Using SWAT to inform the placement of agricultural BMPs that mitigate phosphorus and sediment pollution in overland flow on Chino Farms in Chestertown, Maryland

Erika L. Koontz

A senior thesis submitted to the Department of Environmental Science and Studies in partial fulfillment of the requirements for the degree of Bachelor of Arts at Washington College.

I promise that I have fulfilled this assignment in the spirit of the Washington College Honor Code.

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Thesis Advisor: Rebecca Fox

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1. ABSTRACT

In the Chesapeake Bay watershed, best management practices (BMPs) are being used by urban governments and rural farmers to reduce non-point source pollution of nitrogen, phosphorus, and sediment into the Bay to meet the United States Environmental Protection Agency's (USEPA) total maximum daily load (TMDL) standards. Nonpoint source pollution of phosphorus and sediment and their transport in overland flow, or surface runoff, on agricultural fields were the focus of the study. The soil and water assessment tool (SWAT) was used to inform the placement of BMPs on a field-level scale. SWAT utilized regional slope, soil, landuse, and weather data from Queen Anne's county, Maryland to develop a watershed model that spatially predicted and ranked areas of overland flow on the 5,323 acre farm property. Approximately 7.3% of the model results were randomly selected and groundtruthed during two separate precipitation events in January and February 2017.The results indicated that the model was not able to predict areas of overland flow above 28.60% accuracy. Identification of concentrated non-point source pollution locations has the potential to be achieved through the utilization of GIS modeling at increasingly smaller spatial scales, but requires refinement. This study analyzed an unconventionally small agricultural watershed and stretched the capabilities of the model to predict overland flow at the field-scale. The use of SWAT at smaller spatial scales to identify optimal (i.e. those with high overland flow) regions for BMPs is increasingly promising, but further research is needed to improve modeling in sub watersheds.

2. INTRODUCTION

The Chesapeake Bay is the largest and one of the most diverse estuaries in the United States. The Bay watershed is approximately 64,000 square miles in area and extends nearly two hundred miles from its headwaters in Cooperstown, New York to its mouth in southeastern Virginia. With its extraordinary size and shallow average depth of 6.7 meters, the Bay is capable of supporting a diversity of organisms, which is currently estimated to be greater than 3,600 unique species (Hoagland, 2005). Unfortunately, Bay water quality has been on a steady downward trajectory throughout the last century and has only begun to plateau within the last fifteen years (Ernst, 2003). Nutrient pollution has been cited as the largest problem that the Bay faces (Chesapeake Bay Foundation [CBF], 2016a; Ripa et.al, 2006). The influxes of nutrients and sediment have been connected to declines in various Bay health indicators, such as submerged aquatic vegetation (SAV) coverage, bottom dissolved oxygen concentration, and in organismal populations such as the eastern oyster, striped bass, and blue crab (Ernst, 2003; Kemp et.al., 2005; Rothschild et.al., 1994; Kemp et.al., 1983). As a result of declining water quality in the Bay, Chesapeake Bay specific legislation and regulatory bodies were established and tasked with reversing these declines by solving the nutrient problem (Hoagland, 2005).

20th Century Efforts: Policy and Legislation

Motivated by the establishment of national clean water standards by the Clean Water Act of 1972 and a 1983 report published by the United States Environmental Protection Agency (USEPA) on the problems of the Bay, the Chesapeake Bay Agreement of 1983 was formed to establish a collective partnership between the USEPA, the states of Maryland, Virginia, and Pennsylvania, the District of Columbia, and the Chesapeake Bay Commission (CBC) (Table 1).

Generic goals of improving water quality and collaboration between other organizations were set, but no specific goals were developed following the 1983 agreement, which lead to the Bay Agreement of 1987. The latter improved upon the existing goals by expanding them and making them more specific, for example: “reduce the levels of nitrogen and phosphorus entering the Bay by 40 per cent by the year 2000” (Hoagland, 2005). In 2000, a third agreement, Chesapeake 2000, was established to improve upon the goals of the 1987 Agreement and advance those related to water quality and nutrient pollution (Hoagland, 2005). Although each subsequent agreement has accomplished, set, and improved previous goals, numerous reevaluations of the pollution reduction strategies were conducted, those of which occurred in 1991, 1997, and 2007. The 2007 reevaluation summarized the efforts to improve Bay water quality that formally began with the Chesapeake Bay Agreement of 1983 had not made “sufficient progress…toward improving water quality…[where the Bay was] no longer impaired by nitrogen, phosphorus, and sediment pollution” (USEPA, 2010b). The necessity to create a stronger nutrient pollution reduction strategy was strengthened by former President Obama’s Executive Order 13508 that instructed “the federal government to lead a renewed effort to restore and protect” the Bay and the watershed (USEPA, 2010b). As a result, the Federal Leadership Committee, led by the USEPA Administrator and various cabinet secretaries, was created to establish the new nutrient management strategy, which was known as the Chesapeake Bay total maximum daily load (TMDL, USEPA, 2010b).

Table 1. Timetable displaying the history of Chesapeake Bay legislation and the movement towards improving the health of the estuary.

Year	Action	Result
1972	Clean Water Act	Created national clean water standards
1983	Chesapeake Bay Agreement I	Established a collective partnership between the USEPA, MD, VA, PA, DC, and the CBC

1987	Chesapeake Bay Agreement II	Set goals to reduce N and P nutrient loading by year 2000
1991	Re-evaluation of pollution reduction strategy	Summarized progress and modified goals
1997	Re-evaluation of pollution reduction strategy	Summarized progress and modified goals
2000	Chesapeake 2000	Improved 1987 goals for nutrient reduction
2007	Re-evaluation of pollution reduction strategy	Summarized progress and modified goals
2009	Executive Order 13508	Set the stage to create the Chesapeake Bay TMDL
2010-2025	Chesapeake Bay TMDL	Reduce N, P, sediment pollution; implement all control measures (BMPs,WIPs)

21st Century Efforts: The TMDL and WIPs

The TMDL concept was adapted from Section 303(d) of the Clean Water Act and TMDLs are used by the USEPA to improve water quality nationwide. TMDLs have a long history of success in the United States, with more than 40,000 completed in the country (USEPA, 2016a; USEPA, 2010a). The TMDL is a pollution budget or standard that permits a maximum amount of a pollutant, such as nitrogen, from entering the water before major damage will occur in a given waterbody. TMDLs are set to achieve specific water quality standards such as dissolved oxygen, water clarity, and chlorophyll-*a* (USEPA, 2016a).

In the Chesapeake Bay, TMDL standards have been established for nitrogen, phosphorus, and sediment (USEPA, 2016a; USEPA, 2010a). TMDLs are a standard that is shared among all polluters of nitrogen, phosphorus, or sediment in the Bay, and thus implementation requires a substantial amount of collaboration between polluters to collectively minimize pollution through various control measures. This is especially true for the Chesapeake Bay as the Chesapeake Bay TMDL is far larger than any other that the USEPA has created. As a result, the TMDL structural system was modified to be more manageable, where there is a composite TMDL standard for the entire watershed that was divided into 92 smaller TMDLs by the tidal segments of the

Chesapeake Bay. The tidal segment TMDLs fall into seven jurisdictions, including: Delaware, District of Columbia, Maryland, New York, Pennsylvania, Virginia, and West Virginia. These TMDLs were set to fulfill individual state water quality standards for the following indicators: dissolved oxygen, water clarity, underwater Bay grasses, and chlorophyll-*a* (USEPA, 2010a). These smaller segments enabled states and watersheds to address pollution issues locally through their individual state-wide Watershed Implementation Plans (WIPs) (USEPA, 2010a). In 2010, the USEPA set the goal that by 2017 at least 60% of the planned for control measures (i.e. the best management practices (BMPs)) would be installed, with completion to 100% by 2025 (USEPA, 2017).

Within the TMDL framework, all states are required to develop a Watershed Implementation Plan (WIP) that details the state's strategies to reduce their pollutant loads to at or below the TMDL for the major river basins that fall within their state boundaries. The WIP was also created to provide the USEPA with a way of monitoring the progress of individual states on their nutrient reduction efforts. Such strategies, or control measures, include best management practices (BMPs). BMPs are strategies to reduce nutrient pollution in all areas of pollution production. The WIPs are split into three separate phases. Phases I and II illustrate the proposed actions to be taken that will reduce nitrogen, phosphorus, and sediment loading. These two phases were implemented between the years of 2010 and 2012, with goals to be accomplished by 2017. Phase III of the WIPs have a goal to fine-tune the actions of the first two phases to help meet any TMDLs that have not been met as of 2017. Phase III implementation will occur between 2018 and 2025 (USEPA, 2017).

Since the TMDL is a number that is calculated using a model, it remains to be merely an estimate, albeit a good one. It reflects the sum of point and nonpoint source pollution, the projected increase for each of these sources, and an overestimate that serves as a margin of safety (Maryland Department of the Environment, 2016). The latter considers that the science behind nutrient estimation and geographic information system (GIS) modeling that developed those estimates would not be completely precise and creates space for mitigating mistakes. The annual watershed limit for nitrogen is 185.9 million pounds, 12.5 million pounds for phosphorus and 6.45 billion pounds for sediment, which reflect reductions of 25%, 24%, and 20% of nitrogen, phosphorus, and sediment, respectively. These numbers were developed using historic and current data, including but not limited to: locations of point source pollution, stream flow patterns, land use and land cover, and weather data. The data was utilized to develop a variety of models that predicted actual flow and transport of the pollution, among other outputs, with GIS being heavily utilized in the development of the TMDL (USEPA, 2010a). The TMDL limit accounts for both point and non-point source pollution, where sources of either or both are required to follow the same standard. Since point sources were easily identified, the main goal of the TMDL was to create legislation that worked to successfully address non-point source pollution, which cannot be combated in the same way as point source pollution (USEPA, 2010a).

Types of Pollution: Point and Nonpoint Source

The two main types of pollution are nonpoint and point source. Point source pollution is easier to track and manage in some ways because it has a definite source that can be signified by an x,y point. More technically, point source pollution is that which has a “discernable, confined and discrete conveyance”, such as a pipe or other physical feature that can be marked by a single set of x, y coordinates, for which the pollution is transported and discharged into a receiving body of water (USEPA, 2016b).

A nonpoint source of pollution is that which lacks this concrete and singular point. The pollution is also easily transported in water and becomes virtually impossible to trace back to an industry, whether that be agriculture or otherwise. In a watershed that is 64,000 square miles in area and contains hundreds of thousands of tributaries, there are ample opportunities for pollutants to enter the Bay in an infinite number of ways (Chesapeake Bay Program, 2012c). Nonpoint source pollution is the threat that has largely been ignored because it is difficult to regulate an unknown source and virtually impossible to quantify.

Both non-point and point source pollution negatively affect the water quality of the Bay due to their contributions of nitrogen, phosphorus, sediment, or all of the above. Examples of point source pollution within the Bay watershed include wastewater treatment plants, industrial discharge facilities, stormwater overflows, and concentrated animal feeding operations (CAFOs). Some examples of nonpoint source pollution are: agricultural fields, the atmosphere, forested areas, streambanks, and wildlife (USEPA, 2010c). Among all pollutant sources in Maryland, agriculture is cited as a major nonpoint source contributor of nitrogen, phosphorus and sediment. All three pollutants have been understood to cause the most environmental damage in the Bay's main stem, tributaries, and isolated bodies of water throughout the entire watershed (Legge et.al., 2013, Ganasri & Ramesh, 2015).

Across all states in the watershed, estimates of nitrogen, phosphorus, and sediment contributions by sector (agriculture, forest, stormwater runoff, point source, septic, and nontidal deposition) were modeled using the Chesapeake Bay Phase 5.3 Watershed Model. For Maryland, agriculture was modeled to contribute 16% of nitrogen, 19% of phosphorus, and 15% of sediment for the state. In comparison to the entire watershed, agriculture is estimated to contribute 44% of nitrogen and phosphorus and 65% of sediment to the Bay, making it the "largest single [nonpoint] source" of nutrient pollution (USEPA, 2010c). Agricultural lands also only occupy 22% of the land in the watershed, which translates to "more than 87,000 farm operations and 6.5 million acres of cropland" (USEPA, 2010c). On the Delmarva Peninsula alone, 8% of nitrogen, 10% of phosphorus, and 4% of sediment loading is produced on the Eastern Shore, which is the sum of the drainage basin area in Maryland, Delaware, and Virginia. These pollution percentages are greater than those on the Western shore of the Bay, which is a considerably larger area than the Eastern Shore (USEPA, 2010c). Since agriculture is a known major contributor of nitrogen, phosphorus, and sediment, it is imperative to initiate measures to reduce the pollution to a level at or below the TMDL. In order for BMPs and WIPs to be effective and achieve the TMDL pollution reduction goals, it is necessary to also understand the nature of nonpoint source pollution and how the pollution is transported from agricultural fields to the Chesapeake Bay.

Pollutant Sources and Transport Mechanisms

Before reaching the Chesapeake Bay waters, the pollutants of sediment, phosphorus, and nitrogen must leave the agricultural fields in which they originate. Each pollutant travels via a different mechanism, but are primarily moved as a result of precipitation events. Nitrogen predominantly moves when precipitation meets the soil and infiltrates into the ground. Nitrogen is commonly found in soils as nitrate (NO_3), which is soluble in water. As water infiltrates the soil layers, the nitrate dissolves into the water and is transported deeper into the underlying soil layers. This process is called leaching. If not absorbed by plant root systems or converted to nitrogen gas (denitrification), the dissolved nitrate will enter groundwater sources that will eventually connect to tributaries of the Bay (Lamb et.al, 2016). As a result, nitrogen does not commonly travel in overland flow because of its high solubility in water and subsequent transport downward into the soil layers and groundwater (Lamb et.al, 2016).

Alternatively, phosphorus and sediment are predominantly transported by overland flow. Overland flow is the process where water, from precipitation, travels across the land surface and transports sediment and nutrients to the point of lowest elevation on a given surface, which in this case is agricultural land (Wainwright et.al, 2000). There are two main types of overland flow: infiltration excess and Hortonian (saturation excess) overland flow. They are indistinguishable when observing them in the environment, but occur through two distinct chains of events (Fetter, 2001).

Infiltration excess overland flow occurs when the rate of precipitation exceeds the soil's infiltration capacity. Infiltration is the process by which rainfall enters the soil and is partially pulled downwards by gravity and the tension, or capillary force, that the water exerts on the particles. The infiltration capacity is highest when the soil is dry, but will decrease before reaching a relatively constant rate (Fetter, 2001). The decrease in capacity occurs because soil-moisture content increases, soil particles swell with water, and pore spaces fill with water, which all block the capillary passages and inhibit the ability of water to travel through them. The capacity eventually plateaus after four to five hours of consistent infiltration. The water that is unable to infiltrate the soil layers is termed infiltration excess (Fetter, 2001).

Hortonian overland flow occurs when the rate of precipitation exceeds the infiltration capacity of the soil. Following that, the depression storage of the soil must also be filled. Depression storage is the temporary storage of water on the surface of the land as ice, snow, or in puddles in actual land surface depressions. The movement of the water into depression storage is overland flow (Fetter, 2001). Depending on the soil's infiltration capacity, this type of overland flow may only occur during intense storms or when the soil is already saturated or frozen (Fetter, 2001). In this process, rainfall will pool on the soil surface and then begin to flow down the elevation gradient to the lowest point of elevation (Darboux et.al, 2001). The resulting flow of water from both types of overland flow is also known as surface runoff, and the terms are used interchangeably.

Overland flow primarily transports sediment and phosphorus, but not nitrogen. In soil, phosphorus' common forms are the orthophosphates $H_2PO_4^-$ and HPO_4^{2-}. Some of the phosphorus in these two forms becomes inaccessible to plants because of the molecule's negative charge, which results in a strong attraction to the positively charged soil particles. A negatively charged ion is known an anion, which can be an atom or molecule of a substance. In this case, the molecules are soil particles and orthophosphate. The subsequent ability for the soil to attract the anions, termed the anion exchange capacity (AEC), allows for strong bonds to be formed between the soil particle and orthophosphate molecules. As a result, the orthophosphate adsorbs or strongly bonds to the surface of the soil particles and becomes unusable by plants (University of Hawaii at Manoa, 2017). During instances of overland flow, the orthophosphate is transported in the overland flow as the flow moves the sediment particles that the molecule is adsorbed to. The latter is the primary mechanism of phosphorus movement. When phosphorus molecules are not adsorbed to soil particles, they are highly soluble in water and can be transported in overland flow or leach into the groundwater similar to nitrogen. This movement of phosphorus possesses a much lower potential for contributing to serious phosphorus pollution than movement with sediment particles (Brady & Weil, 2002).

