2015

Identifying Potential Locations for Grassed Waterways using Terrain Attributes and Precision Conservation Technologies

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IDENTIFYING POTENTIAL LOCATIONS FOR GRASSED WATERWAYS USING TERRAIN ATTRIBUTES AND PRECISION CONSERVATION TECHNOLOGIES


ABSTRACT. Grassed waterways (GWWs) are an effective conservation practice for preventing ephemeral gully erosion resulting from channelized surface runoff in agricultural fields. However, field reconnaissance to identify areas of channelized erosion within a watershed can be time-consuming and labor-intensive. Recent advances in precision conservation and light detection and ranging (LiDAR) technologies can provide valuable information on environmentally sensitive areas that cause soil degradation. The objective of this study was to demonstrate that a compound topographic index (CTI) model supplemented with LiDAR data can be used to identify potential GWW locations and inform design recommendations. A LiDAR digital elevation model with a spatial resolution of 3 m was used to derive terrain attributes (slope, drainage area, and plan curvature). The GWW identification and design process was automated in the ArcGIS Python environment. The plan curvature identified erosion channels, but discontinuity in the model output was observed. The CTI model was calibrated to a field with GWWs installed under USDA-NRCS guidelines, which yielded a CTI threshold of 30. The calibrated model (CTI ≥ 30) was able to identify all 14 existing GWWs in the watershed. Field surveys were conducted in the watershed, and areas exhibiting evidence of channelized erosion were identified by the model for GWW placement. Furthermore, the CTI model overestimated (PBIAS = -23.34%) the lengths of predicted GWWs, suggesting a need to further extend the existing GWWs. The total surface area of the predicted GWWs was 29.3 ha in the study watershed, with depth of GWWs reaching 0.3 m. The design process provides an estimate of land to be set aside for conservation practices. The terrain analysis was effective in targeting conservation practice placement and improves the accuracy of field assessments.

Keywords. Grassed waterways, LiDAR, Topographic index, Waterway design.

Soil degradation continues to be a major challenge in achieving food security and sustainability in the 21st century (Delgado et al., 2011a). Soil erosion from agricultural lands by water occurs primarily by three processes: sheet erosion, rill erosion, and gully erosion. Foster (1986) introduced the term “ephemeral gullies” to describe erosion resulting from concentrated overland flow in agricultural fields. Ephemeral gullies are temporary erosion features that are larger than rills but can be easily obscured by tillage (Foster, 1986). Ephemeral gully erosion can contribute significantly to the total soil losses in agricultural watersheds and leads to soil degradation. In the U.S., ephemeral gullies are estimated to account for 30% of total soil loss (Bennett et al., 2000). Studies have identified ephemeral gully erosion as a significant, if not the dominant, source of sediment in agricultural watersheds (Poese et al., 2003; Gordon et al., 2008).

Grassed waterways (GWWs) are effective conservation practices used to prevent ephemeral gully formation along natural drainage ways (Atkins and Coyle, 1977). GWWs reduce ephemeral gully erosion and agrochemical export to surface waters (Briggs et al., 1999; Chow et al., 1999). For example, Chow et al. (1999) found that GWWs combined with terraces reduced runoff by an average of 86% and soil erosion by 95%. In a laboratory experiment, GWWs were found to reduce herbicide loss in runoff by an average of 56% (Briggs et al., 1999). Moreover, there have been extensive hydrologic modeling efforts to evaluate the effectiveness of GWWs on runoff and its constituents (Fiener and Auerswald, 2006; Dermisis et al., 2010). Dermisis et al. (2010) investigated the effects of GWW length on runoff and erosion reductions in an agricultural watershed in Iowa using the Water Erosion Prediction Project (WEPP) model. Sediment yield reductions were found to be directly related to GWW length, and peak runoff rate was identified as the dominant factor influencing the effectiveness of GWWs for sediment yield reduction (Dermisis et al., 2010). These modeling studies determined that GWW characteristics, including length, bottom cross-section, and vegetation roughness, govern the efficiency of runoff and sediment
Reduction. Moreover, the placement of GWWs is crucial for effective soil and water conservation; however, current methods to identify eroded channels resulting from concentrated water flow are limited.

