Precision Conservation in the Zumbro River Watershed Using LiDAR and Digital Terrain Analysis to Identify Critical Areas Associated with Water Resource Impairment in Agricultural Landscapes

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Abstract

Water quality impairment from non-point source (NPS) pollution is a serious concern for the Zumbro River Watershed in southeastern Minnesota where several lakes, rivers, and streams are listed as 'impaired waters' by the Minnesota Pollution Control Agency (MPCA). Agricultural operations are potentially major sources of NPS pollution including soil erosion and the off-site transport of agrochemicals to hydrologic drainage networks. To control NPS pollution and improve water quality, best management practices (BMPs) can be implemented such as buffer strips, grassed waterways, and reduced tillage. However, targeting the most beneficial location can be expensive and time consuming using conventional means. Precision conservation represents a new strategic approach to natural resource management using cutting-edge spatial technologies including geographic information systems (GIS), remote-sensing, and global positioning systems (GPS). The objective of this project was to evaluate the potential for adopting precision conservation methods and digital terrain analysis with high-resolution LiDAR elevation data to accurately identify critical areas in agricultural landscapes where conservation practices would be most effective, both financially and environmentally. Targeting critical areas was facilitated by signatures created from the Stream Power Index (SPI), a terrain attribute that measures the erosive power of flowing water and identifies places of accumulated overland flow.

Introduction

Minnesota is appropriately dubbed *The Land of 10,000 Lakes* for its abundance of lakes, rivers, and streams. The state has over 6,000 natural rivers and streams including the headwaters to the Mississippi River. Water is an important natural resource in Minnesota, vital for supporting recreation, wildlife, agricultural, commerce, etc. However, recently more and more water bodies have succumbed to excess pollution from agricultural landscapes geared towards maximizing crop yield productivity through intense farm practices. This has led to a situation where surface waters are becoming too polluted to meet certain water quality standards and therefore must be listed as *impaired*. A water body is listed as impaired by the Minnesota Pollution Control Agency (MPCA) when water quality standards fall below applicable levels. According to Section 303(d) of the Clean Water Act of 1972 (USEPA, 2009), states are required to identify and restore waters that fail to meet water quality standards. To restore water

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quality, calculations are made to quantify the maximum daily amount of any given pollutant or stressor a water body can receive and still meet water quality standards (USEPA, 2009). These calculations create the framework known as the Total Maximum Daily Load (TMDL) and are used to monitor and manage water quality impairments.

Soil erosion, excess nutrients, sedimentation, turbidity, and fecal coliform are sources of water quality impairment related to agricultural practices. These pollutants are forms of non-point source (NPS) pollution because their distribution is diffuse and intermittent with ill-defined sources across landscapes. This nebulous pollution is considered the most important remaining source of water pollution for the United States, requiring unique assessment tools and control strategies (Ice, 2004).

Wetlands & Agricultural Drainage

In Minnesota, approximately 50% of the original pre-settlement wetlands have been lost due to draining and filling (Anderson and Craig, 1984). The earliest farmers viewed wetlands disparagingly and shared a pervasive sentiment to drain or fill wetlands whenever possible in order to make land arable and potentially more profitable. This movement was facilitated by several mechanisms including installation of artificial subsurface drainage and re-routing surface waters into drainage ditch networks. A field with subsurface drain tile installed can potentially begin planting operations earlier in the growing season because it will shed melting snow-water faster and thus dry out the soil sooner thereby allowing timely access for heavy farm machinery. Consequently, the growing season is extended by several weeks in certain regions, especially in the northern latitudes where significant snow accumulation is common and accessing crop fields is delayed until after the snowpack is gone. These same fields however will also transport nutrients, fertilizers, pesticides and other applied agrochemicals to drainage networks faster if present during runoff events.

Despite the advantages of a hydrologically managed landscape, the draining of wetlands can have dire ecological consequences. Wetlands deftly serve as the proverbial kidneys for a watershed, effectively filtering sediments, nutrients, and other pollutants from water. Furthermore, wetlands control the storm water surge occurrences in drained areas. Drained wetland areas transport water much faster downstream and convey much more sediment material directly into existing water bodies. Lastly drainage ditches and subsurface drain tile convert diffuse flows from a landscape into concentrated flows thus increasing erosion potential and pollution levels.

The Zumbro River Watershed

The Zumbro River Watershed (ZRW), designated by the 8-Digit Hydrologic Unit Code (HUC) 07040004 is located in southeastern Minnesota (Figure 1). The watershed drains a total area of approximately 1,421 sq. miles (909,363 ac) and has 100 minor watersheds at the 12-Digit HUC level with elevation ranging from 1,380 feet above mean sea level in the southwest to 659 feet in the northeast. Parts of the watershed extend into Goodhue, Rice, Wabasha, Steele, Dodge, and Olmsted Counties. The ZRW is drained by the North, Middle, and South Forks of the Zumbro River, in addition to numerous perennial and intermittent streams.

