Simulating phosphorus dynamics in tile-drained agricultural fields: A focused assessment of the RZWQM2-P model and comparative analysis with DRAINMOD-P model

by

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Dedication

This thesis is dedicated to my parents, whose endless love, unwavering support, and sacrifices have paved the path to this achievement.

ABSTRACT

Water quality degradation in surface water bodies is a pressing environmental issue, notably exacerbated by phosphorus (P) pollution originating from agricultural lands. Such pollution, manifesting either as dissolved P in water or P attached to suspended sediments, poses significant risks to aquatic ecosystems and public health. Addressing this challenge necessitates advanced strategies for managing P losses, for which hydrological and nutrient transport models have emerged as indispensable tools. Recent advancements have led to the integration of detailed P components into well-established models, such as RZWQM2 and DRAINMOD, evolving into their enhanced versions: RZWQM2-P and DRAINMOD-P. These models, specifically engineered to simulate the intricate fate and transport dynamics of P within soil-water-plant continuum, particularly in tile-drained agricultural settings, represent a significant leap forward to address P-related water quality issues. However, the efficacy of these models is contingent upon rigorous evaluation against observed data and continuous refinement. Such evaluations are crucial not only for validating the models' predictive accuracy but also for identifying areas requiring improvement, thereby ensuring that the models remain robust tools in the ongoing effort to safeguard water quality. Therefore, the objectives of this study were to compare RZWQM2-P and DRAINMOD-P in simulating P dynamics; to identify subroutines within RZWQM2-P that warrant further improvement; and evaluate the impact of management practices on P loss, subsequent to the successful validation of the model.

RZWQM2-P and DRAINMOD-P were assessed using five years of observed data from a field in Paulding County, Ohio. The results revealed that the performance of RZWQM2-P was satisfactory in predicting daily tile drainage over a five-year period, achieving a daily NSE of 0.56, R^2 of 0.61, and IOA of 0.88. However, the performance of DRAINMOD-P was found to be unsatisfactory, with a daily R^2 value of 0.56 for the same period, though it achieved a higher NSE value of 0.50 and an IOA of 0.85. Both models satisfactorily predicted monthly tile drainage losses, with NSE values greater than 0.50, R^2 values greater than 0.60, and IOA values greater than 0.75. However, both models exhibited limitations in predicting daily dissolved reactive P (DRP) losses, while they were satisfactory in predicting both daily and monthly total P (TP) losses. RZWQM2-P marginally outperformed in predicting monthly DRP losses (NSE > 0.35, R^2 > 0.40, IOA > 0.75). A separate study focusing solely on RZWQM2-P used four years of data from another Ohio field

in Hardin County for model calibration and validation. The model satisfactorily simulated DRP loss from tile drainage on daily and monthly bases (NSE = 0.50, R^2 = 0.52, IOA = 0.84 for daily; NSE = 0.73, R^2 = 0.78, IOA = 0.94 for monthly) and monthly TP loss (NSE = 0.64, R^2 = 0.65, IOA = 0.88), but was less accurate for daily TP simulation (NSE = 0.30, R^2 = 0.30, IOA = 0.59). The model was also used to assess the effectiveness of controlled drainage and winter cover crops in reducing P losses. Simulations indicated that winter rye cover crops reduced DRP and TP from runoff and drainage by 16% and 4%, respectively, compared to the base scenario. In contrast, controlled drainage resulted in a significant increase in DRP losses (ranging from 60% to 129%) and TP losses (ranging from 5% to 17%) through runoff and drainage across three tested outlet elevations, compared to free drainage.

Overall, while RZWMQ2-P satisfactorily simulates P dynamics, it struggles to accurately capture changes in P concentration in subsurface drainage, leading to an underestimation of P loading during high-load events in both studies. This shortcoming is primarily attributed to the RZWQM2-P's subroutines, which employ a linear groundwater reservoir approach to compute the daily P mass balance in subsurface drainage. Future research should concentrate on incorporating spatial discretization and cell-level mass balance equations into the RZWQM2-P framework. Such enhancements will enable a more thorough representation of local variability and transient states, significantly improving the model's accuracy and reliability.

RÉSUMÉ

Notamment exacerbé par la pollution par le phosphore (P) provenant des terres agricoles, la dégradation de la qualité de l'eau en surface constitue un problème environnemental urgent,. Une telle pollution, qui se manifeste soit par du P dissous dans l'eau, soit par du P lié aux sédiments en suspension, présente des risques importants pour les écosystèmes aquatiques et la santé publique. Relever ce défi nécessite des stratégies avancées de gestion des pertes de P, pour lesquelles les modèles hydrologiques et de transport de nutriments sont devenus des outils indispensables. De récents progrès ont conduit à l'intégration de composants détaillés du phosphore dans des modèles bien établis, tels que RZWQM2 et DRAINMOD, évoluant vers leurs versions améliorées : RZWQM2-P et DRAINMOD-P. Ces modèles, spécialement conçus pour simuler le devenir complexe et la dynamique du transport du phosphore dans le continuum sol-eau-plantes, en particulier dans les milieux agricoles équipés de drains souterrains, représente un formidable saut en avant quant à résoudre les problèmes de qualité de l'eau liés au phosphore. Cependant, l'efficacité de ces modèles dépend d'une évaluation rigoureuse des données observées ainsi qu'un affinement continu. De telles évaluations sont cruciales non seulement pour valider l'exactitude prédictive des modèles, mais également pour identifier les domaines nécessitant des améliorations, garantissant ainsi que les modèles restent des outils robustes dans l'effort continu de sauvegarde de la qualité de l'eau. Par conséquent, les objectifs de cette étude étaient de comparer RZWQM2-P avec DRAINMOD-P dans la simulation de la dynamique du P ; identifier les sous-programmes au sein de RZWQM2-P qui justifient des améliorations supplémentaires ; et évaluer l'impact des pratiques de gestion sur la perte de P, suite à la validation réussie du modèle.

RZWQM2-P et DRAINMOD-P furent évalués à l'aide de cinq années de données observées dans un champ du comté de Paulding, dans le nord-ouest de l'Ohio. Les résultats révélèrent que les performances du RZWQM2-P satisfirent ces critères reliés à la prédiction su drainage souterrain quotidien sur une période de cinq ans, atteignant un NSE quotidien de 0,56, un R^2 de 0,61 et un IOA de 0,88. Cependant, les performances de DRAINMOD-P se révélèrent insatisfaisantes, avec une valeur R^2 quotidienne de 0,56 pour la même période, bien qu'il ait atteint une valeur NSE plus élevée de 0,50 et un IOA de 0,85. Les deux modèles prédirent de manière satisfaisante les pertes mensuelles par voie de drainage souterrain, avec des valeurs de NSE supérieures à 0,50, des valeurs R^2 supérieures à 0,60 et des valeurs de IOA supérieures à 0,75.

Cependant, les deux modèles présentèrent des limites dans la prévision des pertes quotidiennes de phosphore réactif dissous (DRP), alors qu'ils étaient satisfaisants dans la prévision des pertes quotidiennes et mensuelles totales de phosphore (TP). RZWQM2-P a légèrement surperformé dans la prévision des pertes mensuelles de DRP (NSE > 0,35, R^2 > 0,40, IOA > 0,75). Une étude distincte portant uniquement sur RZWQM2-P et tirant sur quatre années de données provenant d'un autre champ de l'Ohio dans le comté de Hardin pour l'étalonnage et la validation du modèle. Le modèle a simulé de manière satisfaisante la perte de DRP due au drainage souterrain sur des bases quotidiennes et mensuelles (NSE = 0,50, R^2 = 0,52, IOA = 0,84 pour le quotidien ; NSE = 0,73, R^2 = 0,78, IOA = 0,94 pour le mensuel) et la perte mensuelle de TP (NSE = 0,64, R^2 = 0,65, IOA = 0,88), mais était moins précis pour la simulation de perte de TP quotidienne (NSE = 0,30, R^2 = 0,30, IOA = 0,59). Le modèle a également servi à évaluer l'efficacité du drainage contrôlé et des cultures couvre-sol hivernales pour réduire les pertes de P. Les simulations ont indiqué que les cultures couvre-sol de seigle d'hiver réduisaient le DRP et le TP dus au ruissellement et au drainage de 16 % et 4 %, respectivement, par rapport au scénario de base. En revanche, le drainage contrôlé a entraîné une augmentation significative des pertes de DRP (allant de 60 % à 129 %) et des pertes de TP (allant de 5 % à 17 %) par ruissellement et drainage sur trois élévations de débouchés testées, par rapport au drainage libre.

Dans l'ensemble, bien que RZWMQ2-P simule de manière satisfaisante la dynamique du P, il a du mal à capter avec précision les changements de concentration en P dans le drainage souterrain, ce qui conduit, dans les deux études, à une sous-estimation de la charge en P lors d'événements à charge élevée. Cette lacune est principalement attribuée aux sous-programmes du RZWQM2-P, qui utilisent une approche linéaire de réservoir d'eau souterraine pour calculer le bilan massique quotidien de P dans le drainage souterrain. Dans l'avenir, les recherches devraient se concentrer sur l'intégration des équations de discrétisation spatiale et de bilan de masse au niveau cellulaire dans le cadre RZWQM2-P. De telles améliorations permettront une représentation plus approfondie de la variabilité locale et des états transitoires, améliorant ainsi considérablement la précision et la fiabilité du modèle.

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CONTRIBUTION OF AUTHORS AND THESIS FORMAT

This thesis adopts a manuscript-based format in compliance with the guidelines set forth by the Graduate and Postdoctoral Studies at McGill University, encompassing two research manuscripts (Chapters III and IV). The research findings presented in these manuscripts have been presented at reputable scientific conferences and have been submitted to, or are in the process of preparation for, peer-reviewed journals. **Mr. Harmanpreet Singh Grewal**, the principal author, is pursuing an M.Sc. degree. He was responsible for conceptualizing the research, establishing the study's goals, performing the model simulations, analyzing the data and findings, and composing the original manuscripts. The co-authors contributing to these manuscripts are **Dr. Zhiming Qi**, **Dr. Vinayak Shedekar**, **Dr. Manal Askar**, **Dr. Kevin King**, and **Dr. Liwang Ma**.

Dr. Zhiming Qi, the research supervisor, has actively participated in every phase of the study, from developing the study objectives to supervising the candidate. He provided invaluable scientific guidance, reviewed, and co-authored all the manuscripts. Dr. Vinayak Shedekar, a committee member, supervised and monitored the candidate's work at the Ohio State University. He contributed by assisting in field visits in Ohio and co-authoring and reviewing Chapters III and IV. Dr. Kevin King provided comprehensive water quality datasets crucial for assessing the model's performance in Chapters III and IV. He also co-authored and reviewed these chapters. Dr. Manal Askar recalibrated the DRAINMOD-P simulations used in Chapter III for model comparison, in addition to reviewing and co-authoring the chapter. Dr. Liwang Ma offered insights on improving the RZWQM2-P model and reviewed Chapter III.

The two manuscripts presented in this thesis are as follows:

1) Chapter III: **Grewal, H.S**., Qi, Z., Askar, M.H., Shedekar, V.S., King, K.W., and Ma, L. Comparing RZWQM2- P and DRAINMOD-P in Simulating Phosphorus Losses from a Tile-Drained Agricultural Field.
2) Chapter IV: **Grewal, H.S**., Qi, Z., Shedekar, V.S., and King, K.W. Using RZWQM2-P to Capture Tile Drainage Phosphorus Dynamics in Ohio. Submitted to Journal of Environmental Quality.

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LIST OF ABBREVIATIONS AND SYMBOLS

Act^{IP}	active inorganic P
ADAPT	Agricultural Drainage and Pesticide Transport
ADR	advection-dispersion-reaction
ANIMO	Agricultural Nutrient Model
APEX	Agricultural Policy/ Environmental eXtender
ARS	Agricultural Research Service
BS	Base Scenario
CC	Cover Crop
CD	Controlled Drainage
DRAINMOD-NII	computer model for simulating hydrology and nitrogen dynamics of poorly drained soils
DRAINMOD-P	computer model for simulating hydrology and phosphorus dynamics of poorly drained soils
DRP	dissolved reactive phosphorus
DSSAT	Decision Support System for Agrotechnology Transfer software
EOF	Edge-of-field
EPA	Environmental Protection Agency
EPIC	Erosion-Productivity Impact Calculator model
ET	evapotranspiration
$ferP^{av}$	available fertilizer P pool
$ferP^{res}$	residual fertilizer P pool
$Fres^{OP}$	fresh organic P
GLWQA	Great Lakes Water Quality Agreement
GW	groundwater
HYDRUS	software package for simulating water flow, heat, and solute transport in variably saturated media
ICECREAM	simulation model for predicting phosphorus leaching from arable land
IOA	Index of Agreement
K_{sat}	saturated hydraulic conductivity
Lab^{P}	labile P
Lk_{sat}	lateral hydraulic conductivity

$manP^{H_2O}_{inorg}$	manure water-extractable inorganic P pool
$manP^{H_2O}_{org}$	manure water-extractable organic P pool
$manP^{stbl}_{inorg}$	manure stable inorganic P pool
$manP^{stbl}_{org}$	manure stable organic P pool
NASS	National Agricultural Statistics Service
NOAA	National Oceanic and Atmospheric Administration
NSE	Nash-Sutcliffe Model Efficiency
OARDC	Ohio Agricultural Research & Development Center
P	phosphorus
P_b	soil bubbling pressure
PBIAS	Percent Bias
Pc_b	conductivity curve bubbling pressure
PET	potential evapotranspiration
PLEASE	Phosphorus LEAching from Soils to the Environment
PP	particulate phosphorus
R^2	Coefficient of Determination
RZWQM2	Root Zone Water Quality Model Version 2
RZWQM2-P	Root Zone Water Quality Model Version 2 - Phosphorus
SCS	Soil Conservation Service
SSURGO	Soil Survey Geographic Database
$Stab^{IP}$	stable inorganic P
$Stab^{OP}$	stable organic P
STP	soil test phosphorus
SurPhos	Surface Phosphorus and Runoff Model
TP	total phosphorus
US	United States of America
USDA	United States Department of Agriculture
USLE	Universal Soil Loss Equation
Θ_r	residual water content
Θ_s	saturated water content
λ	air pore index
ρ	bulk density

CHAPTER I

INTRODUCTION

1.1. Background

Freshwater resources are one of the vital components of the hydrological cycle of the Earth and play an important role in sustenance of ecosystems, nurturing agricultural practices, and fulfilling human needs (Ingrao et al., 2023). The projections by Mazzucato et al. (2023) suggest that by 2030, due to mismanagement of freshwater resources, the world may face a shortfall in meeting its freshwater needs by as much as 40% compared to the available supply. Historically, the North American region, specifically Canada and the United States, has been in a much better position regarding freshwater availability, as the Great Lakes, which are shared by both countries, alone constitute 20% of the world's surface freshwater reserves (Cable et al., 2017; Steinman et al., 2017). Given that approximately 45 million basin inhabitants rely on the Great Lakes for their drinking water and other purposes (Maghrebi et al., 2015), prioritizing the protection of these vast water bodies ecological integrity is crucial. However, since the 1960s, the quality of these invaluable resources has increasingly been threatened by various forms of pollution (Bilder, 1972). This includes nutrient enrichment from point sources like sewage and industrial waste, as well as from non-point or diffuse sources, such as agricultural activities (Jordan, 1971; Rockwell et al., 2005).

Within the Great Lakes, Lake Erie is notably facing a significant rise in non-point source pollution from agricultural activities (Environment and Climate Change Canada, 2023), rapidly surpassing point sources as the key driver of nutrient enrichment (Kleinman et al., 2011a). Historically, nitrate-nitrogen loading has been associated with algae blooms and the creation of dead zones in water bodies (Breitburg et al., 2009; Scavia et al., 2003). However, recent studies indicate that phosphorus (P) also plays a critical role (Dodds, 2006; King et al., 2015). In aquatic systems, P is naturally limited and often restricts algal growth, but excessive P loading from agricultural fields disrupts this balance, leading to unchecked algal and cyanobacteria proliferation (Kleinman et al., 2011b). Such blooms can be detrimental, producing toxins, reducing oxygen levels in the water, disrupting aquatic life, and leading to the formation of dead zones where most aquatic organisms cannot survive. A notable example of the impact of these blooms occurred in 2014 in the city of Toledo, Ohio (Steffen et al., 2017). There, half a million residents were unable to drink or use tap water for two days due to excessive algae blooms in the western basin of Lake Erie, underscoring the serious ramifications of nutrient pollution (Jetoo et al., 2015). Therefore, considering these severe impacts, there is an urgent need to mitigate the impact of agricultural P loading on the freshwater surface bodies to preserve both environmental health and public safety (Mohamed et al., 2019; Sharpley et al., 2013).

Traditionally, long-term field-scale experiments are required to evaluate the effects of different management practices on P loading (Johnston, 2008; McCollum, 1991; Morel et al., 2014). For instance, Uusitalo et al. (2018) assessed the impact of no-tillage and autumn plowing on P losses in subsurface drainage and surface runoff over nine years in Finland. In southern Ontario, Tan and Zhang (2011) studied the impact of controlled drainage versus free drainage on P loading for five years. Over eleven years in central Iowa, Tomer et al. (2016) investigated the effect of manure application on P loading during storm events. All such experiments are crucial in identifying effective strategies to minimize P losses from agricultural fields. However, the applicability of these studies is limited to areas with similar soil conditions, management practices, geographical locations, and climatic factors. Therefore, using field experiments to identify management practices that accommodate spatial and temporal variations is often time-consuming and not economically viable (Thorp et al., 2007). An alternative approach is field-scale modeling (Singh et al., 2022). Advanced models can simulate various management scenarios, allowing for the assessment of their impacts on P loading without extensive physical experimentation (Shokrana et al., 2022). This approach is more time- and cost-effective, enabling quicker and broader evaluations of potential strategies. Additionally, modeling can incorporate factors such as climate change (Wang et al., 2016), which significantly affects agricultural practices and aid in developing resilient strategies for nutrient management.

Over the years, field-scale P modeling has evolved significantly. Historically, runoff was primarily considered the main pathway for the transport of dissolved reactive phosphorus (DRP) and particulate phosphorus (PP), while subsurface drainage often neglected due to the belief that P transport through subsurface pathway was "negligible" because of the subsoil's capacity to bind

P (King et al., 2015). However, a landmark review by Sims et al. (1998) in the late 1990s highlighted the critical role of subsurface drainage in P loading. Similarly, many process-based field-scale models have shown shortcomings in addressing the fate and transport of DRP, PP, or both, especially in predicting their movement through soil matrix and macropore flow. The reviews conducted by Radcliffe et al. (2015), which examined nine models, and by Qi and Qi (2017), who reviewed fifteen models, both revealed that, up to that point, only the ICECREAM model was capable of predicting both dissolved and particulate P transport through the soil matrix and macropores. However, they also identified weaknesses in the ICECREAM model, notably its simplistic tile drainage simulation, lacking a water-table-based component and relying on simple water storage routing concept for tile flow simulation.

A holistic and robust model should include a strong hydrology component to simulate water and associated P load through surface runoff, soil matrix, and preferential flow (Radcliffe et al., 2015). It should also predict crop yields to estimate plant P uptake and the various P transformations in the soil, while also being capable of simulating comprehensive management practices (Shokrana et al., 2022). With the recent addition of the P component to the RZWQM2 (Ahuja et al., 2000) and DRAINMOD (Skaggs, 1978), these well-tested models have been modified to become more versatile [RZWQM2-P (Sadhukhan et al., 2019) and DRAINMOD-P (Askar et al., 2021)], with added P simulation capabilities. Currently, only these two models cover all the outlined points for the transportation of P through various pathways in an agricultural setting. As these models have only recently been upgraded with the P component, they are scarcely tested on a daily and monthly basis for their P loss predictions. Furthermore, there is no comparative study of both models that differentiates the processes in each model used and evaluates their performance in predicting P losses.

Therefore, it is crucial to assess the performance of the newly integrated P component within these models. The development of new models or the addition of new components to established ones requires comprehensive testing to obtain valuable insights into their strengths, weaknesses, and limitations (Thorp et al., 2009). This process is vital for advancing the field of modeling and enhancing model credibility through meticulous validation. Moreover, by evaluating the models' performance, users can choose the one that best suits their needs based on its effectiveness for the intended application. This approach will significantly aid in making informed decisions in agricultural water management, utilizing well-tested models to devise customized management practices and address the challenge of P loading.

1.2. Objectives

The primary aim of this research was to assess the performance of the newly developed phosphorus component within the RZWQM2-P model, specifically in its ability to predict daily dissolved reactive phosphorus (DRP) and total phosphorus (TP) losses via subsurface drainage, and to suggest recommendations for further improving the model's subroutines. Only one previous study, conducted by Shokrana et al. (2022), has used daily P loss data and concluded that the RZWQM2-P model performed unsatisfactorily in predicting daily DRP losses through subsurface drainage. The specific objectives to achieve the general objective were as follows:

i. To thoroughly evaluate the RZWQM2-P model's performance in predicting daily P losses, including both DRP and TP, through subsurface drainage, utilizing daily P loss data from two experimental fields in Ohio.
ii. To compare the methodologies and performance of the RZWQM2-P model and the DRAINMOD-P model in predicting daily P losses through subsurface drainage. This comparison aims to identify the strengths and limitations of each model and explore how they can be improved by integrating their respective advantages.
iii. To identify the subroutines/processes in the RZWQM2-P model that require further improvements for satisfactory prediction of P loss through subsurface drainage, especially during high-load (peak) events of the simulation.
iv. To evaluate the model's applicability in predicting management practices for P loss reduction. This involves assessing the effectiveness of two specific management practices—cover cropping with rye and controlled drainage—in reducing P loading from fields with subsurface drainage, using a validated model.

1.3. Thesis outline

This thesis adheres to the guidelines established by McGill University's Graduate and Postdoctoral Studies and is presented in a 'manuscript' format. It consists of six chapters, preceded by a title page, table of contents, abstract, acknowledgments, preface, and a section detailing author contributions. The first chapter introduces the research topic, emphasizing its significance, and outlines the study's objectives. The second chapter offers a concise review of the relevant literature. The third chapter provides a comparative analysis of the RZWQM2-P and DRAINMOD-P models in predicting daily phosphorus loss through subsurface drainage. The fourth chapter evaluates the phosphorus component of the RZWQM2-P model using daily P loss data from the second experimental field in Ohio and examines the impact of cover crop rye and controlled drainage on P loss management. Additionally, chapters three and four identify specific subroutines in the RZWQM2-P model that require modifications. The fifth chapter offers an overarching discussion that integrates the findings from all chapters of the thesis. The final chapter summarizes the thesis and concludes the study. Connecting text throughout the chapters is provided to link the research. References are compiled at the end of the thesis.

CHAPTER II

LITERATURE REVIEW

2.1. Phosphorus use in agriculture: Impacts on freshwater ecosystems

Phosphorus (P) is critical for high agricultural productivity (Mardamootoo et al., 2021). P, an essential and irreplaceable nutrient, plays a pivotal role in promoting cell division, stimulating root development, bolstering plant strength, and enhancing the formation of flowers and seeds (Liu, 2021; Malhotra et al., 2018). Given its vital role in supporting agricultural productivity, the efficient utilization of P has emerged as a crucial concern over the years for a variety of reasons. Firstly, P is commonly applied to cropland in the form of phosphate fertilizers, derived from phosphate rocks. These rocks are a non-renewable resource, and predictions suggest that, given the current rate of extraction and use, they will be depleted within 60-100 years (Johnston et al., 2014). Secondly, various studies and field experiments indicate that only 10-15% of the applied fertilizer P is utilized by crops (Johnston et al., 2014). The remainder becomes fixed in the soil through biotic and abiotic processes, rendering it unavailable to plants, and this accumulation of P persists in the soil as old soil P pool also known as legacy P (Doydora et al., 2020; Osterholz et al., 2023). Various studies have indicated that legacy P significantly contributes to nutrient loads in freshwater bodies, notably Lake Erie (Jarvie et al., 2013; King et al., 2017; Motew et al., 2017; Muenich et al., 2016). This leads to a third issue: excessive leaching of P from agricultural fields into freshwater bodies, resulting in eutrophication by increasing the total P load of the water body (Baker et al., 2014; Han et al., 2012). For instance, 40% of US lakes contain excess P, which deteriorates their quality (Doydora et al., 2020). The P leached from the fields is available in both a dissolved reactive form (DRP), immediately accessible to algae, and as particulate P (PP) bound to soil particles (Nazari et al., 2020).

Given this context, the dynamics of P mobility, from its application on croplands to its eventual accumulation in freshwater ecosystems, highlight a complex environmental challenge (King et al., 2015a). Recognizing the pathways through which P reaches aquatic environments, and the resultant eutrophication, underscores the need for integrated management strategies (Singh et al., 2020). These strategies must aim to optimize P use in agriculture, minimizing its loss to water bodies, and thereby safeguarding both agricultural productivity and aquatic ecosystem integrity (Sharpley et al., 2015).

2.2. Phosphorus loading in Lake Erie

As discussed in the previous section, Lake Erie has been significantly impacted in terms of its water quality due to P loading. The water quality of Lake Erie has been deteriorating since the 1950s (Davis, 1964). Documented instances of algal blooms, directly attributed to P influx from adjacent territories, underscore the gravity of the situation (Dolan & McGunagle, 2005; Schelske, 1979; Zhang et al., 2016).

The topography of Lake Erie plays a crucial role in eutrophication events and significantly influences P dynamics and water quality. The western basin, being the shallowest among the basins with an average depth of 7.4 meters compared to 18.3 meters and 24 meters in the central and eastern basins respectively, has received approximately 61 percent of the total P load entering Lake Erie since 1994 (EPA, 2015). Consequently, the water quality in the western basin has become the most compromised compared to other regions (Berry et al., 2017; Environment and Climate Change Canada, 2023; Sayers et al., 2019).

Figure 2.1 reveals that, from 2013 to 2022, the western basin of Lake Erie has received an average annual P load of approximately 3,328 tonnes (Environment and Climate Change Canada, 2023). Notably, 90% of this load originates from non-point sources, predominantly agricultural lands, with a considerably smaller contribution from urban stormwater runoff. Meanwhile, the central and eastern basins have predominantly been affected by non-point source pollution as well, accounting for 77% and 86% of their P loads, respectively (Environment and Climate Change Canada, 2023). Further analysis, as presented in Figure 2.2, focuses exclusively on the Canadian side, revealing that non-point sources overwhelmingly dominate total P loading. The proportion from non-point sources fluctuated, dropping to a low of 47% in 2010 and peaking at 81% in both 2014 and 2019 (Environment and Climate Change Canada, 2023). This highlights the substantial influence of agricultural practices in the Midwest of the United States and southern Ontario on Lake Erie's water quality. In response to these challenges, the United States and Canada, under the

Great Lakes Water Quality Agreement (GLWQA), have pledged to reduce the total P load entering the western and central basins of Lake Erie by 40% compared to the 2008 levels (EPA, 2015).

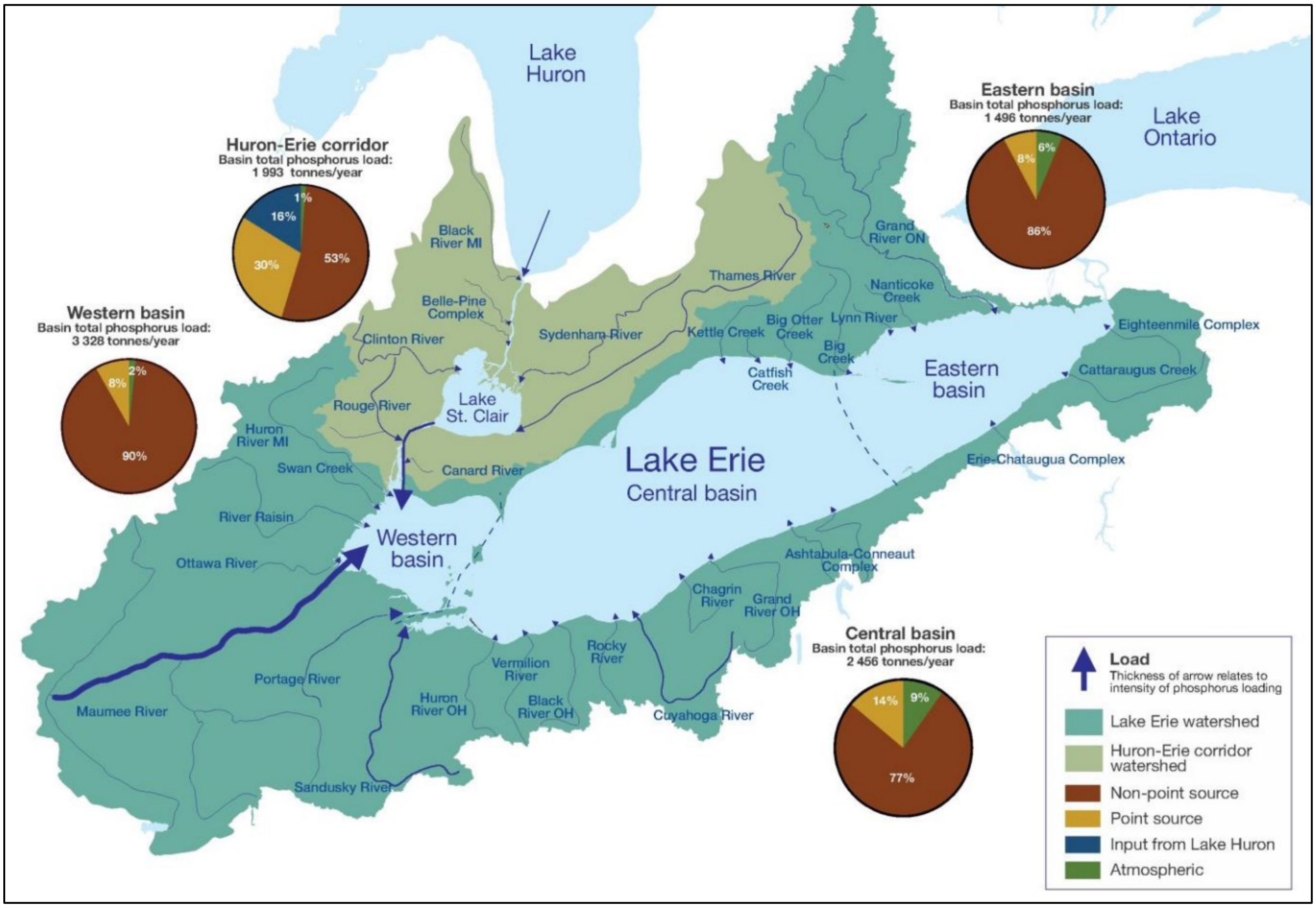

Figure 2. 1 Ten-year annual average (2013-2022) of phosphorus loading to Lake Erie from various sources, with arrow thickness indicating load intensity by basin.
[adapted from Environment and Climate Change Canada (2023)]

Despite pledges from both countries to reduce total P loading by 40%, data from Environment and Climate Change Canada (2023) underscore the significant disparity between commitments and actual results. Figure 2.3 illustrates the trends in total P loading to the Lake Erie basin from 2008 to 2022, indicating no discernible trend over these 14 years. Notably, in 2022, the total P load from the Canadian side exceeded the 2008 levels, despite representing only 22% of the combined load from both Canada and the US. This underscores the necessity for both nations to achieve reductions. The peak combined total P load was approximately 13,533 tonnes in 2019, with the lowest at 5,672 tonnes in 2010 (Environment and Climate Change Canada, 2023). The failure to meet the reduction targets set by the GLWQA, coupled with ongoing high nutrient concentrations and persistent algal blooms, has led the State of the Great Lakes report by the EPA (2022) to classify Lake Erie's water quality as poor and unchanged.

