CONSERVATION INNOVATION GRANTS

Final Report

Grantee Entity Name: North Carolina State University	
Project Title: Development, evaluation, and demonstration of simple tools for a nitrogen credit trading system involving drainage water management.	
Agreement number: 69-3A75-12-184	
Project Director: Dr. Mohamed A. Youssef	
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Project Start Date: 9/21/2012**; Project End Date:** 06/30/2015	

Introduction

Agricultural drainage is necessary for crop production on about 25% of cropland in the United States. Improved drainage increases crop yields, but also increases nitrogen (N) loads that can have negative environmental impacts on waters receiving drainage outflows. Drainage Water Management (DWM), also referred to as controlled drainage or managed drainage, is a practice that can reduce N loads while maintaining or improving crop yields. It involves the use of drainage water control structures that are installed at drainage outlets to regulate drainage intensity and outflow according to farming needs. It works by reducing drainage outflow and promoting denitrification reaction to transform dissolved nitrate into dinitrogen gases. Effective management of the structures reduces the amount of water drained and the amount of N lost from the field. The costs of control structures and the time required to effectively manage the structures has limited the acceptance of DWM among growers. An incentive program based on nitrogen trading where farmers could get financial compensation for the effective operation of the drainage water control structure and reducing N loads will likely increase acceptance of DWM and protect the quality of receiving waters. A nitrogen trading program involving DWM will require a simple and accurate tool to calculate the amount of N loss reductions resulting from DWM. This tool will need to consider the many variables affecting N loading from a drained crop field. Also, the input data to this tool must be readily available and verifiable.

Objectives

The objectives of this CIG were to develop and assess a simple tool for quantifying the impacts of DWM on the reduction of drainage flow and N losses from subsurface drained cropland. This tool can be used with an N trading program involving DWM to estimate the annual N reductions resulted from implementing the practice to a specific farm.

Approach

The proposed design of the tool is a set of simple regression equations that can calculate annual reductions in drainage flow and associated N losses for a specific farm as a function of explanatory variables describing essential farm characteristics. The data set used to build the regression equations is generated by thousands of DRAINMOD and DRAINMOD-NII model simulations over representative ranges of soils, climatic conditions, drainage designs, and cropping practices typical for the region of interest. Two separate studies have been conducted: a) Eastern North Carolina; and b) U. S. Midwest. The Midwest includes many states spanning over several climate zones. The states that were chosen for the current analysis were Minnesota, Iowa, and Illinois due to their intensive agricultural presence, their need for water table management, and their spanning of all Midwestern climate zones.

Methods

Development of the Regression Equations

The following steps were followed to develop the regressions equations for the DWM tools for the four states.

1) Select locations that represent high crop intensity, different climate zones, and soil types.
2) Obtain climate data from National Climatic Data Center of the National Oceanic and Atmospheric Administration (NCDC-NOAA). Thirty years of historical data where obtained.
3) Obtain soil data from the Cooperative Soil Survey (MCSS, 2015) and convert to DRAINMOD format with using ROSETTA model (Schaap et al., 2001). Soil series were selected by indicators of poor drainage and crop appropriateness:
   a) slope <1%;
   b) depth of soil profile >1 m;
   c) seasonal water table depth <18 inch,
   d) a "poorly drained" soil classification by MCSS (2015).
4) Use DRAINMOD and DRAINMOD-N II simulations to determine annual drainage volume and annual N load for all combinations of

	Midwest	North Carolina
Location (Climate data for location)	19 counties	4 counties
Soil Series	more than 120	more than 30
Drain spacings	between 9 and 35 m	Between 15 and 55 m
Drain depths	between 70 and 145 cm	between 80 and 150 cm
Fertilizer applications	between 70 to 170 kg N/ha	between 70 and 260 kg N/ha
Surface storage (surface drainage)	1.5 cm, 2.5 cm, 4 cm	0.5 cm, 1.0 cm, 2.0 cm

Simulated scenarios of cropping system and drainage water management include:
Class 1- Continuous Corn under Controlled Drainage;
Class 2- Continuous Corn under Free Drainage;
Class 3- Corn-soybean (Midwest) or Corn-wheat-soybean (NC) rotation under Controlled Drainage;
Class 4- Corn-soybean (Midwest) or Corn-wheat-soybean (NC) rotation under Free Drainage.

5) Build regression equation for each scenario using the data sets generated by the DRAINMOD and DRAINMOD-N II simulations. SAS (PROC GLMSELECT)
   a) $Y_d = \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \beta_{C1} X_{C1}$ is the generic equation
      i) The βs represent coefficients estimated by SAS and the Xs represent variables and their interactions to be used in the given scenario

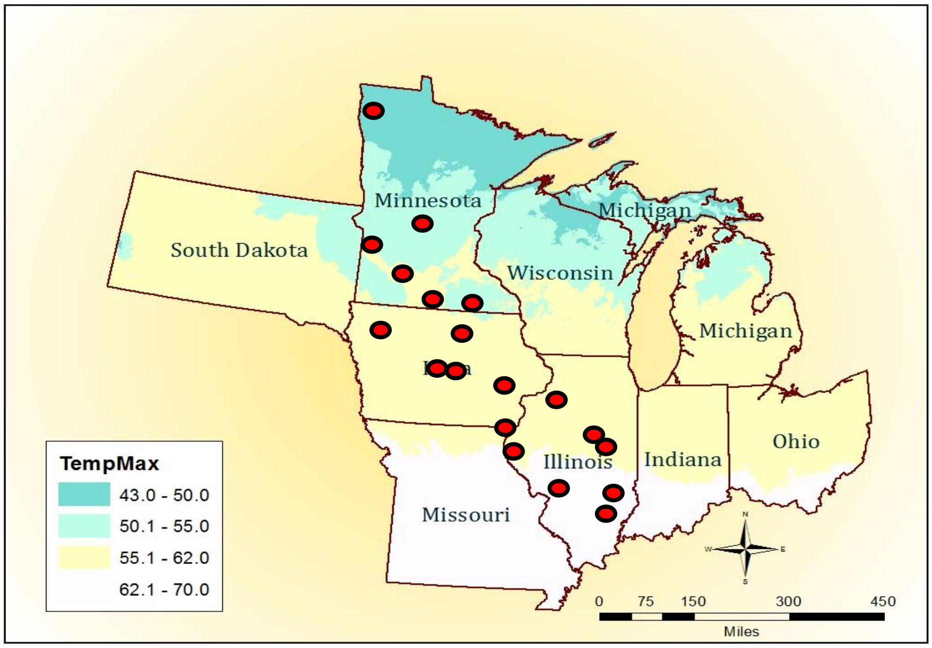


Figure 1. Locations of counties used in the Midwest analyses shown with visual representation of climate divisions: NRCS DATA GATEWAY, 2014

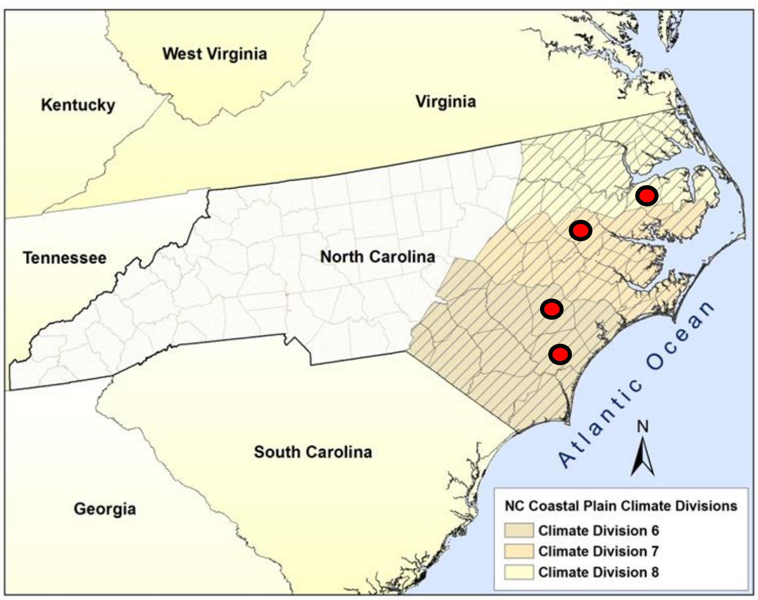


Figure 2. Locations of counties used in the North Carolina analyses shown with visual representation of climate divisions: NRCS DATA GATEWAY, 2014

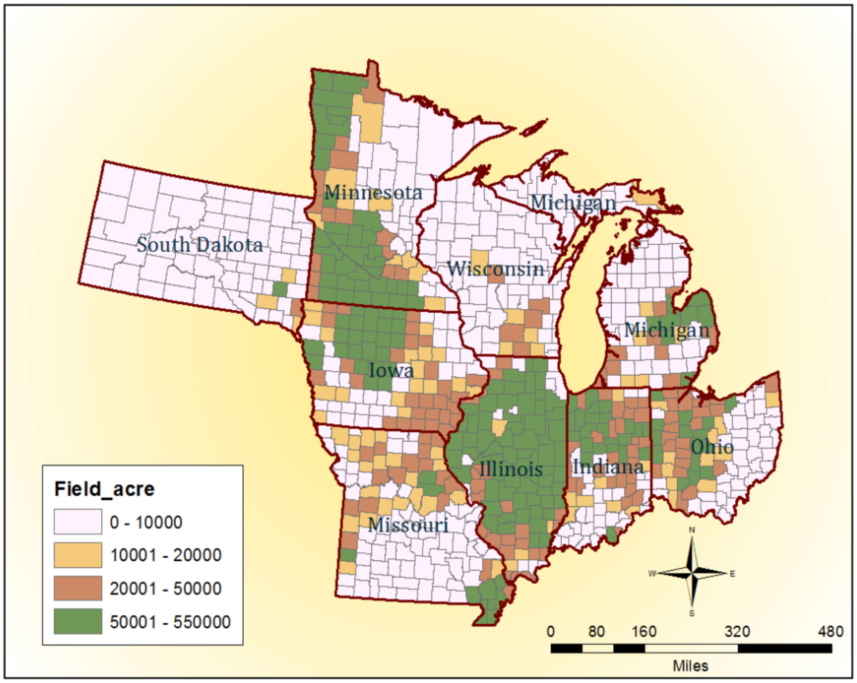


Figure 3. Cropland suitable for drainage water management in the U.S. Midwest. **GIS data sources:* http://datagateway.nrcs.usda.gov. **Cropland county-based tabulated data :* http://www.nrcs.usda.gov/

The explanatory variables (the inputs) required for the regression equations are listed in the following table.

Explanatory variables for regression equations predicting	
Annual Drainage	Annual Nitrogen Loads
Drain spacing (cm)	Annual drainage either predicted by DRAINMOD or by the drainage regression equation
Drain depth (cm)	Annual relative crop yield (%)
Annual rainfall (cm)	Previous year's relative crop yield (%)
Soil texture (% Sand, % Silt, % Clay)	Fertilizer application rate (Kg N/ha)
Soil Organic Carbon Content (%)	Annual rainfall
Surface storage (Level 1, Level 2, Level 3)	Previous year's rainfall
	Soil Organic Carbon Content (%)
	Ratio of rainfall in growing season to annual rainfall (Midwest only)

Testing of the Regression Equations

The developed regression equations were tested by comparing their predictions to the predictions of DRAINMOD and DRAINMOD-N II model simulations. A detailed description of the approach used for testing the regression equations is given in the manuscript attached to this report.

