

**Hydrological and empirical modeling framework for farmed prairie potholes in the
prairie pothole region of Iowa**

by

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A dissertation submitted to the graduate faculty
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Agricultural and Biosystems Engineering

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Iowa State University

Ames, Iowa

2018

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DEDICATION

This Ph.D. dissertation is dedicated to my parents.

TABLE OF CONTENTS

ACKNOWLEDGMENTS	v
ABSTRACT.....	vi
CHAPTER 1. INTRODUCTION TO RESEARCH.....	1
Background.....	1
Objectives	5
Organization of Dissertation.....	6
References	6
CHAPTER 2. EVALUATION OF ANNAGNPS FOR SIMULATING THE INUNDATION OF DRAINED AND FARMED POTHOLE IN THE PRAIRIE POTHOLE REGION OF IOWA	10
Abstract.....	10
Introduction	11
Methods	15
Results	27
Conclusions	33
References	35
CHAPTER 3. EFFECTS OF LAND MANAGEMENT ON INUNDATION OF PRAIRIE POTHOLE WETLANDS IN THE DES MOINES LOBE USING ANNAGNPS.....	39
Abstract.....	39
Introduction	40
Methodology.....	44
Results and discussion	52
Conclusions	61
References	63
CHAPTER 4. ASSESSMENT OF USGS DEMs FOR MODELING POTHOLE INUNDATION IN THE PRAIRIE POTHOLE REGION OF IOWA	68
Abstract.....	68
Introduction	69
Methodology.....	73
Results and discussion	78
Conclusion	86
References	87

CHAPTER 5. ARTIFICIAL NEURAL NETWORK AND ANNAGNPS BASED APPROACH FOR ASSESSMENT OF DRAINED AND FARMED PRAIRIE POTHLES	92
Abstract.....	92
Introduction	93
Methodology.....	96
Results and discussion	105
Conclusions	110
References	111
CHAPTER 6. GENERAL CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE WORK.....	115
Conclusions	115
Recommendations for future research	118

ACKNOWLEDGMENTS

I would like to thank my thesis advisers Dr. Amy Kaleita and Dr. Michelle Soupir. I would also like to thank my other committee members Drs. Steven Hall, Huaiqing Wu, and Rob Malone. The advice and guidance I have received from each of you have led to my success as an aspiring young researcher. It was a journey of personal fulfillment and knowing myself better.

In addition, I would also like to thank my fellow graduate student Alexander Martin for his help with data collection and field works. A special thanks to Dr. Steven Freeman, department faculty and staff, and Preparing Future Faculty (PFF) programme for making my time at Iowa State University a wonderful and great learning experience.

I am also thankful for the useful suggestions and constructive criticism from the anonymous reviewers who gave their time and energy to improve our manuscripts.

ABSTRACT

Closed surface depressions, also known as “potholes” play an important role in the hydrologic cycle and provide multiple environmental services including flood mitigation, water quality improvements, and wildlife habitat. In the Prairie Pothole Region, which covers approximately 715,000 km², including parts of three Canadian provinces (Saskatchewan, Manitoba, and Alberta) and five states in the U.S. (Minnesota, Iowa, North and South Dakota, and Montana), these potholes are typically farmed and are a dominant feature in the landscape. These potholes are also different than the traditional prairie pothole wetlands as the natural vegetation (*Typha* spp., *Scirpus* spp., *Carex* spp., etc.) has been replaced by agricultural crops (mainly Corn and Soybean). In this study, we evaluated the Annualized Agriculture Non-Point Source (AnnAGNPS) model for simulating the inundation behavior of farmed potholes, in the Prairie Pothole Region (PPR) of Iowa. Performance analyses considered the entire growing season (GS), corresponding to the span in which there was observed data, and only days in which water storage (WS) was observed. Our results demonstrate that the AnnAGNPS model can be used to predict the inundation depth of drained and farmed potholes, which is useful for assessing the landscape impacts of these features. We then investigated the influence of different land use practices on depth, duration, and aerial extent of ponding in the two potholes using AnnAGNPS. Three management scenarios were compared — current: conventionally tilled farmed conditions in corn/soybean rotation with surface inlets in the potholes connecting to a subsurface drainage system; retired: pothole is converted to a mixture of grass, weeds, and low-growing brush, with surface inlets removed and the drainage system underneath the potholes disconnected; and conserved: conservation tillage throughout the field with surface inlets and drainage maintained in potholes. The average annual water depth for the conserved

scenario was 7-8% lower than the average annual water depth for the current scenario. It was also observed that the potholes tend to flood more frequently in early stages of plant development, which could lead to delays in management operations and reduced yields.

Next, we assessed the capability of USGS DEMs for modeling pothole inundation in the prairie pothole region of Iowa. We used three DEMs: a 1m DEM prepared from LiDAR data which is readily available for the state of Iowa, USGS 1/9 arc-second DEM (~3m) which covers about 25 percent of the conterminous United States (U.S.) and 1/3 arc-second seamless DEM (~10m) which covers the entire U.S. Modeling performance was evaluated using Nash-Sutcliffe efficiency (NSE), Percent bias (PBIAS), Ratio of the root mean square error (RSR) and R^2 statistical performance criteria. Results show that the water depth simulated from AnnAGNPS model based on 1m DEM which is prepared from the LiDAR data gave Nash-Sutcliffe efficiency (NSE) values of 0.77 and 0.24 in the Walnut pothole and 0.56 and 0.30 in the Bunny pothole, for the GS calibration and validation periods, respectively. The estimates of water depths using USGS 3m and 10m DEMs was also found to be very similar to LiDAR 1m DEM based predictions and are also representative of field conditions.

The developed AnnAGNPS model was then used to simulate the water depths for ten years (2007 – 2016) growing season (May to October) in the three potholes termed Bunny, Walnut and Lettuce. An empirical model based on artificial neural network (ANN) technology was developed on the expanded dataset and tested on the actual water depth observations collected in 2018 at another three potholes termed Turkey, Hen, and Plume. The R^2 statistics were 0.604 and 0.563 during training and validation periods, respectively. A low root mean square error (RMSE) value of 0.057 and mean absolute error (MAE) value of 0.023 were found during both training and validation of the ANN model. In general, results suggest that the ANN

models are able to predict the water depth fluctuations in the potholes during the growing season. These models can be a vital tool to augment the monitoring efforts of prairie potholes and can help stakeholders - farmers and state/federal agencies for management planning and making an informed decision about farming the potholes.

Keywords: AnnAGNPS model, Artificial neural network (ANN), Digital Elevation Model (DEM), Land management, Pothole hydrology, Prairie Pothole Region.

CHAPTER 1. INTRODUCTION TO RESEARCH

Background

Potholes are enclosed depressions, largely farmed throughout the Prairie Pothole Region (PPR), which covers approximately 715,000 km² (276,000 sq. mi), including parts of three Canadian provinces (Saskatchewan, Manitoba, and Alberta) and five U.S. states (Minnesota, Iowa, North and South Dakota, and Montana), and the portion located in Iowa is named the Des Moines Lobe (Gleason, Laubhan, Tangen, & Kermes, 2008; Miller, Crumpton, & van der Valk, 2009, 2012; Roth & Capel, 2012). The PPR is a recently formed glaciated landscape, and its lack of variation in elevation allows the formation of potholes and the occurrence of depressional storage (Fennessy & Craft., 2011; Sloan, 1972). The size of the potholes can vary from a fraction of a hectare to several hectares, and are mostly shallow in depth (0.3m to 1.5m); these morphological characteristics made these features drainable and farmable (Sloan, 1972). In the highly agricultural regions in which they are found, most potholes are under agricultural management, even though they have been shown to accumulate and retain water during the growing season (Logsdon, 2015; Roth & Capel, 2012). These potholes are classified as palustrine wetlands or wetlands (with a small watershed-wetland area ratio). In Iowa, an estimated 94% of potholes have been significantly altered by the installation of drainage systems (Miller et al., 2012), a factor in Iowa's significant contribution of high nitrogen contributions to the Gulf of Mexico (Singh, Helmers, Crumpton, & Lemke, 2007). Despite the preponderance of these features in Iowa and other parts of the PPR, relatively little is known about the hydrologic function of these farmed potholes (Schilling & Dinsmore, 2018).

The ecosystem services provided by potholes have been investigated by numerous researchers (De Leon & Smith, 1999; Euliss & Mushet, 1999). However, the literature mostly explores the behavior of potholes in their natural state as seasonal wetlands. As noted above, most of the potholes in agriculturally intense regions have been significantly altered by decades of cultivation and in many cases, by the addition of subsurface drainage. However, it has been observed that, even with artificial drainage, potholes flood periodically, leading them to be classified as ephemeral wetlands (Serrano, 2015). Despite the benefits that wetlands provide, they have historically been seen as a nuisance and a hindrance to agricultural production (Van der Valk, 1989). This has led to many PPR wetlands being filled, drained, or otherwise manipulated to facilitate crop production (Renton, Mushet, & DeKeyser, 2015).

The shape of potholes – small and shallow with irregular geometry – combined with their lack of a readily-defined outlet makes their hydrology complex and challenging (Liu & Schwartz, 2011). In the absence of observed data on the hydrology of farmed potholes, watershed models are an alternative to study these features. This type of model is a useful tool in the assessment of current conditions as well as in conservation planning of potholes (Rebelo, Le Maitre, Esler, & Cowling, 2015). However, few watershed models have been evaluated for their ability to simulate the hydrologic behavior (hydroperiod and water level rise and fall) of pothole features, particularly those that are farmed and drained. AnnAGNPS is well-suited to small-scale watersheds and is able to produce satisfactory results for the Midwestern United States (Yuan et al., 2011). Here, we assume that the pothole can be simulated as a small wetland. To our knowledge, this model has not been evaluated for its ability to simulate the inundation of potholes.

Farmed potholes are often areas of low productivity compared to the high yielding uplands across the PPR due to conditions such as poor soil quality, erosion, and waterlogging (Muth & Bryden, 2012). This work was initially motivated by farmer consternation at what a nuisance these features are in their operation and then further bolstered by the proposed Waters of the United States rule (2015) that would have put farmed potholes into the same regulatory category as fully intact longer-duration wetlands, under the notion of their impact on downstream waters – an impact which is largely undocumented. Recently, the US Environmental Protection Agency conducted a comprehensive review of over 1350 peer-reviewed papers with the aim of synthesizing existing scientific understanding of how wetlands and streams affect the physical, chemical, and biological integrity of downstream waters (US EPA, 2015). The report concludes that additional research focused on the frequency, magnitude, timing, duration, and rate of fluxes from geographically isolated wetlands (potholes) to downstream waters is needed to better identify wetlands with hydrological connections or functions that substantially affect other waters and maintain the long-term sustainability and resiliency of valued water resources (Wu & Lane, 2017).

Three decades ago, the U.S. adopted a federal policy of “no net loss” for wetlands, following George H.W. Bush’s presidential campaign pledge (1988). Under this policy, wetland losses that cannot be avoided must be mitigated through restoration or creation (Aronson & Galatowitsch, 2008). Changing management of low productivity farmed potholes may be an opportunity to restore some ecosystem services at a lower cost than removing high productivity upland areas from production. Evidence suggests that perennial crops perform better in potholes compared to corn (*Zea mays* L.) and soybean (*Glycine max*) crops (Bailey-Serres, Lee, & Brinton, 2012; Edmonds, 2017; Mann, Barney, Kyser, & Di Tomaso, 2013).

Incorporating alternative management practices, such as conservation restoration programs or planting perennial grasses, may help to minimize or eliminate crop yield losses in flood-prone pothole areas (Edmonds, 2017).

There is limited knowledge of how different pothole management options impact pothole inundation patterns. Therefore, we investigated the influences of agricultural practices (current) and altered land use practices (retired and conserved) on depth, duration, and aerial extent of ponding, with a focus on converting low-productivity land to instead provide some ecosystem services. This information is also important to understand and predict the impact of management operations on pothole inundation and resulting crop yield loss. In the absence of empirical studies on the effect of land management on pothole water dynamics, we chose a modeling approach using the distributed Annualized Agriculture Non-Point Source model (AnnAGNPS).

Digital elevation models (DEMs) derived from fine-scale topographic survey maps and downscaling techniques are often used in small-scale hydrological modeling where precise water logging information for decision making is of prime importance (Bisht et al., 2016; Feifei & Anthony, 2012; Tarolli, 2014; Upadhyay, Pruski, Kaleita, & Soupir, 2018; Xie, Pearlstine, & Gawlik, 2012). Therefore, considering the importance of DEM resolution for precise incorporation of depression and drainage channels in small-scale studies, we explore the potential of USGS DEMs for identifying the extent of small potholes that are located in agricultural fields. A high resolution 1m Light Detection And Ranging (LiDAR) based DEM was compared to DEMs developed by United States Geological Survey (USGS) at ~3m and ~10m resolution for the areal extent, depth and storage volume. Considering the influence of DEM resolution on pothole modeling is particularly important because the high resolution

DEM can take considerable more processing time and also the high resolution topographic information (~1m and ~3m) is not available for the entire prairie pothole region whereas the coarser (~10m) USGS data is seamlessly available for the entire US.

In water management planning and decision-making, it is a common practice to use computer simulation models. These models, which may be very simple or highly complex, based on observed data or theoretical principles, stochastically or deterministically driven, provide a framework for decision-making that is endorsed by the community of water users and water regulators (Nayak, Rao, & Sudheer, 2006). In the case of potholes, there are very few models, which can represent the pothole hydrology. We successfully evaluated the Annualized Agricultural Non-Point Source (AnnAGNPS) model for simulating the inundation of drained and farmed potholes in the Prairie Pothole Region of Iowa. The major disadvantage of physics-based model is that it requires an enormous amount of data and a skilled modeler. When data is not sufficient and getting accurate predictions is more important than conceiving the actual physics, empirical models remain a good alternative method, and can provide useful results without a costly calibration time (Daliakopoulos, Coulibaly, & Tsanis, 2005). Therefore, we developed an empirical model based on artificial neural networks (ANN) technology. ANNs have been proven to be effective in modeling virtually any nonlinear function to an arbitrary degree of accuracy (Nayak et al., 2006).

Objectives

The overall goal of this research was to predict the pothole inundation pattern using hydrological and empirical modeling, which could lead to increased wetland protection and restoration efforts by integrating enclosed depressional wetlands into watershed plans as a conservation practice. Specific objectives of this dissertation were to:

1. Evaluate the AnnAGNPS model for simulating the inundation of drained and farmed potholes in the Prairie Pothole Region of Iowa
2. Document the effects of land management on the inundation of prairie pothole wetlands in the Des Moines Lobe using AnnAGNPS
3. Assess USGS DEMs for modeling pothole inundation in the prairie pothole region of Iowa
4. Use monitoring and modeling data to develop an empirical model to simulate pothole water depth fluctuations

Organization of Dissertation

This dissertation is written in the alternative manuscript format as defined by Iowa State University's Graduate College. Chapter one is the general introduction which outlines the basic ideas behind the research and summarizes the goals and objectives. Chapters two, three, four, and five are four manuscripts formatted for submission to specified journals. Chapter six is general conclusions and recommendations for further research.

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CHAPTER 2. EVALUATION OF ANNAGNPS FOR SIMULATING THE INUNDATION OF DRAINED AND FARMED POTHOLE IN THE PRAIRIE POTHOLE REGION OF IOWA

Manuscript published in *Agricultural Water Management*

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Abstract

Closed surface depressions, also known as “potholes” play an important role in the hydrologic cycle and provide multiple environmental services including flood mitigation, water quality improvements, and wildlife habitat. In the Prairie Pothole Region, which covers approximately 715,000 km², including parts of three Canadian provinces (Saskatchewan, Manitoba, and Alberta) and five states in the U.S. (Minnesota, Iowa, North and South Dakota, and Montana), these potholes are typically farmed and are a dominant feature in the landscape. In this study, we evaluate the Annualized Agriculture Non-Point Source (AnnAGNPS) model for simulating the inundation behavior of two farmed potholes, termed Bunny and Walnut, in Prairie Pothole Region (PPR) of Iowa. Performance analyses considered the entire growing season (GS), corresponding to the span in which there was observed data, and only days in which water storage (WS) was observed. Results show that AnnAGNPS predicted pothole water depth acceptably but not pothole water volume because of the model’s inability to accurately represent the depth-volume relationship of a pothole. When calibrated to depth, Nash-Sutcliffe efficiency (NSE) values were 0.77 and 0.24 in the Walnut pothole and 0.56 and 0.30 in the Bunny pothole, for the GS calibration and validation periods, respectively. Our results demonstrate that the AnnAGNPS model can be used to predict the inundation depth of drained and farmed potholes, which is useful for assessing landscape impacts of these features.

Appropriate applications of this model could include impact of inundation on crop yield or simulations of alternative farm management strategies to compare water delivery to the potholes.

Keywords

AnnAGNPS, Closed depressions, Hydrology, Potholes, Prairie Pothole Region, drained wetlands.

Introduction

Closed surface depressions, often called “potholes”, are a dominant landscape feature in areas where they occur, with unique hydrologic signatures. Potholes are hydrologically closed topographic depressions formed in recently glaciated landscapes, extending from Canada to the United States (Miller, Crumpton, & van der Valk, 2012), a region known as the Prairie Pothole Region (PPR). These can vary in size from fraction of a hectare to several hectares, and are mostly shallow in depth (0.3m to 1.5m); these morphological characteristics made these features drainable and farmable (Sloan, 1972). In the highly agricultural regions in which they are found, most potholes are under agricultural management, even though they have been shown to accumulate and retain water during the growing season (Logsdon, 2015; Roth & Capel, 2012). These potholes are classified as palustrine wetlands or wetlands (with a small watershed-wetland area ratio). In Iowa, an estimated 94% of potholes have been significantly altered by the installation of drainage systems (Miller et al., 2012), a factor in Iowa’s significant contribution of high nitrogen contributions to the Gulf of Mexico (Singh, Helmers, Crumpton, & Lemke, 2007). Despite the preponderance of these features in Iowa and other parts of the PPR, relatively little is known about the hydrologic function of these farmed potholes (Schilling & Dinsmore, 2018).

The ecosystem services provided by potholes have been investigated by numerous researchers (De Leon & Smith, 1999; Euliss & Mushet, 1999). However, the literature mostly explores the behavior of potholes in their natural state as seasonal wetlands. As noted above, most of the potholes in agriculturally intense regions have been significantly altered by decades of cultivation and in many cases, by the addition of subsurface drainage. However, it has been observed that, even with artificial drainage, potholes flood periodically, leading them to be classified as ephemeral wetlands (Serrano, 2015). Furthermore, there is evidence showing that these features do play a role in local ecosystems. Murphy and Dinsmore (2015) investigated the diversity and abundance of waterbirds in drained farmed wetlands during spring migration. During the 4-year study they sampled 1913 unique wetlands and tallied 14,968 individuals of 53 waterbird species. Euliss and Mushet (1999) evaluated the influence of intensive agriculture on invertebrate communities of temporary wetlands and found that prairie pothole wetlands have been negatively impacted by human activities. Questions remain about the role that these features play in overall watershed and ecosystem function.

The shape of potholes – small and shallow with irregular geometry – combined with their lack of a readily-defined outlet makes their hydrology complex and challenging (Liu & Schwartz, 2011). In the absence of observed data on the hydrology of farmed potholes, watershed models are an alternative to study these features. This type of model is a useful tool in assessment of current conditions as well as in conservation planning of potholes (Rebelo, Le Maitre, Esler, & Cowling, 2015). However, few watershed models have been evaluated for their ability to simulate the hydrologic behavior (hydroperiod and water level rise and fall) of pothole features, particularly those that are farmed and drained. Werner et al., (2016) studied the impact of tile drainage on a seasonal wetland basin in South Dakota using the

WETLANDSCAPE model, simulations indicate that the placement of tile drains within the wetland watershed could significantly affect hydrologic function (hydroperiod, mean depth). However, no field data was available to evaluate these simulations. Evenson et al., (2016) used a modified SWAT model to represent the watershed-scale hydrologic effects of geographically isolated wetlands (GIWs) in North Dakota. These simulation results indicated that the modified model replicates streamflow with very good predictive power and an acceptable degree of uncertainty, but the scale of this model makes it not appropriate for in-field evaluation of potholes. Amado et al., (2016) developed a fully integrated, physically-based model (based on HydroGeoSphere) of a drained and farmed wetland complex in the Prairie Pothole Region of Iowa, to investigate their hydrologic connectivity. Tahmasebi et al., (2017) coupled SWAT with a Puddle Delineation (PD) algorithm to evaluate the impact of depressions on the hydrologic modeling of watersheds in North Dakota and found that at the HRU scale surface runoff initiation was significantly delayed due to the threshold control of depressions. Finally, Tangen and Finocchiaro (2017) recently used a catchment water-balance model to assess the potential effect of subsurface drainage on wetland hydrology and to assess the efficacy of drainage setbacks for mitigating these effects. Results suggest that overland precipitation runoff is an important component of the seasonal water balance of Prairie Pothole Region wetlands, accounting on average for 34% or 45% of the annual or seasonal input volumes, respectively. Most of these previous studies were conducted at the watershed scale rather than simulating the pothole wetland (the wetlands are merely included in the watershed area), partly due to inability of models to represent the potholes accurately and also due to lack of data on hydroperiods and water level rise and fall of individual potholes. The HydroGeoSphere study (Amado et al., 2016), in contrast, simulated pothole hydrology at a

small scale, but the complexity of this model makes it less practical for widespread application than a simpler model.

Empirical approaches have also been used, but for identification of potholes in the landscape rather than assessing hydrology. Wu and Lane (2017) used high-resolution LiDAR data and aerial imagery to develop a semi-automated framework for identifying nested hierarchical wetland depressions and delineating their corresponding catchments for improving overland flow simulation and hydrologic connectivity analysis. Previous remote-sensing-based work on the hydrology of prairie wetlands mainly focused on mapping wetland inundation areas (Huang, Peng, Lang, Yeo, & McCarty, 2014; Vanderhoof, Distler, Mendiola, & Lang, 2017) or wetland depressions (McCauley & Anteau, 2014; Qiusheng Wu & Lane, 2016). Thus, there is still a lack of demonstrated simulation of pothole wetland inundation patterns.

Many existing watershed models are not suitable for pothole simulation, because in preparation of the topography data, they will “fill” the depressions to guarantee that runoff will flow from upper to lower areas in the watershed. Another challenge is that potholes are typically fairly small and shallow, and many hydrology models are lumped and not suited for the study of small size features such as these. Therefore, there is a call for treating prairie wetlands and catchments as highly integrated hydrological units because the existence of prairie wetlands depends on lateral inputs of runoff water from their catchments in addition to direct precipitation (Hayashi, van der Kamp, & Rosenberry, 2016; Q. Wu & Lane, 2017). One model that may be appropriate for this type of investigation is the Annualized Agriculture Non-Point Source (AnnAGNPS) model. It is a watershed scale, continuous simulation, daily time-step model. AnnAGNPS model has a GIS based wetland component known as AgWET, which

can be used for identifying and characterizing topographic depressions (puddles/potholes) during DEM preprocessing, and potential wetland sites can be the first stage in generating watershed-wide management plans (Momm et al., 2016). AnnAGNPS is well-suited to small scale watersheds, and is able to produce satisfactory results for the Midwestern United States (Yuan et al., 2011), and is relatively straightforward to implement. Here, we assume that the pothole could be simulated as a small wetland. To our knowledge, this model has not been evaluated for its ability to simulate the inundation of potholes. Thus, the objective of this study is to evaluate the AnnAGNPS model for simulating the inundation behavior of drained farmed potholes in Prairie Pothole Region (PPR) of Iowa. Specifically, we attempted to simulate the occurrence, depth, and duration of ponding in two potholes within a farm field in Central Iowa, USA.

Methods

Site Description

Two potholes located in a single conventional farm field straddling adjacent Hydrologic Unit Code (HUC-12) watersheds in the Prairie Pothole Region of Iowa, known as the Des Moines lobe, just outside of Ames, IA, were monitored for water level (as described below). The pothole positions in relation to the Walnut Creek and Worrell Creek HUC-12 watersheds are presented in Figure 1.

