee, with a 49.6 kg N ha^{-1} yr^{-1} average reduction in NO_3 losses through subsurface drainage lines. The minimum effect of DWM on NO_3 losses in subsurface drainage was a 7.1 kg N ha yr^{-1} average reduction at Fargo, North Dakota. Across the region, reduction percentages for NO_3 mass in

Table 5. Average annual mass balances for water and nitrogen across the region under conventional drainage (CVD) and drainage water management (DWM).

	CVD		DWM	
	Value	% I+SL[a]	Value	% I+SL[a]
Hydrologic Balance				
	(mm yr^{-1})	(%)	(mm yr^{-1})	(%)
Precipitation	892.9	99.9	892.9	99.9
Runoff	25.9	2.9	110.6	12.4
Evapotranspiration	468.1	52.4	519.7	58.2
Drainage	283.4	31.7	132.5	14.8
Seepage	111.5	12.5	125.1	14.0
Δ Storage	-0.9	0.1	-0.3	0.1
I+SL[b]	893.8	100.0	893.2	100.0
Nitrogen Balance				
	(kg ha^{-1} yr^{-1})	(%)	(kg ha^{-1} yr^{-1})	(%)
N fertilizer	78.9	26.8	78.9	27.4
N in precipitation	7.6	2.6	7.6	2.6
N fixation	90.0	30.5	92.9	32.2
N in residue	97.4	33.0	97.4	33.8
Denitrification	12.5	4.2	17.5	6.1
Volatilization	0.2	0.1	0.2	0.1
N in runoff	0.2	0.1	0.8	0.3
N uptake	229.9	78.0	234.5	81.3
N in drainage	37.1	12.6	18.2	6.3
N in seepage	15.3	5.2	17.5	6.1
Δ Storage	-20.9	7.1	-11.5	4.0
I+SL[c]	294.8	100.0	288.3	100.0
Airborne N	12.7	4.3	17.7	6.1
Waterborne N	52.6	17.8	36.5	12.7

[a] % I+SL = values are expressed as a percentage of I+SL.
[b] I+SL = inputs plus storage losses (Precipitation - ΔStorage).
[c] I+SL = inputs plus storage losses (Fert+Precip+Fix+Res - ΔS)

drainage ranged from a 33% reduction (Omaha, Neb.) to a 58% reduction (Memphis, Tenn.). Under CVD and DWM, subsurface drainage was 13% and 6% of N inputs plus storage losses, respectively (table 5). Although the mass of NO_3 lost through subsurface drains was reduced at all the sites, simulations showed that DWM did not substantially affect the flow-weighted average nitrate concentration (FWANC) in subsurface drainage. The average annual FWANC across the region was 14.2 and 14.3 mg N L^{-1} for CVD and DWM, respectively (data not shown). The maximum increase in average annual FWANC was 5 mg N L^{-1} at Memphis, Tennessee, but several sites in the northwestern portion of the region experienced a decrease in average annual FWANC of up to 1 mg N L^{-1}. Therefore, results demonstrated that simulated reductions in subsurface drain flow rather than reductions in FWANC were mainly responsible for reductions in the amount of NO_3 lost in subsurface drainage under DWM. Similar to the patterns of drain flow reduction, both the amount of the NO_3 mass reduction in subsurface drainage (fig. 3a) and the percent reduction of NO_3 loss over the long term (fig. 3b) tended to decrease when moving from the southeastern to the northwestern portions of the region. The simulation results demonstrate that, when considering only climate variability and certain management practices, DWM is more effective at reducing NO_3 loads from subsurface drains in Missouri, Illinois, Indiana, and Ohio than in Iowa, Minnesota, Wisconsin, and Michigan.

Decreases in subsurface drainage N losses were offset mainly by increases in stored soil N, denitrification, and plant N uptake. An interesting result was that, second to NO_3 loss in subsurface drainage, DWM had a considerable effect on the amount of N stored in the soil over the long term. Under CVD, the change in the amount of stored soil N over 25 years