Results and Deliverables

A) Development and Testing of the DRAINMOD-Based Tools:

1. The outcome of this project is a DRAINMOD-based tool for estimate the impact of drainage water management (DWM) on artificially drained crop lands located in the U.S. Midwest and Eastern North Carolina.
2. The tool comprises a set of regression equations estimating the performance of DWM in terms of reducing drainage flow and NO3-N losses without the need for using processes based models such as DRAINMOD and DRAINMOD-NII. The regression equations estimate the annual drainage and N loading for four scenarios combining two cropping systems (continuous corn and corn-soybean for US Midwest or corn-wheat-soybean for North Carolina) and two drainage system management: (conventional drainage and controlled drainage).
3. All regression models were developed using the GLMSelect procedure (PROC GLMSELECT) of SAS software (V 9.3, SAS Institute, Cary, NC). This procedure is suitable for models combining both continuous and categorical predictors (More details about the regression analysis and data manipulation are given in the attached manuscript).
4. All regression models require easy-to-obtain parameters that describe local site conditions, including: weather, soil type, drainage system, nutrient management, and crop yields. To use the developed tool, one must select the regression equation that represent the scenario and provide the required input data that represent the local farm conditions.
5. The regression model estimations of annual drainage flow and NO_3-N losses were highly correlated with DRAINMOD simulated values (Figure 4). For the Midwest, adjusted R-squared values were greater than 0.90 for flow and 0.82 for NO_3-N. For NC, adjusted R-squared values were greater than 0.91 for flow and 0.88 for NO_3-N.
6. The developed regression models were compared on a year-by-year basis to the calibrated DRAINMOD and DRAINMOD-NII models for local conditions of an experimental site in eastern NC over 25 years. A similar comparison was conducted for the U.S. Midwest region. The results indicated that the simple regression method provides an adequate alternative to the processes based DRAINMOD suite of models for estimating annual reductions in drainage rates and N mass losses resulting from implementation of DWM. The comparisons between the estimates of the regression models and the predictions of the process based models for a North Carolina farm are presented in the attached manuscript.
7. However, precautions should be considered when using the regression models to estimate DWM performance under extreme weather conditions (very dry or very wet). Under these extreme conditions, the estimates of the regression models tend to considerably deviate from DRAINMOD/DRAINMOD-NII predictions.
8. A Master student and a post-doctoral associate worked on the project. The student is currently writing his thesis and is expected to complete all degree requirements by the end of Fall 2015.

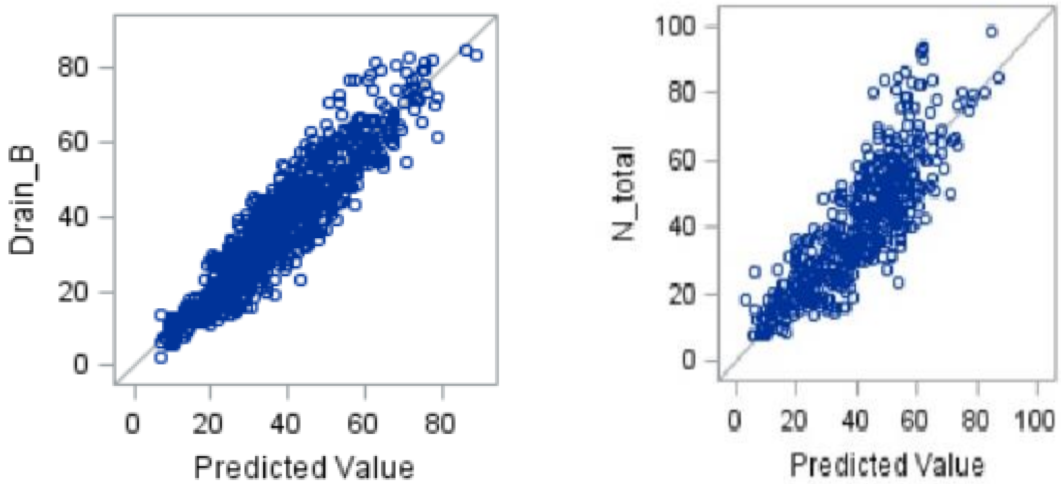
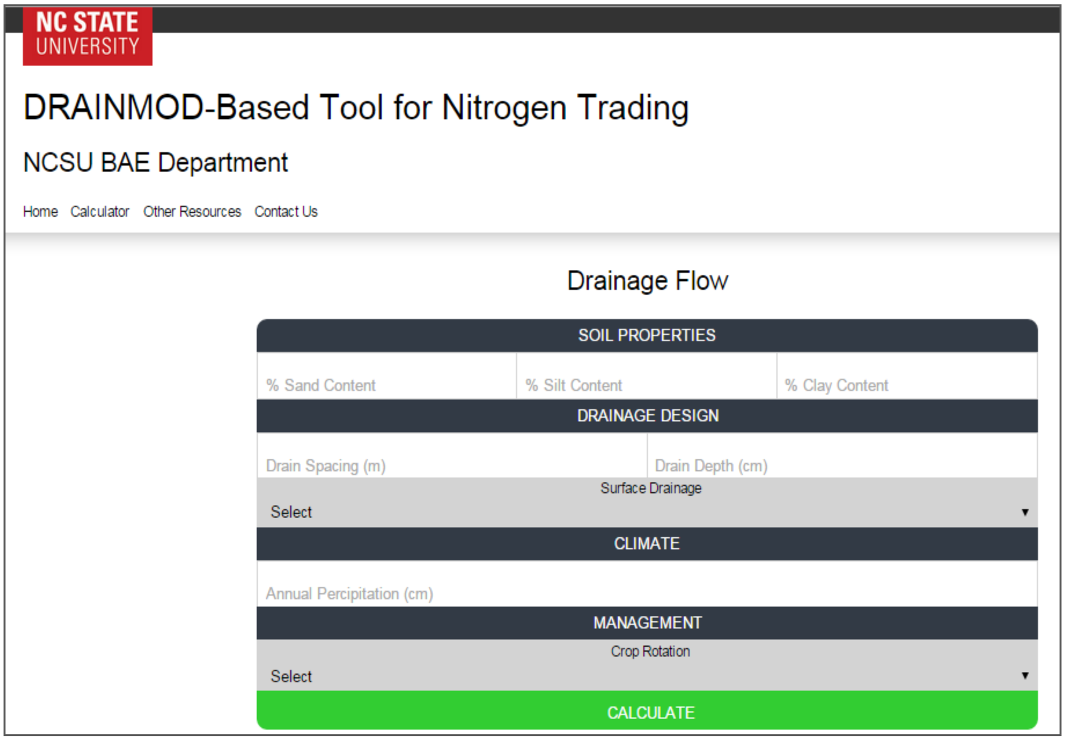


Figure 4. Example output of diagnostic plots comparing DRAINMOD simulation values to the regression predicted values. (PROC REG, SAS procedure).

B) An Online Calculator for the Developed Tools:

An online calculator was designed to help producers and planners to easily apply the tool by simply inserting easy to define parameters describing local site conditions. Screen shots of the online calculator is presented below. This online calculator is primitive and requires significant improvement before it can be readily applied. More funds will be needed to further develop the online interface of the tool.



C) Publication and Presentations:

- Negm, L., Youssef, M., Skaggs, R., and Chescheir, G. DRAINMOD-based tools for assessing the impact of drainage water management (DWM) on annual drainage flow and Nitrate losses from cultivated drained soils in Eastern North Carolina. Submitted for The Journal of Agricultural Water Management.
- Negm, L.M., M.A. Youssef, R.W. Skaggs, and G.M. Chescheir, R. O. Evans. 2014. DRAINMOD-based tools for nitrogen credit trading systems involving drainage water management. Presented at ASABE Annual International Meeting, Montreal, Quebec, Canada, July 14-16, 2014.
- Brooks, F.N., L.M. Negm, M.A. Youssef, G.M. Chescheir, and R.W. Skaggs. 2015. Development, evaluation, and demonstration of simple tools for nitrogen credit trading system involving drainage water management. Poster Presentation, 2015 Conservation Innovation Grants Showcase, Greensboro, North Carolina, July 27, 2015.

Program (EQIP) and CIG grant agreement provisions:

1. A listing of EQIP-eligible producers involved in the project, identified by name and social security number or taxpayer identification number; **None**.

2. The dollar amount of any direct or indirect payment made to each individual producer or entity for any structural, vegetative, or management practices. Both biannual and cumulative payment amounts must be submitted. **$0.0**

3. A self-certification statement indicating that each individual or entity receiving a direct or indirect payment for any structural, vegetative, or management practice through this grant is in compliance with the adjusted gross income (AGI) and highly-erodible lands and wetlands conservation (HEL/WC) compliance provisions of the Farm Bill. **Not applicable.**

DRAINMOD-based tools for quantifying reductions in annual drainage flow and nitrate losses resulting from drainage water management on croplands in eastern North Carolina

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Abstract

Nitrogen (N) lechate of drained agriculture has continued to be pervasive in the nation's water resources. Nitrogen credit exchange program is a trading market to facilitate pollutant reductions and protect the environment. A simple tool suitable for eastern North Carolina (NC) was developed to quantify drainage flow and N mass reductions resulting from drainage water management (DWM); an efficient and common conservation practice for drained agricultural lands. The tool comprises a set of regression equations estimating the performance of DWM as a function of local site conditions. DRAINMOD and DRAINMOD-NII simulations were conducted for a wide range of soil types, weather conditions, and management practices for different locations in eastern North Carolina. Simulation results were used with SAS 9.3 software to develop a set of regression equations to estimate DWM-caused reductions in annual drainage flow and corresponding NO_3-N losses for continuous corn (CC) and corn-wheat-soybean (CWS) cropping systems. The regression model estimations of annual drainage flow were highly correlated with DRAINMOD simulated values with an adjusted coefficient of multiple determination (R^2_{adj}) equaled to 0.91 or higher for different management tiers. Similarly, the regression model estimations of annual nitrate losses achieved an R^2_{adj} of 0.88 or higher for all management tiers. The developed regression models were further compared on a year-by-year basis to the calibrated DRAINMOD and DRAINMOD-NII for local conditions of an experimental site in eastern NC over 25 years. Estimated annual drainage flow and NO_3-N losses were in good agreement with corresponding values simulated by DRAINMOD-based models for CC and CWS under managed and unmanaged drainage modes. In terms of DWM-induced annual reductions in drainage flow and N losses, noticeable differences occurred in several years between predictions of DRAINMOD-NII and the regression models. A comparison based on the 5-year moving average of DWM-induced reductions smoothed out the extreme year-to-year variations and indicated a very similar reduction trends provided by both methods. The results presented in this case study indicated that the simple regression method provides an adequate alternative to the processes based DRAINMOD suite of models for estimating annual reductions in drainage rates and N mass losses resulting from implementation of DWM. Similar tools can be developed for other regions in the US and abroad credit trading system involving DWM.

Keywords: *DRAINMOD, DRAINMOD-NII, regression analysis, agricultural drainage, nitrogen trading, controlled drainage.*

1. Introduction

Nitrogen (N) lechate from drained agricultural lands is a pervasive problem to the nation's water resources. The excess of N fertilizer applied on corn fields of the US Midwest have been identified as the main contributor to seasonal hypoxia in the northern Gulf of Mexico, the nation's largest and most productive fishery (Petrolia and Gowda, 2006; Mitsch et al., 2001; Dinnes et al. 2002, Alexander et al., 2008). In the Atlantic coastal plain, excessive levels of nutrients originated from drained agricultural fields have been identified as being a primary cause of eutrophication in the lower Neuse River basin, Pamlico River estuary, and other waters in eastern North Carolina. "The minimization of these N losses is desirable from an environmental standpoint, and a recent interest in discounted reductions of agricultural N losses that might apply to a project downstream from an agricultural area has resulted in the concept of N credits and associated N trading." (Delgado et al., 2008).