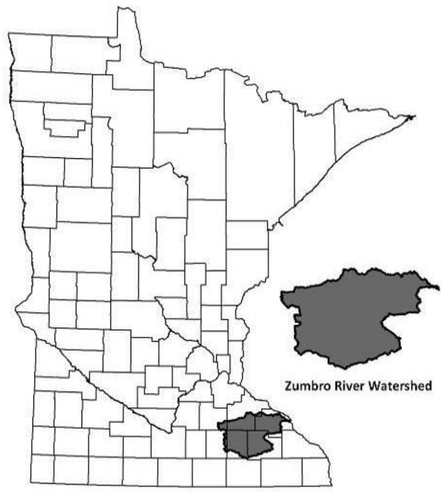

Figure 1. The Zumbro River Watershed (shaded grey), located in southeastern, MN.

The ZRW is geomorphologically diverse, split between the mostly level glacial till landscape of the Western Corn Belt Plains and the rolling deeply incised landscape of the Driftless Area (Figure 2). The

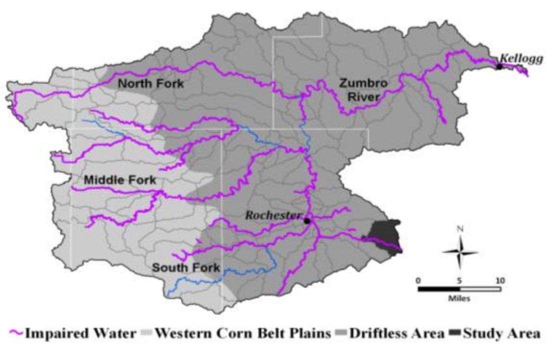

Figure 2. The Zumbro River Watershed.

headwaters for each major branch (North, Middle, and South Forks) of the river originate within the Western Corn Belt Plains before traveling across the Driftless Area and finally draining into the Mississippi River near Kellogg, MN. Nearly every reach in the watershed is listed as impaired water (purple). The study area, the Bear Creek minor watershed is shaded black in the southeast corner.

Precision Agriculture versus Precision Conservation

An estimated 96.4 million acres of corn were planted in the United States in 2012, the highest planted acreage in seventy-five years (USDA, 2012). This increase in acreage is to a certain extent due to favorable growing seasons experienced in recent years but is also the result of advancements in the science of agronomy and the increased use of precision agricultural technologies. Precision agriculture is site-specific farm management that relies on specialized technology and equipment (e.g. global positioning system, remote-sensing, variable-rate farming equipment, etc.) for monitoring field productivity, fertilizer application rates, soil pH and moisture content, yield rates, etc. With precision agriculture, farmers are able to collect and analyze data used to make informed decisions for optimizing crop yield performance and soil productivity.

Similar to precision agriculture, precision conservation is a targeted natural resource management practice that relies on spatial technologies such as global positioning systems (GPS), remote sensing (RS), and geographic information systems (GIS) to link mapped variables to identify the hotspot areas where the greatest conservation good could occur (Berry, Delgado, Khosla, and Pierce, 2003; Cox, 2005). A distinguishing attribute of precision conservation is the broader scope and scale than field-specific precision agriculture. Precision conservation is a watershed approach focused on the interconnected cycles and flows of energy, material and water within three-dimensional contexts for ecosystem sustainability (Berry *et al*., 2003).

Precision conservation is a decision support tool that strategically targets less productive land or environmentally sensitive areas of a landscape to optimize environmental and economic benefits (McConnell and Burger, 2011). Furthermore, precision conservation is scalable and dynamic; applicable to a variety of landscapes including agriculture, forests, rangeland, riparian areas, and other ecosystems where environmental degradation occurs and the demand for cost effective conservation is high.

Critical Areas

Within agricultural landscapes, a place that is responsible for contributing a disproportionate amount of pollution and sediment to hydrologically connected drainage networks via overland flow is a critical area (Galzki, Birr, and Mulla, 2011). By targeting places where such disparity occurs, conservation practices become more cost-effective and attractive to landowners, thus increasing the likelihood such practices will be adopted. These critical areas are the places where the greatest improvement to an impaired water resource can be obtained for the least amount of capital investment (Maas, Smolen, and Dressings, 1985). As such, critical areas should receive priority when allocating conservation resources since a disproportionate amount of soil erosion, off-site transport of suspended material, or other types of environmental degradation occur at these places. Examples of critical areas include ravines, ephemeral gullies, side-inlets, upland depression areas, riparian areas, and sinkholes associated with karst geology. Critical areas associated with agriculture operations experience periods of concentrated flow and therefore can support the off-site conveyance of suspended solids, fertilizers, pesticides, and other agrochemicals.

For the purposes of this project, the definition of a critical area is a place where a disproportionate amount of concentrated flow accumulates in close proximity to surface water drainage networks. A critical area may also include places near karst related landscape features such as sinkholes or springs. Sinkholes provide a direct conduit for surface water to enter underlying aquifers and are prevalent throughout southeast Minnesota where they are considered sensitive landscape features with special restrictions aimed to mitigate the pollution that enters them (MPCA, 2005). Often, sinkholes in agricultural landscapes can be identified by the scattered archipelago of trees in crop fields where farmers have not tilled the land.