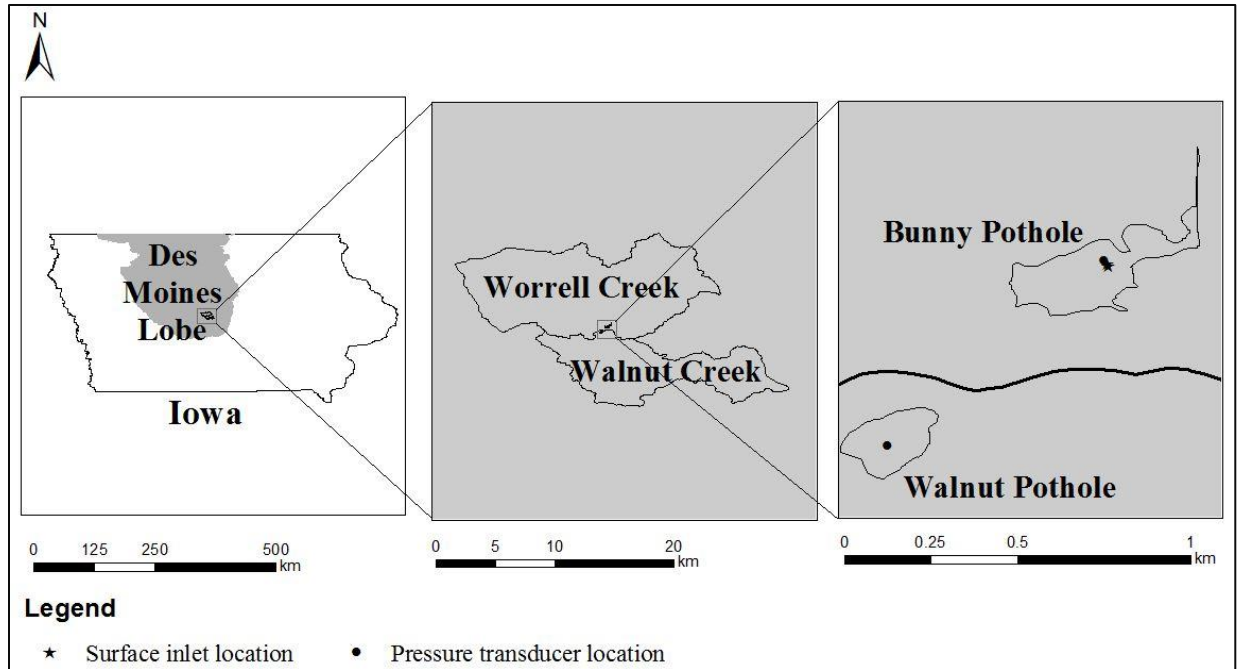


Figure 1: Locations of Walnut and Bunny potholes in central Iowa, USA

The field is managed in a corn-soybean rotation with conventional tillage. Detailed records of the management schedule at this site were not available, so we assumed a typical schedule for Story County, Iowa in which the site is located. Table 1 gives the land management schedule we assumed for this project, spanning a total period of two years.

Table 1: Management practice information for the corn-soybean rotation field

Date	Operation	Vegetation
Nov. 1	Fertilizer application	
May 1	Cultivator	
May 2	Sprayer pre-emergence	
May 3	Planter	Corn
Jun. 7	Sprayer; post emergence	
Oct. 20	Harvest	
Nov. 1	Chisel plow; disk	
Apr. 28	Disk; tandem light	
May 1	Cultivator	
May 10	Sprayer; pre-emergence	
May 11	Planter; double disk	Soybean
Jun. 7	Sprayer; post emergence	
Aug. 1	Sprayer; insecticide	
Oct. 10	Harvest	

According to the USDA NRCS Soil Survey, the field is 10% Okoboji silt clay loam, 25% Nicollet loam, 7% Harps clay loam, 3% Webster clay loam, 9% Clarion loam, 25% Canisteo clay loam, and 21% Clarion loam (USDA-NRCS 2014). Except for the Clarion and Nicollet series, the soils are classified as hydric; these soils are formed in saturated conditions and could support wetland vegetation species when not drained. Relevant properties for each soil type are presented in Table 2.

Table 2: Characteristics of the top soil layer for the soils in the microwatershed*

Soil	Soil texture	Slope (%)	Saturated conductivity (mm/h)	Hydrologic soil group
Nicollet loam ⁺	Loam	1 to 3	5.1 to 50.8	B
Canisteo clay loam, Bemis moraine ⁺	Clay loam	0 to 2	5.1 to 50.8	C
Clarion loam, Bemis moraine	Loam	2 to 6	5.1 to 50.8	B
Harps clay loam, Bemis moraine ⁺	Clay loam	0 to 2	5.1 to 50.8	C
Okoboji silty clay loam ⁺	Silty clay loam	0 to 1	1.5 to 50.8	C
Webster clay loam, Bemis moraine ⁺	Clay loam	0 to 2	1.5 to 50.8	C
Clarion loam, Bemis moraine (moderately eroded)	Loam	6 to 10	5.1 to 50.8	B

*Source: Web Soil Survey; +drained

The potholes, which are located in two different HUC-12 watersheds (Fig. 1), have different drainage areas and depression volumes, and thus the potential to receive and store different volumes of water. The pothole in the Worrell Creek watershed is referred to as “Bunny” and is classified as a “second-level puddle.” It is composed of two depressions with a common outlet (Chu, 2015), which are distinct but merge with sufficient inundation. The locations of the subsurface drainage lines are largely unknown, except where they connect to the surface inlets. Bunny has two surface inlets connected to the drainage system in the west portion of the pothole; the eastern depression in the pothole does not have a surface inlet. The pothole located in the Walnut Creek watershed is referred to as “Walnut” and has a single surface inlet (Fig. 1).

Observed Data

During the growing seasons of 2010 and 2011, a pressure transducer was installed at the bottom of each pothole (Fig. 1), and the depth of ponded water was derived from the hourly transducer data (Logsdon, 2015). Transducers were installed after planting, and removed just prior to harvest. The water depth was monitored for 85 days (12th June to 4th September) in 2010 and 121 days (8th June to 6th October) in 2011 in the Walnut pothole, and 86 days (11th June to 4th September) in 2010 and 121 days (8th June to 6th October) in 2011 in the Bunny pothole. Additionally, the water depth was monitored for 143 days (20th May to 9th October) in 2016 in both the potholes. However, the 2016 data for Walnut is not included in this study, because additional subsurface drainage was added beneath this pothole in 2015, such that we would not expect the pothole's hydrologic response to be the same as in 2010-11. In order to compare the observed data to the model output, which is generated for the end of each simulated day, the last hourly record in the observed data was considered to be the water depth for that day.

Depth-volume relationships for each pothole were developed from the site topography data in order to translate the observed depth data into estimates of pothole water volume. A high-resolution Digital Elevation Model (DEM) of the site was generated from Light Detection and Ranging (LiDAR) data available from the Iowa LiDAR Consortium (available at archive <http://geotree2.geog.uni.edu/lidar/>). The raw data in point cloud format, at 1.4 m average bare-earth data spacing, were in a LASer file format (LAS) containing X and Y coordinates (UTM Zone 15N nad83), orthometric elevation Z (NADV88), return level (1, 2, or 12), and intensity (0-255). The DEM was generated according the procedures proposed by Gelder (Gelder, 2015), using ArcGIS 10.4.1 (ESRI, 2016).

To delineate the pothole extent in the DEM, we identified depressional areas using the fill tool in ArcGIS, which identifies depressions in the surface and fills them to facilitate delineation of basins and streams. Pothole extents were then estimated by subtracting the filled DEM from the original DEM. The result of this subtraction is a layer of only the filled areas, which we assumed were potholes (confirmed with a visual check of the results). Pothole volume and surface area were computed for each 0.1 m rise in elevation from the bottom (lowest elevation) of each pothole respectively. Maximum depth, volume, and flooded area for each pothole are given in Table 3. The area and volume data presented for the Bunny pothole is for the union of both depressions together. We assumed that the water surface elevation was the same for both depressions in this pothole. When the measured water depths was below the elevation of the bottom of the shallower depression, the depth-volume relationships for the deeper depression was used; when the measured depth was above the bottom elevation of the shallower depression, volumes for the two depressions were combined based on common elevation intervals of 0.1 m

Table 3: Depth and storage capacity of the two potholes in the study area

Pothole	Max Depth, m	Max Area, m² (ha)	Max Volume, m³ (ha-m)
Walnut	0.76	25,441 (2.54)	11,571 (1.15)
Bunny	1.0	50,753 (5.08)	28,068 (2.81)

AnnAGNPS Model Setup

We used the AnnAGNPS model, version 5.44. AnnAGNPS is a watershed scale, continuous simulation, daily time-step model designed to simulate water movement and non-point source pollution from agricultural watersheds (Bingner, Theurer, & Yuan, 2015). As such, it includes a hydrology component; surface and near-surface runoff is simulated based on the SCS Curve Number (CN) method for runoff depth, and the extended TR-55 procedure for peak flow rate (Bosch, Theurer, Bingner, Felton, & Chaubey, 1998). In the model, a user-

specific CN is an input parameter, and the model modifies those CNs on a daily basis during the running of the model based on tillage operations, soil moisture content, and crop stage. For purposes of runoff generation and soil water storage, the soil profile is divided into two layers. The top 200 mm are used as a tillage layer whose properties can change (bulk density, etc.). The remaining soil profile comprises the second layer whose properties remain static. A daily soil moisture water budget considers applied water (rainfall, irrigation, and snow-melt), runoff, evapotranspiration, and percolation (Bosch et al., 1998). Actual evapotranspiration is a function of potential evapotranspiration calculated using the Penman equation (Penman, 1948) and soil moisture content. When there is standing water in the wetland ET is handled using the potential ET, and when there is no water in the wetland, then ET is handled as the amount coming from the soil of the cell. The model also considers precipitation to the wetland as a primary water source.

Preliminary water quality sampling (Serrano, 2015) indicated relatively high sediment and phosphorus concentrations paired with relatively low nitrate concentrations, suggesting these potholes were predominantly filled by overland flow rather than by a rising water table (or in the pothole with surface inlets, backflow from the tile drainage system). Amado et al. (2016) also determined that their study potholes were primarily filled by surface flow rather than water table rise. This suggests that the CN approach is appropriate for modeling the hydrology of the potholes, as it estimates surface and shallow subsurface runoff.

The first step is to assess the watershed topography of the drainage area for each pothole to generate the hydrological units or cells and the reaches between cells. AnnAGNPS considers the cells to be independent units where generated runoff will load into the reaches. A conceptual map of the cell and reach framework of AnnAGNPS is shown in Figure 2.

Development of the cells and reaches is automated through the Topographic Parameterization program (TOPAZ) within AnnAGNPS. As in most watershed models, TOPAZ will fill surface depressions in the DEM. However, in this study, all the load generated by the cells is delivered into the pothole, as the wetland feature is the outlet of the last reach of the pothole watershed. The runoff generated from all the cells in a microwatershed will contribute to the potholes, and therefore we treated each pothole as a subwatershed outlet that can be represented by a wetland. The advanced wetland technology AgWET (AGNPS WETland feature) within AnnAGNPS is used to characterize the pothole in a microwatershed (Momm et al., 2016).

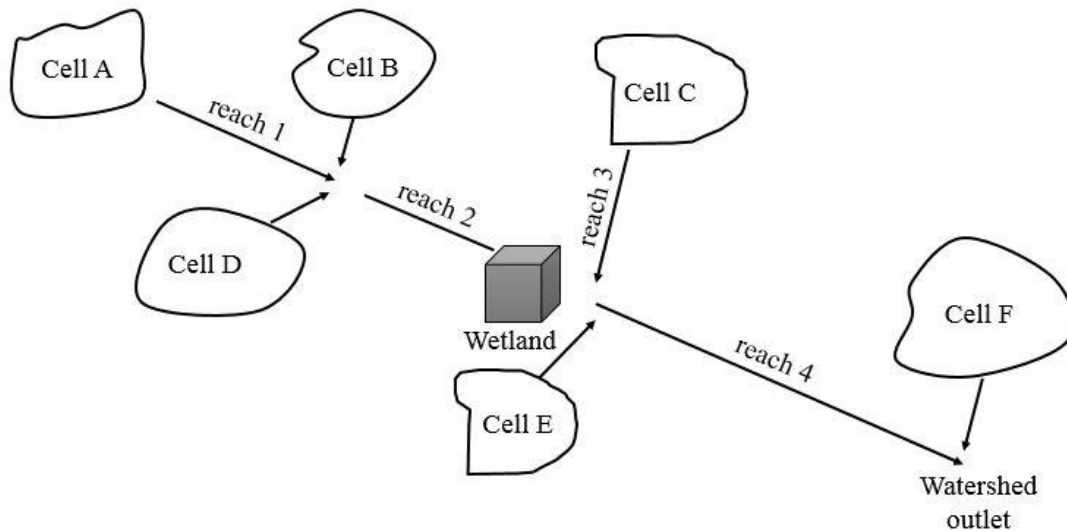


Figure 2: Cell hydrology simulation in AnnAGNPS. For this simulation, the wetlands are located in the reach before the outlet to capture all the load generated by the watershed

After the cells were generated, they were populated with soil, management, and weather information. The precipitation data is downloaded from Parameter-Elevation Regressions on Independent Slopes Model (PRISM) datasets, PRISM Climate Group gathers climate observations from a wide range of monitoring networks, applies sophisticated quality control measures, and develops spatial climate datasets which can be downloaded at any point

location or in gridded format for larger areas. The other weather parameters (maximum temperature, minimum temperature, dew-point temperature, wind velocity, wind direction and solar radiation) data is obtained from the ‘Sustaining the Earth's Watersheds, Agricultural Research Data System’ (STEWARDS) project which provides access to soil, water, climate, land-management, and socio-economic data from fourteen watersheds. It is developed by Conservation Effects Assessment Project (CEAP) - Watershed Assessment Studies (WAS) and is supported by United States Department of Agriculture (USDA). The STEWARDS weather station used in this assessment was located approximately 5 km from the field site.

The model allows the user to enter the minimum AnnAGNPS cell area that will be treated as a homogeneous unit, and the minimum reach length for uniform surface flow. These mechanisms, denoted as “Critical Source Area” (CSA) and “Minimum Source Channel Length” (MSCL), allow the user to study spatially variable watersheds of various sizes, and the number and division of generated cells is determined by the hydrology patterns suggested by the topography. For each cell, parameter values describing soil, land cover and climate are attributed according to input data described below. Here, CSA and MSCL values were reduced until a detailed stream network was generated. Suitable CSA and MSCL values were selected to generate a small number of cells to characterize the area since the entire drainage area of the potholes was under the same management and comparatively little variability is expected. The CSA selected was 1 hectare and the MSCL was 10 meters. Because these values correspond to 10% of the default value, we use the term “microwatersheds” to refer to the drainage area of the potholes in this paper. The final delineation resulted in microwatersheds with approximately 9.5 and 40 hectares of area for Walnut and Bunny potholes, respectively, and the generation of 13 cells and 6 reaches for Walnut; and 52 cells and 22 reaches for Bunny.

AnnAGNPS computes runoff, percolation, evapotranspiration, lateral subsurface flow, and tile drainage flows separately, then updates daily soil moisture estimates using a water balance approach. When there is rainfall, surface runoff is computed using the CN method (Cronshey, Roberts, & Miller, 1985). The CN for average conditions (CN_2) is defined by the user, and, based on soil moisture conditions, the value for dry (CN_1) and wet (CN_3) conditions is computed internally by the model, as a function of soil moisture content for that day. The remaining soil moisture can be lost by evapotranspiration (ET) or be added to soil moisture for the next day computation. Reference evapotranspiration (ET_0) is computed on a daily basis with the Penman-Monteith equation, and is then adjusted for crop evapotranspiration (ET) through a crop coefficient procedure (Allen, Pereira, Raes, & Smith, 1998). One limitation of AnnAGNPS is that it considers all the load generated in a given day to be delivered to the outlet. While this may not be reasonable for larger watersheds, given the small scale of the pothole watersheds this may be more consistent with reality (Das et al., 2008).

Subsurface flow consists of the sum of lateral subsurface flow and tile drain flow. This will only be simulated when either an impervious layer or a subsurface tile drainage system is indicated by the user. Because of the limitation that AnnAGNPS assumes surface runoff and subsurface flow produced by the cells will merge before being loaded into the reaches, it is not possible to simulate scenarios with artificially drained cells that represent reality, since the water load in the potholes would increase instead of decrease. To address this limitation, we accounted for the amount of water that is flowing out of the pothole by increasing the infiltration (I) rate.

The AnnAGNPS wetland component models the pothole as a cuboid pool with a fixed surface area, height, and weir properties, as well as constant infiltration throughout its extent.

The outflow consists of the water leaving the pothole through a weir, going to the downstream reaches. The user determines the properties of the weir, and its height in relation to the bottom of the pothole, according to observed conditions. This conceptualization, however, does not account for common features of farmed potholes, such as subsurface drainage systems and surface inlets, and a surface area that varies with depth. To address the shape limitation, we simulated depth and volume variations separately in two different model calibrations.

Model Parameterization And Calibration

The parameters adjusted during calibration were the CN, which regulates the water load produced by the cells, and therefore the load into the potholes; and the wetland infiltration rate, which influences the rate at which water leaves the system. The initial CN considered in the assessment was the "Straight Row Crop" for poor conditions; from there the CN was adjusted upwards. Evaluation metrics, discussed below, were computed for the delivery of water to the pothole only, and a final calibrated CN was determined based on the best performing CN value.

Once the water load into the potholes was determined by the calibration of the CN, then the water retention time was regulated by calibrating the infiltration rate. The initial infiltration rate was the default value for loam soils, and from there was increased until the model output best matched the drop in observed water depth as the inundation receded.

Because the AnnAGNPS representation of potholes assumes that the depth of potholes is linearly related with its volume, it is not possible to model both depth and volume variations with a single calibration. Therefore, for the assessment of depth and volume, different calibrated values for infiltration rate and CN were determined. In the case of the volume-based simulation, the model output is water depth in the wetland pool, simulated depths were converted to simulated volume by multiplying the model depth output by the model wetland

area; observed depths were converted to observed volume using the lidar-based depth-volume relationships described above.

Weir height was set as the maximum depth of the potholes, weir width and maximum water depth comes into play when the pothole in the model overflows. A default value of 10m was selected for weir width of both the potholes. For the depth-based simulations, wetland area was equivalent to the pothole surface area as determined by using the LiDAR data. For the volume-based simulations, the area was determined by dividing the LiDAR-derived pothole volume by the maximum water depth. Table 4 presents model wetland parameters adopted for the calibrations of depth and volume variations in the potholes.

Table 4: Wetland properties adopted for the calibrations of depth and volume variations in the potholes

	Wetland ID	Wetland Area (ha)	Max Water Depth (m)	Weir Width (m)	Weir Height (m)
Depth	Walnut	3.0	0.76	10	0.76
Calibration	Bunny	5.0	1.00	10	1.00
Volume	Walnut	1.5	0.76	10	0.76
Calibration	Bunny	2.8	1.00	10	1.00

Statistical Assessment of Model Performance

In the absence of long-term records of pothole inundation, we used the split sample technique for model calibration and assessment, where we divided the observed data collected in 2010 as one part and the data collected in 2011 as another part. For the Bunny pothole only, we also performed leave-one-out cross-validation using 2010, 2011 and 2016 data. Performance analyses were based on two schemes: one used the entire growing season (GS), corresponding to the span in which there was observed data, with zero values when there was no inundation; the other considered only days in which water storage (WS) was observed or simulated. Furthermore, we restricted the calibration process to exclude (or treat as zero, for

the GS analysis) days when observed or simulated depth was below 0.05m for non-consecutive days. We used four evaluation metrics, each providing different insights into model performance, to evaluate the calibration against the validation data. Table 5 describes these metrics and their interpretation.

Table 5: Selection of evaluation criteria, their corresponding formulation and specific values

Criterion	References	Mathematical formulation	Interpretation
NSE	(Nash & Sutcliffe, 1970)	$NSE = 1 - \left[\frac{\sum_{i=1}^n (Y_i^{obs} - Y_i^{sim})^2}{\sum_{i=1}^n (Y_i^{obs} - Y_i^{m-o})^2} \right]$ <p>Range: $(-\infty, 1]$</p>	NSE indicates how well the plot of observed versus simulated data fits the 1:1 line. Values between 0.0 and 1.0 are generally viewed as acceptable levels of performance, with 1 being the optimal value.
PBIAS	(Moriasi et al., 2007)	$PBIAS = \left[\frac{\sum_{i=1}^n (Y_i^{obs} - Y_i^{sim}) \times 100}{\sum_{i=1}^n (Y_i^{obs})} \right]$ <p>Range: $(-\infty, \infty)$</p>	PBIAS measures the average tendency of the simulated data to be larger or smaller than their observed counterparts. The optimal value of PBIAS is 0.0, with low-magnitude values indicating accurate model simulation. Positive values indicate model underestimation bias, and negative values indicate model overestimation bias.
RSR (RMSE-sd)	(Moriasi et al., 2007)	$RMSE - sd = \frac{\sqrt{\sum_{i=1}^n (Y_i^{sim} - Y_i^{obs})^2}}{STDEV_{obs}}$ <p>Range: $[0, \infty)$</p>	RSR incorporates the benefits of error index statistics and includes a scaling/normalization factor. The lower RSR, the lower the RMSE, and the better the model simulation performance.
R ²	(Krause, Boyle, & Bäse, 2005)	$R^2 = \left[\frac{\sum_{i=1}^n (Y_i^{obs} - Y_i^{m-o})(Y_i^{sim} - Y_i^{m-s})}{\sqrt{\sum_{i=1}^n (Y_i^{obs} - Y_i^{m-o})^2} \sqrt{\sum_{i=1}^n (Y_i^{sim} - Y_i^{m-s})^2}} \right]^2$ <p>Range: $[0, 1]$</p>	R ² describes how much the observed dispersion is explained by the prediction. A value of zero means no correlation at all whereas a value of 1 means that the dispersion of the prediction is equal to that of the observation.

Y_i^{obs} = observed data, Y_i^{sim} = simulated data, Y_i^{m-o} = mean of observed data, Y_i^{m-s} = mean of simulated data and n = number of events.

Results

Observed Data

During the observation period 2010-2011, standing water occurred for 32 days in 2010 and 11 days in 2011 in the Walnut pothole, and 35 days in 2010 and 14 days in 2011 in the Bunny pothole. In 2010, there were four to five inundation events, whereas in 2011 there were only two. These data are also presented in Logsdon, 2015, in which the Walnut and Bunny potholes are referred to as South and North, respectively. During the observation period 2016, standing water occurred for 10 days in the Bunny pothole, over three events.

Volume Simulation

For the volume simulation, calibrated CN values were generally outside the range of published CN values for these land use and soil types, and calibrated infiltration rates were very high. Furthermore, the evaluation metrics indicated that the model performance in validation was poor. We attempted another calibration approach in which we calibrated distinct CN values for cells inside the pothole extent and those outside the pothole extent, and these results were also poor. For this reason, we conclude that the model is not capable of simulating pothole inundation based on volume. The rest of the results will thus focus in greater detail on the depth-based simulation.

Depth Simulation

Calibrated CN and Infiltration Rates

The values for the final calibrations of the CN and infiltration according to the depth analysis are illustrated in Table 6 and Table 7 for the one-year and two-year calibration, respectively. For both potholes, calibrated values of CN were the same as or close to published values for straight row crop in poor hydrologic condition (81 and 88 for soil groups B and C,

respectively) when 2010 and 2011 were validated against each other. Calibrated values of infiltration rate were higher at Bunny, presumably because the observed data reflects the influence of the surface inlets.

Table 6: CN and infiltration values determined in the depth calibration of the potholes.
Parameters are listed by calibration year

Pothole	Walnut		Bunny	
Calibration Year	2010	2011	2010	2011
Daily infiltration (mm/day)	33	33	79	75
CN Hydr. Soil Group B	81	81	81	82
CN Hydr. Soil Group C	88	88	88	88

For the two-year calibrations at Bunny in which the 2016 data were included, calibrated infiltration rates were similar or identical to those of the one-year calibrations. Calibrated CN values, however, varied by which year was left out, and did not correspond as well to standard CN values for this land use.

Table 7: CN and infiltration values according to depth calibration in the Bunny pothole,
calibrated using two years

Calibration years	2010 and 2016	2011 and 2016	2010 and 2011
Daily infiltration (mm/day)	79	79	79
CN Hydr. Soil Group B	78	71	71
CN Hydr. Soil Group C	85	79	79

Figure 3 illustrates observed and simulated flooded depth for both potholes for the depth calibration and validation, according to pothole properties, CN and Infiltration values available in Table 4 and Table 6, respectively.