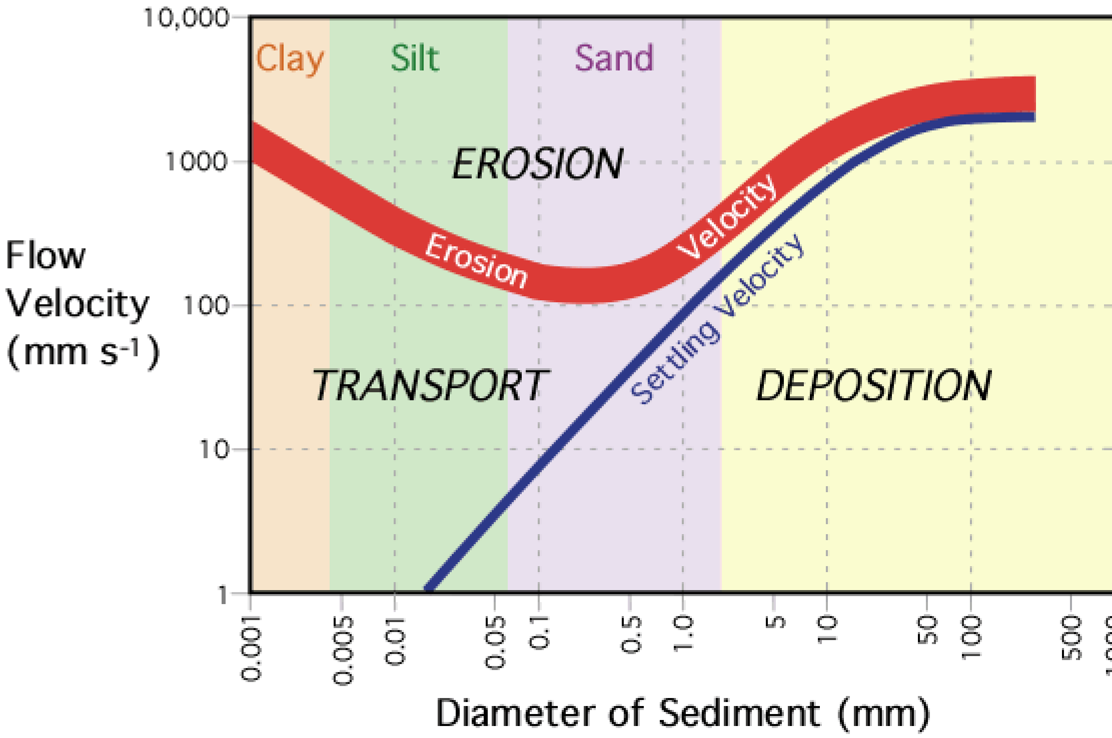

Figure 1. The Hjulström diagram describes the relationship between sediment particle size (mm) and flow velocity (mm/s) of wind or water (Pidwimy, 2006).

The movement of sediment particles, and thus the phosphorus, are dependent on the flow velocity of the overland flow and the size of the particle (Figure 1). The three possible movements for soil particles are erosion, transport, and deposition. For transport to occur in overland flow, the soil particles have a greater chance of movement at slower flow velocities if the particles have diameters between 0.01 and 1.0 mm, such as silt or fine grain sand. Clay requires higher flow velocities because the particles aggregate and stick together in a process called flocculation (Van Rijn, 2007). As a result, the movement and erosion of clay particles requires a high flow velocity. Comparatively, silt and sand particles can be moved at lower flow velocities because they do not aggregate via flocculation.

The orthophosphates readily adsorb to clay particles due to their large surface area (University of Hawaii at Manoa, 2017). If the overland flow velocity is substantial enough to move the sediment, the particles become entrained, a process by which water flows fast enough to incorporate soil particles into the water column, and transported within the water across the farm field (Busman et.al, 2016). The velocity required for a soil particle to be entrained is the critical entrainment velocity, which differs depending on the size of the particle. As the flow velocity of the water reaches below the critical entrainment threshold, which is different for each particle size and type, the particles will fall out of solution and be deposited (Figure 1).

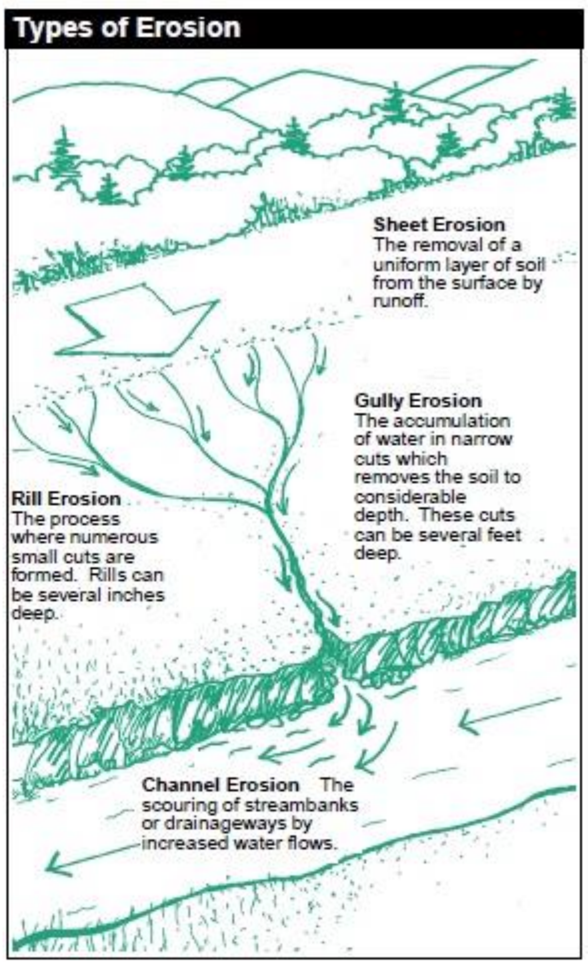

Figure 2. The four main types of soil erosion: sheet, rill, gully and stream/channel erosion (Fairfax County Government n.d.).

When overland flow consistently occurs in the same regions, distinct patterns of soil erosion arise. There are four classes of soil erosion: sheet, rill, gully, and channel/streambank (Figure 2). Sheet erosion is the least severe and is characterized by the movement of soil in a uniform layer. Sheet erosion is identified by the presence of bare areas, water puddling, the presence of visible grass/tree roots, and exposed subsoils. Subsoils are present below the organic and surface soil layers. Rill erosion is moderate erosion and is recognized by the presence of shallow channels of drainage that are less than 30 centimeters in depth and can be generally removed through the tilling process. Gully erosion is advanced rill erosion, where drainage channels exceed 30 centimeters in depth. Channel/streambank erosion is found on the banks of streams and is characterized by exposed tree or plant roots, steep banks, and little to no vegetative cover on the banks ("Soil erosion solutions..", n.d.; Brady & Weil, 2002). All four types of erosion lead to significant soil loss on farm fields, which are especially vulnerable if the land is overgrazed and bare of vegetation (Brady & Weil, 2002). The most soil erosion comes from sheet and rill erosion. Slope is an additional factor that contributes to erosion by increasing the velocity of overland flow, which results in more severe soil erosion (Figure 1; Brady & Weil, 2002). In order to reduce rainfall induced soil erosion on agricultural lands, various best management practices (BMPs) can be used to prevent soil loss and remediate soil erosion during precipitation events.

BMPs and the Role of GIS

The estimates of BMP effectiveness are difficult to assess due to the high costs associated with continuous monitoring pre- and post-installation to determine effectiveness in nutrient management. To combat this, a growing number of researchers are decreasing their area of study to the watershed and sub-watershed (subbasin) scale to evaluate the effectiveness of multiple BMP types (Fisher et.al 2010; Lizotte et al 2014). These and more studies are also monitoring nutrient movement in surface and groundwater that have an associated BMP to assess its efficiency in nutrient retention over time frames that exceed 10 years (Hoffman et.al, 2009; Fisher et.al, 2010; Kroger et.al, 2012; Lizotte et.al, 2014). Additionally, studies are seeking to utilize models to identify the optimal locations for BMPs and provide cost-benefit optimization analyses (Meals et.al, 2012; Shen, Chen & Zu, 2013; Zou et.al, 2015; Jang et.al, 2015). Within the agricultural industry alone, there are a multitude of BMPs that are being utilized to meet TMDL standards. Some examples of erosion and sediment control BMPs to install on conventionally farmed agricultural land include: conservation tillage, land retirement, riparian grass and forest buffers, and stream protection with fencing and off-stream watering for animals (Maryland Department of Agriculture, 2012). In order to evaluate the ability of these BMPs to reduce pollutants and improve water quality, GIS can be used as a less expensive means of analysis that can eliminate the need for continuous monitoring.

The process of discerning how, when, where, and why the Bay has declined through the last century is a task that has been aided by the use of remote sensing satellite technology and GIS. Previous applications of these technologies have been used on the large scale to assess long-term changes, such as tracking the rate of agricultural expansion across the surface of the Earth, assessing seasonal changes in vegetation growth, and understanding the impact of environmental changes on wildlife populations (Berry, 1999). Since the 1970s, satellite technology has dramatically increased in resolution and temporality. A satellite with a thirty meter pixel resolution used to be considered a high spatial resolution (Rose et al., 2015), but there are satellites with capabilities to produce images with less than two meter resolution and low-flying aircraft that carry cameras that capture the landscape in images with inches of resolution (DigitalGlobe, 2016). The technology of aircraft and spacecraft is now capable of sensing changes more frequently and at a much higher resolution, meaning that tracking temporal changes is no longer restricted to a watershed scale, but can also be done accurately on a field by field scale. Following these improvements in technology, GIS has also evolved from simply characterizing changes to evaluating why they are occurring and assessing management strategies that minimize or reverse changes. In essence, GIS has become a powerful tool that synthesizes information in a spatial presentation to increase the level of understanding while decreasing the time expenditure (Berry, 1999). Technological and reasoning advancements of GIS have led to the refinement of analysis techniques, thus allowing for finer-scale analysis, especially in agriculture.

GIS has the capacity to inform the installation, management, and effectiveness of conservation practices at a watershed or field scale (e.g., Shen, Chen, & Xu, 2013). Using high resolution satellite imagery and an existing GIS model, the ArcGIS extension of the Soil and Water Assessment Tool (SWAT), was used in this study to identify areas of overland flow on active agricultural land. The tool is widely used within the scientific community and has been consistently improved and updated over the past three decades (e.g., Gitau, Gburek & Bishop, 2008; Tuppad, 2009; Amatya & Jha, 2011; Niraula et.al, 2013). The tool was specifically created to assess water and nonpoint source pollution loading and supports the science used to establish, implement, and enforce the TMDLs. SWAT is a model fit for basin-scale evaluations that can predict impacts of different types of water, soil, and chemical management in watersheds dominated by agriculture, but can be modified to address smaller spatial scales (e.g., Gitau, Gburek & Bishop, 2008; Shen, Chen & Xu, 2013). The model incorporates a variety of weather based data, such as precipitation, temperature, humidity, and wind speeds, but not all simulations of the model require the same inputs, a token of its wide-range of applications (Gassman et.al, 2007). This study will use the tool to identify areas most vulnerable to erosion at the sub-watershed level (0.00074 to 17.46 acres; or 0.000003-0.070694 km^2), with the output of this analysis producing a visual of the specific areas vulnerable to overland flow erosion on Chino Farms in Chestertown, Maryland.

By identifying areas where overland flow is either occurring or likely to occur, SWAT will be used to inform the current management of the farm by suggesting locations where BMPs could be installed to mitigate the greatest amount of overland flow. By using this targeting methodology, SWAT directs conservation funding to BMP projects that will have the greatest impact towards TMDL achievement. The goal is to ameliorate the most phosphorus and sediment transported in the flow efficiently over a variety of spatial and temporal scales (Renschler & Lee, 2005). As a result of the efforts made in the last 40 years to reduce nutrient inputs to the Chesapeake Bay, there is evidence to support that water quality is improving. However, GIS can help to further this trend through finer-scale spatial characterization of data than the current Bay model, using modeling to improve management, and improving spatial reasoning (Chesapeake Bay Foundation, 2016b). I will test the hypothesis that the locations of future agricultural BMPs that mitigate the greatest amount of phosphorus and sediment pollution at the source and in transport can be pinpointed in the landscape and predicted within 70% accuracy using the SWAT model.

3. METHODOLOGY

Study Area

Chino Farms is a 5,323 acre agricultural property located in Queen Anne's County, Maryland outside of the town of Chestertown. Approximately 2,109 acres of the land is farmed conventionally with pesticides, and nutrients are managed with a nutrient management plan, a requirement for all farmers in Maryland, and best management practices (BMP) (Maryland Department of Agriculture, 2017). The remaining 3,223 acres is composed of shrub and forestland, along with a small section of restored grasslands (~200 acres) in the northern part of the farm. All of the land is preserved in conservation easements.

Data Acquisition and Pre-Processing

ArcGIS software (Environmental Systems Research Institute 2016) and the soil and water assessment tool (SWAT) extension version 10.3 were used for methodology and map creation (Texas A&M University, 2012). Data required by the model was acquired from a number of sources (Table 2). Before running the SWAT model, the data was shrunk to capture the footprint of Chino Farms. Extract by Mask (Spatial Analyst) was used to the clip the elevation data to the Chino Farms property boundary, which became the Source Digital Elevation Model (DEM). Soil data was also clipped to the Chino Farms property boundary layer and to the field boundaries layer in ArcMap (USDA & NRCS, 2017).

Table 2. Summary of data type, sources, timeframe of data collection, and metadata used in this experiment.

