A SURFACE RUNOFF MODEL FOR CENTRAL NEW YORK AGRICULTURAL FIELDS

A Thesis

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ABSTRACT

Nonpoint source (NPS) pollution continues to be the leading cause of US surface water degradation, especially in agricultural areas. In humid regions where variable source area (VSA) hydrology dominates storm runoff, NPS pollution is generated where VSAs coincide with polluting activities. Mapping storm runoff generating areas could allow for more precise and informed targeting of NPS pollution mitigation practices in agricultural landscapes. Previous efforts to do this have relied on simulation models or potentially over-simplifying assumptions about the interactions between rainfall and landscape features that generate storm runoff. Here we used direct measures to empirically derive relationships between topographic wetness indices (TWI) and soil volumetric water content (VWC) and rainfall frequencies to develop runoff risk maps. We surveyed VWC across five agricultural fields in central New York over two years (2012–2014) to develop runoff probability maps based on a soil topographic index (STI). We assumed that the threshold for runoff occurred when the combination of antecedent soil water and rainfall were sufficient to saturate the soil. The linear relationship between VWC and STI was strong for all seasons sampled (spring, summer, autumn). All sites followed a logistic relationship between probability of runoff and STI, although the relative risks between sites shifted from season to season. This work suggests that by developing and using runoff risk maps, the risk of NPS pollution in runoff can be reduced by 70–80% by taking 10% of the agricultural land out of production or halting polluting activities in high risk areas. Reducing the risk of polluted runoff from VSAs depends on the management decisions made at each field, whether the focus is on removing a consistent amount of land from production or setting a threshold for acceptable runoff probability. This analysis can be used to determine the optimal placement of conservation easements or management practices for the protection of water quality.

BIOGRAPHICAL SKETCH

Kathryn Hofmeister grew up in Minnesota and Wisconsin, where she was raised with respect for the environment and interest in preserving water resources, fueled by annual family vacations on the shore of Lake Superior. Born into a family of scientists and educators, she became passionate about engaging with and communicating about nature and science to the public, as well as doing research related to environmental issues. From 2007-2011 Kathryn worked at the Sciencenter, a hands-on science museum in Ithaca, NY, as a counselor, Assistant Director of Summer Camp, and an Educator. She also spent two years working at the Hitchcock Center for the Environment in Amherst, MA where able to help students gain an understanding of the natural features of western Massachusetts through outdoor-based activities and adventures. In 2013 she graduated from Hampshire College with a strong interest in research related to the effects of climate change on the natural environment, particularly water resources, and a clear understanding of the pressing need to translate research findings effectively to non-scientific audiences. While at Hampshire, Kathryn designed her own academic program including numerous research projects that provided a solid foundation for quantitative ecological and hydrological research and science education and community outreach programs. In 2013 Kathryn joined the Soil and Water Lab at Cornell University to study with Dr. M. Todd Walter in Biological and Environmental Engineering. At Cornell, Kathryn has continued to use both field research and predictive modeling methods to explore how water moves through and interacts with ecosystems as well as working to increase awareness about water resource issues and stimulating interest in the environment in the broader community.

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SECTION 1

Introduction

Water storage in the soil is a key intermediary in the hydrologic cycle between precipitation and terrestrial hydrology. Soil water influences evapotranspiration, water drainage to streams and deeper groundwater, and surface runoff (Western et al., 2002; Tenenbaum et al., 2006). Soil moisture is also an important control for a number of ecosystem processes such as vegetation growth and cover and distribution (Rodriguez-Iturbe et al., 1999; Tenenbaum et al., 2006) and carbon and nutrient cycling (Seneviratne et al., 2010). Its role in storm runoff generation influences which parts of a watershed are likely to contribute nonpoint source (NPS) pollution (Walter et al., 2000; Gburek et al., 2002; Agnew et al., 2006).

Surface runoff can occur as infiltration-excess overland flow, also known as Hortonian flow, as was described by Robert Horton (1933, 1940), or as saturation-excess overland flow (e.g., Dunne, 1970; Dunne and Black, 1970). Soil moisture status plays central roles in both mechanisms. Hortonian runoff occurs when rainfall intensity exceeds the infiltration capacity of the soil (Horton, 1933; 1940) and the capacity decreases with increased soil moisture. In contrast, saturation excess runoff is generated when the capacity of a soil to store water is exceeded (Hewlett and Hibbert, 1967; Dunne, 1970) and the capacity to store additional water decreases with increased soil moisture. Saturation excess runoff is the dominant runoff process in the humid Northeastern US (e.g., Walter et al., 2000; Walter et al., 2003; Lyon et al., 2006). In this situation the intensity of the rain event is not the dominant factor in runoff generation. Landscape features including vegetation, soil depth and infiltration capacity, underlying restrictive layers, local topography, and total rainfall depth control saturation excess runoff generation (e.g., Dunne and Black, 1970; Dahlke et al., 2009). The situation in which the majority of runoff is generated from a relatively small area of the landscape has been described as variable source area (VSA) hydrology (Hewlett and Hibbert, 1967; Dunne, 1970; Walter et al., 2000). These VSAs are responsible for generating saturation excess runoff and can expand and contract in size depending on rainfall depth (Hewlett and Hibbert, 1967; Walter et al., 2000; Agnew et al., 2006; Dahlke et al., 2009).

Nonpoint source (NPS) pollution from agricultural areas is one of the leading contaminant sources to lakes and rivers, and a significant source to wetlands, estuaries, and groundwater (U.S. EPA, 2009). Areas of the landscape prone to saturating (i.e., likely to be VSAs) are more likely to produce runoff and potentially transport pollutants from the landscape directly to surface waters (Walter et al., 2000; Gburek et al., 2002). Best management practices (BMPs), such as riparian buffers, filter strips, and no-till farming, are promoted to reduce soil erosion and nutrient loss in runoff to surface waters (Dosskey et al., 2011). However, many of these practices are based on the premise that Hortonian runoff is the primary form of runoff being generated and may not be the most effective way to reduce NPS pollution in VSA hydrology-dominated areas (Walter et al., 2000; Agnew et al., 2006; Qiu et al., 2007). In an effort to reduce water quality degradation, several management tools have been developed that are based on the VSA physical runoff process and the related water quality concepts of hydrologically sensitive areas (HSAs) and critical source areas (CSAs) (e.g., Walter et al., 2000; Gburek et al., 2002; Agnew et al., 2006; Walter et al., 2009; Marjerison et al., 2011; Buchanan et al., 2013). HSAs are areas of the landscape that have a high probability of generating runoff, which can transport pollutants, such as fertilizer or pesticides, to surface waters. CSAs exist where potential pollutant loading and HSAs intersect (Walter et al., 2000; Agnew et al., 2006; Dahlke et al., 2009). Identifying HSAs can allow for targeted best management practices (BMPs) around CSAs, potentially increasing the effectiveness and value of BMPs in agricultural areas (Agnew et al., 2006; Qiu et al., 2007; Dahlke et al., 2009; Tomer and Locke, 2011).

Previous studies have shown that antecedent soil moisture is correlated with the risk of VSA runoff generation (Walter et al., 2000; Gburek et al., 2002; Agnew et al., 2006; Lyon et al., 2006; Easton et al., 2008; Shaw and Walter, 2009; Cheng et al., 2014). Given the relationship between saturation excess runoff and soil water storage, mapping soil moisture across the landscape can be an effective method for modeling water flow and storage patterns (e.g., Moore et al., 1993; Western et al., 1999; Lopez-Vicente, 2009; Penna et al., 2011). The spatial and temporal variability of soil moisture patterns requires a sampling procedure that captures this variability. Time domain reflectometry (TDR) probes are commonly used to measure soil

volumetric water content (VWC) in the field (Noborio, 2001); however, due to the challenges of long-term and large-scale soil moisture sampling field campaigns, remote sensing or modeling approaches to soil moisture are popular (Western et al., 1999; Wagner et al., 2007; Dorigo et al., 2012; Brocca et al., 2013). One method used to model soil moisture is to relate a terrain index value of relative moisture to field-measured soil moisture values (e.g., James and Roulet, 2007; Buchanan et al., 2014). Beven and Kirkby (1979) first proposed the topographic wetness index (TWI) concept based on topography and upslope area to indicate soil moisture which takes the form,

$$TWI = \ln\left(\frac{a}{\tan(\beta)}\right) \tag{1}$$

where a is the upslope area per unit contour and B is the local slope angle, both determined from a digital elevation model (DEM). The TWI concept has been incorporated into many hydrologic models, including TOPMODEL (Beven and Kirkby, 1979), VSLF (Schneiderman et al., 2007), and SWAT-VSA (Easton et al., 2008). Soil properties have also been included in the topographic index calculation, with Walter et al. (2002) and Lyon et al. (2004) developing a soil topographic index (STI) for thin soil overlaying shallow restrictive layers,

$$STI = \ln\left(\frac{a}{K_s D\ tan(\beta)}\right) \tag{2}$$

in which K_s is the mean saturated hydraulic conductivity (m day^{-}1) and D is the depth to the restrictive layer (m). The amount of water that can be transmitted horizontally above the restrictive layer, soil transmissivity (m^2 day^{-1}), is calculated as the product of K_s and D. This STI has been used successfully in several Northeast US regional models (e.g., Agnew et al., 2006; Lyon et al., 2006; Easton et al., 2008). Agnew et al. (2006), Reaney et al. (2011), Marjerison et al. (2011), and Buchanan et al. (2014) used the STI as part of pollutant risk models.