Recent advances in the resolution of digital elevation data can be used to more accurately identify environmentally sensitive areas for precision conservation. Delgado et al. (2011b) conducted a comprehensive review of studies demonstrating the use of precision technologies in soil and water conservation. Light detection and ranging (LiDAR) data provides precise terrain attributes that can be used to identify critical source areas for targeted conservation practices (Galgzki et al., 2011). Mueller et al. (2005) used terrain attributes, remote sensing, and soil electrical conductivity data to develop erosion probability maps. Critical source areas can be described as the portions of the landscape that have a disproportionate and significant effect on water quality or soil degradation. Researchers have used precision conservation techniques with high-resolution elevation data to identify critical source areas for best management practice (BMP) placement (Tomer et al., 2003; Luck et al., 2010). More recently, Tomer et al. (2013) demonstrated that terrain attributes obtained from LiDAR (1 m) data can be used to identify critical areas for wetland placement in an HUC-12 watershed.

The primary function of effective GWWs is to prevent ephemeral gully erosion; therefore, locating the areas prone to erosion is necessary to identify potential locations for GWWs (Fiener and Auerswald, 2003). Various studies have developed methods to detect ephemeral gully locations using terrain attributes and topographic threshold values (Moore et al., 1988; Thorne et al., 1986; Parker et al., 2007; Daggupati et al., 2013 Momm et al., 2013). Pike et al. (2009) developed erosion probability maps with 4 m elevation data using logistic regression and neural networks for GWW placement in Kentucky fields. Thorne et al. (1986) developed the compound topographic index (CTI) model and detected ephemeral gully locations in Mississippi fields using soil-specific threshold values. The CTI is a product of slope, upstream drainage area, and plan curvature. Ephemeral gully locations were detected when the CTI exceeded the topographic threshold. Daggupati et al. (2013) investigated four topographic index models to predict ephemeral gully locations in Kansas and concluded that slope-area (product of drainage area and slope) and CTI models predicted the occurrence of ephemeral gullies better than other models. While terrain attributes have been used to locate potential ephemeral gullies, topographic models have not yet been evaluated as tools for predicting placement of GWWs for BMP implementation.

Identifying critical source areas for BMP implementation is crucial for developing an effective watershed management plan. To achieve overall watershed water quality goals, conservation practices must be located where they are most effective. The goal of this study was to evaluate the CTI model in identifying potential locations for GWW placement. The specific objectives were to (1) demonstrate the CTI model in identifying potential locations for GWWs at watershed scale, and (2) design the GWWs at field scale according to USDA-NRCS guidelines. The results are useful to conservationists and farmers for prioritizing BMP sites to meet watershed-scale water quality goals, receive incentive payments through the USDA Conservation Reserve Program (CRP), and determine how much land must be removed from production for BMP implementation to reduce ephemeral gully erosion.

**METHODS**

**STUDY LOCATION**

This study was conducted in the Hickory Grove Lake watershed (HGLW) located in the Des Moines Lobe region of Iowa (fig. 1). The watershed has an area of 1629 ha and drains into an approximately 40 ha lake, which results in a high watershed-to-lake area ratio of 40:1. Land use in the watershed is dominated by agriculture, with 84.7% of the watershed under corn (Zea mays L.) and soybean (Glycine max [L.] Merr.) rotation. The watershed is low-relief with median slopes of less than 2% except near stream corridors. The watershed is composed primarily of poorly drained soils formed in clayey lacustrine sediments deposited from the Des Moines glacial lobe. The agricultural fields in the watershed are supported by artificial subsurface drainage systems, and surface intakes are common in fields and in roadside ditches. Subsurface tile drainage was installed in most of the cropland in the watershed to make agricultural production feasible. The watershed covers 34 agricultural fields with areas ranging from 9 to 116 ha.