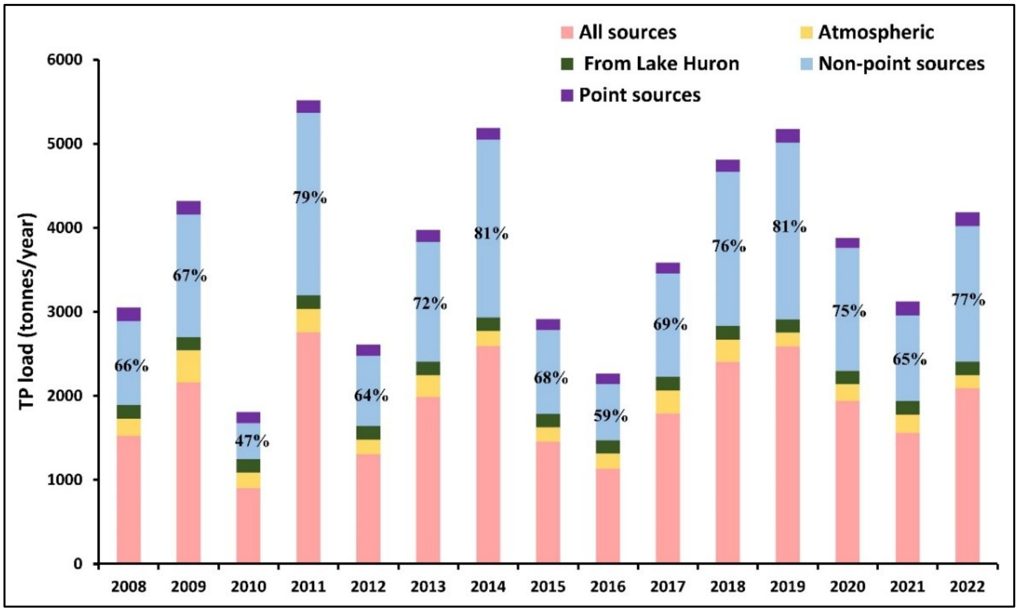

Figure 2. 2 Phosphorus load estimates to Lake Erie by source in Canada, from 2008 to 2022
[data retrieved from Environment and Climate Change Canada (2023)]

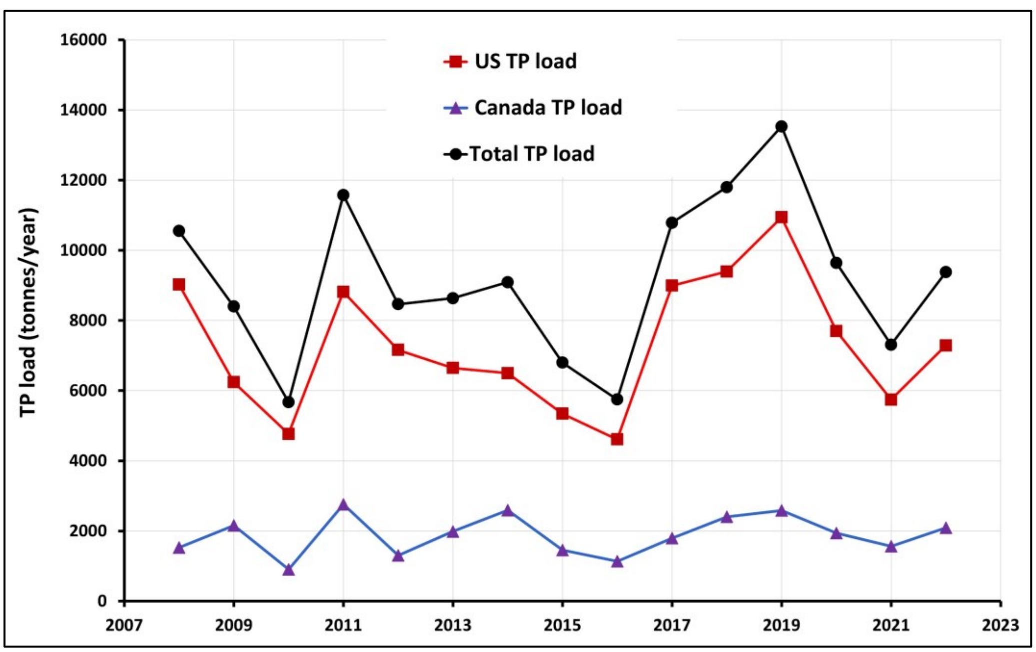

Figure 2. 3 Estimated total phosphorus loading to Lake Erie from 2008 to 2022
[data retrieved from Environment and Climate Change Canada (2023)]. TP, total phosphorus.

2.3. Pathways of phosphorus transport from croplands to surface water bodies

The previous section highlighted that non-point sources, primarily agricultural croplands, pose a significant threat to the quality of freshwater lakes, particularly Lake Erie. Consequently, mitigating these losses through effective management practices is crucial. To effectively tailor these practices, understanding the pathways of P transport from agricultural fields is essential.

2.3.1. Historic perspective on phosphorus transport

Phosphorus transport from agricultural fields primarily occurs through two pathways: surface runoff and subsurface drainage. Twentieth-century research predominantly focused on surface runoff as the principal means of P transfer from croplands to surface water bodies. For a considerable period, there was a strong belief in the minimal P concentrations present in tile drainage (King et al., 2015b). Numerous studies, such as that by Baker et al. (1975), found that P concentrations in tile drainage were negligible compared to those in surface runoff in central Iowa. Similarly, research by Logan et al. (1980) across Iowa, Minnesota, and Ohio concluded that P losses via tiles were insignificant and primarily in a non-bioavailable, or non-reactive, form. As a result, initial efforts to manage P levels focused on reducing soil erosion caused by surface runoff, employing various management practices. These findings significantly influenced early models developed to recommend practices for mitigating P losses from fields. For instance, the Erosion-Productivity Impact Calculator (EPIC) model's P subroutine (Jones et al., 1984; Sharpley et al., 1984), a precursor to later P models, lacked routines to simulate the non-reactive form of P, such as particulate phosphorus, from subsurface drainage. The P indices developed by Dr. Sharpley and colleagues (Osmond et al., 2023) primarily targeted P losses from surface runoff and erosion, suggesting various management practices based on the index to reduce losses through that pathway.

2.3.2. Perspective on phosphorus transport from the late 1990s onwards

The prevailing view underwent a significant shift in the late 1990s, following a study by Sims et al. (1998) conducted in Delaware, Indiana, and Quebec. This research evaluated the role of artificial drainage in P transport and revealed that subsurface drainage plays a critical role in P loading, necessitating equal consideration in management practices alongside surface runoff to address non-point source P pollution effectively. Following this study, numerous investigations in both the US and Canada have echoed Sims et al. (1998)'s findings (Table 2.1).

2.3.3. Extent, significance, and contribution of subsurface drainage to phosphorus transport

Subsurface drainage, in use for over 150 years (King et al., 2015b), plays a crucial role in agricultural productivity by effectively removing excess water from fields (Fausey, 2005). This practice grants farmers enhanced control over their field operations, leading to numerous benefits such as improved trafficability, the opportunity for earlier planting, a wider variety of crop choices, reduced vulnerability of crops to pests and diseases, and ultimately, an increase in crop production (Atherton, 1999; Ghane, 2018; Kornecki & Fouss, 2001; Strock et al., 2011). Research has shown that the implementation of subsurface drainage can potentially boost annual crop yields by 5 to 25% (Eidman, 1997).

The recent census conducted by the USDA National Agricultural Statistics Service (NASS) in 2017 provided detailed insights into the extent of tile drainage in the US. It is estimated that 22.48 million hectares of land in the US are equipped with tile drainage, of which 18.79 million hectares—constituting approximately 83.8%—are located in six Midwestern States alone (Valayamkunnath et al., 2020). In Canada, it is estimated that around 8 million hectares of land are tile-drained, with this figure expected to rise (King et al., 2015b). Further analysis suggests that in the US and Canada, roughly 43 million and 16 million hectares of land, respectively, either necessitate or could significantly benefit from subsurface drainage (Skaggs et al., 1994). Consequently, subsurface drainage is poised to continue playing a crucial role in the coming decades. Moreover, with climate change projected to increase precipitation (Easterling et al., 2017; Picard et al., 2023), croplands are expected to derive even greater benefits from subsurface drainage.

The incorporation of tile drains into fields notably modifies the overall water yield, increasing it by 10 to 25% (King et al., 2015b; Tomer et al., 2005). Although tile drainage elevates the total water yield, it concurrently leads to a substantial reduction in surface runoff and sediment yield (Dolezal et al., 2001). The implementation of subsurface drainage systems is thus associated with decreased P losses from surface runoff by reducing runoff volume (Bengtson et al., 1995). However, numerous findings have highlighted tile drains as a notable contributor of P within agricultural watersheds, with instances where they release equal or even greater amounts of phosphorus compared to surface runoff, as various studies detailed in Table 2.1. Therefore, managing P transport through both tile drainage and surface runoff is absolutely critical to meeting the 40% reduction goal set by the Great Lakes Water Quality Agreement (Smith et al., 2015).

Table 2. 1 Overview of studies on phosphorus losses linked to tile drainage and its contribution to total phosphorus load.

Location and site information	Summary of P load/concentration associated with tile drainage	Reference
Quebec: The field site was located in the Pike River watershed	The study aimed to assess the P load during the snowmelt event and discovered that subsurface drainage contributed to 37.1% of the total P load, establishing it as a significant pathway.	(Jamieson et al., 2003)
Ontario: Tile drained field under free drainage and controlled drainage in southern Ontario	The five-year study revealed that subsurface drainage accounted for approximately 95 to 97% of the total P loss with free drainage, and 65 to 71% with controlled drainage. Additionally, the total P concentration in tile drainage, at 0.48 mg L^{-1}, exceeded the province of Ontario's upper limit of 0.03 mg L^{-1}.	(Tan & Zhang, 2011)
Nova Scotia: 39 tile-drained fields from four different counties	The 20-month study of 39 fields concluded that the mean total P concentration from tile drainage exceeded 0.10 mg L^{-1} in 82% of the fields, and periodically concentrations were occasionally more than 50 times higher than the guidelines.	(Kinley et al., 2007)

Location and site information	Summary of P load/concentration associated with tile drainage	Reference
Wisconsin: Four tile-drained fields in three different counties	The four-year study concluded that tile drainage was responsible for 16-58% of the total dissolved reactive phosphorus (DRP) leaving the field and 17-41% of the cumulative total P load.	(Ruark et al., 2012)
Ontario: Tile drained field under manure application	The eight-year study revealed that tile drainage is the major pathway for DRP load, accounting for 63% of the losses through this pathway. For particulate phosphorus (PP) load, both tile drainage and surface runoff contribute almost equally to the total P load.	(Sadhukhan et al., 2019b)
Ohio: Six tile drains within the Upper Big Walnut Creek watershed in central Ohio	An eight-year study revealed that tile drainage accounted for 48% of the DRP and 40% of the TP load. Additionally, more than 90% of the samples in tile drainage exceeded the recommended level of 0.03 mg L^{-1} P concentration.	(King et al., 2015a)
Ohio: 38 edge-of-field sites spread across various counties in the state	The four-year field experiments concluded that approximately 71% ± 26% (mean ± one standard deviation) of the annual DRP load and 69% ± 27% of the annual TP load were accounted via subsurface drainage.	(Pease et al., 2018)
Indiana: Four fields in the St. Joseph River Watershed	Field experiments demonstrated that subsurface drainage is a significant pathway for P transport, accounting for 49% of the DRP and 48% of the TP load.	(Smith et al., 2015)

P, phosphorus; TP; total phosphorus

2.4. Modeling phosphorus losses

Given the significant concern for the water quality of surface water bodies, relying solely on field experiments to implement management practices across various spatial and temporal scales is insufficient (Thorp et al., 2007). Modeling presents a more effective approach for predicting management practices tailored to specific cropping systems, soil types, and regional climates (Singh et al., 2022). However, for a modeling technique to be deemed comprehensive and reliable, it is essential to account for the full spectrum of dynamics occurring within the field. The review by Radcliffe et al. (2015) outlines the prerequisites for a P model to be considered comprehensive in simulating P dynamics (Figure 2.4). According to them, the model should

i. Partition the water into runoff, soil matrix, and preferential flow.
ii. Represent phosphorus movement across all three water flow pathways.
iii. Simulate processes like sorption and desorption of dissolved reactive phosphorus, as well as the filtering of particulate phosphorus.
iv. Offer an extensive list of management scenarios.

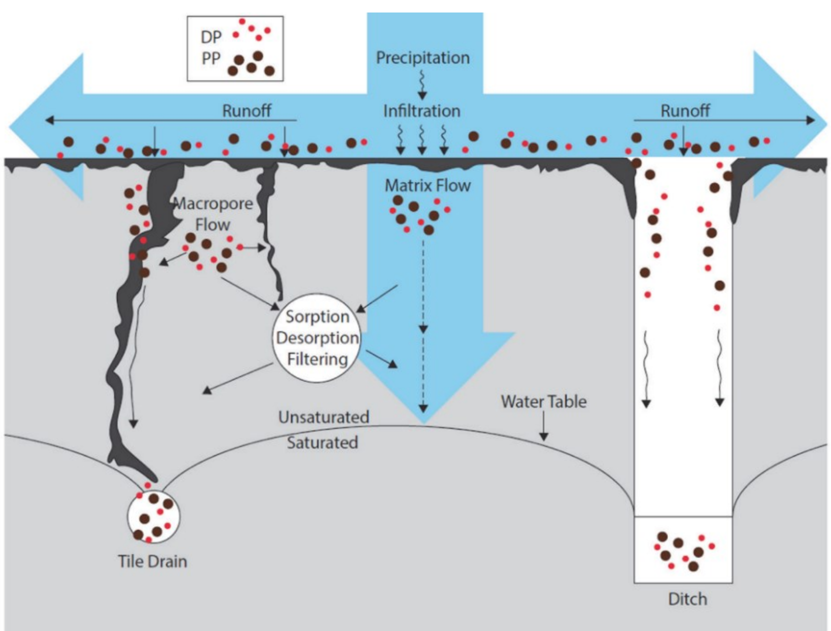

Figure 2. 4 Representation of water and phosphorus dynamics in tile-drained fields
[adapted from Radcliffe et al. (2015)]. DP, dissolved reactive phosphorus; PP, particulate phosphorus.

Sharpley et al. (1984) provided an early representation of P dynamics modeling in soil, proposing five different P pools to accurately reflect actual field conditions, which were incorporated into the EPIC model. They distinguished the P pools based on labile, inorganic and organic categories: labile, active and stable for inorganic pools, and fresh and stable for organic pools (Jones et al., 1984; Sharpley et al., 1984). The EPIC model's approach to P pools was among the first to represent actual field conditions, allowing for the continuous movement among different P pools through processes such as mineralization, immobilization, absorption, and desorption (Sadhukhan, 2021). Although many later models adopted the EPIC model's P routines (Table 2.2), Vadas et al. (2013) concluded that these routines do not meet the need for reliable predictions, noting that they have not been updated in the last 25 years (Qi & Qi, 2017). Vadas et al. (2006); Vadas and White (2010) identified an underestimation of desorption flow and total P in the soil due to the original P subroutines based on Sharpley et al. (1984), leading to modifications in the adsorption factor constant and phosphorus sorption (Qi & Qi, 2017). Furthermore, the hydrology component of the EPIC model does not account for macropore flow, which is crucial for a model to be considered comprehensive for P modeling and to accurately represent actual field conditions.

Subsequent field-scale models, including APEX [Agricultural Policy/ Environmental eXtender (Williams et al., 2006)], ADAPT [Agricultural Drainage and Pesticide Transport (Chung et al., 1992)], ANIMO [Agricultural Nutrient Model (Kroes & Roelsma, 1998)], PLEASE [Phosphorus LEAching from Soils to the Environment (Schoumans et al., 2013)], HYDRUS (Simunek et al., 2005; Šimůnek et al., 2006), and SurPhos [Surface Phosphorus and Runoff Model (Vadas, 2014)], have shown proficiency in particular aspects of either hydrology simulation or P predictions. However, none fully encapsulates all dimensions of the comprehensive P model previously outlined, as described in Table 2.2.

HYDRUS, for instance, offers a sophisticated module for simulating the hydrology component, complete with advanced macropore flow subroutines across three modeling options. Despite this capability, the lack of specialized P subroutines means HYDRUS can only approximate P loss through tile drainage using its solute transport equations. To the best of our knowledge, HYDRUS was only tested once in Canada for simulating P losses through tile drainage fields by Qiao (2014), who found it provided satisfactory results on a weekly scale. However, the absence of P routines for runoff flow and a lack of comprehensive agricultural management options led Radcliffe et al. (2015) to conclude that HYDRUS is unlikely to be adopted for modeling P in tile-drained fields.

SurPhos, on the other hand, features some of the most sophisticated P subroutines designed to predict dissolved P losses through surface runoff. It incorporates four P pools for an accurate representation of manure application and two P pools for fertilizer application, enhancing these with the addition of three P pools from the EPIC model (Vadas, 2014). Furthermore, SurPhos introduces an innovative functionality that dynamically adjusts absorption/desorption rates, addressing the limitations present in the EPIC model's P routines. Despite these advanced features, SurPhos does not serve as a comprehensive model either, as it lacks the ability to independently simulate hydrological processes and omits consideration of P losses through the subsurface pathway (Sadhukhan, 2021).

ICECREAM (Tattari et al., 2001) has long been recognized as a comprehensive tool for predicting P losses from artificially drained fields. Reviews by Qi and Qi (2017); Radcliffe et al. (2015) highlight ICECREAM as a reliable tool for P predictions in fields with tile drainage, noting its capability to encompass all major pathways of P transport—including surface runoff, soil matrix, and macropore flow—and to predict both dissolved and particle-bound P transport. Developed specifically for Nordic conditions, the ICECREAM model has been extensively tested in Sweden (Liu et al., 2012; Rosberg & Arheimer, 2007), proving effective in predicting P dynamics in these regions. However, its application outside the Nordic countries, specifically by Qi et al. (2018) in Canada, revealed challenges in predicting PP loss through tile drainage.

Sadhukhan (2021) commented that despite ICECREAM's comprehensive P module, capable of predicting P transport across all mediums, its subsurface drainage component is relatively weak. It relies solely on storage routing concepts without incorporating a water table-based component. To enhance its predictive accuracy, particularly for tile drainage and water redistribution, it's suggested that the model could benefit from integrating more sophisticated equations, such as Hooghoudt's equation and Richards' equation. These improvements could significantly refine ICECREAM's ability to simulate the complex dynamics of P transport and water movement in agricultural landscapes.

2.5. Recent advances in phosphorus modeling

Over the past decade, several studies (Kleinman et al., 2015; Qi & Qi, 2017; Radcliffe et al., 2015) have underscored the necessity for a comprehensive agricultural management model-based tool capable of accurately predicting P dynamics in tile-drained agricultural fields. The existing models of that time, as discussed in the previous section and presented in Table 2.2, fall short in one or more components. These limitations restrict their effectiveness in aiding scientists and farmers to directly rely on model predictions for efficiently managing P losses.

In response to these challenges, researchers recently developed two models: the Root Zone Water Quality Model version 2 – Phosphorus [RZWQM2-P (Sadhukhan et al., 2019a)], and the DRAINMOD-P model (Askar et al., 2021). Both models incorporate the latest scientific understanding of P transport from agricultural fields, aiming to overcome the limitations identified in earlier models by providing more accurate and reliable predictions of P dynamics.

The RZWQM2 model possesses a robust hydrology component, complemented by macropore and erosion modules, which are essential for accurately predicting P losses. These elements are essential as particle-bound P cannot be predicted accurately by models in their absence. Sadhukhan et al. (2019a) enhanced the model by integrating a P component, by incorporating P modules from the EPIC model and integrating advanced features from the SurPhos model, such as separate P pools for manure and fertilizer applications, into the RZWQM2 model. DRAINMOD, initially lacking the macropore and erosion modules necessary for the inclusion of a P module, underwent significant enhancement by work of Askar et al. (2021); Askar et al. (2020). They developed both the macropore component and an erosion module along with a new P component, culminating in the DRAINMOD-P. This version of DRAINMOD now adeptly simulates the dynamics of P through artificially drained fields, marking a significant leap in modeling capabilities.

The next chapter (Chapter 3) of this thesis will provide a comprehensive overview of both models, detailing their processes, subroutines, and other relevant features, offering an in-depth look at their contributions to agricultural water management and P loss prediction.

Table 2. 2 Comparative analysis of field-scale models for addressing phosphorus loss through subsurface drainage.

Model [reference(s)]	Process vs Empirical approach	Infiltration/ Runoff	Subsurface drainage		Management practices	Subsurface P routines		Soil P pools/ representation	Comments
			Soil matrix	Macropore flow		DRP	PP		
ADAPT [Agricultural Drainage and Pesticide Transport] (Chung et al., 1992)	Mixed	Soil Conservation Service (SCS) curve number method	Hooghoudt's steady state (Bouwer & Van Schilfgaarde, 1963) and Kirkham's equation (Kirkham, 1957)	Simplistic approach based on the function of clay content and the number of dry days (based on PET demand)	Limited management scenarios	✓	✗	Based on the nutrient component of the EPIC model	ADAPT model lacks the capability to simulate PP loss through both surface runoff and tile drainage. Radcliffe et al. (2015) stated that it is unlikely to predict the P losses from fields with tile drainage.
ANIMO [Agricultural Nutrient Model] **(**Kroes & Roelsma, 1998)	Process	✗	✗	✗	Extensive	✓	✗	Linearized solute transport equations	ANIMO model is unable to simulate hydrology and requires input from external hydrological models to simulate nutrient dynamics (McGechan & Hooda, 2010).
APEX [Agricultural Policy/ Environmental eXtender] (Williams et al., 2006)	Mixed	SCS curve number or Green Ampt equation (Green & Ampt, 1911)	Cascade approach	✗	Extensive options	✓	✗	Drawing from the five P pools utilized by the EPIC model.	Review of the APEX model by (Francesconi et al., 2016; Radcliffe et al., 2015) underscores its shortcomings, including the P partitioning processes and the inability to simulate macropore flow.

Model [reference(s)]	Process vs Empirical approach	Infiltration/ Runoff	Subsurface drainage		Management practices	Subsurface P routines		Soil P pools/ representation	Comments
			Soil matrix	Macropore flow		DRP	PP		
DRAINMOD -P (Askar et al., 2021)	Process	Green-Ampt equation for infiltration (Green & Ampt, 1911)	Hooghoudt's steady state and Kirkham's equation (Kirkham, 1957)	Hagen-Poiseuille law (Sutera & Skalak, 1993)	Extensive management scenarios	✓	✓	Inorganic P pools are based on the EPIC model, and organic P pools on the CENTURY model	DRAINMOD has recently been upgraded with a P component, making it one of the few models capable of simulating both DRP and PP transport through surface runoff, macropore flow and subsurface drainage, supported by a robust hydrology component.
EPIC [Erosion-Productivity Impact Calculator] (Gassman et al., 2004; Jones et al., 1984)	Process	Modified SCS curve number	Storage routing technique	✗	Extensive	✓	✗	Five interchangeable P pools proposed by Sharpley et al. (1984)	P subroutines in the EPIC model serve as the foundation for subsequent P models, yet they exhibit specific limitations. While capable of simulating PP transport through runoff, they fail to address PP transport through tile drainage. Additionally, EPIC lack a macropore flow component, which is critical for accurate P transport simulation.
HYDRUS (Simunek et al., 2005; Šimůnek et al., 2006)	Process	Richard's equation (Richards, 1931)	Hooghoudt's steady state equation and Ernst's equation (Ernst, 1962)	Three modeling options: One dual-porosity model and two dual-permeability models	Limited agricultural management scenarios	✗	✗	Simulated using solute transfer equations	HYDRUS lacks specific P subroutines; however, it can simulate P transport through tile drainage using its sorption and solute transfer equations. Yet, it cannot predict P losses bound to surface runoff due to the absence of an erosion simulation component.

Model [reference(s)]	Process vs Empirical approach	Runoff	Subsurface drainage		Management practices	Subsurface P routines		Soil P pools/ representation	Comments
			Soil matrix	Macropore flow		DRP	PP		
ICECREAM (Tattari et al., 2001)	Mixed	SCS curve number method	Storage routing technique	Dual porosity approach (Larsson et al., 2007)	Extensive	✓	✓	Based on the five P pools of the EPIC model	ICECREAM model predicts DRP and PP losses via runoff, macropore, and matrix flow. Review by Qi and Qi (2017); Radcliffe et al. (2015) label it the most adept field-scale P model, yet it lacks a water table drainage component. Its efficacy outside Nordic countries, tested once by Qi et al. (2018), shows limited capacity for PP loss prediction through tile drainage.
PLEASE [Phosphorus LEAching from Soils to the Environment] (Schoumans et al., 2013)	Mixed	✗	Groundwater -drainage-relationship (Van Bakel, 1986)	✗	Limited	✓	✗	P conc. calculations are based on the Langmuir equation (Van der Zee & Bolt, 1991) and empirical exponential equations (Chardon et al., 2007)	PLEASE model simulates P losses only through tile drainage, lacking a surface runoff component. It operates on an annual basis, making it unsuitable for higher resolution applications.
SurPhos [Surface Phosphorus and Runoff Model] (Vadas, 2014)	Empirical	✗	✗	✗	Limited	✗	✗	Basic structure follows the EPIC model's subroutines, with the addition of four subroutines for manure and two for fertilizer simulation.	SurPhos model is designed for integration with other models to simulate DRP losses through runoff, featuring advanced, dynamically changing daily absorption/desorption rates among P pools. However, it does not account for soil-bound P from runoff and cannot simulate P losses through tile drainage.

Model [reference(s)]	Process vs Empirical approach	Infiltration/ Runoff	Subsurface drainage		Management practices	Subsurface P routines		Soil P pools/ representation	Comments
			Soil matrix	Macropore flow		DRP	PP		
RZWQM2-P [Root Zone Water Quality Model version2 – Phosphorus] (Sadhukhan et al., 2019a)	Process	Green-Ampt equation for infiltration and Richards' equation for water distribution	Hooghoudt's steady state equation	Hagen-Poiseuille law	Extensive management scenarios	✓	✓	Based on the five P pools of the EPIC model, with the addition of four pools for manure application and two pools for fertilizer application, adopted from the SurPhos model.	RZWQM2 model has recently been upgraded with P subroutines. It can simulate losses of both DRP and PP through surface runoff, matrix flow, and macropore flow. The model also features advanced capabilities, such as dynamically changing rates for absorption/desorption and additional pools for fertilizer and manure application. Given its recent development, it requires further testing. To date, it has been tested outside of Canada only once, by Shokrana et al. (2022).

✓, model can simulate the process; ×, model cannot simulate the process; conc., concentration; DRP, dissolved reactive phosphorus; P, phosphorus; PP, particulate phosphorus; PET, potential evapotranspiration.

2.6. Evaluation and testing of the RZWQM2-P model

The RZWQM2-P model has been evaluated by its developers for its ability to predict P loss resulting from both fertilizer (Sadhukhan et al., 2019a) and manure applications (Sadhukhan et al., 2019b). In these studies, the model satisfactorily predicted DRP and PP losses via surface runoff and subsurface drainage. However, these evaluations utilized aggregated field data over periods rather than daily P loss data. When Shokrana et al. (2022) applied the model in Michigan—marking its first use outside of Canada with daily P loss data—the model's performance in predicting DRP losses was found to be unsatisfactory (NSE<0.35), and while its predictions for TP losses were satisfactory (NSE<0.50), it overestimated P losses, indicated by an unsatisfactory PBIAS.

Given these findings, it is imperative to further test the RZWQM2-P model using daily P loss data to accurately assess its performance in predicting P losses. Accurate daily predictions are crucial for applications such as assessing the impact of storm events on P loading, which typically last only a few days. Hence, simulating with higher temporal resolution is greatly appreciated and seen as a major benefit, particularly when the model is capable of precisely forecasting specific events.

FOREWORD TO CHAPTER III

Chapter II offers an in-depth analysis of the critical role of phosphorus (P) in agriculture and the issue of eutrophication in freshwater bodies, with a particular focus on Lake Erie. The previous chapter also reviews existing field-scale P models and their significance in reducing P losses from agricultural lands. As discussed, the RZWQM2-P and DRAINMOD-P models have been recently developed to address the shortcomings of previous P models. However, they have not been compared with each other in terms of their subroutines, capabilities, and effectiveness in predicting P losses from artificially drained fields. Chapter III presents the first-ever comparison of these models, which were evaluated using data from a tile-drained field in the watershed of the western Lake Erie basin. The chapter concludes with recommendations for enhancing these models.

Part of the manuscript was presented at the annual meeting of the Canadian Society for Bioengineering in July 2023 in Lethbridge, Alberta. The complete chapter is intended for submission to a peer-reviewed journal for publication.

CHAPTER III

COMPARING RZWQM2-P AND DRAINMOD-P IN SIMULATING PHOSPHORUS LOSSES FROM A TILE-DRAINED AGRICULTURAL FIELD

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Abstract

Phosphorus (P) losses from agricultural soils in Canada and the United States, whether dissolved in water or attached to suspended sediment, are a significant source of P pollution in surface water bodies. Hydrological and nutrient transport models are instrumental in developing better management practices to mitigate P losses from agricultural soils. This study represents the first effort to compare the accuracy of two recently developed field-scale models, RZWQM2-P and DRAINMOD-P, in simulating dissolved reactive P (DRP) and total P (TP) losses in subsurface drainage. The models' accuracy was assessed using a five-year observed data set from a subsurface-drained field in northwest Ohio. The performance of the RZWQM2-P and DRAINMOD-P models in predicting P losses was compared using efficiency criteria including the Nash-Sutcliffe Model Efficiency (NSE), Coefficient of Determination (R^2), Index of Agreement (IOA), and Percent Bias (PBIAS). Both models predicted subsurface drainage satisfactorily over the five-year period. However, DRAINMOD-P significantly overpredicted surface runoff compared to observed data, while RZWQM2-P also overpredicted, but to a lesser extent and closer to the observed data. With an NSE greater than 0.35, an R^2 exceeding 0.40, and an IOA above 0.75, the calibrated RZWQM2-P model demonstrated a better ability to predict monthly DRP losses with satisfactory performance compared to DRAINMOD-P. Nonetheless, both models performed unsatisfactorily in predicting daily DRP losses. In contrast, both models yielded satisfactory to good predictions for daily and monthly TP losses, with NSE values over 0.35, R^2 greater than 0.40, and IOA values above 0.75. A primary reason for RZWQM2-P's poor performance in predicting daily DRP loss through subsurface drainage was its failure to modulate changes in DRP concentration. Future modifications to the model's subroutines, particularly those related to the linear groundwater reservoir, are necessary to enhance its reliability in capturing high load peak events in subsurface drainage.

Keywords: Dissolved Reactive Phosphorus (DRP), DRAINMOD-P, Lake Erie, Management Practices, Phosphorus (P) loss, Root Zone Water Quality Model version 2-Phosphorus (RZWQM2-P), Subsurface Drainage, Total Phosphorus (TP)

3.1. Introduction

Fueled by the direct impact of phosphorus (P) on water quality in freshwater ecosystems, global concern over P losses from agricultural fields has increased considerably in recent years (Hanrahan et al., 2019). One of the key nutrients applied to fields as a fertilizer is P and it often ends up leaching into nearby water bodies, causing a cascade of environmental problems. The most prominent and alarming manifestation of P loss is observed in freshwater lakes, where excessive P concentrations can lead to eutrophication (Wurtsbaugh et al., 2019). Lake Erie, for instance, has been a prominent victim of P-induced eutrophication, experiencing harmful algal blooms that have not only disrupted aquatic life but also posed a threat to human health (Askar et al., 2023; Jetoo et al., 2015; Smith et al., 2015). According to recent estimates, non-point sources, such as agricultural fields, contribute to nearly 71 to 90 % of the total P load entering Lake Erie's western basin (Environment and Climate Change Canada, 2023; Scavia et al., 2016). Such losses are predominantly due to complex interactions between farming practices, hydrological processes, and soil P dynamics (Daloğlu et al., 2012). The occurrence of large-scale eutrophication events, as witnessed in Lake Erie in 2014 (Jetoo et al., 2015), has brought the issue to the forefront of environmental policy, necessitating a critical evaluation of the factors influencing P losses from tile-drained agricultural fields. In a concerted effort to enhance the water quality of Lake Erie and mitigate the accompanying health hazards, the governments of the United States and Canada have jointly resolved to curtail by 40% the overall annual P and dissolved reactive P loads originating from the Lake Erie basin (Baker et al., 2019). The severity of the problem accentuates the need for precise modeling and management strategies to understand and mitigate P losses, thus safeguarding our valuable freshwater resources.

Modeling P losses from tile-drained agricultural fields present a complex challenge due to the multitude of factors involved, including soil characteristics, hydrological processes, climate conditions, and management practices. Predicting and managing these losses requires detailed and accurate modeling and simulations that capture the underlying dynamics (Sadhukhan et al., 2019b). Various hydrological and nutrient transport models [e.g., ADAPT (O. Chung et al., 1992), APEX (Francesconi & Co, 2016), EPIC (Sharpley, 1990), HYDRUS (Boivin et al., 2006), ICECREAM (Tattari et al., 2001), SurPhos (Vadas, 2014), PLEASE (Dupas & van der Salm, 2010), SWAP (van Dam, 2000) have been employed to predict P transport through soil to tile drainage. While each of these models offers specific insights into different aspects of P transport (*e.g.*, hydrological processes, soil-P interactions, and plant uptake); however, their application to real-world scenarios is often limited by certain shortcomings (Qi & Qi, 2017; Sadhukhan et al., 2017), incapacitating them from reliably predicting P losses from tile-drained fields. An effective model must represent not just the physical flow of water but also the chemical reactions, biological processes, and human interventions that govern P transport (Sadhukhan et al., 2019b). This complexity necessitates the development of more precise and tailored models to understand the dynamic interactions of hydrology, soil, and crop management.