The topographic index concept has been used to generate TWIs in different catchments and relate them to field soil moisture values, although most often on very small spatial scales (hillslopes, fields, and

plots) or short time scales (Buchanan et al., 2014). The observed relationship between TWI values and soil moisture has been used to examine the influence of topography on hydrological soil processes, although the results have been variable, with R^2 values ranging from 0.7 to 0.87. Moore et al. (1988) measured soil moisture in the upper 100 mm of an Australian soil and found that the TWI explained 26-33% of the spatial variation in soil moisture, while Western et al. (1999) only found a significant relationship between TWI and soil moisture ($R^2 = 0.45$) under wet conditions in the Tarrawarra catchment in Victoria, Australia. In Kansas, Ladson and Moore (1992) observed that TWI explained less than 10% of the variation in soil moisture. Nyberg (1996) found that the TWI explained 34-42% of the soil moisture variation in Sweden. Lopez-Vicente et al. (2009) observed no significant relationship between TWI and surface soil moisture in northwestern Spain, but did see a positive trend in summer. Penna et al. (2009) found that TWI values explained 58% the variation in soil moisture in the first 6 cm of soil, but only 45% of the variation in the top 12 cm of soil in a mountainous catchment in Italy. When comparing small urbanized and forested catchments in Baltimore, Maryland, Tenenbaum et al. (2006) found that the relationship between TWI and soil moisture was strongest ($R^2 = 0.1$-0.56) when a fine resolution LiDAR-based DEM was used for the urbanized watershed to resolve finer scale, more heterogeneous topographic details, while a coarser scale DEM was sufficient to illustrate the same relationship ($R^2 = 0.43$-0.87) in the forested catchment. The TWI and soil moisture relationship was consistently strong in the forested watershed ($R^2 = 0.43$-0.87) (Tenenbaum et al., 2006). In the same Maryland forested catchment, Tague et al. (2010) observed an average R^2 of 0.74 over the study period. The wide variation in the strength of the relationship between TWI and field soil moisture observed across all these studies leaves room for additional study to explore if a multi-year soil moisture data or data from numerous sites improve the strength of the relationship between TWI and field soil moisture.

The methods for calculating the TWI have been evaluated by others and efforts have been made to improve the terrain index initially proposed by Beven and Kirkby (1979). Different algorithms have been developed for calculating the flow direction, upslope contributing area, and slope, as well as the DEM data

source and cell size (O'Callaghan and Mark, 1984; Quinn et al., 1991; Barling et al., 1994; Tarboton, 1997; Beven and Freer, 2001; Borga et al., 2002; Orlandini et al., 2003; Hjerdt et al., 2004; Lanni et al., 2011). Guntner et al. (2004) and Sorensen et al. (2006) compared some of the TWI calculation methods with field soil moisture values. Buchanan et al. (2014) conducted an extensive exploration of over 600 possible TWI and STI component calculation methods. They found that a 3 m LiDAR based DEM was better than a 10 m USGS DEM, and that including soil properties in the STI formulation better explains agricultural field moisture patterns in the Finger Lakes region of New York than topography in the TWI alone.

Previous efforts to map storm runoff risks and inform targeted NPS pollution mitigation practices in agricultural landscapes have relied predominately on simulation models or have potentially over-simplified the interactions between rainfall and the landscape features that generate storm runoff. The objectives of this study were to (1) explore the relationship between soil moisture and STI over a multi-year timespan at multiple agricultural sites, (2) develop a method to identify where saturation excess runoff is generated across the landscape, (3) estimate the probability of runoff being generated from any point in the landscape based on soil moisture and precipitation, and (4) define thresholds that can be used to target management practices for the reduction of NPS pollution.

To address these objectives, we have established a soil VWC database that covers broad spatial and temporal variation to test the relationship between TWI and VWC across a range of agricultural conditions in the Northeastern US. We hypothesized that we could use these direct soil VWC measures to empirically derive relationships between STI values and soil VWC and rainfall frequencies to estimate the probability of runoff being generated from any point in an agricultural field. The runoff probability analysis will allow us to identify HSAs across the landscape and determine how much the risk of polluted storm runoff from VSAs can be reduced by removing these HSAs from agricultural production. This analysis will provide information to target BMPs in an agricultural setting to reduce NPS pollution from specific areas of the landscape.

SECTION 2

Methods

Study Area

Soil moisture (as VWC %) was measured across five agricultural sites (each site covering 1-4 distinct fields) in four different watersheds in the Finger Lakes region of New York (Figure 1). Agricultural fields were identified as hay/pasture or cultivated crop land cover based on the 2011 National Land Cover Database and Tompkins and Cortland County 2013 tax parcel data (Jin et al., 2013). Sampling points were selected across a range of STI values at each site. The sites varied in area from 0.23-0.76 km^2, had moderate slopes (2.2-5.0%), and were planted with soybean, corn, or grass or left fallow during the sampling time (Table 1). Selecting a range of agricultural fields allowed us to incorporate the range of soil VWC into saturation excess runoff probability estimates for other agricultural fields in the Finger Lakes region of NY. Soils were predominately channery silt loams derived from siltstone, sandstone, shale, and limestone and underlain by a fragipan restrictive layer around 0.4 m into the soil profile (USDA-NRCS, 2009). This analysis was scaled to estimate the risk of runoff from any agricultural field in the Sixmile Creek watershed, where site 3 is located (Figure 1). The Sixmile Creek watershed is 128.5 km^2 at the outlet to Cayuga Lake, with 28.0 km^2 of agricultural land designated as hay/pasture or cultivated crop land. Average annual rainfall in the study region for 1981-2010 is 94.74 cm, with 163.58 cm of snowfall, based on the 30 year climate normal calculated from 1981-2010 (NRCC, 2014). There was less rain during 2012 (83.31 cm) than the 30 year climate normal, while 2013 and 2014 were wetter years with 99.06 cm of rain in 2013 and 101.09 cm in 2014. Meteorological data were collected from Cornell University Northeast Regional Climate Center weather stations near site 2 and site 5.

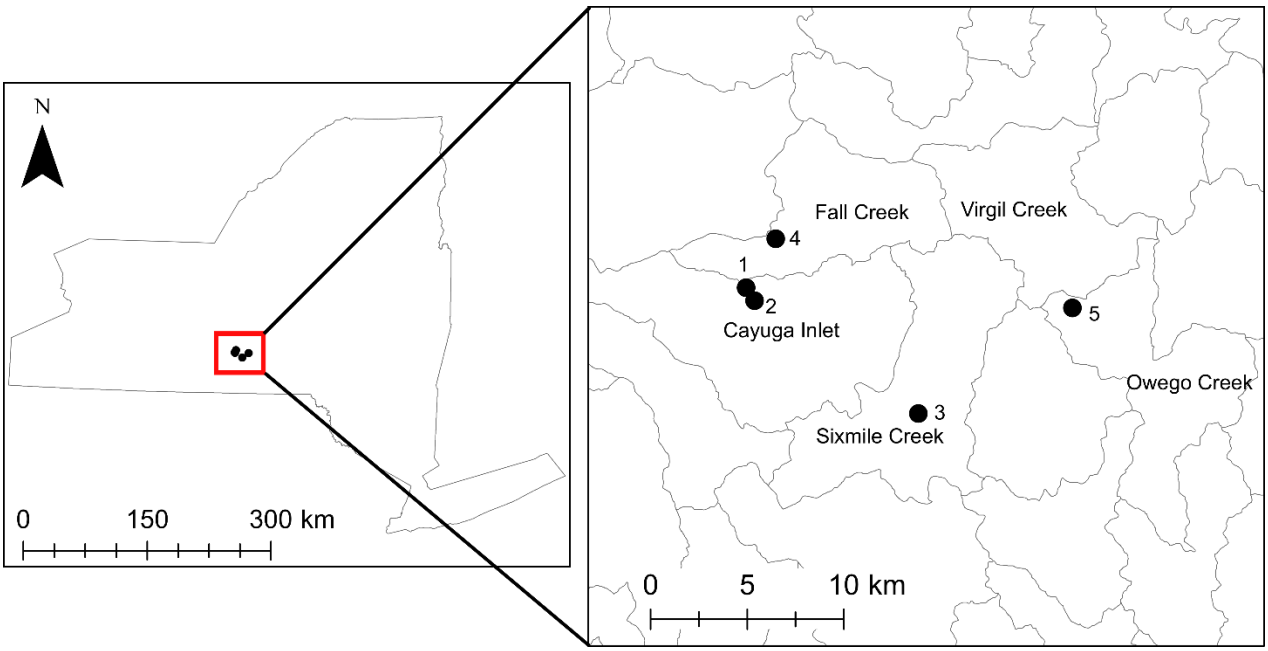

Figure 1: Study site locations (black dots) and watershed boundaries in central NY (USGS 12-digit hydrologic unit codes). Meteorological stations are located between sites 1 and 2, and at site 5 (NRCC, 2014).