Ground truthing and aerial imagery acquired by National Agricultural Imagery Program (USDA-FSA, 2014) in 2009 were used to identify and digitize the existing GWWs in the watershed. The watershed has 14 GWWs with lengths varying from 193 to 886 m, and the widths of the waterways vary from 10 to 34 m. The total surface area covered by the existing GWWs in the watershed is 16.3 ha. The GWWs in field 30 (fig. 1) were designed and installed according to USDA-NRCS specifications. Ground truthing and farmer surveys conducted in the watershed indicated that the GWWs in fields 5, 16, and 31 are undersized and require frequent regrading (every couple of years) due to erosion in the GWWs.

**ELEVATION DATA**

A digital elevation model (DEM) in raster format containing elevation data was used to provide the terrain attributes for topographic models. Studies have previously evaluated DEM spatial resolution for topographic attributes and subsequent model results (Kienzle, 2004; Momm et al., 2012). The topographic attribute values for a raster grid cell vary with DEM resolution, and finer DEMs were recommended for locating ephemeral gullies, as coarser DEMs present limited topographic information (Daggupati et al., 2013; Momm et al., 2013). The LiDAR data (horizontal resolution of 3 m) for the study area were collected by the Iowa Department of Natural Resources in 2008 under Iowa’s LiDAR program. The primary terrain attributes (slope, upstream drainage area, and plan curvature) were derived from the 3 m DEM using ArcGIS (ESRI, 2012). These terrain attributes have previously been used to study
topographic features in various landscapes (Galzki et al., 2011). The “pit-filling” operation was conducted on the 3 m DEM before calculating the terrain attributes to remove small depressions that would cause water impoundments. This was also necessary to enforce flow pathway conveyance to downstream waters due to the impoundments caused by road structures.

The slope was calculated using the finite-difference slope estimation method (Gallant and Wilson, 1996). The hydrologic flow model commonly referred to as the D8 method was used to calculate flow direction and flow accumulation in ArcGIS (Jenson and Domingue, 1988). The upstream drainage area (or flow accumulation) refers to the total upland area that drains into any single cell, and this function can be used to determine the drainage area boundary. The plan curvature is a measure of flow convergence or divergence across the surface and determines the local flow geometry and the degree of concentration of the runoff (Zevenbergen and Thorne, 1987).

COMPOUND TOPOGRAPHIC INDEX MODEL

The CTI model has been previously used to predict the location of ephemeral gullies (Thorne et al., 1986; Parker et al., 2007; Momm et al., 2013; Daggupati et al., 2013). The CTI model uses slope, drainage area, and plan of curvature to characterize the spatial variability of the stream network occurring on the landscape. The CTI was calculated on each DEM pixel based on the following formula:

$$CTI = A \cdot S \cdot PLANC$$  

where $A$ is the upstream drainage area (m$^2$), $S$ is the slope of the surface (m m$^{-1}$), and PLANC is the plan curvature (m per 100 m). The upstream drainage area and the slope of the surface indicate the stream power, which is a proxy for flow intensity for predicting sediment carrying capacity. The plan curvature identifies the change in slope on the surface perpendicular to the downhill flow direction. The plan curvature indicates the concavity or convexity of the topography in that pixel across the surface, and the concavity of the topography can identify areas of flow convergence. The PLANC data can provide preliminary information for locating GWWs in a field.

Although topography is one of the most important factors controlling ephemeral gully formation, other factors also affect ephemeral gullies, such as rainfall depth and intensity, land use, and soil properties. Previous studies have researched thresholds for rainfall depth and intensity and soil water content for the formation of ephemeral gullies during different seasons (Casali et al., 1999; Nachtergaele et al., 2001; Cerdan et al., 2002; Capra et al., 2009). The erosion resistance of the topsoil controls ephemeral gully erosion, along with hydrology and topography (Knapen et al., 2007). The soil critical shear stress, determined by the soil properties, as well as vegetation cover and type of vegetation affect the susceptibility to ephemeral gully formation (De Baets et al., 2007; Prosser and Slade, 1994). A process-based approach to determine potential locations for GWWs is limited by the availability of rainfall, soil, and land use data. The CTI model is an empirical approach, and the findings of this study are applicable to watersheds with similar land use, slope, and soils.