Data Type	Source	Timeframe of Data	Metadata
LiDAR for Queen Anne's County, Maryland	Maryland iMAP, 2013	2013	2 feet pixel resolution; ±12.5 cm vertical accuracy
Chino Farms Property and Field Boundaries	Washington College GIS, 2016	2012	
Land Use and Land Cover, Lower 48 States	National Land Cover Database; Department of the Interior and the United States Geological Survey, 2016	2011	
Weather (Precipitation (°C), precipitation (mm/day), wind speed (m/s), relative humidity (fractional/day), and solar radiation (MJ/m2))	Texas A&M University, 2017	12:00AM January 1, 1979-12:00AM December 31, 2013	Bounding coordinates: S latitude: 39.1306, W longitude: -76.0831, N latitude: 39.2663, E longitude: -75.8510
Soil Type	United States Department of Agriculture and Natural Resources Conservation Service	2017	Bounding coordinates same as weather data

The SWAT Model

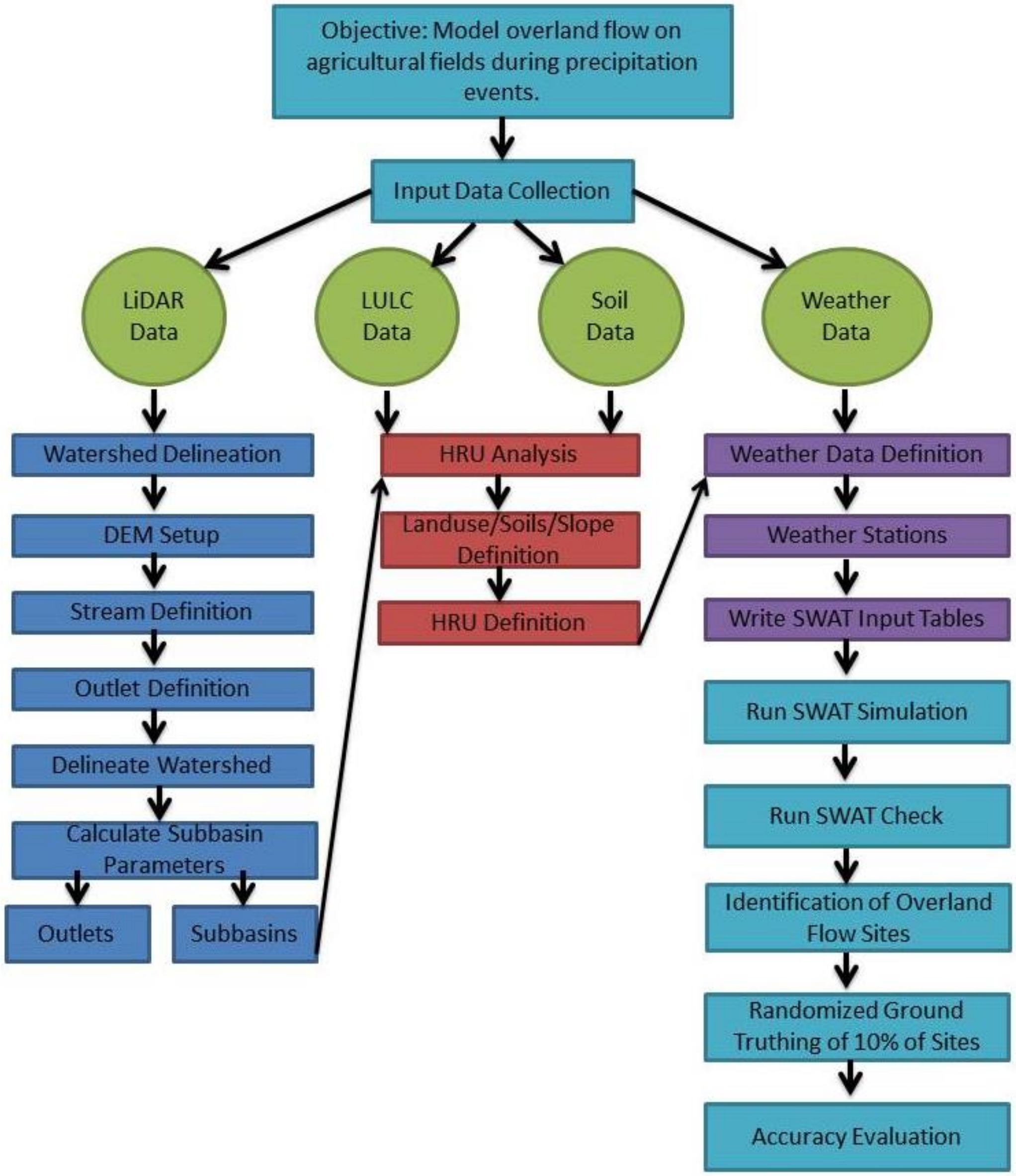

Figure 3. Schematic model of the Soil and Water Assessment Tool and accompanying user-defined methodology that described the three main workflows that the model required before the simulation was produced. Those workflows were: Watershed Delineation (dark blue), HRU Analysis (red), and Weather Data Definition (purple/teal, Duy Liem, 2012). Abbreviations legend: light detection and ranging (LiDAR), land use and

land cover (LULC), digital elevation model (DEM), hydrologic response units (HRU), soil and water assessment tool (SWAT).

The first section of the model's workflow began with the watershed delineation of Chino Farms, outlined in the leftmost third of Figure 3. The watershed delineation was performed on the sum area of active agricultural land, which is 2109.38 acres (8.53 km^2) of the property's total 5,323 acres. This methodology produced a polygon layer of the subbasin[1] boundaries and outlet locations of those subbasins (670 total) within the overall study area. Subbasins are the sub-watersheds within the agricultural fields, and are delineated using the digital elevation model. The outlet points were identified by the model as areas where there would likely be overland flow collecting at that point within the subbasin. Each point represented the singular convergence point of all overland flow contained within each subbasin, thus this variable represented the most likely locations where overland flow has occurred (Merwade & Rajib, 2014). The spatial variability present on the farm was incorporated into the model through addition of the soil and land use data which was clipped to the farm fields using the Extract by Mask (Spatial Analyst) tool. The model produced 670 subbasins, and 670 outlets, one for each subbasin.

Within the second section (middle section; red) of the model's workflow, the hydrologic response unit (HRU) analysis divided the subbasins into areas that contain unique land use, management, or soil attributes that improved the model's conceptualization of the heterogeneity of the subbasins. Therefore, each subbasin was divided into multiple HRUs and the total study area was divided into 1,317 HRUs. This improved the overall quality of the SWAT model simulation due to the increased resolution and analysis of the variability within each subbasin (Texas A&M University, 2012). During the input of the soil data, the NLCD 2001/2006 table

[1] Note: subbasin and watershed were synonymous terminology for the purpose of this study.

option was chosen to correlate to the land use dataset, and the ArcSWAT STATSGO and Stmuid dropdowns were selected for the soil dataset. To form a slope layer from the existing elevation data, the single slope option was kept as the default (Merwade & Rajib 2014). At the final stage of the HRU creation, the thresholds of 20%, 10% and 20% were set for land use, soil and slope at the recommendation of Strauch et.al (2014).

The model was calibrated and run using 34 years of air temperature, precipitation, wind speed, relative humidity, and solar radiation data (Table 2; purple section of Figure 3). The SWAT model simulation had a warm-up period, where a section of data was used to calibrate the model. This data was excluded from the simulation. The weather data from 1979 through 2007 was used for this purpose following recommendations from the SWAT user group (SWAT User Group, n.d.; Abbaspour, n.d.). The ArcSWAT simulation was run on the 2008-2013 weather data and produced a model output for each of the six years of weather data (Merwade & Rajib, 2014). The SWAT Error Checker was used to evaluate the model for potential calibration or other issues.

Surface Runoff Values per Subbasin

A map of average surface runoff for each subbasin was produced for the months of January and February. The values for surface runoff in millimeters were averaged for each subbasin across the six years of the simulation, 2008 to 2013. Each of the 670 subbasins had one value for surface runoff produced per month. This average represents the surface runoff for each subbasin across January and February in the six year simulation period (2008-2013). This value is the average runoff rate for each subbasin, and the values were divided into three categories that were produced using the quantile method. This method split the data into even thirds dependent on the distribution of data values.

January and February were chosen to correspond to the dates and times available for ground-truthing the model output because of optimal hydrological conditions. In the winter months, the water table is closest to or at the ground surface and therefore created conditions for the highest chance of saturation excess overland flow (Fisher et.al, 2010). The surface runoff data was incorporated into a map using ArcGIS. The map allows exploration of the variability in average surface runoff that the 670 subbasins of Chino Farms experience on average during these two winter months (Figure 4).

Surface Runoff Ranking Index

The values for overland flow produced by the model were not intuitive for a landowner to interpret; therefore, a ranking index was created (Figure 4). The ranking system was created after standardizing the overland flow predictions by area. The overland flow created in each subbasin per unit area (SURQ Area, mm/km^2) was calculated according to:

$$SURQ\ Area = \left(\frac{SURQ_{Gen}}{Area_{SUBBASIN}}\right) \tag{1}$$

where $SURQ_{gen}$ (mm) is the total amount of overland flow created in each subbasin and $Area_{SUBBASIN}$ (km^2) is the area of each individual subbasin. A value of SURQarea was produced for each subbasin and this value was used to calculate the relative percent contribution of that subbasin to the total overland flow produced within the entire study area ($\%SUBBASIN_{rel}$) using:

$$\%SUBBASIN_{rel} = \frac{SURQ\ Area}{Total\ SURQ\ Area} \times 100$$

(2)

where $SURQ_{Area}$ is the overland flow in units of mm per km^2 per month that is produced by each subbasin, this value is the average of the January and February overland flow predicted by the model. Total SURQ Area is the sum of overland flow produced by all of the subbasins in units of mm per km^2. Multipled by 100, a value of $\%SUBBASIN_{rel}$ was produced for each subbasin, and this value indicates each subbasin's relative contribution of overland flow in the property's watershed. These values were ordered from lowest to highest percent contribution and were evenly divided into four classes named below average, moderate, severe, and extreme. When the study area subbasins were mapped and color coordinated according to the four classes, an easy to understand visual demonstration depicting the range of water erosion across the subbasins on Chino Farms was produced (Figure 5).

Ground-Truthing the Model

The model's accuracy was evaluated by comparing the model output to field based observations. Randomly, 10% of the 670 outlet points were evaluated. Randomization was achieved using the RAND function in Excel. The 67 points were pre-loaded onto a Garmin GPSMAP 76CSx using the Minnesota DNRGarmin application for ArcGIS 10.2 (Minnesota Department of Natural Resources, 2017). Since overland flow can be observed during and after a precipitation event, I groundtruthed each point on foot during precipitation events during January and February of 2017. To maximize the chance of overland flow observation, ideal site conditions would include total saturation of the soils, which would occur during a heavy and consistent rain after a variable period of time that was dependent on the pre-precipitation soil saturation.

Approximately 49 of 670 outlet sites were surveyed for evidence of overland flow during the course of the study. Surveying was conducted during ideal conditions, where rainfall occurred during the day and for a minimum period of two hours. These conditions were rare during the surveying time period, preventing all 67 sites from being surveyed. Sites were surveyed over two days, January 23 and February 12, 2017, and heavy rain was consistent during each three and half hour period of surveying. Brief rainless periods of fifteen minutes or less occurred once or twice during the surveying period, but surveying continued through those periods. Surveying concluded within forty-five minutes after rainfall stopped. Site locations varied, but the majority (24) were found in the middle of agricultural fields, 6 were found in depressions in farm fields, 2 within depressions in buffer zones, 5 within field ditches, 2 within roadside ditches, 6 on agricultural field edges, 2 in grassland fields, and 2 in grassland roadways (Table 3). Depressions in farm fields and in buffer zones, defined by areas of vegetation that was not in active cultivation, were observed as noticeable slopes in the landscape while I was surveying. The distinction of noticeable depressions or slopes at the groundtruthed sites was made to better judge an area’s likelihood for overland flow in the absence of overland flow.

Table 3. Locations of the 49 surveyed sites.

Number of Sites	Location
6	Depression, farm field
2	Depression, buffer zone
5	Ditch, field
2	Ditch, roadside
24	Agricultural field
6	Agricultural field edge
2	Grassland, field
2	Grassland, roadway

Evidence of sheet, rill, gully, and channel/streambank erosion (Figure 2) were noted at each outlet point. Overland flow was recorded for each site as present or absent (Fetter, 2001). Present was defined as points where water was clearly pooled and/or flowing across the land surface. Absent was defined as points where there was no noticeable pooled or flowing water on the land surface. Sites with high overland flow potential included those within a depression (two types: buffer zone and farm field) or a ditch (two types: farm field and roadside). In these locations, I surmised that it was highly probable for overland flow to be present, but that I may not have observed it due to the absence of ideal site conditions.

Images and videos of the immediate area of each site, within three meters of the exact location, were captured *in situ*. The immediate area of three meters was selected because it corresponds to the approximate accuracy of the GPS operating unit (CNET, 2017).

4. RESULTS

A total of 1,317 HRUs, 670 subbasins, and 670 outlets were created by the model (Appendix A: Figures 8 and 9; Appendix C: Results Table).

Table 4. Summary values for 12 of 49 groundtruthed outlets, sorted by smallest to largest area (km^2).

Ground-truthed	Surface Runoff	Subbasin	Area (km^2)	Averaged Surface Runoff in January & February in 2008 and 2013 (mm/month) (Figure 4)	Surface Runoff Rating (Figure 4)	% Surface Runoff Standardized by Area (Figure 5)	Surface Runoff Rating (Figure 5)
		61	0.000004	4.37	Low	190,095.75	Extreme
		140	0.000004	13.10	High	481,729.21	Extreme
x	Yes	103	0.000204	2.22	Low	1,912.02	Severe
x	Yes	200	0.003144	7.95	Medium	381.07	Moderate
x	No	626	0.007285	20.38	High	415.82	Moderate
x	Yes	162	0.008498	1.74	Low	42.75	Below Average
x	Yes	134	0.012945	2.16	Low	29.06	Below Average
x	Yes	149	0.01337	0.83	Low	18.22	Below Average
x	Yes	424	0.014666	8.31	Medium	83.17	Below Average
x	Yes	607	0.018796	2.74	Medium	23.91	Below Average
x	Yes	48	0.019188	7.87	Medium	59.63	Below Average
x	No	572	0.035045	15.53	High	67.26	Below Average

Table 4 shows a representation of the diversity of values for subbasin area ($SURQ_{Area}$) average surface runoff ($SURQ_{gen}$), surface runoff rating, % surface runoff standardized by area ($\%SUBBASIN_{rel}$), and the surface runoff rating. Subbasin area varied considerably from the lowest value of 0.000004 to the highest value of 0.039314 km^2. The average area was 0.0127408 km^2. The minimum and maximum average surface runoff value ($SURQ_{Gen}$) for January and

February were 0.22 and 20.48 mm, respectively. The amount of surface runoff from each subbasin ($SURQ\ Area$) relative to the average surface runoff for the whole area ($\%SUBBASIN_{rel}$) ranged from 3.45% to 481,729%. Values over 100% indicate that the runoff from that subbasin was greater than the average runoff for the entire area. A value of 481,729% indicates that this subbasin was predicted to be a large contributor of surface runoff in the study area.

Table 5. Summarized outcomes of Figure 4, showing the number of subbasins in each surface runoff category.

Surface Runoff (mm)	# of Subbasins
Low (0.00-7.97)	223
Medium (7.98-8.82)	232
High (8.83-20.48)	215

Average surface runoff values ($SURQ_{Gen}$) for each subbasin for the months of January and February for 2008-2013 varied from 0.00 to 20.48 mm/ month. These values were divided into three categories to aid in visualization and were low (yellow, 0.00 to 7.97 mm/month, 223 subbasins), medium (orange, 7.98 to 8.82 mm/month, 232 subbasins), and high (red, 8.83 to 20.48 mm/month, 215 subbasins) (Figure 4, Table 5). The low category was concentrated in the northernmost portion of the property in and around the grasslands and agricultural fields. The medium category was distributed uniformly around the map without a discernable pattern. The high category was also dispersed randomly throughout the farm property (Figure 4).

Table 6. Summarized outcomes of Figure 5, showing the number of subbasins in each relative surface runoff category.

Surface Runoff Contribution (%)	# of Subbasins
Below Average (3-100%)	308
Moderate (101-500%)	287
Severe (501-1,000%)	22
Extreme (1,001-500,000%)	53

When the data was standardized by area (Equations 1 and 2), predicted hotspots of overland flow emerged (Figure 5). The values were divided into four categories: below average (3-100%, 308 subbasins), moderate (101-500%, 287 subbasins), severe (501-1,000%, 22 subbasins), and extreme (1,001-500,000%, 53 subbasins) (Figure 5, Table 6). On Figure 4, arrow #1 is pointing to one of the subbasins (Table 4) which has a high predicted average surface runoff (Figure 4). When the average surface runoff value (mm/month) is standardized by area (km^2), the overall contribution of surface runoff per km^2 land area is below average (Figure 5, arrow #1). At arrows #2 and #3 (Figures 4 & 5), a similar pattern emerges between the figures, which represent what occurred for the majority of the subbasins when standardized by area. A general trend revealed clear concentrations of below average and moderate predicted surface runoff ($SURQ_{Gen}$) in the northern half of the property, and an increase in the prevalence of the severe and extreme rankings in the southern half (Figure 5).