Digital Terrain Analysis

Digital terrain analysis was used in this project as a means for modeling and describing hydrologic events that occur across an agricultural landscape inside a GIS environment. The principles and techniques of digital terrain analysis have been applied successfully for several decades as a decision support tool for watershed resource management (Moore, Gessler, Nielson, and Peterson, 1993; Wilson and Gallant, 2000; Galzki *et al*., 2011).

In the Seven Mile Creek watershed, located north of Mankato, MN, the applications of precision conservation using digital terrain analysis and 3 m (9.8 ft) LiDAR elevation data to identify fine-scale erosional features associated with contaminant-producing features in agricultural landscapes was explored (Galzki *et al*., 2011). These features included ephemeral gullies and side-inlets with significant flow concentration and hydrologic connectivity to agricultural ditches and streams. Additionally, the study gave economic merit to digital terrain analysis by demonstrating how signatures from the Stream Power Index (SPI) can aid field crews in locating small, field-scale features from a desktop workstation thus reducing project time and costs.

In another study Yang, Chapman, Gray, and Young (2007) developed a GIS model for delineating soil landscapes using digital terrain analysis and the Compound Topographic Index (CTI) to generate soil landscape facet maps. CTI describes the spatial distribution and extent of zones of saturation for soil erosion modeling (Wilson and Gallant, 2000). Their study reported overall 93% accuracy for delineating soil landscape facets using digital terrain analysis.

The foundation of any digital terrain analysis is the DEM (digital elevation model) and the myriad of terrain attributes derived from it. To improve model accuracy and analytical results it is imperative to use the highest resolution DEM available (e.g. LiDAR).

LiDAR

The DEM used in this project was derived from LiDAR (Light Detection and Ranging) technology. LiDAR data is an optical remote sensing technique with a high spatial resolution that allows for precise surface modeling and accurate terrain analysis. Until recently, most elevation data came with a spatial resolution of 10 m (32.8 ft) or greater. The LiDAR data used in this project had a spatial resolution of 1 m (3.3 ft). With 1 m LiDAR, landscape features can be detected with greater accuracy than elevation data with coarser resolution. Figure 3 is a side-by-side comparison of 10 m (32.8 ft) LiDAR and 1 m (3.3 ft) LiDAR.

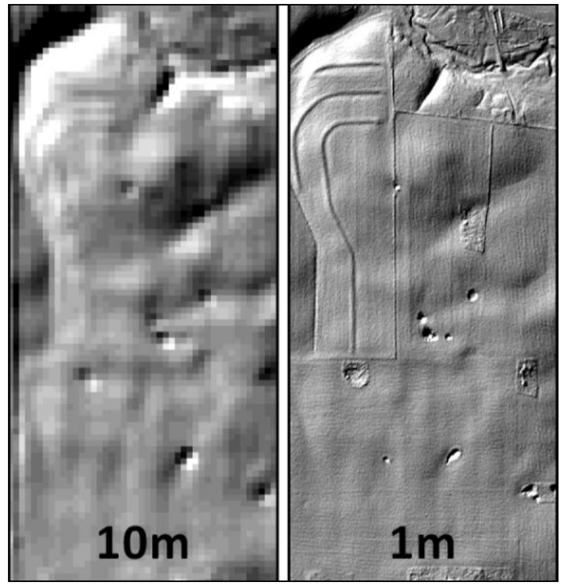

Figure 3. Resolution matters; the DEM on the left has 10 m (32.8 ft) resolution compared to 1 m (3.3 ft) resolution of the DEM on the right. Sinkholes and terraces on the left are much fuzzier and less recognizable compared to those same features on the right. The DEM on the right shows more detail and will yield greater model accuracy and thus more potential conservation value. Both images are at a common same scale of 1:12,000.

LiDAR data is typically captured via a fixed-wing aircraft or helicopter carrying a laser and rangefinder unit mounted onboard. The laser sends pulses of light energy to the ground and measures the return time for each pulse. The laser ‘paints’ the ground surface with a massive amount of return points (1.5 million per square mile for 1-meter resolution) creating a point cloud that is used to generate the high-resolution DEM. Each point return has horizontal coordinates and an elevation value. A GPS unit measures and records the position and time of each elevation point and an Inertial Measurement Unit (IMU) onboard accounts for any pitch, roll, or yaw of the aircraft.

Elevation data collected using

LiDAR technology can be used to generate a DEM with sub-meter accuracy that is especially useful for accurate surface representation and precision digital terrain analysis. In the emerging field of precision conservation, LiDAR data has become a valuable resource for fine-scale digital terrain analysis and hydrologic modeling including modeling potential flood scenarios and delineated areas prone to flood-related impacts. LiDAR data is especially useful in landscapes with low relief due to its ability to model subtle topographic features that are difficult to capture from ground surveys.

High-resolution LiDAR data can significantly reduce the time and cost of detecting small features at the field scale level compared to traditional field surveys. Galzki *et al*. (2011) compared critical area detection results between 30 m (98 ft) and 3 m (9.8 ft) elevation data and found that coarser resolution data could not accurately target individual erosional features as well as high resolution LiDAR data.