The output of the CTI model is a map with a topographic index value assigned to each pixel. Potential locations for GWWs are identified when the CTI value exceeds the topographic threshold value. The CTI model has been previously used to identify ephemeral gullies and has been shown to be a better model than other topographic index models (Daggupati et al., 2013; Parker et al., 2007). How-
however, the CTI method requires a trial-and-error approach to determine the most appropriate threshold specific to each study site, as the likelihood of ephemeral gully formation is not dependent on terrain data alone. Therefore, in this study, a pragmatic approach was adopted to identify the critical CTI threshold for the HGLW. The CTI model output (potential ephemeral gully locations) may not be a smooth trajectory and may be discontinuous (pixels in the output may not be connected to each other). Therefore, a snapping procedure was used to convert the model output to line features to obtain a smooth trajectory and determine the lengths of the predicted GWWs (Daggupati et al., 2013). A snapping distance of 3 m was used in the snapping procedure.

**Grassed Waterway Design**

An automated process to design GWWs according to the effective stress methodology (USDA-NRCS, 2007) was built in the interactive development environment (IDLE) in Python (v. 2.7) interfaced with ArcGIS (ESRI, 2012). This process requires the GWW attributes listed in table 1 and drainage area characteristics specific for each GWW. The designed GWWs were tested under long grass and short grass conditions to examine if the runoff velocities during the design storm are within the permissible velocities for vegetation in the waterway. The Scientific Python (SciPy) computing environment in Python was used to determine the optimum depth and top width for the GWWs. The GWWs were designed so that they would be able to convey the overland runoff for a 10-year 24-hour storm event from the entire upstream drainage area.

**Model Evaluation**

The error matrix approach was used to summarize the agreement between the model-predicted ephemeral gully locations and ground truth data (GWW features). The error matrix approach was previously used in studies identifying the locations of ephemeral gullies (Gutierrez et al., 2009). The error matrix uses a binary scale (1 = GWW present, 0 = GWW absent) to estimate the number of correct and incorrect predictions. The entries in the error matrix (table 2) are defined as follows:

- \( a \) = the number of GWW line features for which the model predicted a need for GWWs when GWWs were actually present.
- \( b \) = the number of GWW line features for which the model predicted a need for GWWs when GWWs were absent (false positive, or error of commission).
- \( c \) = the number of GWW line features for which the model did not predict a need for GWWs when GWWs were present (false negative, or error of omission).
- \( d \) = the number of GWW line features for which the model predicted no need for GWWs, and no GWWs were present.

False negative values likely indicate poor model performance, whereas false positive values do not necessarily indicate poor model performance, as the model may identify new locations for GWWs that are not present in the watershed. The false positive rate was calculated as the number of false positives divided by the total GWW features predicted by the model, whereas the false negative rate was calculated as the number of false negatives divided by total number of GWWs present in the watershed.

The kappa statistic (\( \kappa \)), which indicates a quantitative measure of agreement between observers, was used to evaluate the model performance (Viera and Garrett, 2005). The classification rate was used to determine the accuracy of the model in predicting the existing GWWs, which involved distinguishing the model-predicted pixels that are inside and outside a GWW boundary. The classification rate was calculated as the number of pixels inside a GWW divided by the total number of pixels identified as potential erosion regions in a field. If all the model-predicted pixels are inside a GWW feature, then the GWW was considered correctly classified. The percent bias (PBIAS), which indicates overestimation or underestimation bias, was used to evaluate the performance of model predictions for GWW lengths (Gupta et al., 1999).

Field 30, in the southern part of the watershed, already has GWWs designed and installed according to USDA-NRCS recommendations. A range of CTI thresholds, from 2.5 to 200, was evaluated for field 30, and a threshold value was identified for which there were no false negatives (i.e., no GWW need predicted where a GWW actually existed) and a low number of false positives (i.e., a GWW need predicted where no GWW existed). That CTI threshold was then used to identify potential locations for implementing GWWs in the rest of the HGLW. The CTI model was thus calibrated to field 30. Field 30 is representative of the HGLW due to its 100% row crop land use, three soils (Clarion, Nicollet, and Webster) comprising 93.5% of the field, and slopes of less than 2%. The HGLW has 85% row crop land use, three soils (Clarion, Nicollet, and Webster) comprising 83.5% of the watershed, and median slope of about 2%. Daggupati et al. (2013) used CTI = 62 to locate ephemeral gullies in two Kansas fields, whereas Parker et al. (2007) determined that critical CTI thresholds varied from 7 to 62 to locate ephemeral gullies for ten sites in Mississippi.