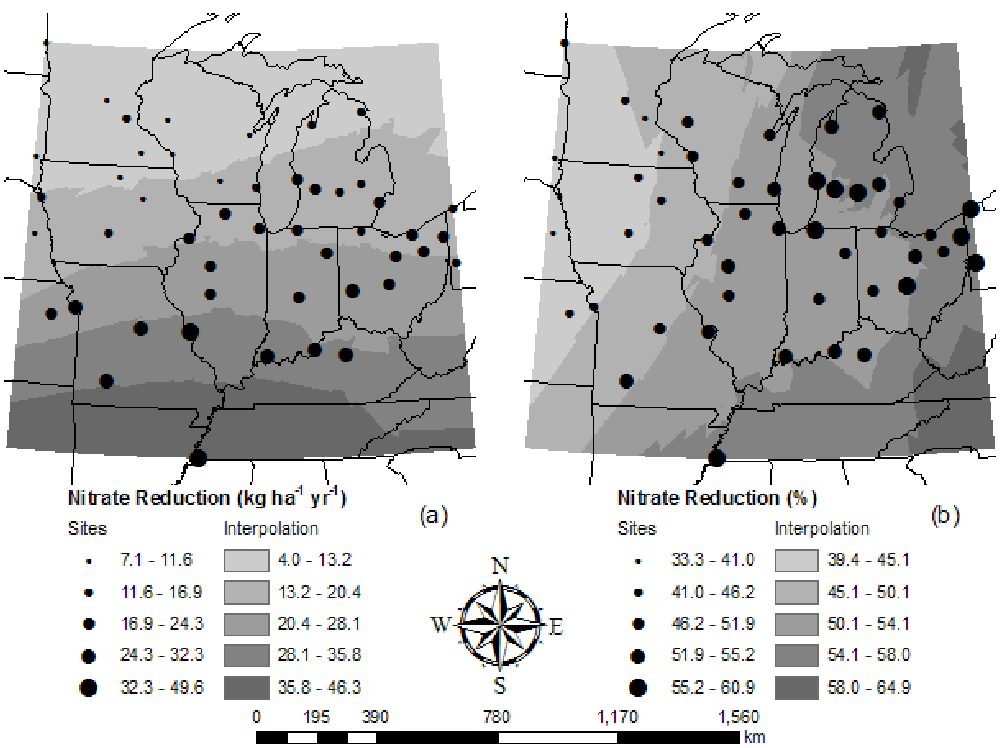

Figure 3. (a) Average annual reduction in NO_3 losses through subsurface drains, and (b) long-term percent reduction of NO_3 losses through subsurface drains when using drainage water management instead of conventional drainage across the midwestern U.S.

of simulations across the region ranged from a 1488 kg N ha^{-1} decrease (Memphis, Tenn.) to a 7 kg N ha^{-1} increase (Alpena, Mich.). Under DWM, changes in soil stored N ranged from a 1017 kg N ha^{-1} decrease (Memphis, Tenn.) to a 210 kg N ha^{-1} increase (Youngstown, Ohio). At all sites, the storage of N in the soil after 25 years of DWM simulations was greater than the N storage after 25 years of CVD simulations, and the regional average increase in stored N was 9.4 kg N ha^{-1} yr^{-1} (table 4). Nitrogen mineralization, which was 8.6 kg N ha^{-1} yr^{-1} lower across the region under DWM, was the greatest contributor to the increase in stored soil N, but slight increases in N immobilization also increased storage. Regional net mineralization decreased from an average value of 118.7 kg N ha^{-1} yr^{-1} under CVD to 109.9 kg N ha^{-1} yr^{-1} under DWM (data not shown). Increased denitrification was the primary mechanism by which DWM was originally thought to remove N from agricultural systems (Gilliam et al., 1979). Our results also showed a substantial change in denitrification under DWM, with an average increase of 5.0 kg N ha^{-1} yr^{-1} across the region. This corresponded to a 40% increase in denitrification in response to DWM (table 4). The minimum effect of DWM on denitrification was a 0.9 kg N ha^{-1} yr^{-1} increase at Fargo, North Dakota, and the maximum effect was a 10.8 kg N ha^{-1} yr^{-1} increase at Youngstown, Ohio. Percent increases in denitrification under DWM ranged from 10% (Fargo, N.D.) to 76% (Youngstown, Ohio). Under CVD and DWM, denitrification was 4% and 6% of N inputs plus storage losses, respectively (table 5). Although the mass of N lost through denitrification is low relative to other pathways, the change in denitrification when using DWM instead of CVD was substantial. Compared to CVD, DWM increased the average plant uptake by 4.6 kg N ha^{-1} yr^{-1} across the region, which corresponded to a 2% increase over 25 years. The maximum effect of DWM on plant uptake was simulated at St. Louis, Missouri, with a 15.7 kg N ha^{-1} yr^{-1} average uptake increase; the minimum effect was zero change at Madison, Wisconsin. Percent differences in plant N uptake using DWM ranged from a 0% increase (Madison, Wisc.) to a 6% increase (St. Louis, Mo.). Under CVD and DWM, plant N uptake was 78% and 81% of N inputs plus storage losses, respectively (table 5).