Controlled drainage (CD), also referred to as drainage water management (DWM), is a practice for reducing NO_3-N losses via drainage water (Skaggs et al., 1994; Evans et al., 1995; Drury et al, 1996; Wesström et al., 2001; Zebarth et al., 2009). Unlike conventional or free drainage (FD) characterized by open drain outlets throughout the year; DWM employs a drainage water control structure at drain outlets to regulate drain flow according to the need for drainage for field operations and crop growth. Previous field experiments that have conducted side-by-side comparisons between managed and unmanaged drainage systems, documented reductions in annual drain flow and N drainage loss resulting from DWM by 20% to 60% (Evans et al., 1995; Pitts et al., 2004; Fausey, 2005; Ayars et al., 2006; Zebarth et al., 2009; Poole et al., 2013, Fang et al., 2012). Managed systems conserve more groundwater and nutrients for plant uptake, especially during relatively dry growing seasons. Ghane et al. (2012) reported that the DWM provided up to 3.3% greater yield compared to FD. A North Carolina study by Poole et al. (2013) indicated that DWM achieved a 10% yield benefit for corn and soybean compared to FD. Drainage water management however, had no significant effect on winter wheat yields due to the wet and cold environment although it is the period when water quality benefits are mostly achieved. Therefore, in many locations where DWM can be effectively applied to improve water quality, the relatively modest yield benefits of the practice are not sufficient to increase nationwide adoption of the practice.

Water quality credit trading markets have recently been proposed in the U.S. offering an innovative approach to achieve water quality objectives by controlling pollutant discharge from multiple sources; point and non-point (US Environmental Protection Agency (USEPA), 2007). Through these markets, farmers or stakeholders get monetary compensation based on their application of conservation practices that reduce N losses. Such an approach would be exceptionally effective in promoting the large scale adoption and use of DWM for substantial environmental benefits, as well as, bringing economic and social advantages to farmers and other stakeholders (Corrales et al.; 2013 and 2014). One of the largest water quality trading initiatives in the United States is The Great Miami River Watershed Trading Program in Ohio. This program aims to accelerate reductions of phosphorus and nitrogen runoff coming from fields receiving fertilizer and manure applications (Newburn and Woodward, 2012). According to 2014 trading program fact sheet released by Miami Conservancy District (MCD), more than 1.14 million credits have been generated since the start of the project in early 2005. This is reported to translate to a 572 ton reduction in nutrients discharge at a cost of 1.6 million dollars paid to agricultural producers for these credits.

An essential component of any water quality credit trading system involving DWM is a tool or a method for determining annual N mass conserved by implementing DWM for a specific site and farm conditions (weather, soil, drainage system, cropping system, and farming practices). Several computer simulation models have been developed to predict nutrient losses from agricultural fields as affected by environmental conditions and management practices. Over the past two decades, the DRAINMOD suite of models have been the models of choice for simulating the hydrology and water quality in drained agricultural lands and have been extensively tested and applied nationwide (e.g. Skaggs, 1982; Fouss et al., 1987; Workman and Skaggs, 1989; Cox et al., 1994; Wang et al., 2006a; Ale et al., 2009; Youssef et al., 2006; David et al., 2009; Thorp et al., 2009; Luo et al., 2010; Ale et al., 2012). However, the use of such process-based models requires detailed input data and modeling experience which limit their applicability for this purpose on a production scale. Developing simple decision support tools based on process-based models that can be used by farmers and policy makers for the purpose of nutrient credit trading markets has been well introduced (Delgado et al., 2008; Gross et al., 2008; Corrales et al., 2014; Saleh et al., 2011). Skaggs et al. (2012a) demonstrated the potential of DRAINMOD-based models to formulate trading tools necessary to assess the environmental benefits of installing DWM. Their proposed tool to estimate the effect of DWM on N losses was presented by a simple linear function of annual subsurface drainage and long-term average flow weighted nitrogen concentration. However, the tool oversight temporal and spatial variations in environmental condition and management design which by its turn constrain the tool application to selected configuration of local site conditions. Further research and analysis, utilizing DRAINMOD-based models, can broaden the application of such tools; not only with water quality trading markets, but also with different water resources management studies and applications. For example, this tool can be extremely useful for management of watersheds dominated with drained agriculture.

2. Purpose and Scope:

The purpose of this project is to develop and evaluate a simple tool for quantifying the impacts of DWM on the reduction of drainage flow and NO_3-N losses from subsurface drained cropland in eastern North Carolina. This is the region where DWM was initiated in the mid 1980's for the purpose of reducing nutrient losses. This tool would be essential for any water quality credit trading system that involves the use of DWM. A similar approach will be used to develop tools for crop production systems on drained lands in the U.S. Midwest.

Three essential features should be considered in developing this tool: 1) accuracy, 2) simplicity, and 3) data availability. Accuracy is at the core of any water quality credit trading system. Estimates of the credits that all stakeholders can accept is a challenge for the non-point source component(s) of the system. Simplicity is essential since the easy use of the tool will promote its adoption. Data availability is also important since the inputs to the tool must be easy to obtain, standardize, and interpret. The conceptual design of the tool is a set of simple regression equations that can assess annual reductions in drainage flow and associated NO_3-N losses for the region of interest as a function of explanatory variables describing essential farm characteristics.

A representative dataset is required to build the proposed regression model and it should comprise a number of observations that consider the inclusion of critical explanatory variables, the temporal and/or spatial variations in each variable, and the response (dependent) variables under investigation (i.e., drainage flow and NO_3-N losses). It is practically impossible, however, to conduct a large enough number of field experiments to quantify DWM performance in response to the wide variation in soil, environmental conditions, and management practices for a given region. Instead, the DRAINMOD suite of models was used to simulate drainage flows and N leaching losses for the wide range of climate year, soil type, drainage design, and farming practices of the NC Coastal plain for both managed (DWM) and unmanaged (conventional drainage) scenarios.

3. Materials and methods

3.1 Description of Study Area

The North Carolina Coastal plain encompasses the easternmost counties of the state on a total area of 22,500 square miles that lies between 33° 52′ and 36° 33′ north latitudes and between 75° and 78 30° west longitudes (Figure 1). This region is characterized by low relief topography becoming more flat and swampy with a larger percentage of the farms artificially drained towards the Atlantic coastal shoreline (Figure 2). The Coastal Plain is the major area for agricultural crop production in the state. The most commonly grown crops in the area are corn, soybean, wheat, and cotton. Installing drainage systems is a common practice by farmers to improve field trafficability and to increase yields and profitability. On average, 40% of the agricultural fields in the area are artificially drained (Pavelis, 1987; Jaynes and James, 2007). Summer temperatures are moderate with daytime high temperatures averaged at 32 °C (90 °F), while winter temperatures are generally mild with 13.4 °C (56.2 °F) average daytime temperatures in the month of January; the coldest month of the season (State Climate office of North Carolina, 2013). The annual precipitation in eastern North Carolina averages at 130 cm (51 inches); mostly in the form of rainfall with no distinct dry or wet seasons within a year. Although NC coastal plain is classified as a humid-subtropical climate division, sever dry conditions occasionally occur resulting in substantial losses in the crop yields.

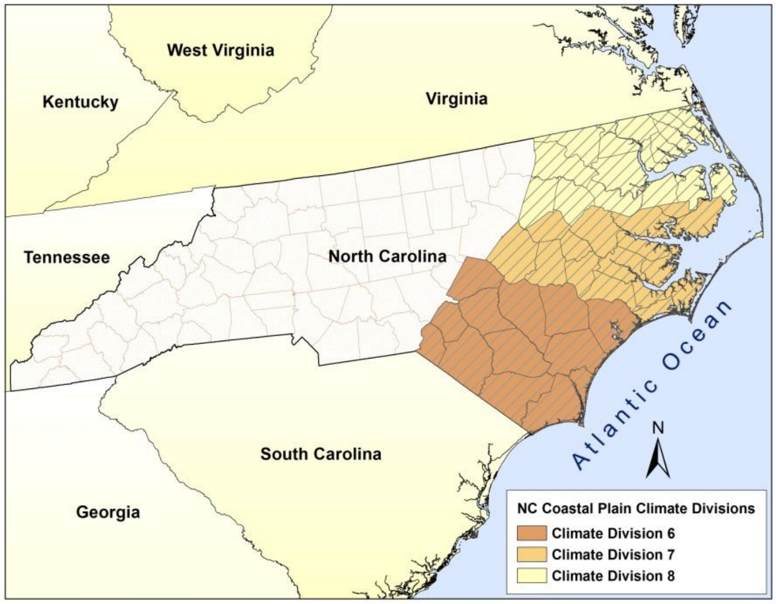


Figure 1. Map of North Carolina Coastal Plain and Climate Divisions of the Region. (GIS data source: http://datagateway.nrcs.usda.gov/)

Figure 2. A map illustrating the distribution of poorly drained soils in North Carolina. (*GIS data source: [http://datagateway.nrcs.usda.gov/)](http://datagateway.nrcs.usda.gov/)*

3.2 DRAINMOD-based Models description:

DRAINMOD (Skaggs, 1978) is a field-scale hydrologic model developed to simulate the hydrology of poorly drained high water table soils. It conducts a one-dimensional soil water balance and predicts subsurface drainage, surface runoff, infiltration, deep seepage, water table depth, and evapotranspiration as affected by changes in weather conditions, crop cover, soil type, and drainage system design. The model applies the Green-Ampt equation to estimate infiltration rates. Subsurface drainage is calculated using Hooghoudt's equation provided that water table is below the surface, otherwise DRAINMOD uses Kirkham's equations when the surface is ponded. Surface runoff is calculated when a user-defined depressional storage is filled as the difference between precipitation and infiltration rates. Daily potential ET (PET) may be internally computed by the model using the Thornthwaite method with monthly correction factors, or daily PET values may be determined independently outside the model by any method (depending on weather data availability) and read in by the model as input data. The model has been widely used to study the effects of drainage design and management on crop yields (e.g. Evans et al., 1991; Wang et al., 2006a; Throp et al., 2009), erosion (e.g. Saleh, 1994), hydrology of high water table soils (e.g. Fouss et al., 1987; Skaggs et al., 1981; Wang et al., 2006a; Throp et al., 2009; Luo et al., 2010), and wetland hydrology (e.g. Skaggs et al., 2005; Jia and Luo, 2006).

DRAINMOD-NII (Youssef et al., 2005); a companion model to DRAINMOD, is a process-based model that simulates Carbon (C) and N dynamics of drained cropland. DRAINMOD-NII simulates a detailed N cycle that considers both mineral N (nitrate and ammoniacal forms) and organic N (ON) and their interaction as affected by C cycling. The organic carbon (OC) dynamics is simulated using a C-cycle adapted from the CENTURY model (Parton et al., 1993) by which the soil organic matter is divided into three pools (active, slow, and passive), two above-and below-ground residue pools (metabolic and structural), and a surface microbial pool. The model performs a numerical solution of the multiphase form of the one dimensional advection–dispersion-reaction equation using the finite difference method to simulate N reactive transport in the soil column among three soil N pools: nitrate (NO3)-N, ammoniacal (NH3/4)-N, and organic nitrogen (ON). Nitrogen processes simulated by the model include atmospheric deposition, plant uptake, N fixation by legumes, mineralization/immobilization, nitrification, denitrification, ammonia volatilization, and N losses via subsurface drainage, vertical seepage and surface runoff. The model has been tested against field measurements and found to reliably predict N losses in drainage water for a range of soils and locations across the U.S. (North Carolina: Youssef et al., 2006; Iowa: Thorp et al., 2009; Illinois: David et al., 2009; Minnesota: Luo et al., 2010; Indiana: Ale et al., 2012). DRAINMOD-NII has also been tested in Europe (Germany: Bechtold et al., 2007 and Sweden: Salazar et al., 2009).

3.3 Data Collection:

This section describes data collection and processing required to conduct DRAINMOD and DRAINMOD-NII simulations of the hydrology and nitrogen dynamics for a wide range of possible scenarios of local site conditions. DRAINMOD and DRAINMOD-NII simulations of annual drainage flow and annual N losses, respectively, were used to extrapolate the results of field experiments to build the regression model since it is practically impossible to conduct large enough number of experiments.