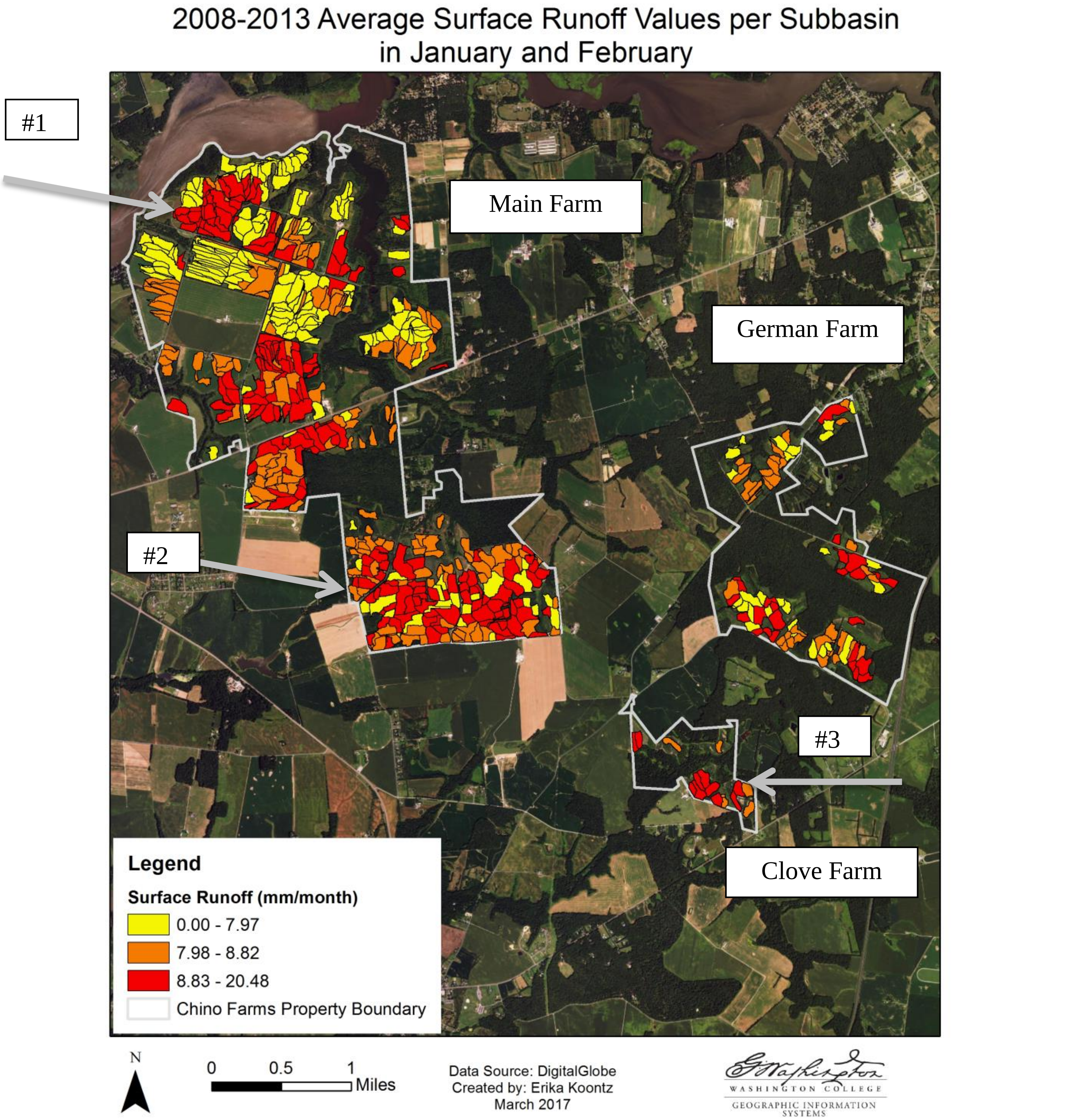

Figure 4. Averaged surface runoff values per subbasin (mm/month) for years 2008-2013 January and February. Values are relative to each subbasin, and higher values indicate more surface runoff.

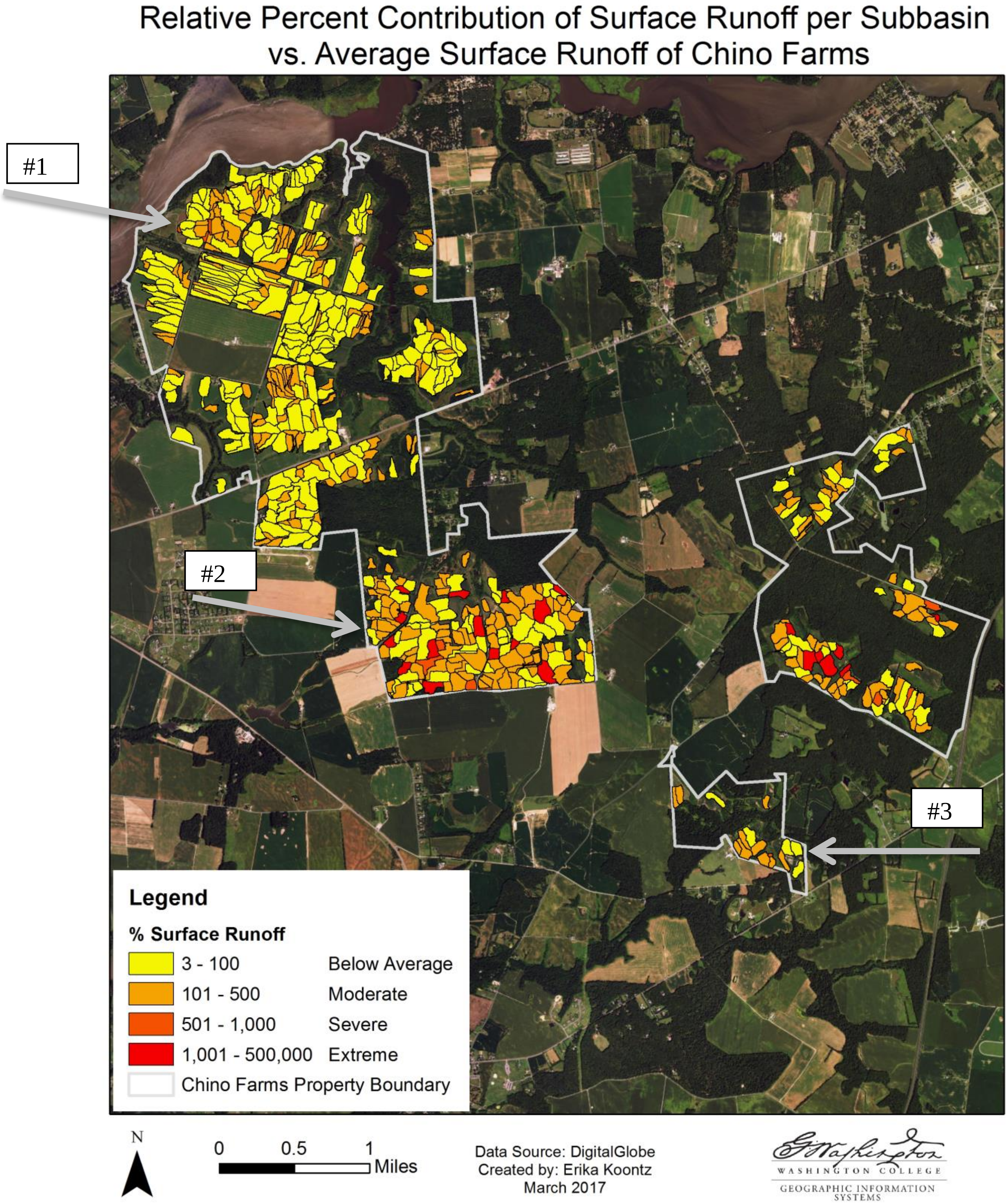

Figure 5. Overland flow ranking index for each subbasin showing below average, moderate, severe, and extreme surface runoff contributions.

Ground-truthing

Forty-nine sites were surveyed on January 23 and February 12, 2017. Total rainfall accumulations of 3.23 inches and 0.22 inches occurred on January 23 and February 17, respectively (Weather Underground, 2017). Of the 49 surveyed sites (Appendix A: Figures 8 and 9), the majority were in the below average category (28), but 18, 1, and 2 fit in the moderate, severe, and extreme categories, respectively. 8 sites showed overland flow (Figure 6). Of these 8 sites, two fell within the moderate, severe or extreme categories (eqn. 2, Figure 5). This results in a 9.5% prediction. 15 of the 49 sites showed potential for overland flow by being located within a depression or ditch. Of these 15 sites, 6 fell within the moderate, severe, or extreme categories (eqn. 2, Figure 5). This results in a 28.60% prediction. This data refutes my hypothesis that SWAT was able to predict with 70% accuracy the occurrence of overland flow.

Figure 6. Sites 162 (top) and 200 (bottom) with overland flow present. Site 162 had flowing water that extended across approximately a twenty foot range of ground.

5. DISCUSSION

My results refuted my original hypothesis, where I proposed that the SWAT model could identify the locations where future agricultural BMPs would be most effective, i.e. reduce the greatest amount of surface runoff. The results also did not support that the SWAT model simulation would predict the locations of overland flow in the landscape at 70% accuracy or better when model results were compared to the groundtruthing observations. The results of my groundtruthing efforts yielded 9.5% accuracy for sites where I observed overland flow, and a 28.60% accuracy at sites that had the potential for overland flow due to their location within a depression or ditch. The random selection of outlets to groundtruth during my field surveying included at least one outlet from the average surface runoff categories in Figure 4 (low, medium, and high), and the percent surface runoff contribution categories in Figure 5 (below average, moderate, severe, and extreme) (Table 4). Additionally, the groundtruthed outlets represented a wide range of the subbasin areas. This supports that the assortment of model outputs was well represented in my groundtruthing efforts. Although my study did not show that SWAT was able to predict locations of high overland flow in an area that is below the average area of study, field-scale modeling on coastal plain properties larger than 5,323 acres can be done successfully using SWAT (Gitau, Gburek & Bishop, 2008; Amatya & Jha, 2011; Niraula et.al, 2013; Jang et.al, 2015).

From the results, Figure 5 was more important to the focus of this study because it takes the area of the subbasin into account when determining overland flow, which figure 4 does not do (Equations 1 and 2). Figure 4 demonstrated the total amount (mm) of surface runoff that each subbasin experiences; however, the sizes of the watersheds vary considerably (see Table 4). By dividing the total amount of runoff that is exiting each subbasin by the area of that subbasin, a runoff rate (mm m^{-2} $month^{-1}$) is calculated. If these values are divided by the average runoff rate for all subbasins, each subbasin's runoff rate is put into the perspective of the average rate (Figure 5). Values less than 100% indicate that these watersheds are responsible for low amounts of runoff whereas values greater than 100% indicate that these watersheds are responsible for more than the average runoff rate. Figure 5 supports that it is possible to rank subbasins by their relative contribution of surface runoff ($\%SUBBASIN_{Rel}$), but the model did not support that these rankings were accurate based on the groundtruthing data. If the model was to work how I intended it to, Figure 5 would be utilized to suggest that the areas of severe ad extreme surface runoff (red subbasins) would be the regions where new agricultural BMPs would be most effective. These two area categories contributed between 500 and 500,000% more surface runoff than the average runoff rate of the total study area. The highest value, 481,729% (Table 4), was an extreme outlier, and was calculated for a subbasin with one of the smallest areas, 0.000004 km^2. This indicates that the values for the extreme surface runoff category above 10,000% (15 subbasins) were outliers due to the subbasin's small areas, which were all less than 0.000109 km^2.

Model Capabilities and Limitations

Some of the issues associated with my model were due to presence of atypical weather conditions, limited groundtruthing efforts, and a small study area. During the two sampling days, the amount of rainfall was very different. On the 23rd of January, precipitation was recorded at 2.32 inches, and rainfall on the 17 of February recorded at 0.22 inches. I am postulating that this difference in rainfall amount impacted the number of sites that had overland flow, where I observed six sites, out of 29, with overland flow on the 23rd of January, and only 2 sites, out of 20 that were groundtruthed, had overland flow on the 17th of February. Four of the six sites with overland flow that were observed on the 23rd of January were predicted as below average (the other two were moderate and extreme), so this comparatively heavy rainfall may have caused more overland flow than expected in the below average areas. Additionally, precipitation has been lower in the months of January and February this year than compared to last year. In January of 2016, the total monthly precipitation was 18.22 inches, and this year's total was 4.25 inches, which is 4.2 times less than last year. The same trend occurs in the month of February, where the monthly precipitation was 9.96 inches in 2016 and only 1.58 inches in 2017, a difference of 6.3 times less than the previous year (Weather Underground, 2017). This supports that the weather conditions for this winter were much drier than they are on average, resulting in a lower water table and lower soil water storage. This resulted in a lower likelihood that saturation excess overland flow would occur this year than in previous years, thus producing atypical conditions that likely contributed to fewer incidences of observed overland flow.

An additional issue with my study setup was the small area of Chino Farms. Within the literature studies that use SWAT to aid in BMP and non-point source analysis, researchers analyzed watersheds and basins ranging from 1.63 to over 330 square kilometers. Chino Farms is a property that is 20 km^2 in size, but the study area was approximately 8.5 km^2. In the literature, it was much more common to see larger study areas that often spanned multiple states (Gitau, Gburek, & Bishop, 2008; Meals et.al, 2012). The majority of studies analyzed watersheds between 70 and 350 square kilometers, with fewer researchers focused on watersheds much smaller than 70 square kilometers (Amatya & Jha, 2011; Niraula et.al, 2013; Meals et.al, 2012). This indicates a potential study limitation based on the size of a watershed, where the area of study needs to be a certain minimum size in order to produce accurate results. There are a growing number of papers that are improving BMP evaluation over smaller spatial scales, and support that an in-depth BMP analysis may be done within any watershed size, and are becoming increasingly more accurate in smaller watersheds (Gitau, Gburek & Bishop, 2008; Shen, Chen & Xu, 2013; Amatya et.al, 2011). Some of the watersheds produced during my model were only fractions of the size of the smallest watersheds studied in the literature, and my average size was 0.012 km^2, which is smaller than the lowest watershed area, 0.08 km^2, studied by Shen, Chen & Xu (2013). Due to the abundance of studies that analyzed larger watersheds, my study falls into the below average category due to the small size of the watershed.

Ground-truthing and Verifying the Model

Beyond using the latitude and longitude points generated with the outlet locations, it was difficult to evaluate the accuracy of the model’s numerical estimates. During the surveying aspect of the study, the GPS unit that was used possessed an accuracy of ±3 meters. I took this into consideration while I was in the field looking for evidence of overland flow by visually surveying a 3 meter by 3 meter area using the outlet location as the center point. I did not have access to a GPS unit with greater accuracy, and this may have enabled me to more easily confirm the presence or absence of overland flow at some of my sites. The outlet sites were surveyed over two separate days, which equates to two different sets of weather and soil water content conditions, and contributes to site condition variability. The presence of overland flow in some of the survey sites was encouraging and validated the model to an extent, but also reflects the limitations of the model’s capabilities in this study.

To resolve this in future uses of the model, I would expand the time period of my study to a six month or yearlong period. This would likely provide more days of precipitation, which was a major limitation for my groundtruthing efforts. Two months was a fairly short time period, and yielded less than five days of precipitation that occurred during the day and was sustained for more than a few hours at a time, which are two requirements for conditions to be optimal for surveying. With a larger time frame for the study, an additional advantage would be the opportunity to groundtruth more sites and visit the same sites multiple times. The latter would enable me to better understand how individual sites vary during diverse rainfall conditions (light vs. heavy rainfall, for example), where I would be able to see if a site experiences overland flow some days and not others- and why that might occur. An additional strategy to have utilized would have been deliberate sampling of the outlet locations within more of the severe and extreme categories to see if these areas showed surface runoff (Figure 5).

It would have been optimal to survey all sites during each day of sampling to confirm that each site behaved similarly during two precipitation events; however, this was not feasible. A possible alternative would be to work in a research team and have multiple people able to survey more sites during a precipitation event. If other researchers were not available, it would potentially be feasible to set up a system of cameras that would be set to record photographs and video of the sites. This, however, would potentially be expensive. Finally, a further improvement that could be made to the groundtruthing would be to understand the impact of pre-existing BMPs that were located near the sites by noting where BMPs were installed. In future surveying, deliberate selection of some sites within or near BMPs would potentially improve future study results.

Timing of Model Simulation

Even though the average rainfall for the study period was much lower than in the previous year, this study was conducted during one of the most optimal times of the year because of the position of the water table. In the winter months, the water table is closest to or at the ground surface and therefore the highest chance of saturation excess overland flow (Fisher et.al, 2010). Although the average precipitation for the month of January ranks only 7th highest in the year for Chestertown, the probability of overland flow would be higher because the soil is saturated by the water found within the water table (Your Weather Service, 2017). At other times in the year, the water table is not as close to the surface, decreasing the chance that overland flow would occur. This study also alerts farmers and farm managers that their fields are most vulnerable to overland flow and sediment erosion during the winter months. In Reddy et.al (1977), cover cropping was shown to decrease sediment and phosphorus losses in overland flow. This supports the need for cover cropping during these higher vulnerability times of the year when it is too cold to grow conventional crops and when the water table is exceptionally high.