Table 1: Summary of agricultural field site characteristics. Slope derived from LiDAR-based DEM, transmissivity and porosity values derived from SSURGO soil data (USDA-NRCS, 2009).

Site	Area (km^2)	Mean (range) Slope ($m\ m^{-1}$)	Mean Transmissivity ($m^2\ d^{-1}$)	Mean Porosity	Primary Land Cover	Mean (range) Sample Point STI
1	0.133	4.99 (0.01-34.65)	1.72	0.53	Orchard, Pasture	5.80 (3.48-15.56)
2	0.341	2.85 (0.03-31.93)	0.84	0.55	Corn, Soybean, Pasture	7.91 (2.60-15.36)
3	0.402	3.77 (0.01-31.08)	1.32	0.51	Pasture	7.95 (1.85-12.99)
4	0.791	2.18 (0.0-43.39)	0.37	0.52	Corn, Soybean, Pasture	8.94 (2.92-18.43)
5	0.956	4.07 (0.01-25.66)	2.58	0.51	Corn, Soybean, Pasture	7.14 (0.41-16.06)

Field Data

Soil VWC readings for the top 10 cm of soil were collected at sampling points across a range of STI values at each field site with Time Domain Reflectometry (TDR) probes (Hydrosense, Hydrosense II; Campbell Scientific, Inc.). The initial number of sampling points per field (50 ± 17) was reduced to 35 (± 7) points per field in April 2014; there was no statistical change in the linear relationship between TWI and soil VWC. A minimum of three TDR readings were taken at each sampling point, within a 1-3 m diameter area, to determine an average VWC at each point for each date. TDR readings were taken at least twice each month at each site for two years (August 2012 – August 2014), excluding months with snow cover (December – March). TDR measurements were not made during rain events. Natural precipitation events allowed us to sample in conditions that were both wetter and drier than the 30 year average monthly rainfall totals. There was less rainfall during the spring 2013 season (April, May) than the climate normal, while spring 2014 was a wetter season. The 2012 summer season (June, July, August, September) was dryer than the average, while summer 2014 was wetter than the climate average and summer 2013 was even wetter than summer 2014. Both fall sampling seasons (October, November) were dryer than the 30 year average, with fall 2012 dryer than fall 2013. Daily rainfall measurements were used to calculate 3-, 5-, 7-, and 14-day antecedent rainfall for soil moisture sampling days.

Sampling points were located in the field with GPS units (Garmin GPSMAP 60CSx, Garmin Ltd.) with a horizontal accuracy of 3 m. The TDR probes were calibrated from gravimetric soil moisture measurements made from soil cores taken across a range of wetness conditions at each site. A calibration curve was constructed to relate the TDR period and VWC measurements with the gravimetric measurements (R^2 = 0.84 and 0.90 for Hydrosense II and Hydrosense TDR probes, respectively).

Topographic Wetness Index (TWI) Formulation

The topographic wetness indices for this analysis were generated using Equation 2, which accounts for the topographic and soil characteristic controls on terrestrial water movement. Based on the work by

Buchanan et al. (2014), the STIs generated for this study were calculated using a 3 m cell size LiDAR-based DEM, with the maximum triangle slope calculation (MTS; Tarboton, 1997), the multiple triangular flow direction algorithm (MD∞; Seibert and McGlynn, 2007), and without a low-pass digital filter. SAGA-GIS and the RSAGA package in R (version 3.0.1) were used to generate the STIs (Brenning, 2007; R Core Team, 2015). Soil properties for the STI calculation were derived from the USDA-NRCS Soil Survey Geographic (SSURGO) database using the Soil Data Viewer application (USDA-NRCS, 2009). Figure 2 gives an example STI map of site 2 and soil VWC sample points.

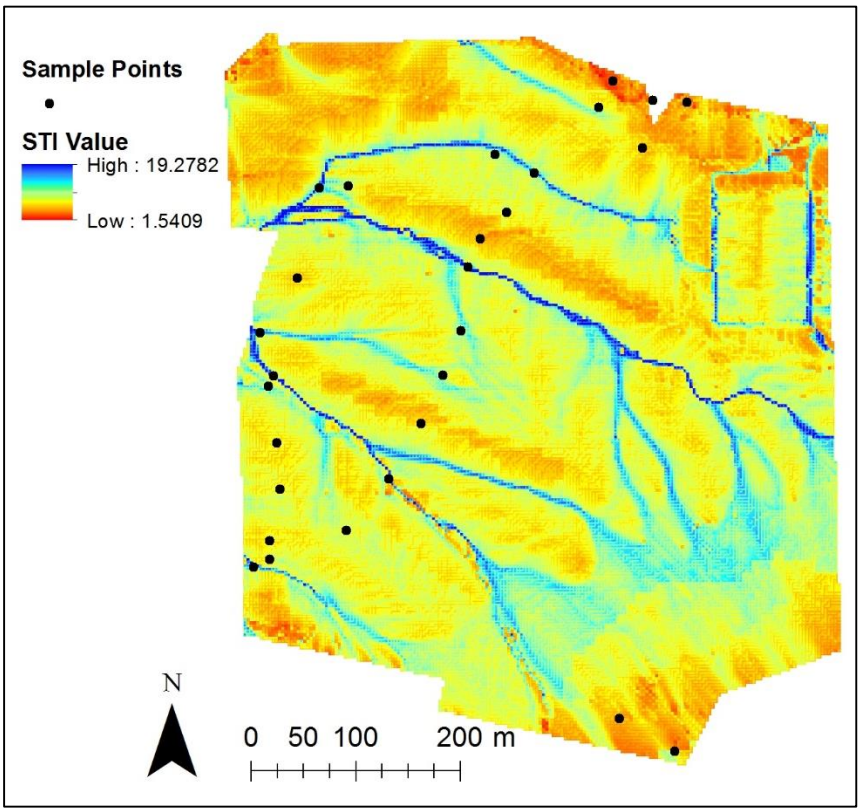

Figure 2: Example of a soil topographic index (STI) map for study site 2. High STI values (blue) indicate wet areas of the field, while low STI values (red) indicate dry areas of the field based on topography and soil properties. Soil VWC sample points indicated by black points.

Statistical Analysis

VWC was grouped by season to provide a more nuanced estimate of runoff throughout the year. Seasonal divisions were made based on average crop planting (spring), growing season (summer), and post-harvest (autumn) timing for central NY, with April and May as spring months, summer samples during June – September, and October and November as autumn months. R was used for all statistical analyses. Scatterplots and boxplots of the field-measured soil VWC and STI values were generated for each agricultural field. The statistical assumptions were addressed by plotting histograms of the data and Q-Q plots (theoretical quantiles vs. standardized residuals) to assess normality of the data and the residuals. Residuals were plotted versus the fitted values to assess the homogeneity of variance, and versus the explanatory values to assess the independence of the data. Single factor Analysis of Variance (ANOVA) was used to compare the mean VWC measured annually and during each sampling season at each field site. Linear regressions were performed to assess the strength of the relationship between measured VWC and modeled STI values. A linear mixed effects model was employed to control for the lack of independence among sampling points and agricultural fields, given the repeated samples taken during this study. In this model the sampling date, agricultural site, and point identifier were random effects. The average R^2 values for each sampling season were used to compare how well STI values explained variations in soil VWC among seasons and field sites. The linear relationship between the VWC averaged for each STI integer bin (e.g., STI value 1-2, 2-3) and STI was also determined for each sampling season. The Akaike Information Criterion (AIC) values were used to compare the linear mixed effects models, linear regression models, and logistic regression models generated for each field site or season (Akaike, 1974). The models were not considered statistically different if the AIC values were within 2 units of each other, AIC values within 3-7 units of each other were considered moderately different, and AIC values > 10 units apart were considered significantly different from each other (Burnham and Anderson, 2002). For all statistical analyses, $\alpha = 0.05$ was used to determine statistical significance. The Bonferroni correction, where the significance level is set at α divided by number of repeated tests ($n = 33$), was applied to the α level for the linear regression and

linear mixed effects models to account for repeated statistical tests, resulting in a corrected p-value of 0.00152 (Bonferroni, 1936).

Probability of Surface Runoff Calculation

Rainfall data were used to generate a probability distribution for all the rainfall events within the 2012–2014 spring, summer, and autumn sampling periods. The rainfall distributions from the two weather stations were not significantly different from each other, therefore the same rainfall probability distribution was used for analysis at all sites. Soil VWC distributions were also calculated within the same time periods for each agricultural field. These distributions represent a range of soil moistures that are possible at all the sites within each season and the range of rainfall events that are likely within each season. The soil VWC and rainfall distributions were used to determine the probability of saturation excess runoff. The probability of runoff for each STI integer bin (Figure 3c) was calculated as the joint probability of soil moisture probability (Figure 3a) and rainfall probability (Figure 3b) for conditions in which the sum of antecedent soil water and rainfall equaled or exceeded the soil saturation capacity. For each field site the soil saturation capacity threshold above which runoff would be generated was the sampling point weighted average field porosity (Table 1). The soil porosity was calculated for each soil type from SSURGO bulk density and organic matter percentage values with an assumed mineral solids particle density of 2.65 g cm^{-3}. A logistic regression was used to model the estimated probability of runoff generation for all STI values at each site. The soil VWC data from all five agricultural sites were used as a representation of reasonable soil moisture distributions across a range of agricultural field types in the Finger Lakes region, given differences in agricultural land cover, local topography, and soils. These soil VWC data were compiled into a VWC probability distribution and used with the rainfall probability distribution to generate a logistic regression model for the probability of runoff with 95% confidence intervals for any agricultural field in the Sixmile Creek watershed.