3.3.1 Weather Data

Historical weather data including hourly precipitations and daily maximum and minimum temperatures were obtained from the North Carolina State Climate Office for different spatially distributed locations across the Coastal Plain. These data covered up to 50 year time span of weather records. A simple analysis using a paired T-test showed that annual rainfall patterns measured for stations within the same climate region were not significantly different ($Pr \geq 0.16$). Therefore, and in order to avoid weather related factors overwhelming the influence of other factors, weather station selections was limited to a few stations at different locations within the North (climate region 8), Middle (climate region 7), and South (climate region 6) of the coastal plain (Figure 1). These weather satiations coinciding with four counties; namely from north to south: Washington, Pitt, Duplin, and Pender counties. Rainfall and temperature data were the only climatic data required since Potential evapotranspiration (PET) was computed by the model using the temperature-based Thornthwaite method, with monthly correction factors. All required input weather parameters were then processed to conform to the required DRAINMOD formatting.

3.3.2 Soil Data

The boundary of each of the counties listed above was considered as a buffer zone of the weather station each encompasses; and the soils within each buffer zone and suitable for installing DWM systems were identified through the National Cooperative Soil Survey (MCSS, 2010) and considered in the current analysis as distinct farm units.

This selection criterion granted the inclusion of more than 30 different soil series that collectively occupies at least 50% of the cropped land suitable for DWM in eastern North Carolina. For many of the selected soil series, soil water characteristics data (soil water content versus pressure head) were available based on previous laboratory measurements on soil cores using standard pressure plate methods. When measured soil water characteristics were not available, soil physical properties were obtained from SSURGO soil data base (MCSS, 2010) and utilized in the ROSETTA model (Schaap et al., 2001) to estimate van Genuchten water retention and unsaturated hydraulic conductivity parameters. Estimated soil water characteristics were further processed using DRAINMOD 6.1 soil utility program to estimate detailed soil related parameters including the volume drained and upward-flux relationships and Green and Ampt infiltration parameters, all as a function of water table depth. Other biogeochemical parameters required to simulate soil carbon and nitrogen dynamics were obtained from previous DRAINMOD-NII applications for NC conditions (Youssef et al, 2006). Organic soils were excluded from this analysis.

3.3.3Crop management and drainage design:

Two crop rotations were considered in the current study: continuous corn (CC) and corn-winter wheat-soybean rotation (CWS). Crop planting and harvesting dates (Table 1) were defined according to usual operational dates stated by the USDA National Agricultural Statistics Service (NASS) (USDA, 2010). Fertilizer management was set based on recommended practices documented by the Agronomic Division of the North Carolina Department of Agriculture & Consumer Services (NCDA&CS). We considered the reported varying rates of fertilizer application to address all possible levels considered within the region. Fertilized crops; corn and wheat, received 30% of the total amount at planting as a starter, with the remainder sidedressed at the recommended time after planting (Table 1).

Similarly, drainage system design parameters included in the simulations were set according to common practices in the region to represent realistic conditions for the proposed water management scenarios. Drain depth and spacing were allowed to vary within a range of values listed in the Field Drainage Guide for Coastal Plain Area of North Carolina (NC USDA SCS, 1976). Recommended drain spacings varied between 15 to 50 m placed at depths ranging from 90 to 150 cm. Surface drainage was considered at three different levels: good (depressional storage

(DS) ≤ 0.75 cm), fair (0.75 cm < DS ≤ 1.5 cm), and poor (DS ≥ 1.5 cm). Weir settings that define the control structure depths under the DWM scenario were adjusted based on the recommendations of the NC Agricultural Cost Share Program (ACSP).

Table 1: Summary of crop and fertilization management inputs for continuous corn and corn-wheat-soybean rotation at Eastern North Carolina

Cropping System	Crop	Planting Date	Harvest Date	Fertilizer application	
				DAP[1]	Kg N/ha
Continuous Corn	Corn	15 - April	10 - September	0	40 - 66
				30	90 - 154
Corn-wheat-soybean	Corn	15 - April	10 - September	0	40 - 66
				30	90 - 154
	Wheat	10 - November	15 - June	0	27 - 51
				100	63 - 119
	Soybean	19 - June	10 - November	NA[2]	NA

[1] DAP= days after planting.

[2] NA = not applicable

3.4 Set-up of hydrologic and water quality simulations:

DRAINMOD and DRAINMOD-NII simulations were conducted to predict annual drainage flow and associated nitrogen losses for a wide range of environmental factors and management practices within each geographic region considered. More than ten thousands of simulations were conducted. Input data at the county level were organized in ASCII-formatted files that list benchmark soils and related soil input files, common drain depths and spacing, as well as, range variations in fertilization rate. DRAINMOD and DRAINMOD-NII models were integrated through a batch mode that allows for: 1) updating the models input files for different subsets of scenarios each representing a unique combination of soil type, drainage design, and fertilizer rate, 2) executing DRAINMOD model to simulate the hydrology and DRAINMOD-NII to continuously simulate nitrogen dynamics for both managed (DWM) and unmanaged (conventional drainage) conditions for 20 to 50 years of available historical weather data and for each proposed scenario, and 3) exporting simulation output to databases that comprise records of simulated annual drainage flow and N losses (response variables) along with controlling input parameters (explanatory variables) required to build the regression models. The identification of input variables that simulated drainage flow and nitrate losses are sensitive to, was based on previous experimental work and modeling studies (Kladivko et al, 2004 and 2005; Youssef et al., 2006; Negm et al., 2014; Skaggs et al., 2005, 2013).

The output databases were screened to identify inconsistencies, then merged and organized under two main categories: Database 1 comprised a total of 80,000 records for building a regression model to estimate drainage flow and, Database 2 comprised of more than 200,000 records to estimate N-losses. Database 2 included a greater number of records due to the inclusion of additional parameters that have significant impact on N-losses (e.g.: fertilization rate) while having no impact on predicted drainage flow. Note that estimated relative yield (predicted crop yield/ potential yield) predicted by DRAINMOD was considered among the explanatory factors affecting N-leaching losses since it is used by DRAINMOD-NII to simulate N-plant uptake.

3.5 General Linear Regression (GLR) Analysis:

General linear regression (GLR) is an approach by which a response (dependent) variable is related to multiple explanatory (predictor) variables through a linear relationship. However, building a regression model that comprises a relatively large number of predictor variables and based on large number of records is challenging and requires advanced computational techniques. At this phase of the project, we conducted statistical analysis through the SAS 9.3 (SAS Institute, Cary NC); a high performance computing software capable of handling large databases and performing robust regression analyses.

We chose the GlmSelect procedure “PROC GLMSELECT” to build the proposed regression model since it supports features that are not supported by other regression procedures implemented in SAS software. GlmSelect procedure supports the “Class” statement that is required to distinguish categorical variables from continues variables. Dissimilar to other generalized linear modeling procedures (e.g.: PROC GLM), the GlmSelect includes multiple effect selection methods: forward, backward, stepwise, Least Angle Regression (LAR) (Efron et al., 2004), and Least Absolute Shrinkage and Selection Operator (LASSO) regression (Tibshirani, 1996 and 2011). It allows the modeler to specify different degrees of interaction among different variables. Another option that the GlmSelect procedure supports, utilized herein, is the data partitioning statement that allows for subdividing the input datasets into: a) training data used to build the regression model, b) validation data based on which the predicted error for the model is estimated to avoid regression over-fitting, and c) testing data that played no role in model building and could be used solely to assess the model predictive power. A typical partition fraction assigns 50% for the training data set and 25% each for validation and testing data sets. This procedure was followed in the current study.

The regression analysis was initiated by including all candidate explanatory variables (Table 2) that affect a particular constituent (i.e.; annual drainage flow and N losses). Explanatory variables that could be strongly influenced by one or more other explanatory variables were identified through using scatter plots and correlation statistics [p-values and Pearson correlation coefficient (r)]. These variables were excluded from the model to avoid multi-collinearity.

The criteria for determining best model from a set of potential models based on the adjusted coefficient of multiple determination (R_{adj}^2). R_{adj}^2 differs from the commonly used coefficient of determination; R^2, which typically increases as the number of explanatory variables in the regression model increases. R_{adj}^2 compares models that have different numbers of explanatory variables by penalizing models that have additional coefficients (Helsel and Hirsch, 1995) and thereby provides a stronger indicator of the strength of the model.

Although the GlmSelect regression, particularly the “Stepwise” selection method, evaluates the contribution of each variable added to or removed from a model, an explanatory variable statistical significance could be exaggerated due to the inclusion of huge number of records used to build the model. Therefore, and through an iterative processes, variables that were identified as significant; i.e., assigned a high t-static, but had no substantial impact on reducing the root mean squared error (RMSE), or on increasing R^2_{adj} were excluded from the analysis. Since the GlmSelect procedure does not support regression diagnostics, the developed models were further investigated by assessing the relation between simulated values predicted by DRAINMOD-based models with their correspondence estimated by the regression models using a simple linear regression; i.e., PROC REG. Residuals plots and Cook’s distance (Cook’s D) statistic were used to determine outliers or highly influential records.

Table 2. Candidate explanatory variables for the proposed regression models.

Category	Explanatory variable	Symbol	Numerical	Categorical	Descriptive statics [1]			Variable Levels [2]		
					minimum	maximum	mean	level 1	level 2	level 3
Climate	Annual precipitation, cm	Rain	●		100	160	129.6			
Soil	Silt content , %	Silt	●		5.2	32	18			
	Clay content, %	Clay	●		5	43	20			
	Sand content, %	Sand	●		25	87	62			
	Organic Carbon, %	OC	●		0.4	6	1.3			
	Saturated hydraulic conductivity, cm/hr	Ksat	●							
Sub-surface drainage	Drain depth, cm	D-depth	●		80	150	115			
	Drain spacing, m	Spacing	●		15	55	30			
Surface drainage	Surface drainage conditions	S-Storage		●				good	fair	poor
Crop management & yields	crop relative yield, %	Yield	●		40	100	85			
	crop cover [3]	Crop		●				Crn-Wh	Wh-Sb	––
	Fertilizer applied, Kg N/ha/yr	Fert	●		70	260	150			
Preceding year conditions	Climate	L-rain		●				dry	normal	wet
	crop production	L-Yield		●				high	medium	low

[1] Descriptive statics for numerical variables only.
[2] Different levels for categorical variables only.
[3] Used within a corn-wheat-soybean crop management scenario.

4. Results and Discussion

The final product of the current study is a set of regression equations or models designed to estimate annual drainage flow and corresponding annual NO_3-N losses under four tiers of management scenarios: **Tier 1**: A continuous corn cropping system operated under conventional drainage (FDCC), **Tier 2**: A continuous corn cropping system operated under controlled drainage or drainage water management (DWMCC), **Tier 3**: A corn-wheat-soybean cropping system operated under conventional drainage (FDCWS), and **Tier 4**: A corn-wheat-soybean cropping system operated under controlled drainage (DWMCWS).

In this section, we report the different regression models, the corresponding fit statistics, and an assessment of their predictive power using the data withheld for model testing. Also, we present an example application that compares the predictions of the regression model to DRAINMOD predictions for a specific site conditions. It should be noted that the regression models were built allowing first degree interaction among different explanatory variables. Allowing a higher degree of interaction did increase model complexity with no additional performance improvements.

4.1 Regression models for annual drainage flow prediction

The selected form of the GLM models developed to estimate annual drainage flow included six numerical variables and two categorical variables. The numerical variables included sand, silt, and clay contents, annual rainfall, and drain depth and spacing. The categorical variables are the surface drainage condition and crop cover in a corn-wheat-soybean rotation tiers. Although DRAINMOD predictions of drainage flow have been found to be sensitive to changes in the soil lateral saturated hydraulic conductivity (K_{sat}) (Hann and Skaggs, 2003; Wang et al., 2006b), the values of K_{sat} were found to be highly correlated with soil texture parameters; sand ($r = 0.67$), silt ($r = -0.49$), and clay ($r = -0.63$). This finding is expected as numerous studies have shown the dependency of K_{sat} on soil texture (e.g. Saxton et al., 1986; Tietje and Hennings, 1996; Rawls et al., 1998; Kosugi, 1999). Therefore, K_{sat} were not included in the regression models. Predicted annual drainage flow was not significantly affected by parameters related to crop management, yields, as well as, parameters describing preceding climatic conditions. Annual precipitation was the most significant parameter controlling the variation in drainage flow with an $r = 0.52$. These results showing the sensitivity of drainage flow to different explanatory variables agreed with previous experimental findings (Youssef et al., 2006; Kladivko et al, 2005; Wang et al., 2006a; Jaynes and Colvin, 2006).