In recent years, the field of field-scale P modelling has seen significant advancements, particularly with the refinement of the P components in established models such as RZWQM2 (Ahuja et al., 2000) and DRAINMOD (Skaggs, 1985). Widely employed to simulate agricultural management practices such as drainage, irrigation, fertilization, water table depth monitoring, and tillage, both RZWQM2 and DRAINMOD can serve to assess the impact of climate change on the hydrology, water quality, and crop yield (Cordeiro & Ranjan, 2015; Gillette et al., 2018; Qi et al., 2013; Skaggs et al., 2012; Wang et al., 2023; Youssef et al., 2021). With the integration of P components, these models have undergone significant enhancements, reflected in the meticulous design of the P component in RZWQM2-P (Sadhukhan et al., 2019a), and in DRAINMOD-P (Askar et al. (2021). The P components in both the RZWQM2 and DRAINMOD models exclusively deal with P dynamics. However, the overall models serve as a fundamental platform, simulating a wide range of complex physical, biological, chemical, and hydrological processes that impact P behavior. These processes include, but are not limited to, crop growth, runoff, drainage, sediment yield, macropore flow, residue decomposition, and various agricultural management practices (Askar et al., 2021; Sadhukhan et al., 2019b). The meticulous design of the P components that has enhanced the ability of these models to simulate P cycling and transport in tile-drained agricultural lands, encompasses critical processes including organic and inorganic fertilizer applications, manure applications, plant P uptake, sediment-bound and dissolved P loss in both surface runoff and subsurface drainage, tillage practices, P adsorption and desorption, and P mineralization and immobilization (Askar et al., 2021; Sadhukhan et al., 2019a). By embedding these intricate processes within the models, a more detailed and precise representation of P dynamics is achieved. Hence, these advancements signify a critical milestone in understanding and managing P-related environmental concerns in tile-drained agricultural lands, paving the way for informed decision-making and sustainable agricultural practices.

When new models are developed or when two existing models are combined to form an integrated framework, the importance of thorough testing and evaluation becomes crucial (Ale et al., 2013; Du et al., 2017). An in-depth examination of existing or newly formulated models, such as RZWQM2-P and DRAINMOD-P, enriches our understanding of their strengths and shortcomings, paving the way for further enhancements and supporting future research and trustworthiness. By comparing the efficacy of field-scale models, we can determine their dependability in predicting realistic outcomes that are valuable to agricultural management strategies (Thorp et al., 2009). Since RZWQM2-P and DRAINMOD-P have been developed recently, there are no existing comparative studies that evaluate their performance in predicting the daily losses of dissolved reactive phosphorus (DRP) and total phosphorus (TP) from tile-drained fields. The side-by-side assessment not only illustrates the distinct advantages and disadvantages of each model but also fosters improvements in computational methods (Thorp et al., 2009), assisting practitioners in choosing the model best suited for their specific objectives in simulating P losses in tile-drained agricultural fields. Therefore, this study takes an essential step in thoroughly assessing the daily performance of both models in predicting P losses from subsurface-drained field, clearly highlighting their respective strengths and weaknesses.

3.2. Materials and Methods

3.2.1. Site description

Data collected from 2013 to 2017 at a field site in Paulding County, Ohio, (Figure 3.1) were utilized to evaluate the RZWQM2-P and DRAINMOD-P models regarding their capability to predict P losses from a subsurface-drained field. This field is a part of the Edge-of-Field network, which is operated by the USDA-ARS in Columbus, Ohio (Williams et al., 2016). The dominant soil types are Paulding clay and Roselms silty clay, both of which are known for being poorly drained and low saturated hydraulic conductivity. These soils are high in clay content and tend to swell under wet conditions and crack during dry periods (Askar et al., 2021). Prior research and field investigations conducted on this site have established that preferential flow is a significant factor at this field, with cracks ranging from 2 to 5 cm in width (Askar et al., 2020) commonly observed during the summer months (Figure 3.2). The field features a gentle slope of approximately 2%, a tile depth of about 60 cm (2 feet), and a tile spacing of nearly 1220 cm (40 feet). The field contains two separate measuring points, one dedicated to assessing surface runoff and the other to subsurface drainage. This leads to a disparity in the contributing areas, with the surface runoff being measured from an area of 8.7 hectares and the subsurface drainage from an area of 10.5 hectares. The experimental field followed a rotational planting scheme with corn (*Zea mays* L.), soybean [*Glycine max* (L.) Merr.], and wheat (*Triticum æstivum* L.). In the first year, oat (*Avena sativa* L.), serving as a cover crop, was planted following the harvest of the winter wheat. The producer also applied inorganic fertilizers periodically to maintain soil fertility. Periodic tilling was carried out using a chisel plough. Soil sample analysis revealed that the average soil test phosphorus (STP) concentration, using the Mehlich-3 P method, was 18.2 mg kg^{-1} for the upper 15 cm layer of soil at this site (Askar et al., 2021). Detailed information of the site management and cropping data can be found in Table 3.1.

3.2.2. Water quality sampling and analysis

Precipitation at the study site was recorded in ten-minute intervals using a tipping bucket rain gauge (Teledyne Isco, Lincoln, NE). For other necessary weather parameters required to initialize the models, data were acquired from the OARDC weather station located in Hoytville, Wood County, which is about 45 miles distant from the research site. Detailed methodologies for measuring hydrology, water quality, and conducting laboratory analyses have been comprehensively documented in earlier studies (Ford et al., 2017; King et al., 2015; Pease et al., 2018). In brief, stage data were recorded using the ISCO 4230 Bubbler Flow meters within a specified control volume. This involved the use of an H-flume for surface runoff and a compound weir for tile drainage, with the application of established stage-discharge relationships. Additionally, the ISCO 2150 Area-Velocity Sensor was placed in the tile drainage outlet pipe, ensuring accurate discharge measurements, especially under conditions when the sensors were submerged. For the quantification of surface runoff, the study adopted a flow-proportional sampling method. In this approach, every 1 mm increase in volumetric water depth from the 8.7

ha field area channeled through the H-flume resulted in the collection of a 200 mL sample. These samples were then aggregated, with ten aliquots forming a single composite sample. Conversely, tile drainage analysis employed a time-proportional sampling technique, gathering 100 mL samples every six hours. These samples were pooled into a single bottle to create a comprehensive two-day composite. This routine was complemented by additional sampling during specific events, identified based on the rate of change in the stage data.

Subsequent laboratory analysis involved the filtration of all collected samples using a 0.45 µm vacuum filter. The DRP load in these samples was determined using the colorimetric method, as outlined by Murphy and Riley (1962). For TP assessment, unfiltered samples were analyzed using the alkaline persulfate oxidation method. The procedures for the first two years followed those detailed by Koroleff (1983), while in subsequent years, the methodology described by Patton and Kryskalla (2003) was used.

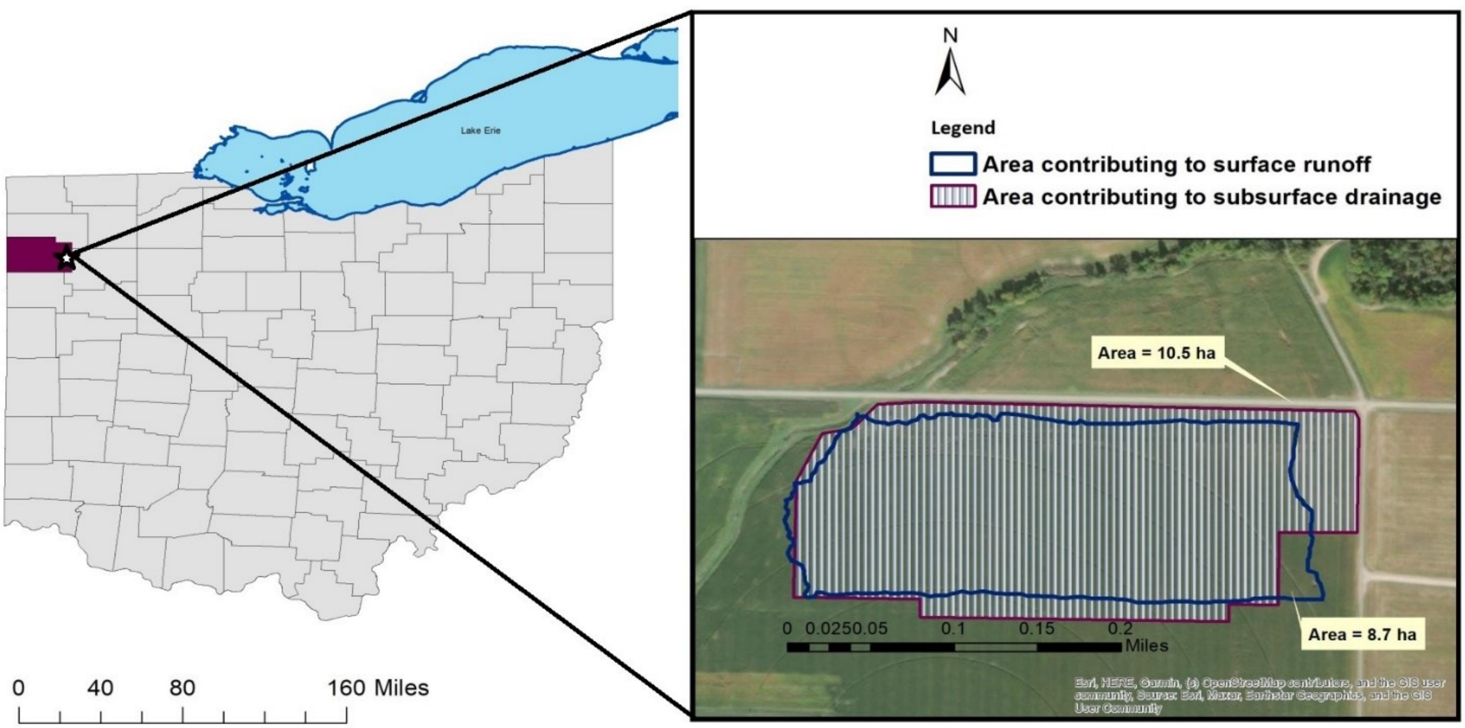

Figure 3. 1 Location and layout of the monitored tile drained field in Paulding County, Ohio.

Figure 3. 2 Significant presence of wide-open soil cracks between corn rows observed in July 2018 [Credit to Dr. Manal H. Askar (Askar, 2019)]

3.2.3. Model description

3.2.3.1. RZWQM2-P

The RZWQM2-P is a one-dimensional field scale model that simulates crop growth, hydrological cycles, and the fate and transport of nutrients and pesticides while considering various agronomic management practices and climate patterns (Ahuja et al., 2000). It integrates well-established equations such as the Green-Ampt equation (Green & Ampt, 1911) for water infiltration, the Richards' equation (Richards, 1931) for water redistribution, the Hooghoudt equation (Bouwer & Van Schilfgaarde, 1963) for drainage flux, and the Shuttle-Wallace equation (Shuttleworth & Wallace, 1985) for potential evapotranspiration. The model simulates preferential flow using Poiseuille's law. Crop growth simulation is facilitated through one of three options: the integrated DSSAT 4.0 model (Jones et al., 2003), a generic crop production model (Hanson, 2000), or the HERMES crop model (Malone et al., 2017). The original RZWQM2 model, typical of most field-scale models of its era, had limited capacity to simulate P dynamics. However, the RZWQM2-P iteration offers improved functionality in this regard. Traditional models mainly focused on surface runoff-bound P losses, neglecting the dynamics of P arising from fertilizer or manure applications, as well as the role of macropores and tile drainage (Sadhukhan et al., 2019a). The RZWQM2-P model addresses these limitations, providing a more comprehensive understanding of P dynamics in the environment. Recently developed phosphorus subroutines have been incorporated into the RZWQM2 model to enhance its functionality (Sadhukhan et al., 2019a).

3.2.3.2. DRAINMOD-P

DRAINMOD is a field scale model for simulating the hydrology of artificially drained fields with shallow water tables (Skaggs, 1978; Skaggs et al., 2012). The model employs two simple water balance equations to simulate hydrology both at the soil surface and for a section of the soil profile located midway between two adjacent drains (Skaggs, 1985; Skaggs, 1978; Skaggs et al., 2012). DRAINMOD accounts for surface water storage, defined by the user as depressional storage, and initiates surface runoff once this storage reaches its maximum capacity. The model calculates infiltration using the Green-Ampt equation (Green & Ampt, 1911). Two different equations are used for drainage flux calculation, depending on the field's ponding conditions: the Kirkham equation (Kirkham, 1957) is used when surface ponding exceeds the user-defined Kirkham's depth, otherwise, the steady-state Hooghoudt equation (Bouwer & Van Schilfgaarde, 1963) is used. The model simulates potential evapotranspiration using the Thornthwaite (1948) method. For crop yield simulation, DRAINMOD employs a simple yield reduction approach (relative yield) by assessing soil moisture dynamics and their impact on plant growth, focusing primarily on the effects of water stress (Singh & Helmers, 2008). Recently, DRAINMOD-P has been developed to simulate P dynamics and transport in agricultural settings. Other enhancements include macropore flow computation, which is based on Hagen-Poiseuille's law, and a soil erosion component. Preferential flow occurs when ponding depth is greater than Kirkham's depth, facilitating free movement to the drains (Askar et al., 2020). The new P component predicts P losses through runoff and tile drainage both in the dissolved and particulate forms (Askar et al., 2021). However, macropores are the only pathway through which particulate P (PP) can reach subsurface drains.

3.2.3.3. RZWQM2-P and DRAINMOD-P comparison

Although RZWQM2-P and DRAINMOD-P are both utilized for simulating hydrology and phosphorus dynamics at the field scale, they exhibit distinct approaches in their simulation methodologies for both hydrology and phosphorus dynamics. In terms of hydrology, the primary differences lie in aspects such as surface storage, soil water distribution, tile drainage flux, preferential flow, and ET computations (Singh et al., 2022). RZWQM2-P does not consider surface water storage, leading to runoff when precipitation exceeds soil infiltration rate. However, DRAINMOD-P accounts for surface water storage and runoff occurs only after reaching the maximum storage capacity. Furthermore, RZWQM2-P exclusively uses the Hooghoudt equation (Bouwer & Van Schilfgaarde, 1963) for drainage flux calculations, whereas DRAINMOD-P utilizes both the Kirkham (Kirkham, 1957) and Hooghoudt equations, adapting to field ponding conditions. For soil water distribution, a notable distinction is that RZWQM2-P applies the numerical solution of Richards (1931) equation, which DRAINMOD-P does not incorporate. Regarding preferential flow, both models use Hagen-Poiseuille's law; however, RZWQM2-P accounts for dead-end macropores (Li et al., 2023), whereas DRAINMOD-P focuses solely on macropores directly connected to subsurface drains, assuming that the effect of dead-end macropores can be represented by increasing effective soil layer hydraulic conductivity (Askar et al., 2020). In calculating potential evapotranspiration, RZWQM2-P employs the Shuttle-Wallace equation (Shuttleworth & Wallace, 1985), while DRAINMOD-P uses the temperature-based Thornthwaite (1948) equation.

Both models are designed to simulate P dynamics based on the framework of the soil P pools identified by Sharpley et al. (1984) and Jones et al. (1984). In DRAINMOD-P, the organic P pools are derived from the CENTURY model (Parton et al., 1993), while RZWQM2-P bases all five P pools on the EPIC model. A key feature in both models is the labile P pool, noted as the most dynamic and the sole source for plant P uptake. However, the models differ in their simulation of plant P uptake. In DRAINMOD-P, the approach for simulating plant P uptake is similar to the method used for nitrogen (N) uptake in DRAINMOD-NII (Youssef et al., 2005). The model calculates yield as a function of both relative yield and potential yield, the latter being defined by the user based on observed yields. However, in the current model version relative yield is considered to be 100% to set predicted yield equal to actual yields and eliminate uncertainty in P predictions arising from yield predictions. Plant P uptake in DRAINMOD-P is then estimated using predicted yield and nutrient availability along with other user-defined plant characteristics, such as root-to-shoot ratio, harvest index, and P content in each of the crop constituents (i.e., root, shoot, and grain). On the other hand, RZWQM2-P utilizes the DSSAT model (Jones et al., 2003) to perform more nuanced crop yield simulations. This model accounts for a range of factors, including weather variability and nutrient dynamics like N and P, which influence plant growth. For plant P uptake, RZWQM2-P integrates subroutines from the SWAT model Neitsch et al. (2011). These subroutines are centered around key user-defined parameters, including the biomass P fraction at various stages of plant development — emergence, 50% maturity, and full maturity. These parameters are flexible and can be adjusted during the model calibration process. Another notable distinction between the models lies in their computation of P dynamics within the soil matrix. DRAINMOD-P uses a one-dimensional advection-dispersion-reaction (ADR) equation, similar to that in DRAINMOD-NII, for simulating P dynamics through the soil profile (Askar et al., 2021). Conversely, RZWQM2-P adopts a linear groundwater reservoir-based approach, as suggested by Steenhuis et al. (1997). Additionally, a unique feature about DRAINMOD-P is that it enables sedimentation and release of soil-bound P in the tile drainage system based on the drainage intensity. Although the models exhibit these differences, they both simulate the movement of DRP to tile drains via two pathways: through the soil matrix and through macropores. In contrast, the transport of PP occurs exclusively through macropores in both models. A comprehensive comparison of the critical subroutines/processes used for simulating P dynamics in each model can be found in Table 3.2.

Table 3. 1 Cropping and management information for the field from 2012 to 2017.

Crop	Date	Management Practice	Notes
Wheat	14 Oct. 2012	Planting	
	14 Oct. 2012	N and P application	23.59 kg N ha^{-1} + 24.33 kg P ha^{-1}
	18 Feb 2013	N application	53.76 kg N ha^{-1}
	22 March 2013	N application	69.30 kg N ha^{-1}
	12 July 2013	Harvesting	83.6 bu $acre^{-1}$ (5,622.2 kg ha^{-1})
Oats (cover crop)	13 Aug. 2013	Planting	
Corn	9 May 2014	Planting	
	9 May 2014	N and P application	38.94 kg N ha^{-1} + 15.58 kg P ha^{-1}
	31 May 2014	N application	196.76 kg N ha^{-1}
	04 Oct. 2014	Harvesting	193 bu $acre^{-1}$ (12,114.2 kg ha^{-1})
Soybeans	14 Oct. 2014	Tillage	Chisel plough
	21 May 2015	Tillage	Chisel plough
	25 May 2015	Planting	
	06 Oct. 2015	Harvesting	49.5 bu $acre^{-1}$ (3,328.9 kg ha^{-1})
Corn	20 Oct. 2015	Tillage	Chisel plough
	19 Apr. 2016	Planting	
	19 Apr. 2016	N and P application	38.8 kg N ha^{-1} + 15.52 kg P ha^{-1}
	25 May 2016	N application	168.32 kg N ha^{-1}
	19 Oct. 2016	Harvesting	141 bu $acre^{-1}$ (8,850.2 kg ha^{-1})
Soybeans	25 Oct. 2016	Tillage	Chisel plough
	05 June 2017	Planting	
	25 Sep. 2017	Harvesting	43 bu $acre^{-1}$ (2,891.8 kg ha^{-1})
Wheat	25 Sep. 2017	Tillage	Chisel plough
	25 Sep. 2017	Planting	
	25 Sep. 2017	N and P application	33.35 kg N ha^{-1} + 17.46 kg P ha^{-1}

Table 3. 2 Comprehensive overview of essential subroutines and processes in RZWQM2-P and DRAINMOD-P for simulating phosphorus dynamics.

Processes	RZWQM2-P modeling method	DRAINMOD-P modeling method	Comments
Infiltration and water redistribution	Green-Ampt equation for infiltration (Green & Ampt, 1911) Richards' equation for water distribution (Richards, 1931)	Green-Ampt equation for infiltration (Green & Ampt, 1911) Simplified approach for soil water distribution	DRAINMOD-P distinguishes two key zones: the 'wet zone,' starting at the water table and possibly reaching the surface, and the 'dry zone,' where ET surpasses the available water supply. The model dynamically calculates water distribution between these zones at each time step of simulation. It utilizes the soil water characteristic curve to accurately determine the moisture content and movement within these zones (Skaggs et al., 2012). Whereas, RZWQM2-P uses the iterative finite difference method to solve the Richards equation for water distribution (Ma et al., 2012).
Tile drainage	Steady state Hooghoudt equation (Bouwer & Van Schilfgaarde, 1963)	Kirkham equation (Kirkham, 1957) Steady state Hooghoudt equation (Bouwer & Van Schilfgaarde, 1963)	Parameters such as drain depth, drain spacing, soil texture, radius of drains, hydraulic conductivity, and bulk density play a crucial role in both models. In DRAINMOD-P, surface storage is also considered; therefore, parameters such as the drainage coefficient, maximum surface storage, and Kirkham's depth for flow to drains play an important role. In RZWQM2-P, bubbling pressure is an important parameter, in addition to other soil parameters, which affects the subsurface drainage.
Preferential flow	Hagen-Poiseuille law (Sutera & Skalak, 1993)	Hagen-Poiseuille law (Sutera & Skalak, 1993)	In RZWQM2-P, the model assumes cylindrical macropores in the topsoil layers and planar cracks in the lower soil horizons. Additionally, it is presumed that continuous macropores extend vertically through the soils, with a portion of them being blocked within the soil matrix, forming dead-end macropores. Parameters such as macroporosity, width, radius, length, and depth of cracks play a crucial role in RZWQM2-P. In contrast, DRAINMOD-P does not account for dead-end macropores. A notable feature of this model is that it allows for changes in crack width over time, influenced by user defined dryness and wetness coefficients during wet and dry periods in the simulations. Unlike RZWQM2-P, which considers both cylindrical pores and planar cracks, DRAINMOD-P simulates macropore flow exclusively through either cylindrical pores or planar cracks.

Processes	RZWM2-P modeling method	DRAINMOD-P modeling method	Comments
Soil Erosion	Integrated GLEAMS model (Leonard et al., 1987)	RUSLE equation (Renard et al., 1991)	Soil erosion is a significant factor in the transport of particulate phosphorus (PP). RZWQM2-P uses the integrated GLEAMS model for predicting soil erosion. Whereas, DRAINMOD has been modified by Askar et al. (2021) to include the RUSLE equation.
Plant growth	Integrated DSSAT Crop model (Jones et al., 2003)	Empirical yield model (relative yield)	DSSAT is a more versatile model that considers the effects of weather parameters, such as solar radiation and air temperature, as well as nutrient impacts, including nitrogen (N) and phosphorus (P) stresses. RZWQM2-P with integrated DSSAT model can simulate 28 different crops.
Plant P uptake	Subroutines have been adopted from the approaches used by Neitsch et al. (2011) in the SWAT model.	Subroutines have been adopted from the approaches used by Youssef et al. (2005) in the DRAINMOD-NII model.	In both models, P uptake is dependent on the availability of P in the labile P pool. Consequently, the critical factors influencing P uptake, aside from the labile P pool and crop yield, include user-defined parameters such as the biomass P fraction at various stages of plant growth in RZWQM2-P, and the P content of different plant parts, root to shoot ratio, and harvest index in the DRAINMOD-P model.
P pools	EPIC model (Jones et al. 1984)	EPIC model (Jones et al. 1984) CENTURY model (Parton et al., 1993)	RZWQM2-P is structured around five soil phosphorus (P) pools: labile P (Lab^{P}), active inorganic P (Act^{IP}), stable inorganic P ($Stab^{IP}$), fresh organic P ($Fres^{OP}$), and stable organic P ($Stab^{OP}$). These pools are all adopted from the EPIC model's P pools. DRAINMOD-P has the same three inorganic pools (i.e., Lab, Act, and Stab), while the organic P pools are based on the CENTURY model.
Stable and active inorganic P ratio	User defined ratio for each soil layer (Pan et al., 2023b)	EPIC model (Jones et al. 1984)	In DRAINMOD-P, there is a fixed ratio of four ($Stab^{IP} = 4.0 \times Act^{IP}$) based on the recommendations of Sharpley et al. (1984). However, RZWQM2-P has recently been modified, allowing users to define the ratio for each soil layer.
DRP loss (surface runoff)	Approaches suggested by Neitsch et al. (2011)	Function of labile P concentration (Askar et al., 2021)	In both models, the losses of DRP through surface runoff are highly sensitive to the availability of the Lab^{P} pool that interacts with overland flow. DRAINMOD-P assumes that overland flow interacts with the top 2.5 cm while in RZWQM2-P surface runoff interacts with the top 1.0 cm. Apart from the Lab^{P} pool, RZWQM2-P DRP losses also depend on two fertilizer-specific pools and two water-extractable manure P pools (explained in detail in the fertilizer and manure P dynamics sections).

Processes	RZWQM2-P modeling method	DRAINMOD-P modeling method	Comments
PP loss (surface runoff)	Approaches suggested by McElroy (1976)	Function of eroded soil particles and enrichment ratio (Askar et al., 2021)	In both models, the transport of PP through runoff is significantly influenced by eroded soil particles and enrichment ratios. A notable distinction between the two models is their assumption of PP origin depth: RZWQM2-P assumes PP originates from the top 1 cm of the soil profile, while DRAINMOD-P considers PP to originate from a depth of 2.5 cm.
DRP loss (tile drainage)	Linear groundwater reservoir-based approach by Steenhuis et al. (1997); Steenhuis et al. (1994), and the approaches suggested by Francesconi et al. (2016)	One-dimensional advection-dispersion-reaction (ADR) equation based on DRAINMOD-NII (Youssef et al., 2005)	In both models, the soil matrix and macropores act as conduits for DRP transport. In DRAINMOD-P, the transport of P through the soil matrix is calculated using the ADR equation, while its movement through macropores is determined by a separate equation that depends on the concentration of labile P in top layer and macropore flow. In contrast, RZWQM2-P calculates DRP leaching through the soil matrix based on the approach proposed by Francesconi et al. (2016), and for macropore flow, it employs the methodology developed by Steenhuis et al. (1994).
PP loss (tile drainage)	Linear groundwater reservoir-based approach by Steenhuis et al. (1997) and Colloidal particle transport approach (Jarvis et al., 1999; Larsson et al., 2007)	Sediment accumulation-based approach (Askar et al., 2021)	In both models, PP transport to drains occurs exclusively through macropores. DRAINMOD-P has a dedicated pool for PP entering through macropores that represents sediment-bound P accumulation and release from tile drains. It calculates daily PP loss based on the amount accumulated in this pool and drainage intensity. This approach enables DRAINMOD-P to simulate PP loss even on days without macropore flow, as long as PP remains accumulated in tile drains. In RZWQM2-P, PP transport through tiles follows the colloidal particle transport approach (Jarvis et al., 1999; Larsson et al., 2007). Initially, PP contributes to the groundwater reservoir, and then, following daily mass balance calculations, it is lost through tile drainage.
Fertilizer P dynamics	Two fertilizer-specific P pools, based on the approaches suggested by Vadas (2014)	Soluble fertilizer dissolution approach (Askar et al., 2021)	In RZWQM2-P, upon fertilizer application, 75% of the amount is allocated to the available fertilizer P pool ($ferP^{av}$) and 25% to the residual fertilizer P pool ($ferP^{res}$). During the first rainfall after application, all of $ferP^{av}$ is released. In the second rainfall, 40% of $ferP^{res}$ is released, and in the third and subsequent rainfalls, 7.5% of the phosphorus from $ferP^{res}$ is released until it is completely depleted. In DRAINMOD-P, fertilizer is added to the labile pool after dissolution using a dissolution rate determined by the user.

Processes	RZWQM2-P modeling method	DRAINMOD-P modeling method	Comments
Manure P dynamics	Four manure-specific P pools, based on the approaches suggested by Vadas (2014)	Organic and inorganic partitioning approach (Askar et al., 2021)	In the RZWQM2-P model, upon manure application, the manure P is divided into four distinct pools: the manure water-extractable inorganic P pool ($manP^{H_2O}_{inorg}$), the manure water-extractable organic P pool ($manP^{H_2O}_{org}$), the manure stable inorganic P pool ($manP^{stbl}_{inorg}$), and the manure stable organic P pool ($manP^{stbl}_{org}$). This division is based on the total P content, the type of application (surface or subsurface), and the manure type (liquid or solid). The water-extractable pools represent P that can be released by rain, while the stable pools represent P that is released slowly as the manure decomposes. The model has a comprehensive database comprising fourteen distinct types of manure, each with four different application methods. For further details on how the model divides and defines the size of each pool, please refer to Sadhukhan and Qi (2018). In DRAINMOD-P, rather than dividing manure into four pools, it simply categorizes the manure into inorganic and organic portions based on user-defined input. The inorganic portion, entered by the user, is treated as a fertilizer application. This represents the immediate availability of inorganic phosphorus for plant uptake or potential leaching. Meanwhile, the organic portion is processed as an organic animal waste application, undergoing decomposition processes before becoming available for plant uptake (Askar et al., 2021).
Tillage effect	P pools integration and redistribution based on tillage parameters (Pan et al., 2023a)	Based on the approaches used in DRAINMOD-NII (Youssef et al., 2005)	In both models, tillage incorporates surface-available P into soil P pools, influenced by the tillage intensity and depth of tillage operation. A notable feature of the RZWQM2-P model is that the user can define the P mixing efficiency as an input, rather than having it calculated by simply subtracting 1.0 from the tillage intensity (Pan et al., 2023a).

Act^{IP}, active inorganic P; $ferP^{av}$, available fertilizer P pool; $ferP^{res}$, residual fertilizer P pool; $Fres^{OP}$, fresh organic P; Lab^{P}, labile P; $manP^{H_2O}_{inorg}$, manure water-extractable inorganic P pool; $manP^{H_2O}_{org}$, manure water-extractable organic P pool; $manP^{stbl}_{inorg}$, manure stable inorganic P pool; $manP^{stbl}_{org}$, manure stable organic P pool; $Stab^{IP}$, stable inorganic P; $Stab^{OP}$, stable organic P

3.2.4. Models' parameterization and initialization

In this study, we utilized the calibrated DRAINMOD-P, initially calibrated by (Askar, 2019) to evaluate the efficiency of the P module. Since that time, some of the observed data has been modified or changed during the quality check process. To incorporate these changes, we recalibrated DRAINMOD-P, making slight adjustments to some parameters to enhance hydrology predictions. These minor modifications were made to the vertical and horizontal seepage parameters, while all other parameters remained unchanged. To evaluate DRAINMOD-P, initial soil series data were sourced from the literature or the SSURGO database, as most parameters were not measured in the field.

The RZWQM2-P model requires several sets of input parameters, including soil data, weather data, management practice information, and soil test phosphorus (STP) values, to simulate hydrological and phosphorus dynamics. For this study, we primarily adopted the initial soil data values from Askar's (2019) previous study, which were utilized to initialize DRAINMOD-P. Similarly, RZWQM2-P was initially set up using the same hydraulic conductivity values as DRAINMOD-P, but these were later adjusted during the calibration process. However, the number of soil layers were different from those represented in Askar (2019) as DRAINMOD-P allows the users to have a maximum of five-layers for the soil profile. In this study, RZWQM2-P utilized seven soil layers by subdividing the soil layers with similar properties (Table 3.3). Similar approaches have been used in previous studies comparing DRAINMOD and RZWQM2. For example, Thorp et al. (2009) implemented ten layers simulation in RZWQM2, and Singh et al. (2022) used seven layers, whereas DRAINMOD was limited to five layers. In RZWQM2-P, crop planting and harvesting dates, along with other parameters like fertilizer rate and tillage operations, were set according to actual field practices. For the depth and intensity of tillage operations, we utilized the exact values used in the DRAINMOD-P calibration (depth = 20 cm for chisel plow and intensity of tillage = 0.60). For weather data, onsite measured hourly precipitation was used in both models. In a previous study, Askar (2019) used daily minimum and maximum temperature values from the OARDC weather station. We utilized the same data in the RZWQM2-P model. Additionally, RZWQM2-P required daily values for solar radiation, relative humidity, and wind speed, which were obtained from the same weather station for the duration of this study.