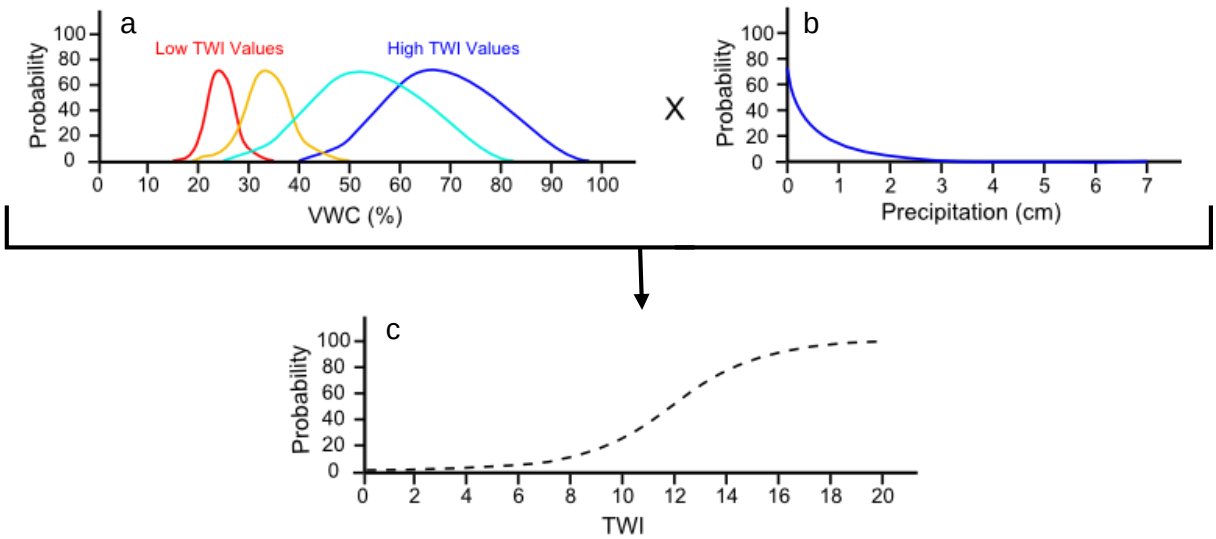

Figure 3: Soil moisture (VWC %) probability distributions for each TWI integer bin (a) and rainfall probability distributions (b) are multiplied to calculate a probability of saturation excess runoff distribution (c) for conditions in which the sum of antecedent soil water and rainfall equaled or exceeded the soil saturation capacity.

SECTION 3

Results

This study analyzed a multi-year soil moisture dataset from multiple agricultural sites in the Finger Lakes region of NY. Probability distributions of soil VWC and rainfall were used to identify which regions of agricultural fields were at or above soil saturation and therefore likely to generate saturation excess runoff. This empirical soil moisture dataset was then used to estimate the probability of runoff being generated from any agricultural field in the region. Finally, acceptable thresholds of runoff generation were defined and compared for use in targeted management practices with the goal of reducing NPS pollution from agricultural lands.

We observed variations in field soil moisture patterns across the five agricultural sites that justifies our use of fields with different land covers, cropping practices, local topography, and soil types to capture the range of soil VWC that could occur across other agricultural fields in the Finger Lakes region of NY. The seasonal mean soil VWC for each of the five agricultural sites, weighted by percent of land in each STI integer bin, measured from August 2012 – August 2014 varied from 31.4% to 43.6% (Table 2). Soil VWC at site 5 was significantly lower than soil VWC at the other sites for all seasons. When soil VWC was separated by seasonal sampling periods, mean field soil moisture was not significantly different between the spring and autumn periods at sites 1, 3, or 4. Mean soil VWC was lower during the summer than in the spring or autumn periods at all sites except at site 1, where there was no difference between summer and autumn soil VWC.

Table 2: Summary of measured mean soil moisture (VWC % ± SD %) across each site weighted by the percentage of land in each STI integer bin in spring, summer, and autumn seasons. Statistical differences compared within sites only to examine seasonal differences and with a significance level of $\alpha = 0.05$.

Site	Dominant Field STI (land area %)	Spring VWC (%)	Summer VWC (%)	Autumn VWC (%)
1	5 (27.4%)	37.4 ± 9.4	33.2 ± 10.0 *	34.8 ± 8.5
2	6 (25.4%)	43.6 ± 8.8 **	35.0 ± 10.1 **	39.4 ±7.5 **
3	7 (23.7%)	36.3 ± 11.8	33.1 ± 11.1 ***	36.4 ± 9.5
4	7 (26.3%)	39.8 ± 10.9	37.5 ± 11.0 ***	40.8 ± 10.5
5	5 (20.3%)	33.2 ± 11.4 **	31.4 ± 10.8 **	37.9 ± 9.9 **

* Statistically different from Spring only
** Statistically different from all other seasons
*** Statistically different from Spring and Autumn

The relationship between measured soil VWC and STI was linear for all agricultural sites in every sampling seasons (Figure 4). Linear mixed effects models were used as a method for comparing the soil VWC and STI relationship across sites for all soil VWC data points. Antecedent rainfall did not have a significant influence on soil VWC. The linear relationship between all soil VWC measurements and STI value was strong for all sites across all seasons, with a range of R^2 between 0.05-0.65 (Table 3). The linear relationship for site 1 during the spring season was significant when the significance level was $\alpha = 0.05$, but was not significant with the Bonferroni corrected p-value of 0.00152. All other statistical analyses were significant under the corrected significance level. The R^2 values were strongest in the autumn sampling period for all sites except site 3. On the basis of R^2 values, the sites where the STI value explained the greatest variation in soil VWC was site 3 during the spring ($R^2 = 0.58$) and summer ($R^2 = 0.58$) periods and site 1 ($R^2 = 0.65$) during the autumn period. The linear models for all sites and sampling seasons were statistically different from each other as they were all greater than 10 AIC units apart. The relationship between soil VWC and STI was improved greatly for all sites when VWC measurements were averaged for each STI integer value (Figure 4). The linear relationship between mean soil VWC for each STI integer and STI was also strong for each sampling season, with a range of R^2 between 0.63-0.98 (Table 4). The R^2 values were strongest at site 3 for the mean soil VWC linear regression during all sampling period seasons.

At the individual agricultural fields, the mean VWC v. STI integer relationship was strongest during the spring and autumn periods at site 3 ($R^2 = 0.98$) and at site 1 during the summer period ($R^2 = 0.93$). Using AIC values, the linear models for spring and autumn were not statistically different for sites 1, 2, 4, and 5, and were moderately different at site 3. The spring and summer models were not significantly different at site 3, were moderately different at site 1, and were significantly different at sites 2 and 5 (Table 4). The summer and autumn linear models were moderately different at site 1 and site 4, and significantly different at all other sites.