A preliminary assessment of the regression models' performance showed that their estimation of annual drainage flows in either extreme dry or extreme wet years were associated with very high residuals and Cook's D values. As a result, records with the most extreme 5% of the rainfall distribution (Rain < 99 cm or Rain > 160 cm) were eliminated from all data subsets and the regression process was repeated. Therefore, the regression equations may not provide accurate estimates of the annual drainage flow if to be applied on years with extremely high or low annual precipitation.

The response variable Y_H; annual drainage flow (cm), can be estimated from the following equation:

$$Y_H = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots\ldots + \beta n\, Xn + \beta_{L1} X_{L1} + \beta_{L2} X_{L2} + \ldots\ldots\ldots\ldots + \beta_{Lm} X_{Lm} \qquad \text{(Eq. 1)}$$

where m and n are the number of equation terms without and with a categorical variable, respectively. β_i is the regression coefficient corresponds to i^{th} equation term (X) representing a numerical variable or an interaction between two numerical variables for i = 1, 2, 3,….n. β_{Lj} is the regression coefficient corresponds to j^{th} equation term (X_L) representing a categorical variable, or an interaction between a categorical and numerical variable, or an interaction between two categorical variables.

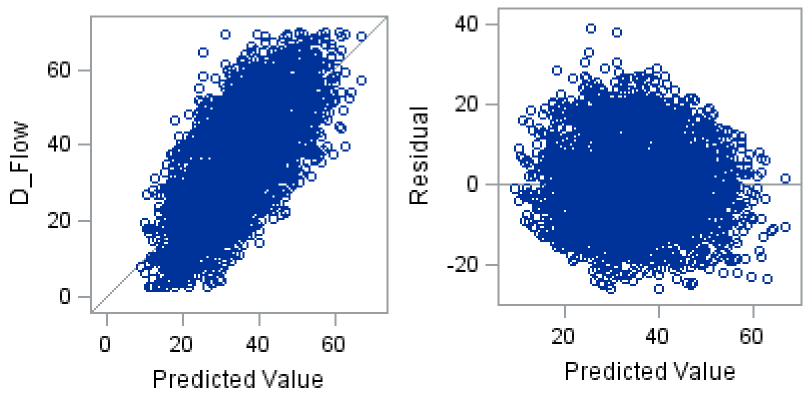
All the equation terms and corresponding parameter estimates for different management tiers are listed in Table S1 and Table S2. In most cases the selected explanatory variables can be easily defined with no need for intensive or expensive field measurements. This was the goal of the study, to develop a simple tool that can be used with easily accessible data.

The four tiers' regression models developed to estimate annual drainage flow achieved an R^2_{adj} higher than 0.88, and a root mean squared error (RMSE) less than 10.5 cm (Table S1 and Table S2). These numbers indicate a high correlation between simulated and estimated annual drainage flow which is mainly attributed to simultaneously assessing the effects of various explanatory variables on the response variable through the utilization of the GlmSelect procedure and through a factorial design structure of the modeled data (Pedhazur, 1997). The factorial design considers a multi-dimensional space that combines all possible combinations of several factors, each with several numerical or categorical levels. However, caution must be used in applying the models for years with extremely low or high annual rainfall.

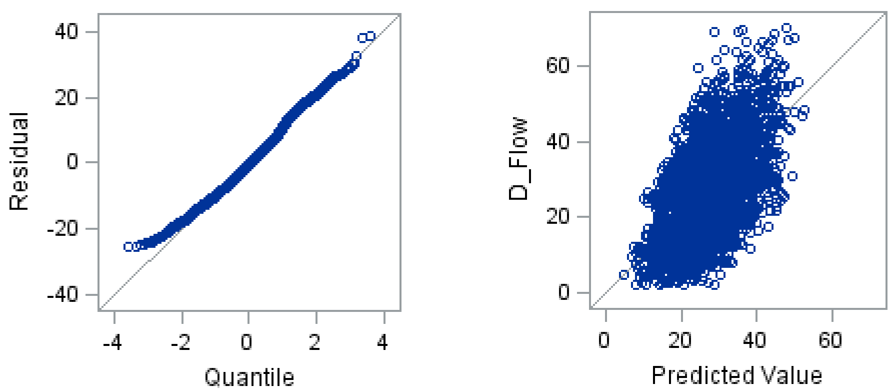
The different terms of the developed equations (Table S1 and S2) emphasized that joint effects between parameters generally govern the variation in the response variable (Y_H) more than what the main effect of each explanatory variable. This could be attributed to the strong inherent interaction among different environmental and management design variables in their contribution to controlling the system performance.

Figures 3 illustrates comparison between DRAINMOD simulated annual drainage flow and their corresponding estimated by the four-tiers regression models utilizing the dataset withheld for model testing. Both simulated and estimated annual drainage values were highly correlated with a R_{adj}^2 equals to 0.93, 0.92, 0.94, and 0.91 for tier 1, tier 2, tier 3, and tier 4 regression models, respectively. These values are as good as those estimated for the training dataset indicating an unbiased regression model. The random distribution of the residual in the diagnostic residual plots, as well as the proximity of the quantile plots to straight lines (Figure 3) indicate that regression model assumptions including residuals normality and homoscedasticity (equal variance) were preserved.

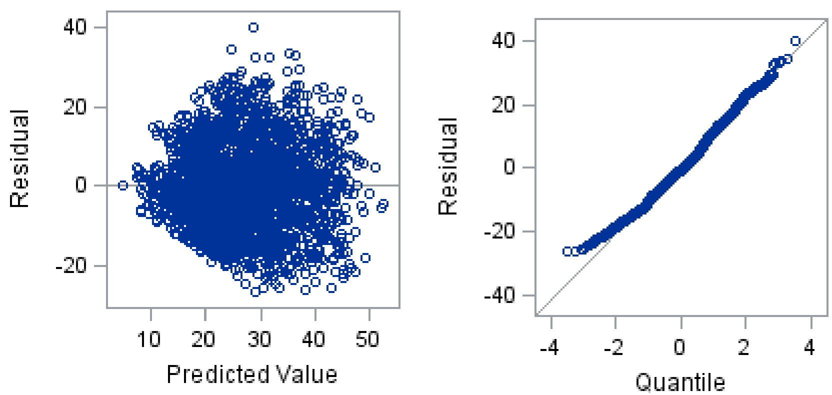
a.

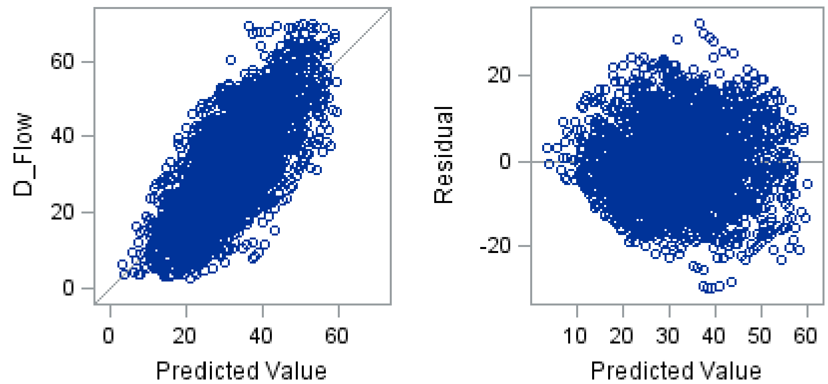

D_Flow
Predicted Value
Residual
Predicted Value

b.

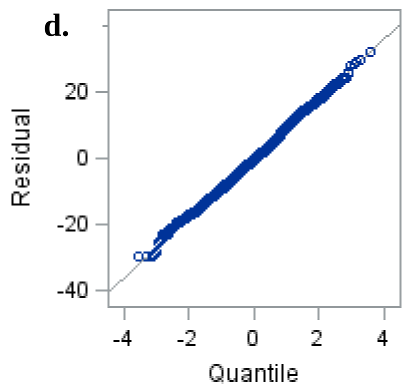

Residual
Quantile
D_Flow
Predicted Value

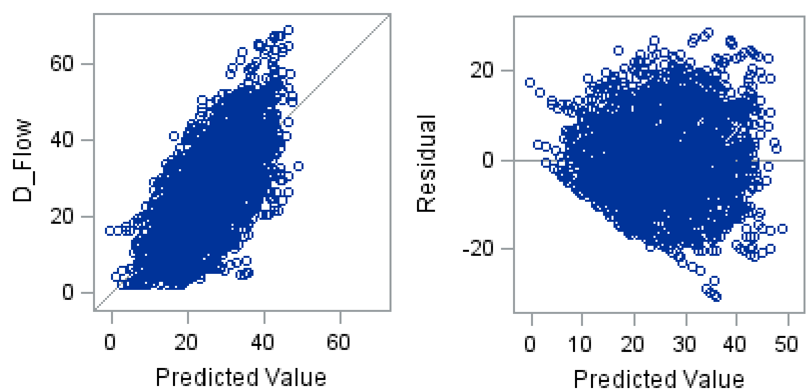
c.


Residual
Predicted Value
Residual
Quantile


D_Flow
Predicted Value
Residual
Predicted Value

d.


Residual
Quantile


D_Flow
Predicted Value
Residual
Predicted Value

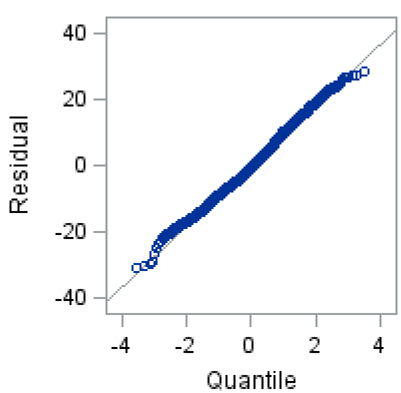

Residual
Quantile

Figure 3. Correlation between simulated and estimated annual drainage flow (cm/year), scatter residual plots, and residual-quantile plots using the data withheld for model testing for a) FDCC, b) DWMCC, c) FDCWS, and d) DWMCWS management scenarios.

4.2 Regression models for predicting annual NO_3-N losses

The strategy used to develop regression models for estimating annual NO_3-N losses was similar to that described in Section 4.1 for drainage outflows. We started building the model by implementing all categorical and numerical variables that showed significant effect on estimating annual drainage flows and then added parameters related to crop management. However, the large number of explanatory variables caused the resulting models to be very complicated. Several modeling and experimental studies documented that rates of NO_3-N leaching losses are highly correlated with rates of drainage flow (Kladivko et al., 2004; Youssef et al., 2006; Ale et al., 2009; Luo et al., 2010; Skaggs et al., 2012a; Negm et al., 2014). Thus, predicted annual drainage flow was used as an explanatory variable to estimate annual NO_3-N loss to simplify the equation. Using a simple correlation statement; i.e. PROC CORR, annual drainage flow rate was the most correlated parameter with annual nitrate losses ($r > 0.5$).

The final regression models to estimate annual NO_3-N losses included four numerical variables and two categorical variables. The numerical variables included annual drainage flow, soil organic carbon, relative yield, and fertilizer application rate. Selected categorical variables included preceding year crop production level and climate conditions, in addition to crop cover in corn-wheat-soybean rotation settings.

The response variable Y_N; annual NO_3-N losses (Kg N ha^{-1}), can be estimated from the regression model (Equation 1) where all the equation terms and corresponding parameter estimates for different management tiers are listed in Table S3 and Table S4. Annual drainage flow may be estimated as described in section 4.1. An alternative is to run DRAINMOD model directly to compute annual drainage flow for a local site conditions of interest. Although this alternative is expected to yield more accurate estimation of drainage flow, it does require modelling experience and data availability.