In 2009 LiDAR data became publically available in Minnesota for nine southeastern counties in response to a destructive rainfall event that occurred in August 2007. The damage caused by the storm was extensive and costly with seven counties declared disaster areas. This led the Minnesota Legislature to provide mitigation against future flood events including the acquisition of LiDAR data for the worst hit counties. The project was managed by the Minnesota Department of Natural Resources (MnDNR) and has continued to include the entire state with an expected completion date of 2012. Figure 4 represents the extent of available LiDAR data for Minnesota (MnDNR, 2012). As of July 5th, 2012 all 87 counties in Minnesota have LiDAR data collected, however a small percentage are still in the processing stages and have not yet made the data publically available.

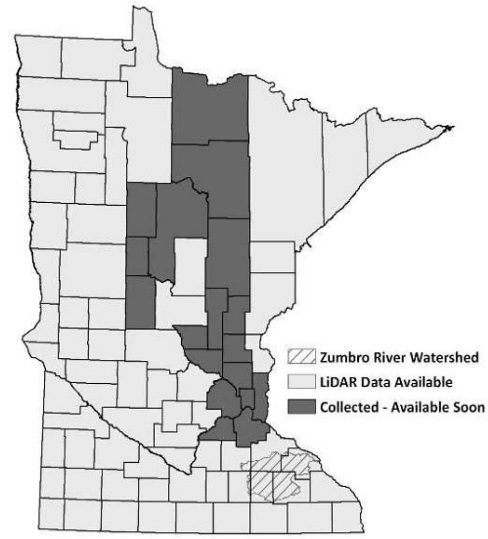

Figure 4. Graphic of LiDAR availability in Minnesota as of July 5th, 2012.

Methods

Description of Study Area

The study area for this project was the Bear Creek minor watershed, a minor watershed of the Zumbro River Watershed located entirely within Olmsted County, MN. The Bear Creek minor watershed is designated by the 12-Digit HUC 070400040106, with elevation ranging from 1,328 feet above mean sea level in the northeast to 1,080 feet in the west. The study area was chosen for the following three reasons: (1) the watersheds namesake river, Bear Creek, is listed as impaired for excessive turbidity (MPCA, 2010) indicating active pollution; (2) the total drainage area is 8,917 ac (3,609 ha), a manageable land unit size for digital terrain analysis and computer processing requirements; (3) the dominant industry is farming with approximately 5,604 ac (63%) classified as agricultural land according to the Minnesota Land Cover

Classification System (MLCCS, 2011). Figure 5 shows the study area along with the location of feedlots, land cover, and the impaired Bear Creek.

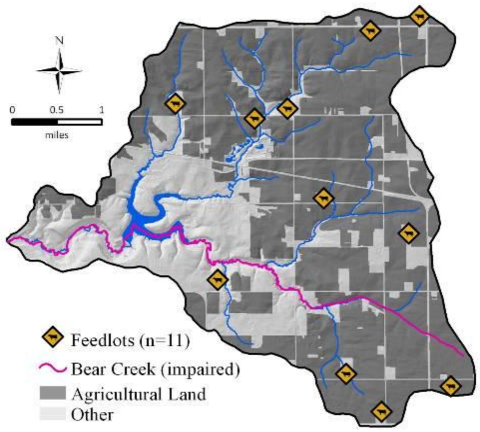

Figure 5. Land cover map of the Bear Creek minor watershed. Eleven registered feedlots are shown. Bear Creek flows through Chester Woods Lake and is listed as impaired water by the MPCA.

The Minnesota Pollution Control Agency (MPCA, 2009) recognizes eleven registered feedlots consisting of 4,704 animals with the majority animal type represented by pigs (4,000), followed by bovines (543) and birds (140). Feedlots, especially large operations, can be major sources of agriculture pollution if managed improperly.

The underlying geology of the Bear Creek watershed is primarily composed of Prosser Limestone from the Galena Group. This carbonate bedrock type is known for being soluble to mildly acid waters and can form landform features called karst. Karst features include sinkholes, sinking streams, springs, and caves. Parts of the Bear Creek watershed are influenced by karst features, with approximately 72 sinkholes and 21 springs mapped. Karst aquifers are susceptible to ground water contamination when solution-enlarged fractures and sinkholes form conduits for surface water runoff to enter the aquifers below (Alexander and Maki, 1988). In agricultural landscapes extra care must be taken to minimize the risk of contaminating ground-water supplies with fertilizers, pesticides, nutrients, and other agrochemicals.

Data Acquisition

The GIS data layers used in this project were retrieved from the following agencies:

DNR Data Deli, hosted by the Minnesota Department of Natural Resources (MnDNR).

- 24k_streams polyline shapefile
- 1 meter LiDAR elevation raster
- Karst Feature Inventory point shapefile
- land cover – Minnesota Land Cover Classification System polygon shapefile
- HUC 08 watershed polygon shapefile

The Minnesota Pollution Control Agency (MPCA).

- feedlot point shapefile
- 303(d) impaired waters – Streams (2010) polyline shapefile

The Natural Resources Conservation Service (NRCS), United States Department of Agriculture (USDA) Web Soil Survey.