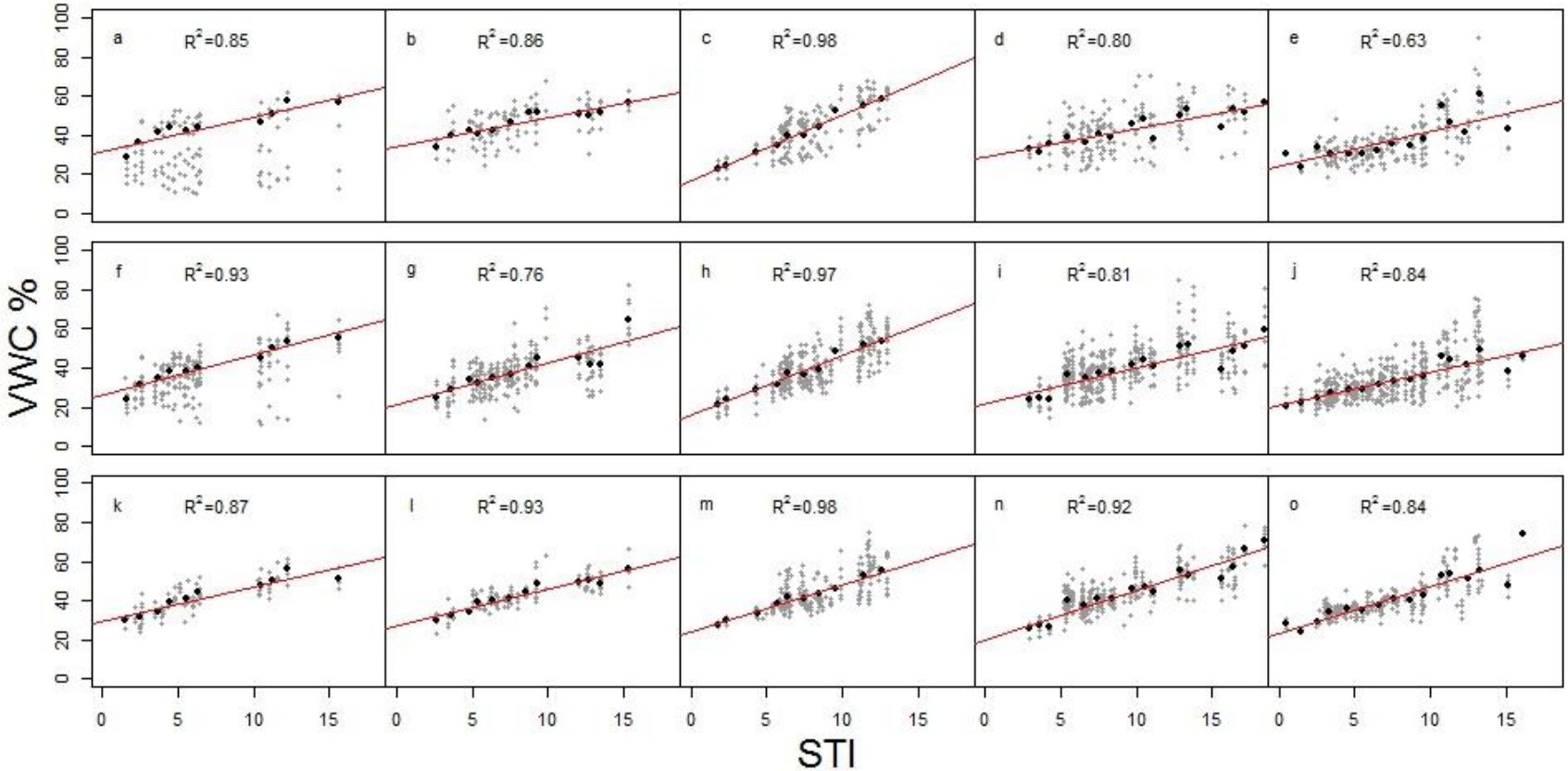

Figure 4: Measured soil VWC v. STI value for all sample points (grey) and mean soil VWC v. STI integer values (black) for spring (top), summer (middle), and autumn (bottom) seasons. VWC v. STI integer values linear regression model (red line) and model R^2 values added. Plots for site 1 (a, f, k), site 2 (b, g, l), site 3 (c, h, m), site 4 (d, i, n), and site 5 (e, j, o).

Table 3: Linear regression models relating soil VWC and STI value for spring, summer, and autumn for individual sample point soil VWC measurements. All slope estimates are significantly different from 0 (p-value < 0.05). With the Bonferroni corrected p-value = 0.00152, all linear models are significant except for the site 1 spring season model. All the linear models are statistically different from each other based on being greater than 2 AIC units apart.

Site	Season	Intercept estimate	Slope (STI estimate)	R^2	AIC
1	Spring	26.350	0.891	0.054	894.22
	Summer	25.960	1.702	0.301	1509.14
	Autumn	29.408	1.840	0.647	625.76
2	Spring	34.523	1.443	0.282	758.90
	Summer	22.420	1.918	0.366	1883.43
	Autumn	28.845	1.712	0.636	738.39
3	Spring	17.010	3.293	0.579	1145.76
	Summer	15.382	3.060	0.583	2228.51
	Autumn	24.249	2.406	0.461	1582.74
4	Spring	28.722	1.547	0.283	1293.45
	Summer	24.675	1.673	0.338	3165.69
	Autumn	24.598	2.146	0.631	1999.19
5	Spring	21.087	2.144	0.420	1487.06
	Summer	19.820	1.932	0.402	3283.57
	Autumn	25.349	2.118	0.570	1760.03

Table 4: Linear regression models relating soil VWC and STI value for spring, summer, and autumn for soil VWC measurements averaged into STI integer bins. All slope estimates are significantly different from 0 when p-value = 0.00152 and statistically different models for each site are indicated where models are > 10 AIC units apart.

Site	Season	Intercept estimate	Slope (STI estimate)	R^2	AIC
1	Spring	32.141	1.726	0.849	58.04
	Summer	26.045	2.037	0.929	52.84
	Autumn	29.520	1.761	0.873	56.38
2	Spring	34.099	1.472	0.860	60.65
	Summer	21.086	2.138	0.758	77.77*
	Autumn	27.264	1.859	0.926	57.75
3	Spring	16.658	3.372	0.982	43.18
	Summer	15.685	3.049	0.972	45.98
	Autumn	23.715	2.435	0.981	37.17
4	Spring	28.736	1.445	0.803	91.29
	Summer	21.460	1.850	0.808	98.71
	Autumn	19.821	2.518	0.916	93.44
5	Spring	24.540	1.761	0.629	101.87
	Summer	21.093	1.686	0.844	90.69*
	Autumn	23.377	2.399	0.838	102.75

*Seasonal model is statistically different from other seasons for the individual site

The probability of saturation excess runoff being generated from the agricultural sites was calculated based on soil VWC and rainfall probability distributions measured during the study period (Figure 3). A logistic regression model was fit to these calculations and used to estimate the probability of runoff for any STI value. The saturation excess runoff probabilities calculated using logistic regression models varied among agricultural sites, as was expected given the different characteristics of the agricultural fields and the observed variation in soil VWC patterns. The logistic regression models varied between the sites and sampling season with no quantifiable pattern using model equation or AIC values. During the spring season, the probability of runoff was not statistically different at sites 2 or 3. In the summer and autumn seasons, runoff probability models for sites 1 and 2 were not statistically different, while probability estimates for sites 4 and 5 were also not statistically different. There was also variation in the seasonal runoff probability estimates when comparing the logistic models for each agricultural site individually, although none of the models were statistically different with AIC values greater than 10 units apart. Based on AIC values, the logistic models of the probability of runoff at sites 1 and 4 were not statistically different for any of the sampling seasons. At site 2 all of the seasonal runoff probability models were moderately different from each other. At site 3 the summer and autumn logistic models were moderately different, while the other models were not significantly different. At site 5 the summer and autumn models were not different, while the spring and summer models were moderately different. The differences observed in soil moisture patterns and estimated storm runoff probabilities among the sites suggests that one agricultural field alone should not be used as the only data point for widespread soil moisture or surface runoff modeling. To estimate the probability of saturation excess runoff occurring across other agricultural fields in the Finger Lakes region of NY, the soil VWC measurements from all five agricultural sites were used as a representation of reasonable soil moisture patterns across the region. The logistic regression analysis carried out for agricultural fields in the Sixmile Creek watershed indicated that the probability of runoff estimates were not statistically different for the summer and autumn seasons, based on AIC values less than 3 units apart (Figure 5).