The developed regression models for estimating annual NO_3-N losses resulted in an adjusted R^2 of 0.88 or higher for all management tiers indicating high correlation between DRAINMOD-NII simulated and estimated annual NO_3-N losses. Incidences at which the estimated annual drainage losses were poorly correlated with DRAINMOD-NII simulated values (high value of the residual) were scattered between the upper and lower bounds of the response variable. Such differences could be attributed to DRAINMOD models capability of simulating dynamic environmental conditions and their interaction with management practices. The regression models are not capable of considering such interactions. For example, the intensity of rainfall events and their timing relative to the growing season and fertilizer application dates in a given year affect N concentration in drainage waters, and, in turn, annual N load. Rainfall at a different intensity and date with respect to fertilization may result in a very different annual N loss, even though the annual rainfall and fertilization are similar.

Figure 4 illustrates the diagnostic plots for assessing the ability of the regression models to estimate annual N loads in comparison to DRAINMOD-NII simulated values for the four tiers of management scenarios. The achieved R^2_{adj} equaled to 0.9, 0.88, 0.92, and 0.92 for tier 1, tier 2, tier 3, and tier 4 regression models, respectively. This indicates consistently good performance of the developed regression equations in estimating N drainage losses under both conventional and controlled drainage. This performance was achieved despite lumping a large number of interacting complex hydrological and biogeochemical processes. This simple model provides a calculation tool for estimating the effect of implementing DWM on N loads at the field outlet.

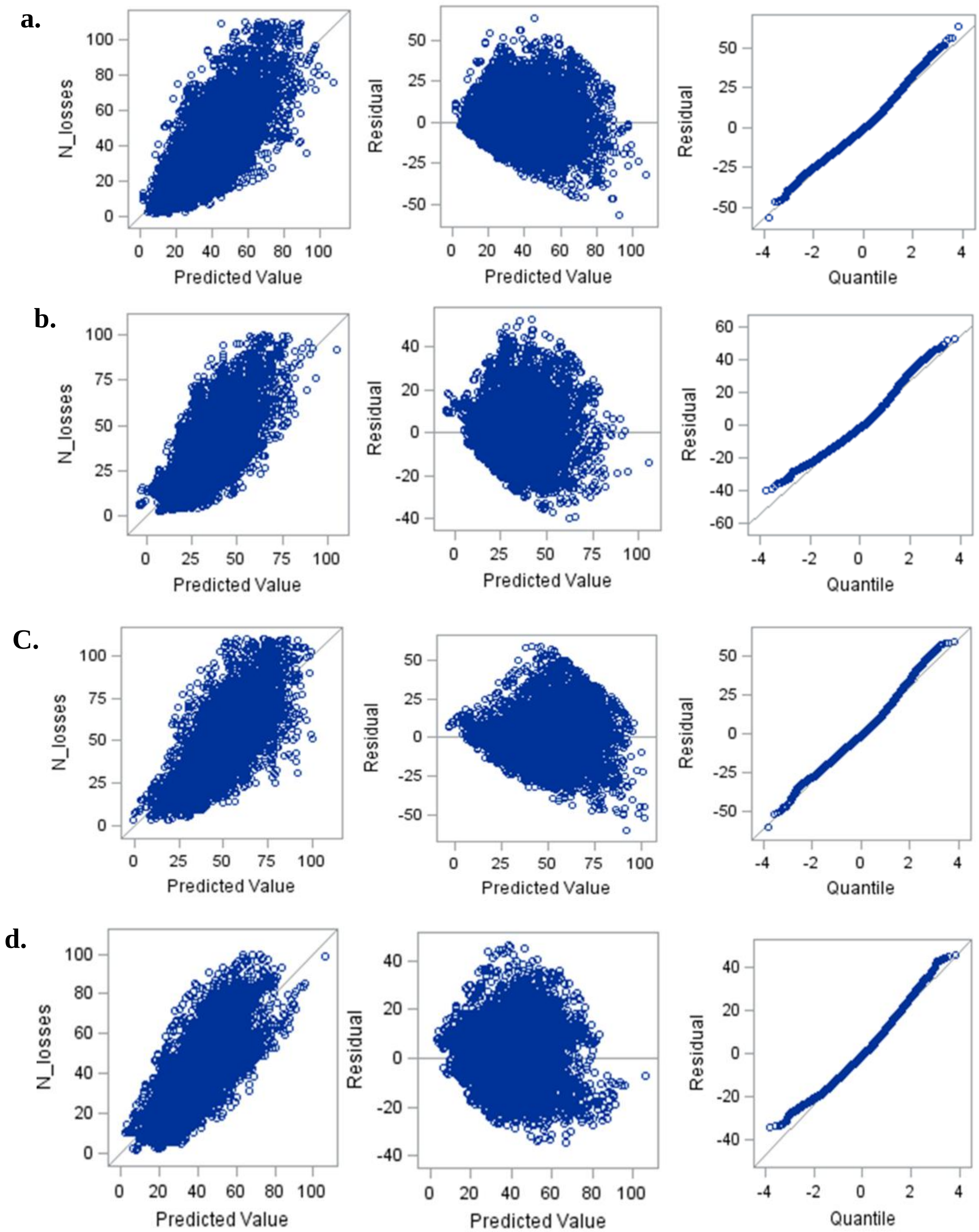


Figure 4. Correlation between simulated and estimated annual drainage flow (cm/year), scatter residual plots, and residual-quantile plots using the data withheld for model testing for a) FDCC, b) DWMCC, c) FDCWS, and d) DWMCWS management scenarios.

4.3 Case Study:

In the this section, the regression models' estimation of drainage flow and NO_3-N leaching losses were compared, on a year by year basis, to the predictions of DRAINMOD and DRAINMOD-NII, calibrated for a drainage water management site located at the Tidewater Research Station (TRS) near the town of Plymouth, in the North Carolina lower coastal plain (Skaggs et al., 2012b, Youssef et al., 2006). Throughout this example application, we refer to drainage flow and NO_3-N losses predicted by DRAINMOD and DRAINMOD-NII as "simulated", while the values calculated by the regression models are referred to as "estimated".

4.3.1 Description of the Agricultural System

The soil on the nearly flat, 13.8-ha site is Portsmouth sandy loam, which is very poorly drained under natural conditions. The surface soil horizon characterized by a relatively high organic carbon (3.5%). The subsurface drain pipes were spaced at 23 m and placed at 118 cm below the soil surface. The site is planted to a corn-wheat-soybean rotation; however, a continuous corn scenario has also been proposed for complete demonstration and comparison purposes. A 25-year period (1976-2000) of measured weather data (daily temperatures and precipitation records) was utilized for this example application. Table 3 summarizes variables that describe site characteristics required by the regression models. Detailed description of DRAINMOD and DRAINMOD-NII parameterization is described by Youssef et al. (2006) and Skaggs et al. (2012b).

Table 3. Summary of soil property and site parameter inputs for the TRS site.

Variable	Value
Drain depth, m	1.18
Drain spacing, m	23.0
Depressional Storage, cm[1]	1.25
Sand content, %	75.5
Silt content, %	14.0
Clay content, %	10.5
OC, %	3.5
Fertilization, Kg N ha $^{-1}$	
Corn	175
Wheat	120
Soybean	NA

[1] The 1.25 cm of depressional storage is equivalent to Level 2 of surface storage in the regression equation.

[2] In a corn-wheat-soybean rotation, annual applied fertilizer for a CW year depended on the total amount of fertilizer applied for corn plus the starter amount applied for wheat, and for a WS year, the annual fertilizer applied equaled to the sidedressed application for wheat.

4.3.2 Annual Drainage Flow

Annual drainage flow simulated by DRAINMOD and estimated by the regression models are visually compared in Figure 5. For the FDCC and DWMCC, the Percent Difference (PD) between estimated and simulated annual drainage flow was within ±15% in over 56% of the years, and within ±25% in over 82% of the years. Over the 25-year period, the PD between estimated and simulated average annual drainage flow was -2.3% for the FDCC (estimated = 39.8 ± 12.7 cm, simulated = 40.8 ± 13.5 cm), and PD was 1.6% for the DWMCC (estimated = 32.2 ± 12.6 cm, simulated = 31.7 ± 10.6 cm). Years when estimated drainage substantially differs from simulated values were mostly associated with years experienced extreme climate conditions; years with extreme annual precipitation and/or years that has monthly precipitation patterns that sharply deviated from long-term means. For example, in the extreme dry year of 1993 (annual precipitation = 100 cm) estimated annual drainage was 42% and 47% less than their corresponding values simulated by DRAINMOD for the FDCC and DWMCC, respectively. In 1999 when annual perception were similar to long-term averages, estimated and simulated annual drainage flows respectively were 42.6 and 34.3 cm (PD = +24%) for the FDCC, and were 35 and 26.9 cm (PD = +30%) for the DWMCC. These differences could be mainly attributed to the significant divergence of seasonal rainfall from normal conditions. The period of February till August 1999 which received 56.5 cm of rainfall and reported as the third driest period in a 49-year record, was followed by a series of hurricanes and tropical storms with a total of 55.5 cm of rainfall during September and October 1999. This was the wettest period in a 49-year historical weather record (1951 -1999) (Shelby et al., 2006). Under such conditions, DRAINMOD simulated near zero drainage in the prolonged dry period followed with large drainage volumes associated with excessive surface runoff in the short but extremely wet period. However, estimated drainage values by the regression model were close to long term estimated drainage values since it is based on annual rainfall amounts and does not consider the seasonal extremes.

For the FDCWS and DWMCWS, PD between estimated and simulated annual drainage flow was within ±15% in over 52% of the years, and within ±25% in over 76% of the years. Estimated and simulated average annual drainage over the case study period were 40.8 and 38.5 cm for the FDCWS (PD = 5.1%); 34.1 and 31.3 for the DWMCWS (PD = 9.1%). Similar to the continuous corn management scenarios, seasonal distribution of rainfall events was a critical factor impacting the difference between estimated and simulated annual drainage flow in some of the years. For 1999, estimated annual drainage flow were 36% and 19% higher than the simulated values respectively for FDCWS and DWMCWS. Under the extreme dry conditions of 1993, estimated annual drainage flow were 27.7% and 30.7% lower than the simulated values for the FDCWS and DWMCWS, respectively. Another exceptionally dry year was 1997, which was similar to 1993 in terms of annual rainfall and crop cover (corn-wheat). The regression model estimated similar annual drainage flows for the two years. DRAINMOD simulated lower drainage flow in 1997 than in 1993. In 1997, around 50% of annual rainfall occurred during the hot growing season when evapotranspiration demands normally exceed drainage rates. In contrast 70% of the annual rainfall in 1993 occurred during the fallow period resulting in greater drainage volumes. Such differences cannot be predicted by the simple regression equations. Yet, overall, they do a very acceptable job in predicting annual outflows.

A fair correlation between estimated and simulated percent reduction in annual drainage due to DWM can be inferred from the year-by-year comparison illustrated in Figure 6 for CC and CWS. The 5-year moving average curves reduced the effects of temporal variations and identified no over- or under-estimation trends predicted by the regression models, in comparison to annual flow reductions predicted by DRAINMOD.

Overall, the simple regression models showed comparable performance to DRAINMOD in estimating annual drainage flow under different management and climate scenarios. They provide a simple, reliable method of estimating annual drainage flow, which can be used to estimate annual NO_3-N losses as described in the following section. These equations may also be useful in other water conservation and environmental management applications where estimates of annual drainage outflows are needed.