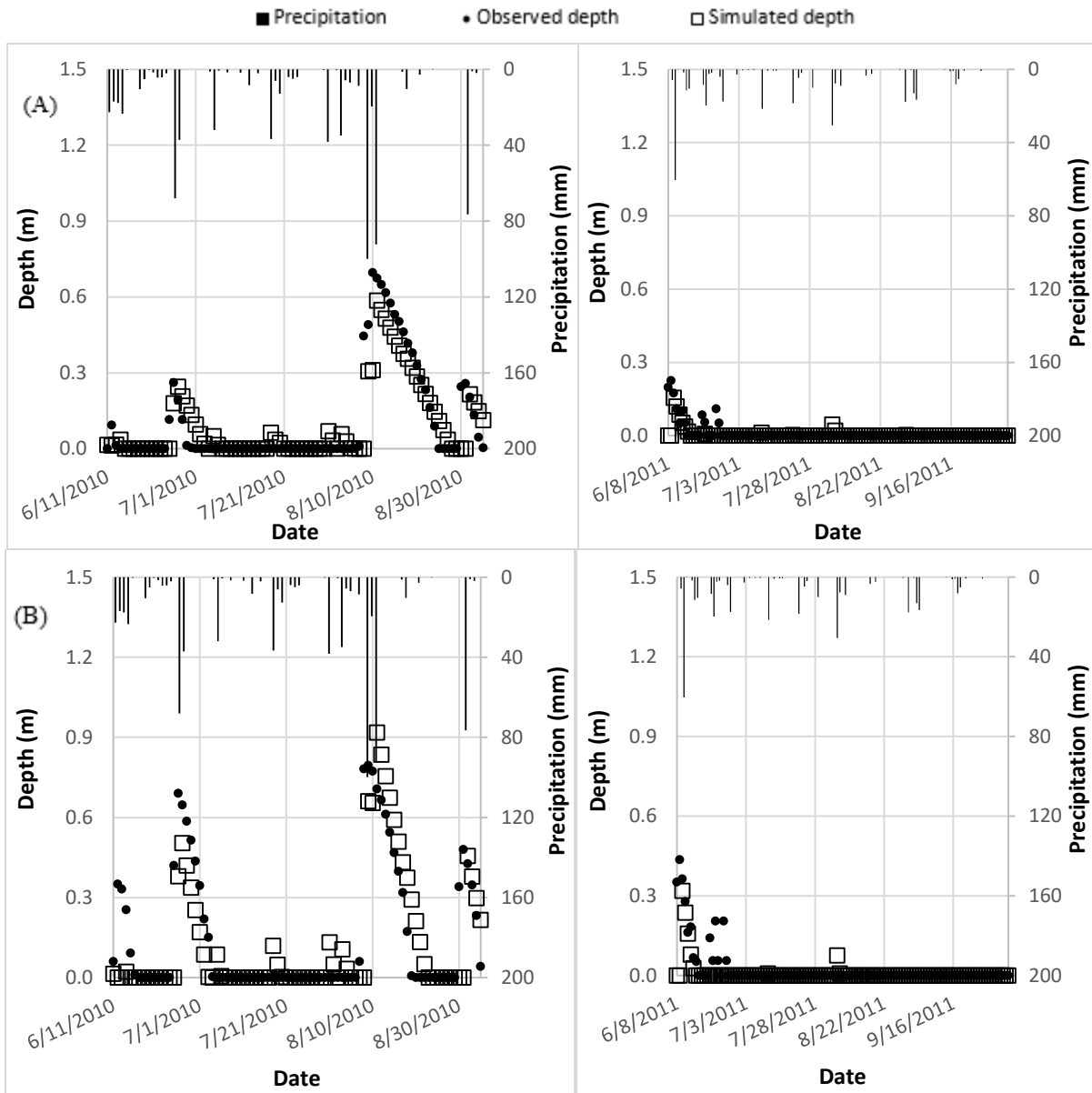


Figure 3: Simulation of water depth variation (2010 – calibration and 2011 – validation) in Walnut (A) and Bunny (B) potholes during the growing season

Model Evaluation

Tables 8 and 9 show the model evaluation metrics for the various models: the two one-year calibrations at both Walnut and Bunny, and the three two-year calibrations at Bunny.

Table 8: Simulation performance of potholes considering the NSE, PBIAS, RSR and R^2 efficiency models for the whole growing season (GS) and for days in which water storage (WS) was observed

	Calibration				Validation			
	Walnut		Bunny		Walnut		Bunny	
	2010	2011	2010	2011	2011	2010	2011	2010
NSE - GS	0.77	0.24	0.56	0.31	0.24	0.77	0.30	0.55
NSE - WS	0.71	-0.41	0.34	-0.47	-0.41	0.71	-0.49	0.34
PBIAS - GS	11.41	54.15	15.58	60.34	54.15	11.41	65.22	9.54
PBIAS - WS	11.41	54.15	15.58	60.34	54.15	11.41	65.22	9.54
RSR - GS	0.48	0.87	0.66	0.83	0.87	0.48	0.84	0.67
RSR - WS	0.42	0.44	0.60	0.45	0.44	0.42	0.46	0.61
R^2 -GS	0.79	0.27	0.60	0.34	0.27	0.79	0.34	0.59
R^2 -WS	0.73	0.05	0.46	0.14	0.05	0.73	0.16	0.45

NSE- Nash-Sutcliffe Efficiency, PBIAS- Percent bias, RSR- Ratio of the root mean square error, R^2 - Coefficient of determination, GS- Growing season, WS- Water storage.

Table 9: Simulation performance of the Bunny pothole considering the NSE, PBIAS, RSR and R^2 efficiency models for the whole growing season (GS) and for days in which water storage (WS) was observed

	Calibration			Validation		
	2010 and 2016	2011 and 2016	2010 and 2011	2011	2010	2016
NSE - GS	0.53	0.23	0.51	0.28	0.46	0.24
NSE - WS	0.28	-0.39	0.04	-0.87	0.05	-0.16
PBIAS - GS	0.89	21.16	39.57	71.64	31.27	-31.71
PBIAS - WS	0.89	21.16	39.57	71.64	31.27	-31.71
RSR - GS	0.69	0.88	0.70	0.85	0.73	0.87
RSR - WS	0.49	0.44	0.52	0.48	0.68	0.42
R^2 -GS	0.56	0.31	0.55	0.34	0.52	0.40
R^2 -WS	0.37	0.06	0.38	0.15	0.36	0.12

NSE- Nash-Sutcliffe Efficiency, PBIAS- Percent bias, RSR- Ratio of the root mean square error, R^2 - Coefficient of determination, GS- Growing season, WS- Water storage.

Nash-Sutcliff Efficiency values were higher when the entire observation period (GS), including all days in which neither the model nor the observations indicated water in the pothole, than when the data were restricted to only days in which there was water observed and/or simulated (WS). For the one-year calibrations, the validation NSEs were all greater than zero, and in some cases, greater than 0.5 for GS data. Using WS data only, several NSE values

were less than zero. The differences between the GS and WS results suggest that the model is better able to simulate when there is or is not standing water in the pothole than it is at precisely simulating how deep the standing water is. For the two-year calibrations at Bunny, that same trend holds, but the NSE-GS results tend to be lower. Moriasi et al. (2007) suggest $NSE > 0.5$ for satisfactory model performance at monthly streamflow simulation. While pothole depth and streamflow are quite different, using this benchmark we would conclude the model performance is often unsatisfactory at depth simulations when using NSE as the metric, depending on the calibration and validation data.

RSR values in validation ranged from 0.42 to 0.87. In the case of RSE, higher values indicate lesser model performance. Unlike with NSE, the RSR-WS values were lower and thus more favorable than the RSR-GS values. Using the streamflow recommendations of Moriasi et al. (2007) that $RSR \leq 0.7$ is satisfactory, and $RSR < 0.5$ is very good, we would conclude that when used to simulate non-zero inundation depths (WS), the model performance is very good, whereas it is often satisfactory when considering all the data (GS).

PBIAS values, representing a percentage over- or underestimation, indicate that the model tends to underestimate pothole water depth. Depending on the calibration and validation data used, PBIAS values were frequently greater in magnitude than the ± 0.25 recommended for satisfactory model performance, and always positive, indicating observed values higher than the simulated values. Using the streamflow modeling criterion we would conclude that the model in general has unsatisfactory underestimation of ponded depth.

However, given the sparser nature of pothole inundation data, it is reasonable to use less stringent criteria for determining satisfactory model performance than those for streamflow modeling. On the whole, we conclude that AnnAGNPS has potential in this

application, but will require further study to determine when and where modeling failure occur. Some of the reasons for lower model performance are known; for one, given the interannual variability in precipitation, and the very small size of the watersheds being simulated, some years generate standing water in the potholes more frequently than others, and indeed in some years there may be only one or two occasions where the potholes fill with any observable standing water. This makes it difficult to generate a sufficient dataset for model calibration and validation.

There are also difference between potholes; in general the AnnAGNPS model gives better performance in the simulation of Walnut compared to Bunny. The probable reason for the better performance in the simulation of Walnut pothole is the presence of just one surface inlet, which allowed it to be modeled more precisely through infiltration. Bunny pothole has two surface inlets through which water leaves the pothole. Another cause might be the size of the microwatersheds, and the shape of the potholes. Walnut microwatershed was smaller than Bunny microwatershed, and the water load coming to Walnut is lower than Bunny; given the model's tendency to underestimate water depth, this underestimation may be more pronounced when the watershed and pothole are larger.

An example of AnnAGNPS performance was assessed in a 45-month simulation in two Kansas watersheds. AnnAGNPS underestimated the extreme runoff generation in comparison to the observed data and another watershed model (Parajuli, Nelson, Frees, & Mankin, 2009). This situation was also observed in another study in Ontario, which investigated the occurrence of high peaks of runoff generation (Das et al., 2008). In this study, 2010 was a wet year with recorded rainfall of 1,214mm, which is 42.7% more than the average annual rainfall (850.9 mm, 1992 to 2016). Given the evidence that AnnAGNPS underpredicts runoff under very wet

conditions, our assessment of the model performance may be complicated by the fact that our dataset, particularly WS, is dominated by wet conditions because those are the more likely cases for the pothole to fill to a substantial depth.

In general, the model is able to capture the occurrence of ponding, as well as the initial depth of ponding in the potholes. The model simulated the duration of ponding better than the depth, it is likely due to the observed data reflecting the influence of short-duration, high-intensity events, whereas the model operates on a daily basis and will assume less intense rainfall events over a 24-hour period, and potentially divides the rainfalls across multiple days when a single event lasts more than a day.

Taken in total, we conclude that AnnAGNPS is a useful tool for the determination of inundation and water-depth in the potholes, but further research is necessary for a better estimation of the runoff generation from the microwatershed.

Conclusions

AnnAGNPS was capable of simulating inundation of the drained and farmed potholes in this study, when comparing model output of ponded depth to observations of the same, but was not capable of simulating potholes on a volume basis. This suggests that the model may be used for applications such as assessing occurrence of crop failures associated with standing water, or investigating agricultural management strategies that would reduce potholes' tendency to flood. The model cannot, however, be readily used in applications such as assessing downstream streamflow effects, or estimating pollutant loads from spillover or drainage fluxes, which rely on accurate estimates of water volumes. In such cases, water volumes may be estimated by simulating the pothole depth, and using terrain data to convert pothole depth to water volume. To expand model application to volume-based scenarios,

further development of the AnnAGNPS wetland component could include expanded options for wetland or pothole topography, so that the depth-volume relationship might better represent site characteristics of the pothole. This may allow for simultaneous simulation of both depth and volume, with a single calibration.

The variable performance of the model with different calibration data and for different evaluation metrics indicates that longer-term datasets will be beneficial in understanding the model's limitations. There are a number of factors influencing model performance, many of which are areas for further study. For example, some of our observed data and the work of others eg. Amado et al., (2016) suggests a need to more effectively distinguish between surface runoff and shallow subsurface flow; both appear to be influential in filling potholes, but the percentages of ponded water deriving from these two pathways, with different travel times, is not known. Likewise, the role of subsurface drainage, and the variability of drainage conditions - including extensively drained with multiple surface inlets, extensively drained without surface inlets, somewhat drained with older drainage lines nearby but perhaps not directly underneath the pothole, and not drained at all – are largely unknown in terms of their effect on filling and draining the pothole. Accurately modeling unknown pathways is a significant challenge.

The role of input data quality – including model parameterization as well as driving weather data – on model performance and output uncertainty is another area for further study. Finally, further research is needed to expand the simulations to other potholes, and in other locations, to determine if similar trends are observed.

Funding sources

This work was supported by the Iowa Department of Natural Resources and the US Environmental Protection Agency.

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CHAPTER 3. EFFECTS OF LAND MANAGEMENT ON INUNDATION OF PRAIRIE POTHOLE WETLANDS IN THE DES MOINES LOBE USING ANNAGNPS

Manuscript submitted to *Agricultural Water Management*

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Abstract

The Prairie Pothole Region (PPR) of North America contains millions of shallow wetlands, called potholes, in a landscape that was originally midgrass and tallgrass prairie. Land use of these potholes have been altered to make the land suitable for agriculture. Currently most of these potholes are under agricultural management but they are often areas of poor crop yields because the potholes tends to flood during the early growing season. Therefore, the objective of this study was to investigate the influence of different land use practices on depth, duration, and aerial extent of ponding in two potholes in central Iowa. Three management scenarios were simulated using Annualized Agriculture Non-Point Source model (AnnAGNPS) — current: conventionally tilled farmed conditions in corn/soybean rotation with surface inlets in the potholes connecting to a subsurface drainage system; retired: pothole is converted to a mixture of grass, weeds, and low-growing brush, with surface inlets removed and the drainage system underneath the potholes disconnected; and conserved: conservation tillage throughout the field with surface inlets and drainage maintained in potholes, and the inundation was compared. The average annual water depth for the conserved and retired scenarios was 7-8% lower than the average annual water depth for the current scenario. However, in the retired scenario opposite was observed in Bunny because of reduced infiltration resulting from disconnecting the surface inlets. The potholes tend to flood more

frequently in early stages of plant development, causing delay in management operations, which could result in reduced yields. Bunny exceeded its maximum volume storage capacity, resulting in an overflow 5 times in the 17-year simulation period. This information is important to prioritize areas for restoration in a highly modified agricultural landscape.

Keywords

AnnAGNPS, Hydrology, Inundation, Land management, Pothole/Prairie Pothole Region, Seasonal wetlands.

Introduction

The Prairie Pothole Region (PPR) of North America extends through three Canadian provinces (Saskatchewan, Manitoba, and Alberta) and five U.S. states (Minnesota, Iowa, North and South Dakota, and Montana). The portion of the PPR that extends into Iowa is referred to as the Des Moines Lobe. Agriculture and urban development have led to the drainage of nearly 90% of the four million acres of wetlands and prairie potholes which existed prior the 1900s in the PPR of Iowa (Hewes & Frandson, 1952). Potholes are seasonal wetlands that typically flood during the early growing season, and thus are drained to support agricultural production, and the vast majority of the potholes in this area are now under agricultural land use (Gleason, Laubhan, & Euliss, 2008; Miller, Crumpton, & van der Valk, 2009, 2012; Roth & Capel, 2012). Prairie potholes also provide a range of ecosystems services such as sediment entrapment, water quality improvement, flood control, and groundwater recharge (Gleason et al., 2008; Werner, Johnson, & Guntenspergen, 2013). Despite the benefits that wetlands provide, they have historically been seen as a nuisance and a hindrance to agricultural production (Van der Valk, 1989). This has led to many PPR wetlands being filled, drained, or otherwise manipulated to facilitate crop production (Renton, Mushet, & DeKeyser, 2015). Farmed

potholes are often areas of low productivity compared to the high yielding uplands across the PPR due to conditions such as poor soil quality, erosion, and water logging (Muth & Bryden, 2012). Although the impacts of farmed potholes on downstream waters is largely undocumented, in 2015 the Waters of the United States rule have established the protection of all waters in the country, that would have put farmed potholes into the same regulatory category as intact longer-duration wetlands, which were earlier not included in the Clean Water Act (CWA). Therefore, this work was initially motivated by farmer consternation caused by nuisance these features are in their operation and then bolstered by the need to understand their hydrological patterns and nexus downstream. Recently, the US Environmental Protection Agency conducted a comprehensive review of over 1350 peer-reviewed papers with the aim of synthesizing existing scientific understanding of how wetlands and streams affect the physical, chemical, and biological integrity of downstream waters (US EPA, 2015). The report concludes that additional research focused on the frequency, magnitude, timing, duration, and rate of fluxes from geographically isolated wetlands (potholes) to downstream waters is needed to better identify wetlands with hydrological connections or functions that substantially affect other waters and maintain the long-term sustainability and resiliency of valued water resources (Q. Wu & Lane, 2017).

The understanding of the hydrology of prairie potholes can be achieved by monitoring some features, and with the use of watershed models, such as the Soil and Water Assessment Tool (SWAT), Annualized Agriculture Non Point Source Model (AnnAGNPS), among others. Watershed models consist of tools that can be used to simulate a diverse number of features and flow patterns within a given basin of study, contributing with the decision-making process (H. Momm, Bingner, Wells, R., & Dabney, 2011; P. Nejadhashemi, A. Woznicki, & R.

Douglas-Mankin, 2011; Tsai, Chen, Fan, & Lin, 2017; J. Wu, Stewart, Thompson, Kolka, & Franz, 2015; Zema et al., 2010). The limitation of models, however, is that they usually require large amounts of data as inputs, and require technical knowledge from the user (Tsai et al., 2017). Regarding the prairie potholes, some limitations to use the model is the small size of the feature, and the fact that they have been functioning for a long time differently than their natural condition (Upadhyay, Pruski, Kaleita, & Soupir, 2018). In an attempt to simulate prairie pothole hydrology, Amado et. al. (2016) have developed a model, termed HydroGeoSphere, to simulate the hydrological connectivity of a densely farmed and drained landscape in the Prairie Pothole region, and have concluded that although intermittent ponding was frequent for the length of the simulated six years, hydrologic connectivity was infrequently established. Despite the fact that information on pothole hydrology is important for current and future management decisions regarding the region, there is still need to evaluate the potential impacts of the conversion of these features. Because of the new legislations regarding wetlands, a more conservation management can be adopted for farmed potholes, or these can even be removed from agricultural production, and either of these directions will impact pothole hydrology and potentially the downstream flow of the basin.

Prairie strips are a farmland conservation practice and research shows that by converting 10% of a crop-field to diverse, native perennial vegetation, farmers and landowners can reduce total water runoff from catchments by 37%, resulting in retention of 20 times more soil and 4.3 times more phosphorus (Schulte et al., 2017). It is possible that applying similar conservation strategies to potholes could also provide disproportionate environmental benefits as these restored potholes have high conservation value (Gleason et al., 2008). However, few studies have been conducted to date on impacts of pothole conservation on water quantity or

water quality benefits, especially in farmed systems. Three decades ago, the U.S. adopted a federal policy of “no net loss” for wetlands, following George H.W. Bush’s presidential campaign pledge (1988). Under this policy, wetland losses that cannot be avoided must be mitigated through restoration or creation (Aronson & Galatowitsch, 2008). Changing management of low productivity farmed potholes may be an opportunity to restore some ecosystem services at a lower cost than removing high productivity upland areas from production. Evidence suggests that perennial crops perform better in potholes compared to corn (*Zea mays* L.) and soybean (*Glycine max*) crops (Bailey-Serres, Lee, & Brinton, 2012; Edmonds, 2017; Mann, Barney, Kyser, & Di Tomaso, 2013). Incorporating alternative management practices, such as conservation restoration programs or planting perennial grasses, may help to minimize or eliminate crop yield losses in flood-prone pothole areas (Edmonds, 2017).

There is limited knowledge of how different pothole management options impact pothole inundation patterns. There are very few studies, which have monitored water depth fluctuations in potholes. For water management planning and decision-making, it is a common practice to use computer simulation models. In the absence of empirical studies on the effect of land management on pothole water dynamics, we chose a modeling approach using a watershed scale, continuous simulation, daily time step Annualized Agriculture Non-Point Source model (AnnAGNPS). Our previous work (Upadhyay et al., 2018) demonstrates that this model is capable of replicating observed patterns of inundation in these features; this provides us the opportunity to use this modeling approach to explore the potential impacts of alternative management strategies. Therefore, the goal of this paper is to investigate the influences of agricultural practices (current) and altered land use practices (retired and

conserved) on depth, and duration, and aerial extent of ponding using AnnAGNPS. This information is also important to understand and predict the impact of management operations on pothole inundation and resulting crop yield loss.

Methodology

Study area

This study focuses on two potholes located in a single conventional farm field straddling adjacent Hydrologic Unit Code (HUC-12) watersheds in the Des Moines lobe region near Ames, IA. These potholes are the same as those presented in Logsdon (2015) and Upadhyay et al. (2018). The potholes are managed in a corn-soybean rotation with conventional tillage and their positions in relation to the Walnut Creek and Worrell Creek HUC-12 watersheds are shown in Figure 1. According to the USDA NRCS Soil Survey, the field is 10% Okoboji silt clay loam, 25% Nicollet loam, 7% Harps loam, 3% Webster clay loam, 9% Clarion loam, 25% Canisteo clay loam, and 21% Clarion loam (USDA-NRCS, 2014). Except for the Clarion and Nicollet series, the soils are classified as hydric; formed in saturated conditions and could support wetland vegetation species when not drained.

The potholes have different drainage areas, and thus the potential to store different volumes of water. The pothole in the Worrell Creek watershed is referred to as “Bunny” and is classified as a “second-level puddle”. It is composed of two depressions with a common outlet (Chu, 2015), which are distinct but merge with sufficient inundation. Bunny has two surface inlets to the drainage system in the western portion of the pothole; the eastern depression in the pothole does not have a surface inlet. The pothole located in the Walnut Creek watershed is referred to as “Walnut” and it has one surface inlet. The locations of the subsurface drainage lines in the field are largely unknown, except where they connect to the surface inlets.

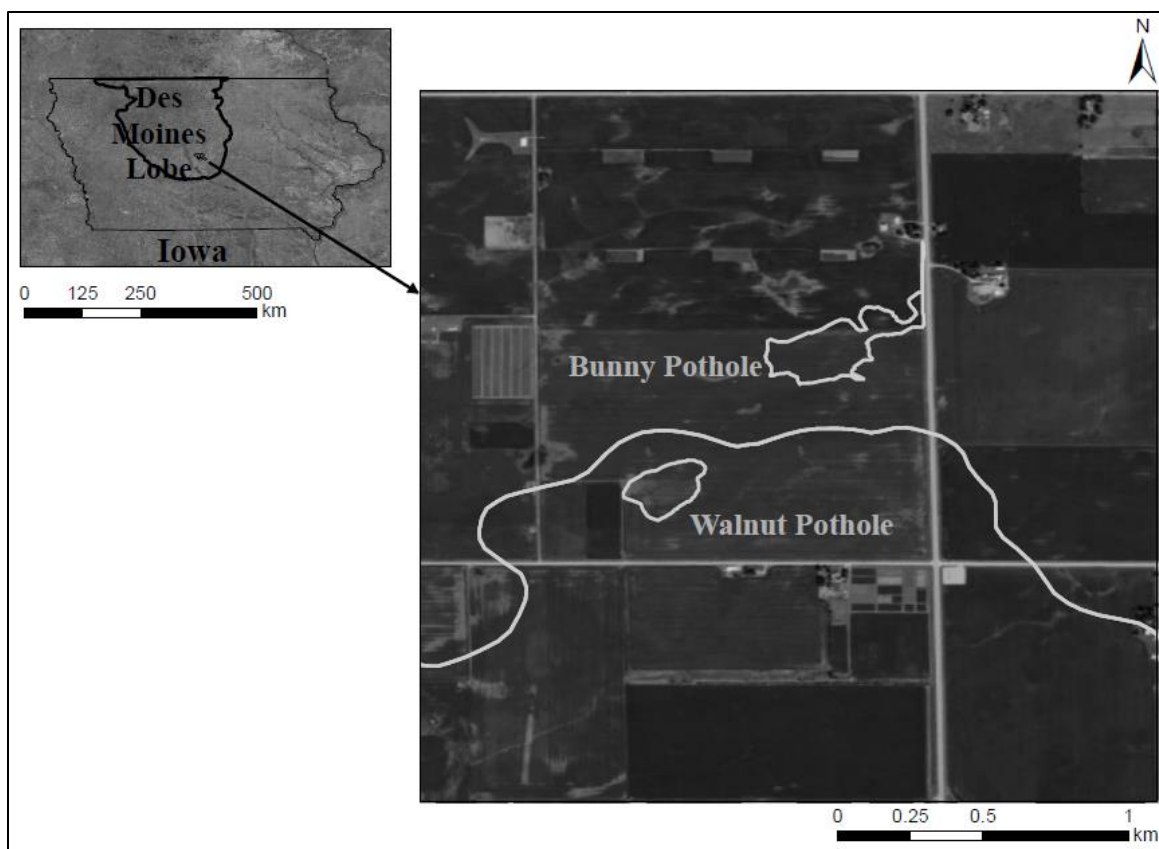


Figure 1: Pothole locations Left: general field location within the state of Iowa and the Des Moines Lobe. Right: pothole locations within the field, with the HUC-12 watershed boundary separating them

Current, retired and conserved management scenarios

Three management scenarios were compared, the current scenario corresponded to conventionally farmed conditions with corn/soybean rotation and with surface inlets in the potholes connecting to a subsurface drainage system. In the retired scenario the pothole is converted to a mixture of grass, weeds, and low-growing brush, with surface inlets removed and the drainage system underneath the potholes disconnected. For the retired scenario, retired areas are located toward the outlet of the microwatersheds; these areas are saturated more frequently than upland areas, and more suitable for conversion to alternative vegetation (Fig. 2). The cells with a centroid located inside the pothole boundary were 21.17% and 9.13% area

of the Walnut and Worrell microwatersheds, respectively, and were considered retired while the remainder of the microwatershed remained in row crop production. Lastly, a conserved scenario considered row crop under conservation tillage practices that leave significant surface residue (>75%), good hydrologic condition, and with surface inlets maintained in the potholes. The representation of each scenario in the model parameters is described below.