Both models require input data to initialize the phosphorus module. The initial value of Mehlich-3 STP was measured in the field as 18.2 mg kg^{-1} for the top 15 cm. In their study, Askar (2019) calibrated the values for the deeper layers in the DRAINMOD-P model. We adopted similar Mehlich-3 P values in the RZWQM2-P model to initialize the labile P pool. Furthermore, the RZWQM2-P was initiated with a residue amount of 5000 kg ha^{-1} which was also the value used in DRAINMOD-P *(*Askar*,* 2019*)*. In the RZWQM2-P model, user can modulate the stable and active inorganic phosphorus ratio for each soil layer. However, DRAINMOD-P, following the guidelines set by Sharpley et al. (1984), maintains a fixed ratio of four. To ensure consistency between the two models, we also applied this fixed ratio of four to all layers in the RZWQM2-P model.

Table 3. 3 Initial soil properties and soil test phosphorus (STP) levels used for initializing both DRAINMOD-P and RZWQM2-P.

Soil Layer	Depth	ρ	Particle size distribution			Θ_s	Θ_r*	Mehlich-3 STP
			Sand	Silt	clay			
	cm	g cm^{-3}	------------------%------------------			-----cm^3 cm^{-3}-----		mg kg^{-1}
1	0-1	1.45	0.17	0.38	0.45	0.45	0.09	42.6
2	1-15	1.45	0.17	0.38	0.45	0.45	0.09	18.2
3	15-23	1.48	0.16	0.37	0.47	0.44	0.09	13.2
4	23-76	1.48	0.16	0.37	0.47	0.44	0.09	7.1
5	76-122	1.50	0.16	0.37	0.47	0.42	0.09	1.0
6	122-170	1.50	0.20	0.35	0.45	0.39	0.09	0.01
7	170-200	1.50	0.20	0.35	0.45	0.39	0.09	0.01

ρ, bulk density; Sand, soil sand content; Silt, soil silt content; Clay, soil clay content; ϴs, saturated water content; ϴr, residual water content; * data source-RZWMQ2 parameterization guide

3.2.5. Models' calibration

Both models were subjected to a five-year simulation period (2013 to 2017). Within this timeframe, the initial three years (2013 to 2015) served in calibrating the models, while the subsequent two-year period (2016 to 2017) served in validating the calibrated model. In this study, as previously noted, only the horizontal (lateral) and vertical (deep) seepage parameters were modified from the calibrated DRAINMOD-P scenario used by Askar (2019) for evaluating the P module. Therefore, we activated horizontal seepage, which was not included in the original setup. Adjustments were also made to deep seepage parameters, such as the piezometric head of the aquifer and the conductivity of the restricting layer, to enhance deep seepage. Table 3.4 presents the adjusted hydrology parameters employed in the current study. Askar (2019) provides a detailed explanation of the procedure followed for calibrating both the hydrological and phosphorus parameters, including their specific values.

During the calibration phase, RZWQM2-P was initially calibrated for hydrology, specifically focusing on tile drainage and runoff, as P losses are inherently tied to these hydrological processes. The calibration process for tile drainage in RZWQM2-P involved careful adjustment of several key parameters, including saturated hydraulic conductivity, lateral hydraulic conductivity, surface soil resistance, bubbling pressure, and the pore size distribution index. These adjustments were made iteratively, using a trial-and-error method, until the model outputs aligned closely with the observed data. For DRAINMOD-P, a high hydraulic conductivity value (3 cm hr^{-1}) was set for the first soil layer. Initially, RZWQM2-P was configured with similar values for the top layers but was later modified to better match observed data. The rationale behind DRAINMOD-P's high conductivity values is to simulate the fraction of dead-end macropores by enhancing the soil matrix's conductivity. In contrast, RZWQM2-P distinctly represents dead-end macropores within its macropore component; therefore, it does not require such high values of hydraulic conductivity for poorly drained soil. The field under study is characterized by a significant presence of macropores, as depicted in Figure 3.2, and an estimation of the macropore width was provided by Askar et al. (2020). We adopted these width measurements in the RZWQM2-P model to accurately represent the macropores. Additionally, the macropore component in RZWQM2-P necessitates the input of various parameters, including the fraction of dead-end macropores, macropore radius, and the depth and length of cracks. We calibrated these parameters to ensure that the macropore flow in RZWQM2-P aligns with the flow previously simulated by DRAINMOD-P in an earlier assessment. Additionally, during the calibration of the bubbling pressure for the bottom layers, it was intentionally set close to zero (-8 cm for the last layer compared to -21 cm for the first layer), as shown in Table 3.5. This adjustment aimed to enhance the layers' conductivity, thereby facilitating deep seepage flow through the restricting layer, a critical factor for accurately calibrating tile drainage flow in this field. The albedo of both soil and crops was a key factor in the accuracy of evapotranspiration (ET) predictions. Furthermore, parameters such as surface soil resistance and minimum soil resistance played a critical role in fine-tuning these ET predictions.

After aligning hydrology predictions, the calibration of dissolved reactive phosphorus (DRP) and particulate phosphorus (PP) parameters was carried out. Earlier, during the hydrology calibration phase, DSSAT parameters were adjusted to align with observed crop yields. Crop yields significantly influence plant phosphorus uptake and play a vital role in calibrating DRP losses in both runoff and subsurface drainage. The distribution of plant P uptake and the biomass P fraction at all growth stages was calibrated to match observed DRP levels. Additionally, the phosphorus extraction coefficient was further refined to align with observed DRP runoff values. The calibration of soil erosion parameters was crucial for accurately estimating PP losses in runoff. The values for field slope and length, sourced from the DRAINMOD-P study and based on observed data, were not recalibrated. Specifically, Manning’s n (NFACT) was adjusted to more accurately reflect PP losses. Additionally, the initial levels of DRP and PP in the groundwater reservoir had a critical impact on the losses of DRP and PP through subsurface drainage. Parameters such as the replenishment rate coefficient, detachability coefficient, and filtration coefficient were further refined to match observed P loadings in subsurface drainage. All the parameters calibrated for RZWQM2-P are presented in Tables 3.5 to 3.8.

Table 3. 4 Recalibrated hydrologic parameters in the DRAINMOD-P model.

	Parameters	Calibrated values
Deep seepage	Piezometric head of aquifer (cm)	100
	Thickness of restrictive layer (cm)	100
	Vertical conductivity of restricting layer (cm hr^{-1})	0.00042
Lateral Seepage	Thickness of transmissive layer (cm)	50
	Hydraulic head of receiving waters (cm)	150
	Distance to receiving waters (cm)	1500
	Horizontal hydraulic conductivity of transmissive zone (cm hr^{-1})	0.1

Table 3. 5 Calibrated soil properties in the RZWQM2-P model.

Soil Layer	Depth	K_{sat}	Lk_{sat}	P_b	Pc_b	λ
	cm	-----------cm h^{-1}-----------		-------------cm--------------		-
1	0-1	0.77	3.7	-21.7	-44.2	0.130
2	1-15	0.46	3.7	-21.2	-44.2	0.125
3	15-23	0.30	3.0	-10.7	-6.7	0.125
4	23-76	0.29	4.6	-10.7	-6.7	0.125
5	76-122	0.20	3.5	-7.5	-7.5	0.125
6	122-170	0.01	3.4	-8.0	-7.9	0.125
7	170-200	0.01	3.6	-8.0	-7.9	0.125

K_{sat}, saturated conductivity; Lk_{sat}, lateral saturated conductivity; P_b, soil bubbling pressure; Pc_b, conductivity curve bubbling pressure; λ, pore size distribution index

Table 3. 6 Overview of calibrated hydrological and macropore parameters with their calibrated values and default values in the RZWQM2-P model.

	Parameters	Units	Calibrated values	Default values
Hydraulic parameters	Lateral hydraulic gradient	(dh dl^{-1})	0.0000008	0.0001
	Crust conductivity	(cm hr^{-1})	0.1	0.4
	Water table leakage rate	(cm hr^{-1})	0	-
ET parameters	Albedo of crop at maturity	(unitless)	0.2	0.43
	Albedo of fresh residue		0.04	0.4
	Albedo of wet soil		0.03	0.2
	Albedo of dry soil		0.03	0.3
	Surface soil resistance	(s m^{-1})	150	37
Macropore parameters	Total microporosity	(cm^3 cm^{-3})	0.07	0.01
	Fraction dead-end macropores	(unitless)	0.8	0.5
	Radius of cylindrical pores	(cm)	0.5	0.1
	Width of cracks		0.5	0.05
	Length of cracks		10	10
	Depth of cracks		10	10

Table 3. 7 Overview of calibrated phosphorus parameters with their calibrated values and default values in the RZWQM2-P model

	Input Parameters	Units	Calibrated values	Default values
Soil P parameters	Initial DRP in groundwater (GW) reservoir	kg ha^{-1}	7	25
	Initial PP in groundwater (GW) reservoir		25	25
	Replenishment rate coefficient	g m^{-2} d^{-1}	2	1
	Detachability coefficient	g J^{-1} mm^{-1}	2	1
	Filtration coefficient	m^{-1}	0.0001	1
	P Extraction coefficient	unitless	0.66	1
Corn P parameters	P uptake distribution parameter	unitless	15	10
	Biomass P fraction at emergence		0.024	0.024
	Biomass P fraction at 50% maturity		0.016	0.016
	Biomass P fraction at maturity		0.001	0.0008
Soybean P parameters	P uptake distribution parameter	unitless	15	10
	Biomass P fraction at emergence		0.024	0.024
	Biomass P fraction at 50% maturity		0.006	0.016
	Biomass P fraction at maturity		0.0008	0.0008
Wheat P parameters	P uptake distribution parameter	unitless	15	10
	Biomass P fraction at emergence		0.024	0.024
	Biomass P fraction at 50% maturity		0.016	0.016
	Biomass P fraction at maturity		0.0009	0.0008

Table 3. 8 Calibrated DSSAT parameters for simulating crop yields in the RZWQM2-P model.

Component	Parameters	Calibrated values	Default values
Corn[a]			
P1	Thermal time from seedling emergence to the end of the juvenile phase (DD8)	230	215
P2	Delay in development for each hour that day length is above 12.5 hours (0-1)	0.2	0.4
P5	Thermal time from silking to physiological maturity (DD8)	1090	795
G2	Maximum possible number of kernels per plant	800	890
G3	Kernel filling rate during the linear grain filling stage and under optimal conditions (mg day^{-1})	13	8
SR	Minimum leaf stomatal resistance (s m^{-1})	130	200
PHINT	Phylochron interval between successive leaf tip appearances (DD)	62	48
Soybean[b]			
SD-PM	Time between first seed and physiological maturity (PD)	43.4	32.4
LFMAX	Maximum leaf photosynthesis rate at 30℃, 350 vpm CO2, and high light (mg CO2 m^{-2} s^{-1})	1.02	1.03
SLAVAR	Specific leaf area of cultivar under standard growth conditions (cm^2 g^{-1})	395	375
WTPSD	Maximum weight per seed (g)	0.2	0.19
SFDUR	Seed filling duration for pod cohort at standard growth conditions (PD)	20	23
SR	Minimum leaf stomatal resistance (s m^{-1})	180	200
PODUR	Time required for cultivar to reach final pod load under optimal conditions (PD)	15	15
Wheat[c]*			
P1V	Days at optimum vernalizing temperature required to complete vernalization	60	40
G1	Kernel number per unit canopy weight at anthesis (# g^{-1})	40	25
G2	Standard kernel size under optimum conditions (mg)	50	30
G3	Standard non-stressed dry weight (total including grain) of a single tiller at maturity (g)	1.8	1.5
PHINT	Interval between successive leaf tip appearances (DD)	100	80
SR	Minimum leaf stomatal resistance (s m^{-1})	125	200
PECM	Emergence phase duration (°C d cm cm^{-1})	5	10

DD8 = degree days above a base temperature of 8°C; DD = degree days; PD = photothermal days

[a]Cultivar IB1 068 Dekalb 521; [b] Cultivar 990002 M Group 2; [c] Cultivar 990003 Winter-US; *In the actual field study, oats were planted as a cover crop on August 13, 2013. However, since the DSSAT model does not support oats, we substituted them with the winter wheat cultivar to simulate phosphorus uptake. The simulated oats plantation was terminated on November 13, 2013, following the termination date reported in Askar's (2019) scenario.

3.2.6. Evaluation criteria

In assessing our model's effectiveness, we employed four metrics: Nash-Sutcliffe efficiency (NSE), Coefficient of Determination (R^2), Index of Agreement (IOA), and percent bias (PBIAS), following the guidelines set by Moriasi et al. (2007); Moriasi et al. (2015). Model components were individually examined and classified into one of four categories: very good, good, satisfactory, or unsatisfactory. To evaluate the goodness-of-fit between predicted and measured drainage discharge, the following criteria on monthly time step basis were used ('very good' for NSE > 0.75, $R^2 > 0.75$, IOA > 0.90, and |PBIAS| < ±10%; 'good' for 0.65 < NSE ≤ 0.75, 0.70 < $R^2 \leq 0.75$, 0.85 < IOA ≤ 0.90, and ±10% < |PBIAS| < ±15%; and 'satisfactory' for 0.50 < NSE ≤ 0.65, 0.60 < R^2 < 0.70, 0.75 < IOA ≤ 0.85, and ±15% < |PBIAS| < ±25%) (Moriasi et al., 2007). In the context of DRP and TP simulations, a 'very good' rating was assigned for NSE > 0.65, R^2 > 0.80, IOA > 0.90, and |PBIAS| < ±15%; 'good' for 0.50 < NSE ≤ 0.65, 0.60 ≤ R^2 ≤ 0.80, 0.85 < IOA ≤ 0.90, and ±15% < |PBIAS| < ±20%; and 'satisfactory' for 0.35 < NSE ≤ 0.50, R^2 > 0.40, 0.75 < IOA ≤ 0.85, and ±20% < |PBIAS| < ±30% (Moriasi et al., 2007; Moriasi et al., 2015).

NSE (Nash & Sutcliffe, 1970) gauges the accuracy of a model by comparing how closely the observed and simulated data points align with a 1:1 line, as further explained by Moriasi et al. (2007). On the other hand, R^2 quantifies the level of correlation between measured and simulated data. Notably, both NSE and R^2 are influenced by extreme values, or outliers (Krause et al., 2005). However, R^2 can still be useful in determining correlations in scenarios where the model underestimates or overestimates (Askar, 2019). IOA (Willmott, 1981) provides a standardized metric for assessing the extent of prediction error in a model. PBIAS (Gupta et al., 1999) measures the average tendency of simulated values to be larger or smaller than observed data. Positive values indicate a model underestimation bias, while negative values indicate a model overestimation bias. Additionally, beyond statistical methods, a graphical approach was used, comparing observed and simulated values using daily time series and scatter plots. Such a technique proves beneficial in assessing the model's performance, identifying any biases, and evaluating the magnitude of peak flows in the simulated values (ASCE, 1993).

3.3. Results and discussion

3.3.1. Hydrology

Different components of the hydrologic cycle predicted by the models were investigated. Precipitation levels in the field fluctuated significantly, ranging from 81.6 cm in 2014 to 116.6 cm in 2017. On average, the field received 97.2 cm of annual precipitation, surpassing the 30-year average of 94 cm recorded by NOAA for the years 1990-2020 at this location (Figure 3.3). Notably, the years 2015 and 2017 experienced precipitation levels that exceeded NOAA's average by more than 12 cm and 22 cm, respectively.

The annual water budget, as simulated by both models, and model performance evaluation parameters, are detailed in Table 3.9. During the five-year period of model calibration and validation from 2013 to 2017, the RZWQM2-P model in general satisfactorily simulated subsurface drainage discharge on both a daily and monthly basis. The model achieved a daily NSE of 0.56, R^2 of 0.61, an IOA of 0.88, and a PBIAS of 6%. Monthly, it exhibited a similar performance, with an NSE of 0.55, R^2 of 0.63, IOA of 0.88, and PBIAS of 6%. However, during the validation period, the model overestimated tile drainage flow, as indicated by an unsatisfactory PBIAS of -32%. Despite satisfactory performance in both calibration and validation phases for monthly subsurface drainage simulations, as shown in Table 3.9 and Figure 3.4, the model's daily performance was unsatisfactory during the calibration process, with an R^2 of 0.56, but a high NSE of 0.52 and an IOA of 0.85. The DRAINMOD-P model also demonstrated satisfactory to good performance in simulating monthly subsurface drainage discharge over the same period (2013-2017), with NSE, R^2, IOA, and PBIAS values of 0.55, 0.66, 0.89, and 9%, respectively. However, its daily performance did not meet satisfactory criteria, with a low R^2 of 0.56 but high NSE of 0.50 and IOA of 0.85. Like RZWQM2-P, DRAINMOD-P performed well during the calibration period for monthly drainage discharge, achieving an NSE of 0.56, R^2 of 0.66, IOA of 0.89, and a PBIAS of 22%. However, its performance during the validation period was unsatisfactory, with low NSE of 0.40, yet a high R^2 of 0.81, an IOA of 0.90, and a PBIAS of -16%. Upon evaluating the cumulative values over the five-year period, the simulations demonstrate that both the RZWQM2-P and DRAINMOD-P models predicted tile drainage very good. The observed cumulative tile drainage was 75.8 cm, while the predictions by RZWQM2-P and DRAINMOD-P were 71 cm and

68.9 cm, respectively. Both models achieved NSE values of 0.85, illustrating a close correspondence with the observed data, as depicted in Figure 3.5B.

The primary differences between the two models lie in their simulations of runoff and seepage. In terms of runoff, RZWQM2-P's five-year annual average was 10.9 cm, whereas DRAINMOD-P predicted a significantly higher value of 18.3 cm, exceeding the observed annual average of 6.5 cm. Although both models predicted higher runoff values, RZWQM2-P's estimates were closer to the observed data, as it accounted for additional water in deep seepage. RZWQM2-P estimated the average deep seepage at 11.3 cm, compared to DRAINMOD-P's average of 5.3 cm. Moreover, lateral seepage accounted for an average of 3.1 cm of water over a five-year period for DRAINMOD-P, as opposed to 2.8 cm for RZWQM2-P. During the calibration of the DRAINMOD-P model, significant emphasis was placed on accounting for additional water through seepage to make the runoff predictions closer to the observed data, similar to the approach taken for RZWQM2-P predictions. However, further increasing the seepage values resulted in the deterioration of our NSE values for drainage. Therefore, we gradually reduced the runoff until the drainage predictions remained close to the observed data. However, our findings are in line with previous comparative studies of DRAINMOD and RZWQM2, including those by Singh et al. (2022), Thorp et al. (2009), and Youssef et al. (2018). These studies consistently reported that RZWQM2 predicted higher seepage values and lower average runoff compared to DRAINMOD. For example, Singh et al. (2022) reported that RZWQM2 predicted an average seepage and runoff of approximately 14.2 cm and 9.1 cm, respectively, as opposed to DRAINMOD's 8.1 cm and 13.7 cm, with an average precipitation of 95.7 cm in central Illinois. The differences between the models may arise from their distinct methodologies, such as the surface storage component in DRAINMOD and the Richards equation in the RZWQM2-P model, which affect soil matrix flux simulations and soil moisture. These factors influence infiltration rates. Moreover, with the recent incorporation of a macropore component in DRAINMOD-P, both models now differ in their treatment of dead-end macropores, which could also affect the infiltration rates in the soil matrix. The RZWQM2-P model effectively predicted annual runoff for four years, except for 2017. In that year, while the model generally accounted for increased water through seepage, it overestimated runoff by more than double. DRAINMOD-P, on the other hand, overestimated runoff by threefold in 2017. Notably, 2017 was the wettest year in the simulation, yet it recorded only 12.7 cm of water through subsurface drainage and 12.5 cm through runoff, leading to a substantial water budget imbalance of approximately 30 cm. Askar et al. (2021) suggested that this discrepancy might arise from inconsistencies in the observed runoff data or inaccuracies in delineating the area contributing to surface runoff, as there are challenges associated with routing surface runoff from this area to a specific outlet.

Regarding ET, a key component of the water budget, the RZWQM2-P model simulated a five-year annual average of 56.4 cm, while DRAINMOD-P estimated it to be around 56.8 cm. Both values represent approximately 58% of the average annual precipitation, which is 97.2 cm (Table 3.9). These figures fall within the range of earlier modeling studies, such as those conducted by Youssef et al. (2018), which studied seven locations across Ohio, documented ET values ranging from 48.4 to 59.3 cm.

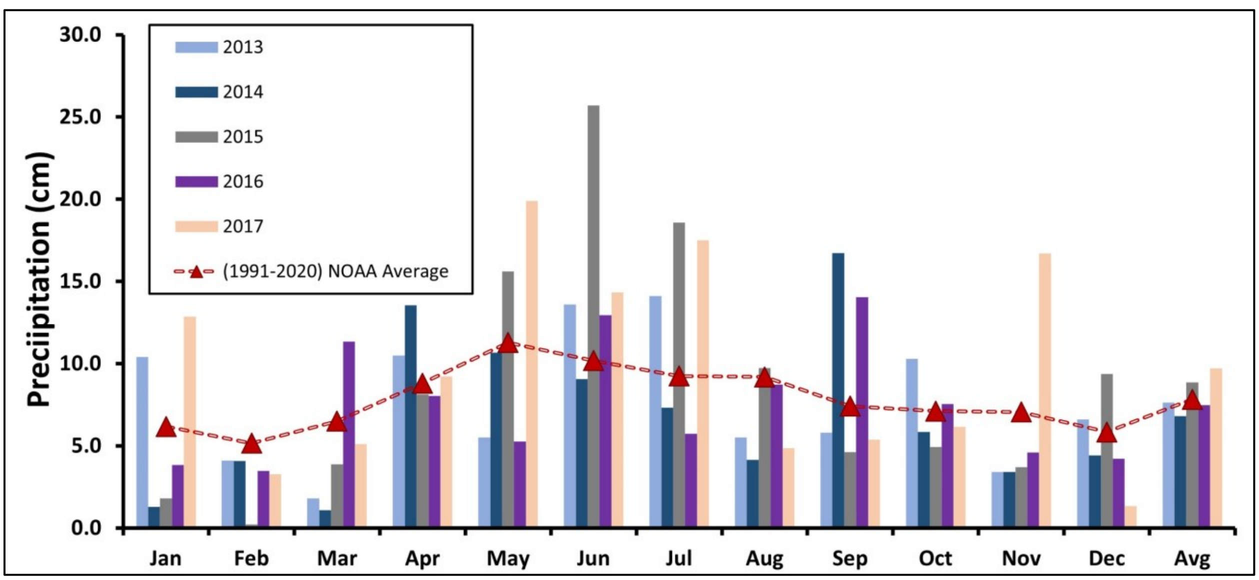

Figure 3. 3 Monthly precipitation and 30-year (1990-2020) NOAA averages for the 5-year simulation period for the test field site in Northwestern Ohio.

Table 3. 9 Annual water budget balance and model performance metrics for daily and monthly tile flow during the simulation period.

Period	Year	-------Observed------			-------------------RZWQM2-P------------------					--------------------DRAINMOD-P-----------------				
		P (cm)	TD (cm)	RO (cm)	ET (cm)	LS (cm)	DS (cm)	TD (cm)	RO (cm)	ET (cm)	LS (cm)	DS (cm)	TD (cm)	RO (cm)
Calibration period	2013	91.5	17.2	3.3	52.5	3.2	13.3	14	8	52.8	3.7	5.6	13.2	16.2
	2014	81.6	13.9	1.8	63	2.2	5.7	7.6	1.9	55.9	2.8	5.1	9.5	7.1
	2015	106.3	19.3	13	51.6	2.9	17.9	16	14.5	57	2.8	5.1	16.6	24.1
	Sum	**279.4**	**50.4**	**18.1**	**167.1**	**8.3**	**36.9**	**37.6**	**24.4**	**165.7**	**9.3**	**15.7**	**39.4**	**47.4**
	Average	**93.1**	**16.8**	**6**	**55.7**	**2.8**	**12.3**	**12.5**	**8.1**	**55.2**	**3.1**	**5.2**	**13.1**	**15.8**
	NSE_{daily} $NSE_{monthly}$							0.52 0.55	-0.76 0.09				0.51 0.59	-2.39 -1.74
	R^2_{daily} $R^2_{monthly}$							0.56 0.63	0.41 0.51				0.56 0.66	0.68 0.67
	IOA_{daily} $IOA_{monthly}$							0.85 0.86	0.71 0.81				0.85 0.89	0.71 0.72
	PBIAS							25%	-35%				22%	-162%
Validation period	2016	89.7	12.7	1.9	60	2.9	7.2	16.7	1.6	62.6	2.6	5	12.3	7.2
	2017	116.6	12.7	12.5	54.9	3.0	12.5	16.8	28.3	55.9	3.6	5.6	17.2	36.7
	Sum	**228.2**	**25.4**	**14.4**	**114.9**	**5.9**	**19.7**	**33.4**	**29.9**	**118.5**	**6.3**	**10.6**	**29.6**	**43.9**
	Average	**114.1**	**12.7**	**7.2**	**57.5**	**2.9**	**9.8**	**16.7**	**14.9**	**59.2**	**3.1**	**5.3**	**14.8**	**22**
	NSE_{daily} $NSE_{monthly}$							0.64 0.50	-1.68 -1.51				0.47 0.40	-3.26 -4.83
	R^2_{daily} $R^2_{monthly}$							0.72 0.91	0.78 0.87				0.57 0.81	0.85 0.95
	IOA_{daily} $IOA_{monthly}$							0.91 0.92	0.76 0.78				0.86 0.90	0.72 0.67
	PBIAS							-32%	-107%				-16%	-205%
All period	Sum	**485.8**	**75.8**	**32.5**	**282**	**14.2**	**56.6**	**71**	**54.3**	**284.2**	**15.5**	**26.3**	**68.9**	**91.4**
	Average	**97.2**	**15.2**	**6.5**	**56.4**	**2.8**	**11.3**	**14.2**	**10.9**	**56.8**	**3.1**	**5.3**	**13.8**	**18.3**
	NSE_{daily} $NSE_{monthly}$							0.56 0.55	-1.24 -0.45				0.50 0.55	-2.84 -2.78
	R^2_{daily} $R^2_{monthly}$							0.61 0.63	0.60 0.62				0.56 0.66	0.76 0.76
	IOA_{daily} $IOA_{monthly}$							0.88 0.88	0.75 0.79				0.85 0.89	0.72 0.70
	PBIAS							6%	-67%				9%	-181%

P, precipitation; TD, tile drainage; RO, runoff; ET, evapotranspiration; LS, lateral seepage; DS, deep seepage

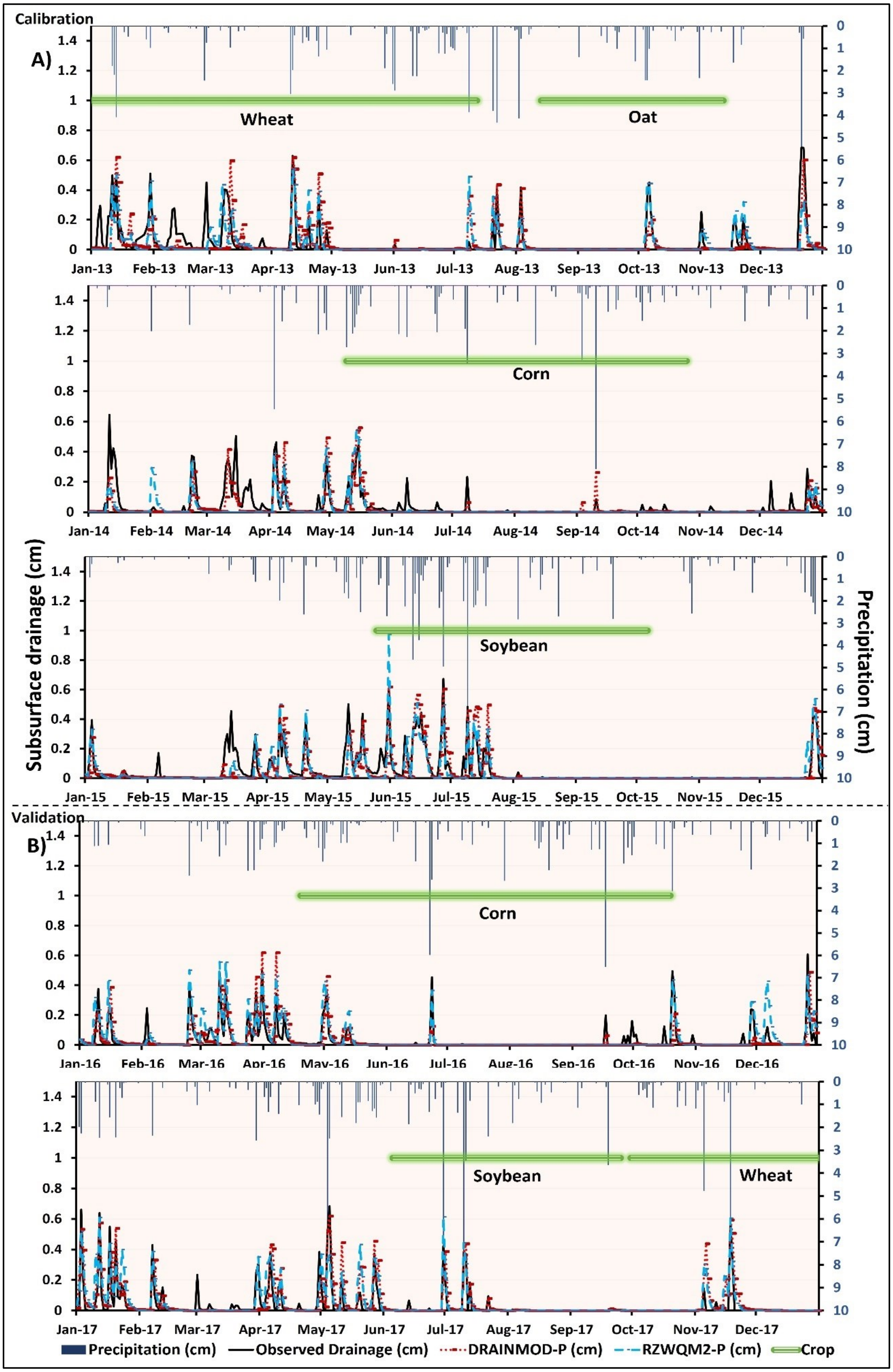

Figure 3. 4 The daily time series of both observed and predicted daily drainage discharge by both models for A) calibration period (2013-2015); B) validation period (2016-2107)

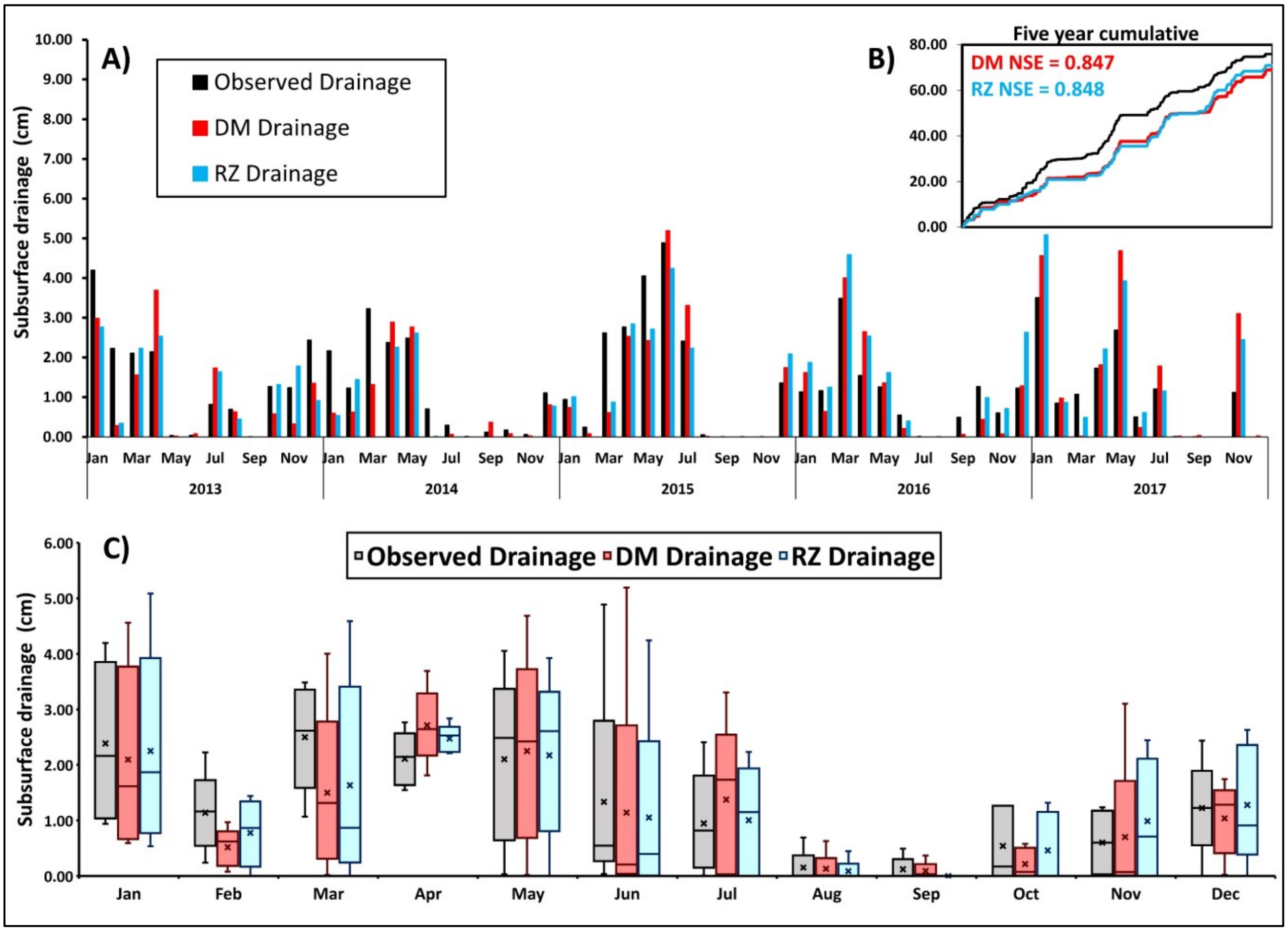

Figure 3. 5 A) Comparative analysis of observed and predicted monthly tile drainage discharge for the simulation period (2013-2017), B) five-year cumulative drainage discharge predicted by both models, accompanied by their respective NSE values, and C) Box-and-whisker plots for monthly observed and simulated drainage flow, where the cross sign represents mean markers, and the dash indicates the median.