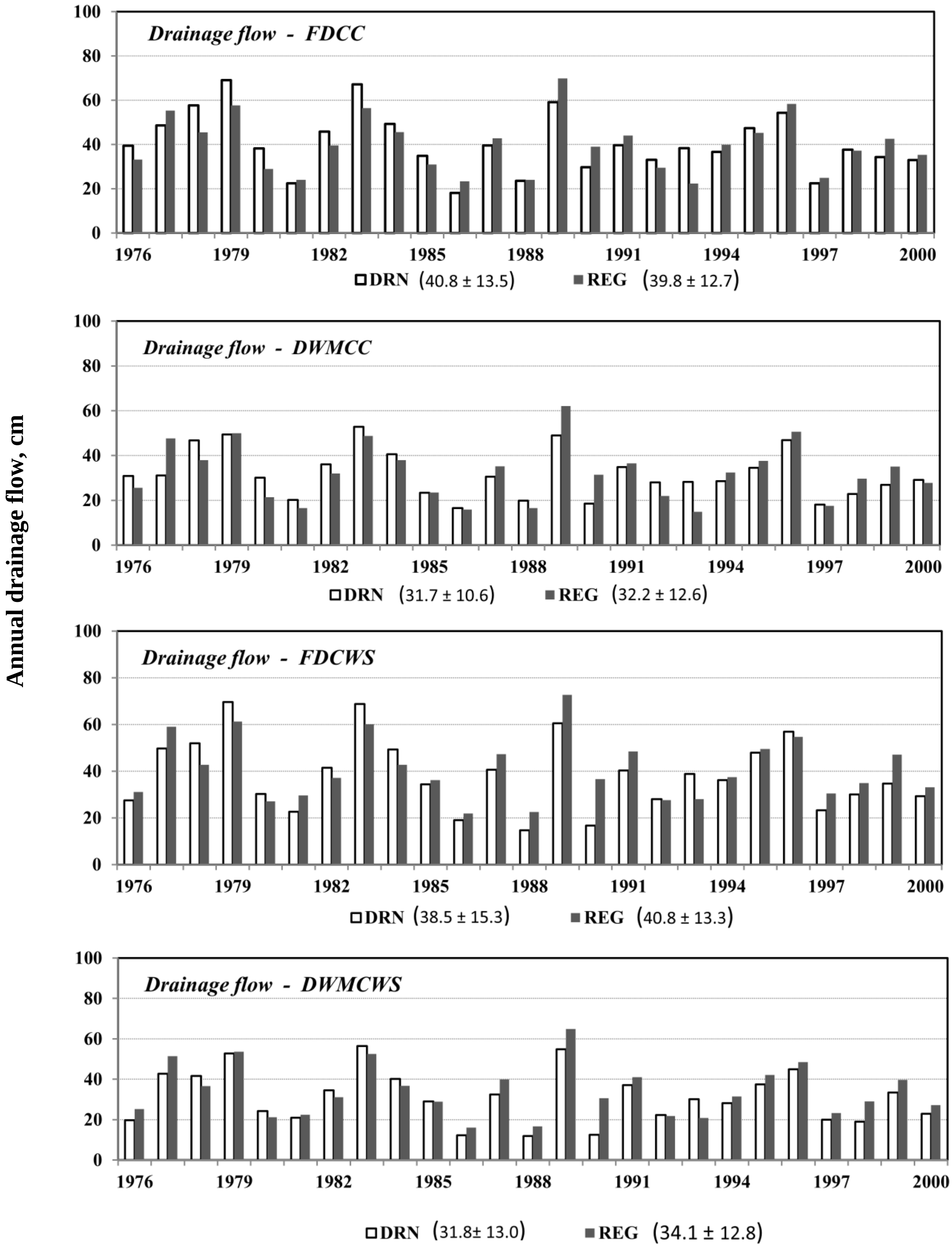


Figure 5. Annual drainage flow as simulated by DRAINMOD (DRN) and estimated by the regression models (REG)for different management tiers. (Values between parentheses represent average annual drainage flow ± standard deviation, all units are in cm).

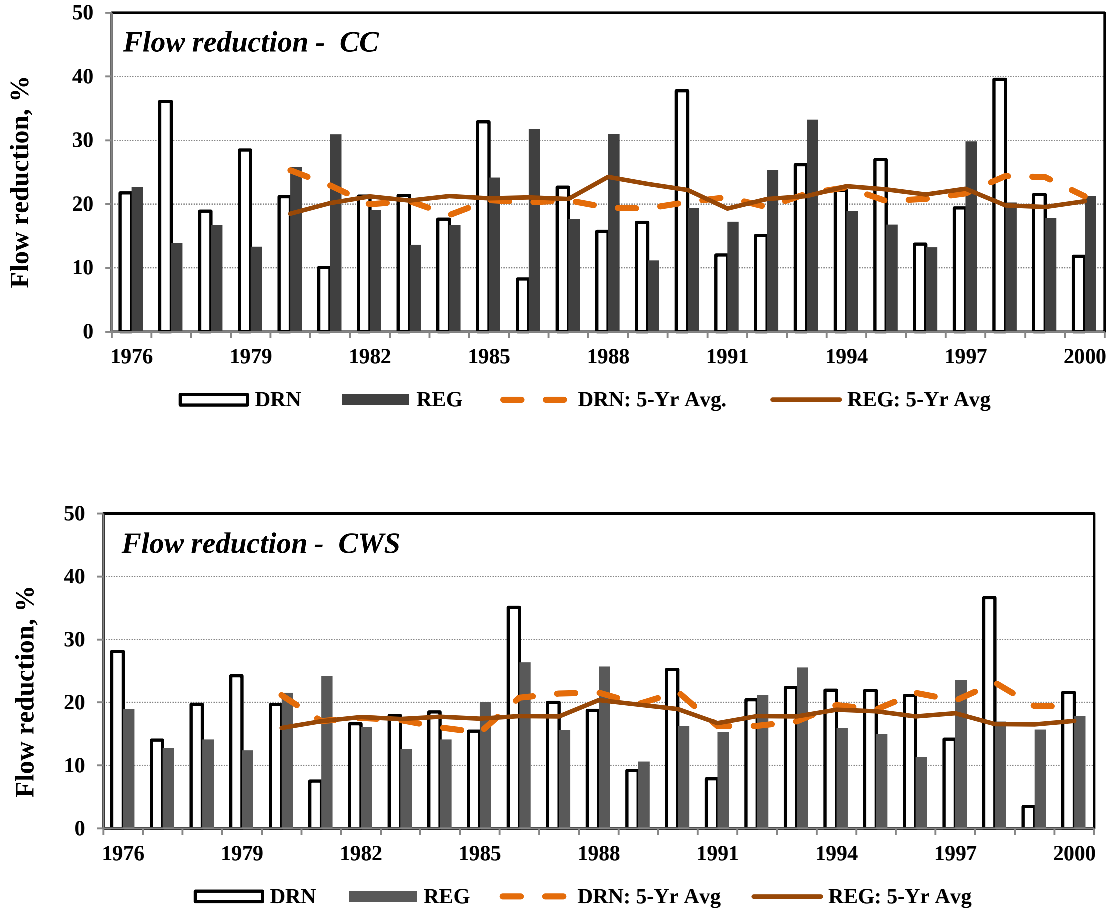


Figure 6. Reduction in annual drainage flow (%) due to DWM as simulated by DRAINMOD (DRN) and estimated by the regression models (REG) for continuous corn (CC) and corm-wheat-soybean (CWS) management tiers. Solid line represents the 5-year moving average of reduction in annual drainage flow (%) as estimated by the regression model (REG: 5-Yr Avg), and the dashed line represents the 5-year moving average of reduction in annual drainage flow (%) as simulated by the DRAINMOD (DRN: 5-Yr Avg).

4.3.3 Annual Nitrate Losses

Utilizing the estimated annual drainage flow discussed in section 4.3.2; annual NO_3-N losses were estimated for the same management tiers considered in this example application. Figure 7 presents the annual NO_3-N losses estimated by the regression models as compared to corresponding values simulated by DRAINMOD-NII for the FDCC, DWMCC, FDCWS, and DWMCWS. The Percent Difference (PD) between estimated and simulated annual N losses was within ±25% over 76%, 72%, 76%, and 56% of the 25 years for FDCC, DWMCC, FDCWS, and DWMCWS, respectively.

Larger PD's occurred in some years for both rotations and drainage modes. As an example, in years 1982, 1983, and 1989; estimated losses were noticeably lower than simulated values for the FDCC and DWMCC (Figure 7). This could be mainly attributed to the timing of heavy rainfall events that coincided or shortly followed site fertilization causing DRAINMOD-NII to simulate high N losses early in the growing season. In addition, estimated drainage flows were lower than simulated values for 1982 and 1983. In the exceptional wet year of 1989 (annual precipitation = 176 cm) heavy rainfall events coincided with or closely followed days when fertilizer was applied. DRAINMOD-NII simulated excessive NO_3-N losses (30 Kg N/ha for FDCC and 23 Kg N/ha for DWMCC) during the very wet month of March as nutrient residues turned over the preceding dry year of 1988 (annual precipitation = 103 cm). For the CWS scenarios, estimated and simulated annual NO_3-N losses for 1989 were in close agreement. In this year (1989), the field was planted to corn following soybean, which received no fertilization in 1988. Therefore, nutrient residuals carried over to 1989 was not as significant as in a CC scenario. Again, the timing of rainfall events relative to nutrient management, growing season and crop cover dramatically affects DRAINMOD-NII simulations. The regression models do not consider such factors, resulting in the discrepancies in N losses, and the effect of DWM on N losses predicted by the two approaches.

Average annual NO_3-N losses over the 25 years estimated by the regression models agreed well with DRAINMOD-NII predictions for the FDCC (estimated = 48.8 ± 8.5 Kg N/ha; simulated = 49.8 ± 18.5 Kg N/ha), and for the DWMCC (estimated = 42.5 ± 10.4 Kg N/ha; simulated = 41.2 ± 14.4 Kg N/ha). Similarly, estimated average annual NO_3-N losses were in close agreement with simulated values for the FDCWS (estimated = 58.0 ± 13.0 Kg N/ha; simulated = 56.5 ± 21.8 Kg N/ha), and for the DWMCWS (estimated = 45.9 ± 16.0 Kg N/ha; simulated = 46.7 ± 18.2 Kg N/ha). The fact that the regression approach predicted results similar to the long-term annual averages predicted by DRAINMOD-NII is expected since a regression model usually performs better as an estimator of normal conditions, than for other conditions that occur less frequently.

The potential application of these regression models in N trading markets was the main motive for developing the current regression model as a tool to estimate DWM-induced reductions in N losses. Figure 8 illustrates annual reductions due to DWM for CC and CWS scenarios as predicted by the regression approach versus DRAINMOD-NII simulations. Average annual reduction in NO3-N losses due to DWM as estimated by the regression model for the CC scenario was 6.3 Kg N/ha versus 8.6 Kg N/ha predicted by DRAINMOD-NII. For the CWS, estimated annual reductions averaged at 6.6 Kg N/ha versus a simulated value of 7.2 Kg N/ha.

On a year-by-year basis, estimated reductions did not agree well with DRAINMOD-NII predictions in many of the years (Figure 8). For CC, noticeable difference between estimated and simulated reductions was in years with extreme dry growing seasons (i.e.; 1981, 1986, and 1997) associated with low crop yields. For the normal-to-wet years followed these dry years (i.e.; 1982, 1987, and 1998), the regression model tends to estimate lower N losses reductions compared to that simulated by DRAINMOD-NII. Estimated reductions in 1979 and 1995 didn't agree with simulated values. These years experienced very wet growing seasons causing significant crop yield reductions (as simulated by DRAINMOD), especially under the controlled drainage mode that caused additional loss to crop yields due to increased wet stresses. For the CWS, discrepancies between estimation of DWM-caused reductions are noticeable in several years. This was especially the case in the first 6 years of simulation when the regression model estimation of annual NO3-N losses didn't agree well with DRAINMOD-NII simulated values under the controlled drainage mode.