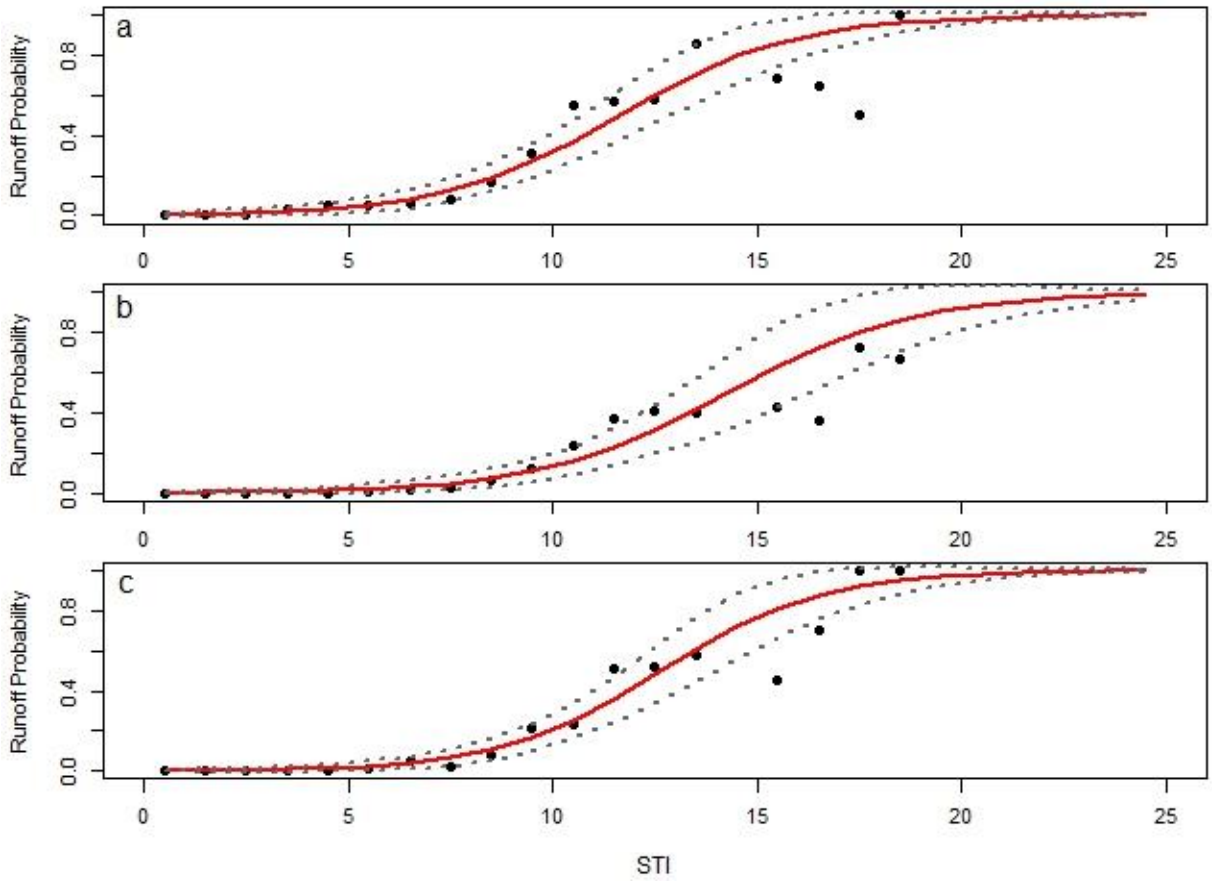

Figure 5: Probability of saturation excess runoff being generated at each STI value for the five study sites. Logistic regression runoff probability estimates (red line), 95% confidence intervals (dashed line), and field measured runoff probability estimates (black points) for spring (a), summer (b), and autumn (c) seasons. AIC values for spring (40.218), summer (37.497), and autumn (37.707) indicate that none of the logistic regression models are statistically different from each other by being less than 3 AIC units apart.

The probability of saturation excess runoff for each STI integer based on the logistic regression model was used to spatially visualize which areas of the landscape have the highest risk of generating runoff. STI values with high probabilities of generating runoff can be identified as HSAs and potential contributors of NPS pollution. With this probability of runoff analysis, we can address important management questions such as "How much is the risk of polluted runoff reduced when agricultural land with high probabilities of generating runoff taken out of production?" This approach could use either a set percentage of land area or an acceptable probability of runoff threshold to identify areas of agricultural fields where conservation easements or BMPs could be implemented. Three land management methods were identified to compare how using a set percentage of land area or an acceptable threshold of runoff risk would change the amount of agricultural land taken out of production. For Method 1, the 10% of land area with the highest probabilities of generating runoff was selected for removal from production or targeting with BMPs. For Methods 2 and 3, acceptable thresholds of the probability of runoff generation were set to compare very low and moderate limits. Method 2 sets a very low threshold for the probability of runoff by removing all land area with a greater than 5% probability of generating runoff, which is comparable to thresholds used by Agnew et al. (2006). Method 3 sets a moderate threshold for the probability of runoff by removing all land area with a greater than 30% probability of generating runoff, which is comparable to methods used by Walter et al. (2000).

These three methods of land management were compared for agricultural sites 2 and 3 during the spring season. Figures 6 and 7 display the amount of land that must be removed from production based on these land management practices. Using Method 1, the 10% of the land area with the highest probability of generating runoff is selected. At site 2, the highest probability of runoff in the remaining land area is 18.9% (Figure 6), while at site 3 the highest probability of runoff is 57.1% (Figure 7). When Method 2 is used, the highest probability of runoff is 5% for the land not selected for removal. This method selects 75.9% of site 2 and 77.5% of site 3 as land that must be removed from production. Method 3 is less conservative than Method 2, with the remaining land having at most a 30% probability of generating runoff.

With this method, only 4.7% of site 2 and 21.0% of site 3 would be removed from production. These three methods of land management select very different amounts of land area that must be removed, with Method 2 indicating that most of sites 2 and 3 have an unacceptable probability of runoff generation. With Method 1, a consistent fraction of each field could be targeted, although this means that the remaining land could have differing probabilities of generating runoff depending on the site. If up to 10% of the agricultural land with the highest probabilities of generating runoff is taken out of agricultural production, the reduction in the risk of runoff varies for the different sites with the largest reduction in risk (90-97%) at site 1 and the smallest reduction at site 3 (40-60%) (Figure 8, Table 5). The remaining 90% of the landscape has a probability of 10% or less of generating runoff at site 1 and 60% or less at site 3. For agricultural fields in the Sixmile Creek watershed, there is a 70-80% reduction in the risk of runoff generation if 10% of the land is taken out of production (Table 5). The remaining 90% of the agricultural land has a probability of 30% or less of generating storm runoff. For some agricultural fields in the Sixmile Creek watershed, the area with a high probability of runoff is concentrated in channels, while in other fields, much of the field has a high probability of runoff and would need to be taken out of production (Figure 9).

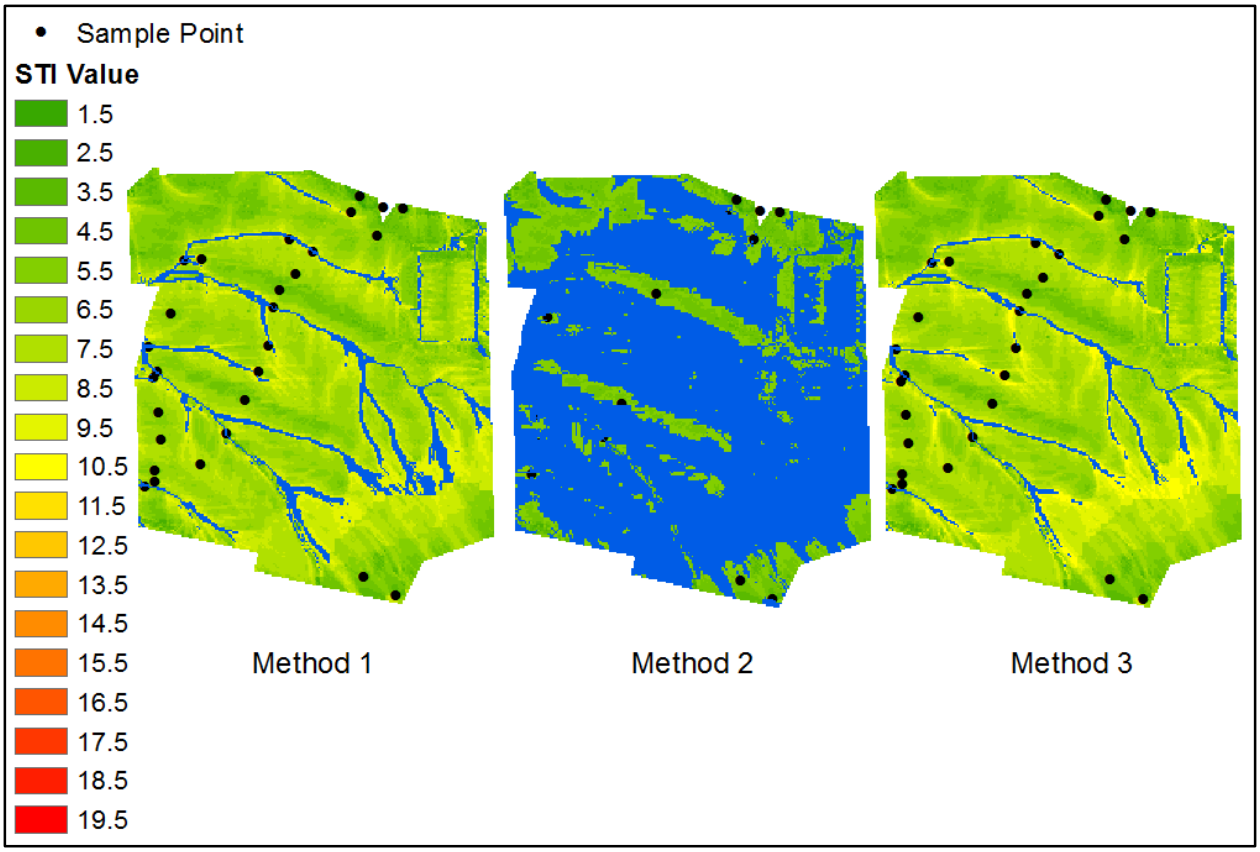

Figure 6: Land management methods applied to site 2 during the spring season. Selected blue areas indicate STI values with high probabilities of runoff that should be removed from agricultural production or targeted with BMPs. Method 1 selects the 10% of land area with the highest probabilities of generating runoff. Method 2 sets a very low threshold for the acceptable probability of runoff (5% probability at most). Method 3 sets a moderate threshold for the acceptable probability of runoff (30% probability at most). High STI values (red) indicate wet areas of the field while low STI values (green) indicate dry areas of the field based on topography and soil properties.