- Soil Map Unit – polygon shapefile

The following methods were used for calculating primary and secondary terrain attributes including the Stream Power Index (SPI) which was based on research published by Wilson and Gallant

(2000), with further considerations made for recent advancements in the quality of digital terrain data and the use of LiDAR by Galzki *et al*. (2011). Terrain attributes were calculated using ESRI's ArcGIS software version 10.0, the 3D Analyst and Spatial Analyst Extensions.

Primary Terrain Attributes

Primary terrain attributes were calculated directly from the 3 m (9.8 ft) DEM and these included the following spatial variables: surface elevation, slope, flow direction, and flow accumulation.

Secondary Terrain Attributes

Secondary (compound) terrain attributes combine two or more primary attributes to produce indices to describe spatial patterns as a function of process (Wilson and Gallant, 2000). In this project the Stream Power Index (SPI) was used as the primary surrogate for critical area detection.

SPI is the product of two primary terrain attributes: flow accumulation and slope. SPI measures the erosive power of flowing water assuming discharge is proportional to a specific catchment area. SPI was chosen for this analysis because its application has been successfully demonstrated and well documented in earlier studies of soil erosion, off-site sediment transport, and geomorphology (Moore *et al*., 1991; Galzki *et al*., 2011).

After calculating SPI each 3x3 meter pixel on the DEM surface was assigned a numeric value that could be ranked among all other pixels in the dataset to identify areas of concentrated flow. These places were where conservation practices should focus efforts because active soil erosion and environmental degradation likely occurs there.

The conservation value of the SPI attribute is its ability to conceptually identify areas of a landscape where erosion potential is high from overland water flow (Wilson and Gallant, 2000). This alone can be a difficult and time consuming task using traditional field surveys.

Data Processing

All GIS data layers used for this project were projected in North American Datum (NAD) 1983 Universal Transverse Mercator (UTM) Zone 15N.

The 12-Digit HUC watershed polygon shapefile for the study area was used to clip out a smaller subset of the original 1 m (3.3 ft) DEM and all other data layers. This polygon was also used to define the extent of all subsequent analytical interpolations.

When modeling surfaces with digital elevation models it is important to screen for small imperfections that can introduce error to analytical results, especially when modeling hydrologic processes (Wilson and Gallant, 2000). In a raw DEM it is possible for isolated cells to have values much higher or lower than neighboring cells. This occurrence can produce 'sinks' in the DEM where no sinks or depressions actually exist in the real world. These false sinks, or pits, can be removed, or filled, by using the Fill operation of ArcGIS. The decision to Fill is dependent on the physiographic characteristics of the landscape. For instances in landscapes with low relief and irregular drainage networks small depression do occur and filling these would not be appropriate. In contrast for landscapes with a higher relief and greater hydrologic connectivity it is appropriate to run the Fill operation. For this study the

DEM for Bear Creek was hydrologically conditioned using the Fill operation. Once hydrologically conditioned, the DEM was resampled to a 3 m (9.8 ft) DEM; a resolution that demands less computing power and yet still maintains a high level of spatial accuracy (Galzki *et al*., 2011).

A slope layer was generated in percent rise with a z-factor of 1. The flow accumulation layer was generated by first running the flow direction operation on the DEM. The output of the flow direction was a raster with cell values indicating the direction from each cell to the steepest downslope neighbor.

For this analysis an accurate stream network layer was required to identify the locations of where SPI signatures intersected existing flow paths. To accomplish this, a modified stream layer was created using the original 24k_streams layer as a template. The original stream layer was created for use at a scale of 1:24,000 and as such was not accurate enough for this analysis in most places. To improve stream representation the streams layer was edited using aerial photographs and hillshade layers as background references. Figure 6 illustrates the incongruity between the original stream layer and the corrected stream network layer using a hillshade layer for a reference. This tedious effort significantly improved analytical accuracy and critical area identification.

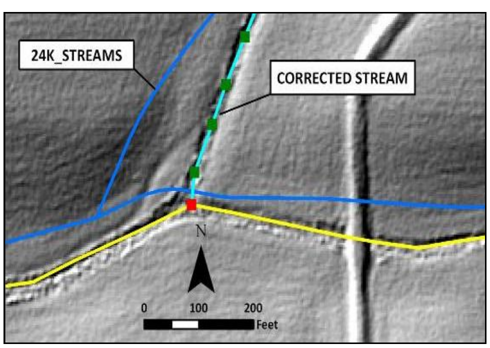

Figure 6. Corrected stream network in the study area using a hillshade layer for a reference.

Analysis

To limit the areal extent for investigation within the study area only those lands classified as both cultivated and within 300 m (984.3 ft) of a stream or river were screened for possible critical areas. This land area was calculated by buffering the corrected streams layer by 300 m (984.3 ft) and intersecting it with the cultivated land layer. Once combined to a single layer the land area for investigation totaled 3,344 ac, approximately 38% of the entire Bear Creek watershed (Figure 7).