The remaining components of the N balance were affected less greatly under DWM. Drainage water management increased regional soybean N fixation by 73 kg N ha^{-1} over the entire 25-year simulation, which is a 5.2 kg N ha^{-1} increase during each of the 14 soybean years. Regional average N loss to deep seepage increased by 2.2 kg N ha^{-1} yr^{-1} with DWM, which corresponded to a 15% increase and a 56 kg N ha^{-1} increase over 25 years. Use of DWM instead of CVD did not change either the regional average N loss through volatilization or the regional average N returned to the soil through crop residue incorporation by more than 0.1 kg N ha^{-1} yr^{-1}. Finally, even though DWM greatly increased the volume of surface runoff, the regional increase in the amount of N lost in surface runoff was only 15.2 kg N ha^{-1} over the entire 25-year simulation, and no site had an average runoff increase greater than 2.5 kg N ha^{-1} yr^{-1}. This can be attributed to the method of N fertilizer applications, which were simulated as injections of anhydrous ammonia. Very little NO_3 was available for mixing with runoff water on the soil surface.

Averaging across sites and across years, the amounts of N inputs, including N fertilizer, N fixation, N in precipitation, and N returned in crop reside, plus storage losses in the soil systems were 294.8 and 288.3 kg N ha^{-1} yr^{-1} for the CVD and DWM simulations, respectively (table 5). Regional outputs of airborne N across sites and years, including the denitrification and volatilization pathways, were 12.7 and 17.7 kg N ha^{-1} yr^{-1} on average for CVD and DWM, respectively. For waterborne N, including surface runoff, subsurface drainage, and seepage pathways, regional average outputs of N were 52.6 and 36.5 kg N ha^{-1} yr^{-1} for CVD and DWM, respectively. Amounts of N moving out of the soil through the plant uptake pathway were 229.9 and 234.5 kg N ha^{-1} yr^{-1} on average across the region for CVD and DWM, respectively. Thus for CVD, the percentages of N inputs plus storage losses that moved through air, water, and plant pathways were 4.3%, 17.8%, and 78.0%, respectively. For DWM, the percentages of N inputs plus storage losses that moved through these three pathways were 6.1%, 12.7%, and 81.3%, respectively. In addition to increasing the amount of stored soil N, simulated DWM also tended to increase the percentage of N flowing through airborne and plant uptake pathways while reducing the percentage of N flowing through waterborne pathways. Although DWM reduced the amount of N moving through the subsurface drainage pathway by 51% over 25 years, simulations showed that DWM increased the amount of N flowing through the runoff and deep seepage pathways by 296% and 15%, respectively. Assuming that the N moving through runoff and seepage pathways will eventually reach surface waters and contribute to water quality problems anyway, the effectiveness of DWM could be greatly reduced if the practice forced N out of agricultural systems through these other waterborne pathways. However, with a reduction in waterborne N from 52.6 to 36.5 kg N ha^{-1} when using DWM instead of CVD, our simulations showed that, overall across the region, DWM was capable of reducing the amount of N moving through undesirable waterborne pathways by 30.6%. The December 2007 report from the U.S. EPA Science Advisory Board, Hypoxia Advisory Panel (EPA, 2007) called for a 45% reduction in N discharged to the gulf to effectively reduce the extent of the hypoxic zone. Thus, DWM may provide a substantial portion of the needed reduction in NO_3 losses from agricultural system to surface waters. However, other techniques for intelligent management of N in agricultural systems, such as cover crops and efficient N fertilizer application rates (Dinnes et al., 2002), will also be needed to insure that hypoxia in the Gulf of Mexico is combated effectively.

DWM Effects on Crop Yield

The crop growth models simulated slight increases in N removal in grain and average annual crop yield at all sites for both corn and soybean crops (data not shown). Of the 4.6 kg N ha^{-1} yr^{-1} average increase in plant N uptake under DWM across the region, 4.5 kg N ha^{-1} yr^{-1} went toward an increase in removal of N in grain. The remaining 0.1 kg N ha^{-1} yr^{-1} went toward increasing soil N storage as crop residue was incorporated into the organic soil N pools after harvest. The maximum effect of DWM on N removal in grain was a 13.0 kg N ha^{-1} yr^{-1} increase at St. Louis, Missouri, while the minimum effect was a 0.2 kg N ha^{-1} yr^{-1} increase at Alpena, Michigan. The average increase in corn yield under DWM across the region was 238 kg ha^{-1} per season in which corn growth was simulated, which corresponded to a 3% increase.