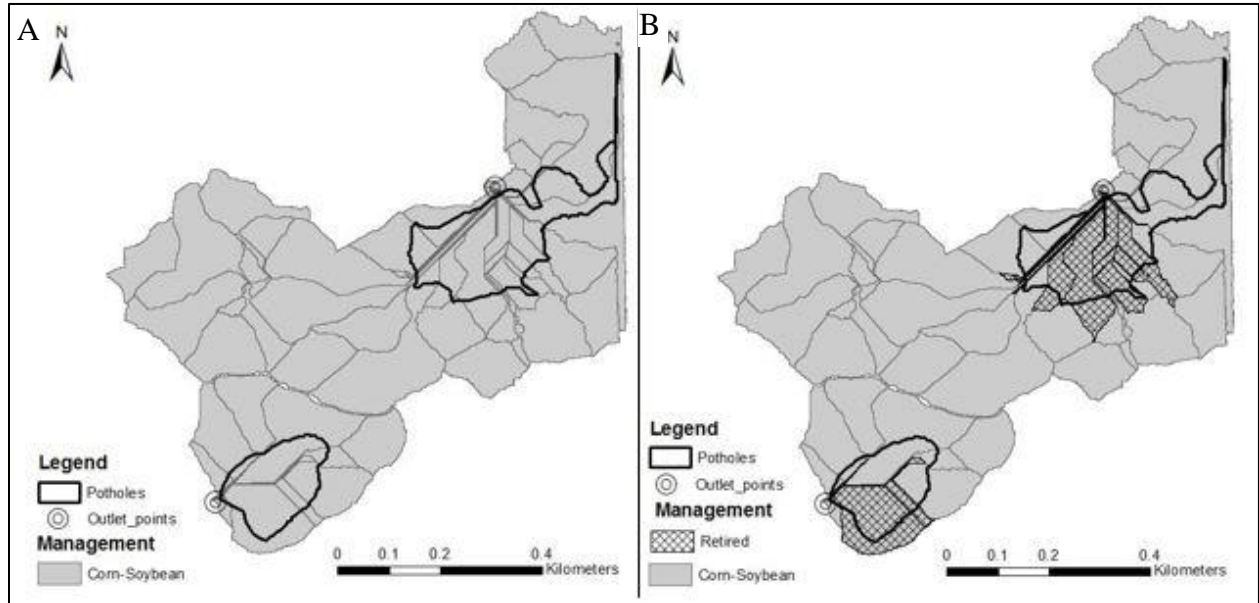


Figure 2: Watershed management distribution in A) current and conserved and B) retired scenarios for both potholes

Watershed model

Annualized Agriculture Non-Point Source model (AnnAGNPS) is a watershed evaluation tool developed jointly by the USDA Agriculture Research Service (ARS), and the USDA Natural Resources Conservation Services (NRCS) (Yongping Yuan, Bingner, & Rebich, 2003). AnnAGNPS is a watershed scale, continuous simulation, daily time step model. The GIS based wetland component of AnnAGNPS known as AgWET can be used for identifying and characterizing topographic depressions (puddles/potholes) during DEM preprocessing, which makes this model appropriate for investigation of the effect of different

land management on pothole inundation (H. G. Momm et al., 2016). AnnAGNPS is well-suited to small scale watersheds, and is able to produce satisfactory hydrologic outputs for the Midwest United States (Richardson, Bucks, & Sadler, 2008; Upadhyay et al., 2018; Y Yuan, Bingner, Locke, Theurer, & Stafford, 2011; Yongping Yuan et al., 2003). For example, the drainage areas computed by AnnAGNPS for Walnut and Bunny potholes are approximately 24 and 100 acres, respectively, and pothole water depth variations was successfully modeled at this scale (Upadhyay et al., 2018). The areas of Walnut and Worrell Creek HUC-12 watersheds, by comparison are approximately 23.2 and 12.5 thousand acres. Thus, because of their very small size, we refer to the drainage areas of potholes as microwatersheds.

First, watershed topography was assessed to generate hydrological units, the cells. To capture the detail of these microwatersheds, the maximum AnnAGNPS cell area that was treated as a homogeneous unit in the model was set to 1 ha and maximum reach length for uniform surface flow was set to 10 meters. These are denoted as “Critical Source Area” (CSA) and “Minimum Source Channel Length” (MSCL). The division of the cells by the model is based on hydrology patterns suggested by the topography.

The MSCL generates the reaches in the watershed. In larger watersheds, the reaches will correspond to rivers. However, at the microwatershed scale, the reaches indicate the preferential flow path of surface water. Based on the DEM and the user-identified outlet location, the model divides the watershed into cells. The objective of the division of the drainage area is to represent the spatial variability. For each cell, parameter values describing soil, land cover and climate are attributed. Daily load generated by the cells is transported through the reaches to the outlet.

AnnAGNPS includes a hydrology component; surface and near-surface runoff is simulated based on the SCS Curve Number (CN) method for runoff depth, and the extended TR-55 procedure for peak flow rate (Bosch, Theurer, Bingner, Felton, & Chaubey, 1998). To calibrate the model, we first regulated the water load generated by the microwatersheds, and therefore the rising water depth in the potholes, by testing a range of curve number (CN) values to achieve the best fit. After the water depth rise was consistent with the observed data, the infiltration rate was calibrated to estimate the rate at which water was leaving the system; tile flow was incorporated through calibration of infiltration rates. Actual evapotranspiration is a function of potential evapotranspiration calculated using the Penman equation (Penman, 1948) and soil moisture content. When there is standing water in the wetland ET is calculated using the potential ET, and when there is no water in the wetland, then ET is calculated as the amount coming from the soil of the cell. Model calibration and efficiency were discussed in detail in Upadhyay et al. (2018). Here, the model is used to estimate the depth, duration, and aerial extent of ponding of the features in the current, retired and conserved scenarios.

For the current scenario, the runoff potential of the microwatersheds is expressed by the curve number while the infiltration rate was adjusted to represent infiltration and drainage. Both values were selected for optimal calibration of water depth. In case of Bunny, since two different calibrated values were obtained for the two calibrated years (2010 and 2011) we took the average of those two for this analysis (Upadhyay et al., 2018). Similar CN values were able to capture the water load in both potholes, as both the fields were under the same crop rotation and have very similar soil types. Alternatively, because of the two surface inlets, the values for infiltration rate were higher for the Bunny pothole. The CN and infiltration rate values for Walnut and Bunny potholes for all three analyzed scenarios are provided in Table 1.

Table 1: Curve number and infiltration values for the three scenarios

Scenario	Current (Calibrated)		Retired				Conserved	
Wetland ID	Walnut	Bunny	Walnut		Bunny		Walnut	Bunny
Daily infiltration (mm/day)	33	77	26		26		33	77
Curve Number Classification	Row Crop – Current Condition	Row Crop – Current Condition	Row Crop – Current Condition	Mixture of grass, weeds, and low-growing brush	Row Crop – Current Condition	Mixture of grass, weeds, and low-growing brush	Row Crop – Good Condition	Row Crop – Good Condition
CN Hydr. Soil Group B	81	81.5	81	61	81.5	61	75	75
CN Hydr. Soil Group C	88	88	88	74	88	74	82	82

For the retired scenario, the curve number was selected based on land-cover type and hydrologic condition descriptions given in the National Engineering Handbook, Chapter 9 (USDA-NRCS 2004). Also, in the retired scenario, pothole infiltration was decreased to 26 mm/day for both features, to simulate the effect of removing surface inlets and disconnecting the subsurface drainage. This value was obtained by calibrating a monitored pothole in similar field conditions and which had been converted back to its natural state of vegetation, and retired from cultivation; using the procedure outlined in Upadhyay et.al. (2018). In the conserved scenario, we simulate conservation tillage throughout the microwatersheds, including the potholes, by selecting a curve number that represents straight row crop in good hydrologic condition with significant residue cover. We assume drainage is maintained in the potholes, so we did not adjust the infiltration rate of the pothole compared to the current scenario, although

in practice, the use of conservation tillage would likely improve infiltration rate over time. Figure 2 illustrates the management of the cells in the current, conserved and retired scenarios.

Weather data and model initiation period

The precipitation data were downloaded from Parameter-Elevation Regressions on Independent Slopes Model (PRISM) datasets, at the field site. The other weather parameters (maximum temperature, minimum temperature, dew-point temperature, wind velocity, wind direction and solar radiation) data were obtained from the ‘Sustaining the Earth's Watersheds, Agricultural Research Data System’ (STEWARDS) project which provides access to soil, water, climate, land-management, and socio-economic data from fourteen watersheds. It is developed by Conservation Effects Assessment Project (CEAP) - Watershed Assessment Studies (WAS) and is supported by the United States Department of Agriculture (USDA). The STEWARDS weather station used in this assessment was located approximately 5 km from the field site.

Twenty five years of daily rainfall, temperature, wind velocity, wind direction and solar irradiance data (1992 – 2016) were obtained from PRISM system and the STEWARDS weather station. The initial 8 years were used as the initialization years in the AnnAGNPS model. The initialization period is the time that the simulation will run before starting to collect results and is needed to initialize variables prior to start of the simulation (Browning, 2014). Daily water depths in the potholes were simulated from 2000 to 2016.

Pothole inundation analysis

We summarized the pothole inundation model output in four ways. First, we assessed the maximum water depth for each month and average water depth for each year in both potholes over the entire simulation period. The average water depth was calculated by

averaging the total water depth simulated over the entire simulation period by the number of days on which water depth was observed. This illustrates the water dynamics of the potholes in the current, retired and conserved scenarios, particularly under extreme events where the potholes are most likely to impact watershed-level storage. Using the maximum depth, an overflow assessment was performed. Overflow occurs when water exceeds the maximum depth of the pothole, this information is important to determine the influence of upstream potholes to downstream potholes and provide insight into surface pothole connectivity in relation to the rest of the watershed.

Second, we counted the total number of days in each simulated year in which there was water in the potholes, as these days of inundation have direct implications for crop production. An analysis of average number of inundation days in the potholes on a monthly basis was also performed, this analysis provides us the information on the months in which inundation was more frequent, and estimations of its impact on management operations and crop yields.

Third, we enumerated the occurrences of consecutive days of inundation. Days of consecutive inundation were considered because this information is important to determine how long water stays in the pothole before it leaves the system. In this analysis, every time inundation is observed in the feature, a count will start. In the next day, if there is still water, one will be summed with the previous value, and this process will continue while water is observed in the pothole. If the water depth is zero, the count ends and will start again with the following inundation event.

Finally, maximum area of inundation was evaluated. First, we calculated the maximum water depth in the potholes in a particular year, then the area corresponding to that maximum depth was obtained using topography data in ArcGIS. That area was compared with the areas

for all other simulated years to find the number of years having inundation more than this particular year. This assessment provided the information on the ponded area, for any given number of years.

Results and discussion

Maximum and average water depth in the potholes

Figure 3 illustrates the monthly maximum water depth over the entire simulation period for the current, retired and conserved scenarios for both the Walnut and Bunny potholes.

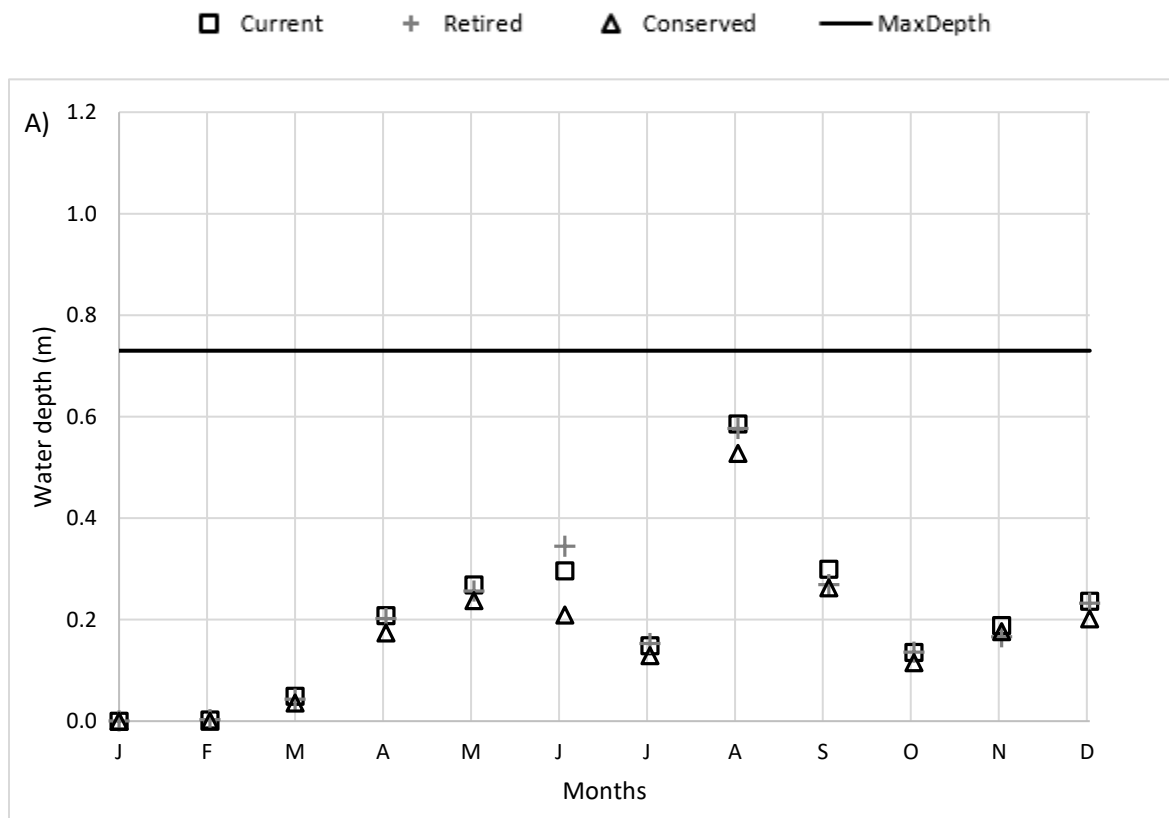


Figure 3: A) Monthly maximum water depth over the entire simulation period in Walnut potholes in the current, retired and conserved management scenarios

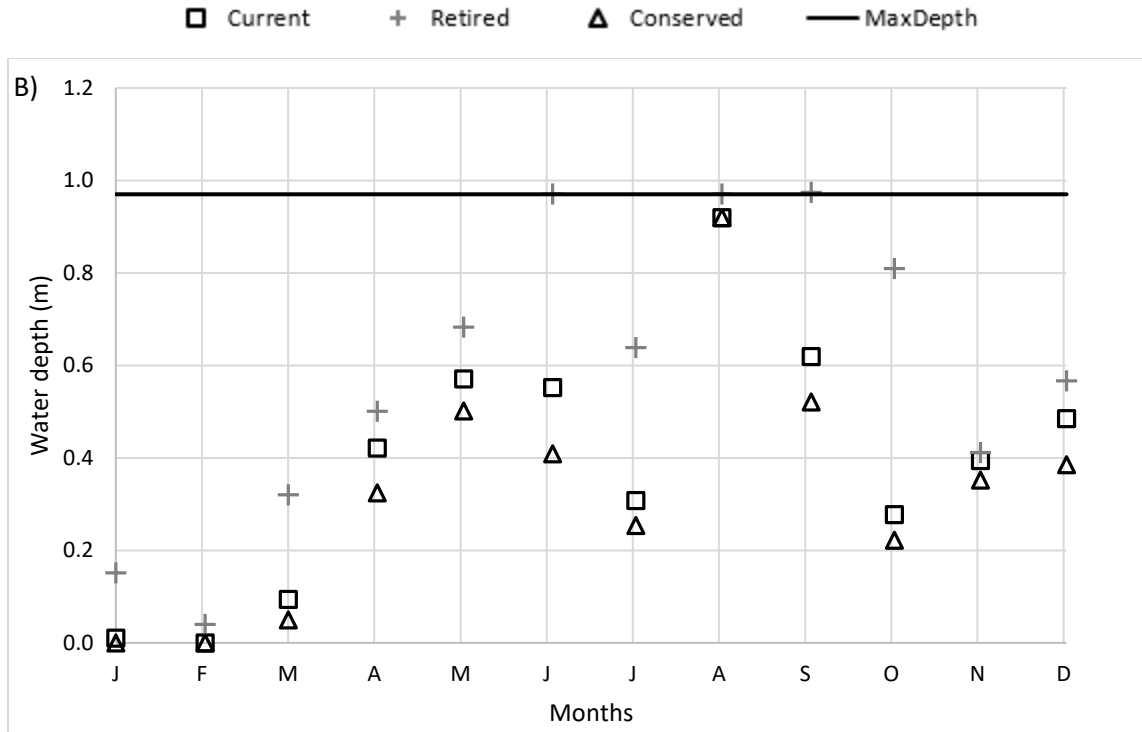


Figure 3: B) Monthly maximum water depth over the entire simulation period in Bunny potholes in the current, retired and conserved management scenarios

From figure 3, we can see that in the Walnut pothole, the monthly maximum water depths are greatest for the current scenario and are lowest for the conserved scenario. From the maximum water depth data we can also consider how often the potholes will overflow, to understand their potential nexus downstream (Leibowitz & Vining, 2003; Singh, 2015). Overflow occurs when water exceeds maximum depth of the potholes, which corresponds to 0.73 and 0.97 m for Walnut and Bunny potholes, respectively, after considering evapotranspiration (ET). Once the wetland reaches the maximum water depth, some water will be lost due to ET. Thus, in case of overflow, the model output appears to be a little lower than the maximum depth (Fig. 3). The potholes did not exceed their maximum volume storage capacity under the current and conserved scenarios. However, in the retired scenario when the vegetation was replaced by mixture of grass, weeds, and low-growing brush, and the artificial tile drainage was removed, the potholes stored more water through the year, and overflowed

during wet conditions. In the retired scenario, during the simulation period from 2000 to 2016, Walnut never exceeded its maximum volume storage capacity, but Bunny exceeded its maximum volume storage capacity 5 times.

For the Walnut pothole, the average annual water depth for the current scenario is approximately 8% higher than the average annual water depth for the retired and conserved scenarios. This is likely because compared to the current scenario, the retired scenario included a portion of the watershed (inside the pothole boundaries) converted to a mixture of grass, weeds, and low-growing brush, which reduced runoff in the model, while the conserved scenario's conservation tillage also resulted in a decrease in runoff to the pothole.

Behavior of the Bunny pothole, however, was different; in this pothole the retired scenario had the greatest water depths (both maximum and average). We attribute this to the disconnection of the surface inlets and drainage system. Because the Bunny pothole had two surface inlets and an initially high infiltration rate as a result of the drainage in the current scenario (Table 1), this change had a more significant impact in this pothole. Additionally, the Bunny pothole has a larger microwatershed area in relation to Walnut, which was probably the reason for the installation of the two inlets. In this case, the effect of the reduced infiltration was high and average annual water depths in the pothole increased when compared to the current condition by 27%. However, the average annual water depth for the conserved scenario was 7% lower than the current scenario for this pothole, again illustrating the effect of reducing runoff through changes in tillage practices.

These findings suggest that in the conversion of potholes with surface inlets and larger microwatersheds, additional conservation practices may be needed to offset the runoff and decreased outflow through surface intakes that occurs.

Pothole days of inundation

Figure 4 shows the total number of inundated days for each simulated year, from 2000 to 2016 for current, retired and conserved scenarios, for both potholes, including all days in which there was any simulated water depth in the potholes respectively.

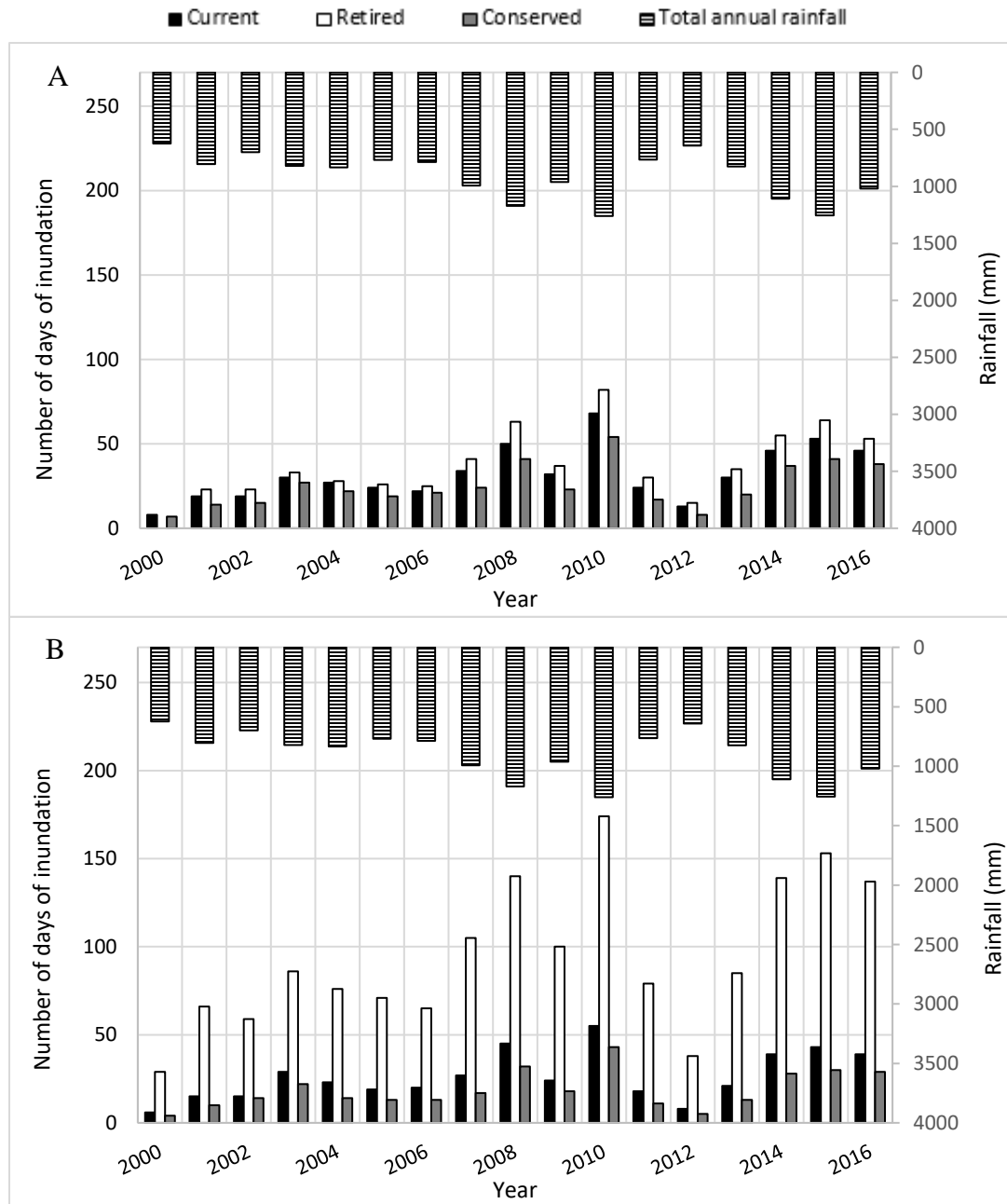


Figure 4: Comparison between the number of days of inundation between current, retired and conserved conditions for A) Walnut and B) Bunny potholes

In the current condition, Walnut and Bunny potholes had similar patterns through the years, which is expected, due to their proximity and similar management. Based on these simulations, the water regime of the potholes can be classified as semipermanent, since these tend to flood every year (Galatowitsch & Valk, 1996). The years of 2008, 2010 and 2015 had the most inundations, whereas 2000 and 2012 had the fewest. In the current scenario, the average number of inundations per year was 32 and 26 for Walnut and Bunny, respectively. For all simulations, the difference between current and retired scenario was higher in Bunny, likely for the reasons discussed above, which suggests that the conservation of this pothole would have a higher impact on downstream hydrology.