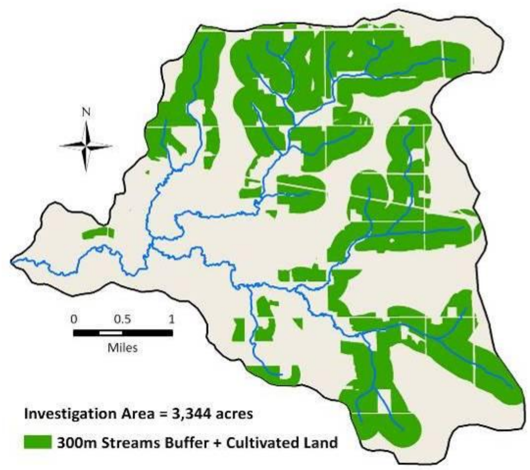

Figure 7. Area of investigation in green; intersection of cultivated lands and 300 m streams buffer totaling approximately 3,344 ac.

Before calculating the Stream Power Index, input layers were first reclassified so any ‘No Data’ values become ‘0’ and then a value of 0.001 was added to each pixel to avoid multiplying by ‘0”. The Stream Power Index was calculated by using the Raster Calculator in ArcGIS with the following equation:

$$SPI = \mathrm{Ln}\,(FA) * (Slope)$$

where FA is Flow Accumulation and Slope is measured in percent rise.

The SPI layer was then reclassified using a threshold value to isolate places of high concentrated flow. Threshold value selection was made initially through visual assessment by overlaying the SPI layer with high-resolution aerial photography. To isolate only the highest SPI values a threshold representing the 80th percentile was used. Other data layers were also used in support of the SPI to identify critical areas. These ancillary data layers included land cover data, proximity to water, and soil types.

Critical areas potentially exist where SPI signatures intersect existing drainage networks. Where SPI signatures intersected an existing drainage network a point was placed to indicate a possible critical area location (Figure 8). Through

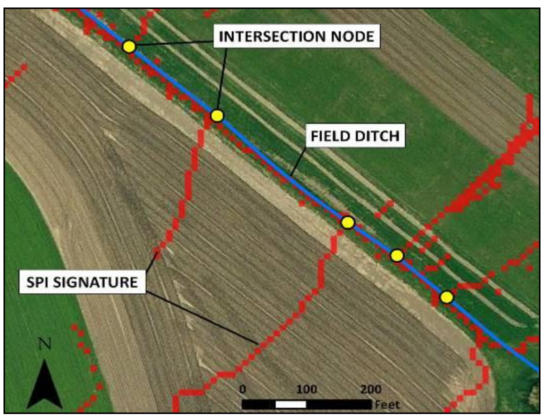

Figure 8. SPI signatures are shown in red identifying places where overland runoff and concentrated flow occurs. Yellow dots are places where a SPI signature intersected with field drainage ditch and potentially represents active erosional features.

surface interpolation using the Add Surface Information tool from the Functional Surface Toolbox (3D Analyst Tools), each point was assigned the value of the underlying SPI layer. This allowed for a closer examination of the SPI values correlated with drainage network connectivity. The attribute table for the critical area points was exported as a spreadsheet into Excel where percentile classes were calculated. Percentile classes were used as thresholds for determining which critical areas should receive priority when allocating conservation resources.

Results

A total of 147 critical area points were identified within the study area using the aforementioned methodology. Of these 147 points, 136 (93%) were at places where the SPI signatures intersected surface water drainage networks, the other 12 (8%) were associated with sinkholes. While sinkholes typically lack direct connectivity to surface water drainage networks, they do represent direct passage to underlying aquifers and therefore were included as critical areas for this analysis. To address each of the 147 critical area point locations would be an unrealistic task and therefore it was important to rank and prioritize all the points to identify only the most critical. Prioritizing the critical areas was achieved by determining which points had values at or above the 80th percentile threshold for SPI values. This resulted in 30 (20%) points qualifying as high priority, 2 of which were associated with sinkholes (Figure 9). These 30 points

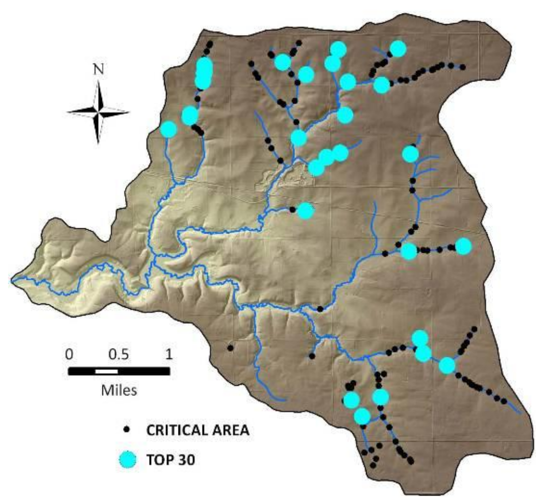

Figure 9. A total of 147 critical areas were located in the Bear Creek study area. The top 30 critical area locations are highlighted in teal.

represent areas of the highest concentrated flow and largest upslope contributing area and therefore should receive priority for allocating conservation resources.