Changes in corn yield in response to DWM ranged from a seasonal average decrease of 12 kg ha^{-1} at Green Bay, Wisconsin, to a seasonal average increase of 865 kg ha^{-1} at St. Louis, Missouri. Percentage increases in corn yield ranged from −0.2% (Green Bay, Wisc.) to 12% (St. Louis, Mo.). The average increase in soybean yield under DWM was 98 kg ha^{-1} per season in which soybean growth was simulated, which corresponded to a 4% increase in yield over the long term. Changes in soybean yield in response to DWM ranged from a seasonal average increase of 8 kg ha^{-1} at Mansfield, Ohio, to a seasonal average increase of 189 kg ha^{-1} at Minneapolis, Minnesota. Percentage increases in soybean yield ranged from 0.3% (Mansfield, Ohio) to 10% (Springfield, Mo.).

Several issues with the current version of RZWQM-DSSAT limited the reliability of the crop growth simulations. First, the model has been previously shown to overestimate N removal in corn grain. During model calibration, this issue was addressed by reducing corn root growth to questionably shallow depths such that the error between measured and simulated N removal in grain was reduced (Thorp et al., 2007). The model also does not currently simulate yield loss due to anaerobic conditions in the soil profile. In our simulations of CVD and DWM across the region, the simulated water table intersected the simulated root depth on average of 1.2 and 3.9 days per year, respectively. Therefore, it is unclear how the simulation results would be different if the model was able to simulate root death in response to saturated soil conditions. Essentially, we parameterized the crop models to ensure that simulations were reasonable with respect to state-level phenology and county-level yield observations. Since RZWQM-DSSAT currently has limitations in its crop simulation, we do not focus heavily on the differences in simulated crop response between CVD and DWM, but merely present them briefly above. We also mention that there is currently no other model available that is able to simulate both DWM practices and species-specific crop growth, developmental, and yield responses to soil water and nutrient conditions. We acknowledge the developmental challenges in joining two models from different origins and recommend further development of the linkage between RZWQM and DSSAT to improve simulations of root growth and uptake of water and nutrients.

Regression Analysis

A spatial regression analysis pinpointed total precipitation (**P**) as the most important variable (table 4) to explain the simulated reduction in drain flow ($\mathbf{R_{flow}}$) in response to DWM. The importance of this variable made sense since DWM has greater opportunity to reduce drain flow in areas where precipitation is higher. A square root transformation was used to bring the observations in $\mathbf{R_{flow}}$ to normality, a requirement for proper use of multiple linear regression. The final simultaneous autoregressive spatial model had the form of:

$$\sqrt{\mathbf{R_{flow}}} = \hat{\beta}_0 + \hat{\beta}_1\mathbf{P} + \mathbf{E}\hat{\gamma} + \hat{\boldsymbol{\varepsilon}} \qquad (2)$$

where $\mathbf{R_{flow}}$ is the (48 × 1) vector of total reductions in subsurface drain flow in response to DWM for all sites, **P** is the (48 × 1) vector of total precipitation over 25 years for all sites, **E** is the (48 × 3) vector of eigenvectors to describe the underlying spatial processes, $\hat{\beta}_0$ and $\hat{\beta}_1$ are the regression coefficients for the dependent variables, $\hat{\gamma}$ is the (3 × 1) vector of regression coefficients for the eigenvectors, and $\hat{\boldsymbol{\varepsilon}}$ is the (48 × 1) vector of residual error. The eigenvector selection procedure initially resulted in four eigenvectors to remove spatial autocorrelation in the model, but the fourth was removed since the final model with three eigenvectors caused Moran's I test for residual spatial autocorrelation to be insignificant with a p-value of 0.11. Removal of any one of the final three eigenvectors from the model caused Moran's I test to be significant. Variance inflation factors (Neter et al., 1996) computed from the correlation matrix of the dependent variables were all equal to 1.0, indicating that there was little intercorrelation among the dependent variables and that multicollinearity was not an issue. The eigenvectors were all uncorrelated by definition.