Verification of the Model's Estimates

Based upon my current review of the model, the numbers produced for surface runoff in my study are not easily compared within the currently available literature. The main reason for this is my unique application of the model, where I attempted to accurately calculate the surface runoff ($SURQ_{Gen}$) for each subbasin. Other studies conducted similar research, but none that were directly comparable to my results. The study with the closest intention and purpose was one done by Niraula et.al (2013), where they predicted the critical source areas of nitrogen and sediment (i.e. the regions with the highest amount of nitrogen and sediment pollution) while also modeling streamflow on a monthly time period. Many other studies have used SWAT, but for slightly different applications.

For example, Shen, Chen & Xu (2013) calculated sediment, total nitrogen, and total phosphorus loading within a similar sized watershed (1100 acres) in China to evaluate BMP placement. In another study, Meals et.al (2012) examined an 82,500 acre watershed in Georgia, United States, to evaluate the impact of BMPs on nitrogen, phosphorus, and sediment loading before and after installation. In a third study, Jang et.al (2015) used SWAT to evaluate rates of erosion within the coastal plain region that extends from Mississippi to southern Virginia to inform BMP placement in regions of highest erosion. Last, Tuppad et.al (2009) utilized SWAT to predict how effective specific BMPs would be at the level of the HRU, sub watershed, and watershed level in a study area that exceeds 1,000,000 acres.

Although no other study that I found in my research mimicked my own, I am still able to draw some conclusions about the reliability of my model's outputs. The spatial pattern of the values ($SURQ_{Gen}$ in Figure 4 and $\%SUBBASIN_{Rel}$ in Figure 5) appeared to be randomly distributed. An obvious pattern would have increased my skepticism of the results. Additionally, the model did not classify each subbasin as possessing the same severity, so there was natural variation in the data and between subbasins. In Figure 5, the model also clearly identified specific subbasins as having a much more substantial contribution to surface runoff than others, and did not identify every one as being in the 'extreme' category.

Evaluation of the Model

Within the literature, there are countless studies that utilize SWAT and other watershed simulation models; however, there is no comprehensive guide that provides a standardized methodology to evaluate a model's accuracy or performance (Moriasi et.al, 2007). Moriasi et.al (2007) conducted an extensive literature review of watershed models, many of them using SWAT, and created a tentative guideline of evaluation. A large part of the guide featured statistical analyses that can be used to compare watershed simulations of streamflow to actual, measured values; however, these analyses are not applicable to my study for two reasons. One, I conducted a study of overland flow, and two, my field data did not produce numerical values suitable for statistics. As a result, my evaluation of the model defaulted to the generalized section of additional considerations in the review by Moriasi et.al. (2007). In this section, Moriasi et.al (2007) suggests evaluating the model's performance based upon the calibration procedure that was utilized.

In my methodology, I calibrated the model with a 29 year warm-up period of weather data that spanned from 1979 to 2007. An ideal calibration included years of data that were representative of wet, average and dry years, which I confidently covered by using nearly three decades of data. Furthermore, an ideal calibration also involves multiple evaluation techniques and calibration of all constituents (Moriasi et.al, 2007). This study incorporated one evaluation technique, which was observational groundtruthing of outlet points. Additional evaluation techniques could be represented in other watershed models. All model constituents, namely the digital elevation model, the weather, soil, and landuse data were calibrated to the study area, but were not individually evaluated for their accuracy in this study. For example, evapotranspiration values that were calculated using the weather data were not verified for their accuracy, which would be conducted in separate study (Moriasi et.al, 2007).

Based upon the applicable portions of the Moriasi et.al (2007) literature review, the model seemed to be calibrated appropriately due to the wide array of data inputs, but lacked observational data, i.e. actual and measured overland flow values from the subbasins, that would verify the accuracy of the model, its values, and its constituents. Additionally, my methodology utilized SWAT in an innovative way, where I sought to extend the model's applications just beyond its current capabilities. The latter further complicates the accuracy evaluation process because such a process has either not been developed or is in the process of being developed.

Recommendations

The overall goal of this research project was to inform the conservation management of the Chino Farms property within the Chester River watershed by providing the farm manager, landowner, and Washington College with a set of priority locations on the fields where BMPs could be installed to most dramatically reduce their surface runoff, and by extension, their phosphorus and sediment pollution (Figure 5). This research provides the necessary information to the above stakeholders to make informed decisions about current and future management on Chino Farms. In addition to informing the management of this farm, the methodology and results of this study are applicable to the Chester River watershed, which Chino Farms is part of, across the eastern shore of Maryland, and throughout the coastal plain on the east coast of the United States. Although the habitat composition of individual farms will differ, SWAT can be used effectively to evaluate non-point source pollution and provide precision-based BMP advice based on actual weather, land use, soil data and more. The only limitation to the application of this methodology and SWAT is time, a basic knowledge of GIS, and the availability of the appropriate computer software. The data and guides on how to use SWAT are freely available to the public, and require computational knowledge; however, this can be gained through practice, trial, and error.

BMPs that would be most effective at reducing surface runoff would be ones that slow the flow of water over the landscape and increase the rate of infiltration (Table 6). Specifically, Lowrance et.al (1997) and Lee et.al (2003) observed reduced transport of sediment, phosphorus, and nitrogen in riparian buffers that featured multiple species, including switchgrass and woody plants. Blanco-Canqui et.al (2004) saw a reduction of 18% of surface runoff, 92% of sediment transport, and 71% nutrients with the installation of switchgrass barriers and vegetative filter strips.

Table 6. Recommended best management practices for reducing surface runoff on agricultural fields (Surry Soil and Water Conservation District, n.d.).

BMP	Management Goal(s)	Action
Grass waterways	Reduce surface runoff and increase infiltration	Plant grass strips within depressions on farm fields to cover bare soil and slow surface runoff flow
Conservation tillage	Reduce sediment loss in surface runoff	Minimum tilling or no-till
Land retirement	Reduce surface runoff	Convert cultivated fields to grassland with perennial vegetation cover
Riparian forest/ grass buffers	Absorb nutrients (N, P) and trap sediment; reduce surface runoff	Plant forest or grassy vegetation in 100 feet widths on both sides of a waterbody
Stream protection and off-stream watering	Reduce sediment erosion at the waterbody	Install fences that prevent animals from accessing the stream and construct alternate water sources

The BMPs listed on Table 6 are included within a broader BMP known as conservation or farm plans, which serves as a collection of the most effective BMPs for erosion, sediment loss, and runoff reduction. These BMPs include conservation tillage, which is a form of active management by the farmer to reduce the amount of tillage necessary when seeding, harvesting, and managing fields. In a study by Zhang et.al (2007), no-till increased the overall stability of the soil and increased the space between soil particles (pore size), which lead to and increase ability of the soil to capture rainfall. This translates to a direct increase in infiltration and less overland flow, which would increase the surrounding water quality by minimizing sediment movement (Zhang et.al, 2007). Land retirement removes marginal and low productivity land from planting rotations, where the land is then planted with perennial vegetation cover, including shrubs, grasses, and trees. Riparian forest buffers are strips of woody vegetative cover that are planted on both sides of the water source and extending 100 feet on both sides to maximize the retention of phosphorus and sediment (Lowrance et.al, 1997; Surry Soil and Water Conservation District, n.d.). Riparian grass buffers follow the same design as the forest buffer, but substitute grass and non-woody vegetation along the edge of water bodies, such as streams, rivers, and fields where they serve as a field border. Both riparian forest and grass buffers are estimated to achieve between 45-60% reduction efficiency for phosphorus and sediment mitigation, with the range accounting for the geologic history of the farmland. Stream protection with fencing and off stream watering is a BMP that relies on fencing to protect the riparian grass or forest buffer from livestock, and installs alternate water sources to support the livestock. It is estimated to be up to 60% and 75% efficient for phosphorus and sediment control, respectively (Pennsylvania Department of Environmental Protection, n.d.).

6. CONCLUSIONS

Identification of concentrated non-point source pollution locations has the potential to be achieved through the utilization of GIS modeling at increasingly smaller spatial scales. By identifying hotspots of overland flow, precision-based BMP placement is possible, but requires refinement. In this study, SWAT was used to analyze a relatively small agricultural watershed and produced unconventionally minute subbasins. Values for surface runoff were calculated using 34 years of weather data, and standardized by area to create a map visual of where non-point source pollution of phosphorus and sediment were the most concentrated on the property. 7.3% of these sites were verified with *in situ* site visits, but these results did not support the study's hypothesis. In future uses of the model, it would be informative to include data on point source pollution to understand the dynamic movements of nitrogen, the last of the three major pollutants to the Chesapeake Bay. Additionally, it would be more informative to the model to increase the number and frequency of groundtruthing site visits to understand if there is individual site variability during diverse rainfall conditions. The use of SWAT at smaller spatial scales is increasingly promising, but is an ever-evolving field as GIS technologies improve and environmental applications increase.

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APPENDIX A: AREA OF STUDY AND METHODOLOGY CONCEPTUALIZATION

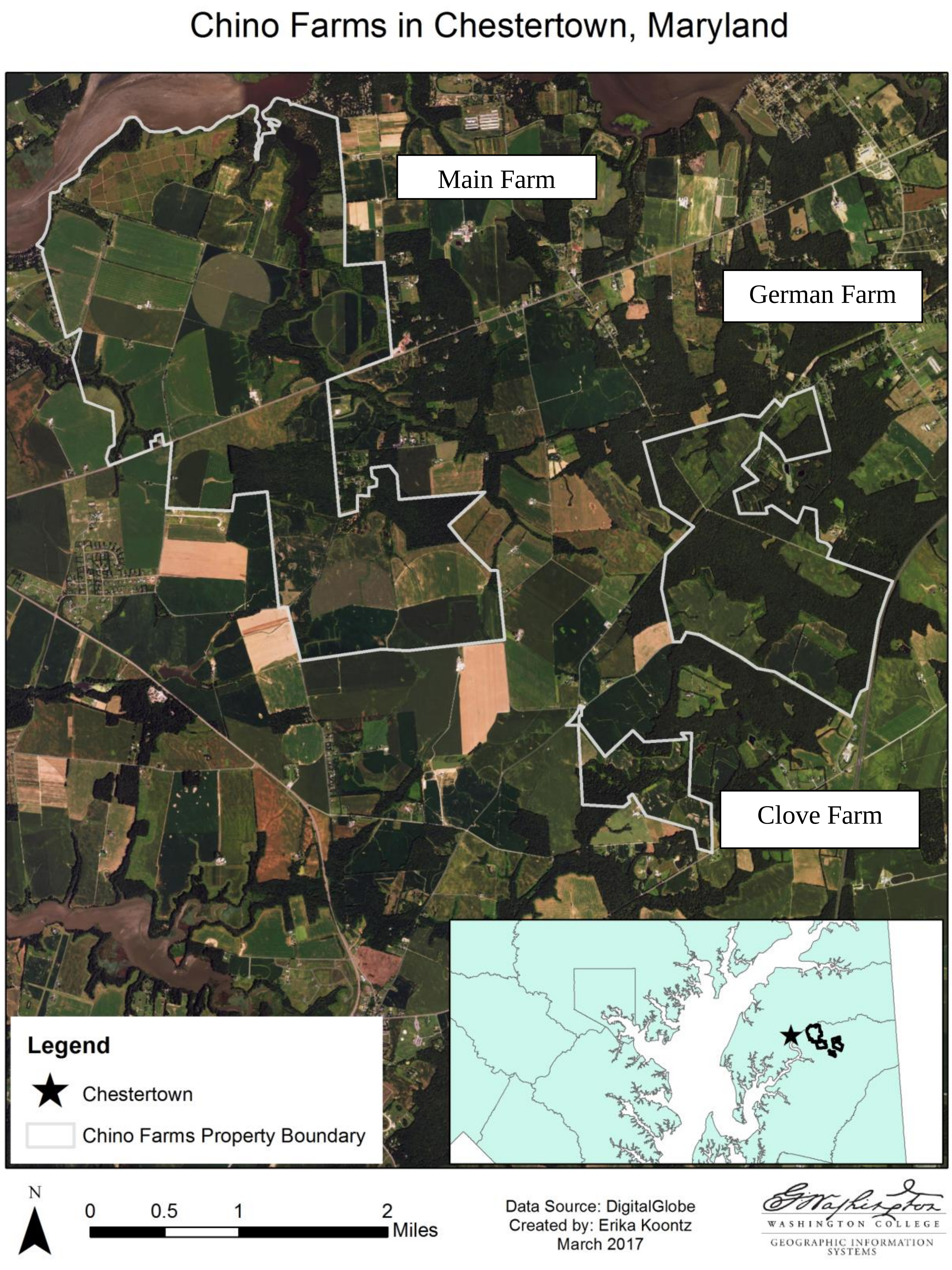

Figure 7. Location of Chino Farms in Chestertown, Maryland.

Figure 8. Main farm of the property with SWAT model produced reaches, outlets, and subbasins, which are represented as watersheds on the map.

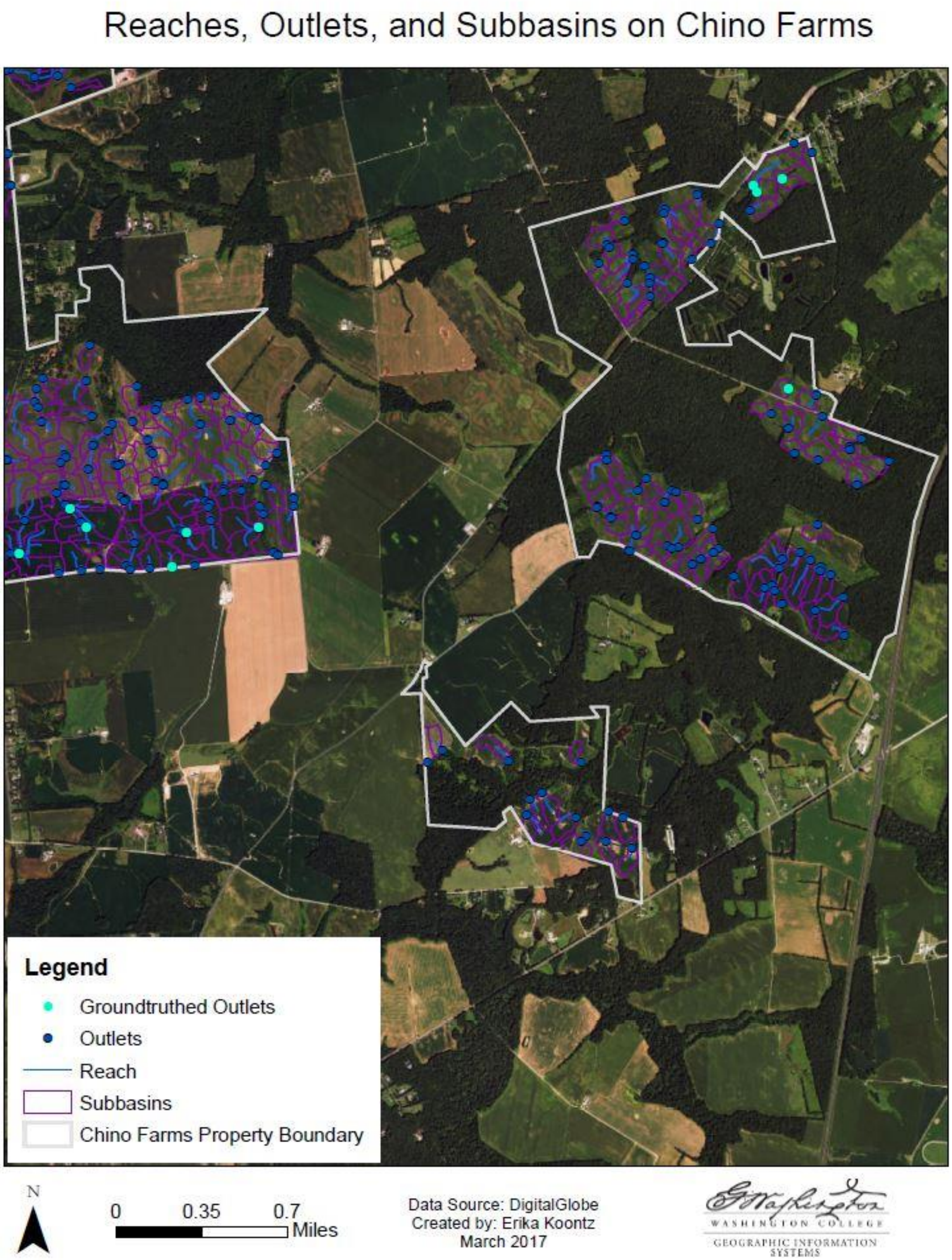

Figure 9. Southern half of the property (part of Main, all of Clove and German Farms) with SWAT model produced reaches, outlets, and subbasins, which are represented as watersheds on the map.