To further quantify these findings an effort was made to calculate the total land area that contributed overland flow to each critical area point. Two methods were investigated for accomplishing this task, an automated approach and a manual approach. The automated approach used the ArcGIS Basin operation from the Spatial Analyst tools while the manual approach involved hand digitizing polygons. The results from the automated approach did not accurately represent actual drainage patterns and therefore the 30 pointsheds were delineated by hand digitizing individual polygons. Galzki *et al*. (2011) also reported that hand digitizing polygons using contour lines and flow accumulation signatures as a reference was more accurate than using the Basin operation in certain landscapes. Acreages were calculated for the 30 pointsheds to establish the total land area within the study area that was directly associated with a critical area. Figure 10 shows an example of the pointsheds that were delineated for each critical area.

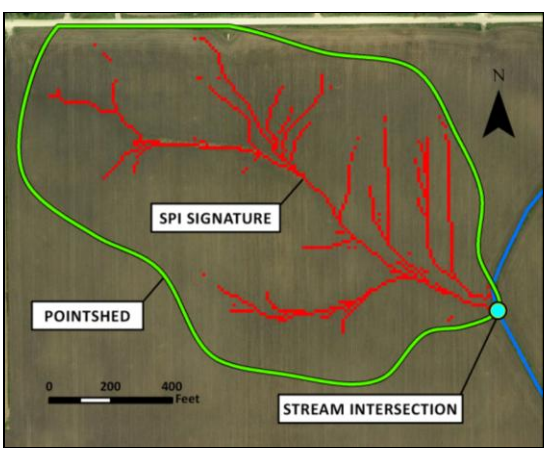

Figure 10. Pointshed delineated around the upslope contributing area for a critical area within the Bear Creek study area. The contributing area shown here measured approximately 30 ac.

For the entire study area (8.917 ac), approximately 498 ac (6%) were within critical area pointsheds. However, it is noteworthy that 334 ac were located in the northern part of the study area where the landscape is absent of surficial depressions caused by karst related sinkholes (Figure 11). These sinkholes are

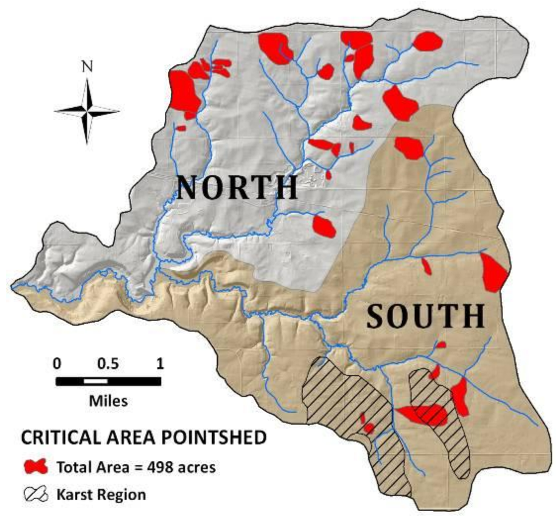

Figure 11. Distribution of critical area pointsheds in the Bear Creek study area. Of the 498 total ac, 334 ac (67%) were located in the northern half and the remaining 164 ac (33%) were located in the southern half where karst features occur.

only located in the southern part of the study area and could have some influence on the amount of overland surface flow. The land area encompassed by each pointshed varied considerably within the study area. The average pointshed size was approximately 17 ac (max 58 ac.; min 2 ac.). When selecting a location for implementing a conservation practice it may be useful to consider the size of the contributing area and assign priority to pointsheds with large contributing areas.

Soil types within the study area were important attributes to further determine the conservation value of critical areas. To accomplish this, a soils polygon shapefile layer representing the Crop Productivity Index (CPI) was clipped to the study area. The CPI is a relative ranking scale from 1 (lowest) to 100 (highest) for soils based on potential yield (NRCS, 2011). The clipped soils layer was converted into raster format and then converted into integer format where upon zonal statistics were calculated using the pointshed polygons as the zones. This operation assigned an average CPI value for each pointshed in the study area and allowed for each pointshed to be ranked by the CPI value with normalization from acreage. Interestingly, these results gave a higher rank to the smaller pointsheds compared to just using area as the only factor in ranking priority. These finding are significant for agricultural operations because from a landowner's perspective it may be more tangible to address the conservation concerns for a smaller area of land, especially when that land has a high crop productivity rating.

Conclusions

The Stream Power Index (SPI) derived from a 3 m (9.8 ft) LiDAR DEM was the most important data layer used for the screening of critical areas. Signatures from the SPI clearly identified places where concentrated overland surface flow occurred and upslope contributing areas were large. Creating a pointshed for each of the most critical areas was useful for quantifying the land area responsible for contributing overland flow to critical areas. Also important was the soils data, specifically the Crop Productivity Index (CPI) which gave priority to those places where highly productive – and valuable – land was most at risk. Combining the total area of land with the CPI value further assisted in ranking and prioritizing critical areas for conservation resources. Based on the findings that indicate only 6% of the study area is classified as high priority, a field crew would become more efficient in surveying for areas where conservation resources could be most effective.