The average number of inundations per month under the current and conserved scenario for both potholes are shown in Table 2 along with the corresponding estimated plant growth stage for corn and soybeans. The retired option is not presented because it assumes crops will not be present in the potholes and thus the occurrence of inundation with respect to the corn/soybean growing season is not relevant. The plant growth stages are: Initial, Development, Maturation, and Senescence, and correspond approximately to 15, 25, 40 and 20% of the growing season, respectively according to the FAO (Doorenbos & Pruitt, 1975).

Table 2: Average number of inundation days in the potholes during the growing season

		Current*		Conserved ⁺	
Growth Stage	Months	Walnut	Bunny	Walnut	Bunny
Initial/Development	May	5	4	4	3
Development	June	5	4	4	3
	July	4	4	3	2
Development / Maturation	Aug	6	5	5	4
Maturation	Sep	4	3	3	3
Senescence	Oct	2	1	1	1
Total days		26	21	20	16

* Row crop with corn and soybean rotation with existing hydrological conditions and surface inlets.

⁺ Row crop with corn and soybean rotation with good hydrological conditions and surface inlets.

As shown in Table 2, the potholes tend to flood more frequently in early stages of plant development. In the current scenario, Walnut pothole is inundated for an average of 5 days in May and 5 days in June and in conserved scenario, Walnut pothole is inundated for 4 days in May and 4 days in June, across all the years of simulation. Considering that these are the months when seeding occurs, it is likely that these conditions could cause delay in field operations, which can result in reduced yields in the areas where the potholes are located.

Consecutive days of inundation

The number of consecutive days of flooding in the pothole has several impacts. For one, crop development in the pothole is affected as soil oxygen is depleted within 48 hours of soil saturation. Without oxygen, the plants cannot perform critical life sustaining functions; e.g. nutrient and water uptake is impaired and root growth is inhibited (Wiebold, 2013). Conversely, when these features are managed as wetlands rather than cropland, prolonged inundation affects the efficiency of the wetland in the improvement of water quality, since, the longer water is stored in potholes, the higher opportunity for nutrient sorption and sediment settling (Johnson, Oslund, & Hertel, 2008; Woltemade, 2000).

Growth stage is a critical factor in survivability due to flooding. Technically, the larger a plant, the more oxygen it requires to stay alive. However, smaller plants are more likely to become submerged and to remain submerged for longer periods. As a rule, smaller crops in the earliest growth stages are more at risk and usually receive greater damage due to flooding, ponding and saturated soils (Butzen, 2017). The major crops grown in the Midwest, corn and soybeans, often survive for two to four days under flooded conditions without requiring replant. Soybeans are thought to be more tolerant to temporary flooding than corn and many other crops. When the growing point of corn is just at or below the soil surface, corn can only

survive two to four days of totally saturated soil conditions (Butzen, 2017), while soybeans easily survive 48 hours underwater, and have even been known to survive submersion for a week under ideal conditions during and after flooding. Four days or more of flooding stresses the crop, delays plant growth, and causes the plants to be shorter with fewer nodes. Flooding for six days may depress yields significantly, and longer periods under water may destroy the entire stand. Any ponding lasting more than two days will have negative impacts on plant growth and yield (Nielsen, 2011).

From 2000 to 2016, at least 47% of the events of inundation lasted more than two days during the current scenario, potentially killing vegetation in the field. Figure 5 illustrates the consecutive days of inundation in a histogram format, for the assessment of consecutive inundations in the current, retired and conserved scenarios.

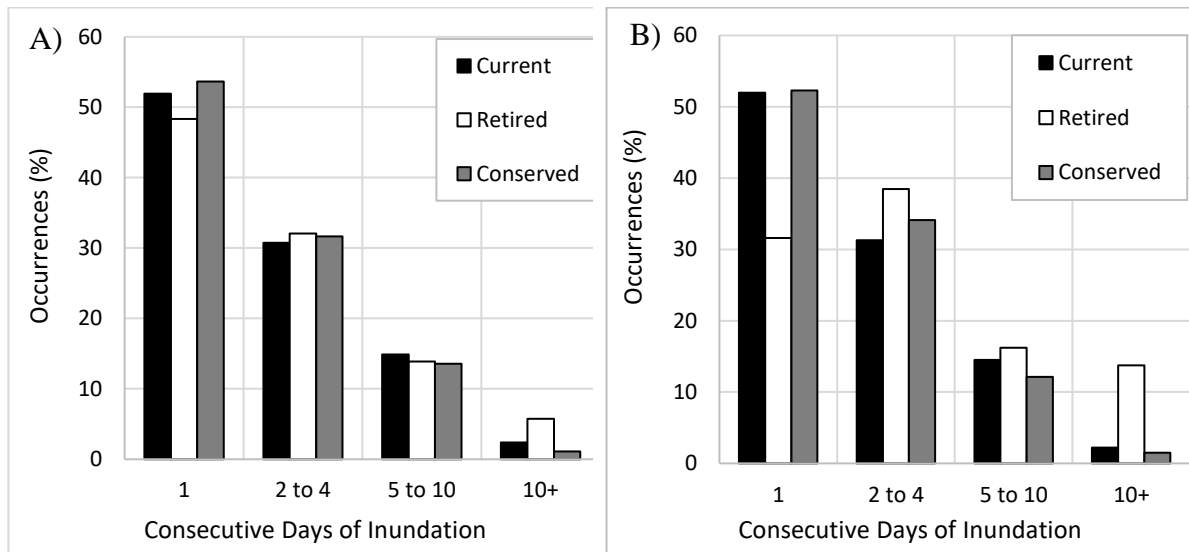


Figure 5: Consecutive days of inundations in the potholes over the entire simulation period A) Walnut and B) Bunny in the current, retired and conserved scenario

For most of the inundation events, the relative number of inundation days (occurrences) was similar for the current and conserved scenarios, which is expected because both scenarios have similar drainage. However, for the retired scenario when we removed the drainage, low

occurrences were observed for a lower number of consecutive days of inundation and relatively high occurrences was observed for higher number of consecutive days of inundation (Fig. 5). For example, in Bunny the retired scenario had 20% less simulated occurrences with only 1 consecutive day of inundation and 12% more 10+ consecutive days of inundation, when compared to the current and conserved scenarios.

Maximum area of inundation

Maximum area of inundation provides insight into the area of the pothole that is not suitable for agricultural crops in the field due to the water depth in the potholes. Figure 6 illustrates the maximum area of the potholes inundated in each year, corresponding to simulated years in percentage, for a better understanding of the area of the inundation.

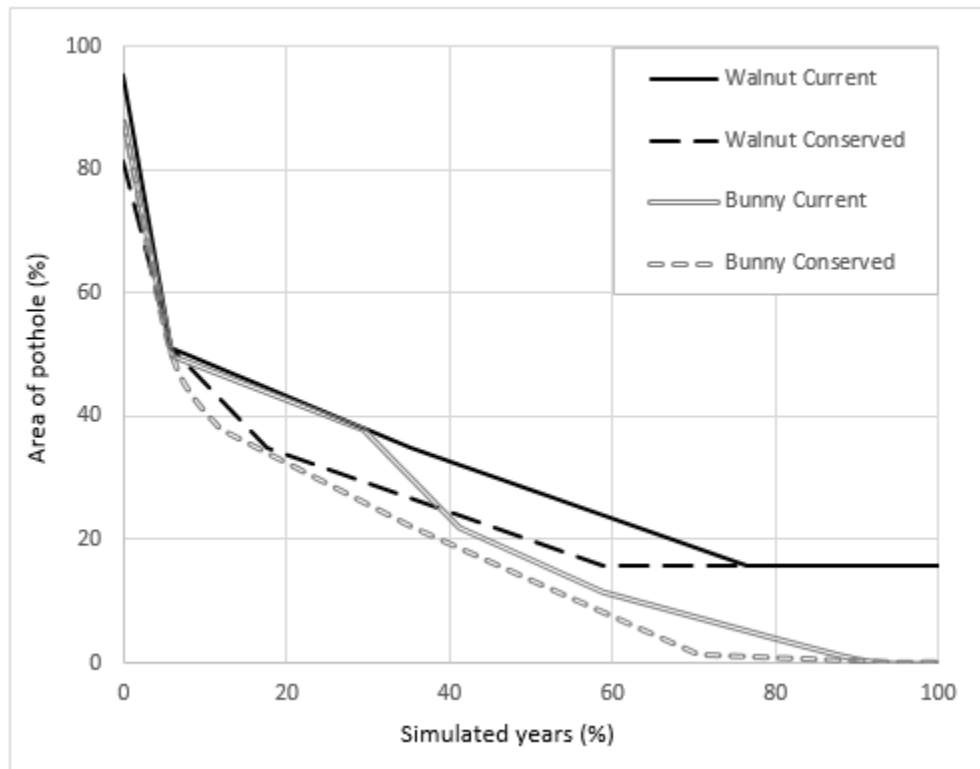


Figure 6: Area inundated corresponding to maximum depth in each year for all simulation years in the current and conserved scenarios

For approximately 6% of the simulated years, the inundation was more than 50% of the total area in all scenarios (Fig. 6). In current scenario, for 50% of the simulated years which is approximately 8 years, 28% and 18% of the total area of the potholes was inundated in Walnut and Bunny potholes, respectively. In the conserved scenario, 20% and 12% area of the Walnut and Bunny potholes was inundated corresponding to 50% of the simulated years, which shows that there was a reduction of approximately 8% and 6% inundated areas in Walnut and Bunny potholes, respectively, when the land management was shifted from current to conserved conditions.

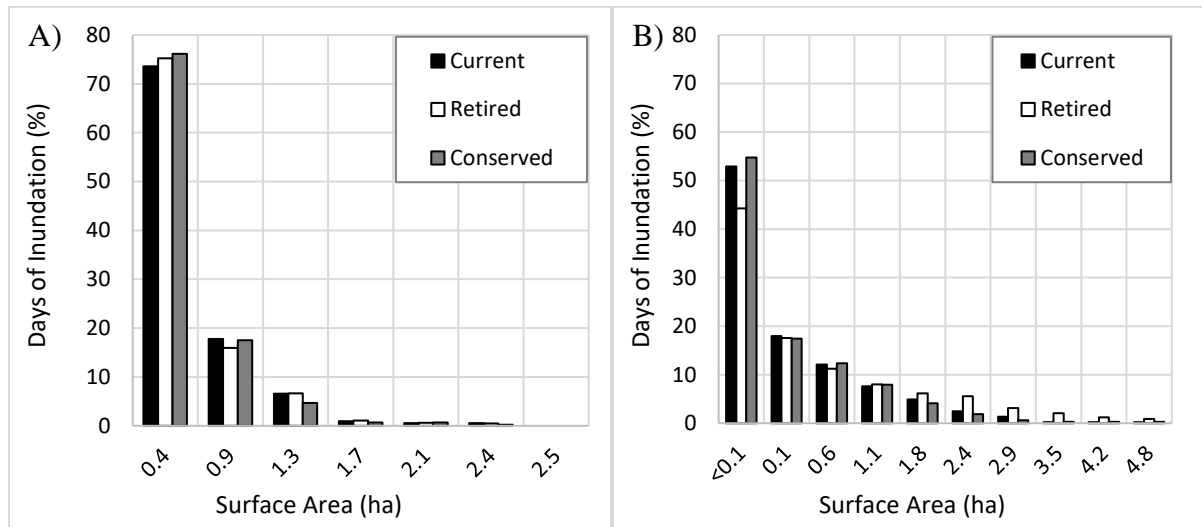


Figure 7: Intensity of inundation in the potholes A) Walnut and B) Bunny in the current, retired and conserved scenarios

Figure 7 illustrates the intensity histogram of both potholes for the three scenarios. With this assessment, we observed that Walnut and Bunny potholes have similar hydrological patterns, and both of them will accumulate shallow depths of water, from 0 to 0.1m depth of surface water for approximately 75% and 50% of the inundations in the current scenario for Walnut and Bunny potholes, respectively. The area compromised for agricultural purposes varies in Walnut compared to Bunny, since the later pothole is larger. In addition to the size of the pothole, the number of potholes in a field also affect the area suitable for agricultural

production. The higher the number of potholes in a field, the higher the percentage of area unsuitable for crop production.

As predicted, the conversion to retired scenario had a higher impact on water depths in Bunny when compared to Walnut, because of the larger drainage area, and higher reduction in infiltration rate due to disconnection from the drainage system. In the retired scenario, in the occurrence of inundation, the water depth in Walnut was usually between 0 and 0.2 m, and the frequency of inundation decreased as the water depth in the potholes increased, similar to the current scenario. On the other hand, although the pattern of higher occurrence of inundation was similar in both the potholes, water depth varies more in the Bunny pothole with relatively more days of inundation at higher depths.

Conclusions

Land management scenarios were analyzed to prioritize areas for restoration in a highly modified agricultural landscape. Two pothole features were assessed with the AnnAGNPS model to estimate their hydrological patterns in different management scenarios. Three different management scenarios were developed and simulated by AnnAGNPS including a baseline scenario based on the current management conditions and two alternatives with modified land management. The three scenarios were current (row crop, current condition with surface inlets), retired (row crop, current condition and mixture of grass, weeds, and low-growing brush with no surface inlets) and conserved (row crop, good condition with surface inlets).

Simulations indicate that potholes frequently flood during the growing season, which is at odds with their current use, lands designated to agricultural production. Results also show that these features have potential to complicate crop production for farmers early in the season,

by interfering in the dates of field operations, and could impact crop yields. Under the current scenario, potholes rarely overflowed, which implies that the features did not directly connect with downstream potholes. When drained, potholes tend to flood less often, however, drained water merges with other sources of flow in the drainage tiles, which suggests an indirect influence and nexus downstream. In the retired scenario, these features were more likely to overflow directly causing effects downstream, although the combined number of overflow events over the entire simulation period was only 5. When tiles in the potholes are disconnected, it is important to consider the use of conservation practices such as conservation tillage, cover cropping, mulching and extended crop rotations to reduce runoff production in the microwatershed.

The identification and prioritization of these land management scenarios can be used as a policy support tool in discussions of alternative management and investment decisions such as applying conservation reserve program (CRP) and wetlands reserve program (WRP) funding to these features. This approach can also be used to estimate the contributing area and the importance of pothole wetlands to perennial streamflow in watersheds, which is needed to support policy and decision making regarding wetland services.

Funding sources

Although the research described here has been funded wholly or in part by the United States Environmental Protection Agency under assistance agreement CD97753901 to Iowa State University, it has not been subjected to the Agency's product and administrative review and therefore might not necessarily reflect the views of the Agency; no official endorsement should be inferred.

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CHAPTER 4. ASSESSMENT OF USGS DEMs FOR MODELING POTHOLE INUNDATION IN THE PRAIRIE POTHOLE REGION OF IOWA

Manuscript submitted to *Geocarto International*

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Abstract

The study aims to compare pothole inundation in two potholes (Walnut and Bunny) using Annualized Agricultural Non-Point Source Pollution model (AnnAGNPS) with three DEMs: a 1m DEM prepared from the LiDAR data which is readily available for the state of Iowa, USGS 1/9 arc-second DEM (~3m) which covers about 25 percent of the conterminous United States (U.S.) and USGS 1/3 arc-second DEM (~10m) which covers the entire U.S. The estimates of average water depths using USGS 3m DEM was found to be 6% and 2% lower than the 1m LiDAR DEM and the estimates of average water depths using USGS 10m DEM was found to be 7% and 12% higher than the 1m LiDAR DEM for the Walnut and Bunny potholes, respectively. In this study, we found that the variations in water depth and presence/absence of ponding in the potholes can be predicted using USGS DEMs.

Keywords

AnnAGNPS model, Digital Elevation Model (DEM), LiDAR, Pothole hydrology, USGS DEMs.

Introduction

Potholes are areas of depressions that flood periodically even with artificial drainage, leading them to be classified as ephemeral wetlands (Serrano, 2015). Typically, potholes are covered by water or have waterlogged soils for long periods during the growing season that influences crop yields. Potholes play an important role in the hydrologic cycle and provide multiple environmental services including flood mitigation, water quality improvements, wildlife habitat, carbon sequestration, groundwater recharge, and pollution abatement (Keddy et al., 2009; Rey et al., 2012). In their natural state, vegetation, soil, and hydrology are the three characteristics typical to potholes which play an important role in their identification (Interagency Workgroup on Wetland Restoration, 2002). Native vegetation in potholes is capable of living in saturated soil conditions for at least part of the growing season while crops are severely compromised when ponded water occurs for more than two days (Nielsen, 2011). Wetland soils typically have low oxygen content because they are under saturation, flooding or ponding long enough during the growing season to develop anaerobic conditions in the upper part; these soils are also commonly referred as hydric soils (Interagency Workgroup on Wetland Restoration, 2002). Pothole inundation refers to the presence of water at or above the soil surface for a sufficient period of the year to significantly influence the crop yields and soils that occur in the area. Currently pothole ecosystems are threatened and often degraded or lost due to agriculture and urbanization (Johnston, 2013).

Nearly 90% of the four million acres of surface depressions in Iowa have been lost to agriculture and urban development (Miller, Crumpton, & van der Valk, 2009). Farmed and drained potholes typify the nature of these features across much of Iowa, in much higher proportion than in the rest of the Prairie Pothole Region (PPR) (Gleason, Laubhan, & Euliss, 2008). Most of the potholes in the agricultural farms are small, ephemeral and tile drained. The

tile drainage significantly alters the natural state of these features and making it suitable for agricultural activity. The identification and mapping of the potholes becomes complicated and challenging due to the altered natural state of these features (McCauley, Anteau, van der Burg, & Wiltermuth, 2015). Most of the existing research on the hydrology of prairie pothole wetlands has focused on potholes that were neither farmed nor drained with subsurface tile drainage (Upadhyay, Pruski, Kaleita, & Soupir, 2018).

The management of farmed potholes has received inadequate attention. The pothole areas are consistently less profitable than upland areas in fields, and often lose money, according to a recent analysis by the Iowa Soybean Association (Morrison, 2016). Identification of pothole location and its extent of inundation is an important part of pothole management, it is important to identify the depth, extent and location of potholes as precisely as possible. Identifying and characterizing topographic depressions can be the first stage in generating management plans for low productivity farmed potholes to restore some ecosystem services at a lower cost than removing high productivity upland areas from production. The most efficient way of identifying these features is by using Digital Elevation Models (DEMs) developed with remote sensing and GIS techniques (Hogg & Holland, 2008; Vogt, Colombo, & Bertolo, 2003). Coarse scale DEMs at 30m to 90m spatial resolutions are often used in large scale hydrological modeling (Patro, Chatterjee, Singh, & Raghuwanshi, 2009; Pramanik, Panda, & Sen, 2010; Samantaray, Chatterjee, Singh, Gupta, & Panigrahy, 2015; Suliman, Katimon, Darus, & Shahid, 2016). However in small scale hydrological modeling such as pothole inundation modeling, fine scale DEM (1m to 10m) should be used for identification and mapping of these small potholes, as DEM provides topographical information for watershed delineation (Fairfield & Leymarie, 1991; Vogt et al., 2003) and hydrological

modeling (Jena, Panigrahi, & Chatterjee, 2016; Liu, 2008; Tarolli, 2014). DEM grid resolution can result in significant differences in the spatial and statistical distributions of contributing areas and the distributions of downslope flow path length (Woodrow, Lindsay, & Berg, 2016).

The importance of large wetlands (1 to 30 ha) is well recognized and they are easily identified; however, the same cannot be said for potholes (generally less than 1 ha). The National Wetlands Inventory (NWI), which is the most comprehensive digital coverage of United States wetlands, typically does not include wetlands smaller than one to three acres, ephemeral wetlands, farmed wetlands, and certain wetland types that are difficult to interpret from aerial photos. Fig. 1 shows the potholes we are evaluating in this study which are interestingly not covered by the NWI. Individually potholes may seem insignificant, but collectively they play an important role in moderating flows and improving water quality in agricultural catchments (McKergow, Gallant, & Dowling, 2007), increased attention to water quality has further increased the need for proper management of these potholes and made the evaluation of small potholes that are located in the agricultural fields even more important.

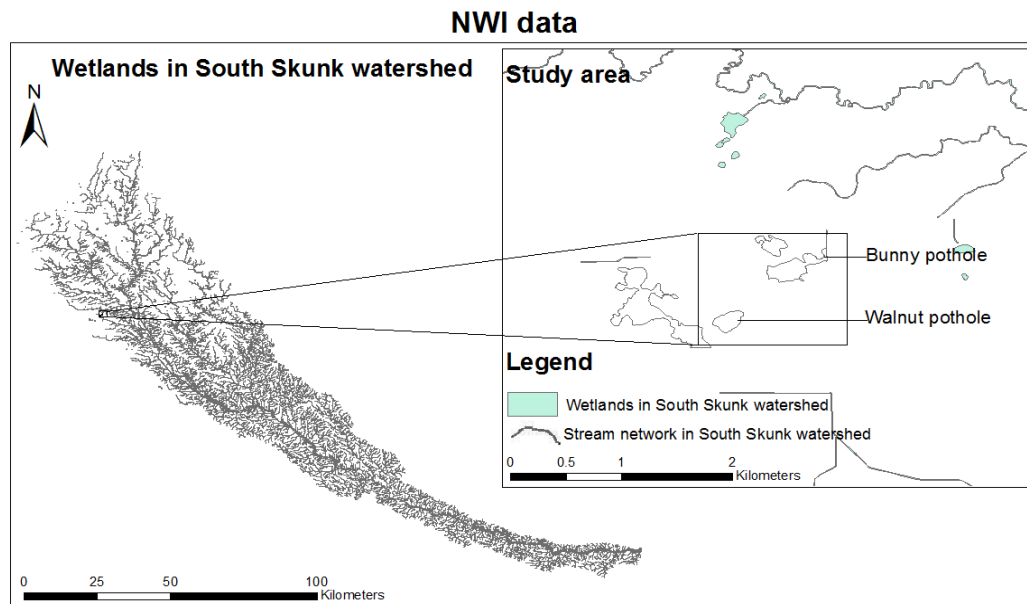


Figure 1: Wetlands covered by National Wetlands Inventory (NWI), it does not include the Walnut and Bunny pothole covered under this study

In small scale studies the spatial resolution of DEM plays a crucial role in precise incorporation of depression and drainage channels. Therefore, DEMs derived from fine scale topographic survey maps and downscaling techniques are often used in small scale hydrological modeling where precise water logging information for decision making is of prime importance (Bisht et al., 2016; Feifei & Anthony, 2012; Tarolli, 2014; Upadhyay et al., 2018; Xie, Pearlstine, & Gawlik, 2012). Maxa and Bolstad (2009) compared the accuracy of the Wisconsin Wetland Inventory maps (WWI) to maps derived from IKONOS and LiDAR data. WWI prepared from the analysis of high altitude imagery in conjunction with soil surveys, topographic maps, previous wetland inventories and field work, was compared to maps derived from 1-m resolution IKONOS data and 1-m resolution Light Detection And Ranging (LiDAR) data for a 63.4 km² study area in north-central Wisconsin. IKONOS/LiDAR data were significantly more accurate (74.5% classification accuracy) than WWI data (56%) when wetlands were categorized into WWI classes. Huang et. al, (2011) developed a 0.5 m bare-earth model from LiDAR data and, in combination with NWI data, delineated wetland catchments and their spilling points within a 196 km² area located in Stutsman County of North Dakota. When compared to field survey spilling points, they found that the catchment and spilling point delineations from the LiDAR bare-earth model captured subtle landscape features very well. Of the 11 modeled spilling points, 10 matched field survey spilling points. There are very limited comparisons such as these for potholes located in agricultural fields.

Here, we explore the potential of USGS DEMs for identifying the extent of small potholes that are located in agricultural fields. The objective of this study was to assess the suitability of DEMs with different spatial resolutions in small-scale hydrological modeling of potholes and compare the difference in its areal extent, depth and storage volume. Using the

previously evaluated AnnAGNPS model Upadhyay et. al, (2018), we examined the effect of different DEM resolutions on pothole inundation. A high resolution 1m Light Detection And Ranging (LiDAR) based DEM was compared to DEMs developed by United States Geological Survey (USGS) at ~3m and ~10m resolution. Considering the influence of DEM resolution on pothole modeling is particularly important because the high resolution DEM can take considerably more processing time and also the high resolution topographic information (~1m and ~3m) is not available for the entire prairie pothole region whereas the coarser (~10m) USGS data is seamlessly available for the entire US.