APPENDIX B: ADDITIONAL SWAT RESULTS

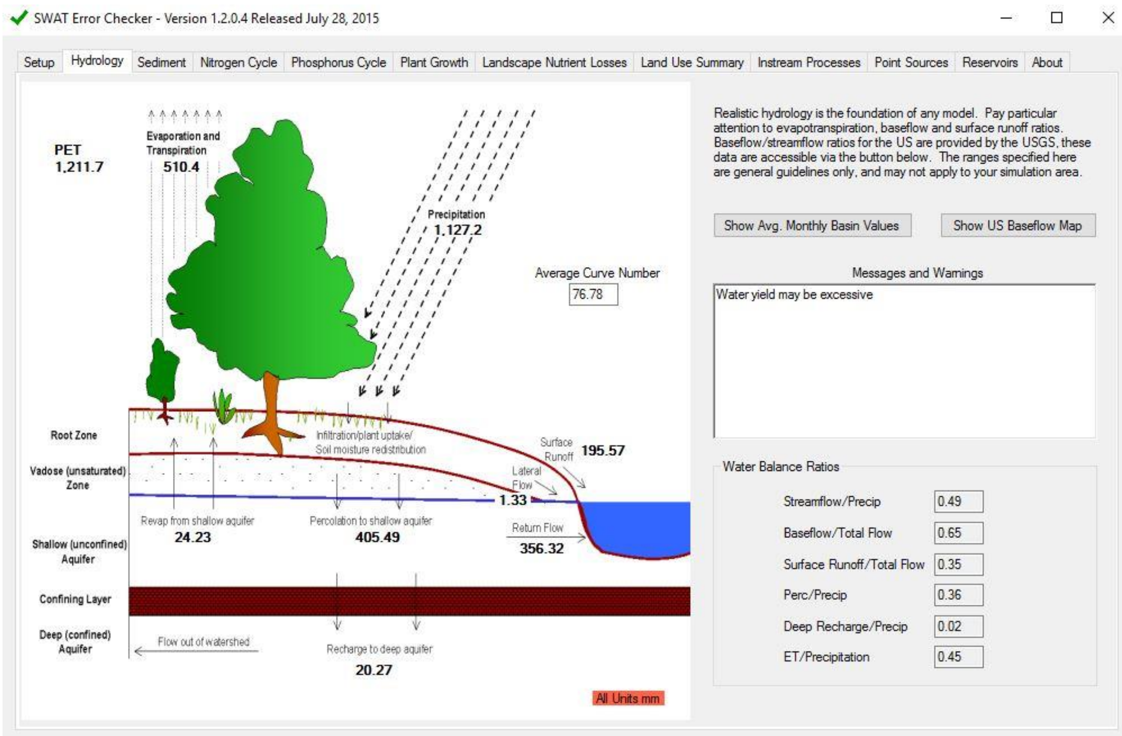

Figure 10. Hydrology model produced from the SWAT Error Checker following the simulation.

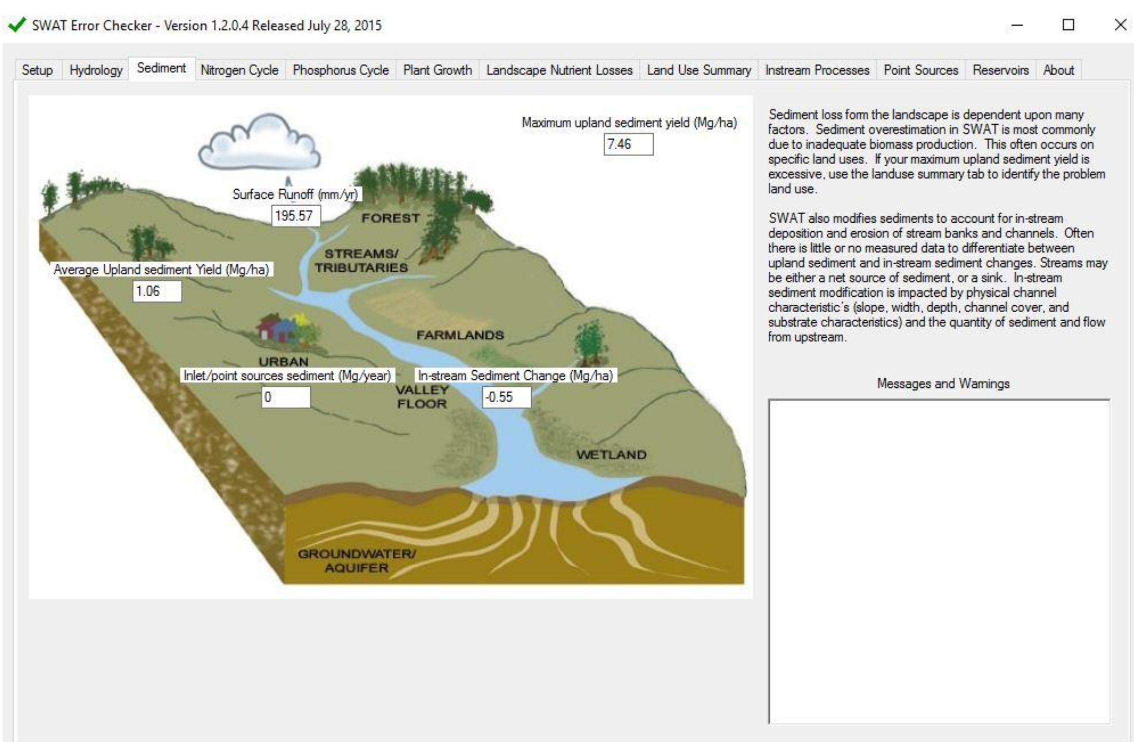

Figure 11. Sediment model produced from the SWAT Error Checker following the simulation.

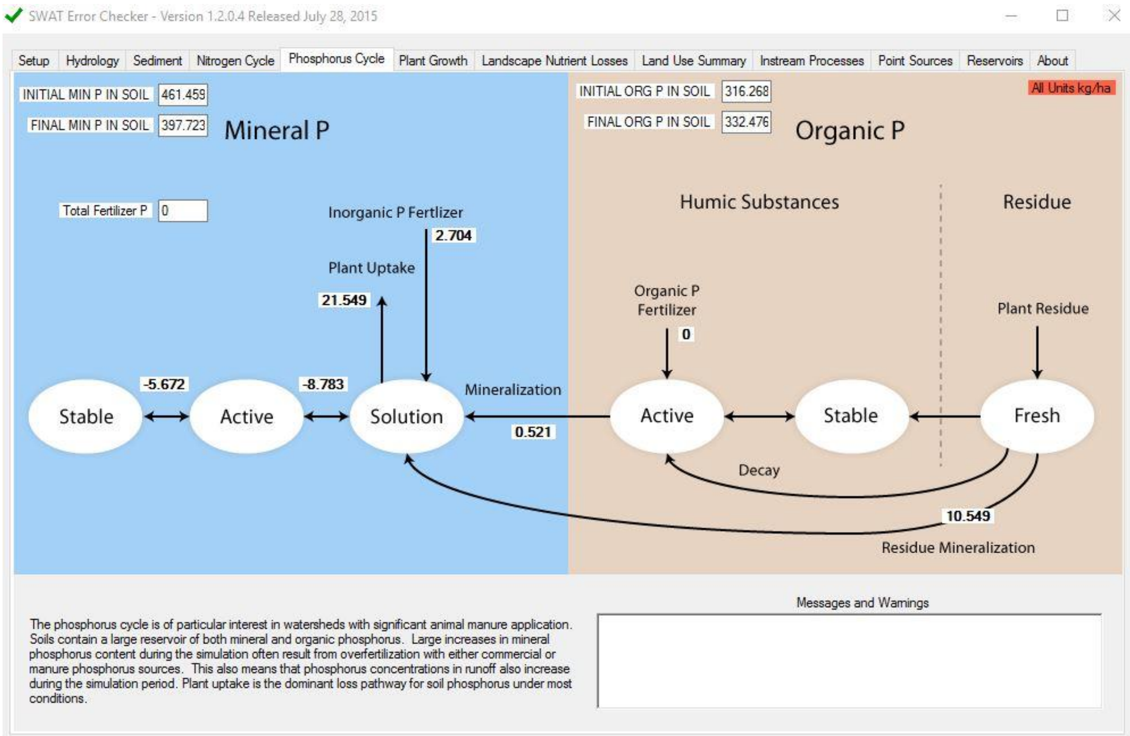

Figure 12.Phosphorus model produced from the SWAT Error Checker following the simulation.

APPENDIX C: RESULTS TABLE

Ground-truthed	Surface Runoff	Subbasin	Area (km2)	Averaged Surface Runoff in January & February in 2008 and 2013 (mm/month) (Figure 4)	Surface Runoff Rating (Figure 4)	% Surface Runoff Standardized by Area (Figure 5)	Surface Runoff Rating (Figure 5)
		1	0.009323	2.04	Low	46.38	Below Average
		2	0.011689	2.04	Low	36.99	Below Average
		3	0.002793	0.99	Low	83.63	Below Average
		4	0.016158	2.04	Low	26.78	Below Average
x	No	5	0.006465	2.03	Low	66.71	Below Average
		6	0.000401	2.04	Low	1,081.04	Extreme
		7	0.015804	2.04	Low	27.39	Below Average
		8	0.007546	2.04	Low	57.24	Below

							Average
		9	0.009052	2.04	Low	47.76	Below Average
		10	0.003476	3.95	Low	197.11	Moderate
		11	0.000508	8.28	Medium	2,471.11	Extreme
x	No	12	0.016457	2.04	Low	26.25	Below Average
		13	0.023384	2.03	Low	18.45	Below Average
x	No	14	0.011372	2.04	Low	38.00	Below Average
		15	0.023849	3.21	Low	24.60	Below Average
		16	0.007531	3.66	Low	83.72	Below Average
		17	0.011763	2.04	Low	36.78	Below Average
		18	0.007601	6.15	Low	122.94	Moderate
		19	0.000666	2.04	Low	649.63	Severe
		20	0.000125	2.04	Low	3,469.96	Extreme
		21	0.000260	2.04	Low	1,668.25	Extreme
		22	0.000330	3.40	Low	1,814.85	Extreme
x	No	23	0.007549	8.80	Medium	166.60	Moderate
		24	0.010198	5.27	Low	81.12	Below Average
		25	0.010550	8.85	High	119.80	Moderate
		26	0.003044	5.26	Low	271.37	Moderate
		27	0.008346	8.86	High	151.60	Moderate
		28	0.007450	2.03	Low	57.81	Below Average
		29	0.009476	8.85	High	133.40	Moderate
x	No	30	0.009851	3.10	Low	57.11	Below Average
		31	0.012035	7.81	Low	94.43	Below Average
		32	0.027743	5.35	Low	31.35	Below Average
		33	0.016236	8.82	Medium	77.63	Below Average
		34	0.040465	8.83	High	31.17	Below Average
		35	0.014192	8.85	High	89.04	Below Average
		36	0.010344	2.03	Low	41.57	Below Average
x	No	37	0.011650	8.83	High	108.31	Moderate
		38	0.000272	8.82	Medium	4,633.18	Extreme
		39	0.016380	8.86	High	77.22	Below Average
		40	0.004448	2.04	Low	97.38	Below Average
		41	0.015603	4.95	Low	50.54	Below Average
		42	0.007672	2.03	Low	56.06	Below Average
		43	0.015500	3.57	Low	39.68	Below Average
		44	0.017643	7.58	Low	62.82	Below Average
x	No	45	0.009105	8.87	High	139.18	Moderate
		46	0.003249	5.20	Low	249.68	Moderate
		47	0.010760	7.99	Medium	107.65	Moderate
x	Yes	48	0.019188	7.87	Low	59.63	Below Average

		49	0.010656	3.86	Low	61.01	Below Average
		50	0.011711	16.39	High	206.45	Moderate
		51	0.012823	2.03	Low	33.49	Below Average
x	No	52	0.006646	14.28	High	315.28	Moderate
		53	0.026000	5.76	Low	33.42	Below Average
		54	0.041361	15.41	High	54.85	Below Average
		55	0.009223	10.40	High	162.71	Moderate
		56	0.018900	20.40	High	160.41	Moderate
		57	0.008503	0.22	Low	7.44	Below Average
		58	0.005284	20.35	High	572.21	Severe
		59	0.007141	13.63	High	279.34	Moderate
		60	0.003922	15.95	High	599.22	Severe
		61	0.000004	4.37	Low	190,095.75	Extreme
		62	0.000077	4.33	Low	9,774.03	Extreme
		63	0.000419	6.13	Low	2,259.78	Extreme
		64	0.016504	0.83	Low	14.77	Below Average
		65	0.020644	2.21	Low	18.65	Below Average
		66	0.000338	4.33	Low	2,225.59	Extreme
		67	0.016144	12.61	High	113.90	Moderate
		68	0.007701	14.13	High	269.11	Moderate
		69	0.010073	8.81	Medium	124.98	Moderate
		70	0.008728	18.23	High	305.23	Moderate
		71	0.013025	8.86	High	97.14	Below Average
		72	0.002207	8.89	High	575.10	Severe
		73	0.014693	11.35	High	112.11	Moderate
		74	0.013967	8.83	High	90.35	Below Average
		75	0.005445	4.15	Low	110.07	Moderate
		76	0.028675	20.40	High	105.71	Moderate
x	No	77	0.011390	0.52	Low	13.20	Below Average
		78	0.009197	6.22	Low	99.48	Below Average
		79	0.012342	7.84	Low	93.60	Below Average
		80	0.007290	8.81	Medium	172.55	Moderate
		81	0.004834	8.80	Medium	260.15	Moderate
		82	0.007004	20.44	High	433.64	Moderate
		83	0.005390	16.87	High	462.09	Moderate
		84	0.013500	20.43	High	224.92	Moderate
		85	0.016738	16.26	High	143.82	Moderate
		86	0.009392	6.55	Low	101.60	Moderate
		87	0.000384	2.49	Low	1,095.10	Extreme
		88	0.004696	15.55	High	486.83	Moderate
		89	0.030554	1.96	Low	11.37	Below Average
		90	0.012630	0.83	Low	19.30	Below Average
		91	0.008480	5.45	Low	95.16	Below Average
		92	0.009953	2.32	Low	38.17	Below Average
		93	0.009363	6.95	Low	108.19	Moderate