3.3.2. Phosphorus dynamics

Annual phosphorus losses, both observed and as simulated by the model, along with performance metrics for these losses on a daily and monthly basis in subsurface drainage, are detailed in Table 3.10. In the evaluation of subsurface drainage DRP load, the first two months of 2013 (January and February) were excluded because they accounted for approximately 127 g ha^{-1} of DRP load, which is disproportionately high. In contrast, the combined DRP load through subsurface drainage for the subsequent four years (2014-2017) totaled around 167 g ha^{-1}. The decision to exclude this unusually high load from the early 2013 data arise from the potential for unforeseen issues during data collection, such as obstructions caused by dead animals in the tile outlet, which could lead to elevated concentration readings. Given that these elevated concentrations are not reflective of typical field losses, they were deemed outliers and thus excluded from the analysis.

Overall, over a five-year simulation period, the RZWQM2-P model shows unsatisfactory performance in predicting daily tile DRP loads but satisfactory performance in predicting monthly DRP loads through subsurface drainage. The daily performance metrics demonstrated a NSE of 0.36, R^2 of 0.36, IOA of 0.70, and a PBIAS of 9%. In contrast, the monthly performance metrics were slightly better with a NSE of 0.48, R^2 of 0.50, IOA of 0.82, and a PBIAS of 9%. Similarly, the model performed satisfactorily in both the calibration and validation periods while predicting the monthly drainage DRP load, as detailed in Table 3.10. In contrast, DRAINMOD-P performed unsatisfactorily for both daily and monthly DRP predictions through subsurface drainage, exhibiting a daily NSE of 0.22, R^2 of 0.38, IOA of 0.76, and a PBIAS of -14%. On a monthly basis, it shows a low NSE of 0.25 but a higher R^2 of 0.50 and an IOA of 0.82. However, both models performed very good in predicting the cumulative DRP load throughout the five-year simulation period, as shown in Figure 3.8. DRAINMOD-P outperforms RZWQM2-P, with a higher NSE of 0.97, compared to 0.76 for RZWQM2-P (Figure 3.8). The primary reason for the RZWQM2-P model's poor performance in predicting daily DRP load through subsurface drainage appears to be its inability to accurately forecast high load (peak) events, as shown in Figures 3.6 and 3.7. For instance, in both 2013 and 2016, which featured one or more peak events in the daily time series data (April, August, and December of 2013, and May of 2016), the RZWQM2-P model consistently failed to predict these high load events. Consequently, this led to an underestimation of the DRP, especially for 2013, as depicted in Figures 3.6, despite successfully predicting the respective drainage events (Figure 3.4). These observations align with the findings of Shokrana et al. (2022), who noted that the model failed to predict all major high load events, leading to an unsatisfactory prediction of daily DRP load through subsurface drainage. However, regarding DRAINMOD-P, the cause of its poor performance in predicting DRP load appears to be an overestimation of the load. For instance, it significantly overestimated the DRP load in 2014 and 2017. Specifically in 2017, this overestimation may be attributed to DRAINMOD-P's significant overestimation of subsurface drainage discharge, which in turn increases its corresponding DRP losses.

For subsurface drainage TP load predictions, both models perform satisfactorily on a daily basis and well on a monthly basis, as shown in Table 3.10. Over the five-year period, RZWQM2-P predicted the monthly TP load with good accuracy, achieving NSE of 0.72, R^2 of 0.73, IOA of 0.90, and a PBIAS of 3%. The calibration and validation periods yielded NSE, R^2, IOA, and PBIAS values of 0.66, 0.67, 0.87, and -1%, and 0.77, 0.77, 0.93, and 6%, respectively. Similarly, DRAINMOD-P predicted the monthly TP load over the same period with NSE, R^2, IOA, and PBIAS values of 0.74, 0.75, 0.92, and 10%, respectively. For the calibration period, these values were 0.82, 0.82, 0.95, and 6%, and for the validation period, they were 0.63, 0.67, 0.90, and 15%. In terms of daily TP predictions (Figure 3.9 and 3.10), both models also achieved satisfactory results, with detailed performance metrics for the calibration, validation, and overall periods provided in Table 3.10. Over the five-year average, RZWQM2-P predicted a TP load through subsurface drainage of 560.1 g ha^{-1}, closely aligning with the observed average of 575.9 g ha^{-1}. In comparison, DRAINMOD-P predicted an average of 516.6 g ha^{-1}. These predictions demonstrate the models' close resemblance in predicting TP load, with very high NSE values for five-year cumulative load predictions: 0.99 for RZWQM2-P and 0.96 for DRAINMOD-P, as illustrated in Figure 3.11.

In terms of surface runoff P losses, DRAINMOD-P significantly overpredicted the surface runoff flow, and consequently, it also overestimated the associated runoff P loading for both DRP and TP. RZWQM2-P, while also overestimating the P load, demonstrated greater consistency with the observed data. Its runoff predictions were closer to the observed values, as indicated in Table 3. 11. Specifically, RZWQM2-P predicted a five-year annual average runoff DRP loss of 55.3 g ha^{-1}, which is closer to the observed average of 49.5 g ha^{-1}. In contrast, DRAINMOD-P's five-year average was significantly higher, around 130 g ha^{-1}, primarily due to greater runoff flow. Regarding total phosphorus loading, the observed five-year average was approximately 486.9 g ha^{-1}. The RZWQM2-P model predicted around 764.4 g ha^{-1}, whereas DRAINMOD-P estimated it to be much higher, at about 2428 g ha^{-1}. This overprediction of phosphorus loading is consistent with the overestimated surface runoff flow. We employed the R^2 metric to determine the correlation between observed and predicted values, alongside the 1:1 line, as depicted in Figures 3.13 and

3.14. Despite the overprediction in total P loading by both models, Figures 3.13 and 3.14 demonstrate that both models exhibit a similar pattern in predicting phosphorus losses, with acceptable R^2 values of 0.85 for DRAINMOD-P and 0.62 for RZWQM2-P for monthly TP predictions over the five-year simulation period. For DRP loading, both models show a reasonable correlation, with R^2 values of 0.71 for DRAINMOD-P and 0.51 for RZWQM2-P. The higher R^2 value for DRAINMOD-P indicates that it accounts for a larger portion of the variance in the data. In contrast, the closer alignment of RZWQM2-P's predictions to the 1:1 line suggests better accuracy in terms of how closely the predicted values match the actual values. All scatter plots for the calibration and validation periods, including the 1:1 line, are presented in Figures 3.13 and 3.14. Overall, in terms of total phosphorus load (runoff + drainage), the observed five-year total load is 5.3 kg ha^{-1}, whereas RZWQM2-P and DRAINMOD-P predicted it to be 6.6 kg ha^{-1} and 14.7 kg ha^{-1}, respectively.

Another important parameter is plant P uptake from the field. DRAINMOD-P predicted the five-year average annual plant P uptake to be about 30.1 kg ha^{-1}, while RZWQM2-P estimated it at approximately 35.9 kg ha^{-1}. The annual plant P uptake for DRAINMOD-P ranged from 43.4 kg ha^{-1} in 2013 to 16.7 kg ha^{-1} in 2015. In contrast, for RZWQM2-P, it was around 50.1 kg ha^{-1} in 2013 and 19.78 kg ha^{-1} in 2015. Additionally, DRAINMOD-P predicted an average annual P mineralization of 15.9 kg ha^{-1} over five years. This process is one of the main pathways through which P is added to the system, apart from fertilizer/manure application. Similarly, RZWQM2-P simulated a five-year average of 17.5 kg ha^{-1} of mineralized P added to the soil from plant residue and soil humus. Moreover, DRAINMOD-P can simulate atmospheric deposition, a process that RZWQM2-P cannot simulate.

Table 3. 10 Annual observed and model-simulated phosphorus losses and model performance metrics for daily and monthly subsurface drainage P losses during the simulation period.

Period	Year	Observed DRP_{tile}	Observed TP_{tile}	RZWQM2-P DRP_{tile}	RZWQM2-P TP_{tile}	DRAINMOD-P DRP_{tile}	DRAINMOD-P TP_{tile}
		---g ha^{-1}---					
Calibration period	2013*	87	365.6	47.1	429.1	75	343.9
	2014	29.8	170.1	29.9	270.6	42.9	188
	2015	51.1	849.5	56.5	694.7	48.7	776.5
	Sum	**167.8**	**1385.1**	**133.6**	**1394.4**	**166.7**	**1308.4**
	Average	**55.9**	**461.7**	**44.5**	**464.8**	**55.6**	**436.1**
	NSE_{daily} $NSE_{monthly}$			0.38 0.50	0.52 0.66	0.29 0.33	0.58 0.82
	R^2_{daily} $R^2_{monthly}$			0.38 0.54	0.53 0.67	0.44 0.53	0.63 0.82
	IOA_{daily} $IOA_{monthly}$			0.71 0.82	0.84 0.87	0.80 0.84	0.81 0.95
	PBIAS			20%	-1%	1%	6%
Validation period	2016	48.8	584.6	49.5	703	54.4	476.7
	2017	35.2	909.8	46	703.1	67.1	798.1
	Sum	**84**	**1494.4**	**95.5**	**1406.1**	**121.6**	**1274.8**
	Average	**42**	**747.2**	**47.8**	**703**	**60.8**	**637.4**
	NSE_{daily} $NSE_{monthly}$			0.32 0.38	0.54 0.77	0.09 0.00	0.45 0.63
	R^2_{daily} $R^2_{monthly}$			0.32 0.48	0.55 0.77	0.28 0.47	0.46 0.67
	IOA_{daily} $IOA_{monthly}$			0.67 0.82	0.81 0.93	0.69 0.78	0.79 0.90
	PBIAS			-14%	6%	-45%	15%
All period	Sum	**251.8**	**2879.6**	**229.1**	**2800.5**	**288.3**	**2583.2**
	Average	**50.4**	**575.9**	**45.8**	**560.1**	**57.7**	**516.6**
	NSE_{daily} $NSE_{monthly}$			0.36 0.48	0.53 0.72	0.22 0.25	0.50 0.74
	R^2_{daily} $R^2_{monthly}$			0.36 0.50	0.54 0.73	0.38 0.50	0.52 0.75
	IOA_{daily} $IOA_{monthly}$			0.70 0.82	0.82 0.90	0.76 0.82	0.80 0.92
	PBIAS			9%	3%	-14%	10%

*** For DRP load, data from March to December 2013 were considered**

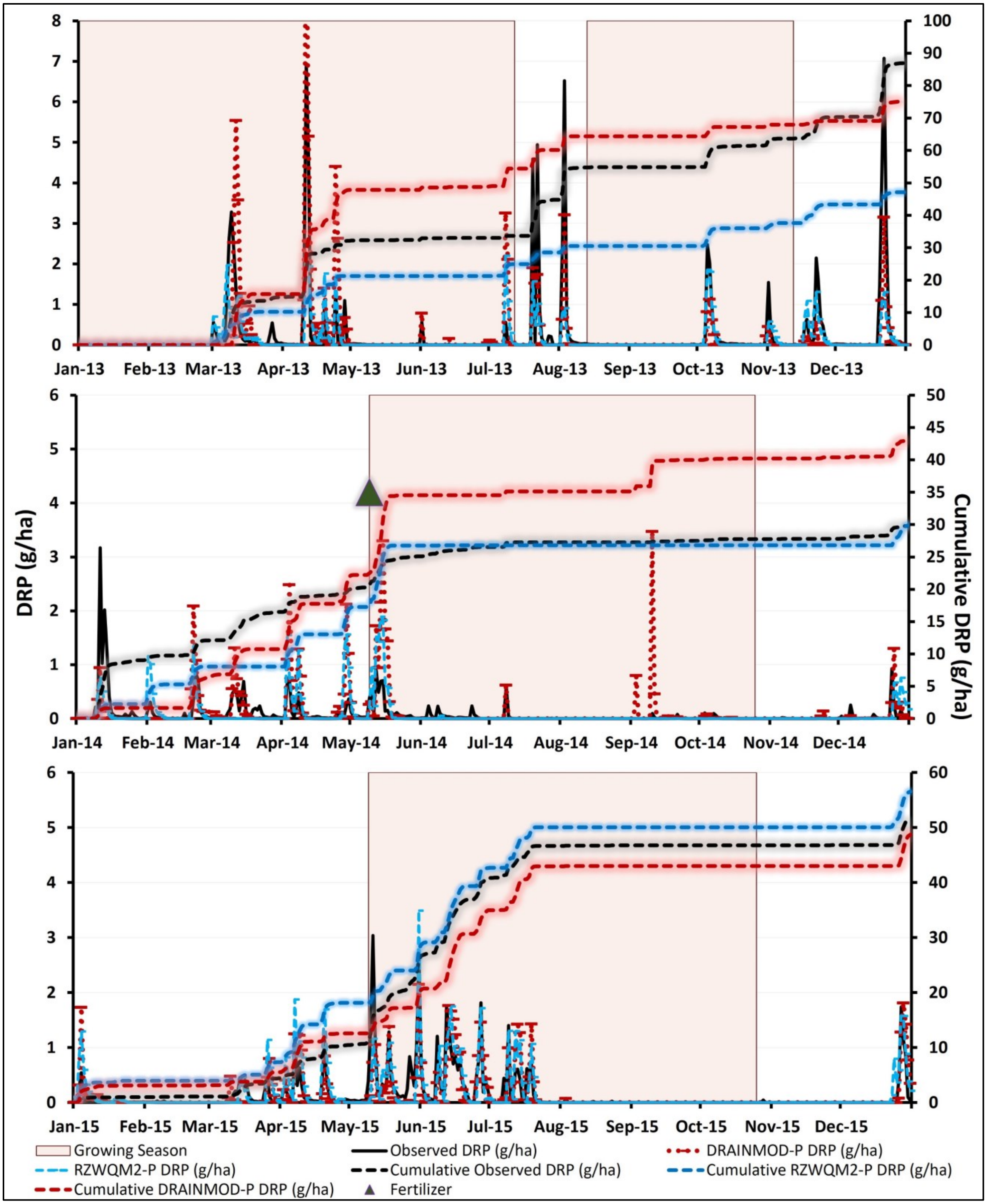

Figure 3. 6 Measured and predicted daily and cumulative DRP losses through drainage discharge for the three-year calibration period (2013-2015)

The shaded area represents the growing season, and the triangles indicate fertilizer application events.

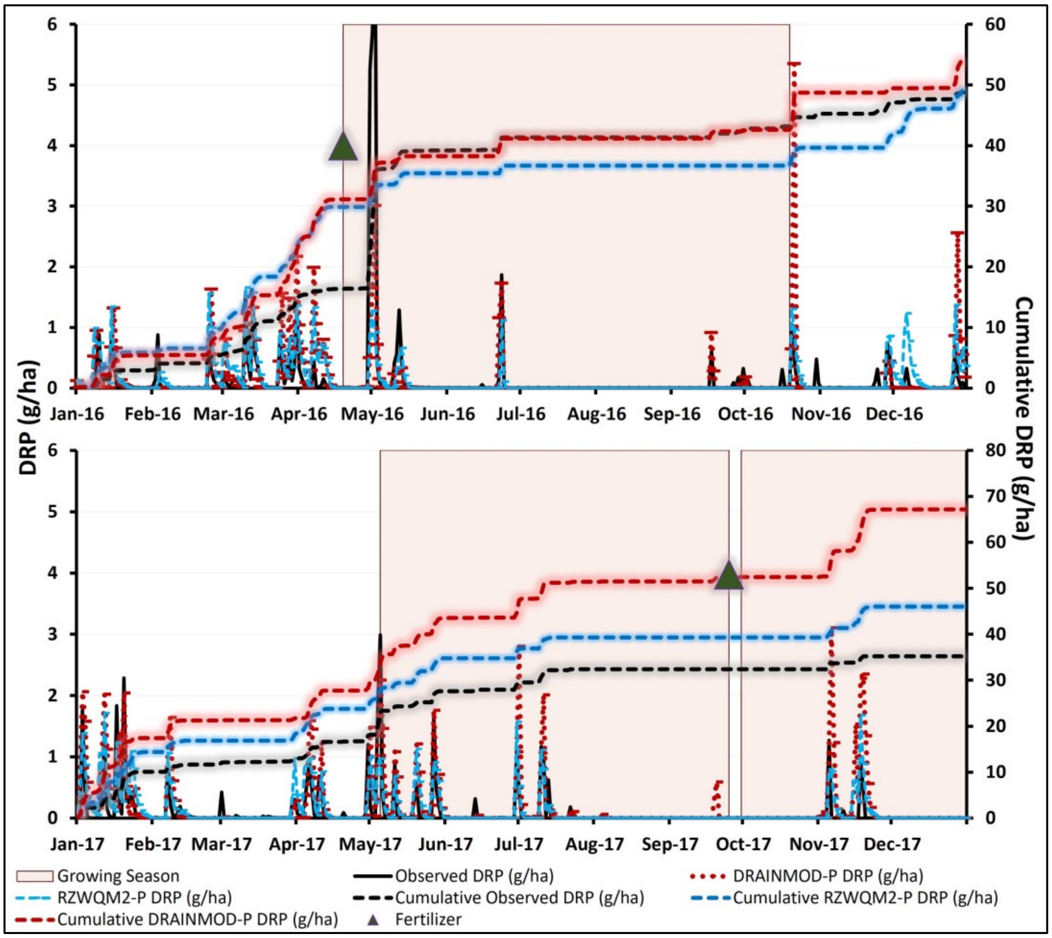

Figure 3. 7 Measured and predicted daily and cumulative DRP losses through drainage discharge for the two-year validation period (2016-2017)

The shaded area represents the growing season, and the triangles indicate fertilizer application events.

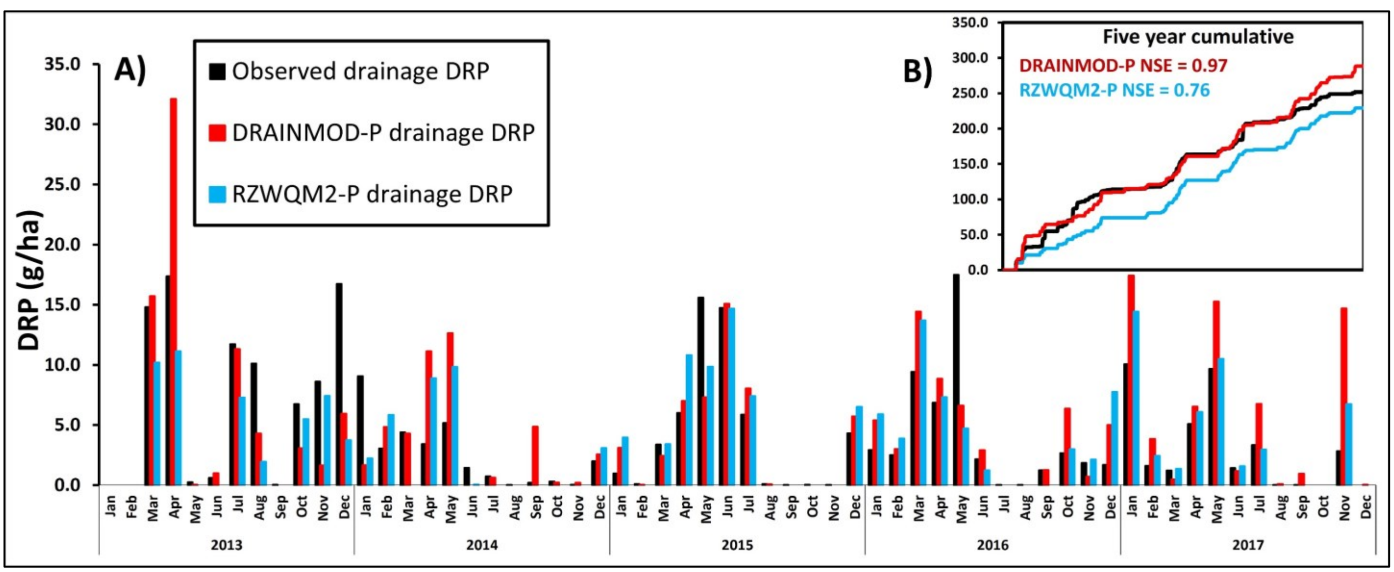

Figure 3. 8 Comparative analysis of observed and predicted monthly drainage DRP load for the simulation period (2013-2017), B) five-year cumulative drainage DRP load predicted by both models, with their respective NSE values

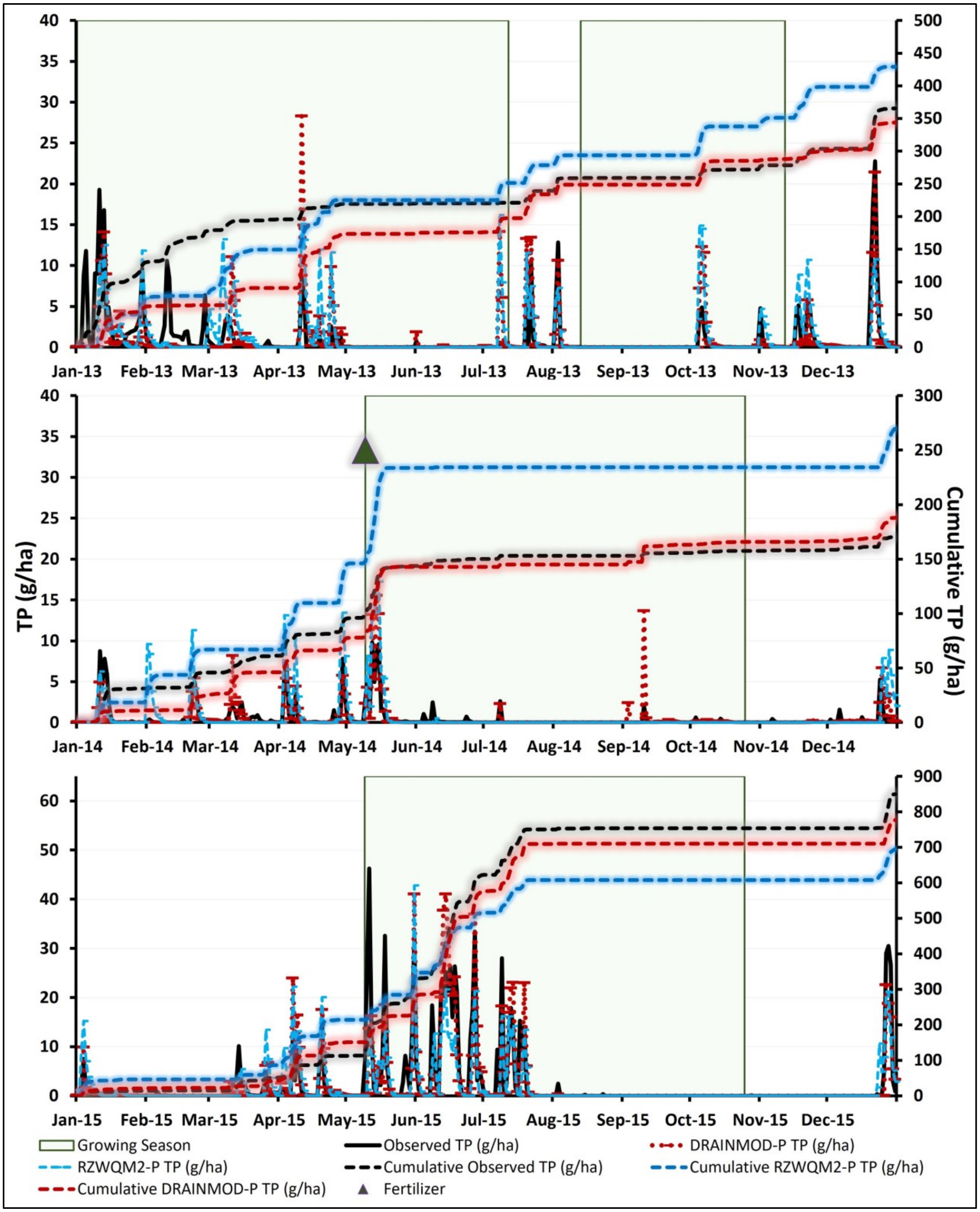

Figure 3. 9 Measured and predicted daily and cumulative TP losses through drainage discharge for the three-year calibration period (2013-2015)

The shaded area represents the growing season, and the triangles indicate fertilizer application events.

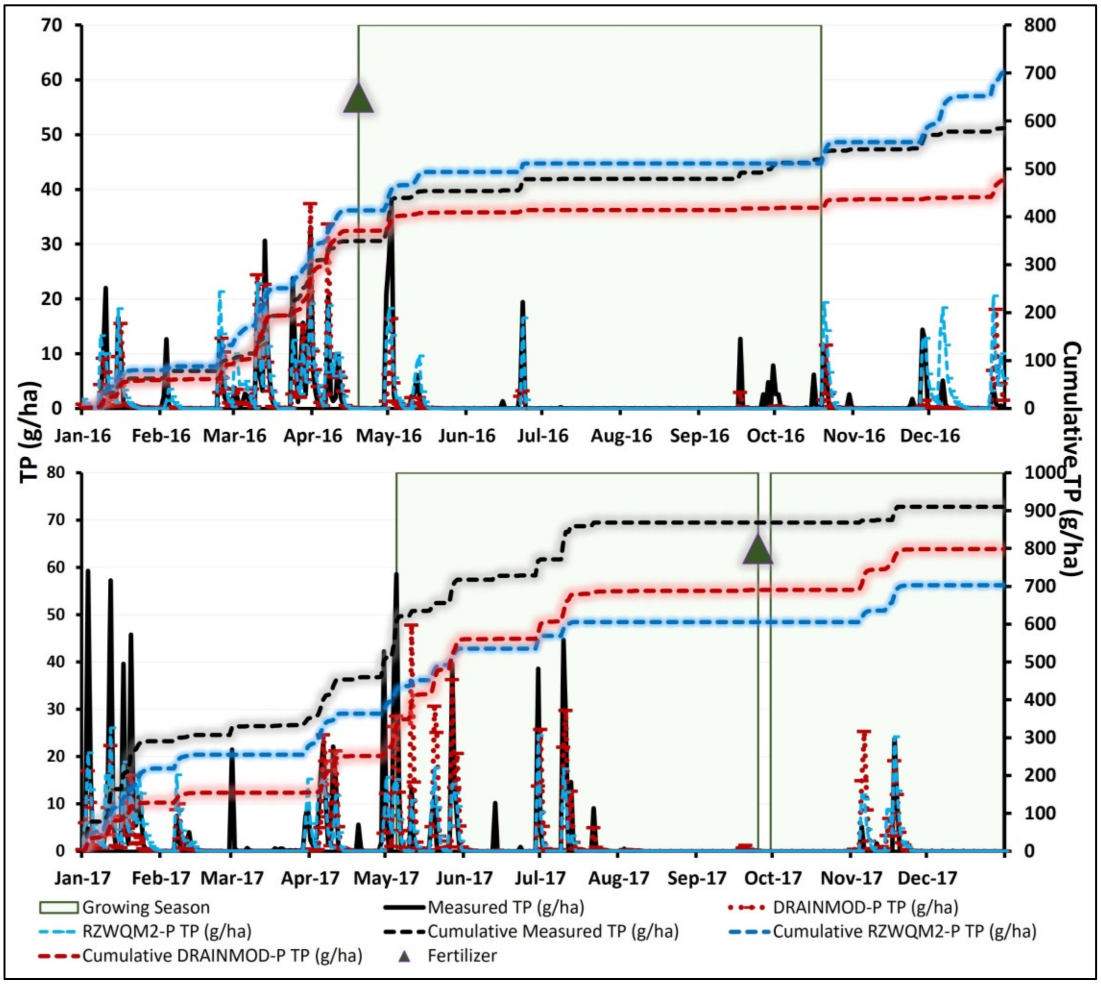

Figure 3. 10 Measured and predicted daily and cumulative TP losses through drainage discharge for the two-year validation period (2016-2017).

The shaded area represents the growing season, and the triangles indicate fertilizer application events.