There was less variability when the comparison is based on the 5-year moving average of the predicted annual reductions of NO_3-N losses (Figure 8), as overestimation in some years was counterbalanced by underestimation in other years within the 5-year period. For CC the effect of DWM on the 5-year moving average of N losses as estimated by the regression equations was within 0.0 to 3.0 Kg N/ha of that predicted by DRAINMOD NII. For the CWS cropping system the absolute differences ranged between 0.0 to 9.0 Kg N/ha, and between 0.0 to 3.0 Kg N/ha if the first 5 years of simulation were excluded from the analysis.

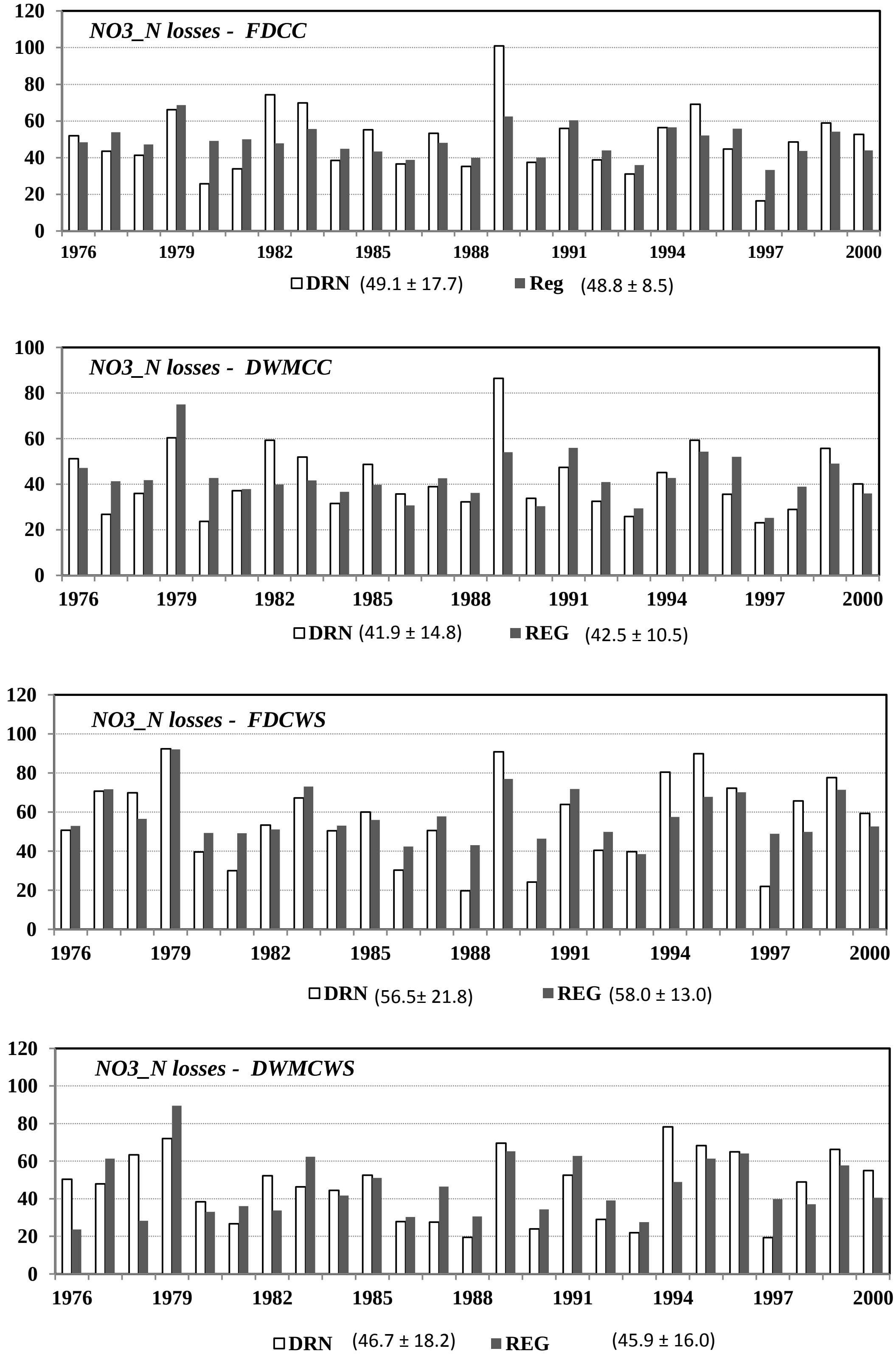


Figure 7. Annual NO3-N losses as simulated by DRAINMOD (DRN) and estimated by the regression models (REG) for the different management tiers. (Values between parentheses represent average annual drainage flow ± standard deviation, all units are in Kg N/ha).

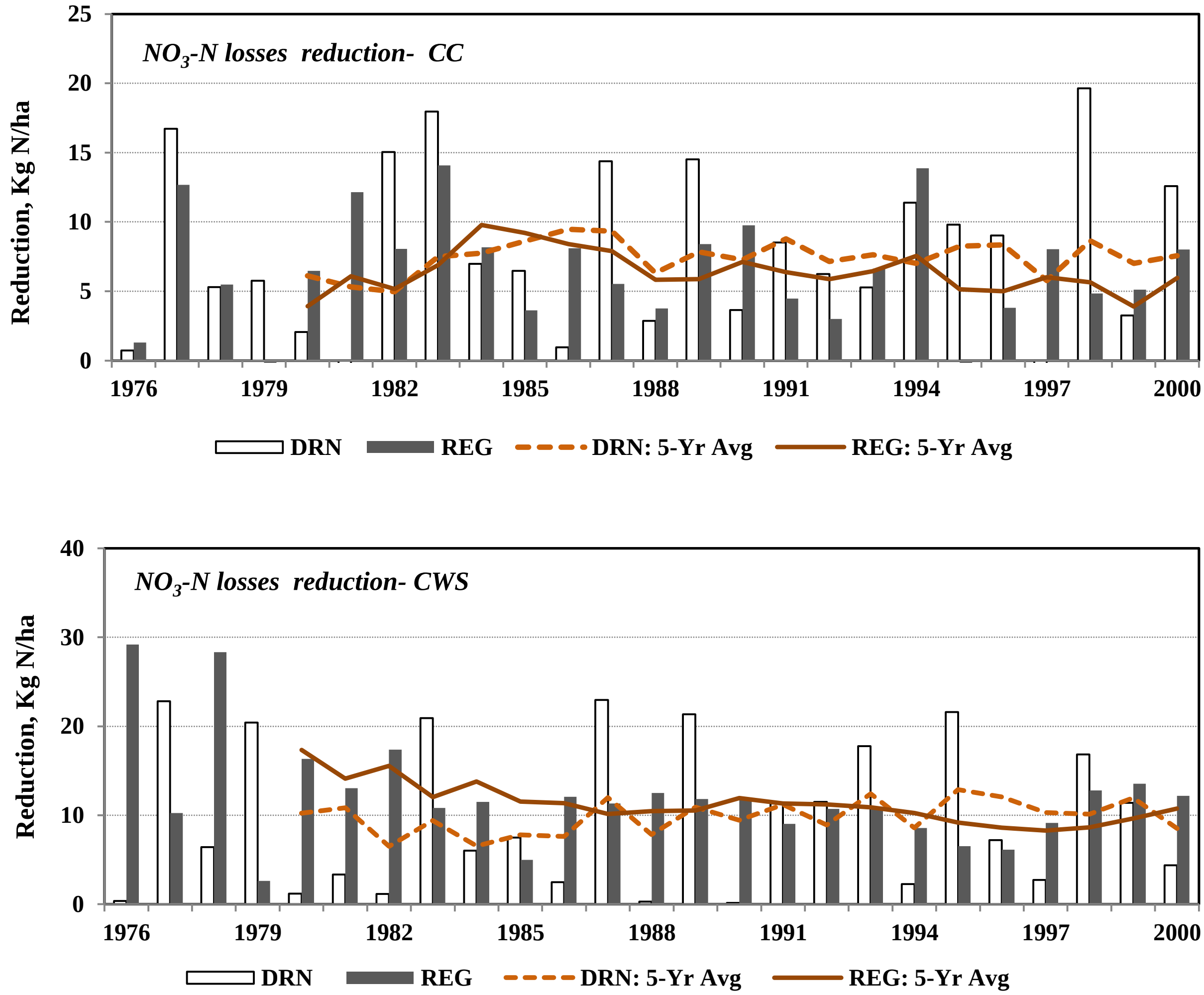


Figure 8. DWM-caused reductions in annual N0$_3$-N losses (Kg N ha^{-1}) as simulated by DRAINMOD (DRN) and estimated by the regression models (REG) for continuous corn (CC) and corm-wheat-soybean (CWS) management tiers. Solid line represents the 5-year moving average of reduction in annual N-losses (Kg N ha^{-1}) as estimated by the regression model (REG: 5-Yr Avg), and the dashed line represents the 5-year moving average of reduction in annual N-losses (Kg N ha^{-1}) as simulated by the DRAINMOD (DRN: 5-Yr Avg).

5 Summary and Conclusion

This article discusses the development of a simple tool suitable for a water quality credit trading system that involves the use of DWM in Eastern North Carolina. In its basic form, the tool is presented by a set of regression equations tracking DWM caused reductions of drainage flows and N mass losses as a function of easy-to-define variables describing site-specific environmental conditions and management practices. DRAINMOD and DRAINMOD-NII were used to conduct long-term simulations of annual drainage flow and NO3-N losses. Results of the simulations were used to build the regression equations.

Simulations comprised numerous scenarios allowing variations in soil type, weather conditions, drainage design, and cultural management practices to represent the many scenarios possible in eastern North Carolina. To accomplish this intensive simulation exercise, efforts were exerted towards data collection and input file preparation, in addition to integrating the DRAINMOD-based models through a batch mode. Regression analysis was performed on the simulated data to develop equations designed to estimate annual drainage rates under four tiers of management scenarios: a continues corn cropping system operated under conventional drainage (FDCC), **a** continues corn cropping system operated under controlled drainage (DWMCC), **a** corn-wheat-soybean cropping system operated under conventional drainage (FDCWS), and **a** corn-wheat-soybean cropping system operated under controlled drainage. Similarly, a set of four regression equations developed and assigned to estimate annual NO3-N leaching losses. The estimations of annual drainage flow and NO_3-N losses by the regression model correlated well with the corresponding DRAINMOD-based simulations ($R^2_{adj} \geq 0.88$).

The regression tool was used to estimate annual DWM-induced reductions for 25 years of historical weather data for an experimental site located in Plymouth eastern North Carolina. In comparison to DRAINMOD and DRAINMOD-NII, previously calibrated and validated for this site, the regression models performed well in estimating most of the year-to-year variation in drainage rates and nitrate losses. Exceptions occurred for years with extreme weather conditions or high variations in inter-annual climate conditions; however, the comparison based on a 5-year moving averages illustrated that both methods yielded similar outcomes.

In conclusion, this regression approach provides producers, local and federal agencies with an easy-to-use alternative to the burdensome use of process based models to facilitate the assessment of DWM under different site conditions exist in eastern North Carolina. Potential errors with the method can occur when inter-annual variations in rainfall are high which can lead to inaccurate estimations of annual N losses for individual years. To compensate for these errors, the trade of N credits could be based on multiple-year contract. Estimates of N losses average out over five year periods. Although the primary intent of building these regression models was to facilitate the quantifications of N credits, the results presented herein introduce that the tool can be used with different water management applications. Next steps for facilitating wider use of these methods include development of regression equations for other areas where drained agriculture is used such as the Midwest US. Development of a user-friendly interface, web-based tools, and educational program to teach the method will also make the method more acceptable for use in a nutrient credit trading system.

Acknowledgment

This study was supported by a conservation innovation grant (CIG) awarded by the USDA-NRCS (Project # 69-3A75-12-177). The authors would like to thank Mr. Brian Phillips and Mr. Chad Poole of the Department of Biological and Agricultural Engineering, North Carolina State University for providing DRAINMOD weather data and soil properties.

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