		94	0.011440	8.80	Medium	109.83	Moderate
		95	0.014421	8.83	High	87.50	Below Average
		96	0.011279	2.21	Low	34.13	Below Average
		97	0.009351	17.70	High	281.57	Moderate
		98	0.031189	20.41	High	97.17	Below Average
		99	0.013930	2.94	Low	39.91	Below Average
x	No	100	0.025848	0.83	Low	9.42	Below Average
		101	0.000772	1.78	Low	385.26	Moderate
		102	0.010620	8.79	Medium	121.84	Moderate
x	Yes	103	0.000204	2.22	Low	1,912.02	Extreme
		104	0.006960	5.48	Low	122.81	Moderate
		105	0.003511	1.64	Low	77.18	Below Average
		106	0.023775	6.33	Low	42.30	Below Average
		107	0.011702	8.82	Medium	107.60	Moderate
		108	0.007395	6.76	Low	139.26	Moderate
x	No	109	0.024996	13.66	High	81.93	Below Average
		110	0.002906	14.82	High	749.71	Severe
		111	0.000410	3.85	Low	1,545.62	Extreme
		112	0.023086	6.93	Low	45.75	Below Average
x	No	113	0.000505	8.23	Medium	2,412.10	Extreme
		114	0.011266	8.66	Medium	109.57	Moderate
		115	0.016346	8.80	Medium	76.89	Below Average
		116	0.000045	8.26	Medium	27,843.64	Extreme
		117	0.006920	7.15	Low	163.17	Moderate
		118	0.012760	8.69	Medium	97.13	Below Average
		119	0.021221	8.74	Medium	59.90	Below Average
		120	0.009770	8.76	Medium	128.00	Moderate
		121	0.000180	8.26	Medium	6,957.55	Extreme
		122	0.014611	5.42	Low	58.98	Below Average
		123	0.002018	5.71	Low	433.71	Moderate
		124	0.006945	4.28	Low	99.77	Below Average
		125	0.004394	3.00	Low	114.81	Moderate
		126	0.008190	7.97	Low	153.02	Moderate
		127	0.018545	6.28	Low	51.68	Below Average
		128	0.029074	20.38	High	104.17	Moderate
		129	0.007922	3.79	Low	78.22	Below Average
		130	0.018475	7.93	Low	65.10	Below Average
		131	0.041065	10.31	High	38.05	Below Average
		132	0.022680	6.55	Low	45.84	Below Average
		133	0.010400	8.12	Medium	116.38	Moderate
x	Yes	134	0.012945	2.16	Low	29.06	Below Average
		135	0.014896	6.58	Low	67.34	Below Average

x	No	136	0.012113	11.88	High	148.92	Moderate
		137	0.031221	15.52	High	73.21	Below Average
		138	0.011568	6.62	Low	87.15	Below Average
		139	0.010401	5.00	Low	76.21	Below Average
		140	0.000004	13.10	High	481,729.21	Extreme
x	No	141	0.009611	8.79	Medium	138.16	Moderate
		142	0.007256	1.80	Low	51.08	Below Average
		143	0.008725	4.94	Low	89.13	Below Average
		144	0.000543	2.16	Low	693.06	Severe
		145	0.016561	6.78	Low	62.47	Below Average
		146	0.007705	7.91	Low	155.59	Moderate
		147	0.000077	13.10	High	24,180.31	Extreme
x	No	148	0.010823	4.09	Low	60.46	Below Average
x	Yes	149	0.013370	0.83	Low	18.22	Below Average
		150	0.027559	14.11	High	77.09	Below Average
		151	0.001926	2.15	Low	194.28	Moderate
		152	0.009992	0.83	Low	24.37	Below Average
		153	0.012197	3.08	Low	42.26	Below Average
		154	0.000176	8.10	Medium	6,843.96	Extreme
		155	0.000838	5.42	Low	1,015.41	Extreme
		156	0.012135	8.10	Medium	99.35	Below Average
		157	0.013717	16.54	High	179.57	Moderate
		158	0.014565	8.71	Medium	92.99	Below Average
		159	0.008240	8.99	High	180.76	Moderate
		160	0.018511	4.75	Low	41.20	Below Average
		161	0.000005	6.95	Low	221,803.56	Extreme
x	Yes	162	0.008498	1.74	Low	42.75	Below Average
		163	0.011888	8.11	Medium	101.47	Moderate
		164	0.000109	8.09	Medium	11,022.21	Extreme
x	No	165	0.013820	6.10	Low	70.50	Below Average
		166	0.008445	7.92	Low	142.34	Moderate
		167	0.007158	1.23	Low	33.36	Below Average
		168	0.014066	0.83	Low	17.30	Below Average
x	No	169	0.009397	8.13	Medium	128.98	Moderate
		170	0.022031	6.82	Low	47.85	Below Average
		171	0.015096	11.53	High	116.77	Moderate
		172	0.016441	8.89	High	87.19	Below Average
x	No	173	0.055589	5.57	Low	15.90	Below Average
		174	0.021459	6.56	Low	47.47	Below Average
		175	0.014371	6.30	Low	66.47	Below Average
		176	0.017101	6.08	Low	54.87	Below

							Average
		177	0.013453	2.78	Low	37.24	Below Average
		178	0.010187	8.10	Medium	118.31	Moderate
		179	0.022878	3.68	Low	26.62	Below Average
		180	0.017860	8.20	Medium	67.67	Below Average
		181	0.013930	8.31	Medium	84.77	Below Average
		182	0.000353	8.32	Medium	3,350.05	Extreme
		183	0.010039	7.93	Low	119.53	Moderate
		184	0.000172	0.63	Low	917.52	Severe
		185	0.032388	2.99	Low	14.89	Below Average
		186	0.000264	0.70	Low	719.72	Severe
		187	0.016949	8.32	Medium	69.72	Below Average
		188	0.034579	1.56	Low	9.48	Below Average
		189	0.004815	8.32	Medium	245.48	Moderate
		190	0.013538	8.32	Medium	87.29	Below Average
		191	0.014738	3.67	Low	38.27	Below Average
		192	0.000038	8.10	Medium	31,700.78	Extreme
		193	0.024212	9.15	High	55.74	Below Average
		194	0.010432	5.87	Low	87.85	Below Average
		195	0.012341	7.06	Low	86.66	Below Average
		196	0.008282	8.11	Medium	145.89	Moderate
		197	0.070694	8.11	Medium	17.07	Below Average
		198	0.002785	7.92	Low	430.96	Moderate
		199	0.009191	8.09	Medium	130.78	Moderate
x	Yes	200	0.003144	7.95	Low	381.07	Moderate
		201	0.004067	8.07	Medium	295.72	Moderate
		202	0.008478	7.91	Low	141.39	Moderate
		203	0.009633	5.94	Low	95.59	Below Average
		204	0.008423	4.84	Low	86.62	Below Average
		205	0.032451	8.09	Medium	37.01	Below Average
		206	0.008549	8.48	Medium	148.95	Moderate
		207	0.015865	8.10	Medium	75.93	Below Average
		208	0.009193	8.14	Medium	135.92	Moderate
		209	0.021780	8.19	Medium	55.66	Below Average
		210	0.012856	5.18	Low	60.61	Below Average
		211	0.043593	2.59	Low	10.49	Below Average
		212	0.017774	7.97	Low	70.50	Below Average
		213	0.023626	8.10	Medium	50.97	Below Average
		214	0.010364	8.07	Medium	116.17	Moderate
		215	0.021816	8.10	Medium	56.46	Below Average
		216	0.012624	3.57	Low	48.01	Below

							Average
		217	0.009582	3.61	Low	63.73	Below Average
x	No	218	0.013640	8.28	Medium	90.97	Below Average
		219	0.008995	7.98	Medium	139.45	Moderate
		220	0.007364	8.09	Medium	163.29	Moderate
		221	0.011236	7.97	Low	111.54	Moderate
x	No	222	0.020617	4.38	Low	34.56	Below Average
		223	0.013201	8.30	Medium	94.55	Below Average
		224	0.001002	8.06	Medium	1,202.73	Extreme
		225	0.013992	8.31	Medium	90.06	Below Average
		226	0.016109	1.87	Low	24.83	Below Average
		227	0.014874	2.31	Low	28.40	Below Average
		228	0.015619	4.19	Low	43.95	Below Average
x	No	229	0.028673	7.96	Low	42.54	Below Average
		230	0.010509	7.97	Low	117.35	Moderate
		231	0.011567	5.37	Low	75.11	Below Average
		232	0.017319	2.77	Low	30.75	Below Average
		233	0.000705	0.75	Low	367.35	Moderate
		234	0.001571	0.46	Low	56.69	Below Average
		235	0.011523	0.64	Low	16.90	Below Average
		236	0.011668	3.87	Low	51.46	Below Average
		237	0.013221	6.13	Low	70.84	Below Average
		238	0.000363	0.37	Low	196.07	Moderate
		239	0.010013	0.76	Low	23.85	Below Average
		240	0.012807	8.08	Medium	94.04	Below Average
		241	0.000620	0.37	Low	114.74	Moderate
		242	0.000971	0.37	Low	73.20	Below Average
		243	0.026573	6.39	Low	37.56	Below Average
		244	0.000097	0.38	Low	730.59	Severe
		245	0.008032	6.14	Low	127.02	Moderate
		246	0.012145	5.65	Low	69.96	Below Average
		247	0.009894	5.36	Low	82.64	Below Average
		248	0.000835	0.43	Low	125.83	Moderate
		249	0.007742	4.33	Low	83.79	Below Average
		250	0.012113	4.90	Low	62.43	Below Average
		251	0.014342	0.63	Low	11.60	Below Average
		252	0.013808	6.09	Low	72.33	Below Average
		253	0.021102	5.23	Low	39.05	Below Average
		254	0.012600	5.33	Low	66.57	Below

							Average
		255	0.014007	6.32	Low	68.86	Below Average
		256	0.010650	5.19	Low	77.07	Below Average
		257	0.019614	0.88	Low	14.93	Below Average
		258	0.021049	11.54	High	81.28	Below Average
		259	0.010584	0.83	Low	23.02	Below Average
		260	0.007221	8.25	Medium	173.22	Moderate
		261	0.009723	8.84	High	129.81	Moderate
		262	0.010209	8.88	High	124.22	Moderate
		263	0.007390	8.21	Medium	168.48	Moderate
x	No	264	0.010086	8.23	Medium	123.76	Moderate
		265	0.007471	0.83	Low	32.58	Below Average
		266	0.015612	8.27	Medium	77.83	Below Average
		267	0.000786	8.41	Medium	1,600.03	Extreme
		268	0.007857	8.82	Medium	160.39	Moderate
		269	0.019363	8.22	Medium	64.37	Below Average
		270	0.032855	8.72	Medium	38.23	Below Average
		271	0.006818	8.57	Medium	184.27	Moderate
		272	0.012814	8.26	Medium	97.72	Below Average
		273	0.017007	12.55	High	110.73	Moderate
		274	0.021570	8.31	Medium	56.92	Below Average
		275	0.008814	20.32	High	342.51	Moderate
		276	0.007133	20.31	High	423.09	Moderate
		277	0.007078	20.32	High	426.72	Moderate
		278	0.003784	13.80	High	545.85	Severe
		279	0.015147	8.85	High	83.41	Below Average
		280	0.015274	8.23	Medium	81.66	Below Average
		281	0.020592	7.78	Low	57.77	Below Average
		282	0.037707	8.03	Medium	32.47	Below Average
		283	0.000228	10.75	High	7,240.68	Extreme
		284	0.005181	8.16	Medium	233.18	Moderate
		285	0.008509	20.34	High	355.19	Moderate
		286	0.017386	17.58	High	149.59	Moderate
		287	0.027539	8.82	Medium	45.75	Below Average
		288	0.014329	8.88	High	88.52	Below Average
		289	0.008025	8.86	High	157.62	Moderate
		290	0.007370	20.32	High	409.74	Moderate
		291	0.011029	12.47	High	167.67	Moderate
		292	0.007425	11.11	High	227.91	Moderate
		293	0.021604	8.16	Medium	58.26	Below Average
		294	0.005666	16.89	High	446.51	Moderate
		295	0.012899	8.00	Medium	97.49	Below Average
		296	0.014609	7.99	Medium	85.95	Below Average

		297	0.010305	15.58	High	224.93	Moderate
		298	0.012035	8.41	Medium	104.74	Moderate
		299	0.014254	8.24	Medium	87.69	Below Average
x	No	300	0.025037	8.12	Medium	48.12	Below Average
		301	0.024819	8.01	Medium	50.75	Below Average
		302	0.008527	8.22	Medium	142.26	Moderate
		303	0.008635	8.29	Medium	153.40	Moderate
		304	0.006462	8.84	High	195.31	Moderate
		305	0.008942	8.83	High	141.07	Moderate
		306	0.020797	8.84	High	60.74	Below Average
		307	0.023189	8.64	Medium	53.73	Below Average
		308	0.041735	8.48	Medium	29.54	Below Average
		309	0.024268	8.85	High	59.21	Below Average
		310	0.016066	8.83	High	78.51	Below Average
		311	0.013052	8.84	High	96.77	Below Average
		312	0.026037	8.72	Medium	53.04	Below Average
		313	0.020869	8.99	High	67.67	Below Average
x	No	314	0.022012	9.06	High	61.72	Below Average
		315	0.017361	8.83	High	72.64	Below Average
		316	0.000021	8.84	High	60,130.85	Extreme
		317	0.008817	7.61	Low	128.43	Moderate
		318	0.001826	5.99	Low	526.22	Severe
		319	0.007874	8.86	High	160.74	Moderate
		320	0.009009	8.35	Medium	132.71	Moderate
		321	0.025382	8.84	High	49.72	Below Average
		322	0.008507	7.16	Low	124.09	Moderate
		323	0.009690	8.28	Medium	129.68	Moderate
		324	0.021716	8.83	High	58.08	Below Average
		325	0.007195	8.28	Medium	174.58	Moderate
x	No	326	0.029085	8.88	High	43.62	Below Average
		327	0.012064	8.29	Medium	104.17	Moderate
		328	0.011484	6.65	Low	89.60	Below Average
		329	0.012080	8.83	High	104.44	Moderate
		330	0.013183	8.84	High	95.81	Below Average
x	No	331	0.008661	8.28	Medium	142.51	Moderate
		332	0.022169	3.83	Low	27.89	Below Average
		333	0.016132	8.82	Medium	78.12	Below Average
		334	0.013923	8.79	Medium	96.84	Below Average
		335	0.000131	9.56	High	12,116.24	Extreme
		336	0.012308	8.26	Medium	101.83	Moderate
		337	0.011551	8.85	High	109.41	Moderate
		338	0.010022	8.82	Medium	125.65	Moderate

		339	0.020027	8.81	Medium	62.84	Below Average
		340	0.050370	8.83	High	25.04	Below Average
		341	0.010279	7.18	Low	105.74	Moderate
		342	0.002218	6.35	Low	449.82	Moderate
		343	0.011954	8.84	High	105.68	Moderate
x	No	344	0.001265	8.84	High	998.21	Severe
		345	0.038454	9.56	High	36.52	Below Average
x	No	346	0.026807	8.85	High	47.17	Below Average
		347	0.006887	10.45	High	233.54	Moderate
		348	0.014395	3.81	Low	40.40	Below Average
		349	0.008974	15.68	High	255.30	Moderate
		350	0.014101	8.25	Medium	88.76	Below Average
x	No	351	0.011311	8.33	Medium	110.71	Moderate
		352	0.012613	8.35	Medium	96.84	Below Average
		353	0.007240	8.26	Medium	172.90	Moderate
		354	0.030685	10.44	High	52.38	Below Average
		355	0.006524	6.34	Low	152.76	Moderate
x	No	356	0.007171	8.83	High	175.80	Moderate
		357	0.011145	10.34	High	142.90	Moderate
		358	0.013769	4.25	Low	46.62	Below Average
		359	0.008453	8.26	Medium	148.19	Moderate
		360	0.032906	9.50	High	44.21	Below Average
		361	0.018991	6.98	Low	58.56	Below Average
		362	0.037203	8.82	Medium	33.88	Below Average
		363	0.017601	8.85	High	71.83	Below Average
		364	0.009824	8.26	Medium	127.56	Moderate
		365	0.029167	15.17	High	76.27	Below Average
		366	0.008123	0.43	Low	11.68	Below Average
		367	0.011650	8.31	Medium	104.84	Moderate
		368	0.031212	8.83	High	40.41	Below Average
		369	0.014305	1.65	Low	23.19	Below Average
		370	0.008265	8.87	High	153.32	Moderate
		371	0.015555	4.74	Low	46.11	Below Average
		372	0.007734	8.33	Medium	158.91	Moderate
		373	0.008701	5.94	Low	102.00	Moderate
		374	0.017993	4.47	Low	39.39	Below Average
		375	0.007235	8.26	Medium	171.41	Moderate
		376	0.016206	8.82	Medium	77.71	Below Average
		377	0.016971	8.27	Medium	73.92	Below Average
		378	0.008179	8.27	Medium	150.37	Moderate
		379	0.024740	8.81	Medium	50.88	Below Average
		380	0.011943	8.31	Medium	102.78	Moderate