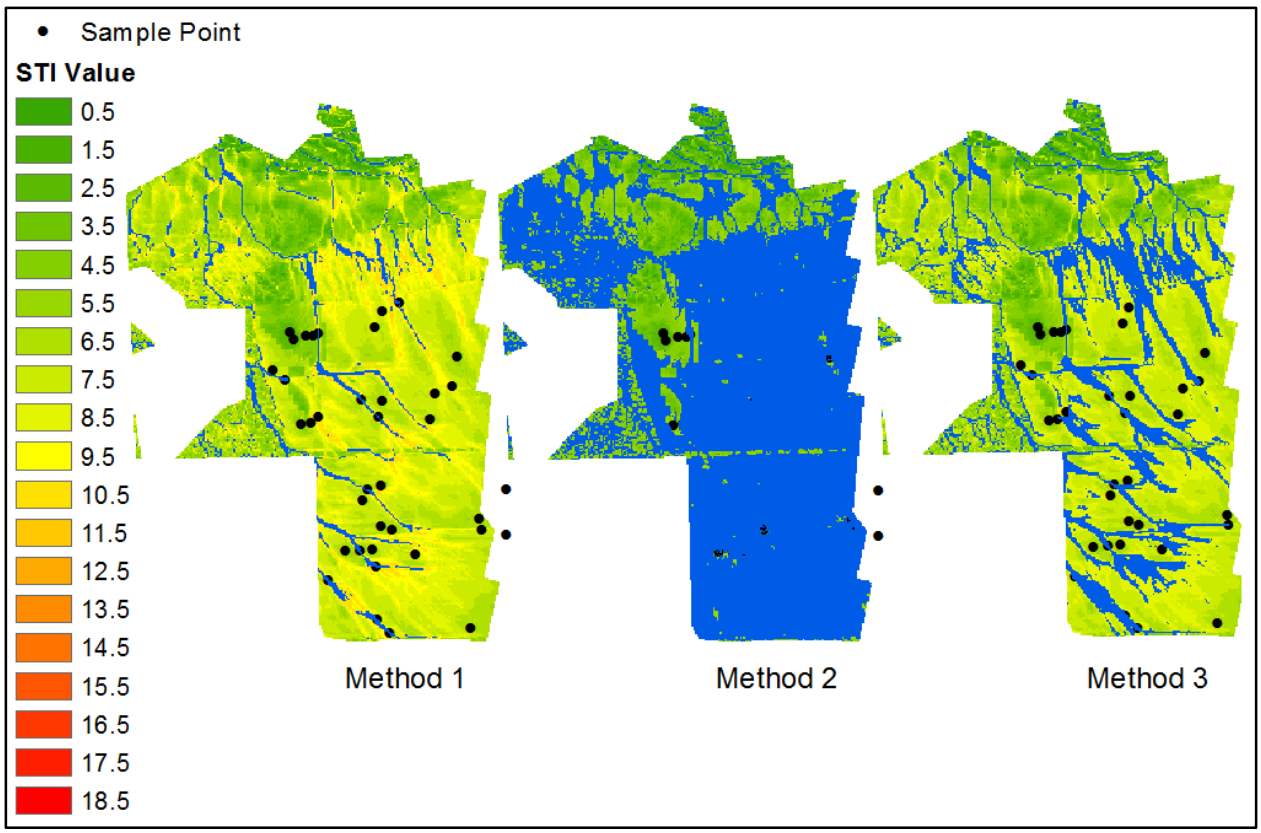

Figure 7: Land management methods applied to site 3 during the spring season. Selected blue areas indicate STI values with high probabilities of runoff that should be removed from agricultural production or targeted with BMPs. Method 1 selects the 10% of land area with the highest probabilities of generating runoff. Method 2 sets a very low threshold for the acceptable probability of runoff (5% probability at most). Method 3 sets a moderate threshold for the acceptable probability of runoff (30% probability at most). High STI values (red) indicate wet areas of the field while low STI values (green) indicate dry areas of the field based on topography and soil properties.

Table 5: Percent reduction in the risk of runoff due to removal of the 10% of agricultural field area with the highest probabilities of runoff generation from production.

Site	Spring (% risk reduced)	Summer (% risk reduced)	Autumn (% risk reduced)
1	90	95	97
2	80	95	95
3	40	60	50
4	70	80	70
5	80	90	80
Sixmile Creek watershed fields	70	80	80

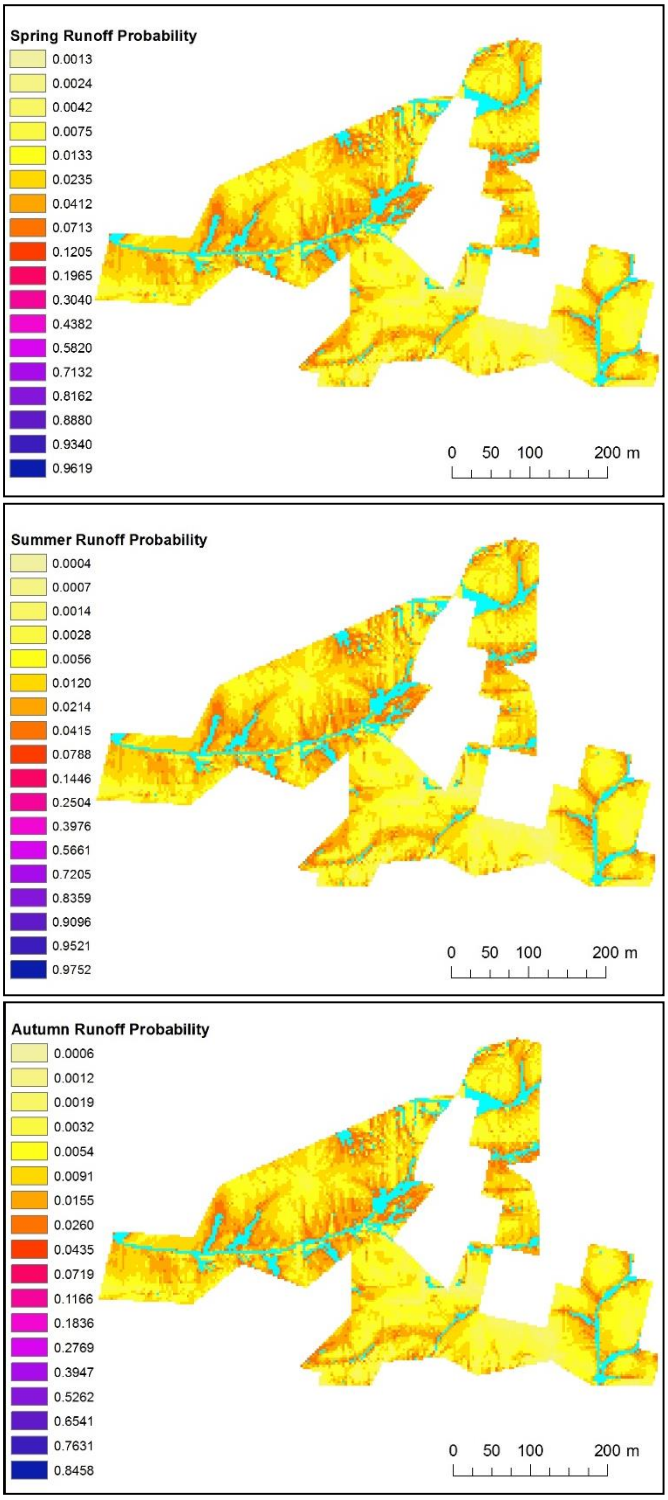

Figure 8: Runoff probability estimates for each STI integer at site 1 for spring, summer, and autumn seasons. Area highlighted in light blue indicates the 10% of the field area with the highest probabilities of generating runoff, with the remaining land having a 10% probability of producing runoff in spring, 5% of in the summer, and 3% in autumn.

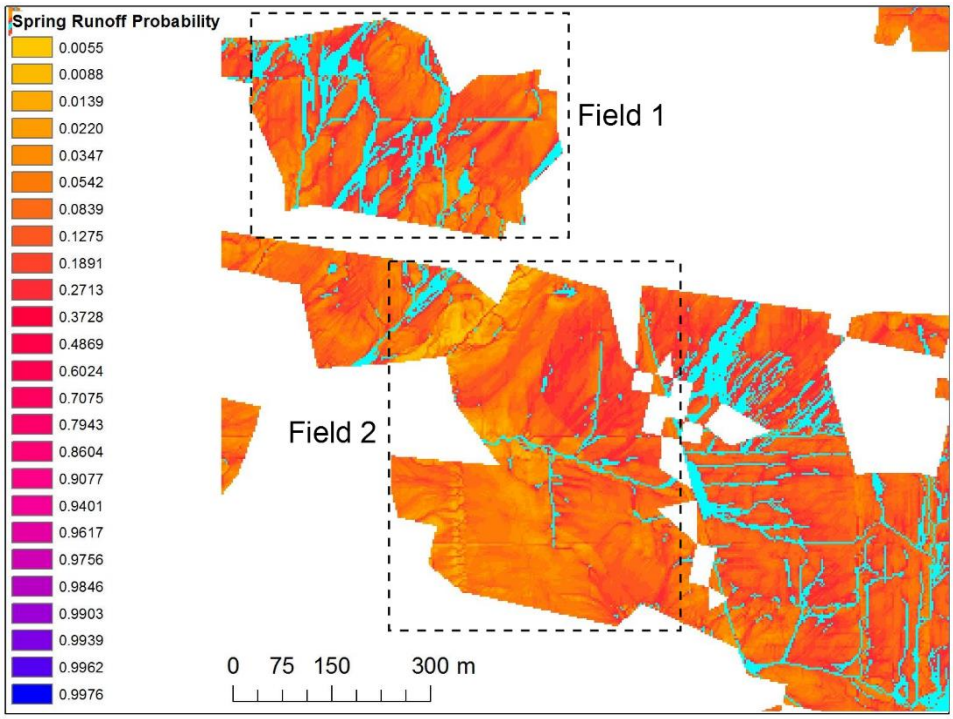

Figure 9: Agricultural fields in the Sixmile Creek watershed where land with a 30% probability of runoff or greater is highlighted in blue. These areas make up 10% of the agricultural field area in the watershed and correspond to areas with STI values of 10.5 or higher. Implementation of conservation easements may be easier in Field 2 compared to Field 1 where more of the field is likely to generate runoff.