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Table 1. Grassed waterway attributes used in the design process.

<table>
<thead>
<tr>
<th>Indices</th>
<th>GWW Attribute or Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shape</td>
<td>Parabolic</td>
</tr>
<tr>
<td>Vegetation</td>
<td>Brome grass</td>
</tr>
<tr>
<td>Retardance curve index</td>
<td>5.60</td>
</tr>
<tr>
<td>Permissible velocity</td>
<td>1.5 m/s</td>
</tr>
<tr>
<td>Design storm event</td>
<td>10-year 24-hour</td>
</tr>
<tr>
<td>Runoff</td>
<td>SCS curve number (USDA-SCS, 1990)</td>
</tr>
<tr>
<td>Peak runoff rate</td>
<td>SCS-TR 55 (USDA-SCS, 1986)</td>
</tr>
<tr>
<td>GWW design</td>
<td>USDA-NRCS effective stress (Temple et al., 1987)</td>
</tr>
</tbody>
</table>

Table 2. Error matrix to assess predictive performance of CTI model.

<table>
<thead>
<tr>
<th>Model Prediction</th>
<th>Presence of GWWs</th>
<th>Absence of GWWs</th>
<th>Total Features Present</th>
</tr>
</thead>
<tbody>
<tr>
<td>Presence of GWWs</td>
<td>(a)</td>
<td>(b)</td>
<td>((a + b))</td>
</tr>
<tr>
<td>Absence of GWWs</td>
<td>(c)</td>
<td>(d)</td>
<td>((c + d))</td>
</tr>
<tr>
<td>False positive rate</td>
<td>(b / (a + b))</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>False negative rate</td>
<td>(c / (a + c))</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

\(a\) = the number of GWW line features for which the model predicted a need for GWWs when GWWs were present.

\(b\) = the number of GWW line features for which the model did not predict a need for GWWs when GWWs were present.

\(c\) = the number of GWW line features for which the model did not predict a need for GWWs when GWWs were present.

\(d\) = the number of GWW line features for which the model predicted no need for GWWs, and no GWWs were present.
RESULTS AND DISCUSSION

PLAN CURVATURE

The plan curvature has been previously described as the most useful terrain attribute in a CTI model and identifies the rapid changes in the slope and areas of flow convergence in the landform topography (Parker et al., 2007; Pike et al., 2009). A negative plan curvature indicates that the surface is concave at that pixel, and thus the flow converges at that location, while a positive plan curvature indicates that the surface is convex at that pixel, and thus flow diverges at that location. A zero value indicates that the surface is planar. Figure 2 shows the plan curvatures for fields 29 and 9 in the study area with the existing waterway boundaries. Most (78% and 67%, respectively) of the negative plan curvature pixels in fields 29 and 9 were within the GWW boundaries and followed the existing GWW shapes. Clearly, the plan curvature located the GWWs in the HGLW, as confirmed by visual interpretation of the plan curvature maps with GWW boundaries. However, the negative plan curvature pixels were not spatially connected, which could be due to areas of reduced flow convergence or flat areas in the GWWs or the fine spatial resolution of the DEM used to generate the PLANC data. The plan curvature also identified the concave surfaces of roadside ditches, as indicated by the clusters of white pixels at the north and east boundaries of field 9. The field boundaries in the watershed were manually digitized using the USDA-NASS cropland data layer (horizontal resolution of 30 m) due to the low resolution of the aerial image, and portions of the roadside ditches were included in the field during the digitization process. Therefore, agricultural fields along roads include concave surface pixels from the roadside ditches.