Methodology

Study Area and Data

The study area is located in a single farm field straddling adjacent Hydrologic Unit Code (HUC-12) watersheds in the Des Moines lobe region just outside of Ames, IA. The pothole positions in relation to the Walnut Creek and Worrell Creek (HUC-12) watersheds are presented in Fig. 2. These potholes are typical of the potholes located in agricultural fields in the Des Moines lobe region of Iowa and chosen for this study because we have two years of observed water depth data, which was collected as part of a preceding project. The field is managed in a corn-soybean rotation with conventional tillage. The site is 10% Okoboki silt clay loam, 25% Nicollet loam, 7% Harps loam, 3% Webster clay loam, 9% Clarion loam, 25% Canisteo clay loam, and 21% Clarion loam (USDA-NRCS 2014). Except the Clarion and Nicollet series, the soils are classified as hydric: these soils are formed in saturated conditions, and could support wetland vegetation species when not drained. The pothole in the Walnut Creek watershed is referred as “Walnut” and the pothole in the Worrell Creek watershed is referred as “Bunny”, both the potholes have different sizes and therefore can store different

volumes of water. They also have different drainage areas, which is discussed in following sections. Bunny is classified as a “second-level puddle”, since it is composed of two depressions, with a common outlet (Chu, 2015). Bunny pothole has two surface inlets connected to the drainage system, while Walnut pothole has one surface inlet. The locations of the subsurface drainage lines are largely unknown, except where they connect to the surface inlets.

Data used for this study includes 1m DEM generated from LiDAR data. The raw data in point cloud format, at 1.4 m average bare-earth data spacing, were in a LASer file format (LAS) containing X and Y coordinates (UTM Zone 15N nad83), orthometric elevation Z (NADV88), return level (1, 2, or 12), and intensity (0-255). USGS 3m and 10m DEMs were downloaded from USGS website. These datasets are selected because they are available for the entire state of Iowa and most commonly used in hydrological studies.

Observed data includes, the depth of ponded water in 2010 and 2011 which was derived from hourly transducer data (Logsdon, 2015) collected by installing pressure transducer (Solinst Levelogger, Model 3001) at the bottom of both the potholes. Depth-volume relationships for each pothole were developed from the site topography data to translate the observed depth data into estimates of pothole water volume (Upadhyay et al., 2018).

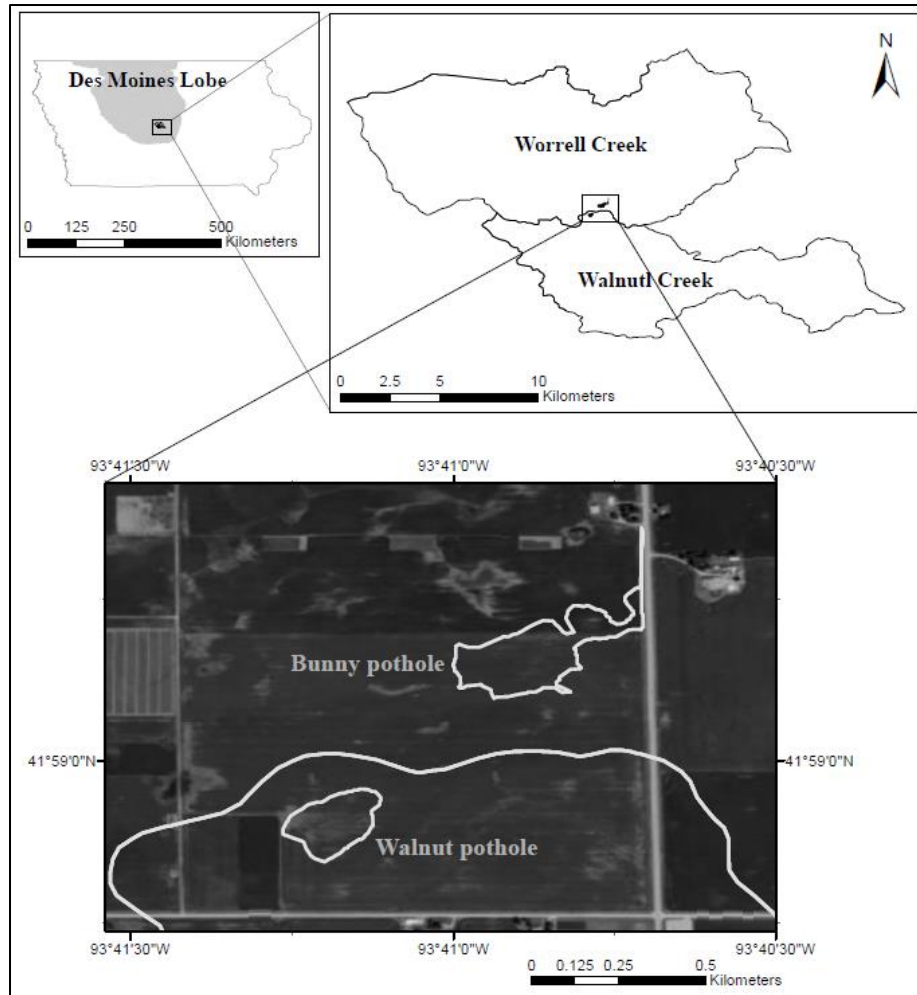


Figure 2: Location of potholes within the state of Iowa

Hydrological Modeling

AnnAGNPS Model Description

AnnAGNPS model version 5.44 was used to simulate water depth in the potholes. AnnAGNPS, a watershed scale, continuous simulation, daily time step model, is well-suited to small scale watersheds, and is able to produce satisfactory hydrological outputs for the Midwest United States (Richardson, Bucks, & Sadler, 2008; Upadhyay et al., 2018; Y Yuan, Bingner, Locke, Theurer, & Stafford, 2011; Yongping Yuan, Bingner, & Rebich, 2003). It was jointly developed by the United States Department of Agriculture (USDA), the Agricultural Research Service (ARS) and the Natural Resources Conservation Service (NRCS).

In AnnAGNPS, the analyzed watershed can be divided into many small, homogeneous (in terms of soil type, land use and land management) drainage areas called cells. They are connected to each other defining a network of channels and reaches, where water, sediment and nutrients are transported. Cells and reaches and their topographic properties are estimated using additional modeling components supporting the development of AnnAGNPS input parameters, such as TOPAGNPS (Topographic Parameterization program used for AGNPS) and AGFLOW (Agricultural watershed Flownet generation program) programs (Bingner R. L., Darden R.W., Theurer F.D., & Garbrecht J., 1997; Bingner & Theurer, 2001; Chahor et al., 2014; Garbrecht & Campbell, 1997).

Surface runoff is estimated based on the Soil Conservation Service Curve Number (CN) method. Three model setups were prepared using 1m, 3m and 10m DEM. As the resolution of DEM affects derived hydrological parameters including slope, aspect and flow length, it will affect the size of cells and length of reaches.

Calibration and Validation of AnnAGNPS Model

All the three AnnAGNPS model setups were calibrated independently because of their distinct DEM sizes (Lee, Tachikawa, & Takara, 2009). Curve Number (CN) and infiltration rate were used as the calibrating parameters in the model. The initial CN considered in the assessment was "Straight Row Crop" for poor conditions, after that the CN values were increased until the best fit between the observed water depth and simulated water depth occurred. Once the water load into the potholes was determined by the calibration of the CN, then the water retention time was regulated by calibrating the infiltration rate, as we are incorporating the surface inlet into the model through infiltration, the infiltration rate was high. The calibration process started with a typical infiltration rate for the given soil type and was

increased until the best fit between the observed water depth and simulated water depth was observed. For the calibration of both, the CN and infiltration rate the observed and simulated water depths were compared based on NSE, PBIAS, RSR and R^2 efficiency model criteria. The observed water depth data (2010 - 2011) in the potholes was split into two segments (2010 and 2011), 2010 was used for calibration and 2011 was used for validation. Calibration and model efficiency for 1m LiDAR model setup were discussed in detail in Upadhyay et al. (2018) and those results are replicated here for comparison.

Evaluation of Model Performance

Performance analyses were based on two schemes: one used the entire growing season (GS), corresponding to the span in which there was observed data, with zero values when there was no inundation; the other considered only days in which water storage (WS) was observed or simulated. The Nash-Sutcliffe Efficiency index method (NSE) was used as the measure of calibration fitness. The NSE method consists of an empirical index used to estimate the agreement between the observations (Y_{obs}), and the simulations (Y_{sim}), for a given day. It is widely used in hydrology studies and in related sciences to compute parameters such as streamflow (Meek, Howell, & Phene, 2009; J Eamonn Nash & Jonh V Sutcliffe, 1970). However, given the sparser nature of pothole inundation data, it is reasonable to use less stringent criteria for determining satisfactory model performance than those for streamflow modeling. The other evaluation metrics used are PBIAS, RSR and R^2 , and are described in Table 1.

Table 1: Selection of evaluation criteria, their corresponding formulation and specific values (Upadhyay et al., 2018)

Criterion	References	Mathematical formulation	Interpretation
NSE	(Nash & Sutcliffe, 1970)	$NSE = 1 - \left[\frac{\sum_{i=1}^n (Y_i^{obs} - Y_i^{sim})^2}{\sum_{i=1}^n (Y_i^{obs} - Y_i^{m-o})^2} \right]$ <i>Range:</i> $(-\infty, 1]$	NSE indicates how well the plot of observed versus simulated data fits the 1:1 line. Values between 0.0 and 1.0 are generally viewed as acceptable levels of performance, with 1 being the optimal value.
PBIAS	(Moriás et al., 2007)	$PBIAS = \left[\frac{\sum_{i=1}^n (Y_i^{obs} - Y_i^{sim}) \times 100}{\sum_{i=1}^n (Y_i^{obs})} \right]$ <i>Range:</i> $(-\infty, \infty)$	PBIAS measures the average tendency of the simulated data to be larger or smaller than their observed counterparts. The optimal value of PBIAS is 0.0, with low-magnitude values indicating accurate model simulation. Positive values indicate model underestimation bias, and negative values indicate model overestimation bias.
RSR (RMSE-sd)	(Moriás et al., 2007)	$RMSE - sd = \frac{\sqrt{\sum_{i=1}^n (Y_i^{sim} - Y_i^{obs})^2}}{n}$ <i>Range:</i> $[0, \infty)$	RSR incorporates the benefits of error index statistics and includes a scaling/normalization factor. The lower RSR, the lower the RMSE, and the better the model simulation performance.
R ²	(Krause, Boyle, & Bäse, 2005)	$R^2 = \left[\frac{\sum_{i=1}^n (Y_i^{obs} - Y_i^{m-o})(Y_i^{sim} - Y_i^{m-s})}{\sqrt{\sum_{i=1}^n (Y_i^{obs} - Y_i^{m-o})^2} \sqrt{\sum_{i=1}^n (Y_i^{sim} - Y_i^{m-s})^2}} \right]^2$ <i>Range:</i> $[0, 1]$	R ² describes how much the observed dispersion is explained by the prediction. A value of zero means no correlation at all whereas a value of 1 means that the dispersion of the prediction is equal to that of the observation.

Y_i^{obs} = observed data, Y_i^{sim} = simulated data, Y_i^{m-o} = mean of observed data, Y_i^{m-s} = mean of simulated data and n = number of events

Results and discussion

Comparison of LiDAR DEM (~1m) and USGS DEM (~3m and ~10m)

The first step is the identification of potholes features. Fig. 3 presents the 1m DEM prepared from the LiDAR data, USGS 3m and 10m DEMs downloaded from USGS website

for the Walnut pothole along with its microwatershed as discretized by AnnAGNPS model. From the Fig. 3, we can see that there are differences in the cell sizes and microwatershed shape. Similarly, there would be differences in slope, aspect, flow length and drainage network which are extracted from the DEMs.

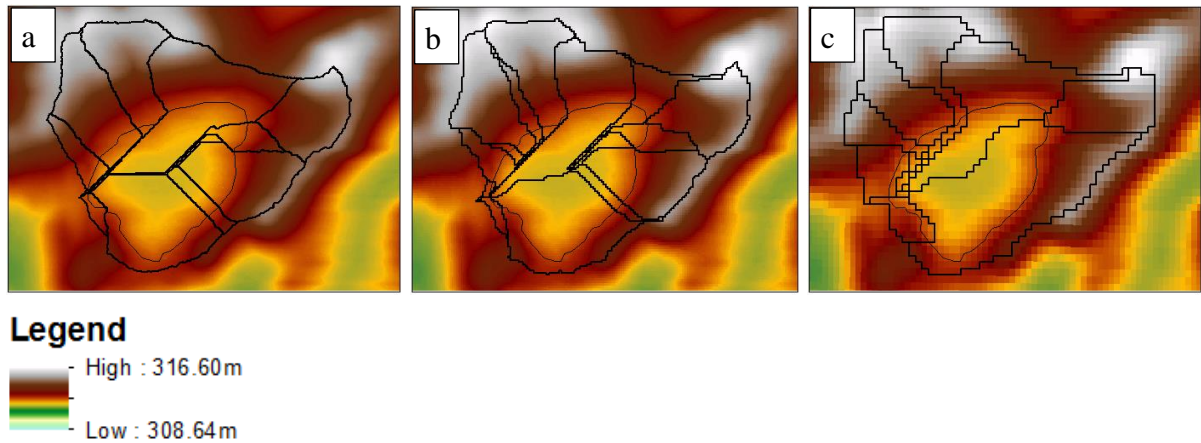


Figure 3: Comparison of the DEMs and the delineated watershed divided into cells by AnnAGNPS model for the Walnut pothole (a) 1m DEM prepared from the LiDAR data, (b) USGS 3m DEM and (c) USGS 10m DEM

Fig. 4 shows the depth area and depth volume relationship for the two potholes using the 1m, 3m and 10m DEMs. From Fig. 4 we can see that there are minor differences in the depth-area and depth-volume relationship between 1m and 3m DEM when compared to 1m and 10m DEM or 3m and 10m DEM. The average percent difference between 1m and 3m DEMs for area and volume is 6.5% and 12.5% for both Walnut and Bunny potholes. The average percent difference between 1m and 10m DEMs for area and volume are 24.7% and 39.7% for Walnut pothole and 22% and 35% for Bunny pothole. The 3m and 10m DEMs suggest the potholes are smaller than they are in the 1m DEM.

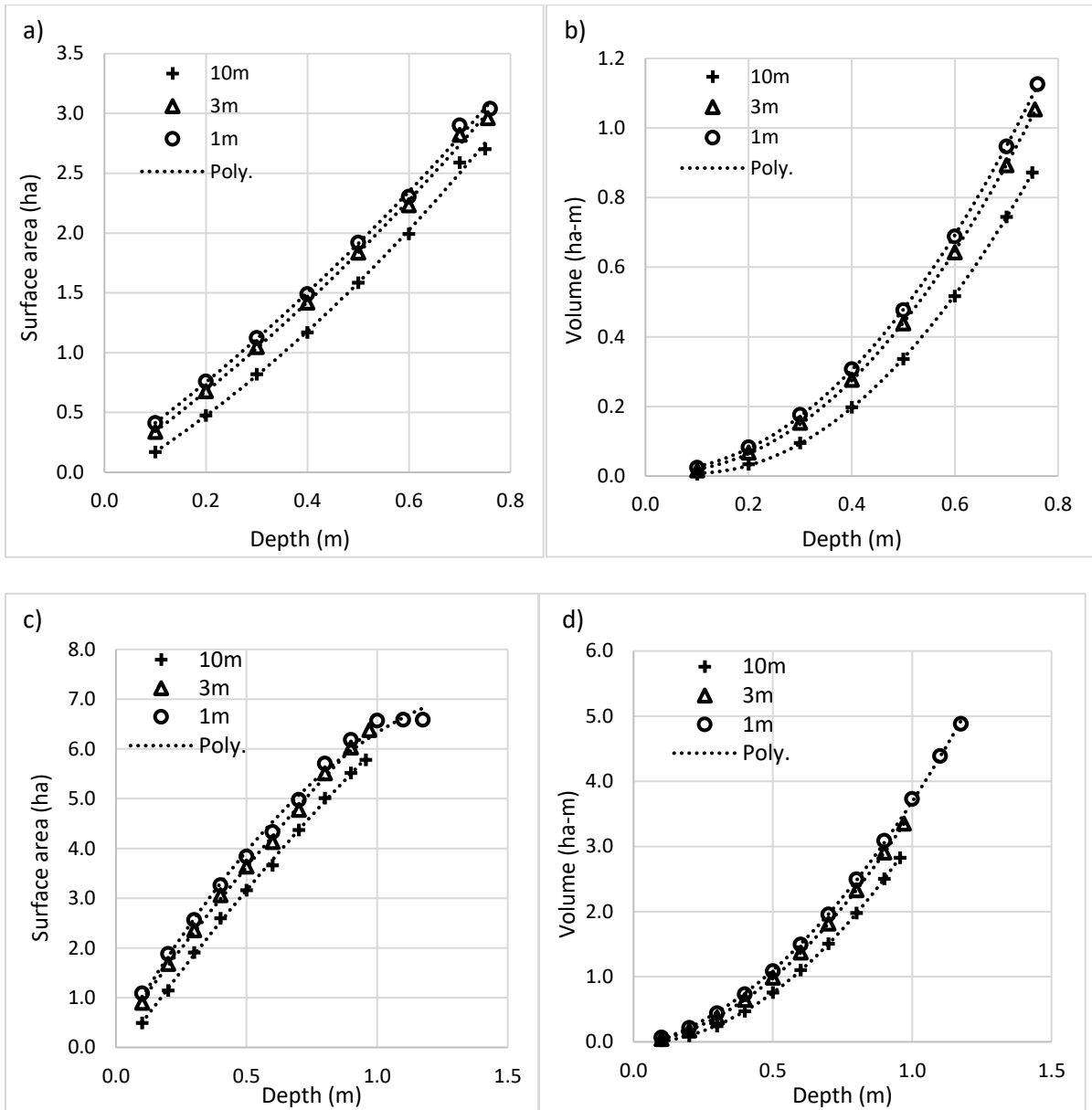


Figure 4: Depth area and depth volume relationship for Walnut pothole (a and b) and Bunny pothole (c and d)

Assessment of DEMs from AnnAGNPS Model Performance

The water depths were simulated with the three DEMs consisting of 1m, 3m and 10m grid size using AnnAGNPS at two pothole locations. As both potholes are under similar crop rotation, soil type and tile drainage, similar CN values were expected from the calibrations.

For all the three cases, we calibrated the CN and infiltration rate in order to obtain the highest model performance based on NSE. Since, Bunny pothole had two surface inlets in it, the values for infiltration rate were higher for Bunny pothole as compared to Walnut pothole. The calibrated values of CN and infiltration rate for Walnut and Bunny potholes according to the depth analysis using the three different DEMs are illustrated in Table 2. For LiDAR 1m DEM these values are also presented in Upadhyay et. al. (2018). In case of Bunny, since two different calibrated values were obtained for the two calibrated years (2010 and 2011) we took the average of those two for this analysis (Upadhyay et al., 2018).

Table 2: CN and Infiltration values according to depth calibration of the potholes

DEM Used	LiDAR 1m DEM		USGS 3m DEM		USGS 10m DEM	
Wetland ID	Walnut	Bunny	Walnut	Bunny	Walnut	Bunny
Daily infiltration (mm/day)	33	77	34	77	33	77
Curve Number Classification	Row Crop	Row Crop	Row Crop	Row Crop	Row Crop	Row Crop
Soil Group B	81	81.5	79	81.5	81	81.5
Soil Group C	88	88	86	88	88	88

The simulated water depths were compared to the observed water depth using NSE, PBIAS, RSR and R^2 efficiency models. The estimates of average water depths using USGS 3m DEM was found to be 6% and 2% lower than the 1m LiDAR DEM, and the estimates of average water depths using USGS 10m DEM was found to be 7% and 12% higher than the 1m LiDAR DEM for the Walnut and Bunny potholes, respectively. A comparison of simulated water depths using 3m and 10m DEMs with 1m DEM at both the potholes are shown in Fig. 5. The reason that the USGS DEMs simulate the water depths similarly for 3m DEM and higher for 10m DEMs suggest the potholes are modeled as smaller than they are in the 1m DEM but they are generating similar amount of runoff from the microwatersheds. Results indicate that

the water depths calculated using all the three DEMs are reasonable and representative of the true conditions based on NSE, PBIAS, RSR and R^2 efficiency model criteria. However, the estimated surface area using 3m and 10m DEM was found to be 45% and 76% lower than the 1m DEM for Walnut and 8% and 46% lower than the 1m DEM for Bunny. The estimated volume using 3m and 10m DEM was found to be 19% and 27% lower than the 1m DEM for Walnut and 15% and 48% lower than the 1m DEM for Bunny. The estimated surface areas and volumes using the 3m and 10m DEMs shows larger variation compared to 1m DEM because a small change in water depth resulted in large variation of surface area and volume of the potholes. Shi et al. (2012) compared the performances of LiDAR-based DEMs (1m and 5m) and the USGS-sourced DEM (10m) in calculating slope gradient as an input for knowledge-based digital soil mapping (KBDSM) by evaluating how closely the DEM-based slope gradient values match the field-measured values for a small watershed in northern Vermont, US. They also found that the results from the 1-m LiDAR-based DEM and the resampled 5-m DEM do not show considerable and consistent differences, though the LiDAR-based DEM perform significantly better than the USGS-sourced DEM.

Fig. 5 illustrates a comparison of simulated water depths, and the estimated surface areas and volumes using the depth-area and depth-volume relationships developed above for both potholes using 1m, 3m and 10m DEMs, according to CN and infiltration values available in Table 2. In case of Walnut (Fig. 5-c), we see that small variations in volume of 1m DEM results in large variations in volume of 10m DEM, because as discussed above in DEM comparison that the 3m and 10m DEMs suggest the potholes are smaller than they are in the 1m DEM, this effect is more prominent in Walnut because of its comparatively smaller size.

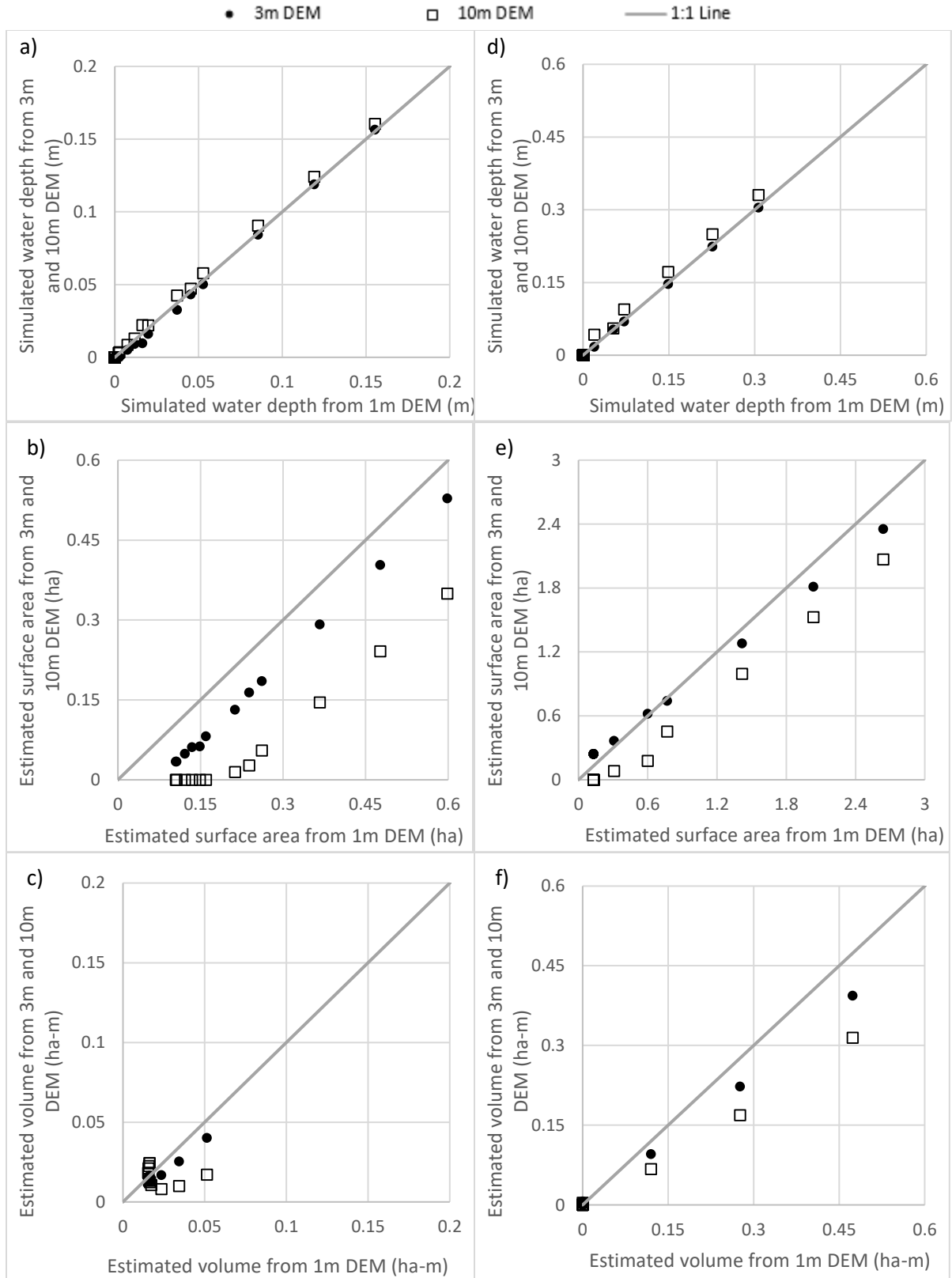


Figure 5: Simulation of water depth, surface area and volume using 1, 3 and 10m DEM in Walnut (a, b, c) and Bunny (d, e, f) potholes for the validation year 2011

In addition to the graphical comparison, performance indices of the three models during calibration and validation were also evaluated (Table 3). The model setup based on LiDAR 1m DEM have NSE ranging from 0.77 for Walnut to 0.56 for Bunny, in the growing season, as detailed in Upadhyay et. al. (2018).