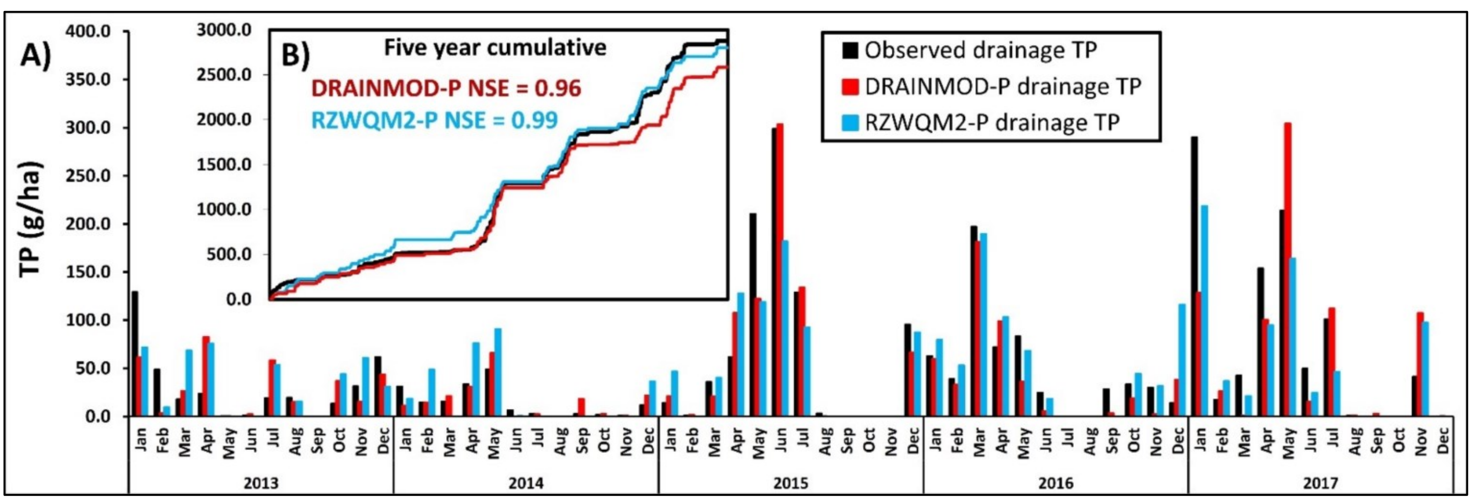

Figure 3. 11 Comparative analysis of observed and predicted monthly drainage TP load for the simulation period (2013-2017), B) five-year cumulative drainage TP load predicted by both models, with their respective NSE values

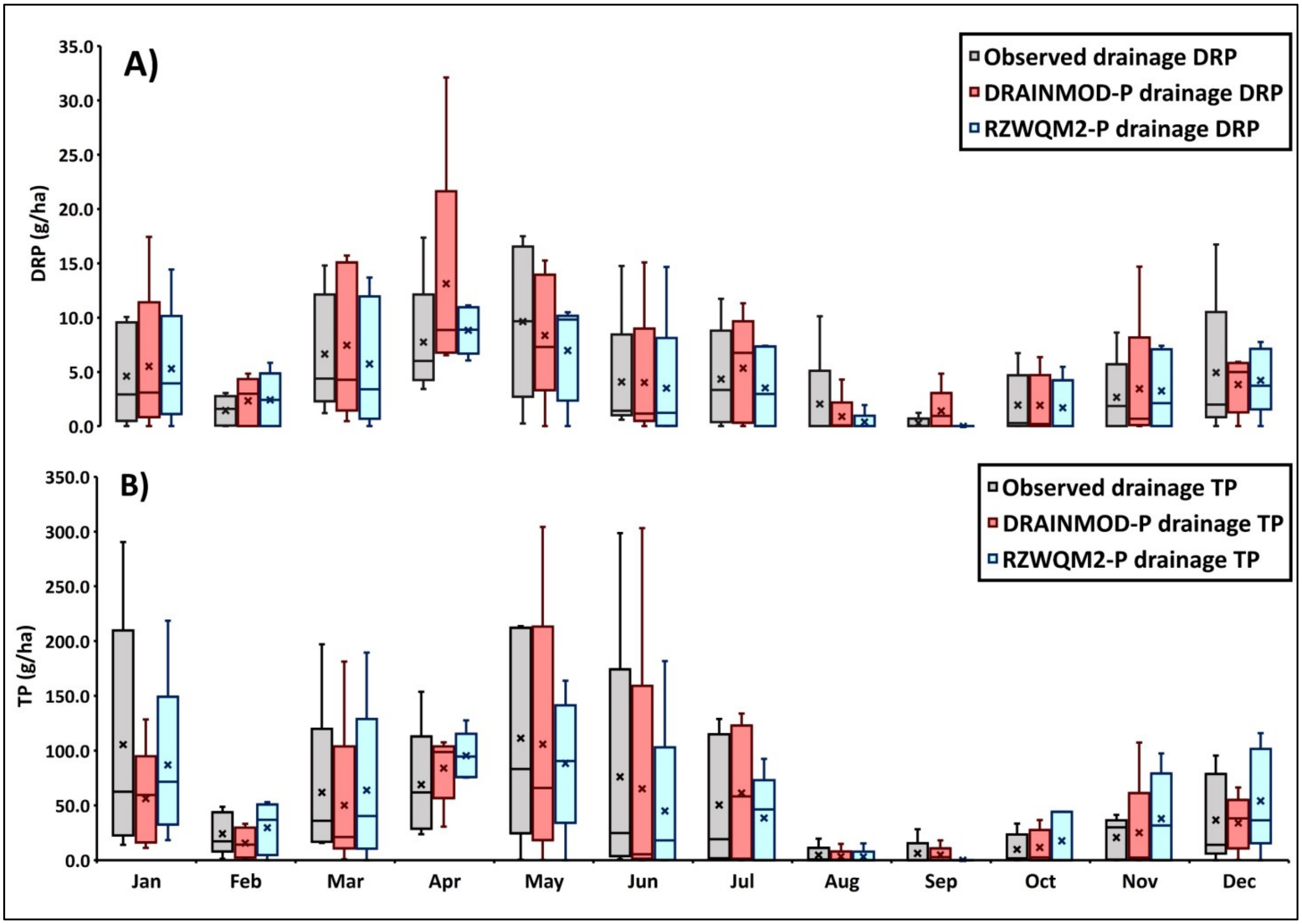

Figure 3. 12 Box-and-whisker plots for monthly observed and simulated drainage of A) DRP and B) TP load, where the cross sign represents the mean markers, and the dash indicates the median.

Table 3. 11 Annual observed and model-simulated phosphorus losses and model performance metrics for daily and monthly surface runoff P losses during the simulation period.

Period	Year	DRP (runoff) Obs.	DRP (runoff) RZ.	DRP (runoff) DM.	TP (runoff) Obs.	TP (runoff) RZ.	TP (runoff) DM.
		g ha^{-1}					
Calibration period	2013	76.9	76.7	203.8	118.8	887.4	733.7
	2014	11.8	21.3	47.6	55.1	157.1	307.3
	2015	59.3	38.1	111.6	758	1232.9	4943.4
	Sum	**148**	**136.1**	**363**	**931.9**	**2277.4**	**5984.4**
	Average	**49.3**	**45.4**	**121**	**310.6**	**759.1**	**1994.8**
	NSE_{daily} $NSE_{monthly}$		0.13 0.28	-1.45 -2.74		-5.86 -1.03	-44.89 -31.28
	R^2_{daily} $R^2_{monthly}$		0.59 0.57	0.71 0.67		0.34 0.57	0.74 0.96
	IOA_{daily} $IOA_{monthly}$		0.84 0.84	0.76 0.69		0.51 0.74	0.36 0.44
	PBIAS		8%	-145%		-144%	-542%
Validation period	2016	15.6	15.3	74	186.8	94.8	877.4
	2017	83.8	125.4	216.4	1316	1449.5	5278
	Sum	**99.4**	**140.7**	**290.4**	**1502.8**	**1544.3**	**6155.4**
	Average	**49.7**	**70.3**	**145.2**	**751.4**	**772.2**	**3077.7**
	NSE_{daily} $NSE_{monthly}$		-1.55 -0.88	-3.55 -4.71		-0.70 0.55	-14.16 -12.39
	R^2_{daily} $R^2_{monthly}$		0.55 0.51	0.75 0.82		0.33 0.75	0.70 0.83
	IOA_{daily} $IOA_{monthly}$		0.72 0.74	0.69 0.65		0.68 0.90	0.51 0.53
	PBIAS		-41%	-192%		-3%	-310%
All period	Sum	**247.4**	**276.7**	**653.4**	**2434.7**	**3821.8**	**12139.8**
	Average	**49.5**	**55.3**	**130.7**	**486.9**	**764.4**	**2428**
	NSE_{daily} $NSE_{monthly}$		-0.43 -0.08	-2.15 -3.35		-1.77 -0.01	-20.53 -18.82
	R^2_{daily} $R^2_{monthly}$		0.55 0.52	0.71 0.71		0.30 0.62	0.68 0.85
	IOA_{daily} $IOA_{monthly}$		0.78 0.80	0.73 0.67		0.61 0.83	0.45 0.48
	PBIAS		-12%	-164%		-57%	-399%

Obs., Observed; RZ., RZWQM2-P; DM.; DRAINMOD-P

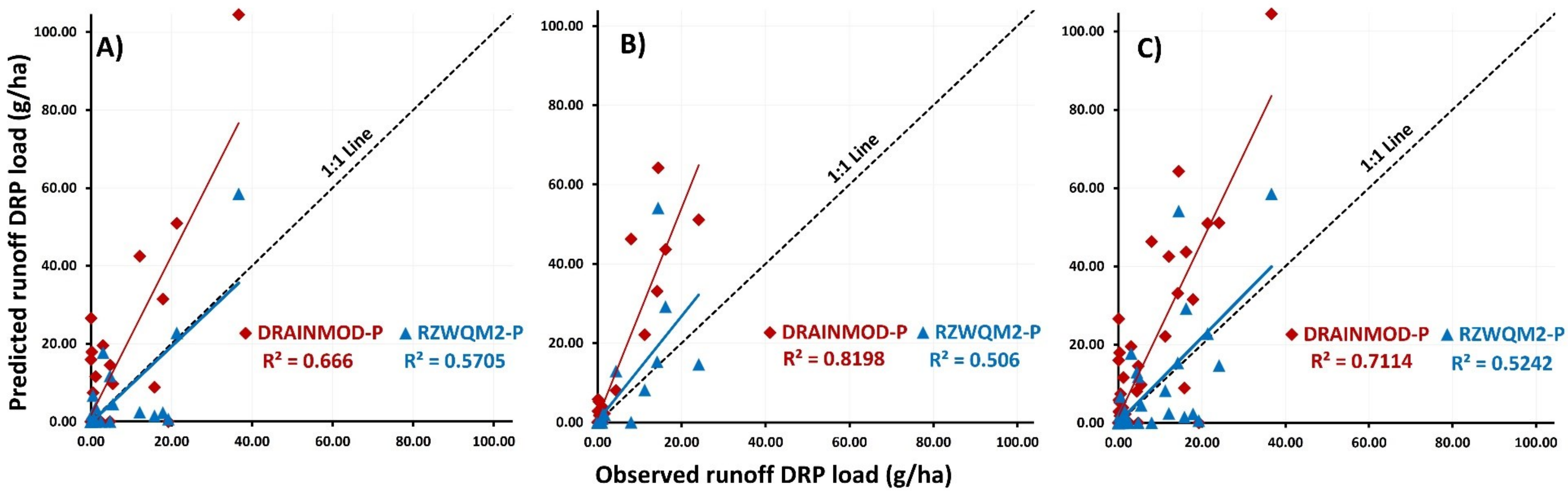

Figure 3. 13 Scatter diagram showing observed and predicted monthly DRP losses through surface runoff by both models, with R^2 values and 1:1 line during A) the calibration period, B) the validation period, and C) the all period.

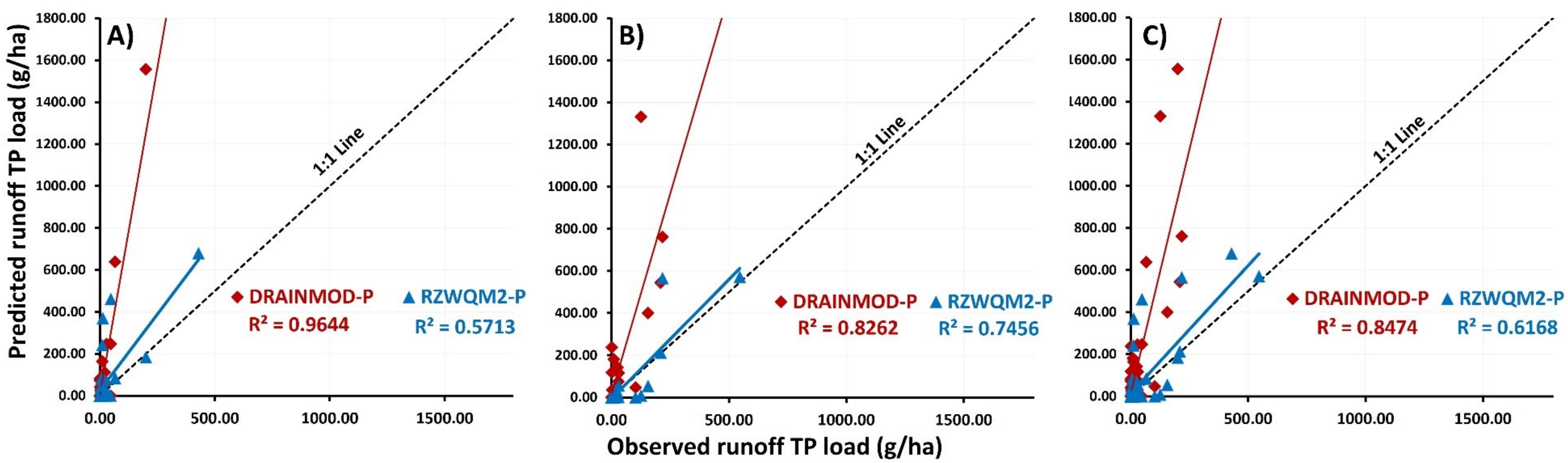

Figure 3. 14 Scatter diagram showing observed and predicted monthly TP losses through surface runoff by both models, with R^2 values and 1:1 line during A) the calibration period, B) the validation period, and C) the all period.

3.3.3. Future work

Throughout the simulation period, the RZWQM2-P model was unable to accurately predict daily high (peak) load P events. This limitation aligns with the findings presented by Shokrana et al. (2022) in their daily evaluation of the model. The model's failure to predict these peak events can be attributed to its consistent prediction of DRP concentration within a narrow range. As illustrated in Figure 3.15 A, the RZWQM2-P model's predictions predominantly ranged between 0.03 to 0.05 mg L^{-1}, in contrast to the significant variations observed in both the actual data and the predictions made by DRAINMOD-P over the same period. We further investigate to identify limitations within the subroutines that contribute to the model's inability to accommodate fluctuations. The primary limitation in RZWQM2-P appears to stem from the methods employed to calculate the daily mass balance of DRP exiting through subsurface drainage. This process is modeled using a linear groundwater reservoir approach. Initially, the model assumes that DRP losses through the soil matrix and macropores are transported to the groundwater reservoir. Upon reaching this reservoir, the new DRP mass is computed using the following mass balance equation:

$$\frac{dy}{dt} = I_{drp} - \frac{y(t)}{S_{gw}} drain$$

Where $y(t)$ is the mass of DRP at any time t in the groundwater reservoir, I_{drp} is the incoming DRP mass, S_{gw} is the storage volume of the groundwater reservoir, and *drain* is the outflow volume i.e. the tile drainage amount. The solution to this differential equation is given by:

$$y(t) = \frac{S_{gw} * I_{drp}}{drain} + \left(y_0 - \frac{S_{gw*I_{drp}}}{drain} \right) * \exp\,(-\frac{drain}{S_{gw}} * t)$$

Where y_0 is the initial DRP mass in the reservoir. Based on these calculations, the model then determines the average DRP concentration in the groundwater reservoir using the equation:

$$C_{drp,gw} = \frac{y_0 + y(1)}{2 * S_{gw}}$$

Where, $C_{drp,gw}$ = Concentration of DRP in groundwater reservoir.

This equation computes the average concentration of DRP by considering the initial mass y_0 and the mass at the end of the day [$y(1)$], divided by twice the reservoir storage volume (S_{gw}).

The limitation of this approach becomes evident when considering scenarios where S_{gw} (the storage volume of the groundwater reservoir) and y_0 (the initial DRP mass in the reservoir) are relatively large compared to *drain* (the outflow volume) and I_{drp} (the incoming DRP mass). In such cases, the system exhibits a high degree of stability, with minimal day-to-day variations in concentration ($C_{drp,gw}$). This stability arises from the significant storage capacity of a large groundwater reservoir combined with a substantial initial mass, which together mitigate the impact of daily inflows and outflows on the overall phosphorus balance. Consequently, the model tends to predict a stable and relatively unchanging DRP concentration, potentially failing to capture the natural variability and dynamic behavior observed in real-world P transport through drainage systems. To evaluate our hypothesis, we adjusted the depth of the restricting layer in our model from 200 cm to 100 cm. This modification was intended to decrease the storage capacity of the groundwater reservoir. As illustrated in Figure 3.15B, this change resulted in the model simulating more variability in P concentration. Although the observed changes in concentration were not as extensive as desired, they were notably more pronounced than those produced under conditions of greater storage capacity.

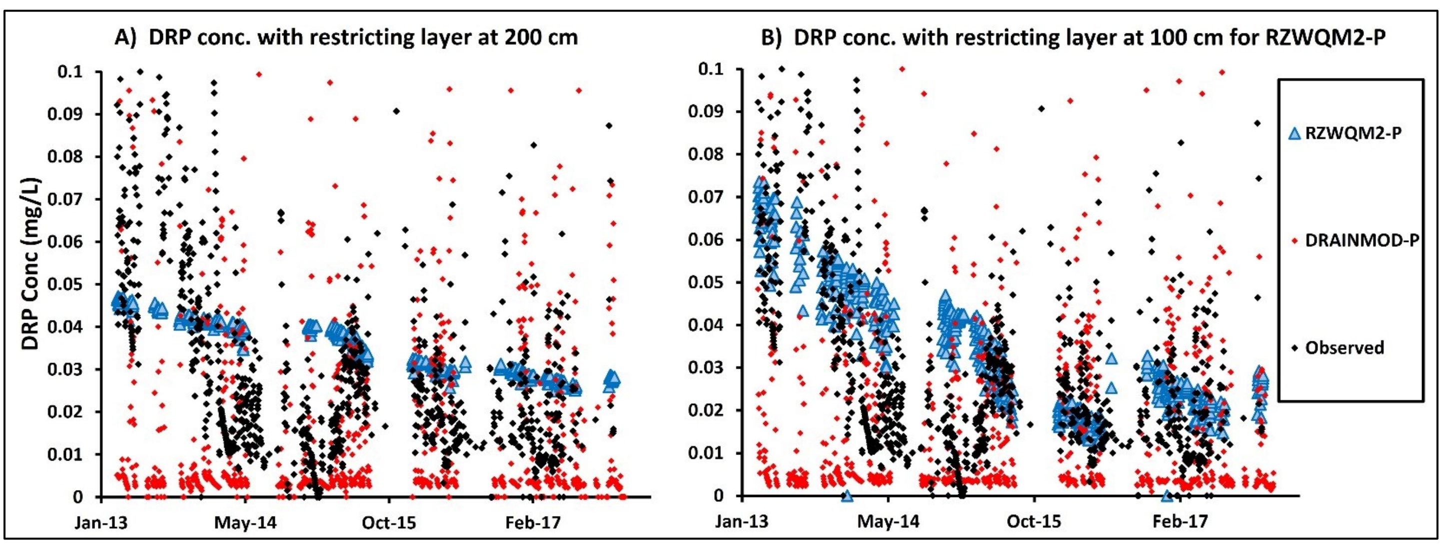

Figure 3. 15 Temporal trends in observed versus simulated DRP concentration ranging from 0 to 0.1 mg/L by both models for the simulation period (2013-2017), with A) the restricting layer at 200 cm and B) the restricting layer at 100 cm for the RZWQM2-P model.

To achieve a more realistic representation of P dynamics, modifications to the existing subroutine of RZWQM2-P are necessary, or alternatively, adopting the modeling approach of DRAINMOD-P could be considered. DRAINMOD-P incorporates detailed spatial discretization and cell-level mass balance equations, providing a more comprehensive account of local variations and transient conditions, as evidenced by its ability to show changes in concentration over time. However, the validity of the methods used in DRAINMOD-P to predict DRP remains uncertain, as it has not satisfactorily predicted the DRP load throughout the simulation period. This may be due to factors such as the overestimation of drainage flow observed in 2017. Since DRAINMOD-P has only been tested once, it requires further evaluation, similar to the extensive testing undergone by RZWQM2-P, before any definitive conclusions can be drawn.

DRAINMOD-P could benefit from adopting approaches like the incorporation of dead-end macropores, as utilized in RZWQM2-P, to simulate hydrology more accurately. Increasing the hydraulic conductivity in the soil profile to high values, representing dead-end macropores, might however compromise the model's performance in predicting subsurface drainage and may not accurately reflect actual soil properties. Therefore, including a dead-end fraction can aid the model in better predicting hydrology and infiltration computations, which in turn can lead to more accurate predictions of phosphorus (P) losses. Additionally, DRAINMOD-P could benefit from adopting the methods used in RZWQM2-P for predicting crop yield and plant P uptake, utilizing the DSSAT model. While DRAINMOD-P already predicts plant P uptake reasonably well throughout the simulation, considering the DSSAT model for crop yield prediction could be advantageous. DSSAT, is a versatile crop growth model, takes into account the effects of nutrients on crop yields, including phosphorus stress in plant growth. This approach offers a more representative view of actual field conditions compared to the empirical yield approach currently employed in DRAINMOD-P. Since DRAINMOD-DSSAT is already available, integrating it with DRAINMOD-P could enhance the model's comprehensiveness.

3.4. Summary and conclusions

This study represents the first effort to compare the performance of the newly developed phosphorus (P) components within the RZWQM2-P and DRAINMOD-P models. Both models were tested using five years of high-resolution daily P loss data from a test field in Ohio. They were calibrated for the period 2013-2015 and validated for 2016-2017. The test field is characterized by significant wide-open cracks, facilitating high preferential flow. The models were compared and evaluated for their ability to predict hydrology and phosphorus components. Statistical measures indicated that RZWQM2-P performed satisfactorily on both a daily and monthly basis in predicting subsurface drainage over the five-year period, achieving metrics of NSE > 0.50, $R^2 > 0.60$, and IOA > 0.75. In contrast, DRAINMOD-P's performance was satisfactory only on a monthly basis and unsatisfactory on a daily basis, with a low R^2 of 0.56, yet high NSE (0.50) and IOA (0.85). Moreover, DRAINMOD-P significantly overpredicted surface runoff compared to observed data, while RZWQM2-P also overpredicted, although to a lesser extent and closer to the observed data. The discrepancies in runoff predictions between the two models might be attributed to their differing methodologies, such as the handling of surface storage components and the dead-end macropore component.

Both models failed to accurately predict daily dissolved reactive phosphorus (DRP) losses through subsurface drainage. While the RZWQM2-P model satisfactorily predicted monthly DRP loss, DRAINMOD-P's performance was unsatisfactory. However, both models performed in a "good" manner in predicting total phosphorus (TP) losses through the same pathway. They also demonstrated very good performance in predicting the cumulative DRP and TP load through subsurface drainage. Both models overestimated runoff-bound TP losses due to an overestimation of runoff flow, yet they showed a strong correlation between observed and predicted values.

A potential explanation for the suboptimal performance of the RZWQM2-P model in predicting daily DRP losses is its inability to accurately reflect fluctuations in the P concentration in subsurface drainage. This limitation arises from the model's reliance on approaches such as the linear groundwater reservoir to compute the DRP mass balance leaving the system, which heavily depends on the storage volume of the groundwater reservoir. This aspect of the model requires modifications to effectively simulate high load peak events.

FOREWORD TO CHAPTER IV

Chapter III presents the first-ever comparison between the newly developed RZWQM2-P and DRAINMOD-P models. Neither model provided satisfactory predictions for daily dissolved reactive phosphorus (DRP) losses. However, RZWQM2-P outperformed DRAINMOD-P, despite its inability to accurately predict peak loads during high-load events. Recommendations for improving this aspect of the model were provided for future development.

Chapter IV progresses the evaluation of the RZWQM2-P model by utilizing daily P loss data from a field in a different Ohio county, distinctively situated within the western Lake Erie basin watershed. The key objective is to highlight that this chapter used data from a field with soil characteristics entirely different from those presented in Chapter III. This approach underscores the importance of a comprehensive model assessment, necessitating the examination of the model against varied datasets. By doing so, Chapter IV not only broadens the scope of the evaluation but also explores the model's applicability in assessing the effects of winter cover crops, like rye, and controlled drainage on P loading in tile-drained agricultural fields, thereby enhancing the understanding of its performance across diverse agricultural environments.

Part of the manuscript was presented at the annual meeting of the Conservation Drainage Network 2023, Maryland, USA. The full chapter has been submitted to the special issue of Journal of Environmental Quality and is currently under review.

CHAPTER IV

USING RZWQM2-P TO CAPTURE TILE DRAINAGE PHOSPHORUS DYNAMICS IN OHIO

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Abstract

Phosphorus (P) loading from tile-drained agricultural lands is linked to water quality and aquatic ecosystem degradation. Extending Dr. Andrew Sharpley and colleagues' foundational work on environmental risk assessment tools like EPIC and SurPhos, the RZWQM-P model was developed to simulate the fate and transport of P in soil-water-plant systems, especially in tile-drained croplands. Comprehensive evaluation and application of RZWQM2-P, however, remains limited. This study evaluates RZWQM2-P in simulating P dynamics using extensive data and assesses the potential of management practices for mitigating P losses. Subsurface drainage and surface runoff flows were monitored at a tile-drained site from 2017 to 2020 in Ohio, and the water flow and P loss data were summarized on a daily basis. RZWQM2-P was calibrated and validated using those observed data and was subsequently used to assess the effectiveness of controlled drainage and winter cover crops in reducing P losses. The model satisfactorily simulated dissolved reactive P (DRP) loss from tile drainage on daily and monthly bases (NSE = 0.50, R^2 = 0.52, IOA = 0.84 for daily; NSE = 0.73, R^2 = 0.78, IOA = 0.94 for monthly) and total P (TP) loss on a monthly basis (NSE = 0.64, R^2 = 0.65, IOA = 0.88), but the daily TP simulation was less accurate (NSE = 0.30, R^2 = 0.30, IOA = 0.59). Simulations showed that winter rye cover crops reduced DRP by 16% and

TP by 4% compared to the base scenario, whereas controlled drainage increased DRP (60%-129%) and TP (5%-17%) losses at three tested outlet elevations compared to free drainage. RZWQM2-P can capture P dynamics in tile-drained cropland and is a promising tool for effective P management.

Keywords: CD, Controlled Drainage; CC, Cover Crop; DRP, dissolved reactive phosphorus; EOF, Edge-of-field; ET, Evapotranspiration; IoA, Index of Agreement; NSE, Nash-Sutcliffe Efficiency; PBIAS, Percent Bias; PP, Particulate Phosphorus; R^2, Coefficient of Determination; STP, Soil Test Phosphorus; TP, Total Phosphorus; USLE, Universal Soil Loss Equation.

4.1. Introduction

Phosphorus (P) is a vital macronutrient for plants, playing a crucial role in biological processes such as Adenosine Triphosphate (ATP)-mediated energy transfer, root development, nutrient absorption, and photosynthesis (Khan et al., 2023; Mitran et al., 2018). Consequently, it is widely used in agriculture to increase crop yields (Sharpley et al., 2001). Indeed, between 1961 and 2013 there was a fivefold growth in worldwide agricultural P consumption with a significant transition from farm-produced waste to industrially produced P fertilizers, indicating a marked change in P usage patterns (Chen & Graedel, 2016). Despite its necessity in agricultural crop production, P misuse or overapplication has environmental consequences (Sharpley et al., 2000; Sharpley et al., 2015). The use of artificial tile drainage systems further exacerbates the downstream water quality issues associated with P loss. For example, P loading via subsurface pathways in the Lake Erie Basin watershed have been tied to the reoccurrence of algal blooms in Lake Erie (Smith et al., 2015), particularly the 'bioavailable' fraction which is primarily dissolved P (Macrae et al., 2021). Tile drainage has been reported to contribute upwards of 50% of the P load in some poorly drained watersheds (King et al., 2015; Smith et al., 2015). Thus, addressing both surface and subsurface agricultural P load is necessary to meet water quality goals (Algoazany et al., 2007; Sims et al., 1998). Sharpley et al. (2006) emphasized the need for a consolidated, scientific approach to identifying and evaluating management practices for reducing P loss.

Identifying and evaluating P focused management practices that can address surface and/or subsurface losses can be accomplished through extensive long-term experiments at the plot and field scale or through rigorous modeling assessments (Morel et al., 2014; Sadhukhan, 2021). However, lengthy field experiments are often both time-consuming and financially demanding, often limiting their practicality (Shokrana et al., 2022; Thorp et al., 2007; Youssef & Skaggs, 2006). Field-scale models offer a robust alternative (Singh et al., 2022), serving as an invaluable tool for the expeditious and cost-effective assessment of management practices. Modeling tools can inform farmers and policymakers, enabling tailored selection of management practices that are economically viable and congruent with specific soil types and field conditions (Pan et al., 2023b).

P modeling in agriculture has evolved from the foundational P-index concept, a simple but effective tool for assessing P loss risk from runoff, extensively explored in Sharpley et al.'s work

(Sharpley, 1995; Sharpley et al., 2012; Sharpley et al., 1993; Sharpley et al., 2003). Notable advancements in the field began with the development of process-based simulation models in the early 1980s, exemplified by the Erosion Prediction Impact Calculator [EPIC (Williams et al., 1984)], which stood as a pioneering effort in field-scale P modeling (Jones et al., 1984; Sharpley et al., 1984). These efforts laid the groundwork for more advanced and process-based models that capture the complexity of P dynamics in agricultural systems. The latest models account for various pathways, including surface runoff, tile drainage, and macropore flow, and P forms such as dissolved reactive phosphorus (DRP) and particulate phosphorus (PP). They also consider P uptake by plants and soil P transformations, as discussed in recent works by Sadhukhan et al. (2019a) and Askar et al., (2021a). The culmination of this evolution is seen in sophisticated models like RZWQM2-P (Sadhukhan et al., 2019a) and DRAINMOD-P (Askar et al., 2021a), which integrates all the above outlined aspects, representing the depth required for effective P management in contemporary agricultural systems.

In this study, we focus exclusively on testing and application of the newly developed RZWQM2-P model. Although, RZWQM2-P was tested and validated by its developers (Sadhukhan et al., 2019a; Sadhukhan et al., 2019b), comprehensive evaluation with daily P loss data, as well as assessment of management practices on P loss, remain limited. Only two previous studies have assessed this model using daily P data, and it found that the model inadequately predicted daily DRP losses via tile drainage. Therefore, the objectives of this study are: 1) to test the RZWQM2-P model in simulating both daily and monthly DRP and TP loss using daily P loss data; and 2) to evaluate the impact of various management practices following successful model validation.

4.2. Materials and Methods

4.2.1. Overview of RZWQM2-P model

The advanced, one-dimensional RZWQM2 model (version 4.3) is capable of simulating a comprehensive range of processes at the field scale, including hydrology; fate and transport of nutrients, pesticides, and ions; soil heat flux; soil erosion and crop growth under various management practices (Ahuja et al., 2000). The recently built P module, which upgraded the model to RZWQM2-P, can predict both DRP and PP losses associated with surface runoff, tile drainage, and macropores, as well as P transformations within the soil matrix, and the dynamics of soil P resulting from fertilizer or manure applications (Sadhukhan et al., 2019a).

The P module is constructed based on the framework of the EPIC model (Jones et al., 1984; Sharpley et al., 1984), which identifies five distinct soil P pools: Labile P (Lab^{P}), Stable Inorganic P ($Stab^{IP}$), Active Inorganic P (Act^{IP}), Fresh Organic P ($Fres^{OP}$), and Stable Organic P ($Stab^{OP}$) (Sadhukhan et al., 2019a). The model incorporates absorption and desorption processes between inorganic P pools to maintain equilibrium, as well as decomposition and mineralization processes for organic P pools. A key enhancement in the RZWQM2-P model is the inclusion of additional P pools specifically designed for management practices. These consist of two surface pools for fertilizer-derived phosphorus and four pools for manure-derived phosphorus which were adopted from Surphos (Vadas et al., 2007; Vadas, 2014), thereby augmenting the model's predictive capacity for phosphorus dynamics following the application of either fertilizer or manure. Such refinements are crucial, as significant research has emphasized the importance of distinguishing between different P sources, as their behavior and transport pathways can vary significantly (Kleinman et al., 2002; Sharpley et al., 1998; Sharpley et al., 2011). The model simulates phosphorus dynamics in agricultural fields more accurately by considering leaching and decomposition from these pools. The model's predictive accuracy for P loss via soil matrix is enhanced by incorporating recommendations derived from various studies (Francesconi et al., 2016; Jarvis et al., 1999; Larsson et al., 2007). Also, to simulate P loss via subsurface drainage, the model adopts a linear groundwater reservoir-based approach (Steenhuis et al., 1997), which calculates a daily mass balance while considering both matrix and macropore flow processes for DRP, and only macropore flow for PP. Additionally, recent updates to the RZWQM2-P model have modified both the soil P partitioning and the tillage effect on P mixing (Pan et al., 2023a; 2023b).

4.2.2. Site description

Four years (2017 through 2020) of surface and subsurface data were secured from a privately owned field located in Hardin County, Ohio (Figure 4.1). The field site is part of the USDA-ARS

Edge-of-field (EOF) research network designed to quantify the role of agriculture in P loss and transport as well as identify management practices that minimize that loss (Williams et al., 2016). The dominant soil type at this site is Blount silt loam, characterized as a somewhat poorly drained soil. The field features a gentle slope of approximately 2%, with a tile spacing of ~900 cm (30 feet) and an average tile depth of ~90 cm (3 feet). The site contains distinct measurement points for subsurface drainage and surface runoff, resulting in different total contributing areas for subsurface drainage (13.5 ha) and surface runoff (7.1 ha). The experimental field was planted with corn (Zea mays L.) in 2017, followed by three consecutive years of soybean [Glycine max (L.) Merr.] cultivation. The producer also applied inorganic fertilizers periodically to maintain soil fertility. During the autumn of 2017, a rye (Secale cereale L.) cover crop was sown via aerial application amidst the standing corn in the field. Periodic tilling was carried out using a chisel plough, followed by disking to smooth the ground. Soil sample analysis conducted in 2016 revealed that the average soil test P (STP) concentration, using the Mehlich-3 method, was 30 mg kg^{-1} for the upper 5 cm layer of soil at this site. A comprehensive overview of the site management and cropping data can be found in Supplementary Table S4.1.