EROSION FEATURE IDENTIFICATION

The PLANC data were multiplied by -1 to convert the negative PLANC (converging pixels) to positive PLANC. This allows for easier interpretation of the CTI. The CTI for each pixel was determined by multiplying the slope, contributing area, and PLANC for each pixel of the DEM. As mentioned in the Methods section, a pragmatic approach was used to identify the CTI threshold for the HGLW. A CTI threshold of 30 in the HGLW produced no false negatives. Figure 3 shows the predicted locations of GWWs (CTI ≥ 30) compared with existing GWWs in the watershed. The boundaries of the existing GWW for field 34 and the model predictions are shown in the inset in figure 3.

The false positives and false negatives in the error matrix (table 1) were used to analyze the performance of the CTI model. The results of the error matrix were as follows: a is 14, b is 18, and c and d are zero. The false positive rate for the HGLW at CTI ≥ 30 was 56.25%, which indicates that more than half of the model predictions were nonexistent in the watershed. The false negative rate and the kappa coefficient of agreement were zero at CTI ≥ 30. Visual interpretation of the CTI model output showed that the model accurately predicted all 14 existing GWWs in the watershed. The error matrix output showed that the model had zero false negatives, indicating excellent model performance at CTI ≥ 30. The CTI model also predicted several GWW locations across the watershed, indicating potential for eroding channels, which can be referred to as false positives. The model output suggested new GWWs, especially in field 10, which drains directly into the lake, and that the existing GWWs in field 29 should extend farther into the field. The model may have overpredicted the need for GWWs in fields 6 and 7, as there was very little evidence of erosion during field observations in fall 2013.

The CTI model also identified some GWW locations that were not spatially connected (before the snapping procedure), which could be due to the influence of plan curva-
ture in identifying areas of reduced flow convergence. Parker et al. (2007) evaluated the significance of plan curvature in a CTI model and concluded that, despite the discontinuity in the model output, better ephemeral gully predictions were observed with CTI than with the slope-area approach.

**Impacts of CTI Threshold on Grassed Waterway Identification**

A range of threshold values (CTI = 2.5 to 200) was examined to understand the effects of calibrated CTI thresholds on GWW identification in the HGLW. The model performance for various thresholds in the HGLW is shown in figure 4. The main goal of this study was to help conservationists locate areas with greater potential for soil erosion and reduce the need for in-field surveys. With this goal in mind, efforts were focused on reducing the false negative rate rather than the false positive rate in model output. An ideal model would have zero false negatives, assuming that the validation field had no unnecessary GWWs installed.

The CTI model had zero false negatives for thresholds up to 30; thereafter, the false negatives increased slightly as the threshold increased. At CTI = 50, the false negative rate was 7.14%, as the model did not detect one of the GWWs.
in field 11. A CTI threshold of 50 did not predict any GWWs in field 30 but did identify GWW locations downstream of this field. The model was unable to detect GWWs in fields 16 and 30 with thresholds greater than 130. This may be due to the lower upslope drainage areas in these fields. Therefore, a CTI threshold of 30 appears to be the best fit for the HGLW because of the zero false negative rate and the low false positive rate. The peak false negative rate of 21% was observed at a CTI threshold of 200. The false negative rate showed an increasing trend with increasing CTI threshold, whereas the false positive rate showed a decreasing trend. Daggupati et al. (2013) observed similar trends in false positives and false negatives in locating ephemeral gullies in two Kansas fields. The false positive rates in the HGLW varied between 77% and 31% for CTI thresholds from 0 to 200. The high false positive rates do not necessarily imply poor model performance but may indicate priority areas for additional GWWs to be implemented in the watershed to control soil loss.

Closer observation of the model output maps revealed that several pixels outside the existing GWW boundaries were identified as locations for potential GWWs (fig. 5). This overestimation of GWW locations was observed in almost all the fields. To analyze the performance of the CTI model in predicting GWW locations, classification rates were calculated for fields 9 and 30 at different thresholds (fig. 4). Field 9 in particular was chosen for this analysis because it had a larger drainage area (722 ha) than any other field in the watershed, which could explain the influence of this terrain attribute on the model output. The classification rates for fields 9 and 30 varied from 46% to 89% and from 47% to 97%, respectively, for CTI thresholds between 2.5 and 200. A classification rate of more than 75% was observed for fields 9 and 30 at a CTI threshold of 30. Fields 9 and 30 had similar classification rates until the CTI threshold reached 100; thereafter, field 9 had a slightly lower classification rate than field 30. This was most likely because field 9 had a larger upslope drainage area. The GWW locations where the model predicted the need for GWWs (i.e., pixels outside the existing GWWs) lowered the classification rate.