Table 3: Simulation performance of pothole water depth considering the NSE, PBIAS, RSR and R^2 efficiency models for the whole growing season (GS) and for days in which water storage (WS) was observed

DEM Used	Criterion	Calibration		Validation	
		2010		2011	
		Walnut	Bunny	Walnut	Bunny
LiDAR 1m DEM	NSE - GS	0.77	0.56	0.24	0.30
	NSE - WS	0.70	0.31	-0.41	-0.82
	PBIAS - GS	11.57	14.55	54.15	68.32
	PBIAS - WS	11.57	14.55	54.15	68.32
	RSR - GS	0.48	0.66	0.87	0.84
	RSR - WS	0.42	0.61	0.44	0.47
	R^2 -GS	0.79	0.60	0.27	0.33
	R^2 -WS	0.72	0.44	0.05	0.15
USGS 3m DEM	NSE - GS	0.77	0.56	0.24	0.30
	NSE - WS	0.70	0.31	-0.50	-0.82
	PBIAS - GS	12.56	15.26	56.66	68.79
	PBIAS - WS	12.56	15.26	56.66	68.79
	RSR - GS	0.47	0.67	0.87	0.84
	RSR - WS	0.41	0.61	0.45	0.48
	R^2 -GS	0.79	0.59	0.27	0.35
	R^2 -WS	0.73	0.44	0.05	0.15
USGS 10m DEM	NSE - GS	0.77	0.58	0.24	0.32
	NSE - WS	0.71	0.37	-0.41	-0.78
	PBIAS - GS	6.10	7.90	50.94	63.82
	PBIAS - WS	6.10	7.90	50.94	63.82
	RSR - GS	0.48	0.65	0.87	0.63
	RSR - WS	0.42	0.59	0.44	0.36
	R^2 -GS	0.78	0.62	0.27	0.35
	R^2 -WS	0.72	0.48	0.05	0.14

NSE- Nash-Sutcliffe Efficiency, PBIAS- Percent bias, RSR- Ratio of the root mean square error, GS- Growing season, WS- Water storage

The performance of the model setups based on USGS 3m and USGS 10m DEMs are also found very close to the performance of the LiDAR model setup, reporting NSEs of 0.77

for Walnut and 0.56 for Bunny in case of USGS 3m DEM and NSEs of 0.77 for Walnut and 0.58 for Bunny in case of USGS 10m DEM, in the growing season (GS). NSE values were higher for the entire observation period (GS), including all days in which neither the model nor the observations indicated water in the pothole, than when the data were restricted to only days in which there was water observed and/or simulated (WS). The differences between the GS and WS results suggest that the model is better able to simulate when there is or is not standing water in the potholes than it is at precisely simulating the depth of standing water.

Simple models with coarser DEMs (~3m and ~10m) may have some advantages compared to more complex models with finer DEM (~1m). Hydrologic model comparison has been an important research topic since 1975 (WMO, 1975). Many model comparison scientific studies concluded that simple models may provide simulations of runoff in small basins as satisfactorily as more complex models (Naef, 1981; WMO, 1975). More recently, scientific objectives of large international projects such as AgMIP include intercompare crop and agricultural models with observed field trials in order to identify model strengths, weaknesses, and uncertainties (Malone et al., 2017; Rosenzweig et al., 2013). Malone et. al, (2017) compared a widely used simple agricultural system model, HERMES predictions to the more complex Root Zone Water Quality Model (RZWQM) for simulating N loss to subsurface drainage, the simulated annual and cumulative drainage were reasonable compared to observed data, similar to the more complex RZWQM simulations, and similar to other model drainage tests reported in the literature. Diekkrüger et al. (1995) reported that simple agroecosystem models may lead to better results than those computed from a complex model.

Conclusion

The resolution of DEM plays an important role in representing topography and hence affects the ability of a model to predict the inundated area and volume of the potholes. However, the estimates of depth and presence/absence of ponding in the potholes using USGS 3m and 10m DEMs was found to be reasonable and are representative of the true conditions based on the NSE, PBIAS, RSR and R^2 efficiency model criteria. Due to the sparse nature of pothole inundation data, it is reasonable to use less stringent criteria for determining satisfactory model performance when calibrating and validating the AnnAGNPS model for the water depth in the potholes than those for streamflow modeling (Upadhyay et al., 2018). A comparison of 1m DEM prepared from the LiDAR data, USGS 3m and 10m DEMs revealed that for this small-scale study, estimates of the pothole water depths using the three DEM resolution were close to each other with NSE of 0.77 for Walnut and NSE of 0.56 for Bunny pothole. The estimates of areal extend and volume have large differences between the 1m, 3m and 10m DEMs, up to 25% for area and 40% for volume which suggests that higher resolution DEMs will not be able to assess areal inundation or potential for crop loss through areal analysis accurately. Model simulations using AnnAGNPS have provided an assessment of DEM resolution on inundation at individual pothole level. This study concludes that for studying the small-scale features like potholes, in terms of depth and presence/absence of ponding, in absence of the expensive LiDAR based DEMs we can still use USGS 3m and 10m DEMs and get reasonable estimates of water depths.

Disclosure statement

No potential conflict of interest was reported by the authors.

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CHAPTER 5. ARTIFICIAL NEURAL NETWORK AND ANNAGNPS BASED APPROACH FOR ASSESSMENT OF DRAINED AND FARMED PRAIRIE POTHOLES

Manuscript to be submitted to *Water Resources Research*

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Abstract

Assessment of water depth fluctuations in potholes is important for the management of the potholes. The objective of this study was to investigate the potential of artificial neural network (ANN) technique to predict water depth fluctuations in potholes located in the Prairie Pothole Region of Iowa. The input parameters are a combination of climatic and landscape characteristics. The most appropriate set of input parameters to the model are selected through a combination of domain knowledge and statistical analysis of the available data series. Due to the lack of long-term water depth observations, established Annualized Agriculture Non-Point Source (AnnAGNPS) models were used to simulate water depths for ten years (2007 – 2016) growing season (May to October) in the three potholes termed Bunny, Walnut and Lettuce. Using this expanded dataset, the ANN model was developed, where it was tested on the actual water depth observations collected in 2018 at another three potholes termed Turkey, Hen and Plume. The results suggest that the ANN models are able to predict the water depth fluctuations in the potholes reasonably well, as evaluated by various statistical indices. The R^2 values were 0.604 and 0.563 during training and validation period, respectively. A low RMSE and MAE value of 0.057 and 0.023 was found during both training and validation of ANN model. This model can be used by stakeholders (farmers and state/federal agencies) for management planning and making informed decision about farming the potholes.

Keywords: AnnAGNPS, Artificial neural network (ANN), Hydrology, Inundation, Potholes.

Introduction

Potholes are one of the most dominant landscape features in the Des Moines lobe of Iowa, which is a part of the Prairie Pothole Region (PPR). The PPR extends approximately 715,000 km², including parts of three Canadian provinces (Saskatchewan, Manitoba, and Alberta) and five states in the U.S. (Minnesota, Iowa, North and South Dakota, and Montana). These potholes are often shallow in depth (0.3m to 1.5m) and considered a nuisance for farmers for their agricultural operations (Upadhyay, Pruski, Kaleita, & Soupir, 2018). Even though more than 90% of the potholes in Iowa are tile drained, they still hold water due to the limited capacity of the tile lines which fills up to the capacity for a larger storm event, the main lines also tend to be undersize, since additional drainage is often added later. After a rainfall event, these potholes are often filled with shallow depth of water, which can last more than a few weeks depending on the rainfall amount, evapotranspiration, land use and pothole to its catchment area ratio. The shallow water depths in the potholes have significant impacts on crop growth, vegetation development and nutrient transport. Furthermore, the stagnant water interferes with the dates of field operations early in the growing season. The consequences of not proper timing of showing and management operations can lead to excessive reductions in yields. According to a recent analysis, the pothole areas are consistently less profitable than upland areas in fields, and often lose money (Morrison, 2016). Therefore, a constant monitoring of water depth fluctuations in the potholes is extremely important. The flooded areas if assessed and identified may help the farmers and state/federal agencies to make an informed decision about farming these potholes for crops or turning it back to its natural state to derive some ecosystem benefits provided by the potholes.

There are very few studies, which have monitored water depth fluctuations in potholes. The monitoring of water depths in the potholes are complicated as there is no standard

guideline for its monitoring, and also the process is time consuming as long period of observations are needed for making a meaningful conclusion out of the observed data. For water management planning and decision-making, it is a common practice to use computer simulation models. These models, can be very simple or highly complex, based on observed data or theoretical principles, stochastically or deterministically driven, provide a framework for decision-making that is endorsed by the community of water users and water regulators (Nayak, Rao, & Sudheer, 2006). In the case of potholes, there are very few models, which can represent the pothole hydrology. In our previous study Upadhyay et. al., (2018) we successfully evaluated the Annualized Agricultural Non-Point Source (AnnAGNPS) model for simulating the inundation of drained and farmed potholes in the Prairie Pothole Region of Iowa. Upadhyay et. al., (2018) also provides a brief review of other hydrological models used for pothole study. The major disadvantage of physics based model is that it requires enormous amount of data and a skilled modeler. Empirical models remain a good alternative method when data is not sufficient and getting accurate predictions is more important than conceiving the actual physics, and can provide useful results without a costly calibration time (Daliakopoulos, Coulibaly, & Tsanis, 2005). In the potholes, relationship between precipitation, evapotranspiration, catchment area, land use, and the water depths are likely nonlinear rather than linear, and the models that approximate the processes in linear form fail to represent the processes effectively. In recent years, artificial neural networks (ANNs) have been used for forecasting in many areas of science and engineering. ANN are powerful nonlinear regression techniques inspired by studies of the brain and nervous systems and are capable of modeling nonlinear functions with a reasonable degree of accuracy (Nayak et al., 2006). There are multitudes of network types available for ANN applications and its choice depends on the

nature of the problem and data availability. The multi-layer perception (MLP) trained with the back propagation algorithm is perhaps the most popular network for hydrologic modeling (ASCE Task Committee, 2000a, 2000b; Nayak et al., 2006). ANN are capable of generating a relationship between input and output variables even without knowing the actual physics behind the process. They are able to provide a mapping from one multivariate space to another, given a set of data representing that mapping. Even if the data is noisy and contaminated with errors, ANNs have been known to identify the underlying rule. These properties suggest that ANNs may be well-suited to the problems of estimation and prediction in hydrology (ASCE Task Committee, 2000b).

ANN have been increasingly becoming popular in the hydrology research because of its ability to model both linear and nonlinear systems without the need to make any assumptions as are implicit in most traditional statistical approaches (ASCE Task Committee, 2000b; Riad, Mania, Bouchaou, & Najjar, 2004). ANNs have already been successfully used for rainfall-runoff modeling, streamflow modeling, water quality modeling and groundwater level forecasting. Daliakopoulos et al. (2005) used ANN for forecasting groundwater levels in Messara Valley in Crete, Greece. They compared seven different types of network architectures and training algorithms and found that the feedforward neural network trained with the Levenberg–Marquardt algorithm provided the best results for up to 18 month forecasts. Nayak et al. (2006) also found that the ANN models are able to forecast groundwater levels up to 4 months in advance reasonably well in a shallow aquifer located in Godavari delta system of Andhra Pradesh, India. Ceyhun and Yalçın (2010) estimated water depths in shallow waters of Foca bay, Izmir, Turkey by relating remotely sensed image reflectance values to in-situ depth measurements using ANN and then the estimated water depths was used to derive

bathymetric maps. Isik et. al., (2013) predicted daily streamflow in small watersheds in western Georgia, USA by combining ANN with the Soil conservation Service (SCS) Curve Number (CN), the CN method was used as an intermediate step to capture the effect of land use and soil type. The developed model makes use of land use/cover, hydrologic soil groups and climatic factors, such as temperature and precipitation, in order to replicate the hydrologic response of a watershed. Noori and Kalin (2016) developed a hybrid model to predict daily streamflow by coupling Soil and Water Assessment Tool (SWAT) and ANN, SWAT served as a transfer function by combining climatic, topographic, soil and land use/cover data and producing two new outputs, stormflow and baseflow. Then the SWAT simulated stormflow and baseflow were used as inputs to the ANN model to predict streamflow. The hydrological applications of ANN models before the year 2000 have been discussed in details by Govindaraju and Rao (2000) and by the ASCE Task Committee on Application of Artificial Neural Networks in Hydrology (2000b). The goal of this paper is to examine the ANN technique for predicting the water depth in farmed potholes in the Prairie Pothole Region (PPR) of Iowa.

Methodology

Study Area and Data

The study area is located in a single farm field straddling adjacent Hydrologic Unit Code (HUC-12) watersheds in the Des Moines lobe region just outside of Ames, IA. The location of potholes within the state of Iowa are presented in Figure 1. These potholes are typical of the potholes located in agricultural fields in the Des Moines lobe region of Iowa. The field is managed in a corn-soybean rotation with conventional tillage. The site is 10% Okoboki silt clay loam, 25% Nicollet loam, 7% Harps loam, 3% Webster clay loam, 9% Clarion loam,

25% Canisteo clay loam, and 21% Clarion loam (USDA-NRCS 2014). Except the Clarion and Nicollet series, the soils are classified as hydric: these soils are formed in saturated conditions, and could support wetland vegetation species when not drained. Six potholes namely Bunny, Walnut, Lettuce, Turkey, Hen and Plume were selected for this study. Three of the potholes having longer period of observed data was used to develop a hydrological model AnnAGNPS, which is then used to simulate the water depths in the potholes for even longer period of time (10 years) on which the ANN model was developed. The developed ANN model was tested on the remaining three potholes namely Turkey, Hen and Plume, for which water depths were collected in 2018. The locations of the subsurface drainage lines are largely unknown, except where they connect to the surface inlets.

The precipitation data is downloaded from Parameter-Elevation Regressions on Independent Slopes Model (PRISM) datasets, PRISM Climate Group gathers climate observations from a wide range of monitoring networks, applies sophisticated quality control measures, and develops spatial climate datasets which can be downloaded at any point location or in gridded format for larger areas. The other weather parameters used for running AnnAGNPS model (maximum temperature, minimum temperature, dew-point temperature, wind velocity, wind direction and solar radiation) and ANN model (maximum temperature) is obtained from the ‘Sustaining the Earth's Watersheds, Agricultural Research Data System’ (STEWARDS) project which provides access to soil, water, climate, land-management, and socio-economic data from fourteen watersheds. It is developed by Conservation Effects Assessment Project (CEAP) – Watershed Assessment Studies (WAS) and is supported by United States Department of Agriculture (USDA). The STEWARDS weather station used in this assessment was located approximately 5 km from the field site (Upadhyay et al., 2018).

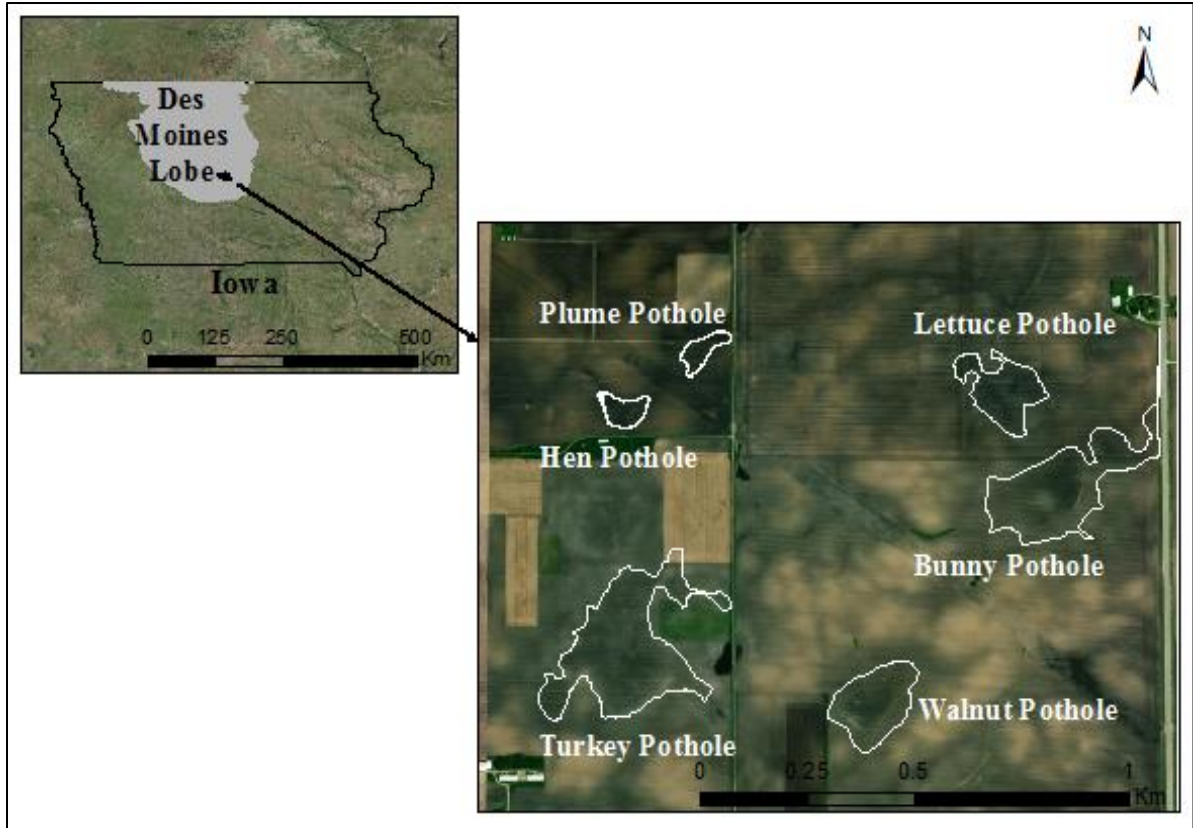


Figure 1: Location of potholes within the state of Iowa

Water depth simulation using AnnAGNPS

AnnAGNPS is a watershed scale, continuous simulation, daily time-step model designed to simulate water movement and non-point source pollution from agricultural watersheds (Bingner, Theurer, & Yuan, 2015). In our previous study (Upadhyay et al., 2018) we have shown that AnnAGNPS model is capable of simulating the water depths in the potholes. The developed AnnAGNPS model at the three pothole locations (Bunny, Walnut and Lettuce) was used to simulate the water depth data during the growing season (May to October) from 2007 to 2016 to expand the monitoring data collected in 2010, 2011 and 2016. Then, the expanded water depth data of 10 years (2007 – 2016) was used to develop the ANN model.

In this study to capture the land use/cover and soil effects, we utilized the SCS-CN method (SCS, 1986) which is incorporated in the AnnAGNPS model, as an intermediate step (Isik et al., 2013). Two management scenarios were compared, the current scenario corresponded to conventionally farmed conditions with corn/soybean rotation and with surface inlets in the potholes connecting to a subsurface drainage system, and a conserved scenario considered row crop under conservation tillage practices, good hydrologic condition (>75% ground cover and light or only occasionally grazed), and with surface inlets maintained in the potholes.

ANN Modeling

Feedforward neural network (FNN)

In this type of network, the artificial neurons, or processing units, are arranged in a layered configuration containing an input layer, usually one “hidden” layer, and an output layer. Units in the input layer introduce normalized or filtered values of each input into the network. Units in the hidden and output layers are connected to all of the units in the preceding layer. Each connection carries a weighting factor (Nayak et al., 2006). In this study, three-layer (input, hidden, and output) feed-forward neural networks with back-propagation learning were constructed for the relationship between input and output using R version 3.4.4 (R Core Team, 2018). Fig. 2 shows a typical feedforward network with one hidden layer consisting of two nodes, two input neurons and one output. The input signal propagates through the network in a forward direction, layer by layer.

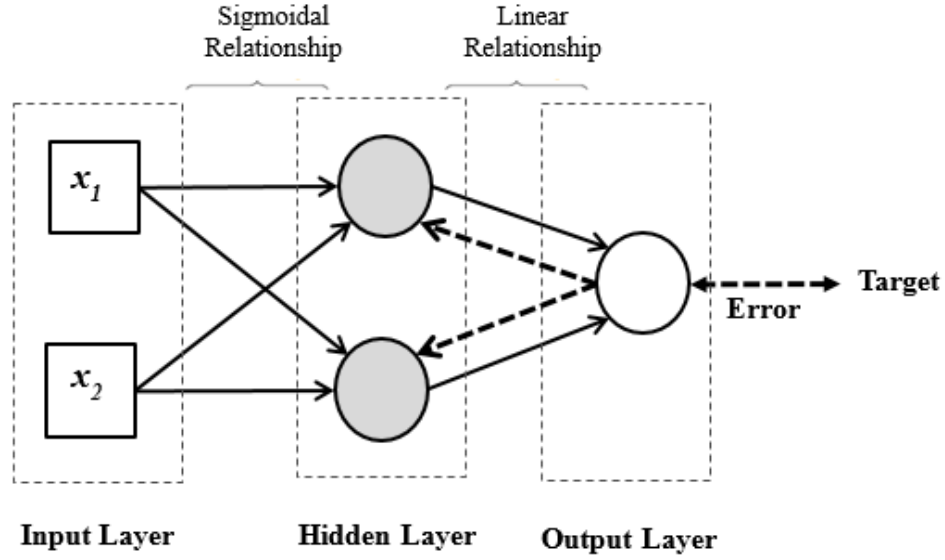


Figure 2: Typical feedforward neural network

Each hidden unit is a linear combination of some or all of the predictor variables. However, this linear combination is typically transformed by a nonlinear function $g(\cdot)$, such as the sigmoidal function (Kuhn & Johnson, 2013):

$$h_k(x) = g(\beta_{0k} + \sum_{i=1}^P x_i \beta_{ik}), \text{ where}$$

$$g(u) = \frac{1}{1 + e^{-u}}$$

The β coefficients are similar to regression coefficients; coefficient β_{ik} is the effect of the i th predictor on the k th hidden unit.

The output is modeled by a linear combination of the hidden units (Kuhn & Johnson, 2013):

$$f(x) = \gamma_0 + \sum_{k=1}^H \gamma_k h_k$$

For this type of network model and P predictors, there are a total of $H(P + 1) + H + 1$ parameters being estimated, which quickly becomes large as P increases.

Training with back-propagation algorithm

Treating this model as a nonlinear regression model, the parameters are usually optimized to minimize the sum of the squared residuals. The parameters are usually initialized to random values and then specialized algorithms for solving the equations are used. The back-propagation algorithm is a highly efficient methodology that works with derivatives to find the optimal parameters (Rumelhart, Hinton, & Williams, 1986).

Neural networks have a tendency to over-fit the relationship between the predictors and the response due to the large number of regression coefficients. To combat this issue, we used weight decay (λ), a penalization method to regularize the model. A penalty is added for large regression coefficients so that any large value must have a significant effect on the model errors to be tolerated. Reasonable values of λ range between 0 and 0.1 (Kuhn & Johnson, 2013).

$$\sum_{i=1}^n (y_i - f_i(x))^2 + \lambda \sum_{k=1}^H \sum_{j=0}^P \beta_{jk}^2 + \lambda \sum_{k=0}^H \gamma_k^2$$

The number of neurons in the hidden unit and weight decay are the optimization parameters for this feedforward neural network trained with the back-propagation algorithm. All analyses were conducted in R (R Core Team, 2018) using ‘caret’ package (Kuhn, 2008), which is specifically designed for this purpose.