Hydrology, water quality and subsequent laboratory analysis were completed using methods previously outlined (Ford et al., 2017; King et al., 2015; Pease et al., 2018). Briefly, the volume of water discharged from surface runoff was estimated using ISCO 4230 Bubbler Flow meters to collect stage data within a control volume (H-flume for surface runoff and compound weir for tile drainage) and applying standard stage-discharge relationships. An ISCO 2150 Area-Velocity Sensor was also installed in the tile drainage outlet pipe to facilitate discharge measurement under submerged conditions. For surface runoff, a flow-proportional sampling approach whereby a 200 mL aliquot was collected for every 1 mm of volumetric water depth from the 7.1 ha area flowing through the H-flume. Ten aliquots were combined into a single bottle. A time-proportional approach was used for tile-drainage, where 100 mL aliquots were collected every 6 hours, with eight samples combined into a single bottle forming a two-day composite. The 2-day composite samples were supplemented with additional samples collected around events that were based on the rate of change in stage. All samples were vacuum filtered through a 0.45 μm filter and assessed for DRP via the colorimetric method described by Murphy and Riley (1962). Unfiltered samples were evaluated for TP following the alkaline persulfate oxidation and techniques detailed by Patton and Kryskalla (2003).

Precipitation data was collected on-site at 10-minute intervals using a tipping bucket rain gauge (Teledyne Isco, Lincoln, NE). For all other weather information was obtained from the OARDC weather station in Hoytville, Wood County (~37 miles from the field). Soil information, specifically hydraulic conductivity, soil texture, soil bulk density, saturated water content, water content at field capacity were obtained from the SSURGO database (Table 4.1).

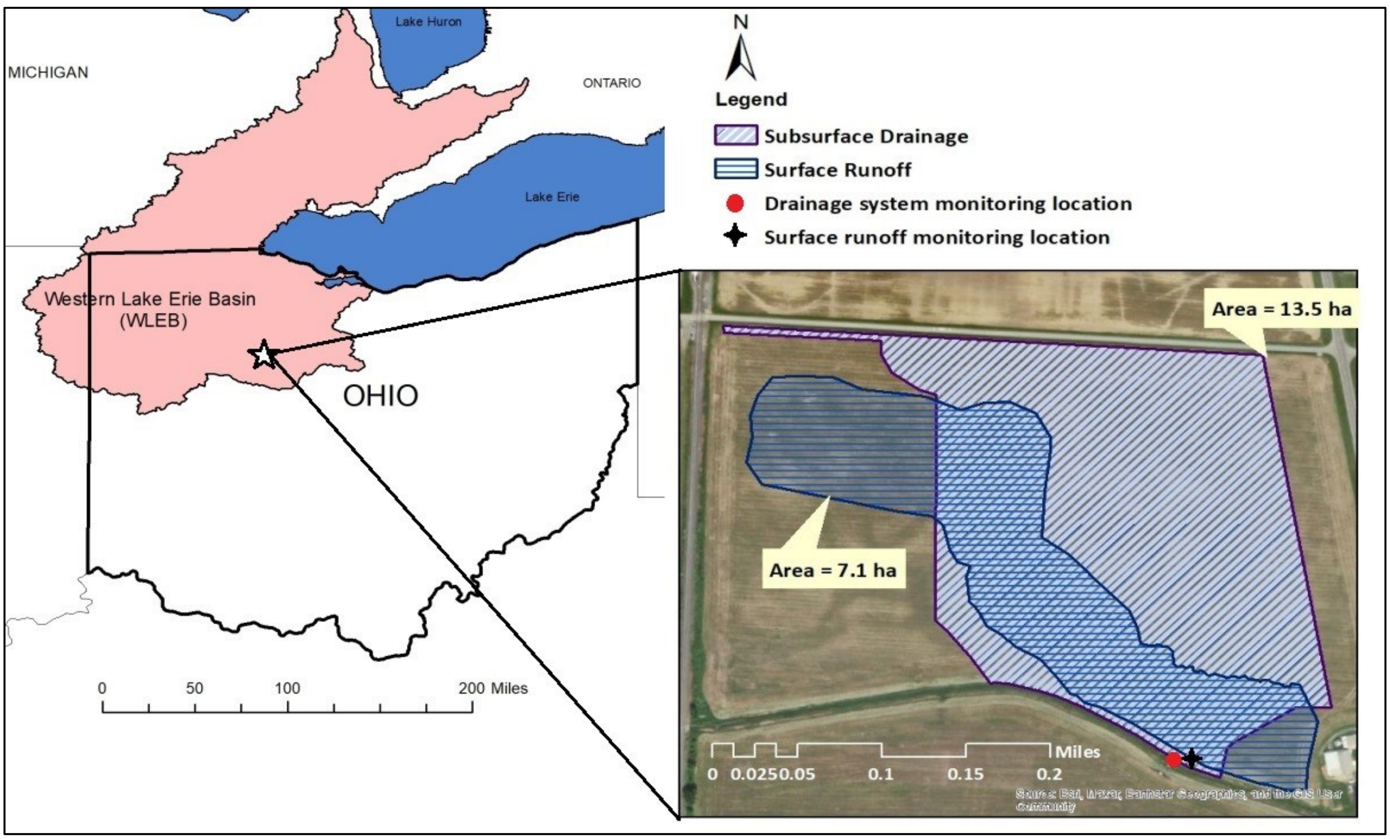

Figure 4. 1 Layout of the monitored field within the Western Lake Erin Basin.

Table 4. 1 Observed and calibrated properties of the soils at the monitored field in Ohio.

Soil Layer Depth	-----------*Initial soil properties[a]----------						#Calibrated soil hydraulic properties				------##Calibrated macropore parameters------					
	ρ	Sand	Silt	Clay	Θ_r[b]	Θ_s	P_b	λ	K_{sat}	Lk_{sat}	M	FM	CP	WC	LC	DC
cm	g cm^{-3}	------------%------------			---cm^3 cm^{-3}---		cm	-	-----cm h^{-1}-----		-	-	----------------cm----------------			
0-5	1.45	23	56	21	0.015	0.45	-30	0.2	1.8	3	0.312	0	0.1	0	0	0
5-15	1.45	23	56	21	0.015	0.45	-30	0.1	1.8	3	0.552	0.5	0	0.05	10	10
15-30	1.45	23	56	21	0.015	0.45	-33	0.3	1.5	3	0.187	0.5	0	0.05	10	10
30-60	1.55	18	43	39	0.075	0.42	-39	0.1	0.6	1.2	0.633	0.5	0	0.05	10	10
60-90	1.80	21	40	39	0.075	0.32	-29.6	0.1	0.2	0.4	0.645	0.5	0	0.05	10	10
90-150	1.90	24	43	33	0.075	0.28	-29.9	0.1	0.01	1.1	0.660	0.5	0	0.05	10	10
150-200	1.90	24	43	33	0.075	0.28	-29	0.1	0.01	0.1	0.658	0.5	0	0.05	10	10

***[a] data source-SSURGO database; ρ, Bulk Density; Sand, soil sand content; Silt, soil silt content; Clay, soil clay content; ϴr, Residual water content; [b] data source-RZWMQ2 parameterization guide; ϴs, Saturated water content. # Pb, Soil bubbling pressure; λ, Pore size distribution index; Ksat, Saturated conductivity; Lksat, Lateral saturated conductivity. ## M, Fraction Microporosity; FM; Fraction dead-end macropores; CP, Average radius of cylindrical pores; WC, Width of cracks; LC, Length of cracks; DC, Depth of cracks.**

4.2.3. Model calibration

Calibration using two years of data (2017 through 2018) was completed by initially adjusting parameters associated with tile drainage, runoff, ET, and crop yields, followed by fine-tuning P related parameters. With respect to hydrology, observed data were available for both surface runoff and tile drainage; however, the focus was given to tile drainage given the primary contribution from that pathway (Pease et al., 2018).

Soil hydraulic parameters such as soil bubbling pressure (P_b), air pore index (λ), saturated hydraulic conductivity (K_{sat}) and lateral hydraulic conductivity (Lk_{sat}) significantly influence tile drainage simulation. Initial values for K_{sat} were set layer-wise based on SSURGO database, and then fine-tuned to align with observed tile drainage. It should be noted that K_{sat} values in the upper soil layer also affect surface runoff simulation. For P_b, initial values were derived from guidelines provided by (Ma et al., 2011), and subsequently calibrated to increase soil infiltration rates. Our observations suggest that as the value of P_b becomes less negative, approaching zero, the rate of soil infiltration increases, which in turn reduces surface runoff and elevates tile drainage. Sensitivity analyses revealed that upper layer values of P_b have a greater impact than those in the lower layers. The albedo parameters were adjusted to ensure that the model's annual estimates of ET corresponded with observed annual ET values for this region in Ohio, as documented in previous studies. A complete list of these calibrated parameters can be found in Tables 4.1 and 4.2. Crop-specific parameters were calibrated to ensure that simulated yields corresponded with observed yields (Supplementary Table S4.2). For rye, the field-measured seeding rate was unavailable. Therefore, a seeding rate of 3738000 seeds ha^{-1} was adopted, aligning closely with figures reported by Qi et al. (2011). This study also incorporated most of the calibrated parameters from Qi et al. (2011) to simulate rye yields. Comprehensive data on the calibrated parameters for soybean, corn, and rye can be found in Supplementary Table S4.2.

Following the successful alignment of simulated tile drainage and crop yields with observed data, and the matching of ET and surface runoff values with those reported in existing literature, the calibration of P parameters was undertaken. Initial level of DRP and PP in the groundwater reservoir were found to significantly influence the accurate simulation of phosphorus loss via tile drainage. Key P parameters such as the replenishment rate coefficient, detachability coefficient, filtration coefficient, and phosphorus extraction coefficient also played pivotal roles.

Initial values for these parameters were adopted from values provided by Sadhukhan et al., (2019a). It was observed that increasing the replenishment rate and detachability coefficients led to increased PP loss through tile drainage. Another critical factor in accurately predicting DRP and PP loads through tile drainage during high-peak events involves the adjustment of macropore parameters and the precise calibration of total microporosity. Sensitivity to the phosphorus extraction coefficient was specifically noted for DRP runoff, whereas erosion parameters affected PP loss through runoff. During the calibration process for P loading from runoff, the aforementioned parameters were fine-tuned to ensure that the model's predicted cumulative P losses closely aligned with the observed data. Comprehensive details on calibrated P parameters are provided in Table 4.2.

In our model assessment, we used four key performance metrics: Nash-Sutcliffe Efficiency (NSE), Coefficient of Determination (R^2), Index of Agreement (IOA), and Percent Bias (PBIAS). Model performance was categorized into four categories: "very good," "good," "satisfactory," or "unsatisfactory" based on established guidelines by Moriasi et al. (2007; 2015). For detailed criteria of these categories, refer to the Supplementary Table S4.3.

4.2.4. Model application

Following the calibration of the RZWQM2-P model, it was employed to investigate the influence of two specific management practices on phosphorus (P) loss from the tile-drained field. The practices under consideration included Controlled Drainage (CD) and Winter Cover Crop Rye (CC). For comparative analysis, a base scenario (BS) was defined, corresponding to the calibrated and validated model settings that feature conventional tillage (chisel plough followed by disking) and incorporated broadcast fertilizer application, as practiced in the field under study. For the CC scenario, the model was configured to include rye as a cover crop for the years 2018, 2019, and 2020, in addition to the year 2017 during which rye was actually grown in the field. Within the model, rye was planted in the fall following the harvest and terminated just prior to the subsequent summer's crop planting. Lastly, in the CD scenario, three sub-scenarios were examined, each characterized by a distinct outlet elevation below the soil surface. The chosen outlet elevations were 30 cm, 45 cm, and 60 cm for non-growing seasons, and 70 cm for growing seasons. The selection of these specific outlet elevations was guided by the recommendations of Youssef et al. (2023). Their study suggested that maintaining outlet elevations between 45 and 70 cm is conducive to optimal root zone aeration, which in turn has a direct impact on plant water uptake (Shokrana et al., 2023; Youssef et al., 2023).

Table 4. 2 Detailed overview of calibrated hydrological and phosphorus loss parameters with their calibrated values and default values.

Input Parameter	Calibrated Value	Default Value
Hydraulic parameters		
Lateral hydraulic gradient (dh dl^{-1})	0.00001	0.0001
Water table leakage rate (cm hr^{-1})	0	-
P parameters		
Initial DRP in groundwater (GW) reservoir (Kg ha^{-1})	3.01	25
Initial PP in groundwater (GW) reservoir (Kg ha^{-1})	25	25
Replenishment rate coefficient (g m^{-2} d^{-1})	2	1
Detachability coefficient (g J^{-1} mm^{-1})	0.6	1
Filtration coefficient (m^{-1})	0.06	1
P Extraction coefficient (unitless)	21	1
Plant P uptake distribution parameter (unitless)		
Corn	3	10
Soybean	3	10
Rye	10	10
Minimum Leaf Stomatal Resistance (s m^{-1})		
Corn	130	200
Soybean	150	200
Rye	130	200
ET parameters		
Albedo of crop at maturity (unitless)	0.47	0.43
Albedo of fresh residue (unitless)	0.35	0.4
Albedo of wet soil (unitless)	0.07	0.2
Albedo of dry soil (unitless)	0.07	0.3
Surface soil resistance for the S-W PET (s m^{-1})	200	37
USLE Coefficients		
Contouring factor for overland flow profile segment (PFACT)	0.01	0.01
Soil loss ratio for overland flow profile segment (CFACT)	0.41	0.01
Manning's n (NFACT)	0.19	0.01

4.3. Results

4.3.1. Hydrology

The model's performance in predicting tile drainage was good, as indicated by a monthly NSE of 0.70, R^2 of 0.80, IOA of 0.94, and a PBIAS of -6%. Daily assessments were also satisfactory, yielding an NSE of 0.57, R^2 of 0.63, IOA of 0.88 and PBIAS of -6%. A comparison of observed and model-predicted average annual water outflows from subsurface drainage over a four-year period — 27.6 cm and 29.2 cm, respectively —corroborates the good match. A thorough statistical evaluation, conducted on a daily and monthly basis for the calibration and validation phases, is presented in Table 4.3. Additionally, graphical representations of both observed and predicted daily tile drainage and monthly drainage discharge are presented in Figure 4.2. In this study, the RZWQM2-P model overpredicted runoff, yielding an average annual value of 6.5 cm, which is considerably higher than the observed values of 1.3 cm. Nevertheless, it is noteworthy that the model's prediction is closer to the other modelling studying done in Ohio and Mid-West US (Shedekar, 2016; Youssef et al., 2018). The predicted ET (60.8 cm) accounts for approximately 60% of the observed annual precipitation (102 cm). Additionally, the model estimates an annual average seepage of around 5 cm, constituting about 5% of the observed precipitation. These predictions for both ET and seepage align well with findings from previous studies conducted in the Midwestern US and Ohio specifically (Askar, 2019; Askar et al., 2021b; Shedekar, 2016; Youssef et al., 2018).

4.3.2. Dissolved reactive and total phosphorus loss

The RZWQM2-P model demonstrated very good performance in predicting monthly dissolved reactive phosphorus ($DRP_{monthly}$) as evidenced by an PBIAS = -3%, NSE = 0.73, R^2 = 0.78, and IOA = 0.94. The model also provided satisfactory results for daily DRP predictions (DRP_{daily}) with an NSE = 0.50, R^2 = 0.52, and IOA = 0.84, alongside a PBIAS of -3%. This study is particularly noteworthy as it marks only the third time where RZWQM2-P has undergone evaluation against daily P loss data, and it is the first study in which the model has yielded accurate predictions for DRP_{daily} (Figure 4.3A and Table 4.3). Turning to TP, the model exhibited good performance (Table 4.3) in predicting monthly TP ($TP_{monthly}$), as indicated by an NSE of 0.64, R^2 of 0.65, IOA of 0.88, and a PBIAS of 9%. In contrast, the model's ability to predict daily TP (TP_{daily}) (Figure 4.3B) was unsatisfactory (with NSE = 0.30, R^2 = 0.30, and IOA = 0.59). Regarding cumulative DRP loading (Figure 4.3C), the model's NSE values of 0.96 for drainage, 0.78 for runoff, and 0.94 for the combined total (runoff + drainage) underscore its very good performance. In cumulative TP loading (Figure 4.3D), the model performed well with an NSE of 0.96 for drainage and 0.91 for the combined total of runoff and drainage. However, its performance was unsatisfactory for runoff, with an NSE of 0.27. Given that our model overestimated runoff, this discrepancy also impacted our predictions for runoff P loading. Consequently, during calibration, our primary aim was to align the model's total P loading predictions as closely as possible with the observed total P load from runoff. The model predicted a four-year total DRP from runoff of 71.9 g ha^{-1}, compared to the observed value of 59.7 g ha^{-1}. Similarly, the predicted total TP from runoff over the four-year period was 432.4 g ha^{-1}, in contrast to the observed 387.3 g ha^{-1}. It is also important to highlight that the model closely aligns with observed data in identifying tile drainage as the principal pathway for nutrient loss. Specifically, the model attributes 66% of total DRP and 76% of total TP losses through subsurface drainage, closely matching the observed values of 70% and 80%, respectively.

4.3.3. Model application

Among the two agricultural management practices examined winter cover cropping with rye (CC) reduced total DRP losses (runoff + drainage) and TP losses (runoff + drainage) by 16% and 4%, respectively. Importantly, these reductions were predominantly observed in P losses from surface runoff, rather than from tile drainage. For instance, surface runoff bound DRP declined by 31%, while DRP losses through tile drainage experienced a modest decrease of 8%. Further, CC had a minimal impact on TP losses via tile drainage, registering only a 3% reduction. Controlled drainage (CD) was assessed using three different outlet elevations. Our findings indicate an inverse relationship between outlet depth and P losses; deeper outlets corresponded with fewer losses. However, each elevation still showed increased P losses compared to the BS, largely due to elevated annual runoff volumes. For instance, the outlet elevation strategy of 30 cm in the growing season and 70 cm in the non-growing season led to a 17% rise in TP losses (runoff + drainage). In contrast, elevations of 45 cm and 60 cm during the growing season, while maintaining a 70 cm elevation during the non-growing season, led to comparatively restrained increases in TP losses (runoff + drainage): 8% and 5%, respectively. Notably, DRP losses were significantly higher than

TP losses, with the 30 cm elevation causing a 129% surge in DRP losses (from both runoff and drainage), in comparison to the increases of 90% and 60% for the 45 cm and 60 cm elevations, respectively. A detailed representation of the findings for both management scenarios is illustrated in Figure 4.4A and 4.4B.

Table 4. 3 Comparative analysis of observed and predicted annual drainage discharge, DRP, and TP loads with model performance statistics across all years.

Period	Year	Drainage								
		Observed	**Predicted**	**NSE_{daily}**	**R^2_{daily}**	**IOA_{daily}**	**NSE_{mon}**	**R^2_{mon}**	**IOA_{mon}**	**PBIAS**
		------------cm-----------								
Calibration	2017	25.5	24.5	0.71	0.73	0.92	0.73	0.83	0.94	4%
	2018	31.4	33.5	0.51	0.58	0.87	0.46	0.65	0.88	-7%
Validation	2019	28.2	32.9	0.57	0.67	0.89	0.82	0.91	0.96	-17%
	2020	25.4	25.8	0.49	0.55	0.85	0.76	0.81	0.94	-1%
All Period	2017-2020	**110.4**	**116.8**	**0.57**	**0.63**	**0.88**	**0.70**	**0.80**	**0.94**	**-6%**
Calibration Period	2017-2018	**56.8**	**58.0**	**0.60**	**0.64**	**0.89**	**0.59**	**0.74**	**0.91**	**-2%**
Validation Period	2019-2020	**53.6**	**58.8**	**0.53**	**0.61**	**0.87**	**0.79**	**0.86**	**0.95**	**-10%**
Period	Year	**DRP load (drainage)**								
		Observed	**Predicted**	**NSE_{daily}**	**R^2_{daily}**	**IOA_{daily}**	**NSE_{mon}**	**R^2_{mon}**	**IOA_{mon}**	**PBIAS**
		----------g ha^{-1}----------								
Calibration	2017	29.8	34.9	0.48	0.54	0.85	0.66	0.84	0.93	-17%
	2018	36.1	41.5	0.44	0.50	0.83	0.51	0.68	0.89	-15%
Validation	2019	39.9	40.2	0.54	0.54	0.84	0.84	0.84	0.96	-1%
	2020	31.8	24.7	0.54	0.56	0.82	0.82	0.89	0.96	22%
All Period	2017-2020	**137.6**	**141.3**	**0.50**	**0.52**	**0.84**	**0.73**	**0.78**	**0.94**	**-3%**
Calibration Period	2017-2018	**65.9**	**76.4**	**0.46**	**0.52**	**0.84**	**0.59**	**0.76**	**0.91**	**-16%**
Validation Period	2019-2020	**71.7**	**64.9**	**0.54**	**0.54**	**0.83**	**0.84**	**0.85**	**0.96**	**9%**
Period	Year	**TP load (drainage)**								
		Observed	**Predicted**	**NSE_{daily}**	**R^2_{daily}**	**IOA_{daily}**	**NSE_{mon}**	**R^2_{mon}**	**IOA_{mon}**	**PBIAS**
		----------g ha^{-1}----------								
Calibration	2017	457.9	327.5	0.27	0.30	0.53	0.70	0.82	0.88	28%
	2018	383.6	427.9	0.43	0.44	0.73	0.66	0.69	0.90	-12%
Validation	2019	302.7	388	0.41	0.42	0.76	0.64	0.77	0.92	-28%
	2020	405.2	263	0.20	0.24	0.44	0.47	0.60	0.81	35%
All Period	2017-2020	**1549.3**	**1406.4**	**0.30**	**0.30**	**0.59**	**0.64**	**0.65**	**0.88**	**9%**
Calibration Period	2017-2018	**841.5**	**755.4**	**0.32**	**0.34**	**0.61**	**0.69**	**0.71**	**0.89**	**10%**
Validation Period	2019-2020	**707.9**	**651**	**0.26**	**0.26**	**0.55**	**0.56**	**0.59**	**0.87**	**8%**

NSE_{daily}, Daily Nash-Sutcliffe Efficiency; R^2_{daily}, Daily Coefficient of Determination; IOA_{daily}, Daily Index of Agreement; NSE_{mon}, Monthly Nash-Sutcliffe Efficiency; R^2_{mon}, Monthly Coefficient of Determination; IOA_{mon}, Monthly Index of Agreement; PBIAS, **Percent Bias.**

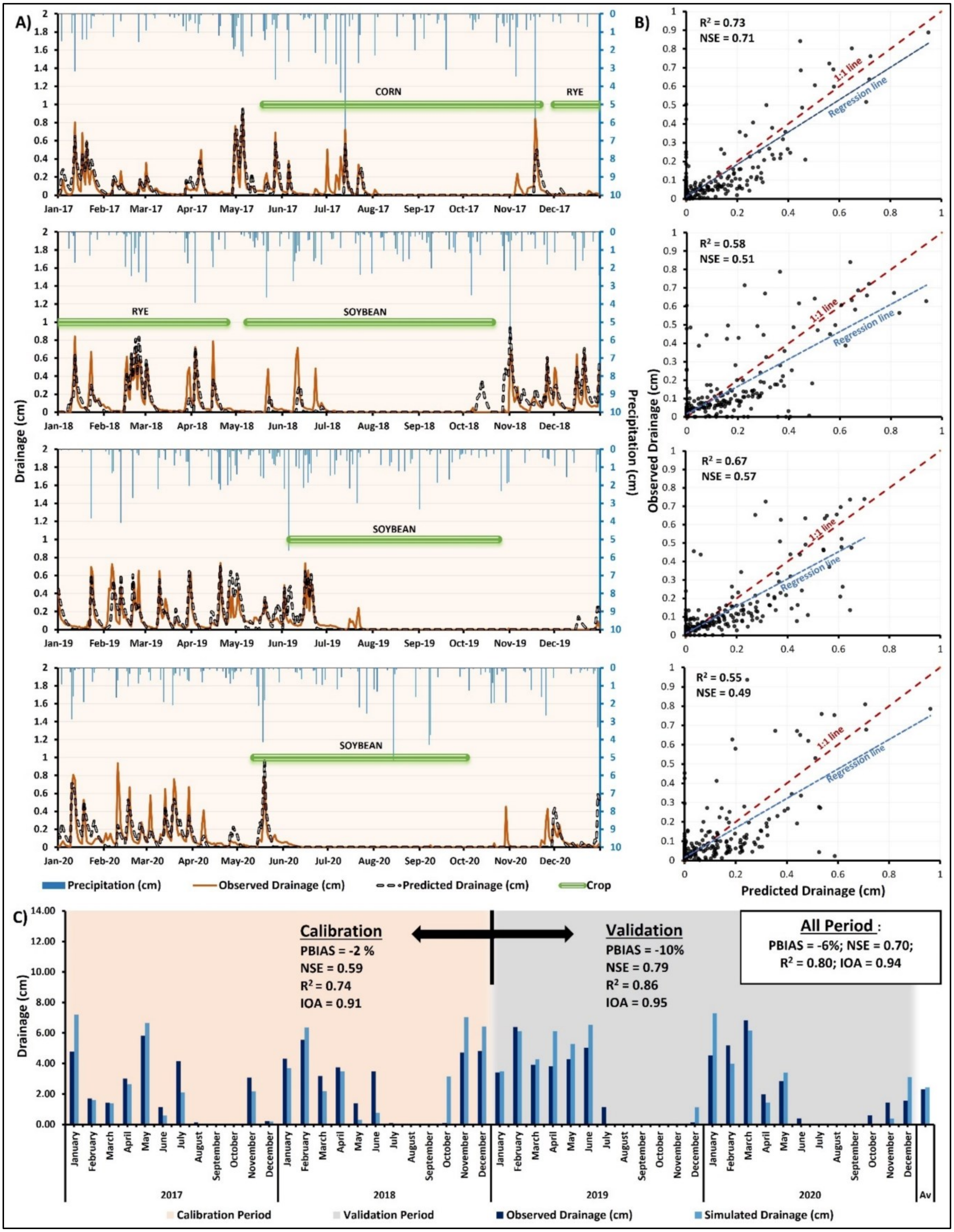

Figure 4. 2 A) The daily time series for both observed and predicted daily drainage discharge over the simulation period (2017-2020) are depicted. B) Corresponding xy scatter plots illustrate the observed versus predicted drainage discharge, including a 1:1 line. C) A comparative analysis of observed and predicted monthly tile drainage discharge for the simulation period (2017-2020) is presented, where 2017 and 2018 serve as calibration years, and 2019 and 2020 as validation years.

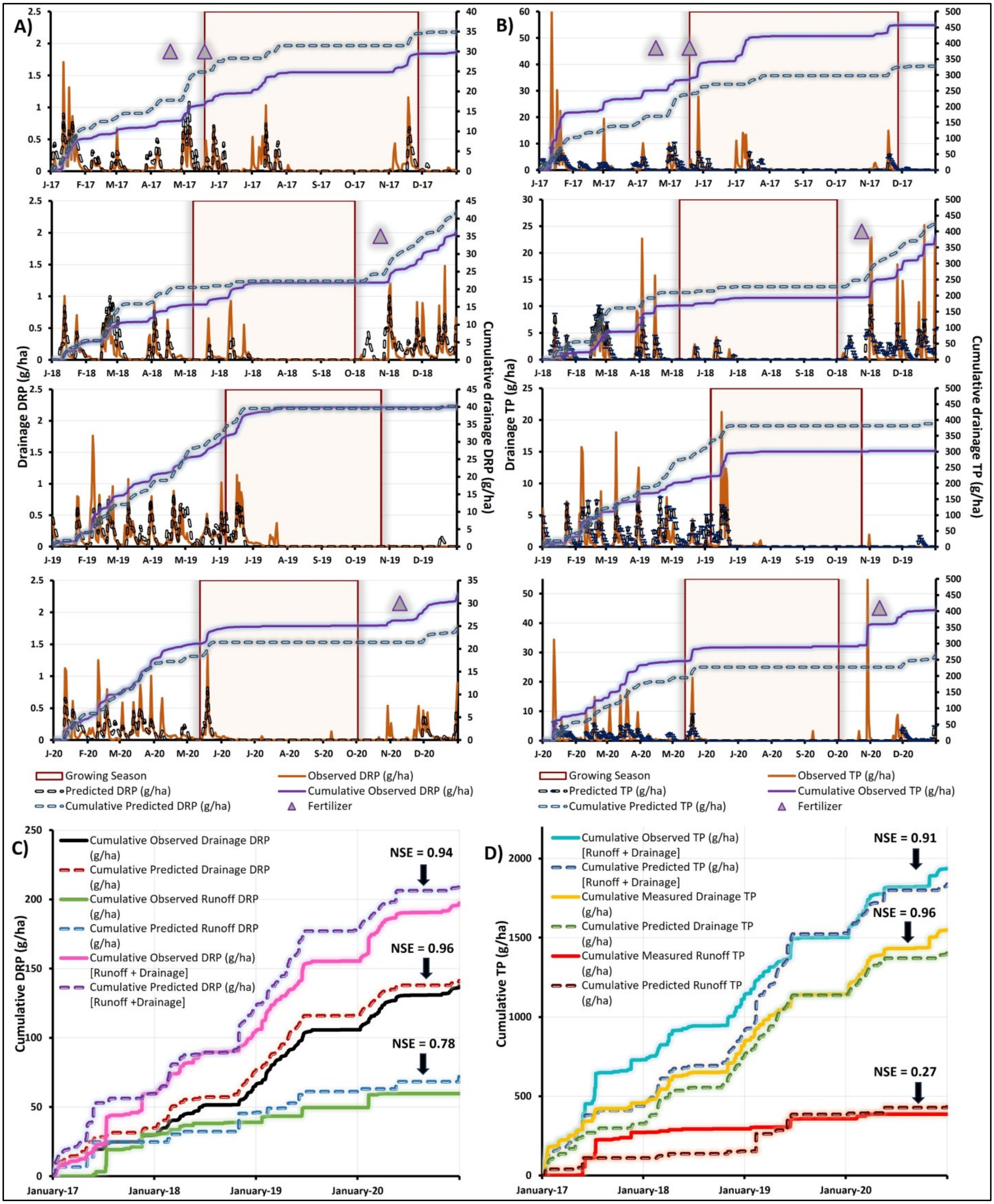

Figure 4. 3 A) Measured and predicted DRP losses through drainage discharge for the four-year simulation period (2017-2020). B) Measured and predicted daily and cumulative TP losses through drainage discharge for the same four-year period. C) Measured and predicted cumulative DRP load from surface runoff, drainage discharge, and the combined total (runoff + drainage) with corresponding NSE values. D) Measured and predicted cumulative TP load from surface runoff, drainage discharge, and the combined total (runoff + drainage) with corresponding NSE values.