**DESIGN OF GRASSED WATERWAYS**

The design specifications were calculated for each identified GWW by the CTI model using the effective stress method (USDA-NRCS, 2007). The time of concentration for the predicted GWWs in the HGLW ranged from 0.8 to 3.6 h, with GWWs in field 9 having the highest time of concentration in the watershed. The snapping procedure was used to connect spatially isolated pixels, and the GWW lengths were determined. The lengths of existing GWWs in the watershed ranged from 193 to 918 m, whereas the lengths of predicted GWWs ranged from 245 to 1530 m. The depth of GWWs was capped at 0.30 m (1 ft) to allow farm equipment to pass through the waterways for maintenance. The top width of predicted GWWs ranged from 3.2 to 87.3 m. The total surface area of predicted GWWs was 29.3 ha, which provides an estimate to the producer of how much land must be removed from agricultural production to reduce ephemeral gully erosion. Figure 6 compares the lengths of existing GWWs with the lengths of predicted GWWs. Of the 14 model-predicted GWWs, four fell below the 1:1 line, indicating underprediction of those GWW lengths. The model underprediction could be due to planar surfaces in the GWWs. For example, the length of the existing GWW in field 11 was 717 m, while the model-predicted length was only 443 m. The PLANC data for field 11 indicated that the surface was planar; therefore, the model underpredicted the GWW length. An $r^2$ value of 0.28 was obtained between the predicted and observed GWW lengths. If field 26 was removed from the comparison, an $r^2$ value of 0.53 was obtained. The CTI model with a threshold of 30 resulted in a PBIAS value of -23.34, indicating that the CTI model overestimated the GWW lengths. The overestimation could be the CTI model suggesting a need for extending the existing GWWs.

Field and farmer surveys in the watershed indicated that
the GWWs in fields 5, 16, and 31 were installed by the producer and need to be regraded every couple of years to control soil erosion. The producers would have been able to better control soil erosion by using field-specific USDA-NRCS design specifications and would have received CRP payments from the USDA Farm Service Agency for GWW maintenance and installation in environmentally sensitive areas.

CONCLUSIONS
This study illustrated an approach that can be used to identify potential sites where GWW placement will be most effective at the watershed scale. The results of this study suggest that LiDAR-derived terrain attributes were able to accurately identify potential locations for GWWs in the HGLW. Farmers and USDA-NRCS conservationists may benefit from the output maps for locating environmentally sensitive areas. The CTI model had satisfactory predictive ability in locating GWWs using 3 m LiDAR data. However, the model calibration may limit the application of this method in other geographic areas with no field-sampled data. The model thresholds played a major role in identifying GWW locations, and model thresholds may vary among physiographic regions. Further research is needed on strategies for establishing model thresholds in the absence of validation data.

Field surveys guided by terrain analysis could identify the majority of the erosion features in a short time and greatly reduce the cost and need for field surveys. Ephemeral gully formation depends on factors such as tillage practices, cover crops, and the magnitude of rainfall events, which were ignored in the CTI model. Therefore, there is also a need to determine if including crop management practices, soil properties, and precipitation characteristics in the methodology used in this study can improve the identification of GWW locations. The design of identified GWWs provided an estimate of the land that needs to be removed from production if the farmer wants to enroll in the CRP incentive program. Targeted placement of conservation practices can mitigate soil degradation and maximize the benefits for water quality.

ACKNOWLEDGEMENTS
The authors would like to thank Aaron Andrews and Rose Danaher (Hickory Grove Lake watershed coordinators) and Nick Terhall and Conrad Brendel for their assistance with the farmer and field surveys.

REFERENCES