Taking these results into the field would involve uploading critical area points to mobile GPS units to guide field survey crews to areas where conservation practices would be effective. Without these data points or being present during a precipitation event such places may be very difficult to locate. Table 1 lists the

Table 1. The top 30 Critical Areas with SPI, acres, elevation, UTM coordinates provided to aid field crews in locating potential candidate sites for conservation practices. CA# 4 & 5 were sinkholes.

CA#	SPI	ACRES	ELEV. (ft.)	UTM_X	UTM_Y
1	6.60	29.17	1271.5	559078	4872565
2	4.26	20.79	1216.6	557379	4871670
3	4.96	47.04	1251.9	558597	4868725
4	4.71	2.69	1267.1	558125	4868677
5	4.70	5.22	1269.8	558295	4868418
6	4.49	5.55	1253.2	559281	4869417
7	4.64	39.89	1265.6	559932	4871107
8	4.41	5.05	1243.8	559049	4871029
9	4.53	27.85	1257.4	558066	4873704
10	4.73	10.59	1269.1	558020	4873185
11	4.90	10.67	1263.6	557393	4873822
12	5.87	10.87	1220.2	557273	4872823
13	4.47	5.18	1259.2	557724	4872515
14	4.78	2.23	1275.4	557946	4872583
15	5.59	2.37	1240.2	557559	4872354
16	4.45	25.65	1262.6	559671	4869227
17	6.22	47.62	1268.2	557017	4874017
18	4.55	25.97	1291.6	557913	4874216
19	5.30	3.24	1278.3	557823	4873999
20	4.25	26.22	1292.7	558876	4874232
21	5.10	43.63	1279.8	558615	4873655
22	5.03	14.30	1262.2	555731	4873716
23	4.28	6.32	1272.1	555756	4873965
24	4.50	4.63	1267.0	555746	4873851
25	4.43	4.98	1266.5	555747	4873842
26	4.19	2.34	1268.7	555756	4873885
27	5.73	57.72	1229.9	555521	4873193
28	4.96	4.51	1230.0	555514	4873154
29	5.05	2.68	1233.5	555177	4872954
30	4.35	3.23	1257.4	559227	4869652

high priority areas and provides the geographical locations to aid field crews.

Such areas would be suitable candidates for implementing cost-effective conservation practices, such as variable-width buffers. Primarily side-inlets and gullies, these features indeed would be difficult to discover without extensive and rigorous field surveys. Compared to the cost of deploying field crews to survey for small features in an agricultural landscape, a desk-top approach using high-resolution LiDAR data and digital terrain analysis is economically advantageous and equally accurate. For example, the analysis conducted in this project could be completed in another watershed assuming LiDAR data was available in less a few hours. Field-crews could take GPS units with the critical area points uploaded and rapidly evaluate the need for implementing conservation practices. This guided survey would reduce field time and costs significantly.

Certain limitations for the SPI exist and should be mentioned. First, the values of the SPI are not transferable from one watershed to another. Each landscape will have certain terrain attributes that require a unique SPI threshold to be determined. Even though the applicability of terrain analysis and the SPI exists across nearly all watersheds, determining the specific threshold values requires site specific analysis. Local knowledge is also an important factor when determining SPI threshold values.

Another limitation of the SPI is the inherent shelf-life of elevation data gathered through remote sensing. The older the data, the less reliable it is. The topography of landscapes, especially those used for agricultural purposes will evolve over time as farm management practices change or extreme weather events occur. Stream channels shift over time causing incongruity between digital elevation models and the real world. While the differences may appear negligible it is always important to consider the date of remotely sensed data when drawing conclusions from the analysis.

This project demonstrated the potential for precision conservation as an effective approach for addressing water quality issues in agricultural landscapes. Specifically, the use of digital terrain analysis and high-resolution LiDAR data has proven capable for targeting environmentally susceptible areas where conservation practices would be most effective. As the processing power of computers increases and the availability of high-resolution, digital elevation data improves, so will the effectiveness of digital terrain analysis as a precision conservation tool. Smaller and smaller features will be detected more rapidly and with greater accuracy in the future thereby further improving conservation efficiencies.

As the global population continues to grow, it will be imperative to adopt sustainable agricultural practices that protect the finite amount of arable land available. This project demonstrated the utility of using high-resolution LiDAR data and the potential it has for improving soil and water conservation practices. Traditional field surveys can take several months and hundreds of man hours to accomplish and as a result many conservation practices are not planned and improvements in water quality are not met.

The value of using GIS and digital terrain analysis as a decision support tool for precision conservation is in its’ ability to collect, store, query, analyze, model and display geospatial data layers within a digital environment. Inside a GIS, numerous data layers can be used as inputs to run models that predict natural phenomena and help identify spatial relationships and patterns useful for land managers. The spatial and temporal variability that occurs regularly in agricultural systems can be accounted for within a GIS by adjusting model parameters accordingly, thus producing meaningful results for any given scenario.

Using precision conservation techniques to identify places in a landscape where the greatest benefit to water quality can be achieved for the least cost will continue to be a valuable asset for watershed management.

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