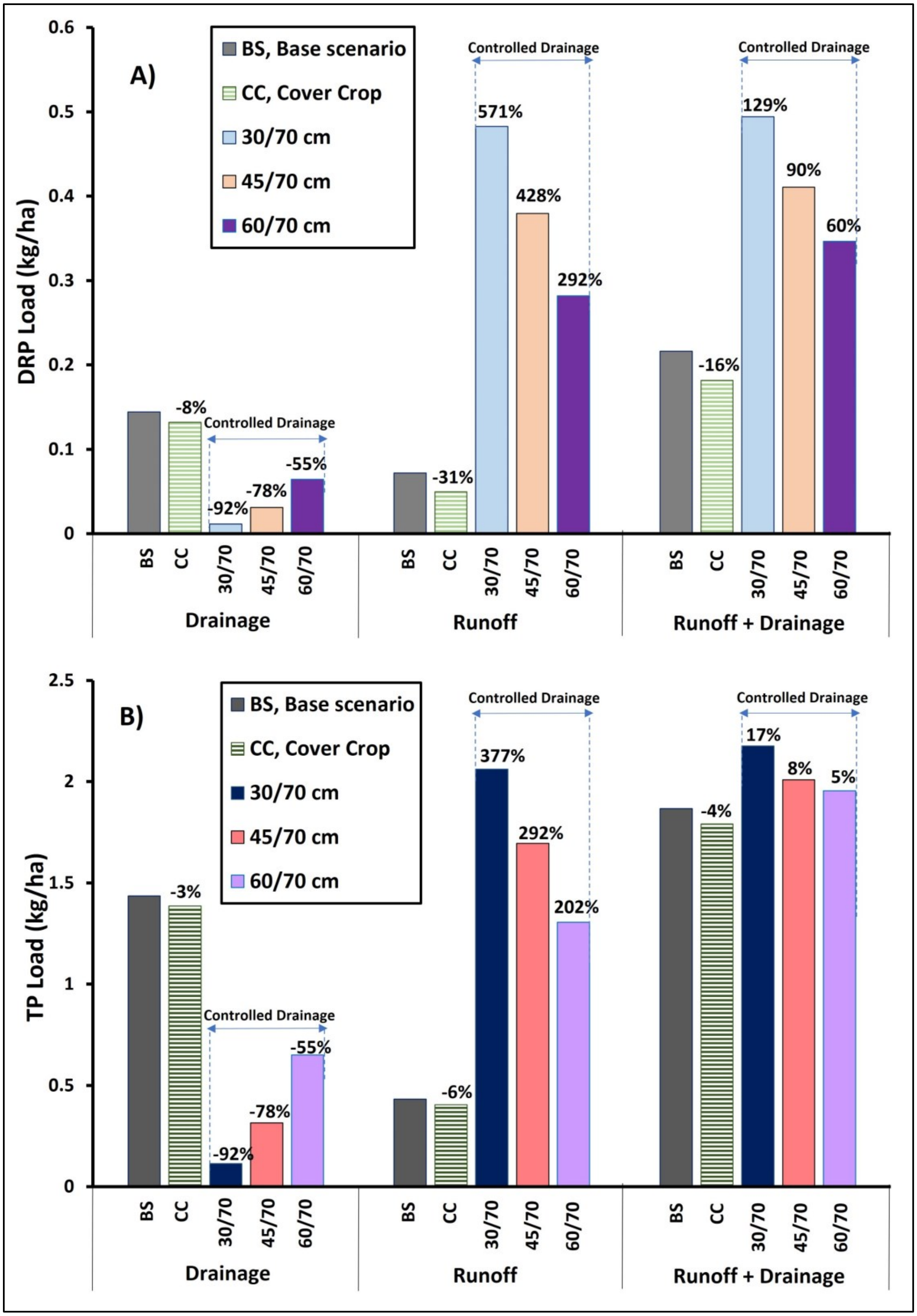

Figure 4. 4 Comparative analysis of Winter Cover Crop (CC) and Controlled Drainage [(CD) at varying outlet elevations (30/70 cm, 45/70 cm, and 60/70 cm)] on A) DRP Load and B) TP load relative to base scenario

4.4. Discussion

The RZWQM2-P model demonstrated a satisfactory performance to simulate P dynamics originating from the tile-drained field, except that simulation in daily TP losses through tile drainage was suboptimal (NSE = 0.30). This unsatisfactory performance on daily TP simulation can be attributed to two primary factors. First, inaccurate simulation of even one or two significant events can substantially affect the overall model performance. For instance, the model's failure to accurately predict two major TP events that occurred in January 2017 and November 2020 led to poor performance in these two years (Figure 4.3B and Table 4.3). However, in 2018 and 2019, the model successfully simulated all major events, achieving satisfactory daily NSE values of 0.43 and 0.41, respectively. This study represents only the third time on which the model's P component has been tested using daily P loss data. In the first study, Shokrana et al. (2022) postulated that the model's poor performance in predicting daily P losses through tile drainage could arise from its insensitivity to fertilizer application. We tested this hypothesis to determine whether it also affects the model's ability to simulate TP losses by modifying the fertilizer application rates in the model; specifically, we doubled the application amount (e.g., from 4.31 kg ha^{-1} to 8.62 kg ha^{-1} on April 18, 2017, and similarly doubled it on three other occasions when P was actually applied in the field). We found that the model adequately adjusted the P pools (Figure 4.5A and 4.5B). However, further testing of Shokrana et al.'s hypothesis is needed under ponding conditions as their study indicated that the model struggled to predict daily DRP particularly under these conditions (Shokrana et al., 2022).

The primary limitation appears to be the model's constant prediction of TP concentration over the four-year simulation period. The model predicted TP concentrations within a narrow range of 0.10 mg L^{-1} to 0.17 mg L^{-1}, while observed TP concentrations fluctuated between 0 and 1 mg L^{-1} and peaked at around 4 mg L^{-1} on specific occasions (Figure 4.5C). Given that the TP load in subsurface drainage is a product of water flow and TP concentration, the model's inability to capture changes in concentration led to an underestimation of P loading during high-load events. Consistent with our findings, Shokrana et al. (2022) also failed to capture the high peaks of TP load in their study. Thus, future research should prioritize refining this aspect of the model to enhance its predictive accuracy for P dynamics during high-flow and high-load events.

The implementation of winter cover cropping with rye (CC) emerged as a viable strategy for mitigating P losses in our agricultural management scenarios. While CC was notably effective in curtailing DRP levels in surface runoff, its influence on DRP and TP losses via tile drainage was less significant. These findings align with a recent study conducted within the EOF network, a research collective to which our study site also belongs, which reported negligible effects of cover cropping (mustard, in their case) on DRP and TP losses through tile drainage (Askar et al., 2023). In our simulations, however, we did observe some reductions in tile drainage P losses, amounting to 8% for DRP and 3% for TP over a four-year period. A potential explanatory factor for these reductions could be the lower initial soil test phosphorus (STP) levels in our field (30 mg kg^{-1}) compared to the field in the aforementioned study (61 mg kg^{-1}) (Askar et al., 2023), as various studies suggest that the initial P pool may modulate the effectiveness of management practices over time (Askar et al., 2023; Pease et al., 2018). Also, previous research has highlighted the substantial impact of rainfall on the effectiveness of cover crops in reducing TP losses; high rainfall can significantly affect the efficacy of cover crops (Askar et al., 2023; Neumann et al., 2012). Askar et al. (2023) suggested that the negligible impact of cover crops on TP losses in their study might be attributed to higher-than-average precipitation during the treatment years as opposed to years without cover crop treatment. In line with these findings, in our simulation, the final year (2020) experienced notably lower precipitation (89 cm) compared to the average (106 cm) of the preceding three years. This reduction in precipitation coincided with the only year where cover cropping decreased TP losses via tile drainage.

In the context of controlled drainage (CD), our simulations reveal an increase in P losses (runoff + drainage) at all tested outlet elevations, however at a lesser rate for deeper elevations. This finding is consistent with a prior modelling study conducted by Sadhukhan et al. (2019b), which observed a 13% rise in total P losses at a 46 cm outlet elevation for CD. On the other hand, research by Tan and Zhang (2011) reported a decrease in P losses with CD. It is important to note the difference in precipitation levels between these studies, which may account for the contrasting results: Tan and Zhang (2011) study area received 78 cm of rain, whereas Sadhukhan et al. (2019b) worked with 91 cm. Given this, Sadhukhan et al. (2019b) cautioned against using CD in areas with high precipitation. This guidance appears to be applicable to our simulations as well, which featured an average annual rainfall of 102 cm, thereby suggesting that frequent rainfall events can exacerbate runoff and associated P losses, ultimately elevating the total P load from the field. Our results add that in high-rainfall areas, employing CD at deeper outlet elevations might mitigate this runoff increment. However, to substantiate this conclusion, further research is warranted across different soil types and varying levels of rainfall.

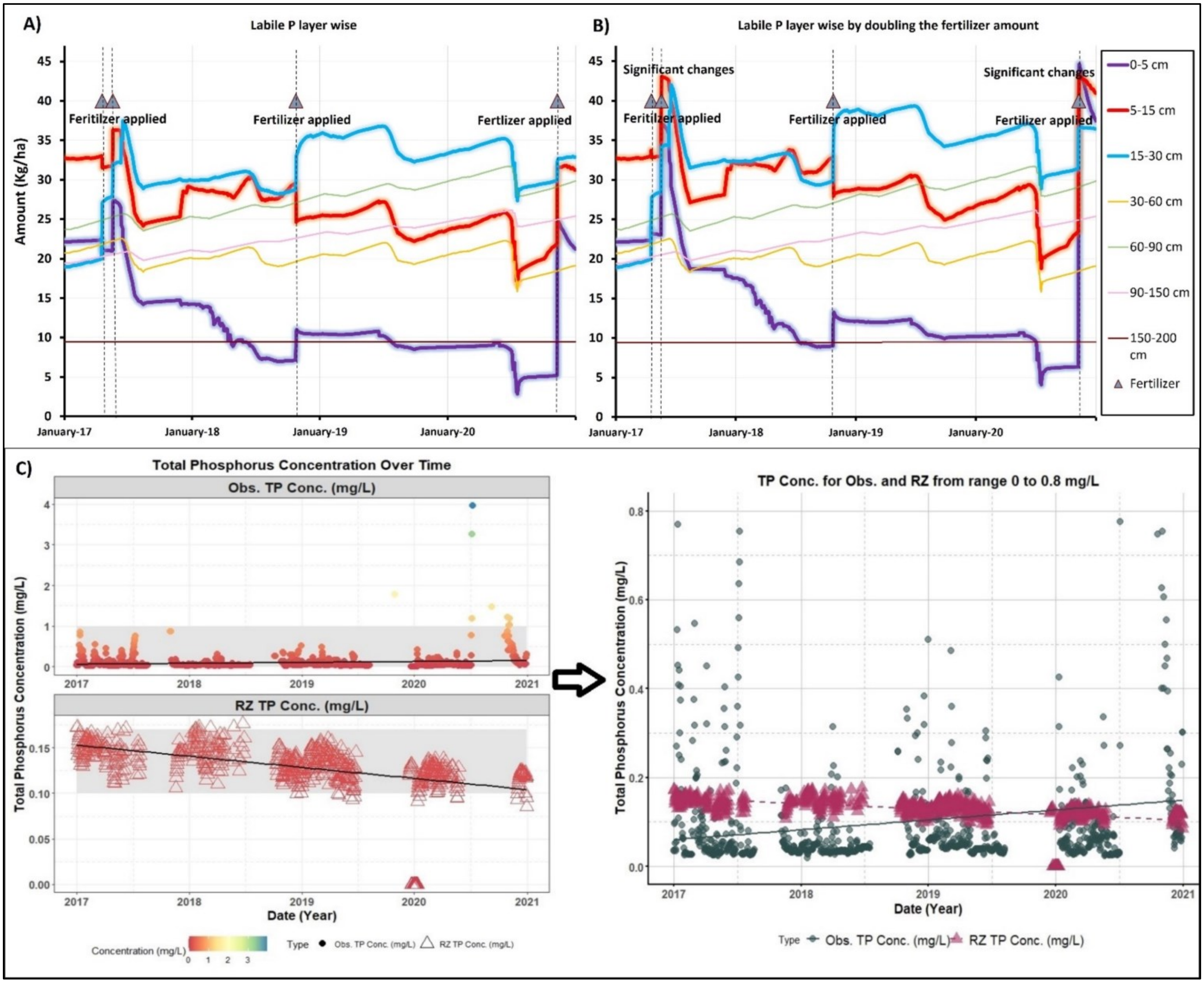

Figure 4. 5 Comparative layered distribution of simulated labile P pools with A) standard fertilizer application rate; B) doubled fertilizer rates; C) Temporal trends in observed vs. simulated TP concentration for the simulation period (2017-2020).
Obs. TP Conc., Observed TP concentration; RZ TP Conc., Model simulated TP Concentration.

4.5. Conclusion

The RZWQM2-P model was evaluated using high-resolution daily data to assess its performance in simulating daily and monthly phosphorus (P) losses from a tile-drained field. This marks the first successful application of the model to accurately simulate daily dissolved reactive phosphorus (DRP) losses. The model also performed satisfactorily in estimating monthly DRP and total phosphorus (TP) losses through tile drainage. However, its performance was suboptimal in simulating daily TP loads. This limitation may be attributed to the model's inability to effectively capture fluctuations in P concentrations in tile drainage over the course of the simulation. Future modifications to this component are warranted to improve the model's prediction of high-load (peak) events. Additionally, our evaluation of two agricultural management practices revealed that winter cover cropping with rye effectively reduced P losses, while controlled drainage at all three simulation outlet elevation levels increased P losses from the field.

4.6. Acknowledgement

We would like to thank the Natural Sciences and Engineering Research Council of Canada (NSERC Discovery 2019-05662), and the Mitacs Globalink research award for supporting this research. The Graduate Mobility Award from McGill University, as well as the International Program for Water Management in Agriculture at the Ohio State University, supported the first author of this paper, covering the travel and accommodation costs for a research exchange term at the Ohio State University. The authors also express their deep appreciation for the technical and advisory assistance provided by Manal Askar, Jed Stinner, and Katie Rumora from the USDA-ARS Soil Drainage Research Unit in Columbus, Ohio, as well as Asmita Murumkar from the Department of Food, Agricultural and Biological Engineering at the Ohio State University.

4.7. Supplementary data

The supplementary Tables S4.1, S4.2, and S4.3 include detailed information on several key aspects. These tables cover the management and cropping data gathered from the field, the calibration parameters applied to the crops in the model, and the criteria used for classifying the model's performance.

Table S4. 1 Cropping and management information for the field from 2017 to 2020.

Crop	Date	Management Practice	Notes
Corn	18 Apr. 2017	P application	4.31 kg ha^{-1} (inorganic)
	19 Apr. 2017	Tillage	Chisel plough followed by disking
	19 May 2017	Planting	84000 seeds ha^{-1}
	19 May 2017	P application**	15.72 kg ha^{-1} (inorganic)
	02 June 2017	P application**	15.72 kg ha^{-1} (inorganic)
	27 Nov. 2017	Harvesting	9866 kg ha^{-1}
Rye (cover crop) *	25 Aug. 2017	Planting	3738000 seeds ha^{-1}
Soybean	08 May 2018	Planting	424840 seeds ha^{-1}
	01 Oct. 2018	Harvesting	3759 kg ha^{-1}
Soybean	24 Oct. 2018	P application	3.33 kg ha^{-1} (inorganic)
	25 Oct. 2018	Tillage	Chisel plough followed by disking
	06 June 2019	Planting	
	24 Oct. 2019	Harvesting	2805 kg ha^{-1}
Soybean	12 May 2020	Tillage	Chisel plough followed by disking
	12 May 2020	Planting	
	02 Oct. 2020	Harvesting	3678 kg ha^{-1}
	09 Nov. 2020	P application	33.34 kg ha^{-1} (inorganic)

*Planting date for simulation 01 Dec. 2017 [On the actual field, rye was planted on 25th August 2017. However, to adhere to the limitations of our model simulation, which does not support concurrent crops, we incorporated rye as a cover crop only after the corn harvest. It was terminated on May 1, 2018, just prior to the soybean planting in the summer] **In the actual field, fertilizer was applied on two distinct dates - 19th May 2017 for the northern half and 2nd June 2017 for the southern half. Yet, to simplify the model simulation, we set the fertilizer application date as 19th May 2017 for the entire field.

Table S4. 2 Calibrated crop parameters and their values.

Crop	Parameter	Calibrated Values	Default Values
Corn[a]			
G2	Maximum possible number of Kernels per plant	775	890
G3	Kernel filling rate during linear grain filling stage under optimum conditions (mg d^{-1})	13.2	8
PHINT	Phylochron interval between successive leaf tip appearance	41	48
Soybean[b]			
SD-PM	Time between first seed and physiological maturity (photothermal days)	43.4	32.4
LFMAX	Maximum leaf photosynthesis rate at 30 C, 350 vpm CO_2, and high light (mg CO_2 m^{-2})	0.8	1.03
WTPSD	Maximum weight per seed (g)	0.13	0.19
SFDUR	Seed filling duration for pod cohort at standard growth conditions (photothermal days)	18	23
SDPDV	Average seed per pod under standard growing conditions (# pod^{-1})	1.1	2.2
Rye[c]			
PECM	Emergence phase duration (°C d cm cm^{-1})	12	10
P1V	Days at optimum vernalizing temperature required to complete vernalization	5	40
P1D	Relative amount that development is slowed when plants are grown in photoperiod 1 h shorter than optimum (d)	12	50
LAVS	Area of standard vegetative phase leaf (cm^2)	5	10
P5	Grain filling (excluding lag) phase duration (°C day)	400	400
PARUV	PAR conversion to dm ratio, before last leaf stage (g MJ^{-1})	4.8	2.8
PARUR	PAR conversion to dm ratio, after last leaf stage (g MJ^{-1})	4.8	2.8
PHINT	Interval between successive lead tip appearances	100	80
LT50S	Lethal temp, 50% kill, unhardened seedling (°C)	-16	-6
LT50H	Cold tolerance when fully hardened (°C)	-40	-20

[a] Cultivar IB1 068 Dekalb 521
[b] Cultivar 990002 M Group 2
[c] Cultivar 990003 Winter-US

Table S4. 3 Model performance classification criteria on monthly basis.

Performance Level	Drainage Discharge Flow Criteria	DRP and TP Fit Criteria
Very Good	NSE > 0.75, R^2 > 0.75, IOA > 0.90, |PBIAS| < ±10%	NSE > 0.65, R^2 > 0.80, IOA > 0.90, and |PBIAS| < ±15%
Good	0.65 < NSE ≤ 0.75, 0.70 < R^2 ≤ 0.75, 0.85 < IOA ≤ 0.90, ±10% < |PBIAS| < ±15%	0.50 < NSE ≤ 0.65, 0.60 ≤ R^2 ≤ 0.80, 0.85 < IOA ≤ 0.90, ±15% < |PBIAS| < ±20%
Satisfactory	0.50 < NSE ≤ 0.65, 0.60 < R^2 < 0.70, 0.75 < IOA ≤ 0.85, ±15% < |PBIAS| < ±25%	0.35 < NSE ≤ 0.50, R^2 > 0.40, 0.75 < IOA ≤ 0.85, ±20% < |PBIAS| < ±30%

IoA, Index of Agreement; NSE, Nash-Sutcliffe Efficiency; PBIAS, Percent Bias; R^2, Coefficient of Determination

FOREWORD TO CHAPTER V

Chapters III and IV assess the RZWQM2-P model's performance in predicting daily phosphorus (P) losses. In Chapter III, the model was unable to accurately forecast daily dissolved reactive phosphorus (DRP) losses. In contrast, Chapter IV demonstrates that although the model accurately predicted daily DRP losses, it did not successfully predict daily total phosphorus (TP) losses. Chapter V synthesizes the findings from Chapters III and IV, offering a general discussion on aspects not previously addressed.

CHAPTER V

GENERAL DISCUSSION

The RZWQM2-P model has been evaluated for its ability to simulate P losses from artificially drained fields, utilizing data on daily P losses from two fields in northwest Ohio, both of which are situated within the watershed of the western Lake Erie basin. The primary aim of the research was to assess the model's efficiency in predicting daily P losses from tile-drained fields and to identify potential areas for improvement in subroutines through this evaluation.

In the first study, which involved evaluating the model's efficiency using five years of data and comparing it with DRAINMOD-P, the model's performance was satisfactory in predicting daily and monthly TP losses, as well as monthly DRP losses. However, it was found to be unsatisfactory in predicting daily DRP losses over the five-year period, as indicated by NSE of 0.36, R^2 of 0.36, and IOA of 0.70. In contrast, the second study, which evaluated the model using four years of data, showed that it performed satisfactorily in predicting both daily and monthly DRP loads from the field, and the predictions for monthly TP loads were also good. Nevertheless, its performance in predicting daily TP loads for the four-year period was unsatisfactory, with NSE, R^2, and IOA values of 0.30, 0.30, and 0.59, respectively.

It is crucial to note that in both studies, the predicted concentrations of P losses, including both DRP and TP, remain nearly constant through subsurface drainage for the entire study period, as detailed in Chapters III and IV. The transport of dissolved P in the model within the soil profile occurs through both the soil matrix and macropores, while the transport of P attached to sediments is confined exclusively to macropores. The determination of dissolved P transport within the soil profile follows methodologies outlined by Francesconi et al. (2016). Conversely, the calculation of particulate P transport utilizes the colloidal particle transport approach, detailed by Jarvis et al. (1999) and Larsson et al. (2007). This differentiation emphasizes that the model adopts distinct methods for simulating the transport of dissolved and particulate P forms within the soil. Despite these differences, a similar aspect of the modeling approach for both P forms is the use of a linear groundwater-reservoir approach to compute the daily mass balance of both dissolved and particulate P concentrations. This method is used to estimate the amount of P leaving the tile drainage system. Therefore, the main reason for the nearly constant predictions of P concentrations lies in the mass balance calculations, rather than in how P transport is modeled through the soil matrix and macropores. As elaborated in Chapter III, the implementation of the linear groundwater reservoir approach grants substantial stability to the system. This method involves the mixing of incoming P mass from the soil profile with the groundwater reservoir. The vast storage capacity and significant initial mass of this extensive reservoir serve to significantly cushion the effects of daily inflows, thereby ensuring the P balance remains steady.

Now, it is crucial to understand the distinctions between the two studies, despite both having constant P concentration predictions by the model across chapters. In Chapter IV, the model satisfactorily predicted the daily DRP load, whereas in Chapter III, the predictions were unsatisfactory. This discrepancy primarily arises from the variation in observed DRP load magnitudes over time in the respective fields. In Chapter III, the DRP load showed significant fluctuations over five years. For example, in 2013 and 2016, the peak P load exceeded 7 g ha^{-1}, as recorded on the daily time series graph. In contrast, in 2014, 2015, and 2016, the maximum load reached only 3 g ha^{-1}. Particularly in 2014, aside from one event peaking at 3 g ha^{-1}, all other events rarely exceeded 1 g ha^{-1}. Consequently, the field in Paulding County exhibited considerable variation in observed DRP load, in stark contrast to the field in Hardin County. The latter, analyzed in Chapter IV, showed minimal variation in observed DRP load over four years, with major events peaking at around 1.5 g ha^{-1} and an average load remaining at 1 g ha^{-1}.

Given the model's constant predictions of P concentration and considering that P load is fundamentally the product of water flows through subsurface drainage and P concentration, the model satisfactorily predicted DRP load in Chapter IV, attributed to the lack of significant variation in the observed data. However, in Chapter III model encountered challenges due to extensive variation in the observed data, resulting in unsatisfactory model performance. This was because the model could not accommodate considerable changes in P load in the simulations compared to the observed data with constant P concentration. This is also partly because the NSE values are extremely sensitive to outliers, where missing even one or two major load events could severely affect performance.

The same issue applies to the unsatisfactory daily simulations of TP losses in Chapter IV, where the observed TP load varied substantially over four years. The model managed to predict daily TP satisfactorily for 2018 and 2019, with no observed event exceeding a load of 25 g ha^{-1}. However, in 2017 and 2020, the observed load exceeded 60 g ha^{-1} in January 2017 and November 2020, respectively, though all other major events fell within the 2018 and 2019 range. These variations led to unsatisfactory performance in these two years, adversely affecting the overall daily TP prediction accuracy over the four-year period and rendering it unsatisfactory.

The potential solution involves achieving a more accurate representation of P dynamics in calculating the mass balance of P in the subsurface drainage, which requires further modifications to the existing subroutines of the model. The RZWQM2-P could benefit from adopting a modeling approach that incorporates detailed spatial discretization and cell-level mass balance equations, offering a more thorough account of local variations and transient conditions. Another solution might involve integrating the P module with the existing chemical transport routines of the RZWQM2 model, for instance, by treating P as a reactive pesticide. Therefore, further research and investigations are essential to enhance the model's reliability in predicting high load events through improvements in its mass balance calculation subroutines.

CHAPTER VI

SUMMARY AND CONCLUSIONS

6.1. General overview

Historically, the United States and Canada have benefited from the vast freshwater reserves of the Great Lakes, which are vital to ecological integrity and potable water supply. However, water quality degradation, particularly from P pollution originating from agricultural lands, has increasingly threatened these water bodies. This pollution leads to eutrophication, a nutrient enrichment problem that endangers aquatic ecosystems and public health, with Lake Erie experiencing severe challenges. Although traditional field-scale experiments have been pivotal in understanding the impact of various management practices on phosphorus loading from croplands, their applicability is often limited by specific local conditions and the significant time and resources required. To address these limitations, field-scale modeling has emerged as a more efficient and flexible approach, enabling the rapid evaluation and implementation of nutrient management strategies that can accommodate a wide range of factors, including the impacts of climate change. However, the effectiveness of these hydrology and nutrient transport models depends on their thorough validation against observed data and continuous refinement. In this study, we conducted an in-depth assessment of the recently developed RZWQM2-P model's ability to predict phosphorus losses, comparing its performance with that of the DRAINMOD-P model. This study also explored the effectiveness of management practices in reducing phosphorus losses using the RZWQM2-P model.

6.2. Conclusions

Objective 1: To thoroughly evaluate the RZWQM2-P model's performance in predicting daily P losses, including both DRP and TP, through subsurface drainage, utilizing daily P loss data from two experimental fields in Ohio.

In the first study, where the RZWQM2-P model was evaluated using five years of field data from Paulding County, Ohio, the model exhibited unsatisfactory performance in predicting daily DRP load but showed satisfactory performance in predicting monthly DRP load through subsurface drainage over the five-year period. The daily performance metrics included a NSE of 0.36, R^2 of 0.36, IOA of 0.70, and PBIAS of 9%. In contrast, the monthly performance metrics demonstrated improvement, with a NSE of 0.48, R^2 of 0.50, IOA of 0.82, and a PBIAS of 9%, indicating satisfactory values. For subsurface drainage TP load predictions, the model performed satisfactorily on a daily basis and well on a monthly basis. Over the five-year period, the RZWQM2-P model satisfactorily predicted the daily TP load with a NSE of 0.53, R^2 of 0.54, IOA of 0.82, and predicted the monthly TP load in a "good" manner with a NSE of 0.72, R^2 of 0.73, IOA of 0.90, and a PBIAS of 3%. In terms of cumulative P loads, the model predicted the total DRP load from subsurface drainage as 229.1 g ha^{-1}, compared to the observed DRP load of 251.8 g ha^{-1} over five years. During the same period, the model predicted the TP load from the same pathway as 2800.5 g ha^{-1}, which closely aligns with the observed TP load of 2879.6 g ha^{-1}.

In the second study, evaluating the RZWQM2-P model with four years of field data from Hardin County, Ohio, it achieved satisfactory results for daily DRP predictions for the first time, with NSE = 0.50, R^2 = 0.52, IOA = 0.84, and PBIAS = -3%. It also exhibited very good performance in predicting monthly DRP, evidenced by PBIAS = -3%, NSE = 0.73, R^2 = 0.78, and IOA = 0.94. Additionally, the model showed good performance in predicting monthly TP, indicated by NSE = 0.64, R^2 = 0.65, IOA = 0.88, and PBIAS = 9%. However, its ability to predict daily TP was unsatisfactory, with NSE = 0.30, R^2 = 0.30, and IOA = 0.59 in this study. Evaluations also emphasize that the model closely matches observed data in identifying tile drainage as the primary pathway for nutrient loss. Specifically, the model attributes 66% of total DRP and 76% of total TP losses to subsurface drainage, closely aligning with the observed values of 70% and 80%, respectively.

Objective 2: To compare the methodologies and performance of the RZWQM2-P model and the DRAINMOD-P model in predicting daily P losses through subsurface drainage. This comparison aims to identify the strengths and limitations of each model and explore how they can be improved by integrating their respective advantages.

For the purpose of this objective, a comprehensive comparison was conducted between the RZWQM2-P and DRAINMOD-P using field data that was gathered over a period of five years in Paulding County. While both models utilize the P structure (consisting of five P pools) of the EPIC model, DRAINMOD-P employs the organic P pools from the CENTURY model. In contrast, RZWQM2-P strictly adheres to the organic P pools of the EPIC model. The primary distinctions between the two models are in the methods employed to compute subsurface DRP loads. DRAINMOD-P utilizes the one-dimensional advection-dispersion-reaction (ADR) equation, which was derived from DRAINMOD-NII. On the other hand, RZWQM2-P calculates the mass balance of the subsurface drainage system using a linear groundwater reservoir-based approach.

In terms of performance, both models were unable to satisfactorily predict daily DRP losses through subsurface drainage. While the RZWQM2-P model satisfactorily predicted monthly DRP loss, DRAINMOD-P's performance was unsatisfactory. However, both models exhibited good performance in predicting TP losses through the same pathway. They also demonstrated very good performance in predicting the cumulative DRP and TP load through subsurface drainage. Additionally, RZWQM2-P predicted a constant P concentration from tile drainage with minimal change over the five-year period, whereas DRAINMOD-P showed the necessary changes.

When evaluating strengths, the RZWQM2-P may benefit from incorporating the cell-level mass balance equations and detailed spatial discretization utilized by DRAINMOD-P, in contrast to the existing linear groundwater reservoir approach. DRAINMOD-P could potentially improve its hydrology prediction accuracy through the adoption of methodologies similar to the ones utilized in RZWQM2-P, such as the incorporation of dead-end macropores. Additionally, DRAINMOD-P can simulate crop yields using the more versatile DSSAT model utilized in RZWQM2-P, as opposed to the current empirical yield approach utilized in DRAINMOD-P, which assumes a 100% relative yield in the current version.

Objective 3: To identify the subroutines/processes in the RZWQM2-P model that require further improvements for satisfactory prediction of P loss through subsurface drainage, especially during high-load (peak) events of the simulation.

The linear groundwater reservoir approach is the primary reason that the RZWQM2-P model is incapable of capturing the high-load (peak) events of the simulation through the subsurface drainage. This is given that the vast storage capacity and significant initial mass of this extensive groundwater reservoir serve to significantly cushion the effects of daily inflows of phosphorus into the reservoir. As a result, the RZWQM2-P model predicts the phosphorus concentration leaving the system without any variation.

Objective 4: To evaluate the model's applicability in predicting management practices for P loss reduction. This involves assessing the effectiveness of two specific management practices—cover cropping with rye and controlled drainage—in reducing P loading from fields with subsurface drainage, using a validated model.

Model simulations indicated that winter rye as a cover crop reduced total DRP losses (runoff + drainage) and TP losses (runoff + drainage) by 16% and 4%, respectively. DRP losses bound to surface runoff declined by 31%, while DRP losses through tile drainage saw a modest decrease of 8%. Furthermore, the cover crop had a minimal impact on TP losses via tile drainage, with only a 3% reduction.

Controlled drainage (CD) was assessed using three different outlet elevations, revealing an inverse relationship between outlet depth and P losses; deeper outlets corresponded with fewer losses. However, each elevation still exhibited increased P losses compared to free drainage, primarily due to elevated annual runoff volumes. Notably, the increase in DRP losses was significantly higher than TP losses under CD. For example, DRP losses increased from 60% to 129% (runoff + drainage) [60% when outlet elevation was maintained at 70 cm during the non-growing season compared to 129% when elevation was at 30 cm], as opposed to the TP loss increment of 5% to 17% (runoff + drainage) with the same outlet elevation setup described above.

6.3. Future recommendations

This study offers insights into the daily evaluation of the RZWQM2-P model in predicting P losses from tile-drained agricultural fields. It also compares the RZWQM2-P model with DRAINMOD-P in terms of predicting daily P losses from subsurface drainage. Furthermore, the study proposes recommendations for modifying the RZWQM2-P subroutines to calculate the daily mass balance of P leaving the tile drainage, aiming to enhance its reliability as a tool for predicting P concentration through subsurface drainage. However, further research is necessary to expand the scope of the model's evaluation. The following suggestions are recommended for designing future studies:

1) The RZWQM2-P model requires daily evaluations to predict P losses from fields treated with manure. While our study did perform daily evaluations of the model twice, these

assessments were limited to fields that received only fertilizer applications. Given the complexity introduced by manure application, including factors like water-extracted organic and inorganic P pools, there is a crucial need for further evaluations with manure application. Such assessments are necessary to establish the model's reliability in predicting daily P losses from fields treated with manure.

2) Building on our recommendation to update the linear groundwater reservoir approach, future research should assess the model's ability to predict P concentrations from subsurface drainage, implementing the changes suggested by our study.
3) In our study, we assessed the impact of management practices, specifically the use of rye as a winter crop and controlled drainage, over a period of just four years. Future evaluations should extend these model simulations over a significantly longer timeframe. Extended evaluations allow for the observation of long-term trends and the potential cumulative effects of management practices on P losses, which short-term studies may not fully reveal. Also, a longer timeframe offers the opportunity to assess the sustainability and efficacy of these practices over multiple growing seasons, contributing to more robust and reliable recommendations for agricultural management.
4) Future studies should utilize the model to assess climate change impacts, offering insights into how changes in weather, temperature, and precipitation could influence P losses in agricultural fields.
5) While the RZWQM2-P model incorporates the robust DSSAT model for simulating crop growth, future versions should expand the crop options to include varieties such as oats and winter rye, allowing users greater flexibility. In our study, we used winter wheat as a proxy for rye and oats, which might not accurately reflect actual field conditions. Expanding the crop selection to directly include these crops will enhance its applicability and precision in predicting field conditions.
6) Lastly, we recommend that future evaluations of the model incorporate additional datasets, such as observed ET and water table depths. Evaluating the model with this information will improve hydrology predictions, which in turn will directly refine the accuracy of P loss predictions generated by the model.

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CHAPTER IV

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CHAPTER V

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