Fitted values for the regression coefficients, all of which were statistically different from zero, are given in table 6. The regression coefficient for total precipitation, $\hat{\beta}_1$, was positive, indicating that the reduction in drain flow between CVD and DWM was positively correlated with precipitation. Thus, under the assumptions of the study, areas of the Midwest having greater amounts of annual precipitation have greater opportunity to reduce subsurface drainage using DWM. With a coefficient of multiple determination (R^2) of 0.97, the spatial model (eq. 2) was able to explain 97% of the variability in simulated drain flow reductions across the region (fig. 4a). Whereas the inclusion of additional climate or management variables into the statistical model sometimes resulted in regression coefficients that were statistically significant, these additional variables did not contribute anything toward improving the statistical model estimates of RZWQM-DSSAT simulated drain flow reductions. Under the assumptions of our study, precipitation was the most important variable determining the ability of DWM to reduce subsurface drain flow.

Regression analysis pinpointed average daily minimum temperature ($\mathbf{T_{min}}$), N fertilizer application rate (**N**), and precipitation (**P**) as the most important variables (table 4) to explain the simulated reduction in NO_3 losses in subsurface drainage ($\mathbf{R_N}$) in response to DWM. Minimum daily temperature was important because the rates of several

Table 6. Significance of the regression coefficients in the statistical models.

Term	Coeff.	Value	Std. Error	z Value	p Value
Model for Drain Flow Reduction (eq. 2)					
Int.	$\hat{\beta}_0$	-6.02E+0	6.97E-1	-8.64	6.07E-11
P	$\hat{\beta}_1$	1.11E-2	3.07E-4	36.24	<2.00E-16
E_1	γ_1	8.06E+0	8.55E-1	9.43	5.04E-12
E_2	γ_2	2.62E+0	8.55E-1	3.07	3.71E-03
E_3	γ_3	-2.98E+0	8.55E-1	-3.48	1.16E-03
Model for Reduction of NO_3 Losses in Drainage (eq. 3)					
Int.	$\hat{\beta}_0$	4.29E+0	1.94E-1	22.08	<2.00E-16
T_{min}	$\hat{\beta}_1$	9.28E-2	1.76E-2	5.27	3.88E-06
N	$\hat{\beta}_2$	4.76E-3	9.42E-4	5.05	8.10E-06
P	γ_1	2.85E-4	9.82E-5	2.90	5.81E-03

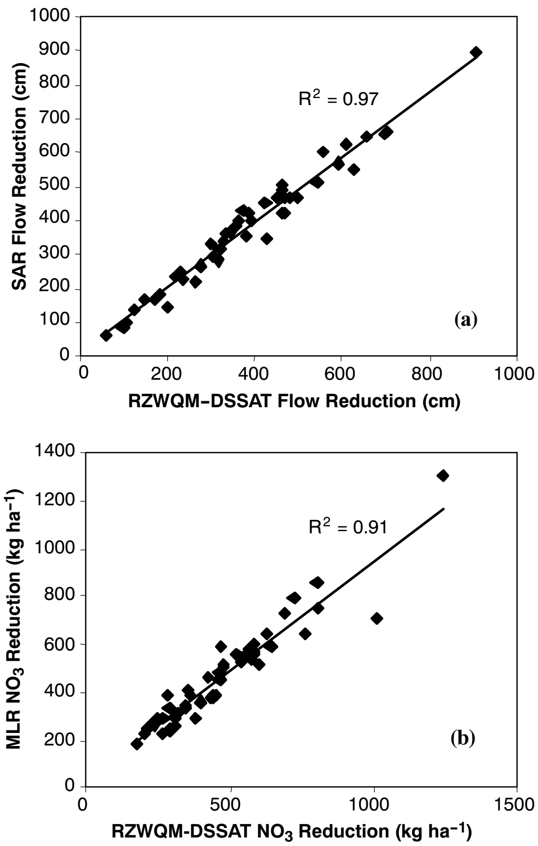

Figure 4. Estimates from (a) a simultaneous autoregressive (SAR) model versus RZWQM-DSSAT simulation results for total reduction in drain flow and (b) a multiple linear regression (MLR) model versus RZWQM-DSSAT simulation results for total reduction in NO_3 losses from subsurface drains.