		381	0.010817	8.81	Medium	116.39	Moderate
		382	0.010140	7.40	Low	112.63	Moderate
		383	0.014065	15.61	High	162.26	Moderate
		384	0.011048	8.26	Medium	113.32	Moderate
x	No	385	0.007393	8.82	Medium	170.41	Moderate
x	No	386	0.046685	8.74	Medium	26.71	Below Average
		387	0.016144	8.29	Medium	75.92	Below Average
		388	0.007592	8.24	Medium	164.64	Moderate
		389	0.013401	8.79	Medium	93.74	Below Average
		390	0.027717	8.80	Medium	45.34	Below Average
		391	0.017553	8.24	Medium	71.19	Below Average
		392	0.012166	8.25	Medium	101.08	Moderate
		393	0.019763	8.63	Medium	62.28	Below Average
		394	0.005149	8.75	Medium	242.61	Moderate
x	No	395	0.011819	8.71	Medium	105.14	Moderate
		396	0.007505	8.83	High	167.98	Moderate
x	No	397	0.014546	8.71	Medium	85.37	Below Average
		398	0.019235	8.68	Medium	64.39	Below Average
		399	0.003876	8.47	Medium	311.08	Moderate
		400	0.000020	8.35	Medium	59,327.70	Extreme
		401	0.007352	8.32	Medium	160.82	Moderate
		402	0.015873	8.81	Medium	79.28	Below Average
		403	0.000459	8.36	Medium	2,588.74	Extreme
		404	0.022728	8.28	Medium	54.00	Below Average
		405	0.016392	8.84	High	77.06	Below Average
		406	0.014487	8.83	High	87.01	Below Average
		407	0.035622	8.81	Medium	35.34	Below Average
		408	0.007570	8.81	Medium	166.32	Moderate
		409	0.012028	7.94	Low	96.36	Below Average
		410	0.007726	8.82	Medium	163.13	Moderate
		411	0.012307	8.79	Medium	102.07	Moderate
		412	0.034563	8.83	High	36.47	Below Average
		413	0.013549	8.60	Medium	91.72	Below Average
		414	0.009221	8.31	Medium	133.26	Moderate
		415	0.015088	8.26	Medium	83.06	Below Average
		416	0.007277	5.67	Low	119.48	Moderate
x	No	417	0.006917	8.30	Medium	179.04	Moderate
		418	0.010087	8.32	Medium	120.52	Moderate
		419	0.008440	8.27	Medium	148.61	Moderate
		420	0.008386	12.35	High	228.70	Moderate
		421	0.013757	8.27	Medium	89.29	Below Average
		422	0.017636	8.30	Medium	69.53	Below Average
		423	0.014400	8.32	Medium	82.78	Below Average

x	Yes	424	0.014666	8.31	Medium	83.17	Below Average
		425	0.010541	8.30	Medium	116.09	Moderate
		426	0.012634	8.25	Medium	99.08	Below Average
		427	0.007764	8.32	Medium	157.08	Moderate
		428	0.027402	8.29	Medium	44.95	Below Average
		429	0.007210	8.36	Medium	166.23	Moderate
		430	0.008942	8.36	Medium	133.96	Moderate
		431	0.008562	8.25	Medium	146.16	Moderate
		432	0.013088	8.25	Medium	95.59	Below Average
		433	0.010202	8.32	Medium	118.65	Moderate
		434	0.001791	6.91	Low	614.76	Severe
		435	0.007378	8.27	Medium	170.07	Moderate
		436	0.008907	8.22	Medium	145.12	Moderate
		437	0.008007	8.94	High	170.23	Moderate
		438	0.008767	8.23	Medium	142.40	Moderate
		439	0.014025	8.30	Medium	87.63	Below Average
		440	0.008581	8.25	Medium	145.73	Moderate
		441	0.020351	8.25	Medium	61.50	Below Average
		442	0.000568	10.48	High	2,839.00	Extreme
		443	0.008634	11.15	High	199.54	Moderate
		444	0.007456	8.21	Medium	167.02	Moderate
		445	0.000339	13.58	High	6,241.80	Extreme
		446	0.004799	11.77	High	379.76	Moderate
		447	0.007768	9.38	High	184.65	Moderate
		448	0.010737	8.24	Medium	116.32	Moderate
		449	0.008692	9.24	High	162.52	Moderate
		450	0.034891	8.32	Medium	34.46	Below Average
		451	0.008257	8.26	Medium	151.80	Moderate
		452	0.021308	8.22	Medium	58.51	Below Average
		453	0.015878	11.53	High	112.38	Moderate
		454	0.023082	8.29	Medium	53.78	Below Average
		455	0.035187	8.25	Medium	35.55	Below Average
		456	0.009116	8.27	Medium	137.50	Moderate
		457	0.014016	8.27	Medium	89.51	Below Average
		458	0.012153	10.18	High	128.80	Moderate
		459	0.034607	8.34	Medium	34.92	Below Average
		460	0.014861	8.34	Medium	81.17	Below Average
		461	0.013359	7.31	Low	84.70	Below Average
		462	0.014293	8.25	Medium	87.47	Below Average
		463	0.026040	12.41	High	76.16	Below Average
		464	0.011241	8.29	Medium	107.76	Moderate
		465	0.012180	8.27	Medium	102.95	Moderate
		466	0.000372	8.26	Medium	3,365.92	Extreme
		467	0.007506	8.25	Medium	166.63	Moderate
		468	0.008087	8.24	Medium	154.45	Moderate

		469	0.010366	8.23	Medium	120.32	Moderate
		470	0.057797	9.13	High	24.12	Below Average
		471	0.008843	8.25	Medium	141.38	Moderate
		472	0.004121	8.28	Medium	304.84	Moderate
		473	0.016278	7.81	Low	73.97	Below Average
		474	0.013277	8.27	Medium	94.48	Below Average
		475	0.007110	8.23	Medium	174.10	Moderate
		476	0.008071	8.28	Medium	155.65	Moderate
		477	0.001795	8.29	Medium	700.53	Severe
		478	0.011148	8.24	Medium	112.03	Moderate
		479	0.008069	8.27	Medium	155.35	Moderate
		480	0.001345	8.30	Medium	936.23	Severe
		481	0.000695	8.29	Medium	1,809.99	Extreme
		482	0.001672	8.29	Medium	751.65	Severe
		483	0.019957	8.26	Medium	62.74	Below Average
		484	0.010564	13.67	High	202.02	Moderate
		485	0.008197	8.27	Medium	153.03	Moderate
		486	0.018732	8.87	High	76.16	Below Average
		487	0.016005	8.33	Medium	75.74	Below Average
		488	0.003553	8.89	High	381.30	Moderate
		489	0.017885	8.27	Medium	70.11	Below Average
		490	0.008006	8.29	Medium	153.48	Moderate
		491	0.009417	8.27	Medium	133.13	Moderate
		492	0.008682	8.25	Medium	141.91	Moderate
		493	0.010739	7.48	Low	108.71	Moderate
		494	0.010148	7.95	Low	120.10	Moderate
		495	0.012058	8.22	Medium	103.36	Moderate
		496	0.001396	7.29	Low	822.82	Severe
		497	0.020833	8.29	Medium	59.24	Below Average
		498	0.020093	7.77	Low	59.66	Below Average
		499	0.022700	8.00	Medium	53.97	Below Average
		500	0.014427	8.10	Medium	85.65	Below Average
		501	0.011202	8.26	Medium	111.83	Moderate
		502	0.011696	8.26	Medium	107.03	Moderate
		503	0.006816	8.24	Medium	183.35	Moderate
		504	0.010163	8.30	Medium	119.67	Moderate
		505	0.027717	8.28	Medium	45.94	Below Average
		506	0.033601	8.28	Medium	36.43	Below Average
		507	0.007754	8.26	Medium	161.50	Moderate
		508	0.014133	8.29	Medium	85.91	Below Average
		509	0.011364	12.19	High	167.74	Moderate
		510	0.008677	8.27	Medium	144.50	Moderate
		511	0.006157	10.23	High	262.31	Moderate
		512	0.000086	9.36	High	16,638.89	Extreme
		513	0.000061	11.65	High	29,580.98	Extreme
		514	0.015885	7.50	Low	73.69	Below Average

		515	0.011392	8.30	Medium	107.70	Moderate
		516	0.000024	8.36	Medium	49,545.63	Extreme
		517	0.000033	13.06	High	61,632.76	Extreme
		518	0.045365	9.32	High	31.92	Below Average
		519	0.007720	9.49	High	188.16	Moderate
		520	0.007376	13.68	High	289.59	Moderate
		521	0.026412	8.26	Medium	46.81	Below Average
		522	0.008134	8.31	Medium	148.87	Moderate
		523	0.026189	8.25	Medium	47.24	Below Average
		524	0.015980	8.32	Medium	76.51	Below Average
		525	0.011290	8.31	Medium	106.85	Moderate
		526	0.007606	6.93	Low	145.15	Moderate
		527	0.011208	8.23	Medium	111.38	Moderate
		528	0.008501	8.33	Medium	140.45	Moderate
		529	0.009454	8.35	Medium	127.81	Moderate
		530	0.009235	11.94	High	197.39	Moderate
		531	0.024602	9.75	High	60.40	Below Average
		532	0.010081	15.13	High	225.99	Moderate
		533	0.015686	7.51	Low	74.68	Below Average
		534	0.007775	10.91	High	214.19	Moderate
		535	0.015669	11.14	High	109.94	Moderate
		536	0.000165	10.42	High	9,944.55	Extreme
		537	0.027525	7.87	Low	43.91	Below Average
		538	0.010627	10.91	High	153.65	Moderate
		539	0.008407	10.44	High	195.36	Moderate
		540	0.013939	8.89	High	97.23	Below Average
		541	0.002100	19.58	High	1,392.11	Extreme
		542	0.019435	8.35	Medium	62.02	Below Average
		543	0.022561	15.94	High	106.15	Moderate
		544	0.011672	14.39	High	179.44	Moderate
		545	0.008282	13.58	High	239.34	Moderate
		546	0.012983	5.40	Low	62.26	Below Average
		547	0.010612	16.87	High	241.25	Moderate
		548	0.008668	13.00	High	234.68	Moderate
		549	0.001581	13.03	High	1,209.92	Extreme
		550	0.009406	12.36	High	199.11	Moderate
		551	0.013043	7.81	Low	92.24	Below Average
		552	0.009031	6.29	Low	100.92	Below Average
		553	0.008068	20.48	High	377.25	Moderate
		554	0.008293	8.24	Medium	149.44	Moderate
x	No	555	0.008643	8.25	Medium	144.80	Moderate
		556	0.009083	3.88	Low	66.53	Below Average
		557	0.012526	11.67	High	137.17	Moderate
		558	0.013791	8.26	Medium	90.81	Below Average
		559	0.011396	7.92	Low	101.40	Moderate
		560	0.044662	10.75	High	37.13	Below Average

		561	0.019467	10.37	High	81.96	Below Average
		562	0.022242	11.10	High	75.79	Below Average
		563	0.003650	8.24	Medium	342.31	Moderate
		564	0.011254	0.45	Low	8.44	Below Average
		565	0.012976	11.76	High	138.34	Moderate
		566	0.039170	8.24	Medium	31.88	Below Average
		567	0.012178	8.25	Medium	104.56	Moderate
		568	0.039314	0.53	Low	3.45	Below Average
		569	0.007613	0.46	Low	12.39	Below Average
		570	0.000317	13.59	High	6,681.17	Extreme
		571	0.031828	14.92	High	70.64	Below Average
x	No	572	0.035045	15.53	High	67.26	Below Average
		573	0.007518	18.74	High	373.69	Moderate
		574	0.007508	12.42	High	242.75	Moderate
x	No	575	0.010676	0.65	Low	19.51	Below Average
		576	0.014811	1.26	Low	14.37	Below Average
		577	0.002095	17.39	High	1,255.53	Extreme
		578	0.007974	17.43	High	330.60	Moderate
		579	0.004213	16.15	High	584.92	Severe
		580	0.011884	7.56	Low	94.88	Below Average
		581	0.025190	7.60	Low	44.49	Below Average
		582	0.008253	17.37	High	318.41	Moderate
		583	0.012760	0.43	Low	7.45	Below Average
x	No	584	0.008068	8.55	Medium	165.42	Moderate
		585	0.014103	14.34	High	151.98	Moderate
		586	0.011965	3.71	Low	55.83	Below Average
		587	0.026669	14.26	High	80.57	Below Average
		588	0.007133	11.26	High	245.77	Moderate
		589	0.028874	12.19	High	65.84	Below Average
		590	0.031020	20.36	High	97.55	Below Average
		591	0.022568	18.66	High	124.02	Moderate
		592	0.010106	16.13	High	243.00	Moderate
		593	0.013724	14.97	High	162.96	Moderate
		594	0.007985	13.42	High	251.82	Moderate
		595	0.022677	4.28	Low	30.15	Below Average
		596	0.023271	1.41	Low	10.42	Below Average
		597	0.011166	16.67	High	219.33	Moderate
		598	0.000214	3.49	Low	2,673.57	Extreme
		599	0.016746	2.64	Low	26.01	Below Average
		600	0.001728	3.48	Low	328.59	Moderate
		601	0.000342	3.47	Low	1,654.32	Extreme
		602	0.024011	3.56	Low	22.80	Below Average

		603	0.009363	11.24	High	180.36	Moderate
		604	0.008464	14.48	High	258.27	Moderate
		605	0.008895	16.76	High	279.51	Moderate
		606	0.001818	3.51	Low	317.07	Moderate
x	Yes	607	0.018796	2.74	Low	23.91	Below Average
		608	0.001777	5.09	Low	445.60	Moderate
		609	0.000161	3.49	Low	3,547.94	Extreme
		610	0.019186	12.31	High	93.34	Below Average
		611	0.002566	20.46	High	1,184.88	Extreme
		612	0.009851	4.82	Low	76.23	Below Average
		613	0.009555	12.05	High	188.03	Moderate
		614	0.009494	18.21	High	285.57	Moderate
		615	0.005589	11.71	High	314.62	Moderate
		616	0.020566	4.87	Low	36.41	Below Average
		617	0.008440	20.39	High	358.98	Moderate
		618	0.007345	19.42	High	395.16	Moderate
		619	0.010555	17.74	High	253.71	Moderate
		620	0.010110	20.34	High	299.04	Moderate
		621	0.017412	10.33	High	88.97	Below Average
		622	0.015388	14.81	High	145.06	Moderate
		623	0.007113	20.41	High	426.38	Moderate
		624	0.000003	5.00	Low	261,947.77	Extreme
		625	0.020908	8.58	Medium	59.39	Below Average
x	No	626	0.007285	20.38	High	415.82	Moderate
		627	0.002779	16.44	High	899.85	Severe
		628	0.023376	15.67	High	101.37	Moderate
		629	0.020877	14.61	High	105.57	Moderate
		630	0.011404	7.70	Low	112.17	Moderate
		631	0.000014	13.13	High	146,942.89	Extreme
		632	0.008490	10.50	High	185.82	Moderate
		633	0.000647	14.39	High	3,236.79	Extreme
		634	0.026659	3.95	Low	24.38	Below Average
		635	0.009741	12.46	High	193.64	Moderate
		636	0.015390	10.53	High	102.75	Moderate
		637	0.006620	8.48	Medium	202.07	Moderate
		638	0.008753	11.70	High	205.77	Moderate
		639	0.001103	11.67	High	1,609.11	Extreme
		640	0.001119	11.92	High	1,624.14	Extreme
x	No	641	0.019174	10.77	High	84.41	Below Average
		642	0.012077	10.90	High	135.03	Moderate
		643	0.017298	7.75	Low	65.57	Below Average
		644	0.006980	10.02	High	208.88	Moderate
		645	0.001944	12.72	High	953.84	Severe
		646	0.010673	7.63	Low	105.10	Moderate
		647	0.002417	8.25	Medium	517.86	Severe
		648	0.028288	9.02	High	48.61	Below Average
		649	0.014220	11.25	High	116.93	Moderate
		650	0.007960	7.36	Low	145.24	Moderate
		651	0.025720	11.65	High	67.29	Below Average

		652	0.008348	12.71	High	224.01	Moderate
		653	0.007961	11.63	High	231.02	Moderate
		654	0.013697	11.24	High	123.99	Moderate
		655	0.013548	18.36	High	203.69	Moderate
		656	0.014980	8.76	Medium	93.04	Below Average
		657	0.009484	18.32	High	288.36	Moderate
		658	0.008508	8.50	Medium	154.81	Moderate
		659	0.012583	10.61	High	124.24	Moderate
		660	0.019507	11.04	High	84.80	Below Average
		661	0.008168	11.96	High	213.00	Moderate
		662	0.015917	9.81	High	92.81	Below Average
		663	0.016549	12.68	High	112.68	Moderate
		664	0.015918	8.39	Medium	75.85	Below Average
		665	0.016602	17.31	High	154.08	Moderate
		666	0.001792	8.38	Medium	665.12	Severe
		667	0.012501	9.45	High	110.58	Moderate
		668	0.014167	14.00	High	144.82	Moderate
		669	0.006946	8.39	Medium	171.91	Moderate
		670	0.014737	8.39	Medium	80.96	Below Average