SECTION 4

Discussion and Conclusions

This study builds upon previous work to quantify the relationship between topographic wetness indices and field moisture patterns as well as efforts to identify key areas of the landscape responsible for generating saturation excess runoff. The differences in soil moisture patterns measured across the five agricultural fields was consistent with our hypotheses as we selected agricultural sites to represent the different types of fields found in upstate New York. The linear relationship between field volumetric soil moisture and STI is similar to the relationship observed by Buchanan et al. (2014) and others. Even with the differences in measured VWC values across the agricultural sites, soil VWC and STI value maintained a linear relationship at all the sites and a logistic model appeared to be an appropriate model to estimate the probability of runoff at all the sites. STI values explained between 5% and 65% of the variation in individual VWC measurements, which is more than in some previous studies. When the soil VWC was averaged for STI integer bins, the linear regression explained between 63% and 98% of the variation in VWC. This dataset comprises one of the largest longitudinal measurements of volumetric soil moisture across a range of STI values and multiple agricultural sites. Based on this extensive dataset, the variation in runoff probability models suggests that certain characteristics of the agricultural fields, such as land quality, crop type, or alterations to natural drainage networks, could be influencing the spatial soil moisture patterns and drainage in the field that is not captured by the STI alone. The lack of consistent trends in runoff probability models among agricultural fields presents challenges for scaling this analysis to other agricultural fields in the Northeastern US and suggest further research is needed to identify the underpinning mechanisms that are governing these differences. The crop cover evapotranspiration, land use history, solar radiation, irrigation, or artificial underground drainage could be significantly influencing soil moisture and flow patterns in these agricultural fields.

This comprehensive dataset of soil moisture provides a completely empirical analysis of saturation excess runoff probability. Prior work by Agnew et al. (2006) and Walter et al. (2000) in mixed forest and

agricultural watersheds in the Catskill Mountains region of New York calculated the probability of saturation excess runoff using soil moisture values modeled with the VSA-based Soil Moisture Routing (SMR) Model (Frankenberger et al., 1999). Agnew et al. (2006) observed a logistic relationship with low STI values having probabilities of runoff less than 5%, and increasing probability of runoff with higher STI values up to 100%. They calculated STI thresholds below which the probability of runoff is less than 5% and could be considered low risk areas. In the spring and autumn months this STI threshold was 8, while in the summer the threshold increased to an STI value of 10 and more of the landscape had a low risk of runoff generation. These STI thresholds are higher than those calculated from the data used for this study. During the spring, the STI threshold above which the probability of runoff is greater than 5% based on logistic model estimates ranged from 5.5 to 8.5, classifying more land as higher risk than the Agnew et al. (2006) predictions. Similar to Agnew et al. (2006), the summer STI threshold increased to 7.5-10.5, however; the autumn STI threshold ranged from 5.5 to 7.5 and is the same as the summer threshold for sites 2, 4, 5, and the Sixmile Creek watershed fields (Table 6).

The STI threshold method used by Agnew et al. (2006) identifies HSAs across the landscape that have a probability of 5% or greater of generating saturation excess runoff. With this method, the amount of land that would be removed from production will vary from site to site. Another method for identifying areas of the landscape likely to generate runoff that should be removed from agricultural production to protect water quality is to select a fraction of land area that will be protected. Walter et al. (2000) estimated that in order to reduce the risk of runoff generation by 70% in two Catskill region watersheds, 10% of the land would be identified as HSAs and should be protected from agricultural activities. The remaining 90% of the land would have a 30% probability of generating runoff or less, which was their hydrological sensitivity limit (L_{HSA}) for the study. This study supports similar estimates; we calculated that identifying 10% of agricultural area to remove from production will reduce the risk of runoff from between 40% and 97% in the Finger Lakes region of New York. Using the Walter et al. (2000) hydrological sensitivity limit of 30% probability of runoff or less, between 3.7% and 21.0% of the agricultural land area in this study

would be identified as HSAs in the spring, 1.6–11.1% in the summer, and 1.6–21.0% in autumn (Table 7). Using a L_{HSA} of 30% probability generally required less land to be removed from agricultural production than setting a standard requirement to remove 10% of the landscape.

All of these methods identify areas of the landscape with the highest probabilities of saturation excess runoff generation. After these areas have been identified, BMPs can be implemented or potentially polluting activities can be halted to protect water quality. Mapping the runoff risk across the landscape based on easily generated STIs could be useful for developing targeted agricultural BMPs or conservation easements by identifying specific areas of the landscape prone to generating runoff during the year. In some of the agricultural fields have areas with high probabilities of generating runoff are concentrated in channels that could be targeted, while in other fields much of the land has a high probability of runoff that would be challenging to target without taking much of the field out of production (Figure 9). Ideally, placing targeted BMPs in areas most likely to generate runoff and contribute nonpoint source pollution would reduce some of the negative impacts for farmers of implementing BMPs in their fields, such as removing less land from production.

These land management methods are focused on targeting BMPs or removing land from production on an individual field by field basis. From a regional water quality perspective, one could consider agricultural land management of the entire watershed when removing land with a high potential for generating polluted runoff. For example, Method 1 could identify 10% of the agricultural land in one field generating essentially all of the runoff, while in another field, 10% of the land area targets only a small fraction of the area with the highest probability of generating runoff. The watershed scale method could support better management decisions for water quality at a regional scale by completely removing the highest risk agricultural fields from production. However, this shift from individual field to watershed scale management could require farmers in high risk areas to remove more than 10% of their land from production or change land management practices.

Future work for improving and applying this model might involve sampling in multiple land cover areas, such as forested or urban landscapes, which is the subject of an ongoing investigation by this research group. Continued long-term monitoring of soil moisture in the study region will provide a dataset across a larger range of climate conditions. The runoff probability models could also be improved by measuring the amount of runoff generated from the areas of the landscape predicted as a method for validating the models. Another aspect of this model that could be improved is how to address winter conditions and snowmelt on the soil VWC vs. STI relationship, and how this could be applied to early spring manure spreading. In addition to validating this logistic regression based runoff probability model for hydrologic accuracy, the model could be used to quantify how targeted agricultural management practices based on TWIs reduce nonpoint source pollution and provide optimal guidance for farmers.

This study used direct measurements of soil moisture to compile a spatially and temporally extensive database of soil VWC across agricultural fields in the Finger Lakes region of New York. The empirically derived linear relationships between soil VWC and STI value was strong at all the agricultural sites surveyed during spring, summer, and autumn seasons. Soil VWC and rainfall frequencies were used to estimate the probability of saturation excess storm runoff being generated from any point in the agricultural fields. With this runoff probability analysis, HSAs across the landscape can be easily identified and mapped based on STI distributions to calculate how much the risk of polluted storm runoff from VSAs can be reduced by removing HSAs from agricultural production. This analysis can be used to determine the optimal placement of conservation easements or management practices for the protection of water quality.

Table 6: STI threshold values below which the probability of runoff is less than 5% based on logistic model estimates. The percent of land in each field above the STI threshold has greater than 5% probability of generating runoff. Agnew et al. (2006) calculated STI thresholds of 8 in the spring and autumn and 10 in the summer and considered land with STI values below these thresholds to have low risk of runoff (< 5%).

Site	Spring		Summer		Autumn	
	STI Threshold	**Land Area Removed (%)**	**STI Threshold**	**Land Area Removed (%)**	**STI Threshold**	**Land Area Removed (%)**
1	7.5	14.9	8.5	8.5	6.5	5.2
2	6.5	75.9	10.5	7.9	10.5	7.9
3	6.5	77.5	7.5	62.6	5.5	77.5
4	5.5	96.9	7.5	64.8	7.5	64.8
5	8.5	20.6	8.5	20.6	8.5	20.6
Sixmile Creek watershed fields	5.5	90.4	7.5	43.5	7.5	43.5

Table 7: STI threshold values below which the probability of runoff is less than 30% based on logistic model estimates. Percentage of land removal required from agricultural production for a 70% reduction in the risk of runoff generation, based on the 30% probability of runoff threshold (L_{HSA}) proposed by Walter et al. (2000).

Site	Spring		Summer		Autumn	
	STI Threshold	**Land Area Removed (%)**	**STI Threshold**	**Land Area Removed (%)**	**STI Threshold**	**Land Area Removed (%)**
1	10.5	3.7	11.5	2.9	13.5	1.7
2	11.5	4.7	14.5	1.6	15.5	1.6
3	9.5	21.0	10.5	11.1	9.5	21.0
4	11.5	8.5	14.5	5.0	11.5	8.5
5	11.5	4.3	13.5	1.9	11.5	4.3
Sixmile Creek watershed fields	10.5	7.8	12.5	2.6	11.5	4.5

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