processes that move N though the agricultural system are governed by temperature. Nitrogen application rate was an obvious factor of importance because it represents a substantial N input to the agricultural system. Precipitation was an important variable since NO_3 loss in subsurface drainage water is highly related to the drain flow volume, the reduction of which is related to precipitation as shown in equation 2. A natural logarithm transformation was used to bring the observations in $\mathbf{R_N}$ to symmetry, and the final multiple linear regression model had the form of:

$$\ln(\mathbf{R}_\mathbf{N}) = \hat{\beta}_0 + \hat{\beta}_1\mathbf{T}_{\mathbf{min}} + \hat{\beta}_2\mathbf{N} + \hat{\beta}_3\mathbf{P} + \hat{\boldsymbol{\varepsilon}} \qquad (3)$$

where $\mathbf{R_N}$ is the (48 × 1) vector of total reductions of NO_3 in subsurface drain flow for all sites; $\mathbf{T_{min}}$ is the (48 × 1) vector of average daily minimum temperature for all sites, $\mathbf{N}$ is the (48 × 1) vector of corn-year N application rates for all the sites; $\mathbf{P}$ is the (48 × 1) vector of total precipitation for all sites; $\hat{\beta}_0$, $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ are the regression coefficients for the dependent variables; and $\hat{\boldsymbol{\varepsilon}}$ is the (48 × 1) vector of residual error. Moran's I test for residual spatial autocorrelation in this multiple linear regression model was insignificant with a p-value of 0.11; therefore, a simultaneous autoregressive spatial model was not necessary to explain the NO_3 reduction data. Variance inflation factors computed from the correlation matrix of the dependent variables were less than 4.5. Mild intercorrelation existed between precipitation and minimum temperature, but not enough to warrant concern for multicollinearity.

Fitted values for the regression coefficients are given in table 6. The regression coefficient for average daily minimum temperature, β_1, was positive, indicating that an increase in minimum daily temperature corresponded to an increase in the reduction of NO_3 loss in subsurface drainage under DWM. An explanation may be that higher rates of N mineralization and nitrification would be expected in areas having higher average minimum daily temperatures. As increased N mineralization and subsequent nitrification increased the amount of NO_3 in the soil profile, there would be greater opportunity for DWM to reduce NO_3 losses in subsurface drain water. The regression coefficients for N application rate, $\hat{\beta}_2$, and precipitation, $\hat{\beta}_3$, were also positive, indicating that greater reductions in subsurface drain NO_3 losses were simulated in areas having higher levels of applied N and precipitation. The appearance of N application rate as a significant variable suggests that sites having higher average N rates are probably applying N in excess of plant needs, thus allowing DWM to reduce subsurface drain losses of excess applied N. Similar to the reasoning for the drain flow reduction model, increases in the amount of precipitation, which would increase the movement of NO_3 to subsurface drains, gives DWM greater opportunity to reduce the amount of NO_3 leaving the agricultural system through the drains. Coefficients for all terms in the model were significantly different from zero (table 6). With an R^2 of 0.91, the multiple linear regression model (eq. 3) was able to explain 91% of the variability in simulated reductions of NO_3 losses in subsurface drains across the region (fig. 4b).

Assessment of Simulations

We found three literature sources that reported short-term, measured subsurface drainage data under CVD in the Midwest for periods within our simulation timeframe (table 7). In Lamberton, Minnesota, Gast et al. (1978) measured annual subsurface drain flows and NO_3 loadings under continuous corn from 1973 to 1975. The closest site to Lamberton was Minneapolis, Minnesota. The model was set to simulate continuous corn from 1973 to 1975 using climate data from Minneapolis with the Gast et al. (1978) N rate of 112 kg N ha^{-1} and subsurface drain depth and spacing of 120 and 2800 cm, respectively. Simulations of CVD under these conditions were comparable to measurements at Lamberton. In 1973 and 1974, the difference in precipitation at the two locations was not greater than 30 mm. Simulations of drain flow equaled Lamberton observations in 1973 and differed by only 37 mm in 1974. In 1975, precipitation at Minneapolis was 301 mm greater than at Lamberton, and this is evident in the 58 mm higher simulated drain flow compared to the Lamberton observation. Simulations of NO_3 loss in subsurface drains responded with an increasing trend from 1973 to 1975 similar to the measured trend at Lamberton.