Input selection

One of the most important steps in the ANN hydrologic model development process is the determination of significant input variables. ANN are data-driven models based on learning and pattern recognition, it is very common in NN-based rainfall–runoff models to use time delay inputs in addition to the current information (Nanda, 2016).

The current study used a statistical approach suggested by Sudheer et al. (2002) to identify the appropriate input vectors. The method is based on the heuristic that the potential influencing variables corresponding to different time lags can be identified through statistical analysis of the data series that uses cross-correlation (CCF), autocorrelation (ACF) and partial autocorrelation functions (PACF) between the variables (Tiwari & Chatterjee, 2011).

The data-driven model studied herein are trained and verified for daily water depth prediction in the potholes using the daily rainfall, daily maximum temperature, catchment to pothole area ratio, drainage condition and land use/soil type. The time-lag for the independent input of rainfall is decided based on the maximum cross-correlation function (CCF) between the rainfall and the observed water depth. Fig. 3 shows the CCFs between the rainfall and water depth. The Pearson cross-correlation analysis illustrated in Fig. 3 between the rainfall and water depth showed a significant correlation for up to a 5 days lag in rainfall data on the water depth. Further analysis (MLR) of the data suggested that rainfall intervals up to a 5 days lag are able to explain 23% of the total variance and no significant improvement is observed when the lag is increased to six or more days. Therefore, to simulate daily water depth in the potholes, the developed ANN model is provided with the significant time-lagged inputs of rainfall to the network. The other input parameters are selected based on the literature review and general understanding of the parameters that can influence water depths. Daily maximum temperature is the maximum temperature during a day. Land use/soil type is of two types, conventionally farmed conditions and conservation tillage. In order to account for the size of catchment relative to size of pothole we took 'catchment to pothole area ratio' as one of the input parameter in the ANN model, which is the ratio of area of catchment to area of pothole. In this study, we have used the water depth data from three different potholes having different

catchment to pothole area ratios. Two of the potholes (Bunny and Walnut) have surface intake (drained) and one of the pothole (Lettuce) have no surface intake (not drained), which also enables us to simulate the surface intake vs. no surface intake condition. The identified input vectors are presented in Table1.

Table 1: Variables in the input vector to ANN model

Variables	Input vector
Daily rainfall	$R(t), R(t-1), R(t-2), R(t-3), R(t-4), R(t-5)$
Daily maximum temperature	$T_{max}(t)$
Land use/soil type (LU/ST)	Current [*] and conserved ⁺ conditions
Catchment to pothole area ratio (AR)	3:1, 7:1, 8:1
Drainage condition (DC)	Surface Intake and No Surface Intake

*Conventionally farmed conditions with corn/soybean rotation and with surface inlets in the potholes.

⁺Row crop under conservation tillage practices, good hydrologic condition (>75% ground cover and light or only occasionally grazed), and with surface inlets maintained in the potholes.

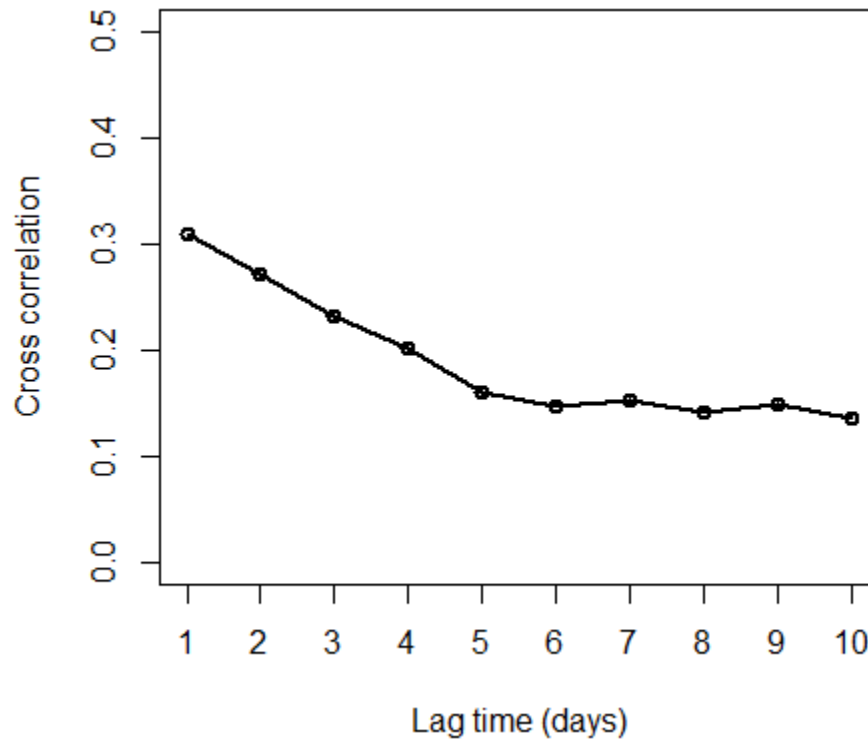


Figure 3: The cross-correlation plot of the rainfall-water depth

Criteria of evaluation

Three different criterias are used in order to evaluate the effectiveness of each network and its ability to make precise predictions.

The coefficient of determination (R^2) efficiency criterion evaluates how close the data are to the fitted regression line. The R^2 values can range from 0 to 1. The R^2 is given by:

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \frac{\sum y_i}{n})^2}$$

where y_i is the observed data, \hat{y}_i is the calculated data and n is the number of observations.

Root Mean Square Error (RMSE) indicates the discrepancy between the observed and calculated values. The RMSE values can range from 0 to ∞ . The lower the RMSE, the more accurate the prediction is. The RMSE is calculated by:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}}$$

where y_i is the observed data, \hat{y}_i is the calculated data and n is the number of observations.

Mean absolute error (MAE) measures the average magnitude of the errors in a set of predictions, without considering their direction. The MAE values can range from 0 to ∞ . MAE is expressed as:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

where y_i is the observed data, \hat{y}_i is the calculated data and n is the number of observations.

RMSE and MAE provide different types of information about the predictive capabilities of the model. The RMSE measures the goodness-of-fit relevant to high flow values whereas the MAE is not weighted towards high(er) magnitude or low(er) magnitude events, but instead evaluates all deviations from the observed values, in both an equal manner and regardless of sign.

Results and discussion

A three layered feedforward neural network trained with the back propagation algorithm was developed through programming in R version 3.4.4 (R Core Team, 2018). Daily rainfall (R) including five daily time-lags ($R(t-1)$, $R(t-2)$, $R(t-3)$, $R(t-4)$ and $R(t-5)$), Daily maximum temperature ($T_{max}(t)$), Land use/soil type (LU/ST), catchment to pothole area ratio (AR) and Drainage Condition (DC) were the ten inputs for the development of ANN model, and daily water depth (d) was the output. LU/ST, AR and DC are landscape parameters whereas R, $T_{max}(t)$ and d are climatic parameters. Summary statistics of input-output parameters are presented in Table 2 and 3.

Table 2: Summary statistics of climatic parameters (R, T_{max} and d)

Parameter	Training		Validation	
	[Min, max]	Mean [st. dev.]	[Min, max]	Mean [st. dev.]
R(mm)	0, 99.88	3.78 [10.23]	0, 99.88	3.66 [9.52]
$T_{max}(t)$	0, 36.70	24.22 [6.01]	0, 36.70	24.06 [6.10]
d(m)	0, 0.92	0.03 [0.09]	0, 0.76	0.03 [0.09]

Table 3: Summary statistics of landscape parameters (AR, LU/ST and DC)

Parameter	Whole growing season (GS)					
	Bunny	Walnut	Lettuce	Turkey	Hen	Plume
AR	8	3	7	3.2	6.8	15.7
LU/ST	0 and 1	0 and 1	0 and 1	0	0	0
DC	0	0	1	0	1	1

LU/ST: 0 = Current, 1 = Conserved; DC: 0 = Drained, 1 = Not-drained

Two-third of the ten year simulated data (2007 – 2016) from AnnAGNPS model for the three potholes (Bunny, Walnut and Lettuce) was randomly selected for training and the remaining one-third was used for validation. Eleven different weight decay values were evaluated ($\lambda = 0.00, 0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.10$) along with a single hidden layer with sizes ranging between 1 and 20 hidden units. The model with smallest repeated RMSE was selected. The repeated RMSE are the averages of RMSEs from fifty repetitions of 10-fold cross-validation. Increasing the amount of weight decay improved model performance, while more hidden units also reduce the model error. The optimal model used 19 hidden units with 229 weight coefficients and the performance of the model is stable for a high degree of regularization ($\lambda = 0.07$). Fig. 4 shows a comparison of ANN predicted water depths using optimized ANN model and AnnAGNPS simulated water depths, for the validation data. From the figure, it can be seen that the ANN predicted water depths are very close to the AnnAGNPS simulated water depth; however, the ANN model misses to predict some water depths, which is simulated by the AnnAGNPS model. It is observed from Table 4 that the model performance is good, and the ANN models have predicted the water depths with reasonable accuracy in terms of all the statistical indices during training and validation periods. In case of potholes, the interannual and spatially variable precipitation and the very small size of the watersheds being simulated, some years generate standing water in the potholes more frequently than others, and indeed in some years there may be only one or two occasions where the potholes fill with any observable standing water. This makes it difficult to generate a sufficient dataset for model calibration and validation. Therefore, it is reasonable to use less stringent criteria for determining satisfactory model performance because of the sparser nature of pothole inundation data (Upadhyay et al., 2018). The R^2 values that evaluates how close the

data are to the fitted regression line was found to be 0.604 and 0.563 during training and validation period, respectively. The RMSE statistic, which is a measure of residual variance that shows the global goodness of fit, is very good as is evidenced by a low RMSE value of 0.057 during both training and validation. The average magnitude of the errors measured by MAE also have a low value of 0.023 during both training and validation.

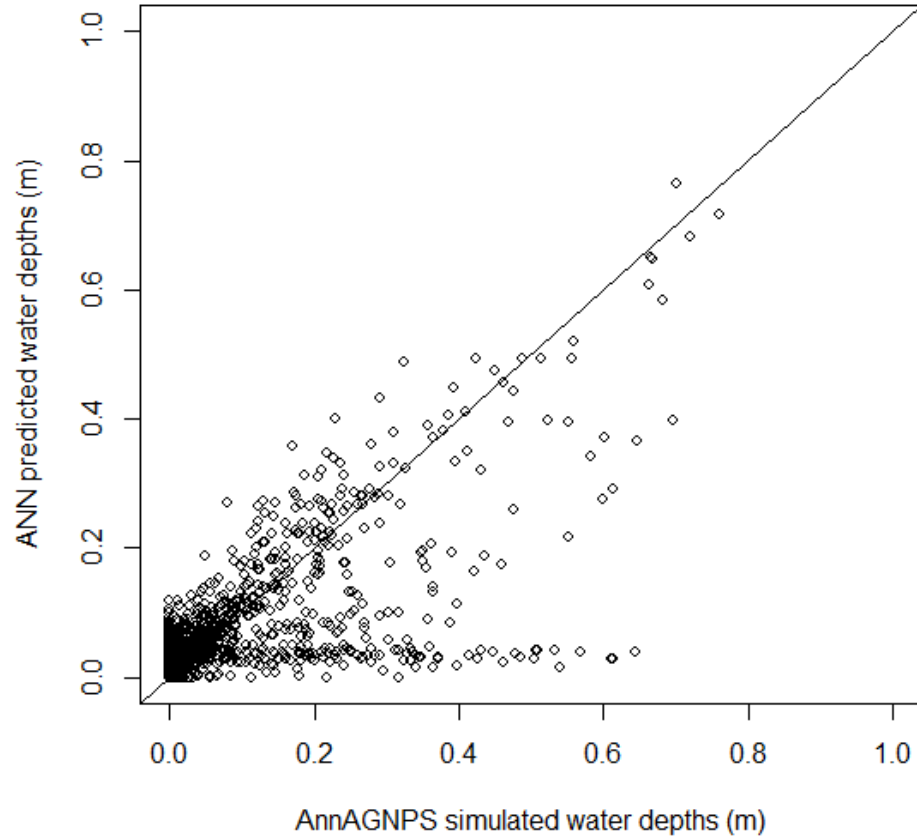


Figure 4: Comparison of validation results of ANN model with AnnAGNPS model

Table 4: R^2 , RMSE and MAE goodness of fit criteria for training, validation and testing of ANN model

Criterion	ANN model				
	Training	Validation	Testing		
			Turkey	Hen	Plume
R^2	0.604	0.563	0.424	0.564	0.163
RMSE	0.057	0.057	0.092	0.089	0.083
MAE	0.023	0.023	0.035	0.068	0.041

For testing purposes, ANN prediction were compared with the actual observed values. The optimized ANN model was tested on three different potholes (Turkey, Hen and Plume) under similar field conditions, where water depth data was collected in 2018. Table 4 summarizes the results of the testing of ANN model. Figure 5 shows the time series of ANN predicted and actual observed water depths for three potholes namely Turkey, Hen and Plume for the 2018 growing season. From the figure, it can be observed that ANN predicted water depths are very close to the actual observed water depths, and it follows the pattern of water depth fluctuations for all the three potholes. The R^2 statistics was found to be 0.424, 0.564 and 0.163 for Turkey, Hen and Plume, respectively. The RMSE and MAE statistic are also found to be very good as evidenced by their low values.

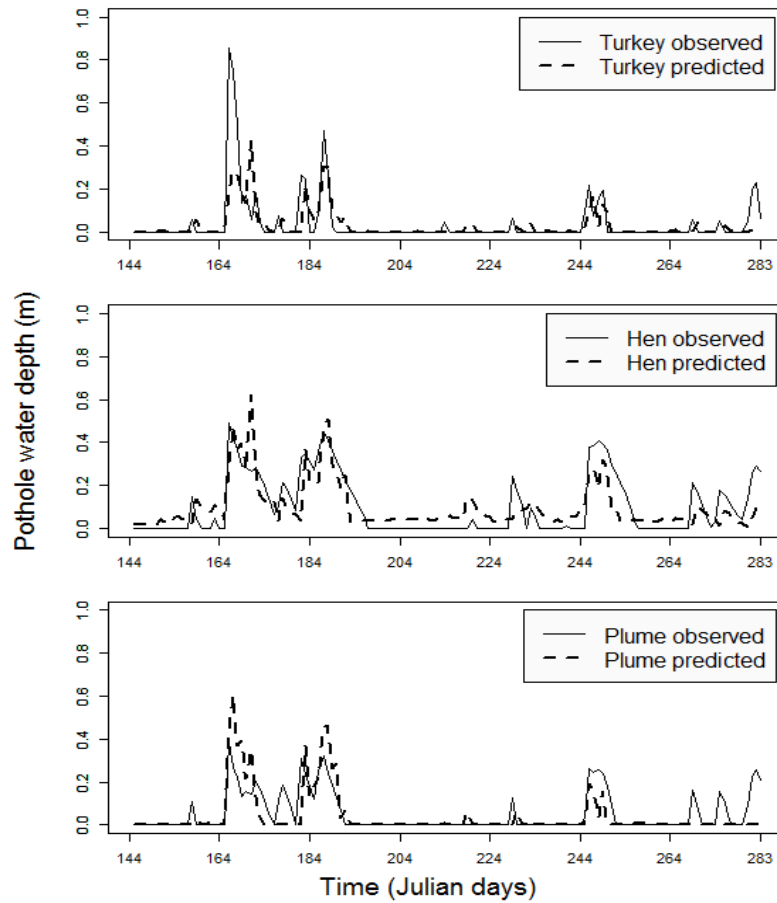


Figure 5: Comparison of ANN predicted water depth with observed water depth for Turkey, Hen and Plume potholes over the entire growing season

The R^2 statistics of Turkey and Hen was found to be satisfactory. However, the R^2 statistics of Plume was low and the predictions also missed some of the peaks in water depth data as can be seen in Fig. 5. The possible reason of why ANN predictions was not able to predict the water depths very well in case of Plume is that the ‘catchment to pothole area ratio’ of Plume is too big (15.7) compared to area ratios which are used for the development of ANN model. This would also be one of the limitation of the developed ANN model. For the ANN predictions to be reliable the potholes should be under similar landscapes and the corresponding input parameters should be in the range of input parameters used for the development of ANN model.

A study done by Van Meter and Basu (2015) on the distributions of wetlands shows a greater than 90% wetland loss in the Des Moines Lobe region, compared to 65% loss seen in the PPR as a whole (Euliss et al., 2006; Leibowitz, 2003). A comparison of percentage area of the landform reveals that current wetlands only comprise of about 1 % of the Des Moines Lobe compared to about 12 % acquired by historical wetlands (Van Meter & Basu, 2015). Most of these wetlands had been drained and were actively under cultivation (Miller, Crumpton, & van der Valk, 2009). Our study site lies in the landform type known as Bemis Advance, which is the sub-region of Des Moines Lobe. According to McDeid, Green, and Crumpton (2018), the 9398 km² Bemis Advance possesses 40,348 ha of depressions ($n = 35,682$), which collectively comprise 4.3% of the area of this sub-region, whereas Van Meter and Basu (2015) found that depressions occupy 8.3% of the areas of the Bemis advance. The discrepancy between the above two studies was attributable to the different assumptions and restrictions (filtering process and depth restrictions) in their methodology.

In Prairie Pothole region of Iowa, the size of individual pothole are generally small, most of them range from little more than a hectare (Van Meter & Basu, 2015) to smaller than 4 hectares (Wangpakapattanawong, 1996). Although the individual wetlands are small in area, as a whole they make up the largest wetland network in North America (A. G. van der Valk, 2005). The smaller wetlands were even exempted from protection under the Clean Water Act (CWA) in 1972. Wetlands less than 1.2 ha in size could be filled with appropriate permitting, and those less than 0.13 ha (1300 m²) could be filled without notification or oversight of the U.S. Army Corps of Engineers (A.G. van der Valk & Pederson, 2003; Van Meter & Basu, 2015). Considering the above-discussed morphology of the potholes, we concluded that the ANN model in its current form can be applied only for the potholes whose landscape parameters lies around the range used for ANN model development. Therefore, the water depth estimates using current ANN model can be reliable only for potholes having catchment to pothole area ratio (AR) less than 10.

Conclusions

In this paper, the potential of artificial neural network technique for predicting water depths in farmed prairie potholes is investigated by developing ANN model for potholes located in the Prairie Pothole Region (PPR) of Iowa. The ANN model was developed on the synthetic data, generated using the established AnnAGNPS model for the potholes (Upadhyay et al., 2018) and tested on the real observations collected in the field. The inputs to the models were selected based on domain knowledge and statistical analysis. The most suitable configuration for this task proved to be a 10-19-1 developed using feedforward network trained with the back propagation algorithm. The performance evaluation criteria namely the coefficient of determination (R^2), the root mean square error (RMSE) and the mean absolute

error (MAE) are found to be good. The R^2 statistics was found to be 0.604 and 0.563 during training and validation period, respectively. The R^2 statistics during testing was also found to be satisfactory for Turkey and Hen (0.424 and 0.564). The R^2 statistic for Plume was found to be low (0.163) because of its big catchment to pothole area ratio. In general, the results of the ANN model are satisfactory and demonstrate that neural networks can be a useful prediction tool in the area of pothole hydrological assessment. Most importantly, this paper presents a unique case where neural networks has been applied in case of limited data by using another hydrological model as an intermediate step.

In future, more observations of water depths in different size of potholes under different management practices and drainage conditions could be collected, in order to build a more robust ANN model.

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CHAPTER 6. GENERAL CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE WORK

Conclusions

This study provides the insights of the pothole inundation pattern and helps in understanding the hydrology of potholes with the help of models, in order to increase wetland protection and restoration efforts. The goal of understanding the pothole inundation was achieved through four set of objectives which are presented in chapters 2, 3, 4 and 5.

The study in chapter 2 focuses on evaluating the AnnAGNPS model for simulating the inundation of drained and farmed potholes in the Prairie Pothole Region of Iowa. It was found that AnnAGNPS was capable of simulating inundation of the drained and farmed potholes in this study, when comparing the model output of ponded depth to observations of the same, but was not capable of simulating potholes on a volume basis. This suggests that the model may be used for applications such as assessing the occurrence of crop failures associated with the standing water or investigating agricultural management strategies that would reduce pothole's tendency to flood. The model cannot, however, be readily used in applications such as assessing downstream streamflow effects or estimating pollutant loads from spillover or drainage fluxes, which rely on accurate estimates of water volumes. In such cases, water volumes may be estimated by simulating the pothole depth and using terrain data to convert pothole depth to water volume. To expand the model application to volume-based scenarios, further development of the AnnAGNPS wetland component could include expanded options for wetland or pothole topography, so that the depth-volume relationship might better represent site characteristics of the pothole. This may allow for simultaneous simulation of both depth and volume, with a single calibration.

The objective of the study in chapter 3 was to document the effects of land management on the inundation of prairie pothole wetlands using AnnAGNPS. Two pothole features were assessed with the AnnAGNPS model to estimate their hydrological patterns in different management scenarios. Three different management scenarios were developed and simulated by AnnAGNPS including a baseline scenario based on the current management conditions and two alternatives with modified land management. The three scenarios were current (row crop, current condition with surface inlets), retired (row crop, current condition and a mixture of grass, weeds, and low-growing brush with no surface inlets) and conserved (row crop, good condition with surface inlets).

Simulations indicate that potholes frequently flood during the growing season, which is at odds with their current use, lands designated to agricultural production. Results also show that these features have the potential to complicate crop production for farmers early in the season, by interfering in the dates of field operations, and could impact crop yields. Under the current scenario, potholes rarely overflowed, which implies that the features did not directly connect with downstream potholes. When drained, potholes tend to flood less often, however, drained water merges with other sources of flow in the drainage tiles, which suggests an indirect influence and nexus downstream. In the retired scenario, these features were more likely to overflow directly causing effects downstream, although the combined number of overflow events over the entire simulation period was only 5. When tiles in the potholes are disconnected, it is important to consider the use of conservation practices such as conservation tillage, cover cropping, mulching and extended crop rotations to reduce runoff production in the microwatershed.

The objective of the study in chapter 4 was to assess the USGS DEMs for modeling pothole inundation in the prairie pothole region of Iowa. A comparison of 1m DEM prepared from the LiDAR data, USGS 3m and 10m DEMs revealed that for this small-scale study, estimates of the pothole water depths using the three DEM resolution was close to each other with NSE of 0.77 for Walnut and NSE of 0.56 for Bunny pothole. Model simulations using AnnAGNPS have provided an assessment of DEM resolution on inundation at individual pothole level. This study concludes that for studying the small-scale features like potholes, in terms of depth and presence/absence of ponding, in absence of the expensive LiDAR based DEMs we can still use USGS 3m and 10m DEMs and get reasonable estimates of water depths.

The objective of the study in chapter 5 was to develop a simple easy to use and computationally less intensive tool for the assessment of the potholes. Assessment of the water depth fluctuations in the potholes is important for the management of the potholes. An empirical model based on artificial neural network (ANN) technique was developed. The ANN model was developed based on the long-term data (2007 – 2016) derived from the established AnnAGNPS models for three potholes (Bunny, Walnut and Lettuce). The ANN model was tested on the actual water depth observations collected in 2018 at another three potholes termed Turkey, Hen, and Plume. The R^2 statistics were found to be 0.604 and 0.563 during training and validation period. A low RMSE and MAE value of 0.057 and 0.023 was found during both training and validation of the ANN model. In general, the results suggest that the ANN models are able to predict the water depth fluctuations in the potholes reasonably well. This model is intended to provide a tool for the rating of the potential impact of potholes and can be used by stakeholders - farmers and state/federal agencies.

Recommendations for future research

Based on the findings of this research the following are recommendations for future research:

- AnnAGNPS model should be evaluated for simulating the inundation of other potholes, and in other locations, to determine if similar trends are observed.
- AnnAGNPS model can be used for assessing the impact of inundation on crop yield or simulations of alternative farm management strategies to compare water delivery to the potholes.
- Monitoring of water depths in some more potholes with different field conditions ('Farmed with no drainage' and 'restored to grassland').
- Application of the AnnAGNPS model for predicting the impact of climate change on the inundation of potholes.
- More observations of water depths in different size of potholes under different management practices and drainage conditions could be helpful, in building a more robust ANN model.