In Ames, Iowa, from 1974 to 1978, Baker and Johnson (1981) measured annual subsurface drain flows and NO_3 loadings under CVD with corn grown in rotation with soybean and oats. The model was set to simulate this rotation, substituting soybean for the oat year, using climate data from Des Moines, Iowa, with the Baker and Johnson (1981) corn-year N rate of 100 kg N ha^{-1} and subsurface drain depth and spacing of 120 and 3700 cm, respectively. Simulations of

CVD for weather data at Des Moines, Iowa, during this time were comparable to observations at Ames. This is particularly true in 1977, where simulated and observed precipitation and drain flow were both within 1 mm of each other, and the model overestimated NO_3 in subsurface drainage by only 4.1 kg N ha^{-1}. In 1976 and 1978, precipitation at Des Moines was 162 mm higher than and 90 mm lower than that observed at Ames, respectively. Simulations of CVD mimicked this trend by simulating 31 mm greater and 24 mm lesser drain flow than Ames observations in 1976 and 1978, respectively. Error trends for simulations of NO_3 in subsurface drainage also tended to follow the error trends for simulations of drain flow. Average precipitation at Ames was 12 mm yr^{-1} less than that at Des Moines over the five-year period, and average simulated drain flow was 18 mm yr^{-1} less than the observation at Ames. In addition, the average simulated NO_3 loss in subsurface drainage was only 4.6 kg N ha^{-1} yr^{-1} less than the average observed value for these five years.

In Butlerville, Indiana, Kladivko et al. (2004) reported annual subsurface drain flows and loadings of NO_3 in drain water under CVD with continuous corn from 1985 to 1990. The model was set to simulate continuous corn using climate data from Indianapolis, Indiana, with N rates as reported by Kladivko et al. (2004) and subsurface drain depth and spacing of 75 and 2000 cm, respectively. Average precipitation at Butlerville and Indianapolis from 1985 to 1990 varied by only 4 mm yr^{-1}, and average simulated drain flow was only 7 mm yr^{-1} less than that observed at Butlerville during the six-year period. In addition, average simulated NO_3 loss in subsurface drainage was only 1.8 kg N ha^{-1} yr^{-1} greater than the average observed quantity for these six years. These results demonstrate the model's ability to reasonably simulate the multi-year average response of subsurface drain flow and NO_3 loss under CVD to local climate conditions and management practices across the region, even though the model was not uniquely calibrated for local soils.

Table 7. Comparison of CVD simulation results and literature-reported observations for select sites and years[a].

Location (and Source)	Year	Precipitation ($mm\ yr^{-1}$) Obs	Precipitation Sim	Drain Flow ($mm\ yr^{-1}$) Obs	Drain Flow Sim	NO_3 Load ($kg\ ha^{-1}\ yr^{-1}$) Obs	NO_3 Load Sim
Lamberton, Minn. (Gast et al., 1978)	1973	516	537	35	35	6.0	4.5
	1974	456	485	91	54	22.0	16.4
	1975	592	893	120	178	25.0	81.5
	Avg.	521	638	82	89	17.7	34.1
Ames, Iowa (Baker and Johnson, 1981)	1974	947	906	216	192	32.3	21.0
	1975	772	803	167	93	40.4	32.7
	1976	600	762	93	124	21.4	23.5
	1977	943	944	90	90	18.0	22.1
	1978	887	797	114	90	21.1	10.5
	Avg.	830	842	136	118	26.6	22.0
Butlerville, Ind. (Kladivko et al., 2004)	1985	1260	1193	159	184	20.2	26.2
	1986	1061	1179	118	143	27.6	19.5
	1987	800	850	67	31	19.9	8.1
	1988	1001	796	118	75	32.0	32.4
	1989	1231	1284	166	121	50.1	78.5
	1990	1255	1281	158	191	33.4	29.3
	Avg.	1101	1097	131	124	30.5	32.3

[a] CVD = conventional drainage, Obs = observed, Sim = simulated.

Literature-reported observations from other studies were useful for assessing the model at additional locations across the region; however, data from these studies were not necessarily collected during the same timeframe as our simulations. In Camargo, Illinois, David et al. (1997) measured 975 mm yr^{-1} of precipitation, 326 mm yr^{-1} of drain flow, and 34.4 kg N ha^{-1} yr^{-1} lost in subsurface drain flow under CVD on average over two growing seasons, 1995 and 1996. Long-term simulations of CVD at Springfield, Illinois, used an average precipitation depth of 904 mm yr^{-1}, and average drain flow and NO_3 losses were 263 mm yr^{-1} and 48.0 kg N ha^{-1} yr^{-1}, respectively. David et al. (1997) reported that cropping systems in east-central Illinois were more efficient with regard to N uptake than systems in Iowa, which may be why our model, calibrated for Iowa conditions, simulated higher losses of NO_3 than that observed in an Illinois drainage system. David et al. (1997) also did not report any drainage system design parameters, so these model inputs could not be adjusted for the specific conditions of their study.

In Wood County, Ohio, Fausey (2004) measured an average precipitation of 845 mm yr^{-1}, drainage volume of 156 mm yr^{-1}, and NO_3 losses of 25.2 kg N ha^{-1} yr^{-1} for CVD in a corn-soybean rotation over four years, 1999 to 2003. The model was set to simulate a long-term corn-soybean rotation from 1966 through 1990 using climate data from Toledo, Ohio, with the Fausey (2004) subsurface drain depth and spacing of 80 and 600 cm, respectively. Application rates for N were not reported by Fausey (2004), so the average Ohio rate of 181 kg N ha^{-1} was used (table 3). Long-term simulations of CVD with these inputs resulted in an average precipitation depth of 862 mm yr^{-1}, and simulated average drain flow and NO_3 losses were 150 mm yr^{-1} and 16.4 kg N ha^{-1} yr^{-1}, respectively. Thus, average simulated precipitation and drain flow were within 17 and 6 mm yr^{-1} of observed values, respectively. The 8.8 kg N ha^{-1} yr^{-1} discrepancy in average NO_3 drainage loss may be the result of dissimilar actual and simulated N rates. Fausey (2004) also collected data from plots using DWM at the Wood County site, and average measured drain flow and NO_3 loss under DWM over the four years were 92 mm yr^{-1} and 13.7 kg N ha^{-1} yr^{-1}, respectively. The model was adjusted to simulate the Fausey (2004) controlled drainage strategy with CVD occurring between April 1 and June 15 and between September 15 and November 15 and with DWM (gates raised to 30 cm) occurring in the remainder of the year. The simulated long-term average drain flow and NO_3 loss with these inputs were 101 mm yr^{-1} and 11.1 kg N ha^{-1} yr^{-1}, which differed from observed values by 9 mm yr^{-1} and 2.6 kg N ha^{-1} yr^{-1}, respectively. Thus, for this measured data under DWM, rough RZWQM-DSSAT simulations show a reasonable response.

Considering that the model was not calibrated for the local soils of these studies and that the weather information used for simulations was up to 150 km away from the study sites, we conclude that RZWQM-DSSAT performed reasonably well at simulating the response of CVD and DWM to climate variability and management practices across the region.

CONCLUSIONS

Simulations of CVD and DWM for climate conditions and common management practices across the midwestern U.S.

demonstrated that DWM has great potential to reduce the amount of NO_3 lost to surface waters from agricultural systems. According to the simulated hydrologic balance, DWM had the greatest regional effect on subsurface drainage, a 53% reduction, which was offset mainly by increases in surface runoff and ET. Results for the nitrogen balance demonstrated that DWM most greatly affect NO_3 losses from subsurface drains, a 51% reduction, which was offset mainly by increases in soil N storage, denitrification, and plant N uptake. When considering the effects of DWM on all undesirable waterborne output pathways for N, including surface runoff, seepage, and subsurface drainage, adoption of DWM across the midwestern U.S. would reduce NO_3 loss to surface waters by a more conservative 31%. While this has potential to substantially improve water quality in the Mississippi River basin and reduce hypoxia in the Gulf of Mexico, these results indicate that DWM cannot be the lone solution for solving problems associated with release of agricultural N to the environment. Rather, a more holistic approach involving several different techniques for managing the N imports to and exports from the agricultural system as well as controlling N processes within the system will be required.

Simulations demonstrated that DWM may be better able to reduce subsurface drain flows and NO_3 losses in subsurface drainage in the southern part of the region. Specifically, DWM typically performed better in Missouri, Illinois, Indiana, and Ohio as compared to Michigan, Wisconsin, Minnesota, and Iowa. Precipitation amount, minimum daily temperature, and N application rate were shown to be the major climatic and management variables affecting the performance of DWM across the region. However, our simulations did not account for regional variation in soil type and drainage system design or the use of alternative management practices for tillage and/or crop rotations. Our study also did not consider the regional variation in DWM implementation practicality due to topographic restraints. Future work will focus on obtaining independent model calibrations for dominant soil types and local drainage systems at each site across the region. In addition, we plan to use the simulation results in conjunction with topographic data to assess regional DWM performance with regard to practical implementation of DWM systems. Further comparisons of CVD and DWM while considering these other important factors is the next step to more fully assess the potential regional impact of DWM on losses of NO_3 from agricultural systems to the environment.

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